ISSUES ON LIQUIDITY, MACROECONOMICS, MONETARY, INVESTMENT AND ENERGY MARKETS

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DECLARATION OF AUTHORSHIP

I, Mohammad Husaini Haji Md Said, hereby declare that this thesis and the work presented in it is entirely my own. Where I have consulted the work of others, this is always clearly stated.

Signed: _____

Date: _____July 2017_____

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ABSTRACT

Liquidity has always been part of finance theory but the importance of liquidity has been magnified due to the recent financial crisis. Although the number of studies on liquidity have increase over the years, some questions remains unanswered as past research tend to focus on US market. Therefore, the objective of this PhD is to answer some of the questions by investigating the potential of illiquid as an investment style, as well as the relationship of illiquidity with variables such as monetary conditions and oil. The PhD thesis also studies countries other than the US.

Chapter one outlined the aims of this PhD thesis, while chapter two provides the literature review. Chapter three is the first empirical chapter and it finds evidence to support the claim that market liquidity and individual stock pricing due to illiquidity are both affected by monetary conditions, justifying the intervention of central banks when required.

Chapter four is the second empirical chapter, which focuses on the ability of illiquidity as an investment style in the UK during the financial crisis. The results show that illiquidity can be a reliable style for the seven years pre-crisis period and it is found to be more stable after the crisis. Chapter five investigates the same issues but with longer periods and two additional analyses involving *covariance versus characteristics* and *January effect.* However, unlike Ibbotson et al. (2013) study on US, illiquidity is found to be strongly correlated to size for both chapters.

Chapter six and seven are the last two empirical chapters and it investigates illiquidity and energy markets by comparing net oil exporters and importers. Chapter six studies the asymmetric effect of oil price and illiquidity shocks on economic growth and it finds evidence contradictory to past literature, as most countries response to negative oil price shocks. Moreover, illiquidity shocks appear to provide clearer results. Chapter seven investigates the relationship between economic growth and predictive variables such as *national liquidity, global liquidity, oil and Baltic Dry.* Results show that oil have the highest explanatory power in predicting economic growth while global liquidity has better explanatory power to national liquidity. Furthermore, it is discovered that oil is more important for the economies of net oil exporters relative to net oil importers.

Chapter eight summarises the overall findings and concludes on the significance of liquidity for finance theory, as central banks can use it to stabilise the market and investors can use it as an investment style. Even though liquidity provides less ability to predict economic growth compared to oil, liquidity still provides some explanatory power.

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LIST OF ABBREVIATIONS

ADF	Augmented Dickey-Fuller test
AIC	Akaike information criterion test
AM	Arithmetic mean
AMEX	American Stock Exchange
AMH	Amihud Illiquidity Measure
AR	Autoregressive
ASD	Arithmetic standard deviation
BD	Baltic Dry Index
B/M	Book-to-market ratio
BOE	Bank of England
Bovespa index	A share index of companies listed on the Sao Paulo Stock Exchange in Brazil
BRL	Brazilian Real - Currency of Brazil
CAD	Canadian Dollar - Currency of Canada
CAPM	Capital Asset Pricing Model
C/P	Cash flow-to-price ratio
CPI	Consumer Price Index
DC	District of Columbia
DEP	Dependent Variables
DFGLS	GLS detrended Dickey-Fuller test
DJIA	Dow Jones Industrial Average - A share index of 30 significant companies traded on the NYSE and the NASDAQ
DKK	Danish Krone - Currency of Denmark
DSE	Dhaka Stock Exchange
DY	Dividend Yield
ECB	European Central Bank
EMH	Efficient Market Hypothesis

EIA	US Energy Information Administration
ERS	Elliot, Rothenberg, and Stock Point Optimal test
EUR	Euro Dollar - Currency of European Union.
EXR	Excess Market Returns
FPE	Final Prediction Error test
FTSE All Share Index	A share index of all the companies listed on the London Stock Exchange in United Kingdom
FV	Financial variables - inclusive of risk free rate (RF), standard deviation or market volatility (SD), excess market returns (XS) and Dividend yield (DY).
G7	Group of seven countries - Consisting of Canada, France, Germany , Italy, Japan, UK and US
GAM	Global illiquidity based on Amihud illiquidity Measure
GBP	Pound Sterling – Currency of United Kingdom
GCC	Gulf Cooperation Council – Consisting of Bahrain, Kuwait, Oman, Qatar, Saudi Arabia and United Arab Emirates
GDP	Gross Domestic Product
GNP	Gross National Product
HLA	High-Low Spread (Adjusted) – Illiquidity measure
HML	Value premium – Value minus growth stocks portfolio
HQ	Hannan-Quinn information criterion test
ILLIQ	Illiquidity measure
IML	Illiquid minus liquid stocks portfolio
IPC index	A stock market index of companies listed on the Mexican Stock Exchange in Mexico
IR	Information ratio
ISE	Istanbul Stock Exchange
JPY	Japanese Yen – Currency of Japan

JSE	Johannesburg Stock market
KPSS	Kwiatkowski, Phillips, Schmidt, and Shin test
LDC	Least Developed Countries
LIBOR	London Interbank Offered Rate
LIQ	Liquidity
LR	Likelihood Ratio test
LSE	London Stock Exchange
MACRO	Macroeconomic Variables
MOM	Momentum Portfolio
MV	Market value
MXN	Mexican Peso – Currency of Mexico
NAM	National illiquidity (Amihud Illiquidity Measure)
NASDAQ	National Association of Securities Dealers Automated Quotations
NBER	National Bureau of Economic Research
NFX	National Foreign Exchange
NIKKEI 225	A stock market index of companies listed on the Tokyo Stock Exchange in Japan
NOK	Norwegian Krone – Currency of Norway
NP	Ng and Perron test
NYSE	New York Stock Exchange
OB	Crude oil Brent
OECD	Organisation for Economic Co-operation and Development
OMXC Index	A stock market index of companies listed on the Copenhagen stock exchange in Denmark
OPEC	Organization of the Petroleum Exporting Countries
Oslo All Share index	A stock market index of companies listed in Norway

OTC	Over the counter
P/B ratio	Price-to-book ratio
P/C ratio	Price-to-cash-flow ratio
P/E ratio	Price-to-earnings ratio
PhD	Doctor of Philosophy
PP	Phillips-Perron test
PV	Predictive variables - inclusive of national foreign exchange (NFX), national illiquidity (NAM), global illiquidity (GAM), crude oil Brent (OB) and Baltic Dry Index (BD)
Prime All Share Index	A stock market index of companies listed in Germany
RE	Roll Estimator – Illiquidity Measure
RF	Risk free rate
S&P 500	Standard & Poor's 500 - A stock market index of 500 leading companies listed in the United States
SBF 120 index	A stock market index of companies listed in France
SD	Standard deviation or market volatility
SGD	Singapore Dollar – Currency of Singapore
SIC	Schwarz information criterion test
SMB	Size premium – Small minus big stocks portfolio
SR	Sharpe ratio
STI Index	A stock market index of companies listed in Singapore
TR	Treynor ratio
TSE	Tokyo Stock Exchange
TSM	Taiwanese stock market
TSX Composite index	A stock market index of companies listed in Canada
UK	United Kingdom

UNCTAD	United Nations Conference on Trade and Development
US	United States
USD	United States Dollar – Currency of United States
WTI	West Texas Intermediate
WW	World–War
XS	Excess market returns
VAR	Vector Autoregression

CHAPTER 1 : INTRODUCTION

The financial crisis of 2007/ 2008 is an important event for the global financial markets, as three top economists agree that this crisis is one of the worse crises since the great depressions (Roubini, Rogoff, & Behravesh, 2009). Brunnermeier (2009) highlights that the crisis might drag on over the next few years and threatens to have large repercussions on the real economy. Due to the severity of the crisis to the global economy, various studies have emerged trying to explain how the crisis happened in the first place. Crotty (2009) highlights that financial deregulation, complex financial products, liquidity dry-outs and investors running for liquidity and safety as some of the reasons for the crisis. Cornett, McNutt, Strahan, and Tehranian (2011) mention that liquidity dried up at banks due to the freezing of interbank markets and the collapse of asset-backed and mortgage-backed securities markets. Nonetheless, liquidity (or illiquidity) appears to be one of the obvious reasons, as some researchers refer to the crisis as either liquidity crisis or liquidity crunch (Iyer, Peydró, da-Rocha-Lopes, & Schoar, 2014).

The importance of liquidity is shown as Citigroup CEO Charles Prince made a comment in July 2007, *"When the music stops, in terms of liquidity, things will be complicated. But as long as the music is playing, you've got to get up and dance. We're still dancing" (Nakamoto & Wighton, 2007)*

Nevertheless his comments as highlighted by Crotty (2009) also reflect both the power of perverse incentives and the destructive dimensions of financial market competition due to liquidity, as companies would be able to take on major risks when there is enough liquidity available. Hence, resulting in the financial crisis.

Due to the financial crisis and developments in the financial sector that have resulted in greater finance access (Rajan, 2006), the study of liquidity has become more prominent. An earlier liquidity research by Amihud and Mendelson (1986) study the relationship between expected returns and bid-ask spreads of *New York Stock Exchange (NYSE)* stocks and they discovered that market-observed average returns are an increasing function of the bid-ask spread. Moreover, Acharya and Pedersen (2005), using *capital asset pricing model (CAPM*) on NYSE and *American Stock Exchange (AMEX)* from July 1962 to December 1999 show that their model provides evidence of the importance of liquidity on asset prices.

Furthermore, it is commonly known that Central Banks such as the Federal Reserve use monetary policy to stabilize the financial system (Cornett et al., 2011) and since liquidity is an issue during the crisis, there are studies done on the effect of monetary conditions on market liquidity. For instance, by studying the NYSE and AMEX for the period from 1962 to 2003, Goyenko and Ukhov (2009) find strong evidence that monetary policy predicts illiquidity while Jensen and Moorman (2010) highlight that expansive shifts correspond with an increase in market liquidity while restrictive shifts bring about a drop in market liquidity. Therefore, chapter three which is our first empirical chapter, focuses on any possible relationship between monetary conditions and illiquidity by using the Jensen and Moorman (2010) framework. Jensen and Moorman (2010) focus on the *United States (US)* market, while we on the contrary focus on the *United Kingdom (UK)* market and also discuss the financial crisis.

Past evidences on illiquidity appears to indicate that returns will increase with illiquidity (Amihud & Mendelson, 1986). This signifies the potential of illiquidity portfolios as an investment style. The relationship between returns and illiquidity is quite obvious, Ibbotson, Chen, Kim, and Hu (2013) mention that investors clearly want more liquidity and hence, illiquidity should be compensated with additional returns. Thus, chapter four investigates the potential of illiquidity as a reliable and consistent investment style during the financial crisis, by using 14 years UK data divided equally into pre-crisis and post-crisis sample periods.

Nonetheless, Beneda (2002) highlights that the research time-period is important as it is shown that over a longer period (at least 14 years), average returns for growth stocks are found to be superior to value stocks. Although research during the financial crisis can provide valuable insights, we believe that research can be improved by using a longer sample period. Hence, chapter five is an extension of chapter four, whereby we will also study illiquidity as an investment style in the UK but using a longer data period of 23 years. We have also included more analysis in chapter five such as an investigation into

the "*covariance vs characteristics model*[1]" and *"January effect*[2]*"*, in order to make the study on illiquidity more thorough.

Similar to liquidity, oil has also some effect on the recent financial crisis of 2007-2008, Taylor (2009) mentions that oil price increases have prolonged the financial crisis. Moreover, some researchers have also acknowledged the relationship between the two variables. For instance, Ratti and Vespignani (2013) find evidence that relative to developed economies, the cumulative impact of China's liquidity (measured by money supply) on the real price of crude oil is large and statistically significant. Due to this development, oil and liquidity research should be fascinating for academics and practitioners within the financial and energy sectors.

Past literature such as Hamilton (1983)[3] appears to show that crude oil does impact the economy of countries. Nonetheless, we believe researching asymmetric effects[4] of oil on economic growth is also important, as earlier research such as Hamilton (1983) tends to focus only on oil price increases. However, Engemann, Owyang, and Wall (2014) study on US states discover that around 35 states are affected by positive oil price shocks only[5]**.** Similar to oil, we feel that there are potential asymmetric effects as far as illiquidity is concerned, as Said and Giouvris (2017) discover that the reaction of liquidity after restrictive monetary shifts appears to be less noticeable compared to expansive monetary shifts. This signifies potential asymmetric effects of positive and negative illiquidity shocks[6] on the economy. Although research on illiquidity asymmetries would be interesting and beneficial within the current environment, surprisingly, there is actually

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[1] "Characteristics model" use financial ratios such as B/M ratio to measure the expected return of stocks while "covariance model" considers returns sensitivity to factors such as value factors (or value premium) (Daniel and Titman 1997). Daniel and Titman (1997) mention that stock returns due to covariance model signifies riskiness of stocks while characteristics model means stocks are under-priced. By comparing the two models, it will allow us to investigate which model construct the better performing portfolio. Ibbotson, Chen et al. (2013) who also test the theory using a different investment style factor namely the illiquidity factor, indicate that the "characteristics model" performs better than the "covariance model".

[2] The January effect is a seasonal anomaly whereby prices or returns increases in the month of January in comparison to other months. Wachtel (1942) is one of the first to observe this in the US market (DJIA). Interestingly, January effect is commonly linked to the various investment styles. For example, Fama and French (1992) signify its appearance within value style while Keim (1983) mentions its existence within size effect. De Bondt and Thaler (1985) comment on it in his study of momentum style while Eleswarapu and Reinganum (1993) highlight of its presence within illiquidity premium.

[3] Hamilton (1983) who underlines that there is a significant increase in the price of crude petroleum prior to seven of the eight post World War II recessions in the US.

[4] Similar to Engemann, Owyang et al. (2014), we define an asymmetric effect when a country responds to either positive or negative oil price shocks while a symmetric effect occurs when a country responds to both shocks (positive and negative) or does not respond at all.

[5] Oil price shocks are calculated by comparing the current oil price with where it has been over the previous one (1) year or previous four (4) quarters as proposed by Hamilton (1996). For instance, positive oil price shocks are calculated as below (Engemann, Owyang et al., 2014):

$$\Delta x_t^+ = max\left\{0, 100 \times ln\frac{x_t}{max(x_{t-1}, x_{t-2}, x_{t-3}, x_{t-4})}\right\} \quad (1.1)$$

Where x_t is crude oil Brent price at quarter t and $x_{t-1}, x_{t-2}, x_{t-3}, x_{t-4}$ are the crude oil Brent price of the previous four (4) quarters. Please refer to chapter four (data and variables section) for more information.

[6] Hamilton (1996) equation for calculating oil price shocks appears to be simple enough and we feel that it can be applied to measure the shocks of other variables including illiquidity shocks.

limited research available. In order to close this gap, chapter six will research the asymmetric effects of oil price shocks and illiquidity shocks on the economy of multiple countries.

As highlighted earlier, past literature such as Hamilton (1983) appears to show that crude oil does impact the economy of countries while Cuñado and de Gracia (2003) study 15 European countries and find evidence of oil price shocks affecting macroeconomic variables such as inflation and industrial production indexes. Similarly, studies have emerged on the impact of liquidity on macroeconomic variables such as Næs, Skjeltorp, and Ødegaard (2011) who mention that at least since World-War II (WWII), market liquidity contains useful information for estimating the current and future state of the US and Norway economy. Galariotis and Giouvris (2015) expand this line of research by studying G7 countries and they find evidence that market liquidity may contain some information for predicting the current and future state of the G7 economies. Even though both oil prices (Hamilton, 1983) and liquidity (Galariotis & Giouvris, 2015) are related to economic growth, there are no research available that investigates the combined effect of the two variables. Therefore, chapter seven studies the impact of oil and market liquidity on the future state of the economy.

Chapter seven also includes *national foreign exchange (NFX)* and *Baltic Dry index (BD)* as part of the variables in order to make the study more comprehensive. *National foreign exchange rate (NFX)* is included because Cunado and De Gracia (2005) highlight that the effect of oil on economic activity becomes more significant when oil is defined in local currencies. *Baltic Dry index (BD)* is included because it is commonly used as an indicator of economic activity reflecting global demand for raw materials (Bakshi, Panayotov, & Skoulakis, 2011).

Since Engemann et al. (2014) highlight that most energy intensive US states appear to respond only to negative oil price shocks, it appears that the characteristics of the states or countries are also important in relation to oil research. Surprisingly, past studies seldom differentiate between oil exporting countries and oil importing countries, as highlighted by Wang, Wu, and Yang (2013). Due to this, chapter six and seven will also investigate the effect of oil on the economies of net oil exporting countries and net oil importing countries.

To summarise, this thesis aims to investigate i) the relationship between illiquidity and monetary conditions in the UK, ii) the potential of using illiquidity as an investment style

during the financial crisis and over longer periods, iii) the covariance versus characteristics portfolio construction models as well as the January effect with regards to the investment styles, iv) responses of multiple countries to oil price shocks and illiquidity shocks and v) the relationship between macro-economy and various predictive variables such as oil, Baltic Dry index and market liquidity for net oil exporting countries and net oil importing countries.

The thesis contributes to the literature in several ways as follows:

- It shows that the relationship between illiquidity and monetary conditions does not exist only in the US market but also in the UK markets. It also supports the claim that market liquidity and individual stock pricing due to illiquidity are both affected by monetary conditions, justifying the intervention of central banks when required.

- It shows that illiquidity can be a reliable investment style for the seven years pre-crisis period. Although it is profitable post-crisis, results are less convincing. Nonetheless, illiquidity portfolios are found to be more stable post-crisis, signifying investors' preference for illiquidity based portfolios as well as profit opportunities with lower transaction costs.

- It shows that over longer periods, illiquidity portfolios are able to outperform the market and enhance the performance of value and momentum styles. Data migration test revealed that illiquidity stocks are stable over time and it appears that the January effect of value and size is actually due to illiquid stocks. Moreover, compared to "covariance model", "characteristics model" may be the best way to construct illiquidity portfolios as it provided consistent results.

- It shows that the countries in our sample consisting of 5 net oil exporters and 6 net oil importers are mostly affected by negative oil price shocks. With regards to illiquidity shocks, most countries significantly respond to positive illiquidity shocks and remarkably, illiquidity shocks appear to be more consistent in comparison to oil price shocks.

- It shows that that global illiquidity (GAM) provides greater overall explanatory power compared to national illiquidity (NAM). Baltic Dry index (BD) also provides some explanatory power while national foreign exchange (NFX) is the only variable that has no predictive ability when all countries are included. Nevertheless,

oil (OB) is the most important predictive variable for net oil exporters while Baltic Dry index (BD) appears to be more important for net oil importers.

- It shows that there is a two-way causality between GDP and our predictive variables namely global illiquidity (GAM), Baltic Dry index (BD) and oil (OB). Oil (OB) continues to be important for net oil exporters, as the two-way causality disappears for net oil importers.

The structure of the thesis is as follows. In chapter two the established literature which is relevant to the economics of liquidity, investment styles, oil price shocks, asymmetric effect and Baltic Dry Index are reviewed. The purpose of the literature review is to provide the theoretical foundations for the empirical studies that has been conducted, in order to highlight related past studies and identify any potential research gaps. Nevertheless, the literature specific to each of the issues studied are also presented at the beginning of each empirical chapters to make it easier for the readers.

Chapter three is the first empirical chapter and discusses the relationship between illiquidity and monetary conditions as well as the financial crisis by studying the UK market, as past research tend to be US focused. The study feels that UK market has strong research potential as its stock market is considered as one of the largest stock markets by capitalisation. The study uses the Jensen and Moorman (2010) framework. Two monetary condition measures are chosen namely the *Bank of England (BOE) base rate* and the *London Interbank Offered Rate (LIBOR).* The chapter starts by investigating if there are any unconditional return differences for illiquid and liquid stocks, followed by a conditional monetary policy investigation involving market liquidity and zero-cost portfolio[7] returns respectively. Overall, our research of the UK market shows that illiquid stocks generate higher returns compared to liquid stocks and when considering monetary conditions, expansive monetary conditions result in an increase in market liquidity and higher zero-cost portfolio returns. Moreover, the crisis has an effect on market liquidity and illiquidity premium but it is more noticeable for the former. Nevertheless, compared to Jensen and Moorman (2010), our overall results are weaker probably due to the lower volatility in the UK market relative to the US market (Bartram, Brown, & Stulz, 2012).

[7] Zero-cost portfolio = long the Illiquid portfolio and short the Liquid portfolio. Therefore, it is similar to the illiquidity premium as described by other researchers such as Eleswarapu and Reinganum (1993).

Chapter four and five are the next two empirical studies and both investigate the potential of illiquidity as an investment style in the UK, as it is believed that it should be given equal standing with other widely known investment styles such as value, growth and momentum. The two chapters are conducted using Ibbotson et al. (2013) framework and Sharpe (1992) four benchmark portfolio criteria[8]. Both chapters start by investigating whether the respective investment styles' premium[9] including illiquidity premium exist within the UK market. This is followed by investigations on double sorted quartile portfolios, which are the intersection between illiquidity and the other investment styles. Lastly, stock migration analysis is conducted to investigate the stability of the portfolios. As highlighted earlier, the difference between the two chapters is that chapter four uses financial crisis data while chapter five uses a longer data period.

Chapter four divides 14 years of financial crisis data equally into pre-crisis and post-crisis sample periods which will allow us to assess the extent to which illiquidity is a good trading strategy pre and post-crisis. Our results show that illiquidity can be a reliable investment style for the seven years pre-crisis period. Although it is profitable post-crisis, results are less convincing. Nonetheless, illiquidity portfolios are found to be more stable post-crisis, signifying investors' preference for illiquidity based portfolios as well as profit opportunities with lower transaction costs. Nevertheless, unlike Ibbotson, Chen et al. (2013) in their US study, illiquidity is found to be strongly correlated to size for both periods.

Chapter five uses a longer data period of 23 years but we have also included an investigation into the *covariance versus characteristics models* and the *January effect*. Our findings show that illiquidity portfolios are able to outperform the market and enhanced the performance of value and momentum styles. Data migration tests revealed that illiquidity stocks are stable over time and it appears that the January effect of value and size is actually due to illiquid stocks. Overall, our results support that illiquidity is a reliable investment style that should have equal standing with the other styles. However, similar to chapter four, illiquidity is found to be strongly correlated to size.

In comparison to Ibbotson, Chen et al. (2013), our results for chapter four and five are also weaker probably due to the different liquidity measure used and characteristic of the

[8] Sharpe (1992) establishes that a benchmark portfolio should be 1) identifiable before the fact, 2) not easily beaten, 3) a viable alternative, and 4) low in cost.

[9] An Investment style premium happens when one specific style performs better than its relevant antagonist style. For example, value premium (value portfolio returns > growth portfolio returns) and growth premium (value portfolio returns < growth portfolio returns).

UK market such as the lower volatility in the UK market relative to US market (Bartram, Brown, & Stulz, 2012).

Chapter six investigate the responses of multiple countries economy to oil price shocks and illiquidity shocks by focusing on asymmetric effects. The chapter uses Engemann et al. (2014) framework but instead of using US states, we will be using eleven (11) countries, categorised as net oil exporting and net oil importing countries. We have developed oil and illiquidity shocks using the Hamilton (1996) equation to investigate their link to the economy. Furthermore, instead of using payroll employment, we decide to use *Gross Domestic Products (GDP)* as a proxy for macroeconomic activity because it is readily available for the countries in our sample.

Chapter six shows that similar to past research, our result shows some relationship between oil price shocks and the economy. However, although our results display an asymmetric effect for oil price shocks, unlike Engemann et al. (2014) the countries in our sample are mostly affected by negative oil price shocks. With regards to illiquidity, most countries respond significantly to positive illiquidity shocks and remarkably, illiquidity shocks appear to be more consistent in comparison to oil price shocks. Overall our study shows that illiquidity shocks appear to be at least an equally important determinant of the state of the economy compared to oil price shocks which are thought to be one of the most important factors for a number of years. Finally, nationalising oil price shocks does not appear to provide any obvious improvement in results when testing for asymmetric effects.

Chapter seven is the last empirical study and it attempts to investigate the ability of five related predictive variables on economic growth. The five predictive variables are consisting of crude oil Brent (OB), national illiquidity (NAM), global illiquidity (GAM), national foreign exchange (NFX) and Baltic Dry index (BD). The study uses the Galariotis and Giouvris (2015) framework and focuses on ten countries, segregated equally into net oil exporters and net oil importers, allowing us to investigate which predictive variables affect macroeconomic activity[10] of the two group of countries. Finally, the study also splits our net oil exporting countries into developed and emerging countries. Our findings show that global illiquidity (GAM) provides greater overall explanatory power compared to national illiquidity (NAM). Baltic Dry index (BD) also

[10] The paper uses Gross Domestic Product (GDP) as a proxy for macroeconomic indicator or variable.

provides some explanatory power while NFX is the only variable that has no predictive ability when all countries are included. Nevertheless, oil (OB) is the most important predictive variable for net oil exporters while Baltic Dry index (BD) appears to be more important for net oil importers. Finally, there is a two-way causality between GDP and our predictive variables namely global illiquidity (GAM), Baltic Dry index (BD) and oil (OB). Oil (OB) continues to be important for net oil exporters, as the two-way causality disappears for net oil importers.

Lastly, Chapter eight summarised the main results of the PhD thesis and the concluding remarks are made.

CHAPTER 2 : LITERATURE REVIEW

2.1. INTRODUCTION

Chapter two provides an overall review of the existing literature that is relevant to this PhD thesis. This chapter discusses various strands of literature such as liquidity, investment styles, oil price shocks, asymmetric effect and the Baltic Dry Index. The purpose of the chapter is to provide the theoretical foundations of past empirical studies in order to evaluate related past studies and identify any potential research gaps.

This chapter is structured as follows: Section 2.2 and 2.3 introduce liquidity literature whereby section 2.2 discusses liquidity in general while section 2.3 compares accounting and market liquidity. Section 2.4 presents the overall literature review on the difference between illiquid and liquid assets as well as the role of liquidity in asset pricing. Since liquidity is the main theme of the PhD thesis, this section discusses the importance of liquidity in asset pricing and is relevant to all five empirical chapters. Section 2.5 presents the literature review that is relevant to our first empirical chapter which covers the relationship between illiquidity and monetary conditions.

Section 2.6 contains a review of literature involving investment styles and the potential of using illiquidity as an investment style which are relevant to the second and third empirical chapters. This section also includes a discussion regarding *covariance versus characteristics models* and the *January effect* which are more relevant to the third empirical chapter.

Section 2.7 presents literature covering the last two empirical chapters. The earlier part of the section includes literature regarding the relationship between the macro-economy and illiquidity as well as oil. Other than that, this section also provides a review regarding the importance of the countries characteristics of being either a net oil exporter or net oil importer.

The latter part of the literature is more specific to the fourth and fifth empirical chapters. The literature review in section 2.8 is in relation to asymmetric effects and it is relevant to the fourth empirical chapter while section 2.9 is related to the fifth empirical chapter since it reviews the Baltic dry index (BD) and national foreign exchange (NFX) relationship with the macro-economy. Section 2.10 involves literature that is also mainly

applicable to the fifth empirical chapter and it is regarding causality between macro-economy and various predictive variables. Finally, section 2.11 provides a summary of the overall PhD hypotheses or research questions that will be investigated in the subsequent chapters.

However, as highlighted in the previous chapter, the literature specific to each of the issues researched are also presented at the beginning of each empirical chapters to make it easier for the readers to follow each chapters.

2.2. WHAT IS LIQUIDITY?

Liquidity in general term relates to the easiness of conversion of assets to cash. Moffatt (2017) defines liquidity as how quickly and cheaply an asset can be converted into cash while Mueller (2017) describes liquidity as the degree to which an asset can be quickly bought or sold in the market without affecting the asset's price. In this regard, the most liquid asset would be cash (or money), as cash is already cash and can be used immediately and easily (Mueller, 2017), while illiquid assets are generally assets that can only be sold (or converted to cash) after a long exhaustive search for a buyer and usually with some penalty (Moffatt, 2017).

Cash (or money) is important for liquidity measurement, as other assets tend to be compared to cash in order to measure the liquidity of such assets. For instance, “certificates of deposit” are considered to be slightly less liquid relative to cash, because there is usually some penalty for converting “certificates of deposit” to cash before the maturity date. Similarly, other financial assets such as stocks and bonds are also considered fairly liquid, because such assets usually can be sold readily and an investor can receive their cash within a few days but sometimes with a minor penalty. Such financial assets can also be considered as “cash or cash equivalents” because the assets can be converted to cash with little effort or penalty (Mueller, 2017).

As mentioned by Moffatt (2017), illiquid assets tend to be more difficult to sell and Mueller (2017) states that such assets take more effort or time before the assets can be converted to cash. For example, although preferred shares are also considered as financial assets, usually preferred shares tend to have covenants dictating how and when the assets

may be sold and hence preferred shares are considered less liquid compared to cash and ordinary shares.

Relative to cash, real estate is another obvious example of less liquid asset because real estate can take weeks or months to sell or convert to cash. For example, if a homeowner plans to sell his/ her real estate to another homeowner, the homeowner may obtain full value with negotiations but it may take time, even with the current technological advancement. Nevertheless, if the homeowner goes to a realtor instead, the homeowner can get his/ her cash quicker but the homeowner may receive less of it due to fees and commissions payable to the realtor. Moreover, a homeowner may have to sell the real estate at a discount, if the homeowner needs immediate cash to meet his/ her financial obligations. Thus, real estate can be considered as an illiquid assets relative to cash and financial assets such as shares. Other examples of illiquid assets include items such as coins, stamps, art and other collectibles (Mueller, 2017)

Liquidity is important for both individuals and companies as a rich individual or successful company may still be in trouble if the individual or company are unable to convert their assets into cash when required. Therefore, banks are important as it provides liquidity for individuals and companies when required but at a price. Nevertheless, individuals and companies should understand liquidity, as proper liquidity management helps individuals and companies from going into future financial troubles. (Mueller, 2017)

2.3. ACCOUNTING LIQUIDITY AND MARKET LIQUIDITY

There are two types of liquidity that should also be considered namely “accounting liquidity” and “market liquidity” (Liquidity, n.d,). Although slightly different, both accounting liquidity and market liquidity relate to cash and how easily the assets can be converted to cash. For instance, accounting liquidity looks into meeting financial obligations using liquid assets such as cash while market liquidity refers to the timing in which assets can be sold and the impact that the selling process has on the stock's price.

There are several ratios and measurements available in order to express accounting liquidity and market liquidity.

2.3.1. ACCOUNTING LIQUIDITY

Accounting liquidity refers to the ease in which individuals or companies can use their available liquid assets (such as cash) in order to meet their financial obligations. According to Mueller (2017), cash should be considered as a company's lifeblood signifying the importance of accounting liquidity. A company can sell lots of products and have good net earnings but if the company cannot collect the actual cash from its customers on a timely basis as well as not having liquid assets available to them, the company will be unable to pay its own financial obligations (such as debts), potentially resulting in bankruptcy (Mueller, 2017). Moreover, a company with illiquid assets (such as real estate) will need to sell its assets at a big discount if the company does not have cash or liquid assets to meet its financial obligations. During hard times for the business or the economy, a company with insufficient liquidity may be forced to make tough choices to meet their obligations. (Wohlner, 2017).

There are a number of ratios that measure accounting liquidity and the measures tend to compare liquid assets to current liabilities based on different portions of the company's current assets and current liabilities taken from the firm's balance sheet. (Wohlner, 2017).

$$\text{Current Ratio} = \frac{\text{Current Assets}}{\text{Current Liabilities}} \tag{2.1}$$

Where current assets are assets that can reasonably be converted to cash within one year while current liabilities are financial obligations with duration of one year or less.

$$\text{Quick Ratio} = \frac{(\text{Cash and Cash Equivalents} + \text{Short Term Investments} + \text{Accounts Receivable})}{\text{Current Liabilities}} \tag{2.2}$$

Where the ratio excludes "inventories" and "other current assets" from the "current assets". Current liabilities are still financial obligations with duration of one year or less.

$$\text{Cash Ratio} = \frac{(\text{Cash and Cash Equivalents} + \text{Short Term Investments})}{\text{Current Liabilities}} \quad (2.3)$$

Where the ratio excludes "accounts receivable" as well as "inventories" and "other current assets" from the "current assets". Current liabilities are still financial obligations with duration of one year or less.

2.3.1.1. SUMMARY OF ACCOUNTING LIQUIDITY RATIOS/MEASURES

Among the three "accounting liquidity ratios", the "current ratio" is considered as the simplest and least stringent ratio. The "quick ratio" (or acid-test ratio) is slightly stricter compared to current ratio because the ratio excludes "inventories" and "other current assets", which are less liquid current assets relative to "cash and cash equivalents", "accounts receivable" and "short-term investments". Thus, relative to current ratio, the quick ratio is conceivably a better barometer of the assets' coverage for the company's current liabilities, should a company experience any financial difficulties (Wohler, 2017).

Nevertheless, the "cash ratio" is the most demanding of the accounting liquidity ratios, as the ratio also excludes accounts receivable and hence the cash ratio shows the level of a company's cash and near-cash investments relative to the company's current liabilities. According to Wohler (2017), the cash ratio is almost like an indicator of a company's value under the worst-case scenario where the company is about to go out of business. The cash ratio will inform investors the value of current assets that could quickly be turned into cash, and the percentage of the company's current liabilities, such assets can covered. Thus, the cash ratio, also assesses a company's ability to stay solvent in a crisis, which is quite important as even highly profitable companies can run into trouble if they do not have the liquidity to react to unexpected events.

A high accounting liquidity ratio appears to be better, as it signifies that a company is better positioned to cover its current liabilities. Nevertheless, companies with a seemingly high liquidity ratio may not be in a safer or better position than a company with a relatively low liquidity ratio. Therefore, an investor should also look at the composition and quality of the company's current or liquidity assets. For instance, with regards to *"current ratio"* a company with good quality current assets such as inventory will allow

the company to liquidate its inventory quicker if required, relative to a company with bad quality current assets (Wohlner, 2017).

Other issues should also be considered, as it is not realistic to assume that a company will liquidate all current assets that is part of a liquidity ratio in order to cover current liabilities because the company still needs a level of working capital to remain a going concern. Moreover, it is not realistic for a company to maintain excessive levels of cash and near-cash assets to cover its short-term debts. In fact, it is often seen as poor asset utilization for a company to hold large amounts of cash on its balance sheet, as the funds can be returned to shareholders or used elsewhere to generate higher returns (Wohlner, 2017).

Finally, Lancaster et al (1998) highlight that changes in company liquidity is sensitive to the sample period and liquidity ratios used. Therefore, while providing an interesting liquidity perspective, the usefulness of the liquidity ratios is still limited especially the cash ratio, as it is seldom used in financial reporting or by analysts in the fundamental analysis of a company (Wohlner, 2017).

2.3.2. MARKET LIQUIDITY

Even though "market liquidity" appears to have a slightly different meaning compared to "accounting liquidity", market liquidity is still related to how assets (such as stocks) can be converted to cash. Market liquidity refers to the extent in which a market, such as a stock market in a country, allows assets to be bought and sold at stable prices. For example, the market for a stock is said to be liquid if the stocks can be sold rapidly and the act of selling has little impact on the stock's price (Mueller, 2017). Thus, cash would be considered as the most liquid asset, while real estates and collectibles are considered relatively illiquid. Please refer to section 2.2 for more information.

Market liquidity also shows where the stocks are traded and the level of interest that investors have in a company. For instance, a company stock traded on a major stock exchange can usually be considered as liquid while a company stock traded "*over the counter (OTC)"* are often considered as non-liquid (Mueller, 2017).

Mueller (2017) mentions that another way to judge liquidity in a company's stock is to look at the "bid-ask spread", which is a common way to measure liquidity. It is expected

that liquid stocks, such as Microsoft, would have a narrow (small value) bid-ask spread while an illiquid stock would have a wider (large value) bid-ask spread.

Other than the simple bid-ask spread, there are a number of ratios (measures) available, which are able to calculate market liquidity. In fact, Goyenko, Holden, and Trzcinka (2009) research more than twenty liquidity measures. Therefore, we are unable to discuss all the available ratios. Nonetheless, some of the common market liquidity ratios are as follows.

$$\textit{Bid-ask spread} = PA_t - PB_t \tag{2.4}$$

Where PA is the Ask Price and PB is the Bid price of a company in the current period.

$$\textit{Relative bid-ask spread} = \frac{PA_t - PB_t}{\left(\frac{PA_t + PB_t}{2}\right)} \tag{2.5}$$

Where PA is the Ask Price and PB is the Bid price of a company in the current period.

$$\textit{Roll Estimator} = 2\sqrt{-Cov(\Delta P_t, \Delta P_{t-1})} \tag{2.6}$$

Where ΔP_t is change in price of a company in the current period and ΔP_{t-1} is the change in price of a company in the previous period. Cov is the serial covariance of the price changes.

$$\textit{Amihud (ILLIQ)} = \frac{1}{t}\sum_t \frac{1{,}000{,}000 \times |return_t|}{price_t \times volume_t} \tag{2.7}$$

Where $|return_t|$, $price_t$ and $volume_t$ is the *absolute return*, *price* and *volume* of a company in the current period.

$$\textit{Amivest} = \frac{1}{t}\sum_t \frac{0.000001 \times price_t \times volume_t}{|return_t|} \tag{2.8}$$

Where $|return_t|$, $price_t$ and $volume_t$ is the *absolute return*, *price* and *volume* of a company in the current period.

$$Traded\ Volume\ in\ GBP\ (TV_t) = \ln\left(\sum\left(vol_t \times price_t\right)\right) \tag{2.9}$$

Where vol_t and $price_t$ is the *volume* and *price* of a company in the current period.

2.3.2.1. SUMMARY OF MARKET LIQUIDITY RATIOS/MEASURES

The "bid-ask spread" is a simple but well known liquidity measure while the "relative bid-ask spread" divides the bid-ask spread by the mid-point of the spread in order to measure liquidity. The "roll estimator", developed by Roll (1984) provides the effective bid-ask spread, is based on the serial covariance of price changes and is indirectly related to trading costs.

"Amihud illiquidity measure" (Amihud, 2002) is a well-known recognisable measure that has been extensively used in recent past literature. "Amivest ratio" is used by researchers such as Amihud, Mendelson & Lauterback (1997) and Hasbrouk (2006) to measure liquidity and is simply the inverse of the Amihud illiquidity measure while "traded volume" looks into volume and price in order to measure market liquidity.

Among the above liquidity measures, bid-ask spread, relative bid-ask spread and roll estimator are used as a proxy for spreads[11] while Amihud, Amivest and traded volume are used as a proxy for price impact[12].

As highlighted earlier, a company stock with a narrow bid-ask spread (small value) signifies higher liquidity relative to a company with a wider bid-ask spread (large value). Such an interpretation applies to most liquidity measures such as relative bid-ask spread, roll estimator and Amihud illiquidity measure.

[11] Spread is between the price at which you can buy an asset and the price at which you can sell the same asset at the same point in time (Damodaran, n.d.)

[12] Price impact is the impact that an investor can create by trading on an asset. Pushing the price up when buying the asset and pushing it down while selling (Damodaran, n.d.)

However, some measures such as traded volume are different, as a higher traded volume implies increased liquidity due higher trading activity (Fernández-Amador, Gächter, Larch, & Peter, 2011). Since Amivest is the inverse of Amhud illiquidity measure, it also indicates that a higher value shows higher liquidity. Therefore, interpreting the liquidity measures should be conducted carefully, as there are various liquidity measures available.

Moreover, Amihud, Mendelson & Panderson (2005) mention that there is hardly a single liquidity measure that can capture all aspects of estimating the effect of liquidity on asset prices while Goyenko, Holden, and Trzcinka (2009) in their research of various liquidity measures mention that different illiquidity measures capture different aspects of liquidity. Thus, signifying that choosing an appropriate liquidity measure is not as straightforward.

Nevertheless, Goyenko et al (2009) mention that a researcher should choose the liquidity measure based on what the researcher wants to measure. For instance, Goyenko et al (2009) suggest using Amihud illiquidity measure for measuring liquidity based on price impact as it does well in measuring it.

2.3.3. PAST RESEARCH ON LIQUIDITY

Due to the recent financial crisis (see Crotty (2009) and Brunnermeier (2009)) and developments in the financial sector that have resulted in greater finance access (Rajan, 2006), the study of liquidity has become more prominent.

Nevertheless, past accounting liquidity research seems to focus on the relationship between a company's liquidity (such as liquidity ratios) and the company's performance or financial statements. For instance, Largay and Stickney (1980) research focuses on the bankruptcy of W.T. Grant Company. They find that traditional ratios including liquidity ratios would not have revealed the company's many problems earlier than careful analysis of the company's cash flows, which would have revealed its impending doom around a decade earlier.

Kirkham (2012) also conclude on the importance of cash flow, as a decision based solely on the traditional liquidity ratios could well have led to an incorrect decision regarding the liquidity of a number of companies. Others accounting liquidity researches such as Lancaster et al (1998) study the relationship of company liquidity (e.g. ratios) to company earnings as well as company cash flow in the US while Eljelly (2004) examines the

relationship between profitability and liquidity (e.g. current ratio) on a sample of joint stock companies in Saudi Arabia.

Market liquidity research seems to focus on the overall market such as Amihud and Mendelson (1986) study on the NYSE shows that market-observed average returns are an increasing function of the illiquidity (bid-ask spread). Similarly, using three different liquidity measures and studying the US market, Jensen and Moorman (2010) find evidence to suggest that returns increases with increase in illiquidity. Since past evidences on illiquidity appears to indicate that returns will increase with illiquidity, illiquidity can potentially be made into an investment style (Ibbotson et al., 2013).

Furthermore, since liquidity is an issue during the crisis, there are studies done on the effect of monetary conditions on market liquidity. For instance, by studying the NYSE and AMEX for the period from 1962 to 2003, Goyenko and Ukhov (2009) find strong evidence that monetary policy predicts illiquidity.

Studies have also emerged on the impact of liquidity on macroeconomic variables such as Galariotis and Giouvris (2015) research suggests that market liquidity may contain some information for predicting the current and future state of the G7 economies. Moreover, Acharya and Pedersen (2005) research on the NYSE and AMEX provides evidence of the importance of liquidity on asset prices by using CAPM.

Overall, accounting liquidity research seems to be more company focus while in contrast, market liquidity research tends to be on the overall financial markets as well as macro-economies. Therefore, since our research interest is in relation to market liquidity, the following sections will be exploring market liquidity literature.

2.4. ILLIQUID VERSUS LIQUID ASSETS

Amihud and Mendelson (1986) who study the relationship between expected returns and bid-ask spreads of *New York Stock Exchange (NYSE)* stocks discover that market-observed average returns are an increasing function of the bid-ask spread. Other studies provide similar results such as Amihud and Mendelson (1989), Brennan and Subrahmanyam (1996) and Kiyotaki and Moore (2012). Moreover, Acharya and Pedersen (2005), using daily return and volume data for all common shares listed on NYSE and *American Stock Exchange (AMEX)* from July 1962 to December 1999 and

using a liquidity adjusted *capital asset pricing model (CAPM)*, show that their model provides evidence signifying the importance of liquidity on asset prices.

Similarly, using three different liquidity measures and studying the US market, based on a vast CRSP data period from September 1954 to December 2006, Jensen and Moorman (2010) find evidence that the zero-cost portfolio earns returns that are both economically and statistically significant, suggesting that returns increases with increase in illiquidity, which is similar to past researches such as Amihud and Mendelson (1986). Furthermore, by segregating their sample into illiquidity quintiles, their evidence even exhibits that returns are increasing monotonically with increase in stock illiquidity.

Nevertheless, there are some contradictory results, which show that illiquid stocks do not necessarily provide consistently higher returns. Ben-Rephael, Kadan, and Wohl (2008) who study the NYSE, find evidence that the profitability of trading strategies based on liquidity premium[13] has declined over the past four decades, rendering such strategies virtually unprofitable especially when using volume as a liquidity measure. Although liquidity measures not related to volume do show some evidence of liquidity premiums, they are considered weak (Ben-Rephael et al., 2008).

Furthermore, Eleswarapu and Reinganum (1993) who empirically investigate the seasonal behaviour of the liquidity premium in asset pricing during the 1961-1990 period, find evidence that the premium is reliably positive only during the month of January suggesting a strong seasonal component. Brennan, Huh, and Subrahmanyam (2013) who analyse the Amihud (2002) measure of illiquidity and its role in asset pricing, state that in general, only the down-days element commands a return premium[14].

However, unlike Eleswarapu and Reinganum (1993), Datar, Naik, and Radcliffe (1998) who investigate the liquidity-return relationship for all non-financial firms on the NYSE, using turnover as measure of liquidity, from 1962 through 1991 find a strong negative relationship between stock returns and liquidity. The liquidity effect is not restricted to the month of January alone and is prevalent throughout the year. The evidence supports

[13] Illiquidity premium or liquidity premium is the premium that investors received for holding a more illiquid asset/ portfolio. Usually it is calculated as follows = illiquid asset/ portfolio minus liquid asset/ portfolio.

[14] Brennan, Huh, and Subrahmanyam (2013) research, signifies that there is evidence of illiquidity asymmetry effect on expected returns during up and down-days while Brunnermeier and Pedersen (2009) highlight that capital constraints are more likely to happen during market downturns. Therefore, such asymmetry in expected returns is anticipated as during down-days, investors is expected to require more premiums for holding the riskier illiquid stocks due to issues such as capital constraints. Moreover, our research appears to also show a similar asymmetry effect for expansive and restrictive periods, as the two periods can be considered as down-days and up-days respectively (Said and Giouvris, 2017)

Amihud and Mendelson (1986) notion of liquidity premium and establishes its role in the overall cross section of stock returns.

Due to conflicting evidence, conducting research on liquid and illiquid stocks still has its merits. Hou, Karolyi, and Kho (2011) highlight the importance of the relationship between monthly returns and various factors such as size, cash flow-to-price ratio (C/P) and book-to-market ratio (B/M), using over 27,000 stocks from 49 countries including the UK over a three-decade period. Hou et al. (2011) highlight that the study of liquidity is likely to be particularly promising, as several new studies have documented strong cross-sectional and time-series relations between returns and various liquidity proxies. Although their research does not cover liquidity proxies, they do highlight the potential of conducting such research on liquidity.

2.4.1. RESEARCH QUESTIONS IN RELATION TO ILLIQUID VERSUS LIQUID ASSETS

Due to the contradictory views from past researchers, conducting research on the relationship between liquid and illiquid stocks still has its merits.

Therefore, our first two research questions are:

1) What is the relationship between illiquid and liquid stocks?
2) Do illiquid stocks produce higher returns relative to illiquid stocks?

2.5. ILLIQUIDITY AND MONETARY CONDITIONS

This section covers literature relevant to the first empirical chapter, which involves the relationship between illiquidity and monetary conditions. This section is divided into four sub-sections as follows: Section 2.5.1 discusses the relationship between market liquidity and monetary conditions while section 2.5.2 discusses the literature involving illiquidity premium across monetary conditions. Section 2.5.3 and 2.5.4 discuss relevant issues involving flight to liquidity as well as sensitivity of illiquid and liquid portfolios. The last sub-section provides potential research questions.

2.5.1. MARKET LIQUIDITY AND MONETARY CONDITIONS

It appears like there are various factors that affect liquidity pricing such as Dimson and Hanke (2004) who show that the ex-ante illiquidity premium is related to proxies such as the small firm premium, closed-end fund discount, bond maturity premium, trading volume, credit spreads, and the futures basis. However, our objective for our first empirical chapter is to investigate whether liquidity pricing is systematically linked to macroeconomic changes or more specifically, changes in monetary conditions similar to Jensen and Moorman (2010).

Unfortunately there is not much research available that focuses on the relationship between illiquidity premium and monetary conditions but there seems to be more research on the effect of monetary conditions on market liquidity such as Söderberg (2008) who studies the ability of fourteen macroeconomic variables' such as interest rate and broad money growth to forecast changes in monthly market liquidity on Scandinavian order-driven stock exchanges such as Copenhagen (Denmark), Oslo (Norway) and Stockholm (Sweden).

Moreover, by studying the US market, Acharya and Pedersen (2005) show that the investor on a company's stock should be concerned with market downturns and market liquidity, shedding light on the total and relative economic significance of liquidity not only at the company level but also at the market level, as both can affect individual asset prices. Thus, signifying that by understanding how monetary conditions affect market liquidity will allow us to explore how monetary conditions affect prices as well as illiquidity premium.

Chordia, Roll, and Subrahmanyam (2001) study the effects of several explanatory variables (inclusive of short-term interest rates and macroeconomic announcements[15]) on aggregate market spreads, depths and trading activity for US stocks (NYSE) from 1988 to 1998, confirm that short-term interest rates significantly affect market liquidity as well as trading activity. Fujimoto (2004) who also studies the US market using NYSE and AMEX during the 1965-2001 period and *Vector Autoregression (VAR)* analysis show that macroeconomic fundamentals are significant determinants of liquidity and their effects are stronger prior to the mid 1980's when business cycle dynamics are more volatile.

[15] Nevertheless, their study focuses on more macroeconomic variables such as Gross Domestic Product (GDP), the unemployment rate and the Consumer Price Index (CPI).

Similarly, by studying the same stock exchanges for the period from 1962 to 2003, Goyenko and Ukhov (2009) find strong evidence that monetary policy predicts illiquidity. Jensen and Moorman (2010) highlight that expansive shifts correspond with an increase in market liquidity while restrictive shifts bring about a drop in market liquidity. A more recent research by Fernández-Amador, Gächter, Larch, and Peter (2013) shed light on the actual impact of monetary policy on stock liquidity and thereby addresses its role as a determinant of commonality in liquidity by considering the data of three major Euro markets namely Germany, France and Italy. Their results suggest that an expansionary monetary policy of the *European Central Bank (ECB)* leads to an increase of aggregate stock market liquidity of the three European markets.

Nevertheless, there are less confirmed results such as Chordia, Sarkar, and Subrahmanyam (2005) who research the cross-market liquidity dynamics by studying stock and bond market liquidity as well as volatility within the US market and obtain results indicating monetary expansions are associated with increased equity market liquidity but only during crisis periods. Even Söderberg (2008) in their study of the Scandinavian stock markets highlights that although some of the macroeconomic variables are able to predict the market liquidity of the respective stock markets but not one variable is able to predict the market liquidity of all three Scandinavian stock markets, signifying that not a single macroeconomic variable have the same effect on all three stock markets.

2.5.2. ILLIQUIDITY PREMIUM ACROSS MONETARY CONDITIONS

Although there is not much research on the relationship between illiquidity premium and monetary conditions, there is some research on the relationship between stock prices and business conditions including monetary conditions such as Fama and French (1989). Fama and French (1989) investigate the effect of business conditions on stock and bond markets within the US market, whereby they highlight that expected stock returns are found to be lower when economic conditions are strong and higher when conditions are weak but they also highlight that further research on monetary policy should be done. Therefore, by extending Fama and French (1989) research, Jensen, Mercer, and Johnson (1996) find evidence to suggest that the monetary environment actually influences investors' required returns. They add that monetary conditions as well as business conditions in part causes the predictability of expected stock and bond returns variation

through time. Along the same lines, Patelis (1997) who studies the NYSE concludes that monetary policy variables are significant predictors of future returns, although they cannot fully account for the observed stock return predictability. Amihud (2002) does highlight that expected market illiquidity affects ex-ante stock excess return positively over time, signifying that if there is an expansionary shift (market liquidity increase), stock returns are expected to decrease. However, contrasting to Fama and French (1989) and Amihud (2002), Thorbecke (1997) who also study the US market find evidence to indicate that expansionary policy increases ex-post stock returns. Therefore, if the monetary *conditions increases market liquidity (expansionary)*, stock returns are expected to also increase.

Rigobon and Sack (2003) who study the US market using *Standard and Poor 500 (S&P 500)* index find evidence of a significant policy response on the S&P 500 index, while Bernanke and Kuttner (2005) highlight the effects of unanticipated monetary policy actions (or *shocks*) on expected excess returns account for the largest part of the response of stock prices, which is acknowledged earlier by Amihud (2002). There are other researchers who investigate the response of asset prices to changes in monetary policy based on the increase in the variance of policy *shocks* such as Rigobon and Sack (2004) but most of the studies so far cover US markets. Nevertheless, Brogaard and Detzel (2012) do investigate economic policy including monetary policy for 21 countries including Great Britain and finds a relationship between stock portfolio returns and the uncertainty of economic policy. They also suggest that there are material and long-lasting real and financial implications due to the indecisiveness in government economic policymaking.

Having discuss the relationship between market liquidity and monetary conditions, we can now investigate if there is any relationship between illiquidity premium and market liquidity to understand whether illiquidity premiums are affected by monetary conditions.

We refer to the illiquidity premium as the required return premium for holding illiquid stocks. Brunnermeier and Pedersen (2009) emphasize that changing monetary conditions are associated with changes in investor funding requirements and find evidence to suggest that the return premium required for holding illiquid stocks increases during periods associated with funding constraints (decreased market liquidity) because such periods decrease the ability of speculators to allocate capital to illiquid stocks. Therefore, the illiquidity premium expected from investors should increase (decrease) as monetary conditions become more restrictive (expansive) implying that during expansive monetary

periods, liquidity conditions improve and the price for illiquid stocks increases relative to liquid stocks.

Similarly, Jensen and Moorman (2010) do highlight that an illiquidity premium arises because investors demand compensation for the costs and risks of holding illiquid assets. Based on the models of Amihud and Mendelson (1986) and Acharya and Pedersen (2005), it is expected that, during periods of high market liquidity, liquidity becomes less valued by investor resulting in the reduction of the illiquidity premium. Therefore, during expansionary periods, when market liquidity increase, it is expected that illiquidity premium decreases when the price of illiquid stocks increases relative to liquid stocks, or when zero-cost portfolio return increases (Jensen & Moorman, 2010).

2.5.3. FLIGHT TO LIQUIDITY

Amihud (2002) also highlights the effects of both expected and unexpected market illiquidity are stronger on the returns of small-firms stock portfolios. Since small firms are usually known to be more illiquid compared to larger firms, their study also indicates that market liquidity affects illiquid stocks more compared to liquid stocks meaning that small stocks are subject to greater illiquidity risk. If priced, illiquidity risk should result in higher illiquidity risk premium. Such a relationship can also be linked to the *''flight-to-liquidity''* or *"flight-to-quality"* phenomenon as in times of dire liquidity large stocks seem relatively more attractive compared to small stocks due to the illiquidity risk.

Brunnermeier and Pedersen (2009) provide a model to indicate that there are associations between an asset's market liquidity[16] and investors' funding liquidity[17]. Their model actually establish various findings such as market liquidity has commonality across shares and is subject to flight-to-quality while Acharya and Pedersen (2005) provide evidence of investors flight-to-liquidity by using a liquidity adjusted CAPM. Likewise, by studying stock and bond markets, Goyenko and Ukhov (2009) also mention flight-to-liquidity episodes due to the effect of stock illiquidity on bond illiquidity.

Nevertheless, Brunnermeier and Pedersen (2009) also show that under certain conditions, the relationship can also lead to liquidity spirals. Moreover, Rajan (2006) mentions that

[16] *Market liquidity* means how easily an asset is traded.
[17] *Funding liquidity* relates to degree of difficulty/ easiness investors can obtain funding.

in times of ample liquidity supplied by the central banks (low interest rates), investors have a tendency to engage in riskier investments to earn higher returns. Therefore, during expansive monetary policy periods where market liquidity is expected to increase, it is likely that investors will increase their holdings of riskier illiquid stocks causing the price of illiquid stocks to increase[18].

Jensen and Moorman (2010) also find results consistent with Brunnermeier and Pedersen (2009), whereby prior to an expansive monetary policy shift, liquidity concerns heightened and the funding constraints (decrease in market liquidity) causes investors to increase the premium they require for holding illiquid stocks and move to more liquid stocks signifying flight-to-liquidity, which continues for several days after the policy shift. Thus, the return of illiquid stocks is driven down relative to liquid stocks resulting in the reduction of the zero-cost portfolio returns.

2.5.4. SENSITIVITY OF ILLIQUID QUINTILE AND LIQUID QUINTILE

Another point that Amihud and Mendelson (1986) discover is that there is a clientele effect, whereby stocks with higher spreads are held by investors with longer holding periods resulting in the returns of higher-spread stocks (illiquid stocks) to be less spread-sensitive giving rise to a concave return-spread relation that is caused by long horizon investors[19] and small investors focusing on the illiquid stocks, who demand a small premium. Therefore, it indicates that illiquid stock investors would react slowly to changes in liquidity of the stocks as they tend to hold the stocks longer.

[18] Jensen, Mercer, and Johnson (1996) suggest that investors' required return are actually influenced by monetary environment while Brunnermeier and Pedersen (2009) highlight that the return premium required for holding illiquid stocks increases during periods associated with funding constraints, signifying the role of monetary conditions for investors' stock returns and illiquidity. Nevertheless, Amihud (2002) mention flight-to-liquidity phenomenon, as in times of dire liquidity, large stocks appear to be relatively more attractive compared to small stocks due to the illiquidity risk. The link between illiquidity and size is quite common, as Eleswarapu and Reinganum (1993) highlight that the illiquidity premium is a result of size effect while Elfakhani (2000) mentions that the returns of small-firms are larger due to the liquidity hypothesis, as small-firms are considered to be less liquid and hence should obtain higher return premiums. The reaction of investors towards illiquidity, size and monetary environment can potentially be explained by the investor sentiment, as the judgement of an uncertainty future event may be affected by the persons' mood and hence happy (optimistic) investors may be more willing to invest in uncertain projects (Wright and Bower, 1992). Thus, a monetary environment can impact investors decision through sentiment, as due to an expansionary period, which is considered to be an optimistic event, investors are more willing to invest into the riskier (uncertain) illiquid or small stocks. Whilst during times of dire liquidity, investors will prefer the more stable liquid (or large stocks). Even though investor sentiment may play some role in our research, we have not covered it. However, we agree that including investor sentiment may be good for our future research.

[19] In order to avoid losses from selling an illiquid stock, some investors tend to hold such stocks longer, resulting in a less sensitive stock. Moreover, there are also investors who use a "buy and hold strategy" (passive strategy) and do not react if there are any movement in the market. Nevertheless, researchers such as Jensen and Moorman (2010) mention that less liquid assets are more sensitive to changes in monetary or funding condition. The studies by Amihud and Mandelson (1986) and Jensen and Moorman (2010) signify that due to the characteristics of illiquid stocks, an investor may decide to either hold or not hold illiquid stocks longer. Thus, causing the illiquid stocks to be more or less sensitive to a specific environment (e.g. monetary condition). There may be other reasons for holding a stock longer or shorter but stock illiquidity is expected to play some role in it.

However, Perez-Quiros and Timmermann (2000) find evidence indicating that small firms can be adversely affected by lower liquidity (obtaining financing) and should be more affected across recession and expansion states. Therefore, it should result in a higher sensitivity of their expected stock returns with respect to variables that measure credit market conditions. Since small firms are usually associated with low liquidity, in a way Perez-Quiros and Timmermann (2000) research signifies that illiquid stocks are more sensitive compared to liquid stocks during expansive or restrictive conditions.

Moreover, using turnover as a measure of liquidity and up to 48 stock exchanges[20], Dey (2005) supports a negative relationship between turnover and returns for the period from 1995 until 2001. However, they find that turnover is significant for emerging market portfolios only, while it is insignificant for developed market portfolios. They highlight that due to the high liquidity of developed markets, liquidity is not a concern for investors. In emerging markets though where liquidity can be restricted, investors would be more concerned with liquidity risk. Therefore, since the UK market is a developed market, investors may not be as concerned with liquidity, resulting in asset prices to be less sensitive to changes in liquidity.

Furthermore, Rajan (2006) mentions that when market liquidity increases, investors have a tendency to engage in riskier investments such as illiquid stocks. Bekaert, Hoerova, and Lo Duca (2013) highlight that lax monetary policy (increased market liquidity) decreases both risk aversion and uncertainty of expected market volatility by studying the VIX[21]. Therefore, it is expected that investors will prefer illiquid stocks making it to be more sensitive compared to liquid stocks during expansive monetary conditions.

2.5.5. RESEARCH QUESTIONS IN RELATION TO ILLIQUIDITY AND MONETARY CONDITIONS

The literature review appears to highlight that monetary policy affects market liquidity (Goyenko and Ukhov, 2009 and Jensen and Moorman, 2010) and hence, justifying Central Banks such as the Federal Reserve using monetary policy to stabilize the financial system (Cornett et al., 2011). Monetary conditions are also associated with return

[20] 48 stock exchanges consist of 22 exchanges from Europe, 7 exchanges from North America, 13 exchanges from Asia/Pacific, 5 exchanges from South America and 1 exchange from Africa.
[21] VIX = Chicago Board Options Exchange (CBOE) Volatility Index, which is the stock market option-based implied volatility of the US S&P500 index.

premiums due to illiquidity, as investors required more premiums for holding illiquid stocks during periods associated with funding constraints (Brunnermeier & Pedersen, 2009). Finally, past evidence shows that small companies (or illiquid stocks) are more sensitive compared to large companies (or liquid stocks) during either expansive or restrictive conditions (Perez□Quiros and Timmermann, 2000 and Bekaert et al., 2013). Thus, our next research questions are:

1) Are there any possible relationships between monetary conditions and market liquidity?
2) How do monetary conditions affect return premiums due to illiquidity?
3) Are illiquid stocks more sensitive than liquid stocks in relation to monetary conditions?
4) How does the financial crisis affect market liquidity?

2.6. ILLIQUIDITY, INVESTMENT STYLES, COVARIANCE VERSUS CHARACTERISTICS AND JANUARY EFFECT

This section covers literature relevant to the second and third empirical chapters, which involves the potential of illiquidity as an investment style. The section is divided into the following sub-sections: Section 2.6.1 discusses different types of investment styles while section 2.6.2 covers past studies in relation to the potential of illiquidity. Section 2.6.3 and 2.6.4 reviews literature regarding *covariance versus characteristics models* and the *January effect* respectively. Finally, section 2.6.5. discusses potential research questions.

2.6.1. INVESTMENT STYLES

Investment styles are strategies or theories used by investors and asset managers to set asset allocation and choose individual assets such as stocks for investment, while Chang, Wang, and Lu (2013) similarly define investment style as the combining of stocks with the same characteristics to construct style portfolios and make investments in the stock markets. The investment style of a portfolio (or fund) helps set expectations for the long-term performance of the portfolio and publicizes it to potential investors looking for a specific type of investment or market exposure as well as aiding the investors in stock-selection. Therefore, most mutual funds and exchange-traded funds (ETFs) use a

consistent form of investment style of which they must comply to. The investment style can be broad such as “international stocks” as well as narrow such as “large size growth stocks” (Investment Styles, n.d.).

Fontinelle (2010) mentions that the major investment styles can be broken down into three main dimensions namely 1) active vs. passive management, 2) growth vs. value investing and 3) small cap vs. large cap companies. Among the three, the most commonly known investment style is active vs passive management.

In comparison to passive management, active management tend to have full-time staff of financial researchers and portfolio managers who carefully select their holdings and are constantly seeking to gain larger returns for investors. However, due to such service, active funds usually have higher fees (expenses) than passive funds (Fontinelle, 2010).

Although the fees of active funds are higher, the $10 trillion invested in active-management funds indicate that investors still trust their fund managers (Stein, 2017). Nevertheless, over the years, more investors tend to prefer passive funds as around a third of all assets in the US are in passive funds, up from about a fifth a decade ago. Moreover, flows into passive funds from active funds, have reached nearly $500 billion in the first half of the year 2017 (Stein, 2017), signifying the growth of passive funds.

More importantly, a study by S&P Dow Jones Indices in 2016, shows that about 90 percent of active stock managers failed to beat their index targets over various periods and that underperformance is significantly due to fees (Stein, 2017)

In relation to growth and value stocks, value stocks tend to be relatively less expensive (e.g. lower price-to-earnings ratio), as opposed to growth stocks that are relatively more expensive (e.g. higher price-to-earnings ratio) because an investor believes that the growth stocks’ price might grow even higher (Israelsen, 2016). By looking at various indices, Israelsen (2016) reports that value outperform growth index in the long run while Pisani (2017) reports that for the first few months of the year 2017, growth stocks (e.g. technology and health care) appears to outperform value stocks (e.g. financials and energy).

However, it should be acknowledged that no one investment style should inherently be considered better than another, as the key is to find a style that suits an investor's appetite for risk while maintaining a sufficient level of diversification (Investment Styles, n.d.).

In the end, investment styles are merely categorical investing and, as such, constitutes some sort of experimental research such as back-testing in order to aid investors in stock-selection in the complex investment or market environments, where there can be complex financial products.

Nonetheless, Chang et al. (2013) highlight that the common type of investment styles are "value versus growth" stocks, "small versus big" stocks and "momentum versus contrarian" stocks, whereby they can be further segregated into 6 styles. Therefore, we will firstly discuss the most common type of investments styles.

2.6.1.1. VALUE VERSUS GROWTH

Value and growth are two popular fundamental investment style whereby value style is where an investor must look for stocks that are undervalued according to companies' financial statements while growth style involves identifying long-term potential and performance. Past literature seems to indicate that value style is an antagonist to growth style, as research tends to compare the two styles with each other, by using a suitable variable such as *book-to-market ratio (B/M ratio)*, *price-earnings ratio (P/E ratio)* and *price-to-cash-flow ratio (P/C ratio)*.

There are various studies available that investigate the performance of the two styles. However most research appears to conclude that value style is considered superior to growth style in the US market resulting in the value premium (Basu, 1983; Rosenberg, Reid, & Lanstein, 1985) (Daniel & Titman, 1997; Fama & French, 1992). For markets other than the US market, Daniel, Titman, and Wei (2001) also find value premium within the Japanese market, while Capaul, Rowley, and Sharpe (1993) who study 6 international markets including UK obtained consistent results to US market studies.

In contradiction, a mixed outcome is obtained by Ding, Chua, and Fetherston (2005) who look into various East Asia markets. Value premium is significant and positive in the Malaysian market, while in Thailand it appears to be significantly negative and in Indonesia it is insignificant. Fama and French (2012) also find mixed results for North America, Europe, Asia Pacific and Japan. In Japan, they do not find evidence of a value premium. However, Gonenc and Karan (2003) who focus only on *Istanbul Stock*

Exchange (ISE) obtain similar results to Ding's study of Thailand market as there is no value premium within the ISE, indicating growth superiority.

Nonetheless, Beneda (2002) who investigates Compustat Industrial Files' data and the *Standard & Poor (S&P)* index highlights that the research time-period is important as it is discovered that over a short period of five years, value style is found to be more profitable but if a longer period (at least 14 years) is chosen, average returns for growth stocks is superior.

2.6.1.2. SIZE EFFECT

Banz (1981) highlights that average returns are negatively related with size. This widely recognized anomaly is known as either small-firm or size effect, which is further supported by Reinganum (1982) and Keim (1983). Such a relationship is expected as small firms are usually considered riskier than large firms and their returns are expected to be higher. Chan, Chen, and Hsieh (1985) confirm this as they state that within an efficient market, the higher average returns of smaller firms are justified by the additional risks borne by such firms.

Nevertheless, the study on size effect is less optimistic after the early 1980s as Van Dijk (2011) highlights that past empirical studies declared the size effect to be dead since then. Gonenc and Karan (2003) actually obtain opposite findings whereby firms with larger capitalization are considered to be superior while Horowitz, Loughran, and Savin (2000) report no consistent relationship between size and realized returns and hence, their results show that the widespread use of size in asset pricing is unwarranted. Amihud (2002) highlights that the size effect is partially due to market illiquidity, as times of dire illiquidity will cause flight to liquidity, resulting in preference for larger stocks and hence small stocks are actually subjected to higher illiquidity risk premium.

Nevertheless, Dissanaike (2002) finds evidence of a size effect within the UK based on FT500[22] sample, while Hou and Van Dijk (2014) study of US market find that there are still a robust size effect in the cross-section of expected returns after adjusting for the price impact of profitability shocks. Furthermore, Van Dijk (2011) does point out that the

[22] FT 500 Index comprises the largest 500 industrial companies in the UK and accounts for well over 70% of the market capitalization of the LSE (Dissanaike, 1997).

size premium in the US has been large in recent years and more empirical research needs to be conducted to examine the robustness of the size effect on the US and international stock markets.

2.6.1.3. MOMENTUM VERSUS CONTRARIAN

De Bondt and Thaler (1985) in their behavioural finance research on stock market overreaction discover that loser stocks perform exceptionally well in comparison to winner stocks over extended time periods of 3 to 5 years horizons and this is particularly noticeable in the month of January. Nevertheless, in contrast, Jegadeesh and Titman (1993) document that investment styles that combined buying winner stocks and selling loser stocks generate significant positive returns of about 1% per month over 3 to 12 months holding periods. Jegadeesh and Titman (1993) also find similar pattern of returns around the earnings announcements of past winners and losers. Jegadeesh and Titman (2001) revisit the subject and their evidence indicates that momentum profits have continued in the 1990s, suggesting that the original results are not a product of data snooping bias.

However, Jegadeesh and Titman (1993) highlight that part of the abnormal returns generated in the first year after portfolio formation dissipates in the following two years while Conrad and Kaul (1998) highlight that contrarian style is profitable for long-term horizons, while the momentum style is usually profitable for medium-term holding periods of between 3 and 12 months.

Shen, Szakmary, and Sharma (2005) findings agree with Conrad and Kaul (1998), who show that contrarian profits in the US market are very dependent on the period examined whereas Schiereck, De Bondt, and Weber (1999) mention that the apparent success of contrarian and momentum styles may be due to institutional factors and risk mis-measurement or it may simply be the result of data mining.

In the UK, Dissanaike (2002) shows results that contrarian style outperformed momentum style and their *loser-winner effect (or contrarian effect)* results are significant.

Nonetheless, Galariotis, Holmes, and Ma (2007) demonstrate that both momentum and contrarian profits are available for the LSE[23].

2.6.1.4. ILLIQUIDITY VERSUS LIQUIDITY

As highlighted in chapter 2.2, the general evidence of the relationship seems to indicate that returns will increase with illiquidity (Amihud & Mendelson, 1986) (Amihud & Mendelson, 1989) (Brennan & Subrahmanyam, 1996). Furthermore, Acharya and Pedersen (2005), using a liquidity adjusted CAPM, find evidence signifying the importance of liquidity on asset prices.

Using three different liquidity measures and studying the US market, Jensen and Moorman (2010) find evidence that the zero-cost investment portfolio[24] earns returns that are both economically and statistically significant, signifying that returns increase with illiquidity.

Nevertheless, there are some contradictory results, which show that illiquid stocks do not necessarily provide consistent higher returns. Eleswarapu and Reinganum (1993) find evidence to suggest that the January effect and size effect are significant, indicating the return for spreads may be a result of seasonal and size effect. Brennan et al. (2013) who analyses the Amihud (2002) measure of illiquidity and its role in asset pricing, state that in general, only the down-days element commands a return premium.

Furthermore Ben-Rephael et al. (2008) who study the NYSE find evidence that the profitability of trading strategies based on illiquidity premium has declined over the past four decades, rendering such strategies virtually unprofitable. Even Lischewski and Voronkova (2012) who investigate various investment styles by focusing on the Polish market, find evidence to support size and value factors but not liquidity factors.

[23] Conrad and Kaul (1998) analyse two strategies diametrically opposed in philosophy and execution whereby contrarian strategy relies on price reversals while momentum strategy is based on price continuations. Schiereck et al (1999) define it slightly differently whereby contrarian strategy buys stocks that performed poorly over the past two to five years (prior losers) and sells short stocks that performed well over the same period (prior winners), while momentum strategy is the opposite of the contrarian strategy. Nevertheless, Harvey (n.d.) highlights that contrarian trading is an investment style that goes against prevailing market trends by buying poorly performing assets and then selling when the assets perform well while momentum trading transacts assets that are moving significantly in one direction. Thus, there are various ways to describe contrarian and momentum styles but for our research, we considered momentum style as simply focusing on winner (price continuation) stocks while contrarian style is the opposite that is trading on loser (price reversal) stocks. For example, momentum style will buy a winner stock whereas contrarian style will buy a loser stock.

[24] Zero-cost portfolio = long the illiquid portfolio and short the liquid portfolio

However, unlike Eleswarapu and Reinganum (1993), Datar et al. (1998) investigate the liquidity-return relationship for all non-financial firms on the NYSE, find a strong positive relationship between stock returns and illiquidity, and the illiquidity premium is not restricted to the month of January alone and is prevalent throughout the year.

Moreover, using three liquidity measures in the UK, Said and Giouvris (2015) reveal that illiquid portfolios consistently earn higher returns compared to liquid portfolios and the zero-cost portfolio returns are statistically significant for at least two of the illiquidity measures used.

Due to the conflicting evidence, conducting research on illiquidity as an investment style still has its merits.

2.6.1.5. RELATIONSHIP AND RETURNS BETWEEN INVESTMENT STYLES

We also notice that past literature appears to try to find links between different types of investment styles. Shen et al. (2005) who study the connections between value versus growth investment styles and momentum styles within international markets, show that momentum profits are much stronger in the growth indices, while adding value indices into the mix reduces the profitability of the momentum styles. This is consistent with Asness, Moskowitz, and Pedersen (2013) who highlight that value and momentum are inversely correlated to each other within and across asset classes.

Size effect seems to be linked to other styles. Bauman, Conover, and Miller (1998) initially believed that the value premium is attributed to small-firm effects but then discover that the large-firm value premium is greater than small-firm value premium, indicating that the superiority of value style is genuine.

Nevertheless, some researchers find less direct evidence of the relationship between styles such as Dissanaike (2002) who finds evidence that within UK, the size effect and *"winner vs loser effect"* (or *"momentum vs contrarian effect")* are not completely independent of each other but he adds that there is no concrete evidence to suggest that the size effect subsumes the *"winner vs loser effect"*.

At the moment, there are studies that connect other investment styles with illiquidity such as Asness et al. (2013) who find significant evidence that funding liquidity risk is

inversely related to value but positively related to momentum globally across asset classes. Similarly, Pastor and Stambaugh (2003) measures of liquidity risk are positively related to momentum in US individual stocks. In addition Sadka (2006) finds evidence that momentum is positively related to liquidity risk or liquidity shock.

One of the most common style connections is between illiquidity and size effect as Eleswarapu and Reinganum (1993) highlight that the illiquidity premium is as a result of size effect. On the other hand, Elfakhani (2000) discovers that the returns of small-firms are substantially larger due to the liquidity hypothesis as small-firms are considered to be less liquid and thus should obtain higher return premiums. This is contradictory to the research conducted by Ibbotson et al. (2013) on US market, who highlight that the returns obtained of illiquidity based portfolios are sufficiently different from those of the other styles. *Considering the research above, one can see that the relationship between illiquidity and size is not clearly defined.*

Nevertheless, Fama and French (1992) highlight that risks may be the reason that investment styles, based on size and simple ratios, performed better. Similarly Ryan and Hajiyev (2004) investigate the *Irish stock exchange* and find that returns of value stocks are superior but conclude that the differences in returns may simply be compensation for risks (ex-ante risk premium). Arshanapalli, Coggin, and Doukas (1998) indicate that value stocks manage to outperform growth stocks while also have a lower level of risk. Therefore, investigating the risks of the investment styles is equally important to researching the different style returns themselves.

Other reasons for the higher returns of investment styles may be due to investor sentiment as mentioned by Baker and Wurgler (2006) in relation to various styles such as small stocks and growth stocks, while Black (1993) highlights the possibility of data mining bias on value and size. Nevertheless, Jegadeesh and Titman (2001) highlight that the positive profitability of momentum strategies are not due to data mining, by addressing the issue in the context of Jegadeesh and Titman (1993).

2.6.2. POTENTIAL OF ILLIQUIDITY AS AN INVESTMENT STYLE

Due to the recent financial crisis, the study of liquidity has become more prominent, as studies such as Crotty (2009) highlights that the financial crisis happened when investors

run for liquidity and safety. Therefore, since our literature highlights that stock returns are an increasing function of illiquidity (Amihud & Mendelson, 1986), liquidity has started becoming a common part of finance literature and researchers have noticed the potential and importance of illiquidity as a finance or investment tool.

Yan (2008) in their research of US mutual funds finds evidence to suggest that liquidity is an important reason why size erodes fund performance signifying the importance of liquidity in investment management. Moreover, Idzorek, Xiong, and Ibbotson (2012) highlight that on average mutual funds that hold illiquid stocks significantly perform better than mutual funds that hold more liquid stocks. Therefore, signifying the potential of liquidity as investment strategy or style.

Nowadays, more studies have been conducted to prove illiquidity as a reliable investment style such as Ibbotson et al. (2013) who find evidence to suggest that liquidity should be given equal standing to other investment styles.

2.6.3. COVARIANCE VERSUS CHARACTERISTICS MODELS

In order to measure the performance of various investment style portfolios, we will be using various relevant financial ratios to rank and construct the portfolios. For instance, as highlighted earlier in the literature, we can use P/E ratio to distinguish between value and growth portfolios whereby a low P/E stock portfolio will be considered as value stocks and high P/E stocks as growth stocks (Beneda, 2002).

Nevertheless, it is not that simple, as according to the CAPM a stock return actually depends on its sensitivity towards market risk (or systematic risk) captured by beta and time value of money (represented by the risk free rate). Fama and French (1993) and Carhart (1997) further expanded on univariate CAPM which is known as Fama-French 3 factor model and Carhart 4 factor model[25] respectively. Therefore, constructing portfolios simply by using relevant financial ratios may not be sufficient.

Daniel and Titman (1997) is one of the first few to recognise and explore the issue. They consider two models namely the *"characteristics model"* and *"covariance model"*. They label *"characteristics model",* the model using only financial ratios such as B/M ratio to

[25] A study by Jegadeesh and Titman (1993) support the momentum factor.

measure the expected return of stocks. Meanwhile, the *"covariance model"* is a financial model and considers returns sensitivity to factors such as value factors (or value premium).

Daniel and Titman (1998) highlight that the persistent better performance of value stocks over growth stocks may be due to either mispricing or riskiness of stocks. They clarify that mispricing of stocks is due to the *"characteristic model"* and means that the market systematically under-prices value stocks. On the other hand, riskiness as measured by the "covariance model" indicates that value stocks are considered riskier resulting in higher returns.

Daniel and Titman (1997) underline that the *"characteristics model"* seems to explain the cross-sectional variation in stock returns better than the *"covariance model"*. Daniel and Titman (1998) find further evidence to support the *"characteristics model"* signifying that investors should be able to construct better portfolios using *"characteristics model"* relative to *"covariance model"* such as Fama-French 3 factor model (Fama & French, 1992, 1993).

Furthermore, Daniel et al. (2001) replicate the Daniel and Titman (1997) study on a Japanese sample from the *Tokyo Stock Exchange (TSE)* between 1971 and 1997 and their test failed to reject the "characteristic model" but rejected the Fama-French 3 factor model. Ibbotson et al. (2013) who also test the theory using a different investment style factor namely the illiquidity factor, indicated that the *"characteristics model"* perform better than the *"covariance model"*.

2.6.4. THE JANUARY EFFECT

Another common issue that can be linked to the various investment styles is the January effect. Fama and French (1992) signify its appearance within value style, which is also confirmed by Loughran (1997). Keim (1983) mentions its existence within size effect whereas De Bondt and Thaler (1985) comment on it in his study of momentum style. Even Eleswarapu and Reinganum (1993) highlight of its presence within illiquidity premium.

The January effect is a seasonal anomaly whereby prices or returns increases in the month of January in comparison to other months. Wachtel (1942) is one of the first to observe this in the US market (DJIA) while Gultekin and Gultekin (1983) mention its existence

in most major industrialized countries including the UK. Reinganum and Shapiro (1987) and Clare, Psaradakis, and Thomas (1995) also find evidence of the January effect in UK stock market.

The market is expected to be at least weakly efficient and the January effect is quite a simple anomaly that can be exploited by any investor inexpensively. Therefore, since it is discovered more than 70 years ago, it is expected that such a simple anomaly would disappear by now but Haugen and Jorion (1996) highlight that the January effect is still going strong in their research and Haug and Hirschey (2006) confirm that the January effect continue to contradict the EMH.

Ritter and Chopra (1989) mention that the January effect may be due to window dressing, as following December tax loss selling, investors rebalance their portfolios in early January. Nevertheless, Haug and Hirschey (2006) highlight that the continuing presence of a January effect since 1987 appears to weaken that argument of tax loss selling.

It may simply be compensation for risks. Chan et al. (1985) mention risk is higher in January or during the turn of the year by looking at bonds. Moreover, Gu (2003) emphasizes that the January effect is positively related to volatility.

Gu (2003) also indicates the pronounced declining trend of January effect in the US for both large and small firm stock indices since 1988, which may be due to macroeconomic variables such as stronger real GDP growth and higher inflation. They also mention that the decline represents a trend towards market efficiency due to knowledgeable investors and technology advancement.

On the other hand, Ahsan and Sarkar (2013) find significant positive return in June instead of January in *Dhaka Stock Exchange (DSE*) in Bangladesh.

2.6.5. RESEARCH QUESTIONS REGARDING ILLIQUIDITY, INVESTMENT STYLES, COVARIANCE VS CHARACTERISTICS AND JANUARY RETURNS.

In general, past evidence seems to signify that returns will increase with illiquidity (Amihud & Mendelson, 1986) while Idzorek, Xiong, and Ibbotson (2012) highlight that on average mutual funds that held illiquid stocks performed better than mutual funds with more liquid stocks, signifying the potential of liquidity as investment strategy or style.

With regards to covariance vs characteristics models, “characteristics model” appears to explain the cross-sectional variation in stock returns better than the “covariance model” for value factor (Daniel and Titman, 1998) and liquidity factor (Ibbotson et al., 2013).

Past research also shows that January effect is a common issue that can be linked to the various investment styles namely size effect (Keim, 1983), value style (Fama and French, 1992) momentum style (De Bondt and Thaler, 1985) and illiquidity premium (Eleswarapu and Reinganum, 1993).

Thus, our next research questions are:

1) Can illiquidity be made into a reliable investment style or strategy?
2) How does the financial crisis affect investment styles?
3) Is covariance model better than characteristics model when constructing portfolios?
4) Does January effect persist within the various investment styles?

2.7. MACRO-ECONOMY, ILLIQUIDITY AND OIL

This section covers literature reviews relevant to the final two empirical chapters. The section is divided into three sub-sections as follows: Section 2.7.1 discusses the relationship between macro-economy and oil while section 2.7.2 involves literature regarding macro-economy and market liquidity. Section 2.7.3 discusses the importance of characterising countries as net oil exporting and net oil importing countries. The last sub-section offers potential research questions.

2.7.1. OIL AND THE MACRO-ECONOMY

In relation to oil and macroeconomic research, one of the earliest key studies is conducted by Hamilton (1983) who highlights that there is a significant increase in the price of crude petroleum prior to seven of the eight post world-war II recessions in the US. Nonetheless, although this does not automatically signify that oil price shocks cause the recessions, oil price shocks are found to be at least a contributing factor, as evidence indicates that over the period between 1948 and 1972, this correlation is statistically significant and non-spurious. (see also Hamilton (1996), Hamilton (2003) and Hamilton (2009)).

Hamilton (2011) updates the count to 10 out of 11 US recessions being preceded by significant rises in oil prices, with the additional three rises occurring in the fall of 1990, 1999-2000 period and 2007–2008 period. As also highlighted in Hamilton (1983), the only exceptional recession is between 1960 and 1961, as there is no preceding rise in oil prices.

As observed, Hamilton's studies are more focused on the US economy and hence, it is important to explore other countries as well such as Cunado and De Gracia (2005) who research six Asian countries namely Japan, Singapore, South Korea, Malaysia, Thailand and the Philippines between 1975(Q1) and 2002(Q2). Their research suggests that oil prices have a significant effect on both economic activity and price indexes, especially when oil price shocks are in national currencies. Farzanegan and Markwardt (2009) also show the expected vulnerability of the Iranian economy to oil price fluctuations. Nevertheless, Chang and Wong (2003) highlight that the impact of oil price shocks on the Singapore economy is marginal but should not be considered negligible even though it is small.

Overall, past literature appears to show that crude oil does impact the economy of countries. However, the degree of development of each country seems to show that there are some differences how countries react towards crude oil. Even the classification of a country as an oil importer/exporter appears to be important. For instance Singapore is only marginally impacted (Chang & Wong, 2003) while Iran is highly vulnerable to oil price fluctuations (Farzanegan & Markwardt, 2009).

2.7.2. MARKET LIQUIDITY AND THE MACRO-ECONOMY

As highlighted earlier, our research in chapter six also looks into the effect of illiquidity shocks on the macro-economy. There are various studies that investigate the relationship between market liquidity and the macro-economy of countries. However, the initial common theme is how macroeconomic variables affect market liquidity. Chordia et al. (2001) discover that market liquidity increases prior to major macroeconomic announcements by studying the effects of several explanatory variables (including macroeconomic announcements[26]) on aggregate market spreads, depths and trading

[26] Their study focuses on macroeconomic variables such as Gross Domestic Product (GDP), the unemployment rate and the Consumer Price Index (CPI).

activity for US stocks from 1988 to 1998. (See also Fujimoto (2004), Söderberg (2008) and Said and Giouvris (2017))

Nevertheless, recently, more studies have emerged on the reverse relationship that is the impact of liquidity on macroeconomic variables. Næs et al. (2011) highlight that market liquidity contains useful information for estimating the current and future state of the US and Norway economy. Galariotis and Giouvris (2015) expand this line of research by studying G7 countries and they show that liquidity may contain some information for predicting the current and future state of the economies but it is found to be more country specific and liquidity-variable dependent.

2.7.3. CHARACTERISTICS OF THE COUNTRY'S OIL INDUSTRY AND THE MACRO ECONOMY.

Although there appears to be some differences in the relationship between net oil exporting countries and net oil importing countries, such studies are still limited. For instance, Mork, Olsen, and Mysen (1994) obtain results which show that Norway, an oil-exporting country, behaves differently relative to oil-importing countries, as its economy benefits significantly from oil price increases and seems to be hurt by price declines but somewhat less significantly. The different behaviour for Norway[27] suggests that the domestic oil sector is large enough relative to the size of the economy. Furthermore, Engemann et al. (2014) highlight that apparently the US states that only respond to negative oil-price shocks are generally energy-intensive US states.

However, Cunado and De Gracia (2005) mention that further research is needed to obtain a more reliable conclusion, even though their results seem to suggest that there are different responses between oil exporters and oil importers.

Overall, it seems that the classification of whether a country is an oil exporter or importer is important when undertaking research on oil. However, past studies seldom differentiate between oil exporting and importing countries, which is also highlighted by Wang et al. (2013). Although they differentiate between oil exporting and importing countries, their focus is on the relationship between oil price shocks and stock markets instead of macro-

[27] Furthermore, the reason that Norway is affected less when the oil price declines even though it is an oil exporter is because the government uses all wealth accumulated in previous years to boost the macro economy of the country when revenue from selling oil diminishes.

economic activity. This is clearly a gap in the literature, highlighting the importance and potential of conducting research on the macro-economy, by investigating the effect of oil prices on the economic activity between oil exporting and importing countries.

2.7.4. RESEARCH QUESTIONS REGARDING MACRO-ECONOMY, ILLIQUIDITY AND OIL.

The literature appears to show that crude oil does impact the economy of countries (Hamilton, 1983). Although countries' classification as either an oil exporter or importer appears to be important, past studies seldom differentiate between oil exporting countries and oil importing countries (Wang et al., 2013)

There are various studies that investigate the relationship between market liquidity and the macro-economy of countries but the initial common theme is how macroeconomic variables affect market liquidity (Chordia et al., 2001). Nevertheless, recently, more studies have emerged on the reverse relationship that is the impact of liquidity on macroeconomic variables (Næs et al., 2011).

Therefore, our next research questions are:

1. Does oil price impact macro-economies?
2. How does oil affect the economic activity of oil exporting and importing countries?
3. Does liquidity influence macro-economies?

2.8. ASYMMETRIC EFFECTS OF OIL AND ILLIQUIDITY SHOCKS

This section covers literature on asymmetric effects that is more relevant to the fourth empirical chapter. This section is divided into two sub-sections: Section 2.8.1 discusses asymmetric effects due to oil price shocks while section 2.8.2 reviews the potential asymmetric effects of illiquidity shocks on the macro-economy. Lastly, section 2.8.3 provides potential research questions.

2.8.1. ASYMMETRY EFFECT DUE TO OIL PRICE SHOCKS

Nowadays, a number of research are focusing on the asymmetric effects of oil price shocks on the economy and the financial markets. One of the prominent earlier studies is conducted by Mork (1989), as an extension of Hamilton (1983) study on the US economy. Mork (1989) highlights that positive oil price changes have a significant negative effect on the US macro-economy measured using GNP, while oil price declines tend to have a small positive but statistically insignificant effect, indicating an asymmetric effect.

Mork et al. (1994) expand their research by covering seven *Organisation for Economic Co-operation and Development (OECD)* countries namely US, Canada, Japan, Germany (West), France, UK and Norway. Mork et al. (1994) mention that asymmetry is not confined to the US, as most countries show evidence of asymmetric effects, with the exception of Norway. This is not surprising as the oil producing sector of Norway is large relative to the economy as a whole. Their results also confirm that oil-price fluctuations are important for the shaping of business cycles of the leading market economies.

Farzanegan and Markwardt (2009) study Iran, one of the largest oil producers and a net oil exporting country, whose economy depends significantly on oil exports. Farzanegan and Markwardt (2009) find asymmetric effects of oil price shocks by investigating the dynamic relationship between oil price shocks and major macroeconomic variables. Interestingly, one of their findings indicates that both positive and negative oil price shocks significantly increase inflation.

Nevertheless, using US data between 1973 (Q2) and 2007 (Q4), Kilian and Vigfusson (2011) show empirically that there is no statistically significant evidence of asymmetry in the response functions of real GDP towards unanticipated changes in the real oil price. Moreover, Engemann et al. (2014) show some contradictory results to asymmetric effects. Their study of fifty US states (plus DC) discover that although most states are affected by positive oil shocks only, ten states experience symmetric responses, five states respond to both shocks and another five states respond to neither shocks. They also find evidence that five states show an asymmetric effect of responding only to negative oil shocks.

Overall, the literature above shows that there are instances where symmetric responses do actually exist. Kilian and Vigfusson (2011) show a symmetric effect in their study of the US economy while Engemann et al. (2014) find symmetric effect evidence on some of the US states. Furthermore, Mork et al. (1994) highlight that only Norway shows

evidence of symmetric effects, which is probably due to Norway's large oil-producing sector. Therefore, the classification of a country as oil exporter/importer may have some impact on the asymmetric effect results.

2.8.2. POTENTIAL ASYMMETRIC EFFECTS DUE TO MARKET ILLIQUIDITY

So far the literature in chapter 2.7.2 does confirm that there is a relationship between macroeconomic variables and liquidity, indicating that there should also be a relationship between business cycles and liquidity. However, unlike oil price shocks, there is not much research available in relation to the asymmetric effects of illiquidity shocks on the economy. Thus, we feel that there is potential in researching the asymmetric effects of illiquidity shocks.

Chordia et al. (2001) have conducted some asymmetric effect research but it is in relation to bid-ask spreads (liquidity) response to market movements. They find that both quoted and effective spreads increase dramatically in down markets, but decrease only marginally in up markets.

Jensen and Moorman (2010) study on the US market finds that liquidity price adjusts substantially around expansive monetary policy shifts but maintains consistency around shifts to a restrictive monetary policy. Similarly, Said and Giouvris (2017) research on UK appears to show that market liquidity increases after expansive monetary shifts but it is less noticeable during restrictive periods, indicating that investors are less concerned with liquidity. Thus, providing more evidence of potential asymmetry effect of liquidity in the US and UK.

Brunnermeier and Pedersen (2009) mention flight-to-quality, whereby when funding becomes scarce speculators cut back on the market liquidity provision especially for capital intensive assets. This indicates that when market liquidity decreases, the state of the economy may potentially worsen due to fewer investment projects. Rajan (2006) mentions that in times of ample liquidity supplied by the central banks, investors tend to engage in riskier investments to earn higher returns. Thus, during expansive monetary condition periods where market liquidity is expected to increase, it is likely that investors will increase their investments in riskier projects, potentially increasing economic growth. The two events of constrained and ample liquidity potentially show a symmetric effect.

2.8.3. RESEARCH QUESTIONS IN RELATION TO ASYMMETRIC EFFECTS OF OIL AND ILLIQUIDITY SHOCKS.

Past literature shows that crude oil does impact macro-economies but earlier research tends to focus on oil price increases (Hamilton, 1983). However, when oil price decreases are also included, the evidence shows asymmetric effect due to oil price increases only (Mork, 1989). Nevertheless, there are studies that indicates the existence symmetric effect (Kilian and Vigfusson, 2011). Thus, the effect of oil on economic growth can either be symmetric or asymmetric (Engemann, Owyang, and Wall, 2014).

Engemann et al. (2014) also highlight that the most energy intensive US states appear to respond only to negative oil price shocks and hence the characteristics of the countries may also be important in relation to oil price shocks research.

Similar to oil, the literature seems to show potential asymmetric effects for illiquidity on the economy, as the reaction of liquidity after restrictive monetary shifts appears to be less noticeable compared to expansive monetary shifts. Although research on illiquidity asymmetries would be interesting and beneficial within the current environment, surprisingly, there is actually limited research available.

Therefore, our next research questions are:

1) Are there symmetric or asymmetric effects of oil price shocks on the economy of multiple countries?
2) Are there symmetric or asymmetric effects of illiquidity shocks on the economy of multiple countries?
3) Does classifying the countries into oil exporters and importers influence symmetric and asymmetric effects results?

2.9. BALTIC DRY INDEX, NATIONAL FOREIGN EXCHANGE AND MACRO-ECONOMY

This section reviews literature relevant to the fifth and final empirical chapter. The section is divided into two sections as follows: Section 2.9.1 discusses the relationship between macro-economy and Baltic Dry index while section 2.9.2 discusses literature regarding

the potential links between macro-economy and national foreign exchange. Finally, section 2.9.3 provides potential research questions.

2.9.1. BALTIC DRY INDEX AND THE MACRO-ECONOMY

The Baltic Dry Index (BD) is a shipping and trade proxy created by the Baltic Exchange and it reflects the rates that freight carriers charge to haul solid raw materials such as iron ore, coal, cement, and grain (Rothfeder, 2016). Lin and Sim (2013) highlight that BD has become one of the most important indicators of the cost of shipping and an important barometer of the volume of worldwide trade and manufacturing activity.

Bakshi et al. (2011) find evidence of positive association between a BD increase and growth on stock/commodity returns as well as in global economic activity by studying the industrial production of 20 countries. Thus, revealing the role of the BD in predicting the future course of the real economy.

Another reason that we consider BD as part of our research is due to its apparently close relationship with oil. Tett (2016) mentions that recently, the behaviour of the BD is almost as dramatic as oil prices due to the current sluggish trade environment. Moreover, Wang et al. (2013) used the global index of dry cargo single voyage freight rates, constructed by Kilian (2009), to estimate the scale of global economic activity as a proxy for global oil demand. Although the dry cargo single voyage freight rates is not actually BD, its concept is the same as the dry cargos consist of grain, oilseeds, coal, iron ore, fertilizer, and scrap metal.

2.9.2. NATIONAL FOREIGN EXCHANGE AND THE MACRO-ECONOMY

We have included *national foreign exchange (NFX) rate* as part of our predictive variables because oil is usually priced in *United States Dollars (USD)*. Moreover, there appears to be a relationship between oil and NFX as Basher, Haug, and Sadorsky (2012) mention that lower USD coincides with higher oil prices and vice versa.

The mechanism behind the relationship between NFX and the economy of countries appears simple. It is expected that as NFX rate change, the prices of goods and services will affect exports and imports. This is a simple policy that is commonly reported in the

mainstream media. For instance in 2015, China's central bank has purposely devalued the Yuan relative to the USD because a cheaper Yuan will make Chinese exports less expensive, potentially boosting overseas sales (exports) that have been among the main drivers of economic growth for China's remarkable rise over the past 30 years (Inman, 2015). Thus, it would be expected that the NFX rate has at least an indirect effect on the growth or decline of macro-economies.

2.9.3. RESEARCH QUESTIONS REGARDING MACRO-ECONOMY, BALTIC DRY INDEX AND NATIONAL FOREIGN EXCHANGE.

The literature shows that Baltic Dry index (BD) has a potential role in predicting a country's economy, as it is an important barometer of worldwide trade and manufacturing activity (Lin and Sim, 2013). Moreover, the BD behaviour is almost as dramatic as oil (Tett, 2016) and BD is also used as a proxy for global oil demand (Wang et al., 2013). Therefore, BD apparently has a close relationship to oil, which is an important variable for our research.

National foreign exchange (NFX) appears to influence economic growth as a cheaper NFX will make a country's export cheaper boosting the country's economy, as shown by China's growth (Inman, 2015). Moreover, it is known that global oil is usually priced in United States Dollars (USD) and since we have various countries in our research it is logical to include NFX of the countries in our research. Basher, Haug, and Sadorsky (2012) also mention that lower USD coincides with higher oil prices and vice versa, indicating that there is a potential relationship between oil and NFX.

Thus, our next research questions are:

1) Does Baltic Dry index (BD) impact macro-economies?
2) Does national foreign exchange (NFX) influence macro-economies?

2.10. CAUSALITY

The final section covers literature relevant to the final empirical chapter, which involves causalities between the macro-economy and our predictive variables. This section is divided into four sub-sections which discuss causality between the macro-economy and

our predictive variables: oil, liquidity, Baltic dry index and national foreign exchange. As before, the last sub-section discusses potential research questions.

2.10.1. CAUSALITY POTENTIAL OF OIL AND THE MACRO-ECONOMY

So far past literature in chapter 2.7.1 appears to show that crude oil does impact the economy of countries as well as financial markets. Moreover, there is a comparable unidirectional effect when looking at the relationship between energy consumption and GDP. Lee (2005) finds evidence that long-run and short-run causalities run from energy consumption to GDP, but not vice versa using as their sample eighteen developing countries. (See also Wolde-Rufael (2004) and Narayan and Smyth (2008))

Nevertheless, we believe that there may also be an inverse relationship between energy and economic growth whereby economic growth can influence oil price. The logic behind this is as follows. As economies improve, it is expected that the energy consumption of those economies will also increase resulting in an increasing demand for oil causing the oil price to also increase. For instance, Kraft and Kraft (1978) find evidence in the US that causality is unidirectional, running only from GNP to energy[28] for the post-war period between 1947 and 1974. (See also Al-Iriani (2006))

However, there are also studies that find a bidirectional causality such as Oh and Lee (2004). They find a long run bidirectional relationship between energy and GDP by studying Korea for the 1970–1999 period. (See also Soytas and Sari (2003))

There are also studies that find contradictory results of no causality between economic growth and energy consumption such as Eden and Hwang (1984) research on US, using data between 1947 and 1979. A more important point is highlighted by Al-Iriani (2006) who mentions in their research of GCC countries that energy consumption is based on aggregate data, so oil consumption may only be a portion of other more relevant energy variables[29]. Wolde-Rufael (2004) actually dis-aggregated the energy series, finding evidence to suggest that there is no Granger causality running in any direction between oil consumption and real GDP but there is only a unidirectional Granger causality running

[28] Energy is represented by Gross energy inputs which include the total of inputs into the economy of primary fuels plus the generation of hydro and nuclear power converted to equivalent energy inputs (BTU's). The primary fuels include both domestic and imports of coal, natural gas and petroleum (Kraft & Kraft, 1978)

[29] Energy consumption for the World Bank (Global Consumption Database) consists of Electricity, Gas and other fuels.

from coal, electricity and total energy consumption to real GDP. This indicates that other energy variables have a stronger effect on economic growth and hence energy consumption may not be appropriately captured by oil.

Basher et al. (2012) investigate the dynamic relationship between oil prices, exchange rates and emerging market stock prices and show that positive shocks to oil prices tend to depress emerging market stock prices. However, a positive oil production shock lowers oil prices while a positive shock to real economic activity increases oil prices. They also show that increases in oil prices are due to increases in emerging market stock prices[30].

Clements and Fry (2008) highlight that commodity exporting countries through their exchange rate can have an impact on commodity prices. This situation can arise if a country is a large producer of a commodity or if a group of commodity exporting countries have the combined market power to influence the world prices of commodities. In fact, Clements and Fry (2008) give example of Saudi Arabia having the ability to influence oil prices. Moreover, Saudi Arabia is part of *OPEC (Organization of the Petroleum Exporting Countries)*, a group of oil exporting countries, which should have the combined market power to influence oil prices. In fact, Kaufmann, Dees, Karadeloglou, and Sanchez (2004) find evidence that *OPEC*[31] Granger cause real oil prices but there is no inverse relationship (or causality), implying that OPEC is able to influence real oil price.

Overall, the literature appears to suggest the possibility of bidirectional relationship between oil and economic growth.

[30] Currently, it is not surprising for oil price to be effected by emerging market stock prices due to the impact that emerging markets have on global economies. For instance, Basher and Sadorsky (2006) highlight that emerging economies are expected to consume an increasing share of the world's oil and become larger players in the global financial markets, which is shown by the rising economic importance of the BRIC (Brazil, Russia, India, and China) economies. Therefore, indicating that emerging economies will use up a significant amount of fossil fuels. Moreover, Basher et al. (2012) in their updated research highlights that over the past ten years, emerging economies have been accounting for a larger proportion of global GDP and such trend is expected to continue in the future. The study also mentions that emerging economies are among the fastest growing economies with GDP growth rates much higher than the growth rates observed in developed economies (Basher et al., 2012). Thus, as oil consumption in most developed economies is either flat or in decline, emerging market economic growth (as proxied by emerging market stock prices) is likely to be an important source of demand side pricing pressure in the oil market (Basher et al., 2012). Due to the influence that emerging economies appears to have on global economies including the oil market, it is expected that emerging market stock prices can somehow affect oil prices.

[31] The variables of the study include *OPEC capacity utilization, OPEC production quotas, the degree to which OPEC exceeds these production quotas* and *crude oil stocks in OECD nations.*

2.10.2. CAUSALITY POTENTIAL OF LIQUIDITY AND THE MACRO-ECONOMY

The literature in chapter 2.7.2 appears to show that there is a potential two-way relationship between illiquidity and macroeconomic variables, as Fujimoto (2004) mentions that macroeconomic fundamentals seem to be significant determinants of liquidity while Næs et al. (2011) highlight the inverse relationship. Pereira and Zhang (2010) do find a bidirectional relationship but their study involves stock market and liquidity while Chordia et al. (2001) find indirectly that there is a potential two-way relationship between macroeconomic variables and liquidity.

Galariotis and Giouvris (2015) have found evidence that there is a two-way causality between macroeconomic indicators and liquidity variables for the six countries in their sample but it is more consistent for global liquidity. When considering both developed and developing markets, Sung and Giouvris (2016) also find that there is a two-way causality between macroeconomic variables and national liquidity but not for global liquidity.

Overall, the literature shows that there is potentially a two-way causality between liquidity and macroeconomic variables but the causality depends on the liquidity measure used. For instance, Galariotis and Giouvris (2015) find a two-way causality for global liquidity whereas Sung and Giouvris (2016) obtain similar results for national liquidity.

2.10.3. CAUSALITY POTENTIAL OF BALTIC DRY INDEX AND THE MACRO-ECONOMY

The literature in chapter 2.9.1 shows that Baltic Dry Index (BD) appears to have some relationship with economic growth as it has the ability to predict economic growth (Bakshi et al., 2011). However, there also seem to be an inverse relationship between macroeconomic variables and BD as well. Klovland (2002) shows that cycles in economic activity are major determinants of the short-run behaviour of shipping freight rates in the years between 1850 and World-War I. Moreover, since Apergis and Payne (2013) indicate that there is a relationship between commodities and BD, a change in demand for commodities should have an effect on BD as well. For example, due to economic growth, an increased demand for commodities will eventually affect BD. Bloch, Rafiq, and Salim (2012) mention that China's demand for coal is surging because of

China's strong economic growth. Hence, there is potentially a two-way relationship between BD and economic growth. In fact, Bloch et al. (2012) find that there is a bidirectional causality between coal consumption and GDP using demand-side analysis. Thus, since coal is part of BD, it should be expected that economic growth may also affect BD.

On a separate note, Lin and Sim (2013) investigate 48 *Least Developed Countries (LDC)* designated by the United Nations using BD as an instrument for trade and they find that a 1% expansion in trade raises GDP per capita by approximately 0.5% on average, emphasizing the importance of trade towards the economic development of LDCs or low income countries. Since we have two emerging countries in our sample, it may be interesting to investigate whether developed and emerging countries would react differently to the predictive variables including Baltic Dry Index (BD). However, Mexico and Brazil are not part of the Lin and Sim (2013) LDCs.

Overall, there is a potential two-way causality between Baltic Dry index and the macro-economy.

2.10.4. CAUSALITY POTENTIAL OF FOREIGN EXCHANGE AND THE MACRO-ECONOMY

The literature appears to show that national foreign exchange (NFX) can influence economic activity because Cunado and De Gracia (2005) highlight that the impact of oil price shocks on economic activity becomes more significant when shocks are defined in national currencies. However, we believe that economic growth can also affect NFX rate, as Inman (2015) highlights that the main reason that China devalue the Yuan is due to its flagging economy. This is also reported by Ryan and Farrer (2015) indicating that the state of the economy of a country can also impact NFX rate. Therefore, the possibility of a two-way relationship between the NFX rate and economic growth.

2.10.5. RESEARCH QUESTIONS REGARDING CAUSALITY

The literature appears to suggest the possibility of bidirectional relationship between oil and economic growth as Cunado and De Gracia (2005) highlight that oil affects economic

activity while Kaufmann et al. (2004) shows that OPEC can influence real oil prices to benefit their economies if required

Potentially, there is also a two-way causality between liquidity and macroeconomic variables as Galariotis and Giouvris (2015) find a two-way causality for global liquidity while Sung and Giouvris (2016) obtain similar results for national liquidity. There is also a probable two-way causality between BD and macro-economy (Bloch et al., 2012).

National foreign exchange (NFX) also seems to show bidirectional relationship with economic growth, as NFX appears to influence economic activity (Cunado and De Gracia, 2005) while Inman (2015) reports that the main reason that China devalue the Yuan is due to its flagging economy.

Therefore, our next research questions are:

1) Is there a bi-directional causality between oil and macro-economies?
2) Is there a bi-directional causality between liquidity and macro-economies?
3) Is there a bi-directional causality between Baltic Dry Index and macro-economies?
4) Is there a bi-directional causality between national foreign exchange and macro-economies?

2.11. SUMMARY OF RESEARCH QUESTIONS

The literature shows the importance of illiquidity for financial markets and macro-economies, and how research on illiquidity becomes more prominent due to financial sector developments (Rajan, 2006) and the financial crisis (Crotty, 2009). Various questions, especially regarding illiquidity, have emerged from the literature review and in order to answer the questions, we have five empirical chapters.

Our first empirical chapter is our overall third PhD chapter and it initially explores the relationship between illiquid and liquid stocks. This will be followed by investigating the impact of monetary conditions on market liquidity and illiquidity premium as well as on the sensitivity of various illiquidity portfolios. Since past research on illiquidity and monetary conditions tends to focus on US market (see Chordia, Roll, and Subrahmanyam (2001) and Jensen and Moorman (2013)), we decide to conduct a research on UK market.

Our second and third empirical chapter hopes to answer the question on whether illiquidity can be made into a reliable investment style, as it is believed that it should be given equal standing with other widely known investment styles such as value, growth and momentum (Ibbotson et al., 2013). The two empirical chapters also use UK data because we agree with Galariotis and Giouvris (2007) that the results on the UK market will be of great interest to the international scientific, corporate and investment community.

Since the financial crisis appears to impact financial markets and instruments, our second empirical chapter investigates the crisis period by dividing 14 years of crisis data equally into pre-crisis and post-crisis sample periods while the third empirical chapter uses a longer data period of 23 years. However, the third empirical chapter also includes an investigation into portfolio construction comparing "characteristics model" and "covariance model", followed by a study on whether January effect persists within the various investment styles.

Our final two empirical chapters research the impact of oil and illiquidity on macro-economies. The two empirical chapters also investigate on whether categorising the countries in our sample into net oil exporters and importers, will provide any valuable insights. The fourth empirical chapter focuses on whether there are either symmetric or asymmetric effects of oil price shocks as well as illiquidity shocks on eleven macro-economies consisting of net oil exporting countries (Norway, Canada, Denmark, Mexico and Brazil) and net oil importing countries (Singapore, UK, Germany, Japan, France and US).

The last and fifth empirical chapter investigates the ability of five related predictive variables namely crude oil Brent (OB), national illiquidity (NAM), global illiquidity (GAM), national foreign exchange (NFX) and Baltic Dry index (BD) on ten macro-economies segregated equally into net oil exporters and net oil importers. The sample countries are similar to the fourth empirical chapter with the exception of US. The empirical chapter further splits our net oil exporting countries into developed and emerging countries. Finally, two-way causality tests are also conducted between GDP and our predictive variables.

CHAPTER 3 : ILLIQUIDITY, MONETARY CONDITIONS AND THE FINANCIAL CRISIS IN THE UNITED KINGDOM

3.1. INTRODUCTION

Ever since Amihud and Mendelson (1986) highlight that stock returns is an increasing function of illiquidity, illiquidity (or liquidity) has become a common part of finance literature. Nevertheless, the study of illiquidity has become more prominent due to the developments in the financial sector that have resulted in greater funding access (Rajan, 2006) and more importantly the recent financial crisis (see Crotty (2009) and Brunnermeier (2009)).

Furthermore, Kacperczyk and Schnabl (2010) mention that due to the crisis, safe products such as commercial paper[32], which is considered to be a safe asset due to its short maturity and high credit rating before the crisis, has nearly dried up and ceased being perceived as a safe haven. Obviously, the flight-to-safety from other kinds of debt as well as stocks, can cause damage to an economy by making it more expensive for businesses to finance their daily operations (Bajaj, 2008). Thus, the effect of the liquidity crisis is not only confined to financial companies[33]. Obviously, the seriousness of the crisis can also be seen at country level[34].

Goyenko and Ukhov (2009) show that there is a relationship between liquidity and monetary conditions, specifically an expansionary monetary policy coincides with increasing market liquidity. (see also Chordia et al. (2001) and Söderberg (2008)).

Due to the importance of liquidity and monetary policy in combating the financial crisis, we feel that it is time that we update current *United States (US)* focused research by studying the *United Kingdom (UK)* market. Our research hopes to investigate any

[32] Commercial paper is an unsecured short-term debt instrument issued by companies.

[33] For example, during the crisis, Keogh (2008) highlights that the credit ratings of *United Parcel Service Inc* and *Toyota* are downgraded while *General Electric Co*., which has held the *Standard & Poor (S&P)*'s top rating since 1956 (longer than any other company) is in danger of being downgraded which would have cost $233 million more in annual payments on the $23.3 billion GE Capital Corp. raise in the US bond market in the first half of 2008, according to data compiled by Bloomberg. Eventually, General Electric Co. does lose its perfect credit rating when Standard & Poor's downgrades the company to "AA+" from "AAA". S&P expects the worsening economy to cause GE's holdings to deteriorate in value (Goldman, 2009). After 5 years, General Electric Co. have not recovered their perfect ratings but at least their 'AA+' long-term corporate credit rating outlook remains stable (StreetInsider.com, 2014).

[34] As expected, there is a domino effect following the liquidity crisis, which is due to the nation's political process and budget issues. Detrixhe (2011) reports it even results in S&P downgrading US' AAA credit rating for the first time, causing stock markets to fall including the *Dow Jones Industrial Average (DJIA)*, which endure its sharpest one-day decline since the financial crisis in 2008 (Browning, 2011). Three years after the downgrade, S&P maintains US' credit ratings as AA+ but the outlook on ratings is stable (Detrixhe & Katz, 2014).

possible relationship between monetary conditions and illiquidity by using Jensen and Moorman (2010) framework. Jensen and Moorman (2010) focus on the US market, while we on the contrary focus on the UK market and also discuss the financial crisis.

We feel that the UK market has strong research potential as its stock market is considered as one of the largest stock markets by capitalisation and turnover ratio indicating that the market is quite liquid and therefore the results will be as immune as possible from biases such as infrequent trading (Galariotis & Giouvris, 2007). In relation to the two monetary condition measures chosen here, namely the *Bank of England (BOE) base rate* and the *London Interbank Offered Rate (LIBOR),* the former is essentially similar to the Federal Reserve System in the US[35], while LIBOR is widely used by institutions globally and it's link to financial instruments are quite significant, whereby about USD 300 trillion financial contracts are pegged to it (Zibel, 2008).

We start our research by investigating if there are any unconditional return differences for illiquid and liquid stocks as Amihud and Mendelson (1986) indicate in their study. This is followed by a conditional monetary policy investigation, which is further separated into two related exercises starting with the relationship between market liquidity and monetary conditions. The next step is to look into zero-cost portfolio[36] returns and monetary conditions. It should be noted that similar to Jensen and Moorman (2010), our study focuses mainly on changes of all monetary conditions over the sample periods but we will also discuss the financial crisis when we conduct our monthly event study.

Overall, our research of the UK market shows that illiquid stocks generate higher returns compared to liquid stocks and when considering monetary conditions, expansive monetary conditions result in an increase in market liquidity and higher zero-cost portfolio returns. However, prior to expansive shifts investors' liquidity concerns heighten resulting in funding constraints and higher risks, making investors to reduce their holdings of illiquid stocks and moving to the less risky liquid stocks, signifying a flight-to-liquidity. Moreover, the crisis has an effect on market liquidity and illiquidity premium but it is more noticeable for the former.

[35] Decisions of BOE Monetary Policy Committee (MPC) are also being tracked by global markets.
[36] Zero-cost portfolio = long the illiquid portfolio and short the liquid portfolio. Therefore, it is similar to the illiquidity premium as described by other researchers such as Eleswarapu and Reinganum (1993).

The remainder of this paper is organised as follows. Section 3.2 presents the literature review while section 3.3 describes the data and variables. In section 3.4, the methodology and empirical results are discussed followed by our conclusion in section 3.5.

3.2. LITERATURE REVIEW

3.2.1. UNCONDITIONAL RETURNS FOR ILLIQUID AND LIQUID STOCKS

Amihud and Mendelson (1986) who study the relationship between expected returns and bid-ask spreads in the *New York Stock Exchange (NYSE)* discover that average returns are an increasing function of the bid-ask spread. Similarly, using three different liquidity measures, Jensen and Moorman (2010) find evidence that the zero-cost portfolio earns returns that are both economically and statistically significant, suggesting that returns increase with increase in illiquidity. Amihud and Mendelson (1989) Brennan and Subrahmanyam (1996) and Kiyotaki and Moore (2012) provide similar results. Moreover, Acharya and Pedersen (2005), using liquidity adjusted *capital asset pricing model (CAPM)*, provide evidence signifying the importance of liquidity on asset prices.

However, there are some contradictory results, which show that illiquid stocks do not necessarily provide consistently higher returns. Ben-Rephael et al. (2008) study of NYSE find evidence that the profitability of trading strategies based on liquidity premium[37] has declined over the past four decades, rendering such strategies virtually unprofitable especially when using volume as a liquidity measure[38]. Furthermore, Eleswarapu and Reinganum (1993) find evidence that the premium is reliably positive only during the month of January suggesting a strong seasonal component while Brennan et al. (2013) who use the Amihud (2002) measure of illiquidity and its role in asset pricing, state that in general, only the down-days element commands a return premium. Nevertheless, Datar et al. (1998) who investigate the liquidity-return relationship for all non-financial firms on the NYSE highlight that the liquidity effect is prevalent throughout the year and is not restricted to the month of January alone.

[37] Illiquidity premium or liquidity premium is the premium that investors received for holding a more illiquid asset/ portfolio. Usually it is calculated as follows = illiquid asset/ portfolio minus liquid asset/ portfolio.
[38] Although liquidity measures not related to volume do show some evidence of liquidity premiums, they are considered weak (Ben-Rephael et al., 2008).

We believe that due to conflicting evidence, conducting research on liquid and illiquid stocks still has its merits.

3.2.2. MARKET LIQUIDITY (AGGREGATE ILLIQUIDITY INNOVATION, E_T) AND MONETARY CONDITIONS

There is more research on the effect of monetary conditions on market liquidity than the relationship between illiquidity premium and monetary conditions. Specifically Söderberg (2008) studies the ability of 14 macroeconomic variables such as interest rate to forecast changes in monthly market liquidity on 3 Scandinavian order-driven stock exchanges[39]. Acharya and Pedersen (2005) highlight that an investor should also be concerned with market liquidity, as the combined effect of both market and individual asset liquidity can affect asset prices. Thus, suggesting that by understanding how monetary conditions affect market liquidity will allow us to explore how monetary conditions affect prices as well as the illiquidity premium.

Chordia et al. (2001) study the effects of several explanatory variables (inclusive of short-term interest rates[40]) confirm that short-term interest rates significantly affect market liquidity as well as trading activity (See also Fujimoto (2004), Goyenko and Ukhov (2009), Jensen and Moorman (2010) and Fernández-Amador et al. (2013)). Nevertheless, Chordia et al. (2005) obtain results indicating monetary expansions are associated with increased equity market liquidity but only during crisis periods. Even Söderberg (2008) highlights that although some of the macroeconomic variables are able to predict the market liquidity of the specific stock markets, not a single variable is able to predict the market liquidity of all three Scandinavian stock markets. Therefore, implying that not a single macroeconomic variable has the same effect on all three stock markets.

3.2.3. ILLIQUIDITY PREMIUM ACROSS MONETARY CONDITIONS

Even though there is limited research on the relationship between illiquidity premium and monetary conditions, there is some research on the relationship between stock prices and

[39] Copenhagen (Denmark), Oslo (Norway) and Stockholm (Sweden).
[40] Nevertheless, their study focuses on more macroeconomic variables such as Gross Domestic Product (GDP), the unemployment rate and the Consumer Price Index (CPI).

business conditions. In particular, Fama and French (1989) highlight that further research on monetary policy should be done. Hence, by extending Fama and French (1989) research, Jensen, Mercer, and Johnson (1996) find evidence to suggest that the monetary environment actually influences investors' required returns. Amihud (2002) even highlights that expected market illiquidity affects ex-ante stock excess return positively over time, signifying that if there is an expansionary shift (market liquidity increase), stock returns are expected to decrease.

However, in contrast to Fama and French (1989) and Amihud (2002), Thorbecke (1997) who also studies the US market finds evidence to indicate that expansionary policy increases ex-post stock returns. Thus, if *market liquidity (expansionary) increases*, stock returns are expected to also increase.

3.2.4. FLIGHT TO LIQUIDITY

Amihud (2002) also highlights the effects of both expected and unexpected market illiquidity are stronger on the returns of small firms stock portfolios. Since small firms are usually known to be more illiquid compared to larger firms, their study also indicates that market liquidity affects illiquid stocks more compared to liquid stocks meaning that small stocks are subject to greater illiquidity risk. Such a relationship can also be linked to the *''flight-to-liquidity''* or *"flight-to-quality"* phenomenon as in times of dire liquidity large stocks seem relatively more attractive compared to small stocks due to the illiquidity risk.

Brunnermeier and Pedersen (2009) provide a model to indicate that there are associations between an asset's market liquidity[41] and investors' funding liquidity[42]. Their model actually establishes various findings such as market liquidity has commonality across shares and is subject to flight-to-quality. See also Acharya and Pedersen (2005), Goyenko and Ukhov (2009) and Jensen and Moorman (2010)

Nevertheless, Rajan (2006) mentions that in times of ample liquidity supplied by the central banks (low interest rates), investors have a tendency to engage in riskier investments to earn higher returns. Therefore, during expansive monetary policy periods

[41] *Market liquidity* means how easily an asset is traded.
[42] *Funding liquidity* relates to degree of difficulty/ easiness investors can obtain funding.

where market liquidity is expected to increase, it is likely that investors will increase their holdings of riskier illiquid stocks causing the price of illiquid stocks to increase.

3.2.5. SENSITIVITY OF ILLIQUID QUINTILE AND LIQUID QUINTILE

Another point that Amihud and Mendelson (1986) discover is that there is a clientele effect, whereby stocks with higher spreads are held by investors with longer holding periods resulting in the returns of higher-spread stocks (illiquid stocks) to be less spread-sensitive. Therefore, such illiquid stock investors will react slowly to changes in liquidity of the stocks as they tend to hold the stocks for longer.

However, using turnover as a measure of liquidity and a sample of 48 stock exchanges[43], Dey (2005) supports a negative relationship between turnover and returns but they find that turnover is significant for the emerging market portfolios only. They highlight that due to the high liquidity of developed markets, liquidity is not a concern for investors. Therefore, since the UK market is a developed market, investors may not be as concerned with liquidity, resulting in asset prices to be less sensitive to changes in liquidity.

Furthermore, Bekaert et al. (2013) mention that lax monetary policy (increased market liquidity) decreases both risk aversion and uncertainty of expected market volatility by studying the VIX[44]. Therefore, it is expected that investors will prefer illiquid stocks making it to be more sensitive compared to liquid stocks during expansive monetary conditions.

3.3. DATA AND VARIABLES

3.3.1. DATA

We use stocks listed under the *FTSE All-Share index* to capture the UK stock market. Our sample starts in January 1987 and ends in December 2013. All data is obtained from

[43] 48 stock exchanges consist of 22 exchanges from Europe, 7 exchanges from North America, 13 exchanges from Asia/Pacific, 5 exchanges from South America and 1 exchange from Africa.
[44] VIX = Chicago Board Options Exchange (CBOE) Volatility Index, which is the stock market option-based implied volatility of the US S&P500 index.

DataStream. Outliers are eliminated and the final data set contains 621 stocks by the year 2013.

3.3.2. LIQUIDITY MEASURES

Choosing the right liquidity measure may be complicated. As Amihud, Mendelson, and Pedersen (2005) highlight there is hardly a single liquidity measure that can capture all aspects of estimating the effect of liquidity on asset prices[45]. Therefore, similar to Jensen and Moorman (2010) and in order to address the issues highlighted by Amihud et al. (2005), we decided to use three liquidity measures namely i) *Amihud illiquidity measure* (Amihud, 2002), ii) *High-Low Spread (Adjusted[46])* (Corwin & Schultz, 2012) and iii) *Roll Estimator* (Roll, 1984). Please refer to table 3.1 for more information.

Since all three measures are mainly used to measure illiquidity, it is expected that there will be strong correlations between the measures but as Goyenko, Holden, and Trzcinka (2009) mention, different measures capture different aspects of liquidity. Table 3.1 provides results that are consistent with expectations as the three liquidity measures are positively correlated to each other and the results are statistically significant at least at 1% level. Nevertheless, since the correlations are not perfect ($\rho < 1$), it shows the uniqueness of each of the three liquidity measures.

[45] Moreover, Goyenko, Holden, and Trzcinka (2009) in their research of various liquidity measures mention that different liquidity measures capture different aspects of liquidity, signifying that choosing an appropriate liquidity measure is not as straightforward. Goyenko et al (2009) suggest using Amihud illiquidity measure, as it does well for measuring liquidity based on price impact but their research focuses on US market while our study focuses on UK market. Hence, their results may not be relevant for our research. Therefore, in order to address the issue of not choosing an appropriate measure, initially we use three liquidity measures, allowing us to investigate its effectiveness in measuring liquidity within UK. Jensen and Moorman (2010) also use three liquidity measures but two of the measures are different from our research.

[46] Corwin and Schultz (2012) makes a few assumptions for calculating the High-Low spread, where one measure is adjusted for overnight price changes whereas the second is not. We decide to use the one that is adjusted for overnight price changes. Nonetheless, the difference in spreads for the two techniques are quite minimum.

Table 3.1: Descriptive statistics of liquidity measures: January 1987 to December 2013.
This table shows descriptive statistics including the correlation of the three liquidity measures used throughout the paper. The measures are derived from daily data but are averaged to produce monthly measures. However, for the correlations, the monthly measures are further averaged to yield annual measures. The sample uses companies listed on FTSE All Share Index between January 1987 and December 2013 (324 months). All data are obtained from DataStream.

1. The Amihud illiquidity measure (ILLIQ) or AMH is calculated for each company, c, every month as follows:

$$AMH_{cm} = \frac{1}{t}\sum_{t} \frac{1{,}000{,}000 \times |return_t|}{price_t \times volume_t} \qquad (3.1)$$

Where t is a trading day within the year the measure is calculated.

2. The High-Low Spread (Adjusted) or HLA is calculated for each company, c, every month as follows:

$$HLA_{cm} = \frac{2(e^{\alpha} - 1)}{1 + e^{\alpha}} \qquad (3.2)$$

Where negative values are converted to zero (0) and the following equations are used to calculate α which is inserted in the above HLA equation

$$\alpha = \frac{\sqrt{2\beta} - \sqrt{\beta}}{3 - 2\sqrt{2}} - \sqrt{\frac{\gamma}{3 - 2\sqrt{2}}} \qquad (3.3)$$

$$\beta = \sum_{j=0}^{1} \left[ln\left(\frac{H_{t+j}^{0}}{L_{t+j}^{0}}\right)\right]^2 \qquad (3.4)$$

$$\gamma = \left[ln\left(\frac{H_{t,t+1}^{0}}{L_{t,t+1}^{0}}\right)\right]^2 \qquad (3.5)$$

Where t is a trading day within the year the measure is calculated.

3. The Roll Estimator or RE is calculated for each company, c, every month as follows:

$$RE_{cm} = 2\sqrt{-Cov(\Delta P_t, \Delta P_{t-1})} \qquad (3.6)$$

Where t is a trading day within the year the measure is calculated.

	Correlation				
	AMH	**HLA**	**RE**	**Mean**	**Std Dev**
AMH	1.00000 -----			2.42280	1.36766
HLA	0.67312 (0.0001)	1.00000 -----		0.00477	0.00226
RE	0.64433 (0.0003)	0.56259 (0.0023)	1.00000 -----	0.00522	0.00123

3.3.3. MONETARY POLICY MEASURES

In order to identify shifts in Federal Reserve's monetary policy, Jensen and Moorman (2010) use two alternative measures namely the *Federal funds rate* and *Fed*[47] *discount rate*. *Federal funds rate* is used to represent monetary policy *stringency* and to identify adjustments in federal *stringency* while the second measure, *Fed discount rate* is used to

[47] *Fed* is the short and informal name of the *Federal Reserve System.*

represent monetary policy *stance* in order to identify fundamental shifts in the overall Fed monetary policy.

Stance can be defined as the contribution made by monetary policy to the economic, financial and monetary developments (ECB, 2010). Fed uses it to identify fundamental shifts in the overall Fed monetary policy (Jensen & Moorman, 2010). The *Bank of England (BOE) base rate* is the best alternative measure for stance in the UK as it is the key interest rate used by BOE to manage monetary policy, which will be a good indicator of economic and financial development in the UK. The BOE base rate is also the rate that the BOE charges banks for secured overnight lending. Changes to the UK *BOE base rate* (if any), is decided and made by the *Monetary Policy Committee* of the BOE on a monthly basis (Bank-of-England, 2014a). This is similar to the Fed discount rate, which is decided by the *Federal Open Market Committee (FOMC)* but they meet only around eight times per year (Board-of-Governors-of-the-Federal-Reserve-System, 2014).

Jensen and Moorman (2010) mention that *stringency* can be defined as the degree of monetary strictness whilst Maddaloni and Peydró (2013) define it as how stringent the capital requirements of the banking sector are within a country. Hence, the *UK 3 months London Interbank Offered Rate (LIBOR)* may be the best alternative measure for stringency in UK as it is the 3 months average interest rates estimated by leading banks in London and it has been known to serve as the benchmark reference for debt instruments such as government bonds and even retail financing. Moreover, LIBOR is the interbank rate in the UK, which is similar to *Federal fund rate*, the rate used to represent stringency in the US. However, the FOMC also decides the Federal funds rate (Board-of-Governors-of-the-Federal-Reserve-System, 2014), unlike the LIBOR which is decided by leading banks in UK. Thus, the two alternative monetary policy measures that we will be using are UK *BOE base rate* and UK 3 months *LIBOR* rate as an indicator of *stance* and *stringency* respectively.

Similar to Jensen and Moorman (2010), the variables are measured as binary variables since we are identifying shifts in monetary conditions. The variables are considered as *expansive* for a given month *(t)* whenever the rate (either *BOE base rate* or *LIBOR*) decreases from month *(t-1)* to month *(t)* while *restrictive* for a given month *(t)* is whenever the rate (either *BOE base* rate or *LIBOR*) increases from month *(t-1)* to month *(t)*. If there are no changes from month *(t-1)* to month *(t)*, the previous month *(t-1)* classification will

be maintained for month *(t)*. In order to avoid look-ahead bias, stock returns are measured subsequent to the identified shifts in monetary policy.

Although the two measures are used to represent different aspects of monetary conditions, panel A in table 3.2 indicates that the two monetary policy measures are highly positively correlated to each other. Furthermore, table 3.2 shows that the mean is higher for *LIBOR* but *BOE base rate* has a slightly higher standard deviation indicating higher volatility and risk.

Panel B and C of table 3.2 reports changes (expansive or restrictive) of the two monetary conditions proxies over the 324 months period. Panel B considers the two measures independently showing that there are more months with expansive monetary conditions than restrictive monetary conditions for either stance or stringency, which is in contrast with Jensen and Moorman (2010) whom have more restrictive than expansive months. This could be due to the current financial crisis which has resulted in prolonged expansive periods, which is part of the data sample.

Panel C identifies the intersection of the two measures. Again contrasting to Jensen and Moorman (2010), panel C shows that there are also more months when both stance and stringency are expansive (128 months) compared to when both are restrictive (72 months). Panel C also shows the uniqueness of the two monetary policy measures, as out of the 324 months, the two monetary policy measures have not intersected for 124 months indicating that the leading banks in London, which determine the *LIBOR,* do not necessarily follow the BOE whenever the BOE change their *base rate*.

Table 3.2: Descriptive statistics for measures of monetary conditions: January 1987 to December 2013.
This table shows descriptive statistics for measures of monetary conditions used throughout the paper. *Stance* is derived from the monthly *United Kingdom (UK) Bank of England (BOE)* Base Rate, which is the key interest rates used by BOE to manage monetary policy. *Stringency* is determined based on UK 3 months *London Interbank Offered Rate (LIBOR)*, which is the average interest rates estimated by leading banks in London that the banks would offer to other banks if they borrowed from them. An increase in the rate from the prior month is labelled *"Restrictive"* and a decrease is labelled *"Expansive"*. For each rate, whenever there is no change from one month to the next, the prior label is maintained. Statistics are derived from the period between January 1987 and December 2013. All data are obtained from DataStream.

Panel A: Correlation of measures of monetary conditions

	Correlation			
	BOE	**LIBOR**	**Mean**	**Std Dev**
BOE	1.00000		5.80216	3.78182

LIBOR	0.99734	1.00000	6.01542	3.76820
	(0.0000)	---		

Panel B: Months across monetary conditions: Measures separated

	Number of months in alternative monetary conditions		
Monetary State Measure	**Expansive**	**Restrictive**	**All**
UK BOE Base Rate (Stance)	199	125	324
UK 3M LIBOR (Stringency)	181	143	324

Panel C: Months across monetary conditions: Measures intersected

	Number of months in alternative monetary conditions		
	UK Stance (BOE)		
UK Stringency (3M LIBOR)	**Expansive**	**Restrictive**	
Expansive	128	53	
Restrictive	71	72	
			All = 324

3.4. METHODOLOGY, EMPIRICAL RESULTS AND ANALYSIS

3.4.1. UNCONDITIONAL RETURNS DIFFERENCE BETWEEN ILLIQUID AND LIQUID STOCKS

Our research starts with an investigation of portfolio returns across illiquidity quintiles without regard to monetary conditions that is the unconditional returns of the quintiles. This will allow us to assess the pricing of illiquidity before any external variables are considered.

Using data obtained from DataStream, the monthly stock prices are initially converted into monthly returns by using the formula below:

$$Ret_t = \frac{P_t}{P_{t-1}} - 1.00000 \qquad (3.7)$$

Where P_t is the share price at time *(t)* and P_{t-1} is the share price one month before at time *(t-1)*.

Table 3.3 shows the equally weighted average monthly returns of the quintiles over the sample period. The prior year *(t-1)* average of the illiquidity measure is used to construct the quintiles for the returns calculation for a given year *(t)*. Therefore, the illiquidity measure for the year 1987 is used to construct the quintiles and then calculate the quintile returns for the year 1988. Using one of the illiquidity measures at a time, the stocks are ranked and the two portfolios that are ranked top 20% and bottom 20% are classified as either liquid or illiquid quintiles. The quintiles are rebalanced annually.

The final column in table 3.3 shows the zero-cost portfolio returns, which takes a long position on the illiquid portfolio and a short position on the liquid portfolio *(illiquid minus liquid stocks portfolio [IML])*. Table 3.3 shows, similar to past research such as Amihud and Mendelson (1986), that the zero-cost portfolio of the first two liquidity measures earns returns that are both positive and statistically significant. However, although the zero-cost portfolio returns for the *roll estimator* shows the highest positive returns, results are not statistically significant. Therefore, there are positive significant zero-cost portfolio returns observed in our data sample based on *Amihud* and *HLA* indicating that illiquid portfolios earn higher returns compared to liquid portfolios.

Jensen and Moorman (2010) also discover that returns are increasing monotonically with stock illiquidity for all three liquidity measures meaning they observe a decrease in returns when moving away from the low liquidity quintile (Illiquid) to the high liquidity quintile (Liquid). However as shown in table 3.3, our research indicates that out of the 3 liquidity measures, only *Amihud* shows returns that increase monotonically with decrease in liquidity.

Table 3.3: Monthly returns on liquidity ranked portfolios (Unconditional portfolio returns): January 1988 to December 2013.

This table shows equally-weighted, average monthly returns (in percentage format) for quintile portfolios based on the three liquidity measures described in Table 3.1. Quintile portfolio ranks are determined by the value of the liquidity measure in the year prior to the year in which returns are measured and are rebalanced annually. Thus, the returns sample period is from January 1988 to December 2013. The *"Illiquid – Liquid"* portfolio is a portfolio that takes a long position in the quintile of stocks with the lowest level of liquidity and a short position in the quintile of stocks with the highest liquidity. Newey-West p-values for long-short portfolios are reported in brackets and underneath the monthly average returns, whereby **bold** figures denote statistically significance coefficient at least at 10% level. The bandwidth parameter for the Newey-West p-value is calculated using the Newey-West automatic lag selection. All data are obtained from DataStream.

	Mean monthly portfolio return (%)					
	Liquidity Portfolio					
Liquidity Measure	**Liquid**	**2**	**3**	**4**	**Illiquid**	**Illiquid - Liquid**
Amihud	0.79068%	0.84669%	0.99227%	1.00362%	1.37744%	**0.58675% (0.0348)**
High Low Spread (Adjusted)	0.87038%	0.90009%	1.06716%	1.04422%	1.31145%	**0.44106% (0.0498)**
Roll Estimator	1.10231%	0.81193%	0.66244%	1.48521%	1.71233%	0.61003% (0.1271)

3.4.2. AGGREGATE ILLIQUIDITY INNOVATIONS, E_T,

We will now proceed with our main research objective of investigating how different monetary conditions affect illiquidity premium but as highlighted before, other than Jensen and Moorman (2010), there is not much research available that investigates such a relationship.

Nevertheless, there are some research on the relationship between market liquidity and monetary conditions such as Chordia et al. (2005) who discover that during the crisis periods, monetary expansions are associated with increased equity market liquidity (or decrease in aggregate illiquidity). Thus, it will be beneficial if we study aggregate illiquidity (market liquidity) in order to understand the effects of monetary conditions on illiquidity premium. As Acharya and Pedersen (2005) state each stock's required return depends not only on its own expected liquidity but also on the market liquidity (aggregate illiquidity).

In this section, we investigate the relationship between aggregate illiquidity and monetary conditions exploring whether aggregate illiquidity changes with different monetary conditions.

Similar to the regression technique adopted by Pastor and Stambaugh (2003) and described by Jensen and Moorman (2010), we use the *aggregate Illiquidity Innovation,*

ε_t, as an aggregate measure of illiquidity which is obtained using a market-wide version of *Amihud (ILLIQ)*. Please refer to table 3.4 for more details.

The residuals, ε_t, from the regression, are considered to be the *aggregate illiquidity innovations,* ε_t, which provide a dynamic measure of market liquidity conditions (Jensen & Moorman, 2010). Using the *aggregate illiquidity innovations,* ε_t, three analyses are conducted in order to investigate the relationship between aggregate illiquidity and monetary conditions. The first analysis investigates the relationship between *aggregate illiquidity innovation,* ε_t *and monetary conditions* followed by the monthly event study, which is achieved by examining *cumulative aggregate illiquidity innovation,* ε_t around a directional change in the BOE base rate. The last analysis involves *aggregate illiquidity innovations,* ε_t, within the most illiquid and most liquid quintile.

3.4.2.1. AGGREGATE ILLIQUIDITY INNOVATION, ET AND MONETARY CONDITIONS

Table 3.4 is constructed by assigning monetary conditions in month *(t-1)* to an *aggregate illiquidity innovation* ε_t in month *(t)*. Since we are using *aggregate illiquidity innovation* ε_t, a negative *aggregate illiquidity innovation* ε_t, value is considered as a decrease in aggregate illiquidity (or increase in market liquidity) whereas a positive *aggregate illiquidity innovation* ε_t value is considered as an increase in aggregate illiquidity (or decrease in market liquidity).

Although the *values* (positive or negative) are similar to past research as table 3.4 shows the values are negative following expansive monetary conditions and vice-versa, the p-value indicates that the results are generally not significant especially for restrictive periods. Table 3.4 also highlights that market liquidity is highest and significant when both stance and stringency are expansive, which is also observed by Jensen and Moorman (2010). Interestingly, the results seem to show that stringency (LIBOR) matters more than stance (BOE base rate), as it produces significant results for expansive periods.

Table 3.4: Aggregate Illiquidity Innovations and Monetary Conditions.
This table shows average monthly innovations in aggregate illiquidity across monetary conditions and the method used is described by Jensen and Moorman (2010) and Pastor and Stambaugh (2003).

The measure is derived from the monthly market wide version of *ILLIQ (AMH)* that is reported in Table 3.1 as in equation (3.1). The aggregate value of illiquidity (*AILLIQ*) is calculated as follows:

$$AILLIQ_t = \frac{1}{N_t}\sum_{i=1}^{N} ILLIQ_{i,t} \qquad (3.8)$$

Where N_t includes all firms with an observation for *ILLIQ* in month *t* except for the highest and the lowest 1% of $ILLIQ_{i,t}$.

Monthly changes in aggregate illiquidity are calculated for each month *t* as follows:

$$\Delta AILLIQ_t = \frac{m_{t-1}}{m_1}(AILLIQ_t - AILLIQ_{t-1}) \qquad (3.9)$$

Where m_{t-1} is the total market value at the beginning of month *t-1* for all firms with an observation for $ILLIQ_{i,t}$ in month *t*. m_1 is the total market value at the beginning of January 1987 for all firms with an observation for $ILLIQ_{i,t}$ in January 1987. We regress the monthly change in aggregate illiquidity on its lag and the scaled lagged value of aggregate illiquidity as follows:

$$\Delta AILLIQ_t = \alpha + \beta\Delta AILLIQ_{t-1} + \lambda\left(\frac{m_{t-1}}{m_1}\right)AILLIQ_{t-1} + \varepsilon_t \qquad (3.10)$$

Aggregate illiquidity innovations are the fitted values of the regression residual, ε_t.

Monetary conditions, as labelled in month *t-1*, are assigned to a value of ε_t in month *t*. Measures of monetary conditions are detailed in Table 3.2. Newey-West p-values are reported in brackets and underneath the monthly average, whereby **bold** figures denote a statistically significant coefficient at least at 10% level. The bandwidth parameter for the Newey-West p-value is calculated using the Newey-West automatic lag selection. Values are calculated over the period from January 1987 through December 2013. All data are obtained from DataStream.

	Aggregate illiquidity innovation		
Monetary policy	***Stance (UK BOE)***		
Stringency (LIBOR)	**Expansive**	**Restrictive**	**All**
Expansive	**-0.71828**	0.14693	**-0.46694**
	(0.0502)	(0.6284)	**(0.0757)**
Restrictive	0.70925	0.46145	0.58449
	(0.3273)	(0.2504)	(0.1576)
All	-0.20639	0.32956	0.00000
	(0.3185)	(0.2938)	(1.0000)

3.4.2.2. AGGREGATE ILLIQUIDITY IMPULSE RESPONSE FUNCTIONS

A *Vector autoregression (VAR)* is also run to further investigate the response of the *aggregate Illiquidity Innovation,* ε_t to a shock in monetary conditions. Dummy variables to represent monetary conditions are used and the following VAR model is used to obtain figure 3.1.

$$Y_t = \delta + \sum_{j=1}^{K} \phi_j Y_{t-j} + u_t \qquad (3.11)$$

Where Y is a vector that includes the *aggregate illiquidity innovation* ε_t, and a dummy variable that measures monetary conditions. δ is a vector of constants.

In order to examine response to an expansive shock for either BOE base rate or LIBOR, the dummy variable takes the value of *one (1)* in month *(t)* when the monetary conditions are expansive and *zero (0)* when the conditions are restrictive. With regards to examining response to a restrictive shock (either BOE base rate or LIBOR), it is the opposite whereby monetary condition is a dummy variable that takes the value of *one (1)* in month *(t)* when the monetary conditions are restrictive and *zero (0)* when the conditions are expansive.

In relation to examining response to an expansive combination of BOE base rate and LIBOR monetary condition (combined), the dummy variable takes the value of *one (1)* in month *(t)* when both monetary conditions namely BOE base rate and LIBOR are expansive and *zero (0)* for other periods. For combined restrictive, it will follow the opposite process.

The lag length K for the above equation are determine by 5 tests[48] and if there are any conflicts, the lag length with the highest number of significant tests is chosen. However, if there are still conflicts, the shortest lag length is chosen.

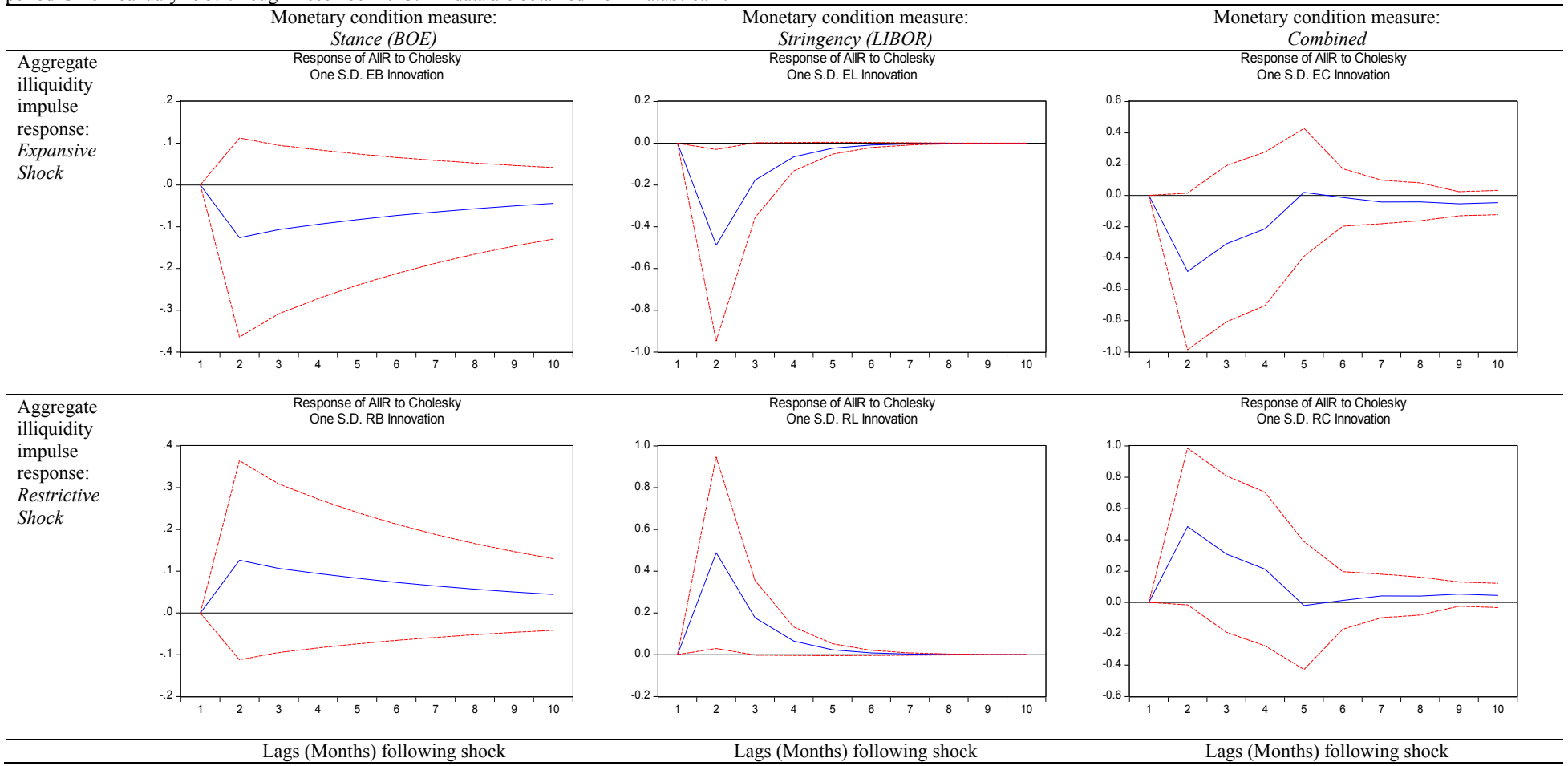
It should be noted that following an expansive monetary condition, a negative value (drop) indicates a decrease in *aggregate illiquidity innovation* ε_t (or market liquidity increase) is expected, whereas a positive value indicates an increase in *aggregate illiquidity innovation* ε_t (market liquidity decrease) is expected after restrictive monetary conditions.

[48] The 5 lag length tests conducted are *Likelihood Ratio (LR), Final Prediction Error (FPE), Akaike information criterion (AIC), Schwarz information criterion (SIC)* and *Hannan-Quinn information criterion (HQ).*

Finally, we consider the variable to be responsive to the respective shocks if the variables respond is statistically different from zero for at least one month.

Figure 3.1: Aggregate Illiquidity Impulse Response Function.

This figure shows the impulse response functions for aggregate illiquidity innovations, ε_t, as defined in Table 3.4, to a Cholesky one standard deviation shock in monetary conditions. The first row of graphs shows the response of aggregate illiquidity to an expansive shock. The second row shows the response of aggregate illiquidity to a restrictive shock. The VAR lag length is chosen according to 5 tests namely Likelihood Ratio (LR), Final Prediction Error (FPE), Akaike information criterion (AIC), Schwarz information criterion (SIC) & Hannan-Quinn information criterion (HQ). The sample period is from January 1987 through December 2013. All data are obtained from DataStream.



The top row in figure 3.1 relates to expansive monetary conditions and it shows that *aggregate illiquidity innovations,* ε_t, decreases (or market liquidity increases) when either stance or stringency are in expansive shock, peaking after 2 months. Similar results are also obtained when both are expansive. The bottom row shows opposite results as expected indicating that *aggregate illiquidity innovation* ε_t increases (or market liquidity decreases) after monetary condition signifies restrictive shock, also peaking after 2 months. However, only LIBOR produce significant results for both expansive and restrictive monetary conditions.

Overall, the impulse response function in figure 3.1 shows some association between monetary conditions and *aggregate illiquidity innovations,* ε_t, but in contrast to table 3.4, figure 3.1 indicates that this is not statistically significant for combined expansive monetary conditions associations. However, the figure apparently shows that LIBOR are significant for both monetary conditions and it appears to occur regularly at the 2nd lag (2nd month), signifying again that stringency (LIBOR) appears to matter more than stance (BOE base rate) when considering aggregate illiquidity.

3.4.2.3. MONTHLY EVENT STUDY: CUMULATIVE AGGREGATE ILLIQUIDITY INNOVATION, E_T AROUND A DIRECTIONAL CHANGE IN THE BANK OF ENGLAND BASE RATE (SHIFTS IN MONETARY POLICY)

So far table 3.4 and figure 3.1 shows some relationship between *aggregate illiquidity innovation* ε_t and monetary conditions but it does not investigate the timing of adjustments in *aggregate illiquidity innovation* ε_t. Therefore, Figure 3.2, shows the timing of adjustments in *aggregate illiquidity innovation* ε_t, which involves examining the changes in *aggregate illiquidity innovation* ε_t around shifts in monetary policy by conducting a *"Monthly Event Study"*. It is assumed that an *"event"* is an incident when there is a shift in monetary policy through a statement or decision issued by the BOE. A change in interest rate (expansive to restrictive or vice-versa) is considered as a shift in monetary policy. Moreover, we also assumed that *"broad shift"* means *"long-term shift"*. Hence, we are investigating long-term shifts in monetary policy.

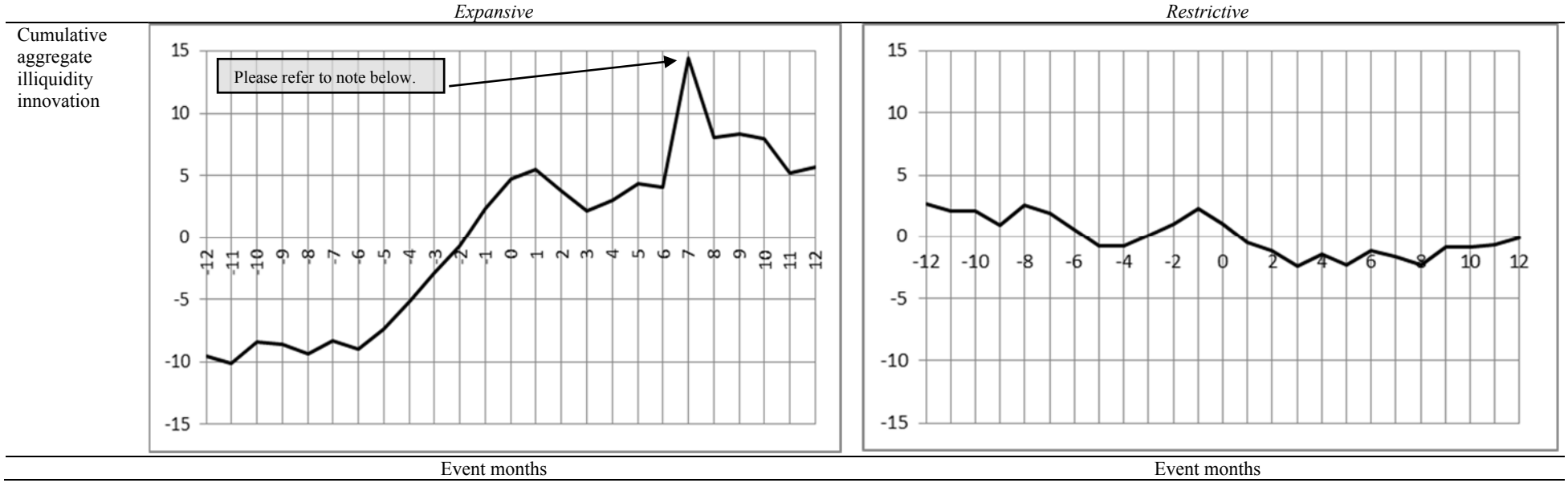
Data of shifts in monetary policy is obtained from the BOE website (Bank-of-England, 2014b), which publishes changes in interest rates since 1694. Between January 1987 and

December 2013 there are 94 changes in interest rates but only 18 are actual changes from expansive to restrictive or vice-versa (shifts in monetary policy). The remaining 76 changes are further (continued) increase or decrease in interest rates in the direction of the prior shifts.

The *"monthly event study"* investigates the behaviour of the markets, 1 year (12 months) before and after an event (directional change in BOE base rate or stance) has occurred whereby month "0" is considered as when the event occurred. If there is a shift within the 12 months period before and after an event, this is considered only as a *temporary shift* and is not included in our research, as our main intention is to investigate only *a long-term shift* in monetary policy. Nevertheless, we have also included the financial crisis period even though there is a minor temporary shift. Thus, including the financial crisis period which obviously results in monetary policy shifts, there are only eight monetary policy shifts between January 1987 and December 2013, namely four expansive and four restrictive shifts.

Figure 3.2: Monthly Event Study: aggregate illiquidity innovations, εt.

This figure shows the event time average of cumulative aggregate illiquidity innovations, ε_t, around a directional change in the UK BOE Base Rate (shift in *Stance*). The monthly version of aggregate illiquidity innovations detailed in Table 3.4 is used. A monetary condition is labelled as *"Expansive"* if the prior interest rate change is a decrease or *"Restrictive"* if the prior change is an increase. Numbers on the horizontal axis are event months. The sample period is from January 1988 through December 2013. All data are obtained from DataStream.



Note:

Based on our analysis, the unexpected significant increase of the event-time average of cumulative aggregate illiquidity innovations, ε_t are caused by three major happenings of which two are from the recent financial crisis, which occurred 7 months after the *directional change in the UK BOE Base Rate (event),* as below:

1. September 11 attacks in the US (7 months after event - September 2001)
2. The fall of one of US leading mortgage lenders IndyMac Bank. (7 months after event – July 2008)
3. Due to investors' concerns after the fall of Fannie Mae and Freddie Mac shares, resulting in the US government plan of saving them (7 months after event – July 2008)

The left side of figure 3.2 shows that six months before the expansive events, *cumulative aggregate illiquidity innovation* starts increasing prior to an expansive shift, indicating that aggregate illiquidity increases (or market liquidity decreases). However, cumulative aggregate illiquidity innovation starts decreasing after the expansive event, signifying that market liquidity has improved but there are some interruptions seven months after the event. These are due to i) the September 11 attacks on the US (McAndrews & Potter, 2002), ii) the fall of one of US leading mortgage lenders, IndyMac Bank (Clifford & Chris, 2008) and iii) Fannie Mae and Freddie Mac shares plummeting due to investors' concerns (Luhby, 2008). Therefore, with the exception of the interruptions, our findings are somehow consistent to our previous findings as market liquidity improves following an expansive monetary condition.

The right side of figure 3.2 shows that the reaction after restrictive monetary shifts are less noticeable compared to expansive monetary conditions indicating that during restrictive monetary policy periods, changes in aggregate illiquidity will have limited implications for pricing of liquidity as investors are less concerned with liquidity, which is similar to the findings of Jensen and Moorman (2010).

3.4.2.4. AGGREGATE ILLIQUIDITY INNOVATIONS: MOST ILLIQUID QUINTILE AND MOST LIQUID QUINTILE

Panel A and B in table 3.5 shows the average monthly innovations in *aggregate illiquidity innovation* ε_t across monetary conditions for the most liquid and illiquid quintiles respectively.

Similar to table 3.4, although the values (either positive or negative) are consistent with past research, the results in table 3.5 are generally not significant. The only significant results are when stringency is expansive as well as when both stance and stringency are expansive for the most liquid quintile.

By looking only at significant results under *stringency*, panel A and B of table 3.5 shows that the most illiquid quintile experiences greater change in *aggregate illiquidity innovation* ε_t values compared to the most liquid quintile, which exhibits minimum changes. Panel C in table 3.5 presents the difference in *aggregate illiquidity innovation* ε_t between the most illiquid and most liquid quintiles. It shows that the values are not

affected by the most liquid quintile confirming that the most liquid quintile experiences only a minimum change in *aggregate illiquidity innovation* ε_t due to monetary conditions.

As before, table 3.5 seems to indicate again that stringency seems to be more important for the UK market as it generates significant results.

Table 3.5: Aggregate illiquidity innovations, εt, and Monetary Conditions: Most illiquid quintile and most liquid quintile.

This table shows average monthly innovations in aggregate illiquidity across monetary conditions separately for the quintile of the most illiquid stocks and the quintile of the most liquid stocks. The aggregate illiquidity innovation measure is detailed in Table 3.4. Panel C shows the difference in aggregate illiquidity innovations for the most illiquid and the most liquid quintile. Newey-West p-values are reported in brackets and underneath the monthly average, whereby **bold** figures denote statistically significant coefficient at least at 10% level. The bandwidth parameter for the Newey-West p-value is calculated using the Newey-West automatic lag selection. Values are calculated over the period from January 1987 through December 2013. All data are obtained from DataStream.

Panel:	**A: Most Liquid Quintile Mean monthly illiquidity innovation**			**B: Most Illiquid Quintile Mean monthly illiquidity innovation**			**C: Illiquid minus Liquid Mean monthly illiquidity innovation**		
Monetary policy	***Stance (BOE)***			***Stance (BOE)***			***Stance (BOE)***		
Stringency (LIBOR)	**Expansive**	**Restrictive**	**All**	**Expansive**	**Restrictive**	**All**	**Expansive**	**Restrictive**	**All**
Expansive	**-0.00655**	-0.00438	**-0.00592**	-2.15471	-0.95894	**-1.84612**	-1.94456	-0.73326	**-1.59268**
	(0.0978)	(0.5425)	**(0.0866)**	(0.1425)	(0.1553)	**(0.0848)**	(0.1456)	(0.1854)	**(0.0858)**
Restrictive	0.00783	0.00700	0.00741	2.83524	1.52680	2.20115	2.66768	1.32894	1.99363
	(0.3419)	(0.1014)	(0.1203)	(0.3195)	(0.3034)	(0.1927)	(0.3218)	(0.3006)	(0.1965)
All	-0.00140	0.00223	0.00000	-0.31775	0.56146	0.00000	-0.29068	0.46415	0.00000
	(0.5870)	(0.6306)	(1.0000)	(0.8112)	(0.6318)	(1.0000)	(0.8106)	(0.6385)	(1.0000)

3.4.3. MONETARY CONDITIONS AND RETURNS TO ILLIQUID, RELATIVE TO LIQUID STOCKS

Up to this point our UK findings do not fully support Jensen and Moorman (2010) but there are some significant results indicating that expansive monetary conditions are associated with eased funding constraints (increase in market liquidity). To investigate the relationship between illiquidity premium and monetary conditions, we undertake four different exercises focusing on the *zero-cost portfolio* or *illiquid minus liquid portfolio (IML)*.

The first exercise investigates the *average return of the IML portfolio across monetary conditions*, which is achieved by examining the IML portfolio equally-weighted average monthly returns across different monetary conditions based on the three different liquidity measures. The second exercise examines the *terminal wealth in different monetary conditions*, which is done by assessing the terminal growth of £100 invested in the IML portfolio within different monetary conditions over 26 years. The third exercise is a monthly event study involving the *cumulative IML portfolio returns* around a directional change in the BOE base rate (shifts in stance monetary policy). The last exercise looks into illiquidity and monetary conditions *beta,* β to determine whether stocks with the highest or lowest illiquidity levels drive the relationship between returns and monetary conditions.

3.4.3.1. AVERAGE RETURN TO THE ZERO-COST PORTFOLIO ACROSS MONETARY CONDITIONS

Table 3.6 shows the IML portfolio equally-weighted average monthly returns across different monetary conditions based on the three liquidity measures. As before, returns are measured in a given month *(t)* based on monetary conditions determined in the previous month *(t-1)*.

Table 3.6 demonstrates that a relationship exists between IML portfolio returns and monetary conditions for all three liquidity measures but it is considerably less noticeable for the *Roll estimator*. Table 3.6 also shows that the IML portfolio return is different across the two monetary conditions. It shows that expansive monetary conditions consistently results in higher IML portfolio returns compared to restrictive monetary

conditions (see *Amihud* (panel A)). Following periods of expansive shifts for *stance (stringency),* the IML portfolio returns is *1.0964% (0.9075%)* whereas after restrictive periods, the IML portfolio returns is *-0.1745% (0.2287%)*. Our results also show that the average IML portfolio returns are generally statistically insignificant when either of the monetary conditions are restrictive. Moreover, the IML portfolio returns are the highest when both monetary conditions are expansive and the results are significant for both *Amihud* and *HLA* measures. In fact, the returns (conditional returns) for the two liquidity measures are more than twice the return of their respective unconditional returns which WAS discussed before, in table 3.3. Also unlike aggregate illiquidity in table 3.4, table 3.6 shows that stance (BOE base rate) has a stronger effect on IML than stringency (LIBOR).

Overall, there is some relationship between the zero-cost portfolio returns and monetary conditions even though the three liquidity measures do not capture the same aspects of illiquidity. Nevertheless, table 3.6 at least shows that there is a relationship between monetary conditions and the price of liquidity.

Table 3.6: Illiquid minus liquid portfolio returns across monetary conditions: January 1988 to December 2013.

This table shows illiquid minus liquid (zero-cost) portfolio, equally-weighted average monthly returns (in percentage format) across different monetary conditions. Each return is for a portfolio long in the quintile of stocks with the lowest liquidity and short in the quintile of stocks with the highest liquidity. Returns are measured in month (t) based on monetary conditions determined in month (t-1) and the portfolios are rebalanced on an annual basis based on the three respective liquidity measures. Liquidity and monetary conditions measures are detailed in Table 3.1 and Table 3.2, respectively. Newey-West p-values are reported in brackets and underneath the monthly average returns, whereby **bold** figures denote a statistically significant coefficient at least at 10% level. The bandwidth parameter for the Newey-West p-value is calculated using the Newey-West automatic lag selection. All data are obtained from DataStream.

Panel:	**A: Amihud**			**B: High Low Spread (Adjusted)**			**C: Roll Estimator**		
	Mean monthly return (%)			**Mean monthly return (%)**			**Mean monthly return (%)**		
Monetary policy	***Stance (BOE)***			***Stance (BOE)***			***Stance (BOE)***		
Stringency (LIBOR)	**Expansive**	**Restrictive**	**All**	**Expansive**	**Restrictive**	**All**	**Expansive**	**Restrictive**	**All**
Expansive	**1.5292%**	**-0.5968%**	**0.9075%**	**0.9002%**	0.0881%	**0.6628%**	1.0928%	1.0353%	**1.0760%**
	(0.0000)	**(0.0889)**	**(0.0053)**	**(0.0345)**	(0.7361)	**(0.0397)**	(0.1693)	(0.1189)	**(0.0660)**
Restrictive	0.3376%	0.1229%	0.2287%	0.2184%	0.1796%	0.1987%	0.3662%	-0.3248%	0.0158%
	(0.4529)	(0.8332)	(0.5952)	(0.5189)	(0.6531)	(0.4611)	(0.1878)	(0.7624)	(0.9751)
All	**1.0964%**	-0.1745%	**0.5868%**	**0.6526%**	0.1418%	**0.4411%**	0.8289%	0.2373%	0.6100%
	(0.0001)	(0.6227)	**(0.0348)**	**(0.0337)**	(0.5538)	**(0.0498)**	(0.1139)	(0.7287)	(0.1271)
Unconditional		**0.5868%**			**0.4411%**			0.6100%	
		(0.0348)			**(0.0498)**			(0.1271)	

3.4.3.2. TERMINAL WEALTH IN DIFFERENT MONETARY CONDITIONS

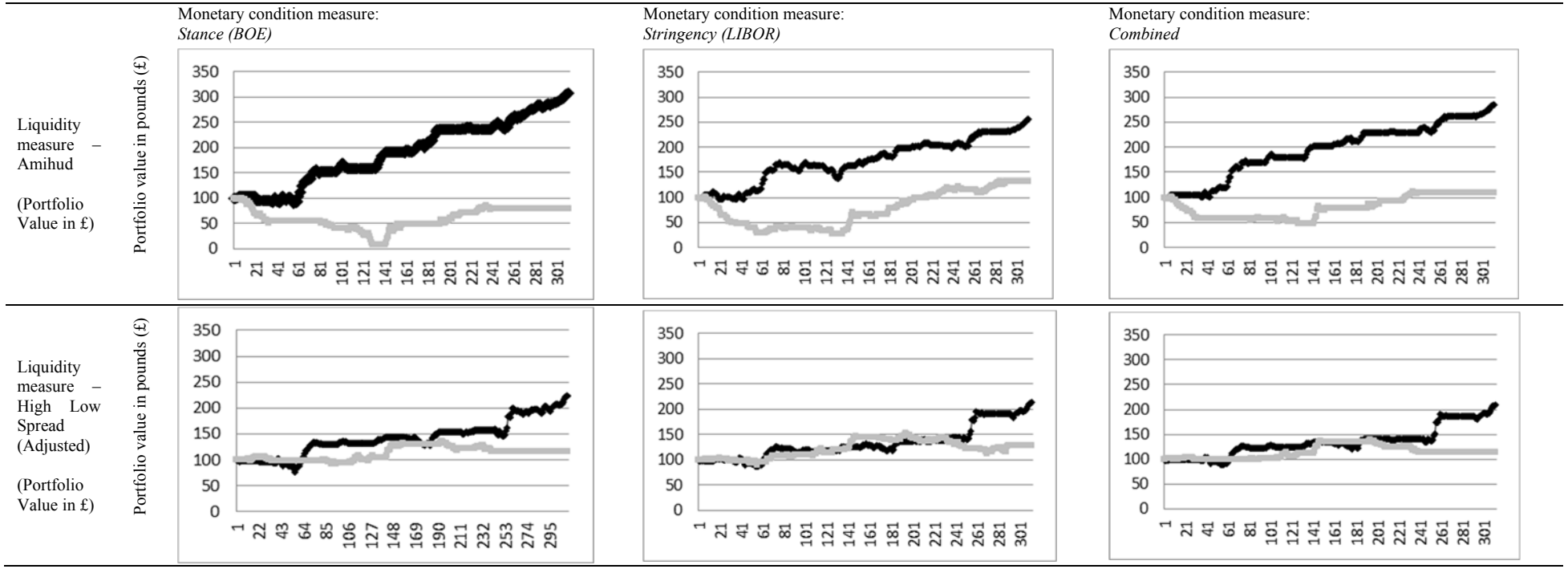
Figure 3.3 shows the growth of £100 after 26 years period (January 1988 to December 2013) by investing on the IML (zero-cost portfolio) using the three liquidity measures, under different monetary conditions. It is assumed that £100 is invested in the beginning (January 1988) growing cumulatively across the respective monetary conditions. In table 3.7, we provide the final results of figure 3.3 and we also include the returns growth for unconditional zero-cost portfolio (in the last row of table 3.7).

Table 3.7 shows that the highest return is actually based on *Amihud* during stance (BOE) expansive monetary condition whereby after 26 years, £100 grew to £308.23. As expected, figure 3.3 and table 3.7 highlights that during restrictive monetary conditions, the portfolios experience less growth and can even result in losses. The lowest growth is shown by *Roll estimator* across *combined restrictive monetary conditions* and the initial £100 investment has fell in value to £76.94.

Interestingly, table 3.7 also shows that the unconditional zero-cost portfolios can actually produce returns higher than when investing only during expansive conditions. Considering HLA, the unconditional return of £237.61 is slightly higher compared to *combined expansive conditions* that results in returns of £208.93 only. This signifies that it may even be better for investors to invest using the traditional buy-and-hold strategy, without regards to monetary conditions within the UK market.

Nevertheless, as a summary, although for a short period of time, portfolio growth during restrictive conditions can actually be higher than during expansive conditions (noticeably for the *Roll estimator*), the figure shows that in the long run, the IML portfolio for all three liquidity measures consistently results in higher growth during expansive monetary conditions relative to restrictive monetary conditions. This is also important as table 3.2 indicates that there are more expansive periods compared to restrictive periods.

Figure 3.3: Illiquid minus liquid portfolio growth of £100 across different monetary conditions (stringency): January 1988 to December 2013.
This figure shows the growth of £100 invested in the following strategy: long illiquid stocks and short liquid stocks in different monetary conditions over the 26 years study period. The black line shows the dollar growth for investing in the long-short strategy for either stance or stringency during expansive conditions and not investing during restrictive periods. The grey line shows the dollar growth for investing in the long-short strategy for either stance or stringency during restrictive conditions and not investing during expansive policy periods. If monetary conditions are expansive for both *Stringency* and *Stance*, then *"Combined"* is labelled expansive and it involves investing when both monetary conditions are expansive and not investing during other periods. If monetary conditions are restrictive for both *Stringency* and *Stance*, then *"Combined"* is labelled restrictive and it involves investing when both monetary conditions are restrictive and not investing during other periods. All data are obtained from DataStream.



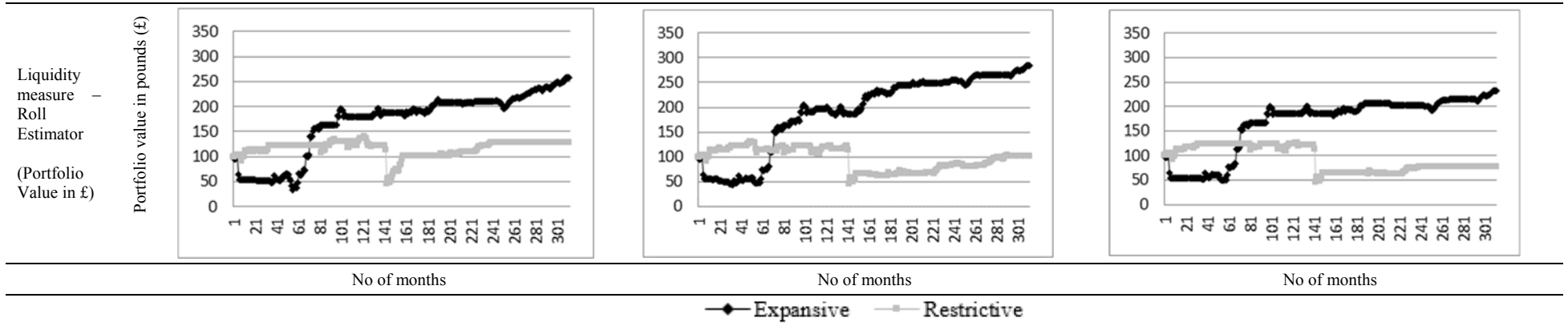


Table 3.7: Illiquid minus liquid portfolio growth of £100 across different monetary conditions: January 1988 to December 2013.
This table shows the growth of £100 invested in the strategy long illiquid stocks and short liquid stocks in different monetary conditions over the 26 years study period. This table provides the end results of figure 3.3 as well as the zero-cost portfolio growth of unconditional monetary condition. The expansive dollar growth long-short strategy for either stringency or stance involves investing during expansive periods and not investing (zero returns) during restrictive periods. The restrictive dollar growth long-short strategy for either stringency or stance involves investing during restrictive periods and not investing (zero returns) during expansive periods. The expansive dollar growth long-short strategy for both stringency and stance (Combined) involves investing following both are expansive periods and not investing (zero returns) during other periods. The restrictive dollar growth long-short strategy for both stringency and stance (Combined) involves investing following both are restrictive periods and not investing (zero returns) during other periods. All data are obtained from DataStream.

Panel:	**A: Amihud £100 portfolio value after 26 years**			**B: High Low Spread (Adjusted) £100 portfolio value after 26 years**			**C: Roll Estimator £100 portfolio value after 26 years**		
Monetary policy	***Stance***	***Stringency***	***Combined***	***Stance***	***Stringency***	***Combined***	***Stance***	***Stringency***	***Combined***
Expansive	£308.23	£255.19	£285.03	£224.00	£213.33	£208.93	£257.49	£283.99	£232.23
Restrictive	£78.88	£132.02	£108.72	£117.16	£127.82	£112.75	£128.71	£102.21	£76.94
Unconditional		£283.07			£237.61			£290.33	

3.4.3.3. ILLIQUID MINUS LIQUID (IML) PORTFOLIO RETURN IMPULSE RESPONSE FUNCTIONS

As before, to explore further the relationship between the price of liquidity and monetary conditions, we estimate a VAR model and report the resulting impulse responses. Amihud (2002) mentions that the largest effect on stock returns comes from the unexpected component of market liquidity (or shocks) but, unfortunately, they do not examine the relationship further. A VAR allows us to assess the ramifications that a shift in monetary policy has on the return of the zero-cost portfolio by considering an alternative lag structure and by showing the timing of the responses (Jensen and Moorman, 2010).

$$X_t = \delta + \sum_{j=1}^{K} \phi_j X_{t-j} + u_t \qquad (3.12)$$

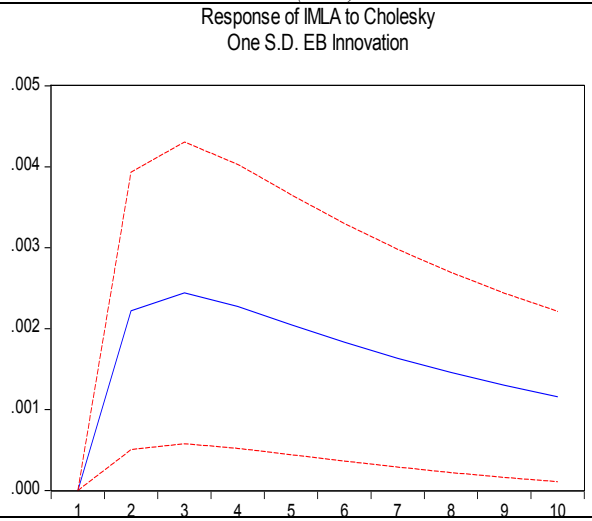
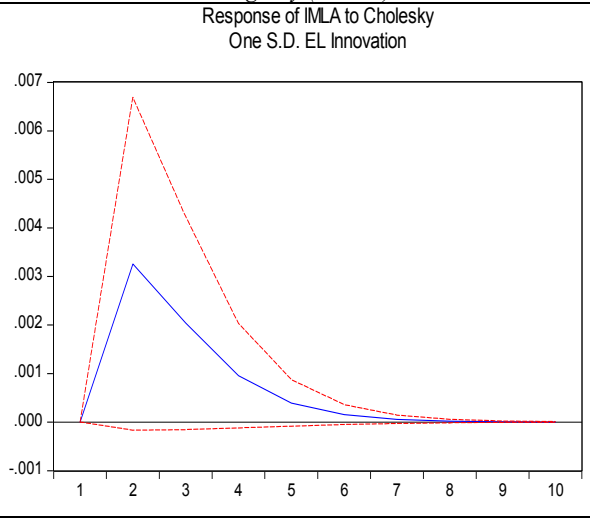
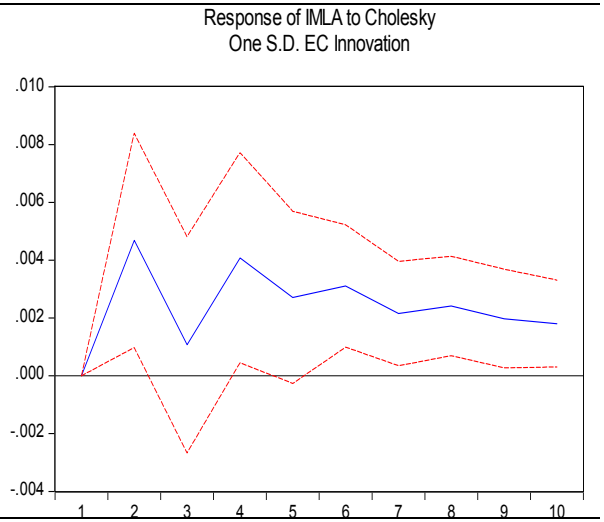
Where X is a vector that includes the *zero-cost portfolio returns* and a dummy variable that measures monetary conditions. δ is a vector of constants.

Monetary condition determinations for figure 3.4 and figure 3.5 are similar to figure 3.1. As before, dummy variables that measure monetary conditions are used and the lag length K for the above equation are determined by 5 tests[49]. If there are any conflicts, the lag length with the most number of positive tests is chosen. However, if there are still conflicts, the shortest lag length is chosen. It should be noted that following a specific monetary condition, a positive value (rise) indicates zero-cost portfolio returns increase, whereas negative value (drop) indicates a decrease in zero-cost portfolio returns. As before, we consider a variable to experience a shock if its response is statistically significant (different from zero) for at least one month.

[49] The 5 lag length tests conducted are *Likelihood Ratio (LR), Final Prediction Error (FPE), Akaike information criterion (AIC), Schwarz information criterion (SIC)* and *Hannan-Quinn information criterion (HQ).*

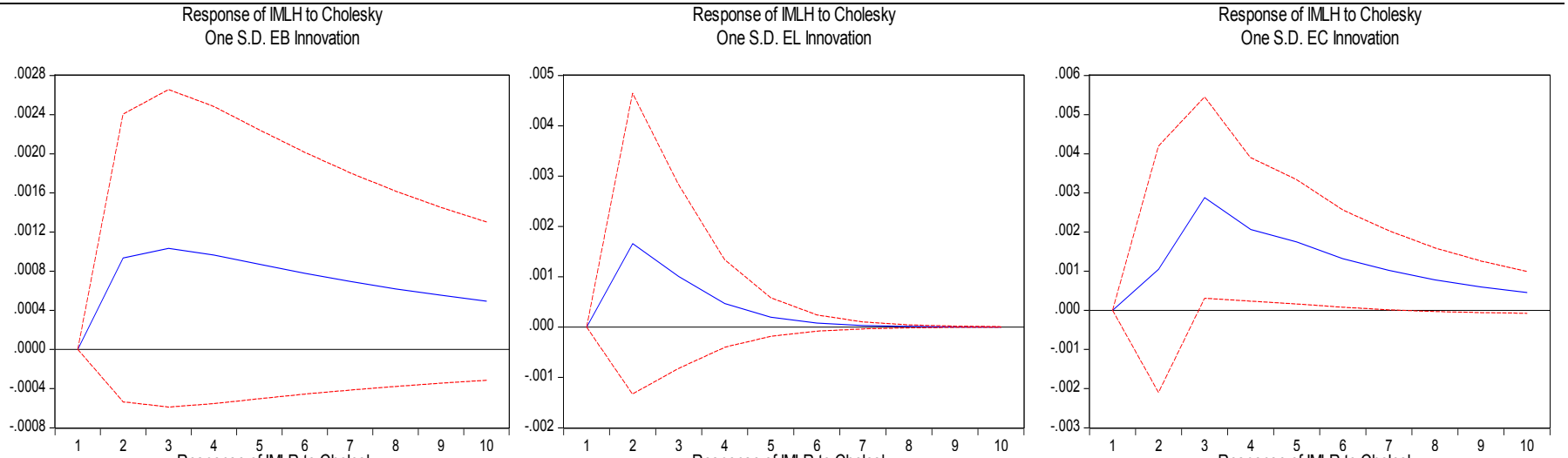
Figure 3.4: Illiquid minus liquid Portfolio Return Impulse Response Function: Expansive Shocks.

This figure shows the impulse response function of the illiquid minus liquid portfolio return to a Cholesky one standard deviation expansive shock in monetary conditions. The VAR lag length is chosen according to 5 tests namely Likelihood Ratio (LR), Final Prediction Error (FPE), Akaike information criterion (AIC), Schwarz information criterion (SIC) & Hannan-Quinn information criterion (HQ). Dotted lines represent two-standard error bands. The sample period is from January 1988 through December 2013. All data are obtained from DataStream.

	Monetary condition measure: *Stance (BOE)*	Monetary condition measure: *Stringency (LIBOR)*	Monetary condition measure: *Combined*
Liquidity measure – Amihud Portfolio return impulse response			

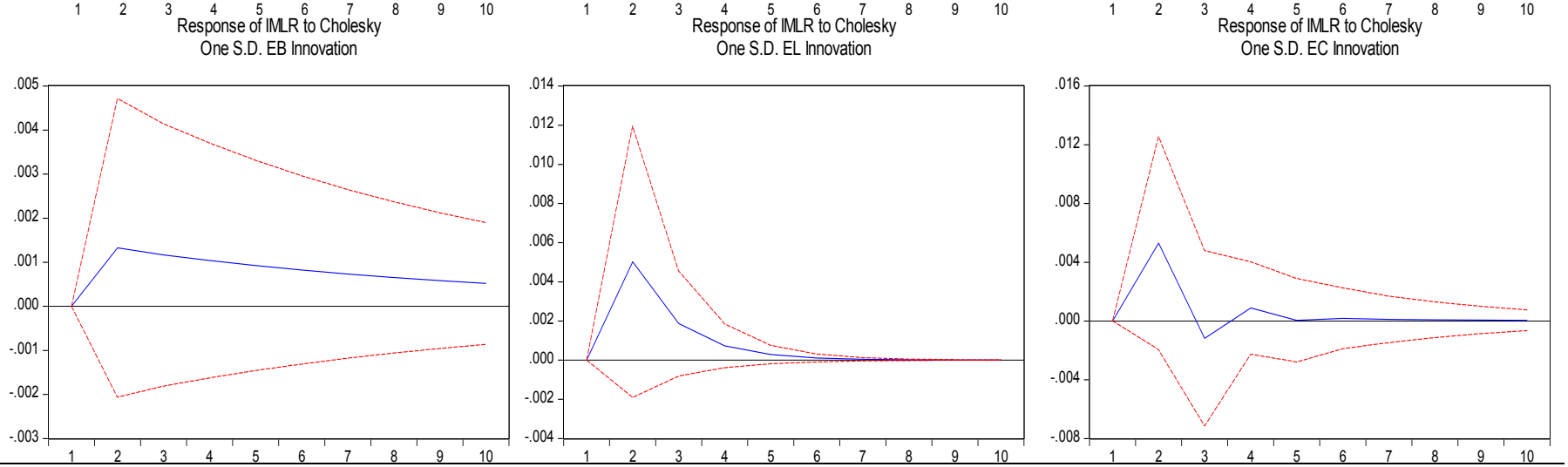
Liquidity measure – High Low Spread (Adjusted)

Portfolio return impulse response



Liquidity measure – Roll Estimator

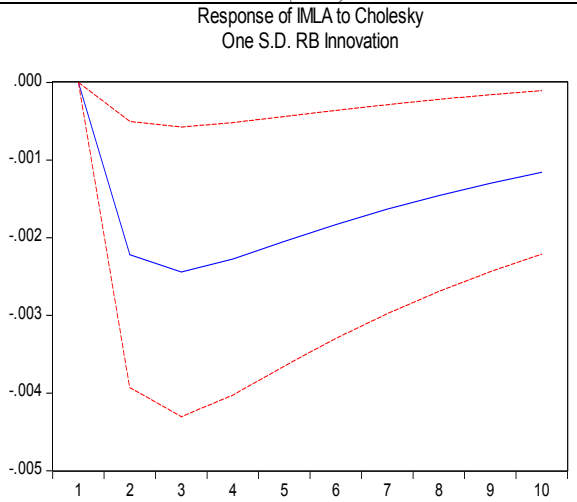
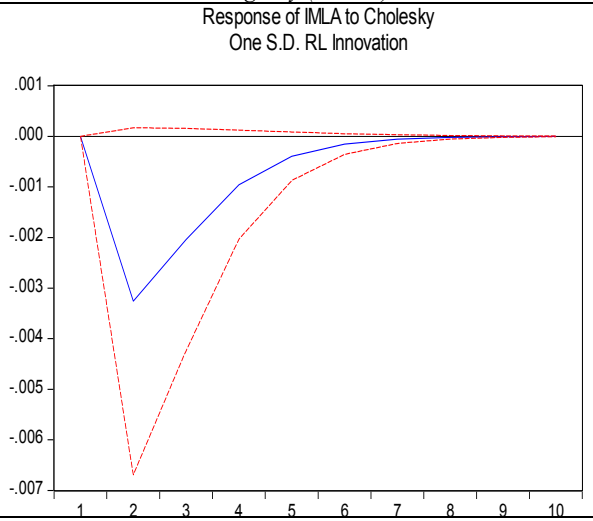
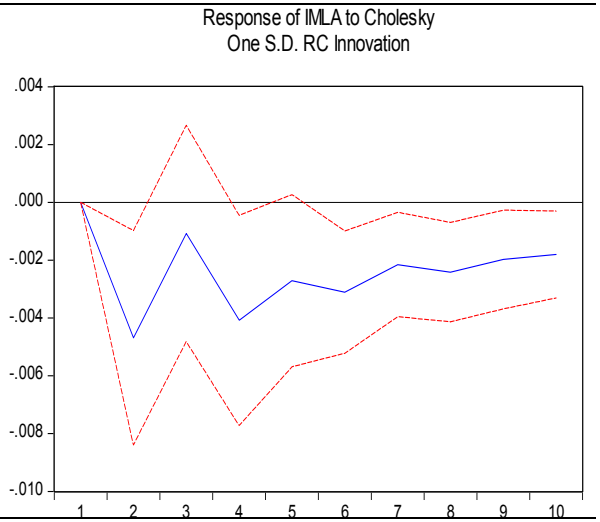
Portfolio return impulse response



Lags (Months) following shock | Lags (Months) following shock | Lags (Months) following shock

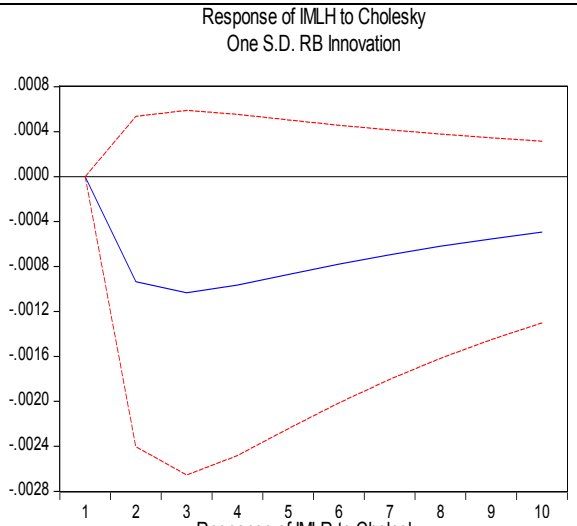
Figure 3.5: Illiquid minus liquid Portfolio Return Impulse Response Function: Restrictive Shocks.

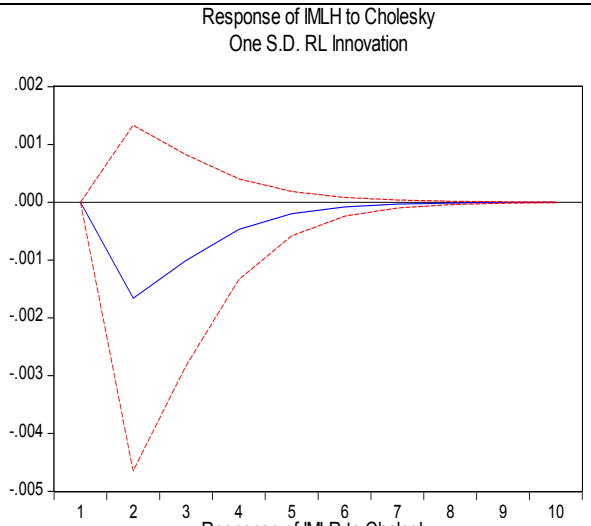
This figure shows the orthogonalized impulse response function of the illiquid minus liquid portfolio return to a Cholesky one standard deviation restrictive shock in monetary conditions. The VAR lag length is chosen according to 5 tests namely Likelihood Ratio (LR), Final Prediction Error (FPE), Akaike information criterion (AIC), Schwarz information criterion (SIC) & Hannan-Quinn information criterion (HQ). The sample period is from September 1988 through December 2013. All data are obtained from DataStream.

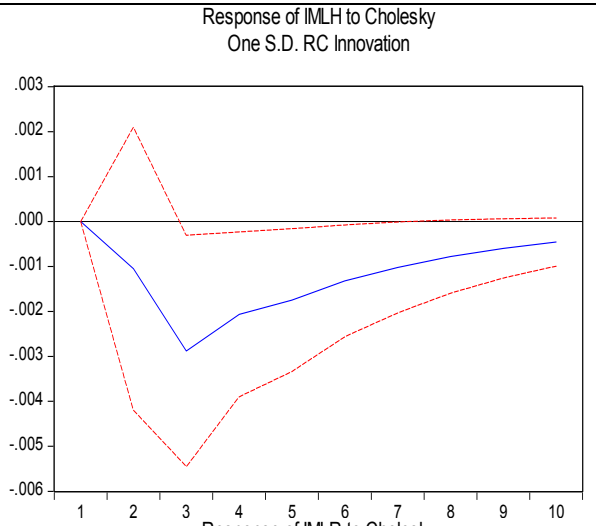
	Monetary condition measure: *Stance (BOE)*	Monetary condition measure: *Stringency (LIBOR)*	Monetary condition measure: *Combined*
Liquidity measure – Amihud Portfolio return impulse response			

Liquidity measure – High Low Spread (Adjusted)

Portfolio return impulse response

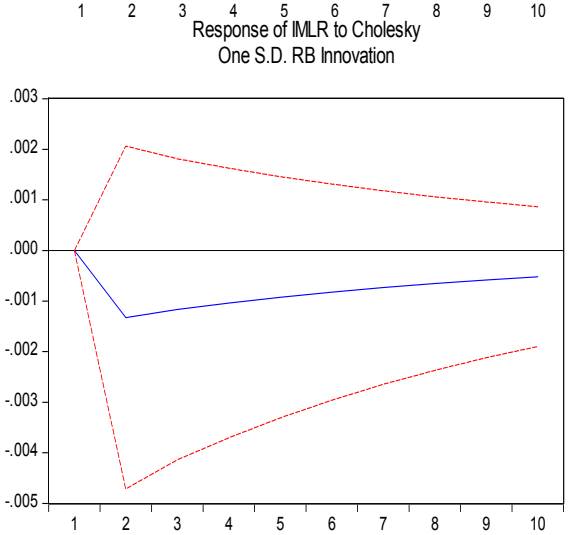


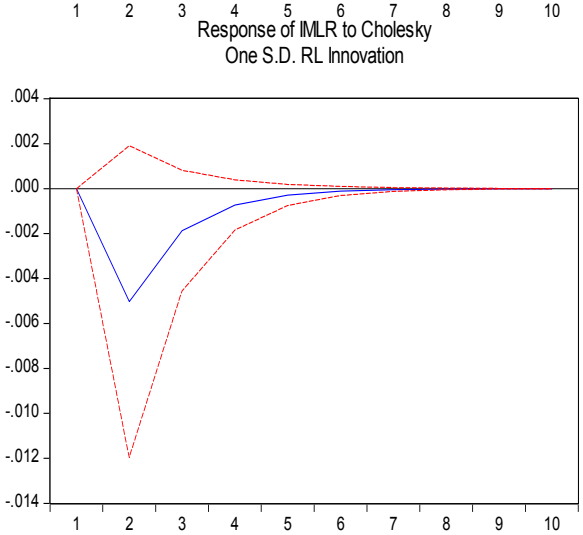


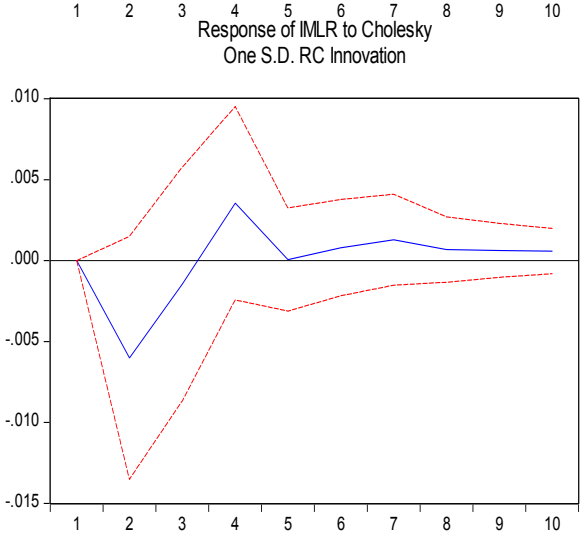


Liquidity measure – Roll Estimator

Portfolio return impulse response







Lags (Months) following shock

Lags (Months) following shock

Lags (Months) following shock

Figure 3.4 and 3.5 shows the impulse response function of the zero-cost portfolio returns to Cholesky one standard deviation expansion shock across different monetary conditions whereby figure 3.4 is based on the three liquidity measures across expansive monetary conditions. As expected, figure 3.4 shows that returns of all zero-cost portfolios have actually increase (positive value) as expected following expansive shock and peaking at either the 2nd lag (2nd month) or 3rd lag (3rd month). Figure 3.5 is based on the three liquidity measures across restrictive monetary conditions and it shows that returns of all zero-cost portfolios have actually decrease (negative value) after a restrictive shock event, where it reach its lowest point after either 2nd lag (2nd month) or 3rd lag (3rd month).

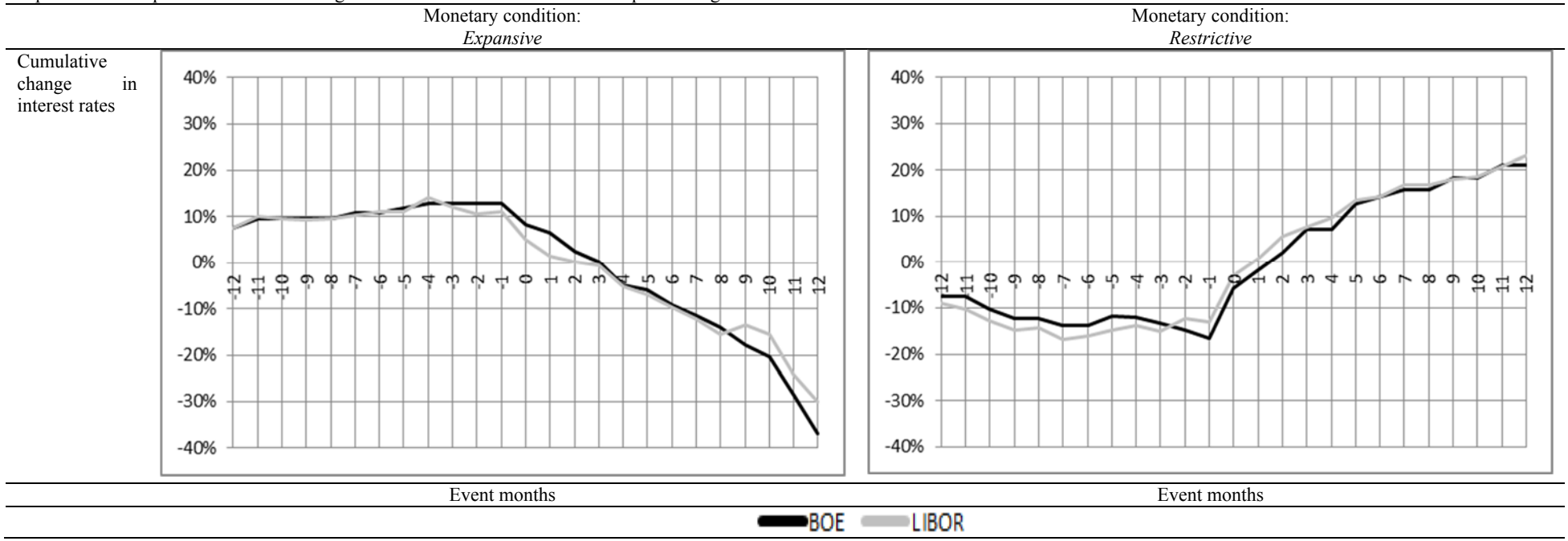
The impulse response function from figure 3.4 and figure 3.5 confirms some association between monetary conditions and changes in zero-cost portfolio returns as reported in table 3.6 before. However, *Roll estimator* does not show any significant results for all monetary conditions and only Amihud produce significant results for both expansive and restrictive monetary conditions according to BOE base rate. In relation to combined expansive shock, only Amihud and HLA produces significant results and the zero-cost portfolio returns are the highest when both conditions are expansive. The significant results for Amihud and HLA can also be observed when both monetary conditions are restrictive but in the opposite direction. Interestingly, similar to table 3.6, the two figures seem to show that stringency (LIBOR) has a weaker effect on IML than stance (BOE base rate).

3.4.3.4. MONTHLY EVENT STUDY: CUMULATIVE ILLIQUID MINUS LIQUID (IML) PORTFOLIO RETURNS AROUND A DIRECTIONAL CHANGE IN THE BANK OF ENGLAND BASE RATE (SHIFTS IN MONETARY POLICY)

So far table 3.6 and figure 3.3 as well as figure 3.4 and 3.5 establish the existence of a relationship between zero-cost portfolio returns and monetary conditions to a certain extent. However, the behaviour of the temporal relationship between zero-cost portfolio returns and monetary policy shifts remains uncertain. Therefore, to investigate the temporal relationship around a directional change in the BOE base rate (shifts in stance monetary policy), we conduct a *monthly event study* for the three liquidity measures similar to before.

Figure 3.6: Monthly Event Study: Cumulative changes in interest rates.

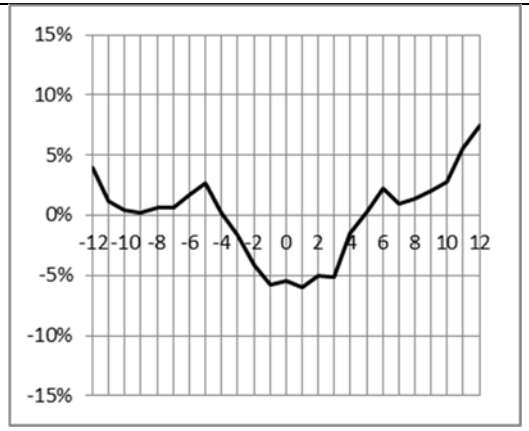
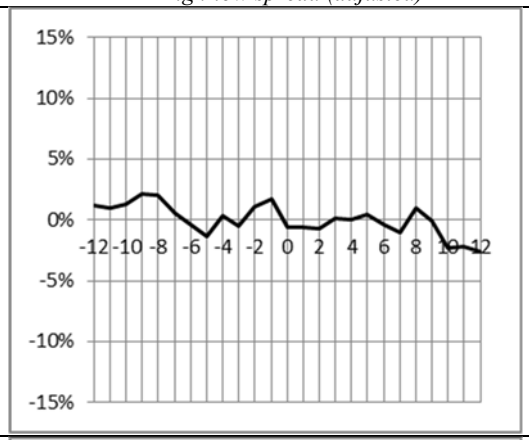
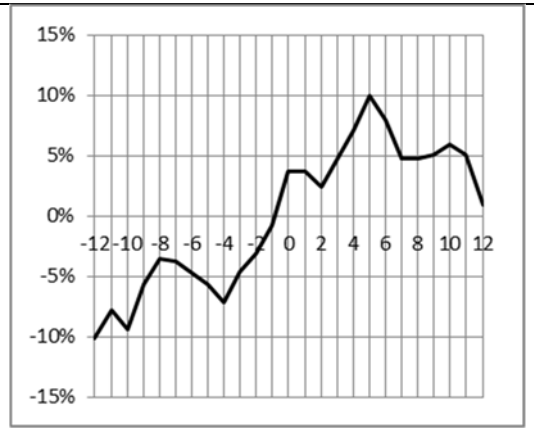
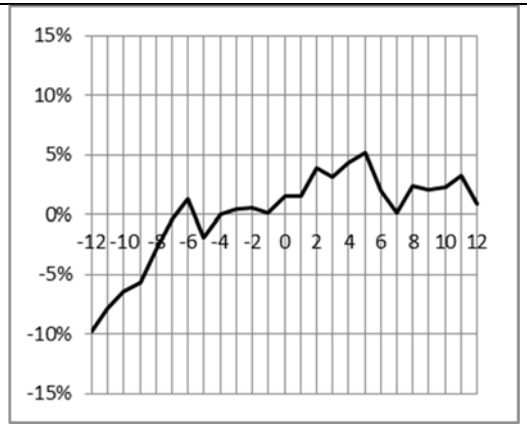
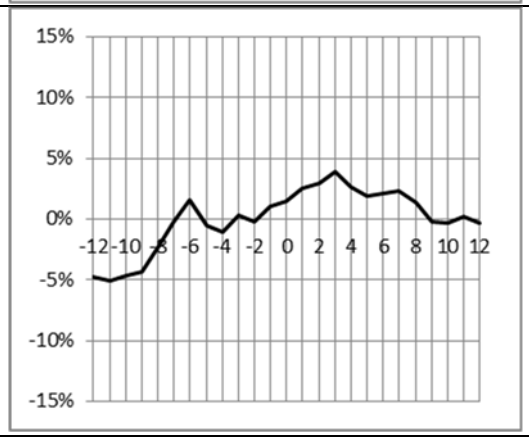
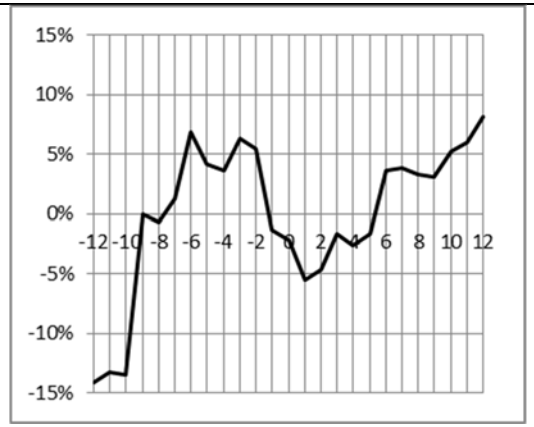
This figure shows the event time average of cumulative changes in the BOE and LIBOR around a directional change in the UK BOE base rate (shift in *Stringency*). A monetary state is labelled as "Expansive" if the prior discount rate change is a decrease or "Restrictive" if the prior change is an increase. Numbers on the horizontal axis are event months. All data are obtained from DataStream.



We have also included an investigation on the event-time average of *cumulative change in interest rate* for both BOE base rate and LIBOR across a shift in expansive and restrictive monetary policy in figure 3.6. Under expansive, figure 3.6 shows that the cumulative change in interest rates has actually started falling around one month before the shift of the monetary policy event from restrictive to expansion (expansive shifts) whilst restrictive shifts show similar results but in the opposite directions also shown in figure 3.6. It can also be observed in figure 3.6 that BOE base rate and LIBOR move very closely to each other, confirming the high correlation between the two variables, as indicated in table 3.2.

Figure 3.7: Monthly Event Study: Cumulative excess illiquid minus liquid portfolio returns.

This figure shows cumulative excess illiquid minus liquid portfolio returns around a directional change in the UK BOE Base Rate (shift in *Stance*). The illiquid minus liquid portfolio is a strategy that is long the quintile portfolio of illiquid stocks and short the quintile portfolio of liquid stocks. The line shows the event time average of cumulative monthly returns in excess of the sample period mean for the long-short strategy. A monetary condition is labelled as *"Expansive"* if the prior interest rate change is a decrease or *"Restrictive"* if the prior change is an increase. Numbers on the vertical axis are percentages. Numbers on the horizontal axis are event months. All data are obtained from DataStream.

	Liquidity measure: *Amihud*	Liquidity measure: *High-low spread (adjusted)*	Liqudity measure: *Roll estimator*
Cumulative excess zero-cost portfolio returns: *Expansive Monetary Policy*			
Cumulative excess zero-cost portfolio returns: *Restrictive Monetary Policy*			
	Event months	Event months	Event months

The top row of figure 3.7 shows the event-time average of *"cumulative excess zero-cost portfolio returns"* around an expansive directional change in BOE base rate (shifts in stance) whilst the bottom row shows the event-time average of *"cumulative excess zero-costs portfolio returns"* around a restrictive directional change in BOE base rate (shifts in stance).

Unlike Jensen and Moorman (2010), the return patterns of the zero-cost portfolio for the three liquidity measures are different proving that the three liquidity measures are able to capture different aspects of illiquidity. Nevertheless, among the three liquidity measures, *Amihud* seems to provide results that are more consistent to our previous findings as the IML portfolio returns increase following an expansive monetary condition.

Based on *Amihud*, our findings are consistent with Jensen and Moorman (2010) when there is an expansive shift. Figure 3.7 shows that 5 months prior to the event, cumulative IML portfolio returns start decreasing reaching their lowest point. This signifies that prior to an expansive shift, investors' liquidity concerns heighten resulting in funding constraints and higher risks. Due to this, investors reduce their holdings of illiquid stocks moving to the less risky liquid stocks (flight-to-liquidity), resulting in the reduction of price and returns of illiquid stocks in comparison to liquid stocks. Nevertheless, after the event, cumulative IML portfolio returns start to stabilize and increase. The pattern after the event indicates that liquidity concerns have improved, resulting in better funding and less risk. Thus, as explained by Rajan (2006), due to the market liquidity increase, investors are less concerned with illiquidity risks and started moving from liquid to the riskier illiquid stocks causing the price of illiquid stocks to increase. Similar to figure 3.2, there is slight interruption seven months after the event due to September 11 attacks and the financial crisis involving IndyMac Bank but it is less noticeable.

Using *Amihud,* when there is a restrictive shift, figure 3.7 shows results that are in the opposite direction of expansive shifts. Five months before the event, IML portfolio returns start increasing, reaching peak 5 months after the event before decreasing. However, similar to figure 3.2, the reaction is less noticeable compared to expansive monetary conditions signifying that during restrictive monetary policy periods, investors are less concerned with liquidity.

As highlighted earlier, *HLA* and the *Roll estimator* do not seem to demonstrate results similar to Jensen and Moorman (2010). For *HLA*, figure 3.7 shows that the price of

liquidity adjusts relatively little around a monetary policy shift whereas the *Roll estimator*, after a restrictive shift, seems to demonstrate a contradictory pattern that would normally be seen following an expansive shift.

Overall, the patterns observed show that the price of liquidity adjusts considerably in the months around an expansive monetary policy shift.

3.4.3.5. ILLIQUIDITY AND MONETARY CONDITIONS BETA, B

In this section, we investigate whether the relationship between portfolio returns and monetary conditions is driven by strong returns for stocks with either the highest or lowest illiquidity levels. The regression framework (as explained in table 3.8) is used for the three liquidity measures, in order to obtain the beta, β, which is used to explore the hypothesis that sensitivities to monetary conditions vary with the level of stock illiquidity.

Similar to Jensen and Moorman (2010), our findings in table 3.8 reveal that illiquid portfolios have higher betas, β than the liquid portfolios indicating that monetary conditions have the largest effect on the returns of illiquid stocks. This is consistent with table 3.5, which also shows that monetary conditions have the largest effect on the aggregate illiquidity of illiquid stocks. Overall, the results provide further support on the relationship between illiquidity premium and monetary conditions.

Table 3.8: Liquidity and Sensitivity to Monetary Conditions: January 1988 to December 2013.
This table reports the coefficient, β from the following regression:

$$ret_t = \gamma + \beta \times Monetary\ Conditions_{t-1} + \varepsilon_t \qquad (3.13)$$

Where ret_t is the equally-weighted return in month *t* either from a liquidity ranked quintile portfolio or from a portfolio long in the quintile of stocks with the lowest liquidity and short in the quintile of stocks with the highest liquidity (Illiquid-Liquid). For the monetary condition measures *Stance* and *Stringency*, *Monetary Conditions*$_{t-1}$ is a dummy variable that is one in month *t-1* when the monetary condition measure is *"Expansive"* and is zero when the measure is *"Restrictive"*. For the monetary condition measure *Combined*, *Monetary Conditions*$_{t-1}$ is a dummy variable that is one in month *t-1* if the monetary condition is *"Expansive"* for both *Stance* and *Stringency* and is zero in other months. Newey-West p-values are reported in brackets for the low liquidity minus high liquidity portfolio, whereby **bold** figures denote a statistically significant coefficient at least at 10% level. The bandwidth parameter for the Newey-West p-value is calculated using the Newey-West automatic lag selection. All data are obtained from DataStream.

	Monetary conditions beta, β					
Panel A: Amihud	**Liquidity Portfolio**					
Monetary conditions measure	**Liquid**	**2**	**3**	**4**	**Illiquid**	**Illiquid – Liquid**
BOE	-0.00498	-0.00026	0.00346	0.00415	0.00773	**0.01271** **(0.0068)**
LIBOR	0.00735	0.01131	0.01419	0.01268	0.01414	0.00679 (0.1037)
Combined	0.00293	0.00935	0.01320	0.01338	0.01811	**0.01518** **(0.0007)**

Panel B: High Low Spread	**Liquidity Portfolio**					
Monetary conditions measure	**Liquid**	**2**	**3**	**4**	**Illiquid**	**Illiquid - Liquid**
BOE	0.00043	0.00153	0.00291	0.00224	0.00553	0.00511 (0.1912)
LIBOR	0.01164	0.01270	0.01254	0.01322	0.01628	0.00464 (0.2137)
Combined	0.01022	0.01177	0.01182	0.01276	0.01753	**0.007306** **(0.0977)**

Panel C: Roll Estimator	**Liquidity Portfolio**					
Monetary conditions measure	**Liquid**	**2**	**3**	**4**	**Illiquid**	**Illiquid - Liquid**
BOE	0.00049	0.00112	0.00033	0.00159	0.00641	0.00592 (0.4749)
LIBOR	0.00966	0.00847	0.00869	0.00790	0.02026	0.01060 (0.1508)
Combined	0.01279	0.00664	0.00593	0.00979	0.02088	0.00809 (0.3370)

3.5. CONCLUSION

This study looks into monetary conditions and how they affect market liquidity and the illiquidity premium for different liquidity portfolios in the UK including the financial crisis period. We start our research by considering *unconditional returns*, where we find evidence similar to past research such as Amihud and Mendelson (1986) to suggest that in general illiquid portfolios generate higher returns relative to liquid portfolios for all three liquidity measures. However, our research indicates that out of the three liquidity measures, only *Amihud* provides a monotonically increase in portfolio returns with decrease in liquidity, which is similar to Jensen and Moorman (2010).

Since our research is on the financial crisis, we feel that it is important to conduct a research on how monetary conditions affect *aggregate illiquidity (market liquidity)*. Generally speaking, our findings indicate that aggregate illiquidity decreases (market liquidity increases) when monetary conditions are expansive. Nevertheless, the results are generally not always significant[50] particularly for restrictive conditions[51]. This can be a result of the high liquidity of the UK market, as Dey (2005) states that investors of developed markets may be less concerned with liquidity.

We also consider how monetary conditions affect the illiquidity premium and on most occasions, our findings reveal that illiquid portfolio returns are higher relative to liquid portfolio when monetary conditions are expansive compared to restrictive and the highest returns occurs when both stance and stringency are expansive. Our research also explores the uniformity of the changes in liquidity across liquidity quintiles and it generally shows that monetary condition changes have more effect on illiquid stocks relative to liquid stocks.

Our monthly event study finds evidence to indicate that market liquidity increases after expansive shifts, but with some interruptions due to major events such as the September 11 attacks in the US and the financial crisis. However, it is less noticeable during restrictive periods, signifying investors are less concerned with liquidity. The monthly

[50] We have also conducted a stock migration investigation using Amihud as measure of liquidity but using quartiles instead of quintiles between January 1991 and December 2014. Basically, our investigation looks into stock migration from each quartile in year (t) (sorting year) to other quartiles in year (t+1) (performance year). The quartiles are only rebalanced annually meaning that stocks are held for at least one year. Our overall results show (not presented here to keep the number of tables as low as possible) that over the period, on average 78.45% of stocks remain in the same quartiles. This could be one of the reasons why our results are not always significant.

[51] Table 3.2 shows that there are more expansive periods compared to restrictive periods, which may be another reason for results that are not significant during restrictive periods.

event study on IML portfolio returns indicates that out of the three liquidity measures, only *Amihud* presents patterns that are consistent to past studies. The IML portfolio returns increase following expansive monetary shifts, signifying that illiquid stocks become more popular during expansive monetary conditions. As Rajan (2006) highlights investors are willing to take more risks during high market liquidity, causing illiquid stock prices to increase[52]. However, prior to the expansive monetary policy shifts, illiquid stocks become less popular signifying 'flight-to-liquidity'.

Using three different liquidity measures, we also obtain evidence to suggest that the three measures capture different aspects of liquidity since there can be some divergence on the results obtained. Our research shows that out of the three measures, *Amihud* seems to produce the most consistent results. Interestingly, we also discovered that the aggregate illiquidity and IML portfolio have different reaction towards BOE base rate and LIBOR. It shows that investors who are concerned with IML portfolio and aggregate illiquidity should focus on BOE decisions and LIBOR respectively. Nevertheless, it can be deducted that when there is an intersection between the two monetary conditions, the reaction is stronger.

In conclusion, our evidence generally shows that illiquid portfolios are found to supersede liquid stocks returns. Market liquidity, stock prices and illiquidity premium are affected by changes in monetary conditions but interestingly enough, it seems that stringency (LIBOR) is more effective than stance (BOE base rate) especially in relation to market liquidity. However, in the long run, the monthly event study does show the usefulness of stance. This justifies the intervention of central banks or monetary authority when required during the financial crisis.

Nevertheless, in comparison to Jensen and Moorman (2010), we obtain weaker evidence probably due to the shorter data sample as well as the different characteristics of the UK

[52] Our findings tend to show that expansionary monetary policy results in higher IML returns, which can be due to investors' willingness to take more risk (Rajan, 2006) by investing into the riskier illiquid stocks relative to liquid stocks. Whilst prior to expansive monetary policy, there is flight-to-liquidity due to dire in liquidity (liquidity concerns) signifying popularity of liquid stocks (large stocks) relative to illiquid (small stock) (Amihud, 2002). One explanation for such a behaviour is investor sentiment, as Wright & Bower (1992) highlights that the judgement of an uncertainty future event may be affected by persons' mood and hence an optimistic investor may be more willing to invest in riskier projects while the opposite may be observed for pessimistic investors. For instance, Al-Hajieh et al (2011) finds that the celebrated holy of month of Ramadan (of the Muslim calendar) appears to have a generally positive impact on stock prices of Islamic Middle Eastern countries. Gavriilidis et al (2016) also conduct a comparable research by focusing on the stock markets of seven majority Muslim countries, where they document the presence of significant herding during Ramadan in most of their sample markets. Moreover, Galariotis et al (2014) highlight the role of sentiment indicators in explaining the differences in momentum profits in the UK but it is not evident when the post-subprime crisis period is excluded. Nevertheless, the research shows the importance of investor sentiment for financial markets and the correlation between monetary expansion and illiquidity in our research may be due to it. Thus, although we did not study investor sentiment, this may potentially be a good research topic for the future.

market relative to US market. According to Bartram et al. (2012) the UK market is less volatile compared to the US market considering companies with similar characteristics. A higher level of volatility will definitively affect prices and consequently market liquidity (See Stoll (1978), Vayanos (2004) and Hameed, Kang, and Viswanathan (2010))[53].

[53] Stoll (1978) shows that bid-ask spreads (illiquidity) are positively affected by return volatility. Vayanos (2004) discovers that during volatile times, investors reduce their willingness to hold illiquid assets, illiquidity premia increase followed by market betas of illiquid assets. Hameed et al. (2010) mention that negative market returns decrease stock liquidity, with the effect being strongest for high volatility firms and during times of market funding tightness. Hameed et al. (2010) also document that market volatility affect liquidity commonality positively. Overall, it shows that there is a relationship between volatility and illiquidity and due to the difference in market volatility between the UK and the US, it would result in different findings for us compared to Jensen & Moorman (2010).

CHAPTER 4 : ILLIQUIDITY AS AN INVESTMENT STYLE DURING THE FINANCIAL CRISIS IN THE UNITED KINGDOM

4.1. INTRODUCTION

Market efficiency signifies that obtaining abnormal returns is not possible but over the years, researchers find evidence to contradict the *Efficient Market Hypothesis (EMH)* and various investment styles (or strategies) have been developed in order to beat the market. Style investments are recommended by Sharpe (1978) who looks at general styles such as passive and active management. This is further extended to include more specific and generally accepted investment styles of size, value/growth and momentum/contrarian. For instance Banz (1981) mentions that average returns are found to be inversely related to size while Fama and French (1992) highlight that value is considered superior than growth investing. However, there are contradictory findings as well, which will be discussed in the literature review.

The financial crisis of 2007 has resulted in the emergence of studies of its impact on financial markets and instruments. Ivashina and Scharfstein (2010) study bank lending[54] while Ben-David, Franzoni, and Moussawi (2012) study hedge fund stock trading[55]. Moreover, the study of illiquidity has gained importance, probably due to the financial crisis[56] (Brunnermeier, 2009) and financial sector development (Rajan, 2006). General evidence seems to indicate that asset returns will increase with illiquidity such as bid-ask spread (Amihud & Mendelson, 1986). The relationship between returns and illiquidity is quite obvious as Ibbotson et al. (2013) mention that investors clearly want more liquidity. Hence, illiquidity should be compensated with additional returns. Surprisingly, even though it is so apparent, for some reason illiquidity is rarely used as a control variable and is not a common investment style, as most studies, generally use the other three styles (Subrahmanyam, 2010). Only lately, research on illiquidity as an investment style has been undertaken (See K. Chang et al. (2013) on the *Taiwanese stock market (TSM)* and

[54] Ivashina and Scharfstein (2010) shows that during the peak period of the financial crisis, new loans to large borrowers fell.
[55] Ben-David et al. (2012) highlight that hedge fund investors are more sensitive to losses compared to mutual fund investors during the financial crisis.
[56] Brunnermeier (2009) mentions that the financial market turmoil in 2007 and 2008, due to liquidity and the credit crunch, has led to the most severe financial crisis since the Great Depression.

Ibbotson et al. (2013) on the *United States (US)* market, who both find evidence to support illiquidity as an investment style).

Given the lack of more recent evidence for other well-known markets, we decide to investigate the potential of illiquidity as a reliable and consistent investment style during the financial crisis. We believe that the *United Kingdom (UK)* market provides a good opportunity because the *London Stock Exchange (LSE)* is considered as one of the largest stock markets by capitalisation, signifying that the market is quite liquid and hence the results will be as immune as possible from biases such as infrequent trading (Galariotis & Giouvris, 2007). We also agree with Galariotis and Giouvris (2007) that the results on the UK market will be of great interest to the international scientific, corporate and investment community. This is further strengthen by our usage of pre-crisis and post-crisis data that will allow us to assess the extent to which illiquidity is a good trading strategy pre and post-crisis.

Using Ibbotson et al. (2013) framework and Sharpe (1992) four benchmark portfolio criteria[57], our research starts by investigating whether the respective investment styles' premium[58] including illiquidity premium exist within the UK market. This will be followed by investigations on double sorted quartile portfolios, which are the intersection between illiquidity and the other investment styles. Lastly, stock migration analysis is conducted to investigate the stability of the portfolios.

Overall, our research for the UK market shows that with the exception of momentum premiums, the other investment styles do generate positive and significant premiums. The illiquid portfolios also consistently outperform the benchmarks and are quite stable during both periods. Nonetheless, illiquidity appears to meet Sharpe (1992) four benchmark criteria pre-crisis only and not post-crisis. This signifies that illiquidity can be classified as a reliable investment style pre-crisis but it is highly correlated to size.

The remainder of this paper is organised as follows. Section 4.2 presents the literature review while section 4.3 describes the data and variables. In section 4.4, the methodology,

[57] Sharpe (1992) establishes that a benchmark portfolio should be 1) identifiable before the fact, 2) not easily beaten, 3) a viable alternative, and 4) low in cost.

[58] An Investment style premium happens when one specific style performs better than its relevant antagonist style. For example, value premium (value portfolio returns > growth portfolio returns) and growth premium (value portfolio returns < growth portfolio returns).

empirical results and analysis of the research are discussed followed by our conclusion in section 4.5.

4.2. LITERATURE REVIEW

4.2.1. INVESTMENT STYLES

Chang et al. (2013) define investment style as the combining of stocks with the same characteristics to construct style portfolios and make investments in the stock markets. They also highlight that the most common types of investment styles are *"value versus growth"* stocks, *"small versus big"* stocks and *"momentum versus contrarian"* stocks. Therefore, we will firstly discuss the most common type of investment styles.

4.2.1.1. VALUE VERSUS GROWTH

Value and growth are two popular fundamental investment styles whereby value style looks for stocks that are undervalued according to companies' financial statements while growth style involves identifying long-term potential and performance. Past literature seems to indicate that value style is an antagonist to growth style, as researchers tend to compare the two styles with each other, by using suitable variables such as *book to market ratio (B/M ratio)* and *price earnings ratio (P/E ratio)*.

Most research appears to conclude that value style is considered superior to growth style in the US market resulting in value premium (Basu, 1983; Fama & French, 1992). Daniel et al. (2001) also find value premium within the Japanese market, while Capaul et al. (1993) who study six international markets including UK, obtained consistent results to US market studies.

In contrast, a mixed outcome is obtained by Ding et al. (2005) who look into East Asia markets. Value premium appears to be significantly negative in Thailand and in Indonesia it is insignificant. Gonenc and Karan (2003) discover that there is no value premium within the *Istanbul Stock Exchange (ISE)*, signifying growth superiority. However, Beneda (2002) highlights that the research period is important, as it is shown that over a

short period of five years, value style is found to be more profitable but for a longer period (at least 14 years), average returns for growth stocks are superior.

4.2.1.2. SIZE EFFECT

Banz (1981) highlights that average returns are negatively related with size. This widely recognized anomaly is known as either small-firm or size effect and is also supported by researchers such as Keim (1983). Such a relationship is expected as small firms are usually considered riskier than large firms and their returns are expected to be higher. Chan et al. (1985) confirm this as they state that within an efficient market, the higher average returns of smaller firms are justified by the additional risks borne by such firms.

Nevertheless, studies on size effect are less optimistic after the early 1980s as Van Dijk (2011) highlights that past empirical studies declare the size effect to be dead since then. Gonenc and Karan (2003) actually obtain opposite findings whereby firms with larger capitalization are considered superior while Horowitz et al. (2000) report no consistent relationship between size and realized returns, and their results show that the widespread use of size in asset pricing is unwarranted. Amihud (2002) highlights that the size effect is partially due to market illiquidity, as times of dire illiquidity will cause flight-to-liquidity, resulting in preference for larger stocks and hence small stocks are actually subjected to higher illiquidity risk premium. Nonetheless, there are still recent evidence of a size effect within the UK (Dissanaike, 2002) and the US (Van Dijk, 2011) but Van Dijk (2011) also mentions that more empirical research needs to be conducted to examine the robustness of size effect on the US and international stock markets.

4.2.1.3. MOMENTUM VERSUS CONTRARIAN

De Bondt and Thaler (1985) in their behavioural finance research on stock market overreaction discover that loser stocks (or contrarian style) perform exceptionally well in comparison to winner stocks (or momentum style) over extended time periods of 3 to 5 years horizons. Nonetheless, in contrast, Jegadeesh and Titman (1993) document that investment styles that combined buying winner stocks and selling loser stocks generate significant positive returns of about 1% per month over 3 to 12 months holding periods. Jegadeesh and Titman (2001) revisit the subject and their evidence indicates that

momentum profits have continued in the 1990s, suggesting that the original results are not a product of data snooping bias.

However, Conrad and Kaul (1998) emphasise that contrarian style is profitable for long-term horizons, while the momentum style is usually profitable for medium-term holding periods of between 3 and 12 months. Shen et al. (2005) findings agree with Conrad and Kaul (1998), who show that contrarian profits in the US market are very dependent on the period examined. In the UK, Dissanaike (2002) shows results that contrarian style outperformed momentum style and their *loser-winner effect (or contrarian premium)* results are significant. Nonetheless, Galariotis et al. (2007) demonstrate that both momentum and contrarian profits are available for the LSE.

4.2.1.4. ILLIQUID VERSUS LIQUID

General evidence seems to indicate that returns will increase with illiquidity (Amihud & Mendelson, 1986; Brennan & Subrahmanyam, 1996) and Acharya and Pedersen (2005), also highlight the importance of liquidity on asset prices. Nevertheless, there are some contradictory results, which show that illiquid stocks do not necessarily provide consistently higher returns. Eleswarapu and Reinganum (1993) find evidence to suggest that 'the January effect' and 'size effect' are significant, indicating that the return for illiquidity may be a result of seasonal and size effect. Brennan et al. (2013) who analyse the Amihud (2002) measure of illiquidity and its role in asset pricing, state that in general, only the down-days element commands a return premium. Furthermore, Ben-Rephael et al. (2008) who study the *New York Stock Exchange (NYSE)* find evidence that the profitability of trading strategies based on illiquidity premium has declined over the past four decades, rendering such strategies virtually unprofitable.

However, unlike Eleswarapu and Reinganum (1993), Datar et al. (1998) find a strong positive relationship between stock returns and illiquidity. The illiquidity premium is not restricted to the month of January alone and is prevalent throughout the year. Additionally, using three liquidity measures in the UK, Said and Giouvris (2015) reveal that illiquid portfolios consistently earn higher returns compared to liquid portfolios and the zero-cost

portfolio returns[59] are statistically significant for at least two of the illiquidity measures used.

4.2.1.5. RETURNS BETWEEN DIFFERENT INVESTMENT STYLES

Past literature shows that there are links between different investment styles. Asness et al. (2013) highlight that value and momentum are inversely correlated to each other, within and across asset classes. However, Bauman et al. (1998) who initially believe that the value premium is attributed to small-firm effects, discover that the superiority of value style is actually genuine.

There are also studies that connect illiquidity with other styles such as Asness et al. (2013) who find significant evidence that funding liquidity risk is inversely related to value but positively related to momentum globally across asset classes. Similarly, Pastor and Stambaugh (2003) measures of liquidity risk are positively related to momentum in US stocks. One of the most common style connections is between illiquidity and size, as Eleswarapu and Reinganum (1993) highlight that the illiquidity premium is a result of size effect. In contrast, Elfakhani (2000) mentions that the returns of small-firms are larger due to the liquidity hypothesis, as small-firms are considered to be less liquid and thus should obtain higher return premiums. This is contradictory to Ibbotson et al. (2013) study on US market, who highlight that the returns obtained of illiquidity based portfolios are sufficiently different from those of the other styles. Considering the research above, one can see that the relationship between illiquidity and size is not clearly defined.

4.2.2. POTENTIAL OF ILLIQUIDITY

Due to the recent crisis[60], the study of liquidity has become more prominent and researchers have noticed the potential and importance of illiquidity as an investment tool. Yan (2008) in their research of US mutual funds finds evidence to suggest that liquidity is an important reason why size erodes fund performance indicating the importance of liquidity in investment management. Moreover, Idzorek et al. (2012) mention that on

[59] Zero-cost portfolio = long the illiquid portfolio and short the liquid portfolio.
[60] Crotty (2009) highlights that the financial crisis happens when investors run for liquidity and safety.

average, mutual funds that hold illiquid stocks perform significantly better than funds that hold more liquid stocks. Thus, signifying the potential of liquidity as investment strategy or style particularly during the financial crisis. Even Ibbotson et al. (2013) suggest that liquidity should be given equal standing to the other investment styles.

4.2.2.1. ILLIQUIDITY AS AN INVESTMENT STYLE

Nowadays, it is normal for different investment styles to be made a *benchmark portfolio*[61]*such as S&P/BARRA Growth stock index* and *S&P/BARRA Value Stock index* (Capaul et al., 1993). Therefore, similar to Ibbotson et al. (2013), we feel that the best way to explore whether illiquidity can be chosen as a reliable investment style during the crisis, is to investigate if a dependable *benchmark portfolio* can be created based on illiquidity. According to Sharpe (1992), a *benchmark portfolio* should meet four criteria namely 1) *"identifiable before the fact",* 2) *"not easily beaten",* 3) *"a viable alternative",* and 4) *"low in cost".*

4.3. DATA AND VARIABLES

4.3.1. DATA

In order to capture the UK stock market, the sample that we use consists of stocks listed under the *FTSE All-Share index* for the 14 years period from January 2001 through December 2014. Although the financial crisis happens around August 2007, we decide to divide equally the 14 years sample period into half, namely pre-crisis (January 2001 to December 2007) and post-crisis period (January 2008 to December 2014). The final data set contains 640 companies (as of the year 2014) after filtering of outliers. All data used in this paper is obtained from DataStream.

[61] A benchmark portfolio is a portfolio consisting of a list of securities that has been constructed based on specific criteria, which can be compared to an actual portfolio's performance. So if the investment style of "illiquidity" appears to be attractive in the UK then we will be seeing benchmark portfolios such as "S&P illiquidity index" in the future.

4.3.2. INVESTMENT STYLES' MEASURES

To determine *"value versus growth"* investment style, Gonenc and Karan (2003) use B/M ratio while Beneda (2002) suggests using P/E ratio and Bauman et al. (1998) use dividend yield. We use *Price to book ratio (P/B ratio),* which is just the inverse of B/M ratio, because it is one of the most widely recognisable variables and allows us to obtain data for more companies compared to P/E ratio. Determining the "*small versus big"* investment style is simpler, as we feel that using the *market value (MV)* of each firm is the most appropriate measure as in Dissanaike (2002). Similarly, choosing the most appropriate variable for *"momentum versus contrarian"* investment style is also straightforward as we will be using *monthly returns* as in De Bondt and Thaler (1985).

For illiquidity, we have decided to choose the *Amihud illiquidity measure*[62] (Amihud, 2002) as it is a well-known measure and has been extensively used in past literature. Moreover, we also thoroughly considered two other liquidity measures namely the Roll estimator (Roll, 1984) and High Low spread by Corwin and Schultz (2012) and we find that Amihud illiquidity measure provides results that are more consistent to past studies. We have chosen *FTSE All-Share index* and *UK 3 months London Interbank Offered Rate (LIBOR)* as benchmarks for market returns and risk-free rate respectively.

4.4. METHODOLOGY, EMPIRICAL RESULTS AND ANALYSIS

4.4.1. ILLIQUIDITY AS AN INVESTMENT STYLE BASED ON ITS ABILITY AS A BENCHMARK

As highlighted earlier, exploring whether illiquidity can be made into a dependable portfolio benchmark seems to be the best way to investigate illiquidity's potential as a reliable investment style and how the financial crisis affects it. Thus, we feel that we should follow Ibbotson et al. (2013) framework, whereby they based it on Sharpe's (1992) specification of a *portfolio benchmark*, which should be 1) *"identifiable before the fact",* 2) *"not easily beaten",* 3) *"a viable alternative"* and 4) *"low in cost".*

[62] It is calculated for each stock, s, every month as follows:

$$Amihud_{sm} = \frac{1}{t}\sum_t \frac{1{,}000{,}000 \times |return_t|}{price_t \times volume_t} \quad (4.1)$$

Where t is each trading day

To meet the *"identifiable before the fact"* criterion, we will be constructing quartiles (or portfolios) based on the prior year (*t-1)* measure of the relevant investment style, which is then used to calculate the results of the portfolios for a given year *(t)*. Therefore, the portfolios are *"identifiable before the fact"*. The next criterion for us to fulfil is the *"not easily beaten"*. This will be achieved by investigating if the returns of the illiquidity portfolios can provide positive returns (if any) and then compare it with the chosen benchmarks and other investment styles. This will be followed by *"a viable alternative"* criterion, which will be achieved by applying the method used by Ibbotson et al. (2013), who distinguish illiquidity from the other styles by constructing double-sorted portfolios. The double-sorted portfolios will allow us to study whether illiquidity is able to enhance the performance of the more recognized styles. Lastly, similar to Ibbotson et al. (2013), we investigate the *"low in cost"* criterion by exploring stock migration, which will allow us to consider whether illiquidity can be managed passively and at low cost.

4.4.2. COMPARISON OF INVESTMENT STYLES' RETURNS AND RISKS.

Our research starts with the investigation of portfolio performance across different investment style quartiles. This section will also allow us to determine whether illiquidity will be able to meet the first two benchmark criteria of *"identifiable before the fact"* and *"not easily beaten"*. More importantly, this section will also confirm whether an illiquidity premium[63] exists in the first place.

Table 4.1 shows the equally weighted average annualised monthly returns and risks of the investment styles based on quartiles. Over the 14 years period, the selection period is between 2000 and 2013 (inclusive), while the performance period is between 2001 and 2014 (inclusive). The two portfolios that are ranked top 25% and bottom 25% are classified as either Q1 or Q4 quartiles and the stocks are rebalanced annually.

The final column in table 4.1 shows the zero-cost portfolio returns (or applicable investment style premium), which takes a long position on Q1 portfolio and short position on Q4 portfolio. Thus, for "*value versus growth"* investment style, it would be the *value premium* if "*High value portfolio (Q1)"* outperforms "*High growth portfolio (Q4)"* and

[63] Illiquid quintile provides higher returns compared to liquid quintile.

growth premium if "*High growth portfolio (Q4)"* is found to perform better than *"High value portfolio (Q1)"*.

The zero-cost portfolio[64] in table 4.1 shows the existence of *value premium, small-firm premium* and *illiquidity premium*[65], consistent with Capaul et al. (1993), Dissanaike (2002) and Amihud and Mendelson (1986) respectively for both periods. As expected, all three premiums dropped in value post-crisis. The best results are achieved by value premium and *small-firm premium* pre-crisis and post-crisis respectively. *Momentum premium* is not statistically significant for both periods, which is not akin to past research such as Jegadeesh and Titman (1993). Dissanaike (2002) who studies the UK market discovers that contrarian performed better while Galariotis et al. (2007) mention that both momentum and contrarian profits are available within UK, which may explain the insignificant results for both periods. In fact, figure 1, shows the growth of *value premium, small-firm premium and illiquidity premium* consistently over the 14 years period while *momentum premium* noticeably drop in value after the financial crisis of 2007, performing worse in comparison to the other premiums and even the two benchmarks (FTSE All Share Index and 3 months LIBOR).

Similar to Ibbotson et al. (2013) study on US, table 4.1 shows that the best performing top[66] investment style is achieved by *"High value portfolio (Q1)"* for both periods. The worst performing portfolio is the bottom investment style of *"High growth portfolio (Q4)"* for the pre-crisis period but post-crisis, it is the *"Mid value portfolio (Q2)"*. One interesting finding is that regardless of periods, all the top and bottom investment styles show higher returns relative to the benchmarks of *FTSE All-Share index* and *3 months LIBOR,* indicating that any of the simple investment styles, allow investors to outperform the market.

In terms of risk, the highest standard deviation and beta is reported by the *"High contrarian portfolio"*, which is not consistent with the traditional theory of *"higher returns come with higher risk"*, as it does not produce the highest returns. Nevertheless, the crisis obviously results in higher risks, as observed in the post-crisis results.

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[64] *Q1-Q4* (for example *value – growth quartile)*
[65] Q1 is greater than Q4
[66] Top investment style means the top 25% ranked based on the relevant investment style or Q1 and it is expected to be Value, Micro, Momentum and Illiquid portfolios. Bottom investment style means the bottom 25% ranked based on the relevant investment style or Q4. It is expected to be Growth, Big, Contrarian and Liquid portfolios.

Table 4.1: Cross-Sectional annualized returns and risks of the investment styles pre and post-crisis.
This table shows equally-weighted, annualised returns (in percentage format) for quartile portfolios based on the investment styles briefly describe below. Although the financial crisis happens around August 2007, we decide to equally divide the 14 years return sample periods into half namely Pre-Crisis (January 2001 to December 2007) and Post-Crisis periods (January 2008 to December 2014). Quartile portfolio ranks are determined by the value of the investment style measure in the year *(t-1)* prior to the year *(t)* in which returns are calculated and are rebalanced annually. Therefore, the style measure for the year 2000 is used to construct the quartiles and then calculate the returns for the year 2001, where the stocks will be held for at least one year. The "Q1 – Q4" portfolio is a portfolio that takes a long position in the quartile of stocks (Q1) and a short position in the quartile of stocks (Q4). For example, in relation to *illiquid vs liquid investment style*, *"Q1 – Q4"* takes a long position in the quartile of *illiquid stocks (Q1)* and a short position in the quartile of *liquid stocks (Q4)*. The table also shows 2 benchmarks namely *3 months LIBOR* and *FTSE All-Share index*. It also shows the total and systematic risks of the portfolios measured based on standard deviation and beta respectively. Beta is calculated based on *FTSE All-Share index*. Newey-West p-values are reported in brackets for the arithmetic mean of the "Q1 – Q4" portfolio, whereby **bold** figures denote a statistically significant coefficient at least at 10% level. The bandwidth parameter for the Newey-West p-value is calculated using the Newey-West automatic lag selection. All data are obtained from DataStream.

1. ***Value effect (value versus growth investment style)*** uses the end of year *price-to-book value (P/B) ratio*.

2. ***Size effect (micro versus big investment style)*** uses the *end of year market value (MV).*

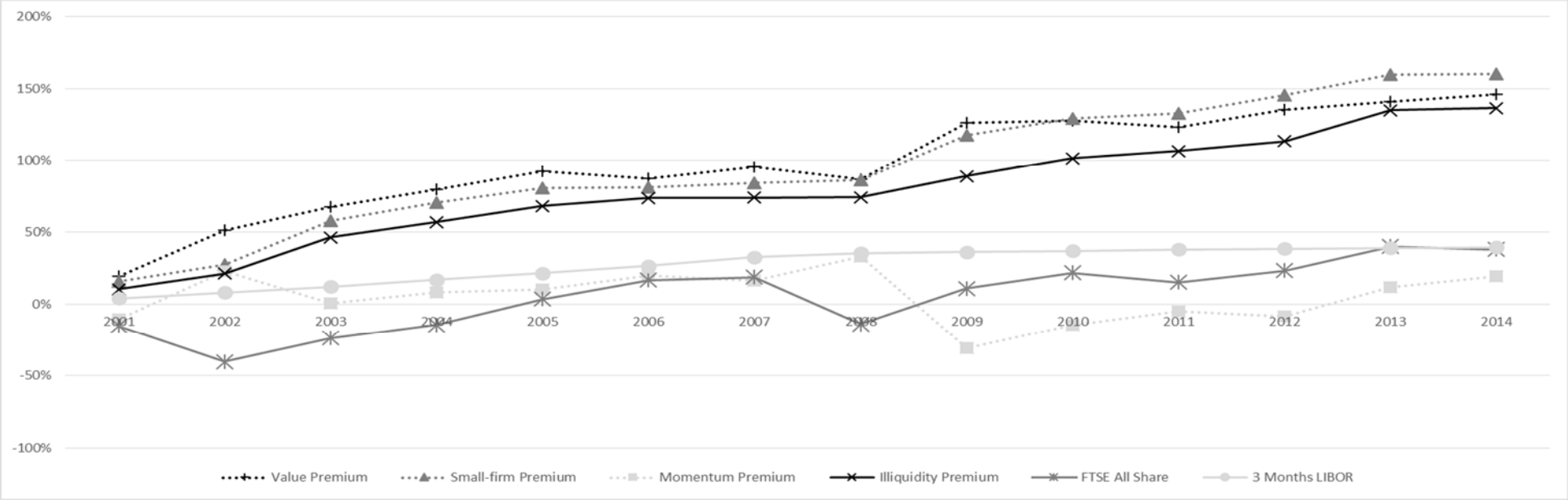
3. ***Momentum effect (momentum vs contrarian investment style)*** used the *annualised monthly returns*. It is also commonly known as *winners versus losers' investment style.*

4. ***Illiquidity effect (illiquid versus liquid investment style)*** uses the *Amihud illiquidity measure (Amihud).*

Cross Section	Result	Pre-Crisis periods (2001 –2007)					Post-Crisis periods (2008 – 2014)				
		Q1	Q2	Q3	Q4	Q1 - Q4	Q1	Q2	Q3	Q4	Q1 - Q4
Value effect	Arithmetic mean	19.66%	7.22%	13.34%	6.05%	**13.61%**	16.80%	4.07%	10.46%	9.58%	**7.22%**
Value vs growth						**(0.0352)**					**(0.0119)**
	Standard deviation	17.13%	22.21%	21.15%	22.83%	11.16%	40.77%	28.81%	29.28%	27.56%	15.67%
(Q1 = Value, Q4 = Growth)	Beta (FTSE All-Share)	0.86	1.16	1.12	1.33	-0.47	2.07	1.51	1.53	1.44	0.63
	Average no. of stocks	113	113	113	112		140	140	140	139	
Size effect	Arithmetic mean	18.34%	11.78%	9.21%	6.32%	**12.02%**	16.20%	10.31%	8.36%	5.30%	**10.91%**
Micro vs big						**(0.0280)**					**(0.0005)**
	Standard deviation	21.53%	21.62%	21.81%	17.41%	9.77%	35.07%	35.40%	29.80%	26.34%	10.58%
(Q1 = Micro, Q4 = Big)	Beta (FTSE All-Share)	1.04	1.17	1.21	1.01	0.03	1.81	1.85	1.56	1.37	0.44
	Average no. of stocks	115	115	115	115		142	142	142	141	
Momentum effect	Arithmetic mean	12.42%	12.75%	10.35%	10.07%	2.35%	10.75%	10.98%	8.36%	10.36%	0.39%
Momentum vs contrarian						0.3412					(0.9463)
	Standard deviation	19.36%	16.07%	19.15%	29.80%	17.60%	28.45%	28.01%	28.38%	46.31%	29.57%
(Q1 = Momentum, Q4 = Contrarian)	Beta (FTSE All-Share)	0.97	0.92	1.08	1.48	-0.51	1.44	1.45	1.47	2.25	-0.81
	Average no. of stocks	115	115	114	114		142	141	141	141	

Illiquidity effect	Arithmetic mean	17.12%	11.32%	9.52%	6.56%	**10.55%**	14.13%	10.97%	9.91%	5.17%	**8.96%**
Illiquid vs liquid						**(0.0135)**					**(0.0002)**
	Standard deviation	21.36%	21.21%	22.53%	17.43%	7.56%	33.30%	33.07%	32.94%	27.37%	7.68%
(Q1 = Illiquid, Q4 = Liquid)	Beta (FTSE All-Share)	1.11	1.16	1.23	1.01	0.10	1.75	1.71	1.71	1.42	0.33
	Average no. of stocks	113	113	113	112		142	142	142	141	
FTSE All-Share index	Arithmetic mean			2.67%					2.75%		
	Standard deviation			16.71%					18.97%		
3 Months LIBOR	Arithmetic mean			4.66%					0.98%		
	Standard deviation			0.76%					0.84%		

Figure 4.1: Comparison of the growth of the respective investment style premiums pre and post-crisis.
This figure shows the growth of the respective investment style premiums over the 14 years study period (7 years pre and 7 years post-crisis). The investment premiums included are *value premium, small-firm premium, momentum premium* and *illiquidity* premium. The percentage growth for investing in the benchmark of *FTSE All-Share index* and *3 months LIBOR* are also included in the figure. All data are obtained from DataStream.



Overall, portfolios constructed based on illiquidity can generate positive returns. Moreover, with the exception of *"High value portfolio"* and *"Micro portfolio",* the *"High illiquid portfolio"* performs better in comparison to the other styles and the two benchmarks for both periods. Hence, it can safely be concluded that illiquidity has met the second benchmark criterion of *"not easily beaten".* Since the portfolios are constructed based on the prior year *(t-1)* measure, this automatically also satisfies the first criterion of *"identifiable before the fact".* Also as expected, the investment styles seem to be superior pre-crisis.

4.4.2.1. INTERSECTION OF ILLIQUIDITY PORTFOLIOS WITH OTHER INVESTMENT STYLES

Although our results in the last section appear to indicate that illiquidity is *"not easily beaten"* for both periods, some researchers highlight that the positive performance of illiquidity is actually due to other styles. Asness et al. (2013) find significant evidence that funding liquidity risk is inversely related to value but positively related to momentum globally, whereas Eleswarapu and Reinganum (1993) highlight that the illiquidity premium is a result of size effect. Therefore, we will implement the *double sorting technique* used by Ibbotson et al. (2013), as this technique will allow us to test whether illiquidity is able to enhanced the other styles and hence meeting the third benchmark criterion of *"a viable alternative".*

4.4.2.2. INTERSECTION OF ILLIQUIDITY AND VALUE/GROWTH INVESTMENT STYLES (PORTFOLIOS)

The first double sorted portfolios are constructed by independent sorting, based on Amihud illiquidity measure and P/B ratio, to produce 16 intersection portfolios as can be seen in table 4.2. As before, the prior year *(t-1)* intersection measure is used to construct and calculate the portfolio performance for a given year *(t).* The stocks are also rebalanced annually.

Unfortunately, due to the limited number of stocks available for the UK market, the number of stocks significantly reduce after segregation into 16 intersection portfolios.

Therefore, we have to ensure that each portfolio is diversified. Past studies have different opinions on the number of stocks required to properly diversify a portfolio such as Evans and Archer (1968) who highlight that 10 to 15 stocks are required. Nevertheless, Reilly and Brown (2012, p. 201) highlight that based on past studies such as Evans and Archer (1968) and Tole (1982) *"…major benefits of diversification were achieved rather quickly, with about 90 percent of the maximum benefit of diversification derived from portfolios of 12 to 18 stocks"*. Thus, we consider portfolios that have at least 12 stocks as *"acceptable portfolios"* because achieving 90 percent of the maximum benefit of diversification is more than satisfactory for us.

Panel A of table 4.2 shows only one portfolio has less than twelve stocks pre-crisis while for post-crisis, all portfolios are considered acceptable. Both pre-crisis and post-crisis periods show results that are less consistent, as across value portfolios (rows), illiquid stocks do not consistently generate higher returns relative to more liquid stocks. Similarly, across illiquidity (columns), value portfolios also do not perform consistently better compared to growth portfolios.

However, although the highest return is not generated by the intersection of *"High value & High illiquid portfolio"*, its return of 20.93% is higher than the return of 19.66% of the *"High value portfolio (Q1)"* in table 4.1 for pre-crisis period. This can also be seen post-crisis, signifying that illiquidity does enhance the value investment style.

Table 4.2: Annualized returns and risks of value/growth and illiquidity intersection portfolios pre and post-crisis.
The table shows the results of intersection quartiles between value/growth and illiquidity investment styles. The portfolios are constructed by independently sorting the portfolios into quartiles based on the two investment styles and then by taking the intersection sets of portfolios to produce 16 intersection groups as below. As before, the prior year *(t-1)* intersection measure is used to construct the portfolios, which are then used to calculate the portfolio returns and risk for a given year *(t)*. The portfolios are rebalanced annually. Thus, the *sorting* period is from January 2000 to December 2013 whilst *performance* period is from January 2001 to December 2014 and the stocks are held for at least one year. The 14 years performance sample periods are divided into half namely Pre-Crisis (2001 to 2007) and Post-Crisis periods (2008 to 2014). Due to the limited number of stocks and to ensure that the results are significant, we only consider portfolios that meet our diversification requirements of at least 12 stocks on average. Thus, acceptable portfolios with 12 or more stocks on average are in **bold**. All data are obtained from DataStream.

	Pre-Crisis periods (2001 –2007)				**Post-Crisis periods (2008 – 2014)**			
Cross Section	**High Illiquid**	**Mid Illiquid**	**Mid Liquid**	**High Liquid**	**High Illiquid**	**Mid Illiquid**	**Mid Liquid**	**High Liquid**
High Value								
Arithmetic mean	**20.93%**	**21.66%**	**15.51%**	11.81%	**17.60%**	**18.90%**	**13.84%**	**10.51%**
Standard deviation	**19.00%**	**16.72%**	**18.59%**	12.78%	**34.21%**	**43.58%**	**46.79%**	**41.11%**
Beta (FTSE All Share)	**1.01**	**0.72**	**0.97**	0.58	**1.78**	**2.11**	**2.33**	**2.06**
Average no. of stocks	**43**	**32**	**25**	10	**56**	**44**	**28**	**15**
Mid Value								
Arithmetic mean	**8.78%**	**7.81%**	**3.47%**	**7.03%**	**4.65%**	**5.25%**	**3.47%**	**0.47%**
Standard deviation	**22.72%**	**21.32%**	**22.88%**	**25.02%**	**28.40%**	**24.08%**	**34.06%**	**36.09%**
Beta (FTSE All Share)	**1.18**	**1.14**	**1.08**	**1.21**	**1.48**	**1.25**	**1.77**	**1.86**
Average no. of stocks	**29**	**30**	**31**	**18**	**33**	**49**	**31**	**22**
Mid Growth								
Arithmetic mean	**20.38%**	**12.63%**	**15.40%**	**7.29%**	**18.35%**	**12.42%**	**8.74%**	**5.27%**
Standard deviation	**26.27%**	**21.17%**	**27.17%**	**16.63%**	**33.26%**	**32.47%**	**28.54%**	**25.15%**
Beta (FTSE All Share)	**1.21**	**1.09**	**1.34**	**0.98**	**1.73**	**1.66**	**1.48**	**1.31**
Average no. of stocks	**22**	**26**	**25**	**37**	**32**	**27**	**37**	**43**
High Growth								
Arithmetic mean	**17.28%**	**3.86%**	**4.05%**	**5.21%**	**18.45%**	**8.77%**	**12.86%**	**5.09%**
Standard deviation	**25.99%**	**31.21%**	**28.12%**	**16.74%**	**38.21%**	**35.78%**	**28.40%**	**22.48%**
Beta (FTSE All Share)	**1.18**	**1.73**	**1.53**	**0.98**	**1.98**	**1.84**	**1.46**	**1.16**
Average no. of stocks	**17**	**21**	**29**	**45**	**18**	**19**	**42**	**59**

4.4.2.3. INTERSECTION OF ILLIQUIDITY AND SIZE INVESTMENT STYLES (PORTFOLIOS)

Unlike Ibbotson et al. (2013), table 4.3 seems to show that within the UK investing in illiquid stocks is almost similar to investing into small firms because the intersection of the portfolios result in a limited number of stocks for some portfolios. This is particularly noticeable for the "*Micro & High Liquid portfolio"*, where the average number of stocks is only 1 for both periods. This is not surprising since it is expected that micro stocks are less liquid compared to other size related portfolios.

Among the "acceptable portfolios", table 4.3 shows conflicting results as both illiquidity and size do not show clear enhancing ability, indicating that illiquidity does not provide additional benefits when combined with portfolios based on size for both periods. Therefore, signifying that size does appear to capture illiquidity, as suggested by Eleswarapu and Reinganum (1993).

Table 4.3: Annualized returns and risks of size and illiquidity intersection quartiles pre and post-crisis.
This table shows the results of intersection quartiles between size and illiquidity investment styles. The portfolios are constructed by independently sorting the portfolios into quartiles based on the two investment styles and then by taking the intersection sets of portfolios to produce 16 intersection groups as below. As before, the prior year *(t-1)* intersection measure is used to construct the portfolios, which are then used to calculate the portfolio returns and risk for a given year *(t)*. The portfolios are rebalanced annually. Thus, the sorting sample period is from January 2000 to December 2013 whilst *performance* sample period is from January 2001 to December 2014 and the stocks are held for at least one year. The 14 years performance sample periods are divided into half namely Pre-Crisis (2001 to 2007) and Post-Crisis periods (2008 to 2014). Due to the limited number of stocks and to ensure that the results are significant, we only consider portfolios that meet our diversification requirements of at least 12 stocks on average. Thus, portfolios with 12 or more stocks on average are in **bold**. All data are obtained from DataStream.

	Pre-Crisis periods (2001 –2007)				Post-Crisis periods (2008 – 2014)			
Cross Section	**High Illiquid**	**Mid Illiquid**	**Mid Liquid**	**High Liquid**	**High Illiquid**	**Mid Illiquid**	**Mid Liquid**	**High Liquid**
Micro								
Arithmetic mean	**18.26%**	**17.40%**	19.63%	11.66%	**16.02%**	**14.75%**	37.26%	-46.99%
Standard deviation	**20.60%**	**28.06%**	23.42%	N/A	**33.76%**	**38.31%**	80.87%	N/A
Beta (FTSE All Share)	**1.04**	**1.29**	2.69	N/A	**1.77**	**1.84**	2.92	N/A
Average no. of stocks	**80**	**29**	2	1	**103**	**38**	2	1
Small								
Arithmetic mean	**15.69%**	**9.53%**	**12.89%**	19.31%	**9.82%**	**9.59%**	**10.95%**	-25.94%
Standard deviation	**23.68%**	**20.73%**	**25.92%**	15.04%	**33.33%**	**32.23%**	**54.09%**	N/A
Beta (FTSE All Share)	**1.26**	**1.17**	**1.15**	1.22	**1.73**	**1.69**	**2.66**	N/A
Average no. of stocks	**27**	**66**	**19**	1	**36**	**82**	**24**	1
Medium								
Arithmetic mean	13.77%	**8.21%**	**8.79%**	9.87%	8.19%	**8.95%**	**8.36%**	**6.62%**
Standard deviation	19.09%	**22.15%**	**22.20%**	23.83%	28.56%	**28.86%**	**28.86%**	**39.75%**
Beta (FTSE All Share)	1.02	**1.09**	**1.23**	1.36	1.35	**1.51**	**1.51**	**1.94**
Average no. of stocks	6	**17**	**82**	9	4	**22**	**100**	**16**
Big								
Arithmetic mean	-3.17%	16.44%	7.30%	**6.26%**	64.09%	16.66%	**10.53%**	**4.74%**
Standard deviation	25.79%	42.05%	24.48%	**16.73%**	N/A	68.39%	**27.55%**	**26.26%**
Beta (FTSE All Share)	1.21	2.70	1.37	**0.97**	N/A	6.90	**1.41**	**1.37**
Average no. of stocks	1	1	11	**103**	1	1	**16**	**126**

4.4.2.4. INTERSECTION OF ILLIQUIDITY AND MOMENTUM/CONTRARIAN INVESTMENT STYLES (PORTFOLIOS)

Table 4.4 which combines illiquidity and momentum/contrarian style is more evenly segregated for both periods, suggesting that the two styles are quite independent of each other. Across momentum portfolios (rows), illiquid portfolios generally produce higher returns in comparison to more liquid portfolios and the highest return is generated by the enhanced portfolio of "*High contrarian & High illiquid portfolio"* and "*High momentum & High illiquid portfolio"* pre-crisis and post-crisis respectively.

Nonetheless, across illiquidity portfolios (columns), highly momentum portfolios sometimes generate better returns than contrarian styles but it is less consistent for both periods. In fact, "*High contrarian & High illiquid portfolio"* produces higher returns than the *"High momentum & High illiquid portfolio"* pre-crisis. Furthermore, compared to the *"High momentum portfolio (Q1)"* and *"High contrarian portfolio (Q4)"* in table 4.1, table 4.4 also shows that illiquidity does manage to enhance the returns of the two portfolios for both crisis periods.

Table 4.4: Annualized returns and risks of momentum/contrarian and illiquidity intersection portfolios pre and post-crisis.
This table shows the results of intersection quartiles between momentum/contrarian and illiquidity investment styles. The portfolios are constructed by independently sorting the portfolios into quartiles based on the two investment styles and then by taking the intersection sets of portfolios to produce 16 intersection groups as below. As before, the prior year *(t-1)* intersection measure is used to construct the portfolios, which are then used to calculate the portfolio returns and risk for a given year *(t)*. The portfolios are rebalanced annually. Thus, the sorting period is from January 2000 to December 2013 whilst *performance* period is from January 2001 to December 2014 and the stocks are held for at least one year. The 14 years' performance sample periods are divided into half namely Pre-Crisis (2001 to 2007) and Post-Crisis periods (2008 to 2014). Due to the limited number of stocks and to ensure that the results are significant, we only consider portfolios that meet our diversification requirements of at least 12 stocks on average. Thus, portfolios with 12 or more stocks on average are in **bold**. All data are obtained from DataStream.

	Pre-Crisis periods (2001 –2007)				**Post-Crisis periods (2008 – 2014)**			
Cross Section	**High Illiquid**	**Mid Illiquid**	**Mid Liquid**	**High Liquid**	**High Illiquid**	**Mid Illiquid**	**Mid Liquid**	**High Liquid**
High Momentum								
Arithmetic mean	**16.37%**	**11.19%**	**8.34%**	**12.44%**	**17.64%**	**7.17%**	**11.29%**	**9.05%**
Standard deviation	**23.25%**	**22.19%**	**19.78%**	**16.54%**	**29.91%**	**32.11%**	**27.68%**	**25.00%**
Beta (FTSE All Share)	**0.91**	**1.11**	**1.00**	**0.92**	**1.47**	**1.62**	**1.43**	**1.24**
Average no. of stocks	**28**	**31**	**31**	**22**	**35**	**32**	**39**	**37**
Mid Momentum								
Arithmetic mean	**17.63%**	**17.08%**	**12.57%**	**5.36%**	**13.69%**	**11.34%**	**10.07%**	**8.69%**
Standard deviation	**17.07%**	**11.84%**	**21.23%**	**15.65%**	**32.34%**	**28.91%**	**26.51%**	**23.36%**
Beta (FTSE All Share)	**0.91**	**0.65**	**1.21**	**0.88**	**1.69**	**1.51**	**1.36**	**1.15**
Average no. of stocks	**28**	**27**	**28**	**30**	**36**	**41**	**32**	**32**
Mid Contrarian								
Arithmetic mean	**15.17%**	**7.44%**	**9.51%**	**6.77%**	**10.50%**	**9.85%**	**9.41%**	**2.53%**
Standard deviation	**19.14%**	**24.07%**	**21.70%**	**16.58%**	**30.44%**	**27.65%**	**27.78%**	**29.40%**
Beta (FTSE All Share)	**1.03**	**1.37**	**1.20**	**0.97**	**1.60**	**1.42**	**1.42**	**1.46**
Average no. of stocks	**27**	**25**	**29**	**30**	**38**	**38**	**33**	**32**
High Contrarian								
Arithmetic mean	**17.77%**	**8.77%**	**7.06%**	**4.10%**	**15.04%**	**13.07%**	**8.78%**	**5.29%**
Standard deviation	**29.49%**	**29.55%**	**34.53%**	**27.15%**	**42.12%**	**48.75%**	**50.06%**	**43.34%**
Beta (FTSE All Share)	**1.44**	**1.51**	**1.71**	**1.43**	**2.15**	**2.24**	**2.44**	**2.08**
Average no. of stocks	**30**	**28**	**23**	**31**	**33**	**31**	**37**	**41**

Overall, tables 4.2, 4.3 and 4.4 show that risks have consistently increased after the crisis but returns can be higher, probably as a compensation for the higher risks. Nevertheless, the essential finding is that with the exception of size, so far our results appear to meet the third benchmark criterion of *"a viable alternative"* as illiquidity managed to enhance both value and momentum investment styles for both periods.

4.4.3. ILLIQUIDITY AS A FACTOR IN COMPARISON TO OTHER INVESTMENT FACTORS

Since illiquidity seems to be able to enhance value and momentum styles, similar to Ibbotson et al. (2013), we conduct further investigation on the ability of illiquidity as an investment style by looking at the risk factors (zero cost or dollar neutral) of the styles. Nevertheless, instead of using annual data, we will be using monthly data for the correlation and regression analysis to ensure more meaningful results.

4.4.3.1. CORRELATION OF THE INVESTMENT STYLES (FACTORS) WITH EACH OTHER AND THE MARKET

The correlation analysis is conducted to see the relationship of the respective factors with each other and the market. Results in table 4.5 are almost similar for the two periods. The illiquidity factor is positively related with size and value factor. It is worth noticing that the illiquidity factor is not significantly correlated with the market pre-crisis but it is negatively correlated post-crisis. We also obtain contradictory results for value, size and momentum factors in relation to the market for the two periods.

The strongest positive correlation is observed between the illiquidity factor and size factor, which comes into contrast with Ibbotson et al. (2013) who find a negative correlation between the two factors. The positive correlation obtained here between the two factors is not surprising as our earlier results in table 4.3, show that there is a close relationship between illiquidity and size. This provides further evidence to indicate that size captures illiquidity in the UK. However, post-crisis, the illiquidity factor is slightly less correlated to size.

Table 4.5: Correlation and descriptive statistics of the monthly returns of the respective factors with each other and the market pre and post-crisis.

This table shows the correlation of the monthly returns of the respective factors with each other as well as the market. The p-values of the correlations are reported in brackets under each respective correlation coefficient, whereby **bold** figures denote a statistically significant coefficient at least at 10%. The sample uses stocks that are listed on *FTSE All-Share index* between January 2001 and December 2014 (168 months), which are divided further into pre (84 months) and post-crisis periods (84 months). All data are obtained from DataStream.

	Pre-Crisis periods (2001 –2007)					**Post-Crisis periods (2008 – 2014)**				
	Correlation					**Correlation**				
	Illiquidity Factor	**Market**	**Value Factor**	**Size Factor**	**Momentum Factor**	**Illiquidity Factor**	**Market**	**Value Factor**	**Size Factor**	**Momentum Factor**
Illiquidity Factor	1.0000 -----	-0.1346 (0.2221)	**0.3763** **(0.0004)**	**0.9418** **(0.0000)**	0.0461 (0.6771)	1.0000 -----	**-0.2381** **(0.0195)**	**0.1995** **(0.0514)**	**0.8416** **(0.0000)**	-0.0939 (0.3628)
Market	-0.1346 (0.2221)	1.0000 -----	**-0.2259** **(0.0388)**	**-0.1885** **(0.0860)**	**-0.2528** **(0.0203)**	**-0.2381** **(0.0195)**	1.0000 -----	**0.3074** **(0.0023)**	-0.0837 (0.4177)	-0.1619 (0.1151)
Value Factor	**0.3763** **(0.0004)**	**-0.2259** **(0.0388)**	1.0000 -----	**0.4911** **(0.0000)**	-0.0516 (0.6408)	**0.1995** **(0.0514)**	**0.3074** **(0.0023)**	1.0000 -----	**0.6004** **(0.0000)**	**-0.8653** **(0.0000)**
Size Factor	**0.9418** **(0.0000)**	**-0.1885** **(0.0860)**	**0.4911** **(0.0000)**	1.0000 -----	-0.0217 (0.8445)	**0.8416** **(0.0000)**	-0.0837 (0.4177)	**0.6004** **(0.0000)**	1.0000 -----	**-0.5366** **(0.0000)**
Momentum Factor	0.0461 (0.6771)	**-0.2528** **(0.0203)**	-0.0516 (0.6408)	-0.0217 (0.8445)	1.0000 -----	-0.0939 (0.3628)	-0.1619 (0.1151)	**-0.8653** **(0.0000)**	**-0.5366** **(0.0000)**	1.0000 -----

4.4.3.2. REGRESSION ANALYSES OF VARIOUS ILLIQUIDITY PORTFOLIOS

Similar to Ibbotson et al. (2013) we will use three asset pricing models (univariate CAPM, Fama-French 3 Factor model and Carhart 4 Factor model) to further explain the average returns of various relevant illiquidity portfolios that is discussed earlier.

Table 4.6 shows the regression results for two portfolios namely the zero-dollar "*illiquidity factor portfolio"* (Panel A) and long only "*High illiquid portfolio"* (Panel B). The table shows that based on CAPM, both portfolios (panel A and panel B) report positive and statistically significant monthly alpha for both periods. The Fama-French 3 factor model shows that after including the value factor and size factor, the monthly alpha disappears for the "*illiquidity factor portfolio"*. However, the long only "*High illiquid portfolio"* monthly alpha remains pre-crisis but it disappears post-crisis. Surprisingly, although slightly reduce, the monthly alpha of the long only "*High illiquid portfolio"* remains even after the introduction of the momentum factor signifying that investing into illiquid portfolios can generate positive returns and thus poses a challenge to the EMH, as it should have resulted in no significant monthly alpha. Nevertheless, this can only be observed for the pre-crisis period, as the financial crisis seems to have cause the monthly alpha to disappear post-crisis.

Table 4.6: Regression analyses of monthly returns of the zero-cost illiquid factor and High Illiquidity portfolio pre and post-crisis.
This table shows results from the following three regression models on zero-cost (or dollar neutral) *Illiquidity factor portfolio* (Panel A) and *long only High Illiquid portfolio* (Panel B). *Illiquidity factor portfolio* (or illiquidity effect) takes a long position in the portfolio of *high illiquid stocks* and a short position in the portfolio of *high liquid stocks.* The p-values are reported in brackets under each respective coefficient, whereby **bold** figures denote a statistically significant coefficient at least at 10%. The sample uses stocks that are listed on *FTSE All-Share index* between January 2001 and December 2014 (168 months), which are divided further into pre (84 months) and post-crisis (84 months). All data are obtained from DataStream.

1. Capital Asset Pricing Model (CAPM)

$$R_p = \alpha_p + \beta_p(R_m - R_f) + \varepsilon_p \quad (4.2)$$

2. Fama-French three factor model

$$R_p = \alpha + \beta_p(R_m - R_f) + V_p(R_v - R_g) + S_p(R_s - R_b) + \varepsilon_p \quad (4.3)$$

3. Carhart four factor model

$$R_p = \alpha + \beta_p(R_m - R_f) + V_p(R_v - R_g) + S_p(R_s - R_b) + M_p(R_{mom} - R_c) + \varepsilon_p \quad (4.4)$$

	Pre-Crisis periods (2001 –2007)							Post-Crisis periods (2008 – 2014)						
	Monthly α (%)	**Market Beta**	**Value**	**Size**	**Moment-um**	**Adjusted R^2 (%)**	**N**	**Monthly α (%)**	**Market Beta**	**Value**	**Size**	**Moment-um**	**Adjusted R^2 (%)**	**N**
Panel A														
Illiquidity factor portfolio (Illiquidity effect)														
CAPM	**0.86%**	-0.0863				0.52%	84	**0.76%**	**-0.1373**				5.41%	84
	(0.0020)	(0.2340)						**(0.0048)**	**(0.0188)**					
Fama-French	0.01%	0.0195	**-0.1251**	**1.0123**		89.38%	84	0.06%	**-0.0032**	**-0.3252**	**0.9726**		84.17%	84
3 factor	(0.9125)	(0.4233)	**(0.0110)**	**(0.0000)**				(0.6027)	**(0.9048)**	**(0.0000)**	**(0.0000)**			
Carhart 4	-0.01%	0.0333	**-0.1161**	**1.0140**	**0.0656**	89.80%	84	-0.10%	-0.0357	-0.0490	**0.9599**	**0.1935**	88.68%	84
factor	(0.9144)	(0.1810)	**(0.0162)**	**(0.0000)**	**(0.0420)**			(0.3146)	(0.1286)	(0.4129)	**(0.0000)**	**(0.0000)**		

	Pre-Crisis periods (2001 –2007)							Post-Crisis periods (2008 – 2014)						
	Monthly α (%)	**Market Beta**	**Value**	**Size**	**Moment-um**	**Adjusted R^2 (%)**	**N**	**Monthly α (%)**	**Market Beta**	**Value**	**Size**	**Moment-um**	**Adjusted R^2 (%)**	**N**
Panel B														
Long only High illiquid portfolio														
CAPM	**1.25%**	**1.0378**				61.99%	84	**0.99%**	**0.9502**				68.90%	84
	(0.0003)	**(0.0000)**						**(0.0025)**	**(0.0000)**					
Fama-French 3 factor	**0.46%**	**1.1376**	**-0.3147**	**1.1643**		88.80%	84	0.19%	**1.0122**	-0.0625	**0.9140**		91.04%	84
	(0.0307)	**(0.0000)**	**(0.0020)**	**(0.0000)**				(0.2821)	**(0.0000)**	(0.3484)	**(0.0000)**			
Carhart 4 factor	**0.41%**	**1.1685**	**-0.2945**	**1.1682**	**0.1467**	89.35%	84	0.15%	**1.0029**	0.0164	**0.9103**	0.0553	91.01%	84
	(0.0487)	**(0.0000)**	**(0.0031)**	**(0.0000)**	**(0.0261)**			(0.4285)	**(0.0000)**	(0.8847)	**(0.0000)**	(0.3899)		

4.4.3.3. REGRESSION ANALYSES OF VARIOUS ENHANCED ILLIQUIDITY PORTFOLIOS

Using the 3 asset pricing models, table 4.7 shows the regression results of 3 enhanced intersected illiquidity portfolios (net of risk free rate). The 3 enhanced portfolios are 1) *"High Value & High Illiquid portfolio"*, 2) *"Micro & High Illiquid portfolio"* and 3) *"High Momentum & High Illiquid portfolio"*. Although the 3 portfolios do not produce the highest returns, we decide to use those to provide consistent comparison between pre-crisis and post-crisis periods. Besides, with the exception of size, illiquidity does manage to enhance the other two investment style returns. Furthermore, Ibbotson et al. (2013) use similar portfolios.

Based on CAPM, all three portfolios generate significant positive monthly alpha whereby the "*High value & High illiquid portfolio"* produces the highest alpha for both periods. All portfolios are found to be positively related to the market but interestingly, the relationship seems weaker post-crisis signifying that the respective portfolios have lower systematic risk. Using the Fama-French 3 factor model, the monthly alpha remains for "*High value & High illiquid portfolio"* and "*Micro & High illiquid portfolio"* for pre-crisis periods but it disappears for post-crisis periods. The alpha of the *"High momentum & High illiquid portfolio"* remains only post-crisis.

Fascinatingly, panel A of table 4.7 shows that the monthly alpha of the *High value & High illiquid portfolio"* remains positive and significant pre-crisis, even after the inclusion of all 3 factors confirming that illiquidity has improved the value portfolio as reported earlier. The table also shows that the portfolio is positively related to value, size and momentum factor pre-crisis. The monthly alpha of the *"Micro & High illiquid portfolio"* and *"High momentum & High illiquid portfolio"* disappears pre-crisis and post-crisis respectively.

Table 4.7: Regression analyses of monthly returns of the enhanced illiquidity portfolio pre and post-crisis.

This table reports results from the 3 regression models of enhanced illiquidity portfolios. There are three enhanced illiquidity portfolios based on its intersection with other investment styles namely *"Micro & High illiquid"*, *"High value & High illiquid"* and *"High momentum & High illiquid"* portfolios. The p-values are reported in brackets under each respective coefficient, whereby **bold** figures denote a statistically significant coefficient at least at 10%. The sample uses stocks that are listed on *FTSE All-Share index* between January 2001 and December 2014 (168 months), which are divided further into pre (84 months) and post-crisis periods (84 months). All data are obtained from DataStream.

	Pre-Crisis periods (2001 –2007)							Post-Crisis periods (2008 – 2014)						
	Monthly α (%)	**Market Beta**	**Value**	**Size**	**Moment-um**	**Adjusted R^2 (%)**	**N**	**Monthly α (%)**	**Market Beta**	**Value**	**Size**	**Moment-um**	**Adjusted R^2 (%)**	**N**
Panel A														
High value & High illiquid														
CAPM	**1.57%**	**1.0422**				61.49%	84	**1.28%**	**1.0108**				61.21%	84
	(0.0000)	**(0.0000)**						**(0.0020)**	**(0.0000)**					
Fama-French 3 factor	**0.43%**	**1.1810**	0.1489	**0.9946**		87.72%	84	0.32%	**1.0100**	**0.1801**	**0.9343**		89.21%	84
	(0.0544)	**(0.0000)**	(0.1560)	**(0.0000)**				(0.1540)	**(0.0000)**	**(0.0311)**	**(0.0000)**			
Carhart 4 factor	**0.35%**	**1.2316**	**0.1819**	**1.0009**	**0.2403**	89.40%	84	0.21%	**0.9882**	**0.3649**	**0.9258**	0.1295	89.44%	84
	(0.0938)	**(0.0000)**	**(0.0647)**	**(0.0000)**	**(0.0004)**			(0.3537)	**(0.0000)**	**(0.0099)**	**(0.0000)**	(0.1016)		
Panel B														
Micro & High illiquid														
CAPM	**1.34%**	**1.0512**				59.53%	84	**1.15%**	**0.9428**				65.88%	84
	(0.0003)	**(0.0000)**						**(0.0010)**	**(0.0000)**					
Fama-French 3 factor	**0.38%**	**1.1721**	**-0.2255**	**1.2447**		89.75%	84	0.27%	**1.0011**	-0.0351	**0.9841**		92.28%	84
	(0.0696)	**(0.0000)**	**(0.0231)**	**(0.0000)**				(0.1107)	**(0.0000)**	(0.5757)	**(0.0000)**			
Carhart 4 factor	0.33%	**1.2048**	**-0.2042**	**1.2488**	**0.1555**	90.35%	84	0.23%	**0.9923**	0.0396	**0.9806**	0.0523	92.26%	84
	(0.1081)	**(0.0000)**	**(0.0345)**	**(0.0000)**	**(0.0168)**			(0.1964)	**(0.0000)**	(0.7104)	**(0.0000)**	(0.3876)		

	Pre-Crisis periods (2001 –2007)							Post-Crisis periods (2008 – 2014)						
	Monthly α (%)	**Market Beta**	**Value**	**Size**	**Moment-um**	**Adjusted R^2 (%)**	**N**	**Monthly α (%)**	**Market Beta**	**Value**	**Size**	**Moment-um**	**Adjusted R^2 (%)**	**N**
Panel C														
High momentum & High illiquid														
CAPM	**1.18%**	**1.0005**				44.42%	84	**1.29%**	**0.9278**				62.04%	84
	(0.0121)	**(0.0000)**						**(0.0006)**	**(0.0000)**					
Fama-French 3 factor	0.57%	**1.0809**	**-0.6528**	**1.3624**		70.72%	84	**0.65%**	**1.0783**	**-0.3927**	**0.9460**		76.05%	84
	(0.1401)	**(0.0000)**	**(0.0005)**	**(0.0000)**				**(0.0337)**	**(0.0000)**	**(0.0007)**	**(0.0000)**			
Carhart 4 factor	0.38%	**1.1985**	**-0.5762**	**1.3771**	**0.5591**	78.17%	84	0.34%	**1.0150**	0.1454	**0.9213**	**0.3770**	79.48%	84
	(0.2533)	**(0.0000)**	**(0.0004)**	**(0.0000)**	**(0.0000)**			(0.2419)	**(0.0000)**	(0.4096)	**(0.0000)**	**(0.0003)**		

Overall, although our results are not similar to Ibbotson et al. (2013) in relation to the illiquidity factor, the significant positive results for the long only "*High illiquid portfolio"* in panel B of table 4.6 for the pre-crisis period does confirm that illiquidity is *"not easily beaten"* and can even be considered as *"a viable alternative"*. Furthermore, the ability of illiquidity to enhance the value portfolio in panel A of table 4.7 with a positive and significant monthly alpha does confirm illiquidity as meeting the third portfolio benchmark criterion of *"a viable alternative"*. Our results also show the substantial effect of the crisis on the portfolios as the monthly alpha disappears post-crisis after the inclusion of all three factors.

4.4.4. ILLIQUIDITY STABILITY AND MIGRATION

The fourth and last benchmark criterion of Sharpe (1992) is whether the illiquidity investment style can be managed at *"a low cost",* which will be assessed by using the technique developed by Ibbotson et al. (2013). It is important to consider costs as Carhart (1997) highlights that investment costs of expense ratios, transaction costs, and load fees all have a direct, negative impact on funds' performance. Furthermore, Kaplan and Schoar (2005) highlight that although private equity partnerships earn returns (gross of fees) exceeding the S&P 500 over the entire sample period (1980–1997), average fund returns net of fees are roughly equal to those of the S&P 500, signifying the negative impact of fees.

Ibbotson et al. (2013) highlight that illiquidity has a cost as the stocks may take longer to trade and even have higher transaction costs but trading costs can be mitigated through longer horizons and less trading, which translates into higher returns for the less liquid stocks. Nevertheless, less liquid portfolios are riskier to liquidate in a crisis compared to more passively held portfolios which can largely mitigate this risk. Therefore, studying migration of the stocks in a portfolio will allow us to understand if any of the portfolios can be managed at a low cost or passively.

4.4.4.1. MIGRATION OF STOCKS OF VARIOUS INVESTMENT STYLES

Table 4.8 shows the migration of stocks from each quartile in *year (t)* (sorting year) to other quartiles in *year (t+1)* (performance year) for all investment styles. As before, the quartiles are only rebalanced annually meaning that the stocks are held for at least one year while diagonal results (underlined & *italics)* represent stocks that remain in their respective quartiles after one year.

Panel A of table 4.8 shows that overall 77.66% of the illiquid stocks remain in the same quartile, pre-crisis. For the "*High illiquid portfolio"* (Quartile 1), 75.54% remain in their quartile while the rest migrated to other quartiles, with the next quartile (Q2) receiving the most stocks (22.21%). However, the most stable quartile is the "*High liquid portfolio"* (Quartile 4) as 93.83% of stocks remain within their quartile.

Pre-crisis, size is considered the most stable as overall 84.20% of stocks remain within their quartile while momentum results in the lowest stability of only 30.87%. Value portfolios are also relatively stable, whereby overall 67.29% remained in the same quartile. Similar results are obtained post-crisis. Table 4.8 signifies that generally the transaction costs in maintaining illiquidity based portfolios are relatively low. Therefore, along with the stable returns and risks reported earlier, illiquidity styles can be regarded as a stable strategy. Moreover, table 4.8 shows that the "*High liquid portfolio"* (Quartile 4) is the most stable (low transaction costs) although the portfolio still generates positive returns with lower risks (table 4.1). However, a fascinating finding is that post-crisis, overall illiquidity portfolios increase in stability while other investment styles decrease in stability, suggesting the preference of illiquidity based portfolios post-crisis.

Table 4.8: Migration of stocks one year after portfolio construction for all investment styles pre and post-crisis.

The table shows the migration of stocks from each quartile in *year (t)* (sorting year) to other quartiles in *year (t+1)* (performance year) for all investment styles. The sample uses companies that are listed on *FTSE All-Share index* between January 2000 and December 2014, which are divided into pre (84 months) and post-crisis periods (84 months). As before, the quartiles are only rebalanced annually meaning that the stocks are held for at least one year. Diagonal results (underlined & *italics)* represent stocks that remain in their respective quartiles after one year. All data are obtained from DataStream.

	Pre-Crisis periods (2001 –2007)				**Post-Crisis periods (2008 – 2014)**			
Year t (Illiquidity)	***Panel A-Illiquidity migration (Overall 77.66% remains in the same quartile)***				***Illiquidity migration (Overall 82.16% remains in the same quartile)***			
	Year t+1 (Illiquidity)				**Year t+1 (Illiquidity)**			
	Q1	***Q2***	***Q3***	***Q4***	***Q1***	***Q2***	***Q3***	***Q4***
Quartile 1	***75.54%***	22.21%	2.13%	0.13%	***83.56%***	15.93%	0.50%	0.00%
Quartile 2	19.71%	***64.08%***	16.21%	0.00%	16.49%	***71.28%***	12.03%	0.20%
Quartile 3	0.85%	12.32%	***77.17%***	9.67%	0.50%	11.00%	***80.52%***	7.98%
Quartile 4	0.11%	0.00%	6.06%	***93.83%***	0.11%	0.00%	6.62%	***93.27%***

Year t (Value)	***Panel B-Value migration (Overall 67.29% remains in the same quartile)***				***Value migration (Overall 66.14% remains in the same quartile)***			
	Year t+1 (Value)				***Year t+1 (Value)***			
	Q1	***Q2***	***Q3***	***Q4***	***Q1***	***Q2***	***Q3***	***Q4***
Quartile 1	***67.07%***	27.10%	2.70%	3.12%	***64.49%***	27.35%	5.55%	2.61%
Quartile 2	29.36%	***56.88%***	13.11%	0.65%	28.85%	***56.72%***	13.90%	0.53%
Quartile 3	2.53%	13.67%	***67.42%***	16.38%	5.29%	13.71%	***63.68%***	17.32%
Quartile 4	2.26%	1.94%	18.03%	***77.78%***	2.53%	0.64%	17.15%	***79.68%***

Year t (Size)	***Panel C-Size migration (Overall 84.20% remains in the same quartile)***				***Size migration (Overall 82.95% remains in the same quartile)***			
	Year t+1 (Size)				***Year t+1 (Size)***			
	Q1	***Q2***	***Q3***	***Q4***	***Q1***	***Q2***	***Q3***	***Q4***
Quartile 1	***86.31%***	13.45%	0.24%	0.00%	***86.83%***	12.86%	0.21%	0.10%
Quartile 2	12.34%	***76.20%***	11.46%	0.00%	12.17%	***74.60%***	12.83%	0.40%
Quartile 3	0.51%	9.95%	***81.27%***	8.27%	0.62%	11.74%	***78.54%***	9.09%
Quartile 4	0.00%	0.13%	6.84%	***93.03%***	0.20%	0.32%	7.66%	***91.82%***

Year t (Momentum)	***Panel D- Momentum migration (Overall 30.87% remains in the same quartile)***				***Momentum migration (Overall 29.39% remains in the same quartile)***			
	Year t+1 (Momentum)				***Year t+1 (Momentum)***			
	Q1	***Q2***	***Q3***	***Q4***	***Q1***	***Q2***	***Q3***	***Q4***
Quartile 1	***31.21%***	25.33%	19.93%	23.53%	***29.89%***	22.44%	21.03%	26.64%
Quartile 2	25.32%	***29.34%***	26.34%	19.00%	25.08%	***28.87%***	26.25%	19.81%
Quartile 3	21.34%	25.60%	***31.22%***	21.85%	19.96%	27.99%	***29.79%***	22.26%
Quartile 4	24.74%	21.19%	22.36%	***31.71%***	26.14%	21.33%	23.53%	***29.00%***

To summarize, the results in table 4.8 indicate that portfolios based on illiquidity can be managed at *"a low cost",* meeting the fourth and final benchmark criterion. The improved stability of illiquid portfolios post-crisis, signifies that investors can even reduce transaction costs by using illiquid portfolios. This means that at least pre-crisis, illiquidity has met all 4 of Sharpe (1992) benchmark criteria signifying that it can be made into a benchmark portfolio and can be categorised as a viable investment style in line with the other more traditional styles such as value style.

4.5. CONCLUSION

Investors have always wanted to find ways to beat the market and thus various investment styles have been established such as value (Fama & French, 1992) and momentum styles (Jegadeesh & Titman, 1993). Recently, illiquidity has gained importance due to the financial crisis. Although researchers such as Amihud and Mendelson (1986) find evidence to suggest that returns are an increasing function of illiquidity, it is never classified as a separate investment style. Ibbotson et al. (2013) even state that illiquidity has the most obvious connection to valuation, as investors will pay more for liquid and less for illiquid stocks. Thus, we feel that it is time to conduct such a study on the UK market as well as on the style's response towards the crisis, using Ibbotson et al. (2013) framework which is based on Sharpe (1992) benchmark criteria of 1) *"identifiable before the fact",* 2) *"not easily beaten",* 3) *"a viable alternative",* and 4) *"low in cost".*

The first criterion of *"identifiable before the fact"* is met by using the prior year (*t-1)* related style measure to obtain the results of the quartiles (or portfolio) for a given year *(t)*. For the traditional style measures, we have decided to use P/B ratio (value), MV (size) and annualised returns (momentum). For measuring illiquidity, we use the *Amihud illiquidity measure* (Amihud, 2002).

The second criterion is *"not easily beaten"* and our results show that value premium, size premium and even illiquidity premium exists but momentum premiums are insignificant for both periods. The *"High illiquid portfolio"* also performs better than the two benchmarks and other styles, with the exception of *"High value portfolio"* and *"Micro portfolio".* Similar to Ibbotson et al. (2013), we use CAPM, Fama-French 3 factor model and Carhart 4 factor model for estimating alpha. The results show that the long only "*High*

illiquid portfolio" is able to generate significantly positive monthly alpha on all three models pre-crisis only. Thus, we consider the *"High illiquidity portfolio"* as *"not easily beaten"* but not for post-crisis.

Since illiquidity is able to outperform the benchmarks, it can be considered as satisfying the third criterion of "*a viable alternative"* but the illiquidity premium may also be due to the other styles. To shed light on this, we construct double sorted illiquidity portfolios with the other styles. Illiquidity is able to enhance the returns of both value and momentum styles. Moreover, using CAPM, all enhanced portfolios are able to generate positive and significant alpha for both periods. The "*High value & High illiquid portfolio"* is even able to generate positive and significant alpha for all three models pre-crisis only. Thus, meeting the third benchmark criterion of *"a viable alternative"* but again not for the post-crisis period.

Illiquid stocks are also found to be overall more stable than value and momentum portfolios for both periods, signifying that illiquid portfolios can be managed at low cost, meeting the fourth criterion of *"low in cost"*. Furthermore, illiquid stocks stability actually improves post-crisis, indicating the preference for illiquid stocks after the financial crisis.

To summarize, our results show that pre-crisis, illiquidity as captured by *Amihud illiquidity measure*, is able to meet the four criteria of Sharpe (1992) benchmark requirements or at least show its profitability as an investment style. Thus, we agree with Ibbotson et al. (2013) that illiquidity can be considered as an alternative investment style in equal standing with the other styles and our*"High value & High illiquid portfolio*" is the best strategy for fund managers to utilize in UK, pre-crisis.

As expected, there is a detrimental effect on the illiquidity portfolios due to the crisis, as the portfolios performance post-crisis is almost consistently worse relative to pre-crisis. Interestingly, although illiquidity is not as successful after the crisis, it does provide steady profits as it is able to perform better than the benchmarks. Furthermore, it is more stable, signifying potential of profit opportunities.

Nevertheless, even though our results appear to confirm illiquidity as a profitable style, one must keep in mind that there is a strong relationship between size and illiquidity. This comes into contrast with Ibbotson et al. (2013), signifying that the favourable performance of illiquidity may actually be due to size. Eleswarapu and Reinganum (1993)

also highlight similar results but Elfakhani (2000) believes that the size premium may actually be due to illiquidity. Moreover, our results are weaker in comparison to Ibbotson et al. (2013), probably due to the shorter periods and different liquidity measure used. Another reason may be the different characteristics of UK and US markets such as the lower volatility in the UK market relative to the US market (Bartram et al., 2012), since the lower level of volatility will definitely affect asset prices and liquidity. Stoll (1978) shows that liquidity is positively affected by return volatility while Vayanos (2004) mentions that investors reduce their willingness to hold illiquid assets during volatile times.

Further studies need to be conducted in different geographical areas and over longer periods. However, we feel that illiquidity still has its merits as an investment management tool and choosing an investment style actually depends on investors' preference. In fact, it is shown that the migration stability of illiquid stocks has improved after the crisis, signifying lower transaction costs. Besides since the crisis is partly attributed on the illiquidity of financial markets, it is expected that investors will expect more compensation for the illiquidity risk of holding stocks longer, indicating profit opportunities with lower transaction costs[67].

[67] It is important to consider costs of investment styles or strategies, as Keim and Madhavan (1996) mention that trading costs are economically significant and even increases with trade difficulty. Moreover, Carhart (1997) highlights that investment costs of expense ratios, transaction costs, and load fees all have a direct, negative impact on funds' performance while Kaplan and Schoar (2005) mention that average fund returns of private equity partnerships (net of fees) are roughly equal to those of the S&P 500. Thus, signifying the negative impact of fees and trading costs on investment styles or strategies. Nevertheless, trading costs can be mitigated through longer horizons and less trading (Ibbotson et al., 2013). Therefore, the stability of our illiquidity portfolios indicates that the negative impact from transaction (trading) costs can be reduced and hence increases the profitability of our portfolios for investors.

CHAPTER 5 : INVESTMENT STYLES, ILLIQUIDITY AND JANUARY RETURNS IN UNITED KINGDOM

5.1. INTRODUCTION

In the previous chapter, we discuss the potential of using illiquidity as an investment style during the financial crisis in the *United Kingdom (UK)* where we apply Ibbotson et al. (2013) framework on 14 years data, equally divided into pre-crisis and post-crisis periods. Our results show that illiquidity can be a reliable investment style for the seven years pre-crisis period but as expected, performance is less convincing post-crisis. However, illiquidity portfolios are found to be more stable post-crisis, indicating investors' preference for illiquidity based portfolios. Although we find some valuable insights, we believe that the research can be improved by using a longer period[68]. Therefore, in this chapter, we will also study illiquidity as an investment style in the UK but using a longer data period of 23 years. Furthermore, we have also included more analysis such as an investigation into the January effect, in order to make the study on illiquidity more concise.

As highlighted before, market efficiency signifies that obtaining abnormal returns is not possible. However, over the years, researchers find evidence to contradict the *Efficient Market Hypothesis (EMH)* known as anomalies. The January-effect (Keim, 1983) is one of the most common type of anomalies.

Due to such anomalies, various investment styles (or strategies) have been developed in order to beat the market. Farrell (1974) is one the first few to raise the issue by looking at homogenous stock groupings. Style investments are later recommended by Sharpe (1978) who looks at general styles such as passive and active management. This is further extended to include more specific and generally accepted investment styles of size, value/ growth and momentum/contrarian. For instance, Banz (1981) mentions that average returns are found to be inversely related to size while Fama and French (1992) highlight that value investing is considered superior in either developed or emerging markets. Lastly, Jegadeesh and Titman (1993) document that styles that combine buying winner

[68] For example, past research tends to conclude that value style is considered superior to growth style (Basu 1983, Rosenberg, Reid et al. 1985) but Beneda (2002) highlights that over a longer period (at least 14 years), average returns for growth stocks are found to be superior to value stocks, signifying the importance of using different time-periods.

stocks (momentum) and selling loser stocks (contrarian) generate significant positive returns. However, there are contradictory findings as well, which will be discussed briefly in the literature review.

Recently, the study of illiquidity has gained importance, probably due to financial sector development (Rajan, 2006) and the financial crisis[69] (Brunnermeier, 2009). General evidence seems to indicate that asset returns will increase with illiquidity. Amihud and Mendelson (1986) discover that market-observed average returns are an increasing function of the bid-ask spread. A more recent paper by Jensen and Moorman (2010) find evidence that the zero-cost portfolio[70] earn returns that are both economically and statistically significant for the US market while Said and Giouvris (2015) obtain similar results for the UK market. Furthermore, the relationship between returns and illiquidity is quite obvious as Ibbotson et al. (2013) mention that investors clearly want more liquidity and avoid illiquidity. Therefore, illiquidity should be compensated with additional returns.

Surprisingly, even though it is so apparent, for some reason illiquidity is rarely used as a control variable and most studies, generally use the other three styles (Subrahmanyam, 2010). Hence, it is not a common investment style even in the *United Kingdom (UK)*. Only lately, research on illiquidity as an investment style has been undertaken (see Chang et al. (2013) on the *Taiwanese stock market (TSM)*, Theart and Krige (2014) on the *Johannesburg Stock market (JSE)* and Ibbotson et al. (2013) on the US market). Ibbotson et al. (2013) find evidence to support illiquidity as an investment style.

Similarly, we feel that it is time that illiquidity be categorised as a reliable and consistent investment style on equal level with the more establish investment styles. Therefore, we have decided to conduct research based on Ibbotson et al. (2013) framework but focusing on the UK market, as the number of such studies conducted are still limited.

We believe that the UK market is a good research opportunity because the *London Stock Exchange (LSE)*, is considered as one of the largest stock market by capitalisation and turnover ratio signifying that the market is quite liquid and therefore the results will be as immune as possible from biases such as infrequent trading (Galariotis & Giouvris, 2007).

[69] Brunnermeier (2009) mentions that the financial market turmoil in 2007 and 2008, due to liquidity and the credit crunch, has led to the most severe financial crisis since the Great Depression.
[70] Zero-cost portfolio = long the illiquid portfolio and short the liquid portfolio

Hence, due to the attractiveness of the UK market, we agree with Galariotis and Giouvris (2007) that the results on the UK market will be of great interest to the international scientific, academics, corporate and investment community.

Using Ibbotson et al. (2013) framework and Sharpe (1992) four benchmark portfolio criteria[71], we start our research by investigating whether the respective investment styles' premium[72] including illiquidity premium exist within the UK market and how the different styles perform against benchmarks. This will be followed by investigations on double sorted quartile portfolios, which are the intersection between illiquidity and the other investment styles.

Since we are constructing portfolios as well as using financial models in our study, we have also conducted a covariance versus characteristics analysis[73]. Finally, we also investigate the January effect because past research shows that it is quite persistent within the 3 styles and illiquidity.

Overall, our research for the UK market report that all 4 investment styles do generate positive premiums similar to past literature but the momentum/contrarian does not show significant results while the illiquid portfolios consistently outperform the benchmarks. Illiquidity satisfactorily meet Sharpe (1992) 4 benchmark criteria signifying that illiquidity can be classified as a reliable investment style but it is highly correlated to size.

We have also find evidence to suggest that the January effect remains for value, size and illiquidity styles but not for the market and momentum/contrarian investment style. However, when independent double sorting is conducted, it appears that the January effect of value and size is due to illiquid stocks.

The remainder of this paper is organised as follows. Section 5.2 presents the literature review while section 5.3 describes the data and variables. In section 5.4, the methodology, empirical results and analysis of the research are discussed followed by our conclusion in section 5.5.

[71] Sharpe (1992) establishes that a benchmark portfolio should be 1) identifiable before the fact, 2) not easily beaten, 3) a viable alternative, and 4) low in cost.

[72] Investment style premium happens when one specific style performs better to its relevant antagonist style. For example, value premium (value returns > growth returns) and growth premium (value returns < growth returns).

[73] Covariance model considers returns sensitivity to variables such as market returns and a popular model is the *Capital Asset Pricing Model (CAPM)*. Characteristics model uses only financial ratios such as book-to-market ratios to construct portfolios. Daniel and Titman (1997) mention that stock returns due to covariance model signifies riskiness of stocks while characteristics model means stocks are under-priced. By comparing the two models, it will allow us to investigate which model construct the better performing portfolio.

5.2. LITERATURE REVIEW

5.2.1. INVESTMENT STYLES, ILLIQUIDITY AND ITS POTENTIAL

The literature review on investment style is similar to the one presented in the previous chapter as well as the broad literature and hence it will not be repeated extensively. Nevertheless, we will briefly discuss some of the key literature on investment styles.

We start off with value and growth investment styles which are two popular fundamental styles that appears to be antagonist to each other. Past research tends to conclude that value style is considered superior to growth style in the US market (Basu, 1983; Rosenberg et al., 1985). Nonetheless, Beneda (2002) highlights that the research time-period is important as it is discovered that over a longer period (at least 14 years), average returns for growth stocks is found to be superior. In relation to size effect, Banz (1981) highlights that average returns are negatively related with size but after the early 1980s, it is less optimistic as Van Dijk (2011) mentions that past empirical studies declare the size effect to be dead since then.

Momentum and contrarian are the other popular investment styles as De Bondt and Thaler (1985) discover that loser stocks (or contrarian style) perform exceptionally well in comparison to winner stocks (or momentum style) over extended time periods of 3 to 5 years horizons. However, in contrast, Jegadeesh and Titman (1993) document that investment styles that combine buying winner stocks and selling loser stocks generate significant positive returns of about 1% per month over 3 to 12 months holding periods.

Finally, the general evidence on illiquidity appears to indicate that returns will increase with illiquidity (Amihud & Mendelson, 1986). However, Ben-Rephael et al. (2008) who study the NYSE finds evidence that the profitability of trading strategies based on illiquidity premium has declined over the past four decades, rendering such strategies virtually unprofitable.

The conflicting evidence of the various investment styles indicates that conducting research on illiquidity as an investment style still has its merits especially since Yan (2008) in their research of US mutual funds finds evidence to suggest that liquidity is an important reason why size erodes fund performance signifying the importance of liquidity in investment management. Moreover, Ibbotson et al. (2013) find evidence to suggest

that liquidity should be given equal standing to other investment styles by studying the US market.

5.2.2. COVARIANCE VERSUS CHARACTERISTICS

In order to measure the performance of various investment style portfolios, we will be using various relevant financial ratios to rank and construct the portfolios. For instance, as highlighted earlier in the literature, we can use P/E ratio to distinguish between value and growth portfolios whereby a low P/E stock portfolio will be considered as value stocks and high P/E stocks as growth stocks (Beneda, 2002).

Nevertheless, it is not that simple, according to the *Capital Asset Pricing Model (CAPM)* a stock return actually depends on its sensitivity towards market risk (or systematic risk) captured by beta and time value of money (represented by the risk free rate). Fama and French (1993) and Carhart (1997) further expanded on univariate CAPM which is known as Fama-French 3 factor model and Carhart 4 factor model[74] respectively. Therefore, constructing portfolios simply by using relevant financial ratios may not be sufficient.

Daniel and Titman (1997) is one of the first few to recognise and explore the issue. They consider two models namely the *"characteristics model"* and *"covariance model"*. They label *"characteristics model",* a model using only financial ratios such as B/M ratio to measure the expected return of stocks. Meanwhile, the *"covariance model"* is a financial model and considers returns sensitivity to factors such as value factors (or value premium).

Daniel and Titman (1998) highlight that the persistent better performance of value stocks over growth stocks may be due to either mispricing or riskiness of stocks. They clarify that mispricing of stocks is due to the *"characteristic model"* and means that the market systematically under-prices value stocks. On the other hand, riskiness as measured by the "covariance model" indicates that value stocks are considered riskier resulting in higher returns.

Daniel and Titman (1997) underline that the *"characteristics model"* seems to explain the cross-sectional variation in stock returns better than the *"covariance model"*. Daniel and Titman (1998) find further evidence to support the *"characteristics model"*

[74] A study by Jegadeesh and Titman (1993) support the momentum factor.

signifying that investors should be able to construct better portfolios using *"characteristics model"* relative to *"covariance model"* such as Fama-French 3 factor model (Fama & French, 1992, 1993).

Furthermore, Daniel et al. (2001) replicate the Daniel and Titman (1997) study on a Japanese sample from the *Tokyo Stock Exchange (TSE)* between 1971 and 1997 and their test fail to reject the *"characteristic model"* but reject the Fama-French 3 factor model. Ibbotson et al. (2013) who also test the theory using a different investment style factor namely the illiquidity factor, indicate that the *"characteristics model"* performs better than the *"covariance model"*.

5.2.3. THE JANUARY EFFECT

Another common issue that can be linked to the various investment styles is the January effect. Fama and French (1992) signify its appearance within value style, which is also confirmed by Loughran (1997). Keim (1983) mentions its existence within size effect whereas De Bondt and Thaler (1985) comment on it in his study of momentum style. Even Eleswarapu and Reinganum (1993) highlight of its presence within illiquidity premium.

The January effect is a seasonal anomaly whereby prices or returns increases in the month of January in comparison to other months. Wachtel (1942) is one of the first to observe this in the US market (DJIA) while Gultekin and Gultekin (1983) mention its existence in most major industrialized countries including the UK. Reinganum and Shapiro (1987) and Clare et al. (1995) also find evidence of the January effect in UK stock market.

As highlighted earlier, the market is expected to be at least weakly efficient and the January effect is quite a simple anomaly that can be exploited by any investor inexpensively. Therefore, since it is discovered more than 70 years ago, it is expected that such a simple anomaly will disappear by now but Haugen and Jorion (1996) highlight that the January effect is still going strong in their research and Haug and Hirschey (2006) confirm that the January effect continue to contradict the EMH.

Ritter and Chopra (1989) mention that the January effect may be due to window dressing, as following December tax loss selling, investors rebalance their portfolios in early

January. Nevertheless, Haug and Hirschey (2006) highlight that the continuing presence of a January effect since 1987 appears to weaken that argument of tax loss selling.

It may simply be compensation for risks. Chan et al. (1985) mention risk is higher in January or during the turn of the year by looking at bonds. Moreover, Gu (2003) emphasizes that the January effect is positively related to volatility.

Gu (2003) also indicates the pronounce declining trend of the January effect in the US for both large and small firm stock indices since 1988, which may be due to macroeconomic variables such as stronger real GDP growth and higher inflation. They also mention that the decline represents a trend towards market efficiency due to knowledgeable investors and technology advancement.

On the other hand, Ahsan and Sarkar (2013) find significant positive return in June instead of January in *Dhaka Stock Exchange (DSE*) in Bangladesh.

5.3. DATA AND VARIABLES

5.3.1. DATA

In order to capture the UK stock market, the sample that we decide to use consists of all the stocks listed under the *FTSE All-Share index* for the 24 years period from January 1991 through December 2014. However, after portfolio construction, 23 years data is available for the analysis. Unfortunately, at the time of data collection, 23 years is the longest period that we are able to collect data, for which sufficiently meets our analysis requirements. We mainly use daily data to calculate the monthly and yearly variables. All the data use in this paper is obtained from DataStream.

Before the calculation of the illiquidity measures and construction of the portfolios, the sample is initially analysed for any unsuitable data to avoid the emergence of bias results. After filtering the data set, the final data set contains 640 companies as of the year 2014 and averages around 456 companies over the 23 years period. Summary statistics of the stock universe can be found in table 5.1.

Table 5.1: Summary statistics of the stock universe by year: January 1991 to December 2014
This table shows the summary statistics for our stock universe including number of stocks as well as mean, standard deviation, median, maximum and minimum market value (in £ millions) for each year. The table consists of stocks with complete relevant data that are listed on *FTSE All-Share index* between the year 1991 and 2013, which is the sorting year *(t-1)* data and are used to calculate the performance *year (t)* results from the year 1992 to 2014. Since the data for the year 2014 is also used for relevant calculation such as data migration, we have also included the year 2014 data in Table 5.1. The last row provides the summary statistics of the whole sample used. All data are obtained from DataStream.

		Market Value (£ Millions)				
Sorting year	**No. of stocks**	**Mean**	**Standard deviation**	**Median**	**Maximum**	**Minimum**
1991	280	881.31	2765.45	119.55	25620.57	0.99
1992	289	1009.20	2997.46	141.78	24932.26	0.58
1993	303	1287.74	3486.58	196.13	29328.07	1.49
1994	330	1129.17	3101.71	162.75	23514.47	1.08
1995	347	1362.39	3805.16	191.11	32024.99	1.24
1996	372	1500.47	4278.21	215.79	39571.24	2.44
1997	387	1853.89	5771.80	236.54	51451.20	2.12
1998	396	2152.41	7849.12	208.29	86904.94	1.91
1999	407	2954.38	11322.88	269.84	121287.90	5.65
2000	420	3260.89	13516.38	293.93	158542.90	4.86
2001	428	2814.94	11684.75	259.63	122427.40	6.12
2002	438	2133.28	8568.69	211.72	95556.69	6.16
2003	448	2473.30	9847.60	279.65	100215.30	15.56
2004	468	2565.36	9889.55	333.79	109351.80	14.50
2005	497	3011.96	11004.31	413.24	127867.00	24.47
2006	524	3166.36	10555.88	497.86	111714.90	9.00
2007	543	3149.46	10913.21	440.09	116372.20	30.49
2008	547	2225.71	8627.21	241.00	98545.13	8.18
2009	549	2961.36	10629.31	388.08	123389.20	18.02
2010	566	3262.21	10810.98	499.36	115152.70	7.54
2011	575	3042.79	10211.20	448.01	89757.75	8.56
2012	583	3288.43	10402.84	543.77	119519.90	32.98
2013	609	3765.18	11679.16	732.91	124728.70	52.01
2014	640	3493.60	10296.94	720.06	116950.40	46.08
Whole Sample		**2619.53**	**9561.04**	**331.49**	**158542.90**	**0.58**

5.3.2. INVESTMENT STYLES' MEASURES

One of the key parts of our research is to investigate the ability of illiquidity as an investment style and we hope to compare its performance with other investment styles as well as the chosen benchmarks.

Nonetheless, initially we need to choose variables that will determine each respective investment style. For example, for *"value versus growth"* investment style, past researchers such as Gonenc and Karan (2003) and Fama and French (1998) use B/M ratio

to rank their portfolio whereby high B/M ratio is categorised as value stocks while low B/M ratio as growth stocks. Beneda (2002) suggests using P/E ratio, Yen, Sun, and Yan (2004) use P/C ratio and Bauman et al. (1998) use dividend yield. However, among the different variables, we have decided to use *P/B ratio,* which is just the inverse of B/M ratio because it is one of the most widely recognisable variables and provides more number of companies compared to P/E ratio.

Determining the variable for size effect (*"small versus big"* investment style) is simpler, as we feel that using the *market value* of each firm is the most appropriate measure as it is used by past researchers such as Dissanaike (2002). Similarly, choosing the most appropriate variable for "momentum versus contrarian" investment style (or winners versus losers) is also straightforward as we will be using *monthly returns* akin to De Bondt and Thaler (1985) but we annualise it.

For illiquidity, we have decided to choose the *Amihud Illiquidity measure (Amihud)*[75] as it is a well-known measure but still simple to calculate and has been extensively use in past literature. Moreover, we also thoroughly consider two other liquidity measures namely the roll estimator (Roll, 1984) and High Low spread by Corwin and Schultz (2012) and we find that Amihud provides results that are more consistent to past studies[76].

We have chosen *FTSE All-Share index* and *UK 3 months London Interbank Offered Rate (LIBOR)* as benchmarks for market returns and risk-free rate respectively.

5.4. METHODOLOGY, EMPIRICAL RESULTS AND ANALYSIS

5.4.1. ILLIQUIDITY AS AN INVESTMENT STYLE BASED ON ITS ABILITY AS A BENCHMARK

Similar to our previous chapter and as highlighted earlier, the best way to investigate whether illiquidity is a reliable investment style, is to scrutinise if illiquidity can be made

[75] It is calculated for each stock, s, every month as follows:

$$Amihud_{sm} = \frac{1}{t}\sum_{t} \frac{1{,}000{,}000 \times |return_t|}{price_t \times volume_t} \qquad (5.1)$$

Where t is each trading day

[76] Amihud, Mendelson, and Pedersen (2005) highlight that there is hardly a single liquidity measure which can capture all aspects of estimating the effect of liquidity on asset prices. Therefore, choosing an appropriate liquidity measure is not straightforward. However, our third chapter shows that among three liquidity measures namely i) Amihud illiquidity measure, ii) High-Low Spread (Adjusted) and iii) Roll Estimator, Amihud illiquidity measure produces results that are consistent to past studies in the UK. Since our fifth chapter also uses UK data, we decide to use Amihud as proxy for illiquidity. Moreover, among the three liquidity measures, Amihud have the advantage of being simple to calculate.

a dependable portfolio benchmark. Therefore, we feel that we should follow Ibbotson et al. (2013) framework, whereby they based it on Sharpe's (1992) specification of a *portfolio benchmark*, which should be 1) *"identifiable before the fact",* 2) *"not easily beaten",* 3) *"a viable alternative"* and 4) *"low in cost".*

To meet the *"identifiable before the fact"* criterion, we will be constructing the quartiles (or portfolio) based on the prior year (*t-1)* measure of the relevant investment style, which is then used to calculate the results of the portfolios for a given year *(t)*. For example, the investment style measure for the year 1991 (selection year) is used to construct the quartiles and calculate the returns and risks for the year 1992 (performance year). Therefore, the portfolios are *"identifiable before the fact".*

The next criterion for us to fulfil is the *"not easily beaten".* This will be achieved by investigating if the returns of the illiquidity portfolios can provide significant and positive returns (if any) and then compare it with the chosen benchmark. Moreover, the portfolio across different investment quartiles will also be investigated, allowing us to examine the performance of illiquidity in comparison to the other styles.

This will be followed by *"a viable alternative"* criterion, which will be investigated by applying the method use by Ibbotson et al. (2013), who distinguish illiquidity from the other styles by constructing double sorted quartile portfolios. The double sorted portfolios will allow us to study whether illiquidity is able to enhance the performance of the more recognized styles.

Lastly, similar to Ibbotson et al. (2013), we investigate the *"low in cost"* criterion by exploring stock migration. Studying stock migration will allow us to consider whether illiquidity can be managed passively and at low cost.

5.4.2 COMPARISON OF INVESTMENT STYLES' RETURNS AND RISKS.

Our research starts with an investigation of portfolio performance across *"different investment style quartiles".* This section will also allow us to determine whether illiquidity will be able to meet the first two benchmark criteria of *"identifiable before the*

fact" and *"not easily beaten"*. More importantly, this section will also confirm whether an illiquidity premium[77] exists in the first place.

Table 5.2 shows the equally weighted average annualised monthly returns and risks of the investment styles based on quartiles over the sample period. Construction of the quartiles starts by calculating each measure on an annual basis whereby the prior year *(t-1)* average of the styles measure is used to construct the quartiles for a given year *(t)*. Therefore, over the 24 years' period, the selection period is between 1991 and 2013 (inclusive), while the performance period is between 1992 and 2014 (inclusive) and hence 23 years data is available for the analysis.

Using one of the investment style measures, the stocks are ranked and the two portfolios that are ranked top 25% and bottom 25% are classified as either Q1 or Q4 quartiles. For example, after using Amihud to rank the sample on a descending basis, the top 25% with the highest (or widest) spreads are considered as the "*high illiquid portfolio (Q1)"* whereas the bottom 25% stocks are classified as "*high liquid portfolio (Q4)"*. After the quartiles are constructed the portfolio performance of each quartile is calculated and the stocks are rebalanced annually, meaning that the stocks are held within each respective portfolio for one year before the portfolios are rebalanced.

It should be noted that the final column in table 5.2 shows the zero-cost portfolio returns or applicable investment style premium, which takes a long position on Q1 portfolio and short position on Q4 portfolio. Therefore, for value versus growth investment style, it will be the *value premium* if "*high value portfolio (Q1)"* outperforms "*high growth portfolio (Q4)"* and *growth premium* if "*high growth portfolio (Q4)"* is found to perform better.

The annualised returns of the portfolios in table 5.2 are calculated based on *arithmetic mean (AM)*[78]. The risks of the portfolios are measured based on *arithmetic standard deviation (ASD)*[79] and *Beta,* β[80] whereby the former is a measure for total risk while the latter represents systematic risk that is the sensitivity of the portfolios to the market benchmark of *FTSE All-Share index*.

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[77] Illiquid quintile provides higher returns compared to liquid quintile.

[78] $AM_s = \frac{1}{n}\sum_{i=1}^{n} r_i$ (5.2)

[79] $ASD_s = \left[\frac{1}{(n-1)}\sum_{i=1}^{n}(r_i - AM)^2\right]^{\frac{1}{2}}$ (5.3)

[80] $\beta_s = \frac{COV(r_s, r_m)}{var(r_m)}$ (5.4)

Table 5.2 reports that the *"high illiquid portfolio (Q1)"* does perform better in comparison to *"high liquid portfolio (Q4)"*, similar to Amihud and Mendelson (1986). In fact, the zero-cost portfolio[81] also shows value premiums and small size premiums[82], consistent with Capaul et al. (1993) and Dissanaike (2002) respectively. Momentum produces the smallest premium but momentum does not show statistically significant results which is not akin to past research on other markets (Jegadeesh & Titman, 1993). Dissanaike (2002) who studies the UK market discovers that contrarian performs better while Galariotis et al. (2007) mention that both momentum and contrarian profits are available within the UK, which may explain the insignificant results.

The highest top[83] investment style return of 20.17% is achieved by *"high value portfolio"* while the lowest return of 8.69% is achieved by the bottom investment style of *"high liquid portfolio"*. Nevertheless, the highest zero-cost portfolio (premium) is attained by the size effect (or small-firm premium). Although Ibbotson et al. (2013) study on US find evidence to signify that their top style is also the *"high value portfolio",* their worst performing style is the *"high contrarian portfolio"*.

Figure 5.1 shows the growth of £100 invested in the strategy of long the portfolio of the top investment style over the 23 years study period. The figure demonstrates *that "high value portfolio"* provides the highest growth of £100 after 23 years while *"high momentum portfolio"* provides the lowest growth. However, all top investment styles achieve higher cumulative returns compared to the benchmarks of FTSE All-Share index and 3 months LIBOR in the long run signifying that by using any of the simple investment style, it allows investors to outperform the market.

In terms of risk, the highest standard deviation and beta is reported by the *"high contrarian portfolio"*, which is not consistent with the traditional theory of *"higher returns come with higher risk"*, as it does not produce the highest returns. Nevertheless, the other styles show consistent results of higher returns achieved by taking higher risks, as *"high value", "micro"*[84] *& "high illiquid"* portfolios have higher risks compared to

[81] *Q1-Q4* (for example *value – growth quartile)*
[82] Q1 is greater than Q4
[83] Top investment style means the top 25% ranked based on the relevant investment style or Q1 and it is expected to be Value, Micro, Momentum and Illiquid portfolios. Bottom investment style means the bottom 25% ranked based on the relevant investment style or Q4. It is expected to be Growth, Big, Contrarian and Liquid portfolios.
[84] "Micro" is the portfolio that consists of the smallest stocks based on size and ranked using market value. Past research such as Dissanaike (2002) simply calls it "small portfolio". Therefore, our quartiles are labelled as Micro (Q1), Small (Q2), Medium (Q3) and Big (Q4).

their opposite styles namely *"high growth", "big" & "high liquid"* portfolios respectively.

This is contrary to Ibbotson et al. (2013), who find evidence that only size has a clear risk dimension by achieving higher returns with higher risks.

Table 5.2: Cross-Sectional annualized returns and risks of the investment styles: January 1992 to December 2014

This table shows equally-weighted, annualised returns (in percentage format) for quartile portfolios based on the investment styles briefly describe below. The return sample period is from January 1992 to December 2014. Quartile portfolio ranks are determined by the value of the investment style measure in the year *(t-1)* prior to the year *(t)* in which returns are calculated and are rebalanced annually. Therefore, the style measure for the year 1991 is used to construct the quartiles and then calculate the returns for the year 1992, where the stocks will be held for at least one year. The "Q1 – Q4" portfolio is a portfolio that takes a long position in the quartile of stocks (Q1) and a short position in the quartile of stocks (Q4). For example, in relation to *illiquid vs liquid investment style*, *"Q1 – Q4"* takes a long position in the quartile of *illiquid stocks (Q1)* and a short position in the quartile of *liquid stocks (Q4)*. The table have 2 benchmarks namely *3 months LIBOR* and *FTSE All-Share*. It also shows the unsystematic and systematic risks of the portfolios measured based on standard deviation and beta respectively. Beta is calculated based on *FTSE All-Share index*. Newey-West p-value are reported in brackets for the arithmetic mean of the "Q1 – Q4" portfolio, whereby **bold** figures denote statistically significance coefficient at least at 10% level. The bandwidth parameter for the Newey-West p-value is calculated using the Newey-West automatic lag selection. All data are obtained from DataStream.

1. ***Value effect (value versus growth investment style)*** uses the end of year *price-to-book value (P/B) ratio*.

2. ***Size effect (micro versus big investment style)*** uses the *end of year market value (MV)*.

3. ***Momentum effect (momentum vs contrarian investment style)*** used the *annualised monthly returns*. It is also commonly known as *winners versus losers' investment style.*

4. ***Illiquidity effect (illiquid versus liquid investment style)*** uses the *Amihud illiquidity measure (Amihud)*. Amihud is calculated for each stock, s, daily as follows:

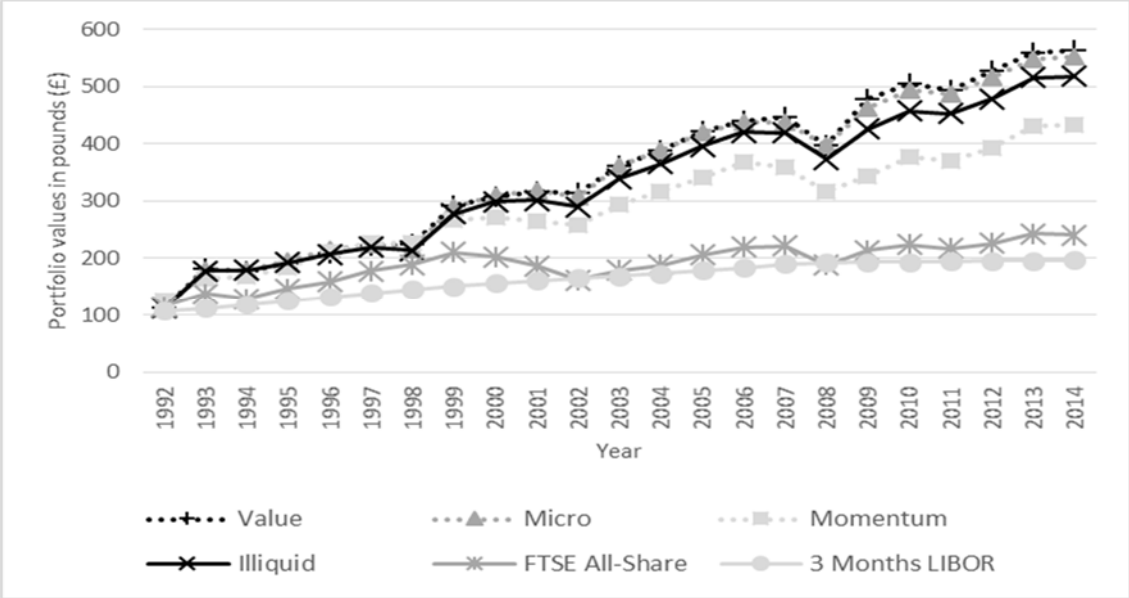
$$Amihud_{st} = \frac{1}{t}\sum_t \frac{1{,}000{,}000 \times |return_t|}{price_t \times volume_t} \qquad (5.1)$$

Where t was a trading day within the year the measure is calculated.

Cross Section	Result	Q1	Q2	Q3	Q4	Q1 - Q4
Value effect	Arithmetic mean	20.17%	6.77%	12.99%	11.74%	8.42%
Value vs growth						**(0.0044)**
	Standard deviation	28.06%	21.49%	20.75%	21.48%	15.18%
(Q1 = Value, Q4 = Growth)	Beta (FTSE All-Share)	1.39	1.16	1.13	1.25	0.15
	Average no. of stocks	110	109	109	109	
Size effect	Arithmetic mean	19.64%	12.48%	10.46%	8.96%	10.68%
Micro vs big						**(0.0000)**
	Standard deviation	27.75%	23.92%	20.91%	18.06%	15.79%
(Q1 = Micro, Q4 = Big)	Beta (FTSE All-Share)	1.34	1.33	1.17	1.09	0.25
	Average no. of stocks	112	112	112	112	
Momentum effect	Arithmetic mean	14.52%	13.17%	11.26%	12.67%	1.86%
Momentum vs contrarian						(0.3791)
	Standard deviation	20.38%	18.79%	20.53%	32.34%	19.72%
(Q1 = Momentum, Q4 = Contrarian)	Beta (FTSE All-Share)	1.13	1.05	1.13	1.62	-0.49
	Average no. of stocks	112	112	111	111	
Illiquidity effect	Arithmetic mean	18.17%	13.11%	10.84%	8.69%	9.48%
Illiquid vs liquid						**(0.0000)**
	Standard deviation	25.96%	24.11%	22.40%	18.18%	13.92%
(Q1 = Illiquid, Q4 = Liquid)	Beta (FTSE All-Share)	1.32	1.32	1.25	1.08	0.24
	Average no. of stocks	104	103	103	103	
FTSE All-Share index	Arithmetic mean			6.11%		
	Standard deviation			15.72%		
3 Months LIBOR	Arithmetic mean			4.21%		
	Standard deviation			2.41%		

Figure 5.1: Comparison of the growth of £100 across the top investment style portfolios: January 1992 to December 2014

This figure shows the growth of £100 invested in the strategy of long the quartile portfolio of the top investment styles over the 23 years study period. The investment styles include *value, micro, momentum* and *illiquid* style. The dollar growth for investing in the benchmark of *FTSE All-Share index* and *3 months LIBOR* are also included in figure 5.1. All data are obtained from DataStream.



5.4.2.1. SIMPLE PERFORMANCE MEASUREMENT OF THE INVESTMENT STYLE PORTFOLIOS

To investigate further, we have also conducted simple performance measurements (risk adjusted returns) namely 1) *Sharpe ratio (SR)*[85], 2) *Treynor ratio (TR)*[86] and 3) *Information ratio (IR)*[87]. A comparison of each portfolio's ratios is then conducted where the portfolio with the highest ratio indicates superior returns.

Consistent to the previous table, table 5.3 shows that *"high value portfolio"* produces the highest Sharpe ratio, but the highest Treynor ratio is indicated by micro portfolio (size) whilst *"high momentum portfolio"* produces the highest information ratio. The weakest performance is shown by the *"high liquid portfolio"* based on Sharpe ratio and Treynor ratio whereas under information ratio, *"high contrarian portfolio"* produces the weakest performance.

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[85] $SR_p = \frac{(R_p - R_f)}{\sigma_p}$ (5.5)

[86] $TR_p = \frac{(R_p - R_f)}{\beta_p}$ (5.6)

[87] $IR_p = \frac{(R_p - R_m)}{\sigma(R_p - R_m)}$ (5.7)

Table 5.3: Simple performance measurements (risk-adjusted returns) of the investment styles: January 1992 to December 2014

This table shows the simple performance measurements of the quartile portfolios based on the investment styles briefly describe in table 5.2. The measurement allows for further analysis of the portfolios performance by scaling the returns. Three performance measurements are used namely Sharpe ratio (SR), Treynor's ratio (TR) and information ratios (IR). Description of the performance measurements is found below. The sample period is from January 1992 to December 2014. All data are obtained from DataStream.

1. Sharpe ratio (SR)

$$SR = \frac{(R_p - R_f)}{\sigma_p} \qquad (5.5)$$

2. Treynor's ratio (TR)

$$TR = \frac{(R_p - R_f)}{\beta_p} \qquad (5.6)$$

3. Information ratio (IR)

$$IR = \frac{(R_p - R_m)}{\sigma(R_p - R_m)} \qquad (5.7)$$

Cross Section	Result	Q1	Q2	Q3	Q4
Value effect	Sharpe Ratio	56.86%	11.90%	42.35%	35.07%
Value vs growth	Treynor Ratio	11.46%	2.20%	7.78%	6.05%
(Q1 = Value, Q4 = Growth)	Information Ratio	75.47%	5.63%	62.91%	58.43%
Average number of stocks		110	109	109	109
Size effect	Sharpe Ratio	55.61%	34.60%	29.92%	26.31%
Micro vs big	Treynor Ratio	11.52%	6.23%	5.33%	4.37%
(Q1 = Micro, Q4 = Big)	Information Ratio	71.78%	49.91%	42.67%	47.50%
Average number of stocks		112	112	112	112
Momentum effect	Sharpe Ratio	50.60%	47.72%	34.33%	26.15%
Momentum vs contrarian	Treynor Ratio	9.13%	8.51%	6.25%	5.21%
(Q1 = Momentum, Q4 = Contrarian)	Information Ratio	82.34%	79.08%	48.82%	29.56%
Average number of stocks		112	112	111	111
Illiquidity effect	Sharpe Ratio	53.77%	36.92%	29.62%	24.67%
Illiquid vs liquid	Treynor Ratio	10.58%	6.75%	5.29%	4.14%
(Q1 = Illiquid, Q4 = Liquid)	Information Ratio	73.46%	52.65%	41.62%	39.64%
Average number of stocks		104	103	103	103

Overall, portfolios that are constructed based on illiquidity can generate positive and significant returns as shown in table 5.2. Moreover, with the exception of *"micro portfolio",* the *"high illiquid portfolio"* performs better in comparison to the other styles and the benchmarks. Although table 5.3 does not show superior performance for the *"high illiquid portfolio"* based on the 3 risk-adjusted returns, it still shows favourable positive performances. Therefore, it can safely be concluded that illiquidity has met the second benchmark criterion of *"not easily beaten"* and since the portfolios are constructed based on the prior year (t-1) measure, this automatically also satisfies the first criterion of *"identifiable before the fact".*

5.4.3. INTERSECTION OF ILLIQUID PORTFOLIOS WITH OTHER INVESTMENT STYLES

Although our results in the previous section seem to indicate that illiquidity is *"not easily beaten",* some researchers highlight that the positive performance of illiquidity is actually due to other investment styles. Asness et al. (2013) find significant evidence that funding liquidity risk is inversely related to value but positively related to momentum globally, whereas Eleswarapu and Reinganum (1993) highlight that the illiquidity premium is a result of size effect. Therefore, in order to investigate whether illiquidity actually deserves to be categorized as an investment style and distinguish it from the other investment styles, we will implement the technique use by Ibbotson et al. (2013) that is to construct double sorted quartile portfolios.

This technique will allow us to test whether illiquidity is able to enhance the other styles and thus whether it meets the third benchmark criterion of *"a viable alternative"*. In fact, Ibbotson et al. (2013) discover that illiquidity mixes well with all three top investment styles of value, micro and momentum by adding an incremental return to it.

5.4.3.1. INTERSECTION OF ILLIQUID AND VALUE/GROWTH INVESTMENT STYLES (PORTFOLIOS)

The double sorted portfolios are constructed by independently sorting the portfolios into quartiles based on Amihud and year-end P/B ratio, to produce 16 intersection groups as can be seen in table 5.4. As before, the prior year *(t-1)* intersection measure is used to construct and calculate the portfolio returns and risks for a given year *(t)*. Similar to before, the stocks are rebalanced annually.

Unfortunately, due to the limited number of stocks available for the UK market, the number of stocks significantly reduce after segregation into 16 intersection portfolios. Therefore, we have to ensure that each portfolio is diversified. Past studies have different opinions on the number of stocks required to properly diversify a portfolio such as Evans and Archer (1968) who highlight that 10 to 15 stocks are required.

Nevertheless, Reilly and Brown (2012, p. 201) highlight that based on past studies such as Evans and Archer (1968) and Tole (1982), *"...major benefits of diversification were*

achieved rather quickly, with about 90 percent of the maximum benefit of diversification derived from portfolios of 12 to 18 stocks…".

Therefore, as before, we consider portfolios that have at least 12 stocks as *"acceptable portfolios"* because achieving 90 percent of the maximum benefit of diversification is more than satisfactory for us.

Table 5.4 shows only one portfolio that has less than 12 stocks. It also shows that across value portfolios (rows), illiquid stocks consistently generate higher returns relative to more liquid stocks while across illiquidity (columns), value portfolios sometimes perform better compared to growth portfolios but it is less consistent.

Table 5.4: Annualized returns and risks of value/growth and illiquidity intersection portfolios: January 1992 to December 2014

The table shows the results of intersection quartiles between value/growth and illiquidity investment styles. The quartiles are constructed by independently sorting the portfolios into quartiles based on the two investment styles and then by taking the intersection sets of quartiles to produce 16 intersection groups as below. As before, the prior year *(t-1)* intersection measure is used to construct the quartiles, which are then used to calculate the quartile returns and risk for a given year *(t)* and the quartiles are rebalanced annually. Therefore, the sorting sample period is from January 1991 to December 2013 whilst *performance* sample period is from January 1992 to December 2014 and the stocks are held for at least one year. Due to the limited number of stocks and to ensure that the results are significant, we only consider portfolios that meet our diversification requirements of at least 12 average stocks. Thus, acceptable portfolios with 12 or more average stocks are in **bold**. All data are obtained from DataStream.

Cross Section	High Illiquid	Mid Illiquid	Mid Liquid	High Liquid
High Value				
Arithmetic mean	**21.71%**	**20.04%**	**16.43%**	14.28%
Standard deviation	**29.90%**	**26.87%**	**30.04%**	24.66%
Beta (FTSE All Share)	**1.38**	**1.28**	**1.50**	1.20
Average no. of stocks	**40**	**28**	**22**	11
Mid Value				
Arithmetic mean	**7.96%**	**7.62%**	**5.33%**	**7.13%**
Standard deviation	**22.77%**	**21.63%**	**22.95%**	**25.01%**
Beta (FTSE All Share)	**1.17**	**1.13**	**1.26**	**1.36**
Average no. of stocks	**25**	**30**	**26**	**15**
Mid Growth				
Arithmetic mean	**19.63%**	**13.04%**	**11.00%**	**8.77%**
Standard deviation	**24.87%**	**23.26%**	**22.89%**	**17.36%**
Beta (FTSE All Share)	**1.24**	**1.22**	**1.07**	**1.02**
Average no. of stocks	**22**	**23**	**23**	**33**
High Growth				
Arithmetic mean	**18.19%**	**12.51%**	**11.17%**	**8.57%**
Standard deviation	**26.39%**	**30.47%**	**24.77%**	**16.50%**
Beta (FTSE All Share)	**1.31**	**1.65**	**1.31**	**1.00**
Average no. of stocks	**14**	**19**	**28**	**42**

Furthermore, the highest return is generated by the intersection of "*high value & high illiquid portfolio"* and figure 5.2 also shows that the enhanced portfolio of "*high value & high illiquid portfolio"* generates the highest cumulative returns against the "*high value only portfolio"* signifying that illiquidity does enhanced the value investment style, which is similar to Ibbotson et al. (2013) results.

Figure 5.2: Comparison of the growth of £100 across the value/growth and illiquidity intersection portfolios: January 1992 to December 2014

This figure shows the growth of £100 invested in selected value/growth and illiquidity intersection portfolios over the 23 years study period. The intersection portfolios used are *High Value & High Illiquid* and *High Growth & High Liquid*. For comparison purpose, the dollar growth for investing in the *High Value only quartile*, *High Growth only quartile* and benchmark of *FTSE All-share index* and *3 months LIBOR* are also included in figure 5.2. All data are obtained from DataStream.

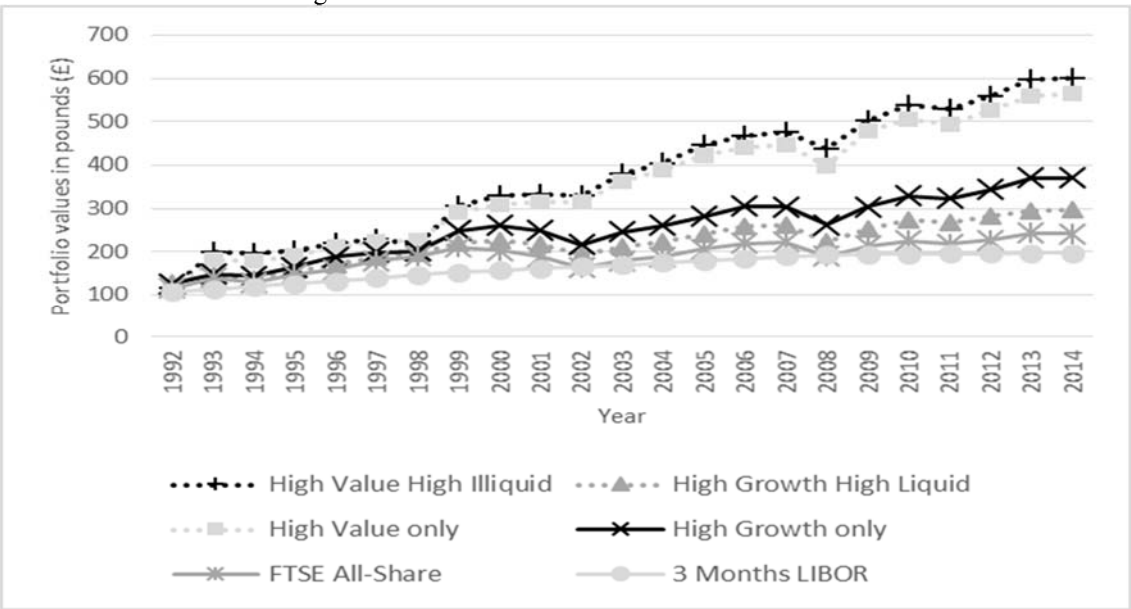


Table 5.5 shows that the enhance portfolio only results in the highest risk-adjusted returns based on Treynor ratio but illiquidity still plays a role as the best risk-adjusted performance is shown by "*mid growth & high illiquid portfolio*".

Table 5.5: Simple performance measurements (risk-adjusted returns) of the value/growth and illiquidity intersection portfolios: January 1992 to December 2014
This table shows the simple performance measurements of the value/growth and illiquidity intersection quartiles describe in table 5.4. The measurement allows for further analysis of the portfolios performance by scaling the returns. Three performance measurement are used namely Sharpe ratio (SR), Treynor's ratio (TR) and information ratios (IR). Description of the simple performance measurements are found in table 5.3. Due to the limited number of stocks and to ensure that the results are significant, we only consider portfolios that meet our diversification requirements of at least 12 average stocks. Thus, acceptable portfolios with 12 or more average stocks are in **bold.** The sample period is from January 1992 to December 2014. All data are obtained from DataStream.

Cross Section	High Illiquid	Mid Illiquid	Mid Liquid	High Liquid
High Value				
Sharpe Ratio	**58.53%**	**58.91%**	**40.68%**	40.86%
Treynor Ratio	**12.67%**	**12.38%**	**8.17%**	8.43%
Information Ratio	**72.86%**	**75.82%**	**50.91%**	50.24%
Average number of stocks	**40**	**28**	**22**	11
Mid Value				
Sharpe Ratio	**16.47%**	**15.79%**	**4.88%**	**11.69%**
Treynor Ratio	**3.22%**	**3.02%**	**0.89%**	**2.15%**
Information Ratio	**13.41%**	**12.09%**	**-6.34%**	**7.17%**
Average number of stocks	**25**	**30**	**26**	**15**
Mid Growth				
Sharpe Ratio	**62.02%**	**37.95%**	**29.65%**	**26.29%**
Treynor Ratio	**12.39%**	**7.24%**	**6.33%**	**4.47%**
Information Ratio	**85.41%**	**50.77%**	**31.46%**	**40.17%**
Average number of stocks	**22**	**23**	**23**	**33**
High Growth				
Sharpe Ratio	**52.96%**	**27.26%**	**28.11%**	**26.43%**
Treynor Ratio	**10.65%**	**5.02%**	**5.31%**	**4.37%**
Information Ratio	**70.25%**	**33.84%**	**34.63%**	**48.31%**
Average number of stocks	**14**	**19**	**28**	**42**

5.4.3.2. INTERSECTION OF ILLIQUID AND SIZE INVESTMENT STYLES (PORTFOLIOS)

Unfortunately, unlike Ibbotson et al. (2013), table 5.6 seems to show that within UK investing in illiquid stocks is almost similar to investing into small firms because the intersection of the portfolios result in a limited number of stocks for some portfolios. This

is particularly noticeable for the "*Micro & High Liquid portfolio"*, where the average number of stocks is only one over the sample period. This is not surprising since it is expected that micro stocks are less liquid compared to other size related portfolios.

Among the *"acceptable portfolios",* table 5.6 shows conflicting results as both illiquidity and size do not show clear enhancing ability. However, figure 5.3 shows that the enhanced portfolio of "*micro & high illiquidity portfolio"* moves alongside "*micro only portfolio"* indicating that illiquidity does not provide additional benefits when combine with portfolios based on size.

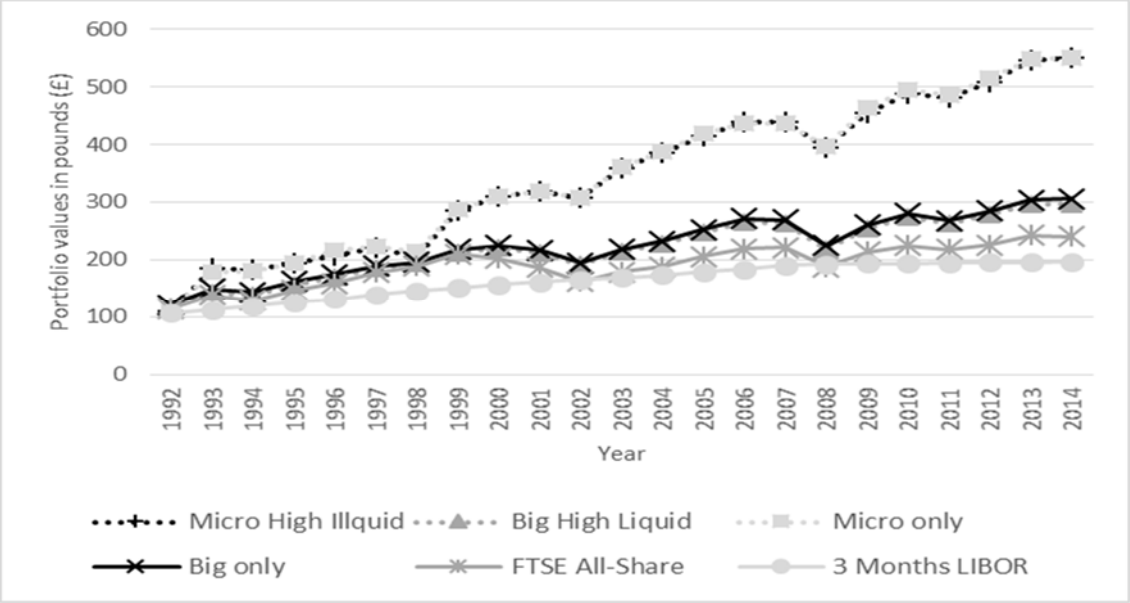
Table 5.6: Annualized returns and risks of size and illiquidity intersection portfolios: January 1992 to December 2014

This table shows the results of intersection quartiles between size and illiquidity investment styles. The quartiles are constructed by independently sorting the portfolios into quartiles based on the two investment styles and then by taking the intersection sets of quartiles to produce 16 intersection groups as below. As before, the prior year *(t-1)* intersection measure is used to construct the quartiles, which are then used to calculate the quartile returns and risk for a given year *(t)* and the quartiles are rebalanced annually. Therefore, the sorting sample period is from January 1991 to December 2013 whilst *performance* sample period is from January 1992 to December 2014 and the stocks are held for at least one year. Due to the limited number of stocks and to ensure that the results are significant, we only consider portfolios that meet our diversification requirements of at least 12 average stocks. Thus, portfolios with 12 or more average stocks are in **bold**. All data are obtained from DataStream.

Cross Section	High Illiquid	Mid Illiquid	Mid Liquid	High Liquid
Micro				
Arithmetic mean	**19.60%**	**20.24%**	29.58%	-11.78%
Standard deviation	**28.78%**	**34.60%**	57.35%	31.05%
Beta (FTSE All Share)	**1.35**	**1.61**	2.56	1.04
Average no. of stocks	**70**	**23**	2	1
Small				
Arithmetic mean	**14.63%**	**11.26%**	**16.03%**	12.41%
Standard deviation	**23.87%**	**24.31%**	**35.10%**	21.12%
Beta (FTSE All Share)	**1.27**	**1.33**	**1.82**	0.90
Average no. of stocks	**28**	**56**	**16**	1
Medium				
Arithmetic mean	18.53%	**11.43%**	**9.35%**	2.11%
Standard deviation	25.00%	**21.21%**	**21.09%**	31.28%
Beta (FTSE All Share)	1.13	**1.16**	**1.17**	1.20
Average no. of stocks	5	**23**	**71**	10
Big				
Arithmetic mean	25.24%	13.27%	**11.01%**	**8.58%**
Standard deviation	53.33%	33.87%	**20.73%**	**17.63%**
Beta (FTSE All Share)	2.24	1.88	**1.19**	**1.06**
Average no. of stocks	1	1	**15**	**95**

Figure 5.3: Comparison of the growth of £100 across the size and illiquidity intersection portfolios: January 1992 to December 2014

This figure shows the growth of £100 invested in selected illiquidity and size intersection portfolios over the 23 years study period. The intersection portfolios used are *Micro High Illiquid* and *Big High Liquid*. For comparison purpose, the dollar growth for investing in the *micro only quartile*, *big only quartile* and benchmark of *FTSE All-share index* and *3 months LIBOR* are also included in figure 5.3. All data are obtained from DataStream.



Furthermore, after taking account of risk, table 5.7 does show that "*micro & high illiquid portfolio"* generates the highest risk-adjusted returns among the portfolios but the risk-adjusted returns of "*micro only portfolio" (table 5.3) performs better*. Therefore, signifying that size does seem to capture illiquidity, as suggested by Eleswarapu and Reinganum (1993).

Table 5.7: Simple performance measurements (risk-adjusted returns) of the size and illiquidity intersection quartiles: January 1992 to December 2014

This table shows the simple performance measurements of the size and illiquidity intersection quartiles describe in table 5.6. The measurement allows for further analysis of the portfolios performance by scaling the returns. Three performance measurements are used namely Sharpe ratio (SR), Treynor's ratio (TR) and information ratios (IR). Description of the simple performance measurements is found in table 5.3. Due to the limited number of stocks and to ensure that the results are significant, we only consider portfolios that meet our diversification requirements of at least 12 average stocks. Thus, acceptable portfolios with 12 or more average stocks are in **bold.** The sample period is from January 1992 to December 2014. All data are obtained from DataStream.

Cross Section	High Illiquid	Mid Illiquid	Mid Liquid	High Liquid
Micro				
Sharpe Ratio	**53.49%**	**46.34%**	44.24%	-51.48%
Treynor Ratio	**11.42%**	**9.95%**	9.92%	-15.34%
Information Ratio	**66.65%**	**55.51%**	48.72%	-257.39%
Average number of stocks	**70**	**23**	2	1
Small				
Sharpe Ratio	**43.66%**	**28.99%**	**33.69%**	38.85%
Treynor Ratio	**8.23%**	**5.29%**	**6.51%**	9.13%
Information Ratio	**61.54%**	**38.35%**	**41.94%**	51.87%
Average number of stocks	**28**	**56**	**16**	1
Medium				
Sharpe Ratio	57.27%	**34.07%**	**24.37%**	-6.72%
Treynor Ratio	12.71%	**6.26%**	**4.41%**	-1.75%
Information Ratio	69.91%	**47.40%**	**30.01%**	-16.10%
Average number of stocks	5	**23**	**71**	10
Big				
Sharpe Ratio	**39.44%**	**26.75%**	**32.84%**	**24.81%**
Treynor Ratio	**9.40%**	**4.82%**	**5.73%**	**4.13%**
Information Ratio	**44.96%**	**26.95%**	**51.64%**	**42.23%**
Average number of stocks	1	1	**15**	**95**

5.4.3.3. INTERSECTION OF ILLIQUID AND MOMENTUM/CONTRARIAN INVESTMENT STYLES (PORTFOLIOS)

Table 5.8 which combines illiquidity and momentum/contrarian investment style is more evenly segregated signifying that the two styles are quite independent of each other. Across momentum quartiles (rows), illiquid portfolios generally produce higher returns compared to more liquid portfolios and the highest return is generated by the enhanced portfolio of "*high momentum & high illiquid portfolio"*. Nonetheless, across illiquidity portfolios (columns), highly momentum portfolios sometime generate better returns compared to contrarian styles but it is less consistent.

Table 5.8: Annualized returns and risks of momentum/contrarian and illiquidity intersection portfolios: January 1992 to December 2014

This table shows the results of intersection quartiles between momentum/contrarian and illiquidity investment styles. The quartiles are constructed by independently sorting the portfolios into quartiles based on the two investment styles and then by taking the intersection sets of quartiles to produce 16 intersection groups as below. As before, the prior year *(t-1)* intersection measure is used to construct the quartiles, which are then used to calculate the quartile returns and risk for a given year *(t)* and the quartiles are rebalanced annually. Therefore, the sorting sample period is from January 1991 to December 2013 whilst *performance* sample period is from January 1992 to December 2014 and the stocks are held for at least one year. Due to the limited number of stocks and to ensure that the results are significant, we only consider portfolios that meet our diversification requirements of at least 12 average stocks. Thus, portfolios with 12 or more average stocks are in **bold**. All data are obtained from DataStream.

Cross Section	High Illiquid	Mid Illiquid	Mid Liquid	High Liquid
High Momentum				
Arithmetic mean	**22.29%**	**14.86%**	**11.76%**	**12.48%**
Standard deviation	**27.74%**	**30.46%**	**20.00%**	**17.78%**
Beta (FTSE All Share)	**1.23**	**1.49**	**1.14**	**1.03**
Average no. of stocks	**25**	**25**	**28**	**25**
Mid Momentum				
Arithmetic mean	**15.79%**	**15.39%**	**12.13%**	**10.43%**
Standard deviation	**25.41%**	**19.90%**	**19.75%**	**16.74%**
Beta (FTSE All Share)	**1.21**	**1.03**	**1.06**	**0.97**
Average no. of stocks	**25**	**27**	**25**	**25**
Mid Contrarian				
Arithmetic mean	**16.51%**	**10.37%**	**10.43%**	**6.40%**
Standard deviation	**23.79%**	**21.45%**	**19.98%**	**18.82%**
Beta (FTSE All Share)	**1.18**	**1.17**	**1.11**	**1.05**
Average no. of stocks	**26**	**26**	**26**	**24**
High Contrarian				
Arithmetic mean	**18.32%**	**11.33%**	**9.32%**	**7.84%**
Standard deviation	**32.17%**	**31.55%**	**35.46%**	**29.87%**
Beta (FTSE All Share)	**1.58**	**1.56**	**1.72**	**1.50**
Average no. of stocks	**27**	**24**	**24**	**28**

Figure 5.4 shows that illiquidity does enhance the returns significantly compared to the other portfolios including "*momentum only portfolio"*. In fact, the return of the enhanced portfolio of *"high momentum & high illiquid portfolio"* is the highest compared to previously discuss double quartile portfolios in table 5.4 and table 5.6.

Figure 5.4: Comparison of the growth of £100 across the momentum/contrarian and illiquidity intersection portfolios: January 1992 to December 2014

This figure shows the growth of £100 invested in selected momentum/contrarian and illiquidity intersection portfolios over the 23 years' study period. The intersection portfolios used are *High Momentum High Illiquid* and *High Contrarian High Liquid*. For comparison purpose, the dollar growth for investing in the *High Momentum only quartile*, *High Contrarian only quartile* and benchmark of *FTSE All-share index* and *3 months LIBOR* are also included in figure 5.4. All data are obtained from DataStream.

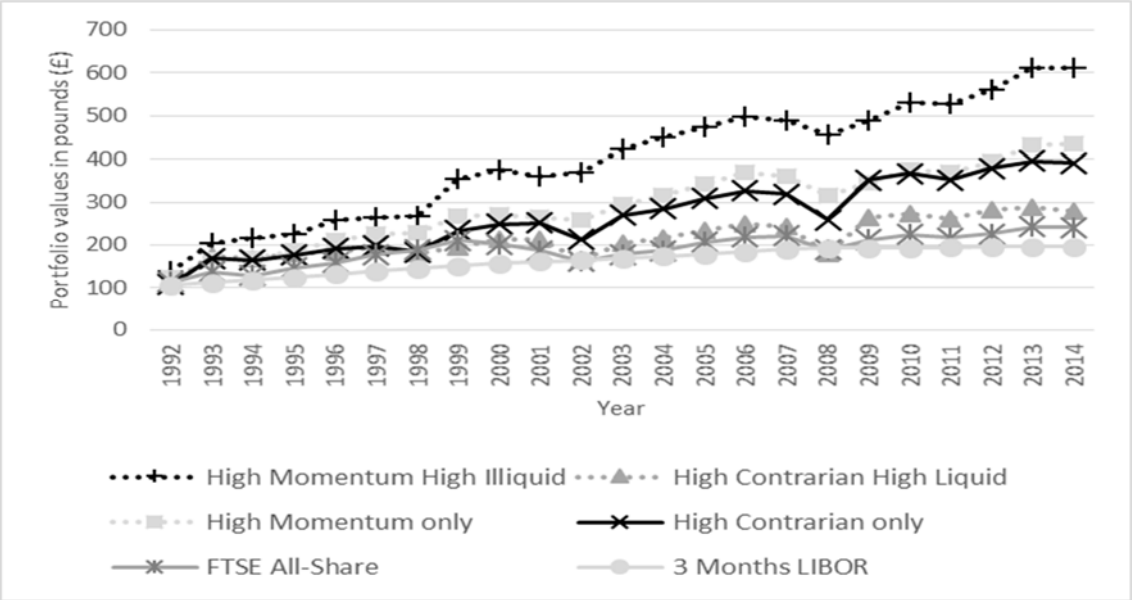


Table 5.9 confirms the strength of the enhanced portfolio as the "*high momentum & high illiquid portfolio"* outperform the other portfolios based on all three risk-adjusted returns.

Table 5.9: Simple performance measurements (risk-adjusted returns) of the momentum/contrarian and illiquidity intersection portfolios: January 1992 to December 2014

This table shows the simple performance measurements of the momentum/contrarian and illiquidity intersection quartiles describe in table 5.8. The measurement allows for further analysis of the portfolios performance by scaling the returns. Three performance measurements are used namely Sharpe ratio (SR), Treynor's ratio (TR) and information ratios (IR). Description of the simple performance measurements is found in table 5.3. Due to the limited number of stocks and to ensure that the results are significant, we only consider portfolios that meet our diversification requirements of at least 12 average stocks. Thus, acceptable portfolios with 12 or more average stocks are in **bold.** The sample period is from January 1992 to December 2014. All data are obtained from DataStream.

Cross Section	High Illiquid	Mid Illiquid	Mid Liquid	High Liquid
High Momentum				
Sharpe Ratio	**65.20%**	**34.97%**	**37.77%**	**46.53%**
Treynor Ratio	**14.67%**	**7.14%**	**6.64%**	**8.07%**
Information Ratio	**80.19%**	**41.82%**	**61.27%**	**84.82%**
Average number of stocks	**25**	**25**	**28**	**25**
Mid Momentum				
Sharpe Ratio	**45.58%**	**56.19%**	**40.12%**	**37.17%**
Treynor Ratio	**9.56%**	**10.83%**	**7.45%**	**6.45%**
Information Ratio	**56.41%**	**80.48%**	**57.00%**	**60.74%**
Average number of stocks	**25**	**27**	**25**	**25**
Mid Contrarian				
Sharpe Ratio	**51.72%**	**28.75%**	**31.13%**	**11.63%**
Treynor Ratio	**10.43%**	**5.26%**	**5.63%**	**2.08%**
Information Ratio	**68.57%**	**37.77%**	**43.14%**	**3.15%**
Average number of stocks	**26**	**26**	**26**	**24**
High Contrarian				
Sharpe Ratio	**43.87%**	**22.56%**	**14.41%**	**12.16%**
Treynor Ratio	**8.91%**	**4.56%**	**2.98%**	**2.42%**
Information Ratio	**54.62%**	**24.01%**	**12.51%**	**8.65%**
Average number of stocks	**27**	**24**	**24**	**28**

5.4.4. ILLIQUIDITY AS A FACTOR IN COMPARISON TO OTHER INVESTMENT FACTORS

With the exception of size, so far our results appear to meet the third benchmark criterion of *"a viable alternative"* as it manages to enhance both value and momentum investment styles. Nonetheless, similar to Ibbotson et al. (2013), we decide to conduct further investigation on the ability of illiquidity as an investment style by looking at the risk factors (zero cost or dollar neutral) of the styles as well as how illiquidity reacts when financial models are utilised. Nevertheless, instead of using annual data, we will be using monthly data for the correlation and regression analysis in order to ensure more effective results.

The risk factors (or investment style premiums) are basically the difference of the monthly returns of the top quartile (Q1) and the bottom quartile (Q4).

5.4.4.1. CORRELATION OF THE INVESTMENT STYLES (FACTORS) WITH EACH OTHER AND THE MARKET

The Pearson correlation analysis is conducted to see the relationship of the respective factors with each other and the market. Table 5.10 shows that the illiquidity factor is significantly negatively correlated with the market whilst positively correlated with size factor and value factor.

Other factors are also negatively correlated to the market with the exception of value factor. Momentum factor is also negatively correlated with both value and size factor whilst value factor is positively correlated with size factor.

Nevertheless, the strongest positive correlation is observed between the illiquidity factor and size factor, which is unlike Ibbotson et al. (2013) who find evidence of negative correlations between the two factors. The positive correlation between the two factors is not surprising as our earlier results especially in table 5.6, appear to show the close relationship between illiquidity and size. Therefore, providing further evidence to indicate that size captures illiquidity within the UK.

Table 5.10: Correlation and descriptive statistics of the monthly returns of the respective factors with each other and the market: January 1992 to December 2014

This table shows the correlation of the monthly returns of respective factors with each other as well as the market. The table also shows the descriptive statistics of the variables. The p-value of the correlations are reported in brackets under each respective correlation coefficient, whereby **bold** figures denote statistically significance coefficient at least at 10% level. The sample uses stocks with complete relevant data that are listed on *FTSE All-Share index* between January 1992 and December 2014 (276 months). All data are obtained from DataStream.

	Correlation				
	Illiquidity Factor	**Market**	**Value Factor**	**Size Factor**	**Momentum Factor**
Illiquidity Factor[1]	1.0000	**-0.1187**	**0.3015**	**0.8839**	0.0376
	-----	**(0.0488)**	**(0.0000)**	**(0.0000)**	(0.5336)
Market[2]	**-0.1187**	1.0000	**0.1555**	**-0.1325**	**-0.1669**
	(0.0488)	-----	**(0.0097)**	**(0.0278)**	**(0.0054)**
Value Factor[3]	**0.3015**	**0.1555**	1.0000	**0.4947**	**-0.6120**
	(0.0000)	**(0.0097)**	-----	**(0.0000)**	**(0.0000)**
Size Factor[4]	**0.8839**	**-0.1325**	**0.4947**	1.0000	**-0.1944**
	(0.0000)	**(0.0278)**	**(0.0000)**	-----	**(0.0012)**
Momentum Factor[5]	0.0376	**-0.1669**	**-0.6120**	**-0.1944**	1.0000
	(0.5336)	**(0.0054)**	**(0.0000)**	**(0.0012)**	-----

Notes:

1 Illiquidity factor = illiquidity effect (Illiquid vs Liquid investment style)
2 Market = FTSE All-Share Index
3 Value factor = Value effect (Value vs Growth investment style)
4 Size factor = Size effect (Micro vs Big investment style)
5 Momentum factor = Momentum effect (Momentum vs Contrarian style)

5.4.4.2. REGRESSION ANALYSES OF VARIOUS ILLIQUID PORTFOLIOS

Nowadays, it is common for asset pricing models to be used in order to investigate and explain the performance of portfolios. Therefore similar to Ibbotson et al. (2013) we will use 3 asset pricing models (univariate CAPM, Fama-French 3 Factor model and Carhart 4 Factor model) to further explain the average returns of various relevant illiquidity portfolios that is discussed earlier.

Although CAPM is considered modest in comparison to the other two models, it is still widely used probably due to its simplicity and attractiveness. Therefore, for our research, we utilise all 3 models to explain the portfolio returns of the illiquidity portfolios.

Table 5.11 shows the regression results using the 3 asset pricing models for two portfolios namely the zero-dollar "*illiquidity factor portfolio"* (Panel A) and long only "*high illiquid portfolio"* (Panel B). The table reports that based on CAPM, the *"illiquidity factor portfolio"* is negatively related to the market whilst the *"high illiquid portfolio"* is positively related. Similar to Ibbotson et al. (2013) both portfolios report positive and statistically significant monthly alpha.

The Fama-French 3 factor model shows that after including the value factor and size factor, the monthly alpha disappears for "*illiquidity factor portfolio"*. However, the long only "*high illiquid portfolio"* monthly alpha remains even after the introduction of the 2 additional factors but it does reduce.

Obviously, after adding the momentum factor, the monthly alpha remains insignificant for the *"illiquidity factor portfolio"*, whereby the *"illiquidity factor portfolio"* is found to be positively related to momentum factor. Surprisingly, although slightly reduce, the monthly alpha of the long only "*high illiquid portfolio"* remains even after the introduction of the momentum factor signifying that investing into illiquid portfolios can generate positive returns and thus poses a challenge to the EMH, as it should have resulted in no significant monthly alpha.

Table 5.11: Regression analyses of monthly returns of the zero-cost illiquidity factor and High Illiquid portfolio: January 1992 to December 2014

This table shows results from the following three regression models on zero-cost (or dollar neutral) *Illiquidity factor* (Panel A) and *long High Illiquid* portfolio (Panel B). *Illiquidity factor* (or illiquidity effect) takes a long position in the quartile of *high illiquid stocks* and a short position in the quartile of *high liquid stocks.* The p-value of the t-statistics are reported in brackets under each respective coefficient, whereby **bold** figures denote statistically significance coefficient at least at 10% level. The sample uses stocks with complete relevant data that are listed on *FTSE All-Share index* between January 1992 and December 2014 (276 months). All data are obtained from DataStream.

1. Capital Asset Pricing Model (CAPM)

$$R_p = \alpha_p + \beta_p(R_m - R_f) + \varepsilon_p \qquad (5.8)$$

Where R_p is the average rates of returns of the portfolio and while the R_f is the risk-free rate and β_p is the systematic risk of the portfolio while R_m is the market return. Together, ($R_m - R_f$) is the excess returns of the market returns over risk-free rate and ε is the residual error or unexplained variable. The overall dependent variable, R_p, can also be the excess return on the specific portfolio (R_p - R_f) but that depends on whether we are measuring either long liquidity portfolio or the illiquidity factor (zero-cost portfolio) because it is unnecessary to deduct the risk-free rate from the zero-cost portfolio.

2. Fama-French three factor model

$$R_p = \alpha + \beta_p(R_m - R_f) + V_p(R_v - R_g) + S_p(R_s - R_b) + \varepsilon_p \qquad (5.9)$$

Where V_p is the sensitivity variable to the value versus growth investment style while S_p is the coefficient for size effect. R_v is returns for value portfolio and R_g is returns for growth portfolio whilst R_s is the returns for micro-firm (because micro-firm is smaller compared to small-firm) and R_b is returns for big-firm. The other variables are as explained earlier under *CAPM (5.8)*.

3. Carhart four factor model

$$R_p = \alpha + \beta_p(R_m - R_f) + V_p(R_v - R_g) + S_p(R_s - R_b) + M_p(R_{mom} - R_c) + \varepsilon_p \qquad (5.10)$$

Where M_p is the coefficient for momentum versus contrarian investment style. R_{mom} is the return for momentum portfolio and R_c represents contrarian portfolio returns. The other variables are as explained earlier under *CAPM (5.8)* and *Fama-French three factor model (5.9)*.

	Monthly alpha (%)	Market Beta	Value	Size	Momentum	Adjusted R2 (%)	N
Panel A							
Illiquidity Factor (Illiquidity effect)							
CAPM	**0.80%**	**-0.0823**				0.93%	276
	(0.0000)	**(0.0593)**					
Fama-French three factor	0.05%	0.0297	**-0.1969**	**0.9831**		80.52%	276
	(0.5456)	(0.1402)	**(0.0000)**	**(0.0000)**			
Carhart four factor	-0.04%	**0.0362**	**-0.0632**	**0.9576**	**0.1373**	82.78%	276
	(0.5814)	**(0.0573)**	**(0.0949)**	**(0.0000)**	**(0.0000)**		

	Monthly alpha (%)	Market Beta	Value	Size	Momentum	Adjusted R2 (%)	N
Panel B							
Long illiquid portfolio							
CAPM	**1.04%**	**0.9818**				60.49%	276
	(0.0000)	**(0.0000)**					
Fama-French three factor	**0.24%**	**1.0806**	**-0.0960**	**0.9631**		87.88%	276
	(0.0363)	**(0.0000)**	**(0.0325)**	**(0.0000)**			
Carhart four factor	**0.23%**	**1.0811**	**-0.0847**	**0.9610**	**0.0116**	87.84%	276
	(0.0474)	**(0.0000)**	**(0.1258)**	**(0.0000)**	**(0.7254)**		

5.4.4.3. REGRESSION ANALYSES OF VARIOUS ENHANCED ILLIQUID PORTFOLIOS

Table 5.12 shows the regression results for the 3 enhanced intersected illiquidity portfolios (net of risk free rate) using the 3 asset pricing models. The 3 enhanced portfolios are 1) *"High Value & High Illiquid portfolio"*, 2) *"Micro & High Illiquid portfolio"* and 3) *"High Momentum & High Illiquid portfolio"*.

Based on CAPM, all three portfolios generate significant positive monthly alpha whereby the "*High Momentum & High Illiquid portfolio"* produces the highest alpha. Moreover, all portfolios are found to be positively related to the market but "*High Momentum & High Illiquid portfolio* "relationship is found to be weaker signifying that the portfolio has the lowest systematic risk.

Using the Fama-French 3 factor model, the monthly alpha for "*High Value & High Illiquid portfolio"* and "*Micro & High Illiquid portfolio"* disappears but it remains for "*High Momentum & High Illiquidity portfolio"*. "*Micro & High Illiquid portfolio"* is also found to be not related to both momentum and value but "*High Value & High Illiquid portfolio"* is found to be positively related to all 3 additional variables.

Panel C of table 5.12 shows that "*High Momentum & High Illiquid portfolio"* is positively related to size and momentum factor but negatively related to value factor. Nonetheless, the important and interesting finding is that the monthly alpha of the portfolio remains positive and significant even after the inclusion of all 3 additional factors confirming that illiquidity has improved the momentum portfolio as reported earlier.

Table 5.12: Regression analyses of monthly returns of the enhanced illiquidity portfolios: January 1992 to December 2014

This table reports results from the 3 regression models (as described in table 5.11) on enhanced illiquidity portfolios. There are three considered enhanced illiquidity portfolios based on its intersection with other investment styles namely *High Value & High Illiquid* portfolio, *Micro & High Illiquid* portfolio and *High Momentum & High Illiquid* portfolio, which are described in table 5.4, table 5.6 and table 5.8 respectively (north-west of the respective tables). The p-value of the t-statistics are reported in brackets under each respective coefficient, whereby **bold** figures denote statistically significance coefficient at least at 10% level. The sample uses stocks with complete relevant data that are listed on *FTSE All-Share index* between January 1992 and December 2014 (276 months). All data are obtained from DataStream.

	Monthly alpha (%)	Market Beta	Value	Size	Momentum	Adjusted R2 (%)	N
Panel A							
High value, High illiquid							
CAPM	**1.32%**	**1.0781**				52.57%	276
	(0.0000)	**(0.0000)**					
Fama-French three factor	0.23%	**1.1528**	**0.1979**	**1.0642**		85.04%	276
	(0.1226)	**(0.0000)**	**(0.0008)**	**(0.0000)**			
Carhart four factor	0.15%	**1.1585**	**0.3163**	**1.0416**	**0.1216**	85.42%	276
	(0.3264)	**(0.0000)**	**(0.0000)**	**(0.0000)**	**(0.0047)**		

	Monthly alpha (%)	Market Beta	Value	Size	Momentum	Adjusted R2 (%)	N
Panel B							
Microcap, High illiquid							
CAPM	**1.15%**	**1.0079**				53.80%	276
	(0.0000)	**(0.0000)**					
Fama-French three factor	0.17%	**1.1089**	-0.0061	**1.0980**		86.74%	276
	(0.1850)	**(0.0000)**	(0.9052)	**(0.0000)**			
Carhart four factor	0.16%	**1.1098**	0.0137	**1.0943**	0.0203	86.71%	276
	(0.2325)	**(0.0000)**	(0.8277)	**(0.0000)**	(0.5912)		

	Monthly alpha (%)	Market Beta	Value	Size	Momentum	Adjusted R2 (%)	N
Panel C							
High momentum, High illiquid							
CAPM	**1.38%**	**0.9702**				41.75%	276
	(0.0000)	**(0.0000)**					
Fama-French three factor	**0.68%**	**1.1431**	**-0.5539**	**1.2071**		66.11%	276
	(0.0027)	**(0.0000)**	**(0.0000)**	**(0.0000)**			
Carhart four factor	**0.41%**	**1.1613**	**-0.1731**	**1.1345**	**0.3910**	70.41%	276
	(0.0537)	**(0.0000)**	**(0.0914)**	**(0.0000)**	**(0.0000)**		

Overall, although our results are not similar to Ibbotson et al. (2013) in relation to illiquidity factor, the significant positive results for the long only "*high illiquid portfolio"* in panel B of table 5.11 does confirm that illiquidity is "not easily beaten" and can even be considered as *"a viable alternative"*. Nevertheless, the ability of illiquidity to enhance the momentum portfolio in panel C of table 5.12 from the weakest performing top investment style to one of the best performing portfolio with a positive and significant monthly alpha does confirm illiquidity as meeting the third portfolio benchmark criterion of *"a viable alternative"*.

5.4.5. LIQUIDITY STABILITY AND MIGRATION

The fourth and last benchmark criterion of Sharpe (1992) is whether the illiquidity investment style can be managed at *"low in cost",* for which we will be using the technique developed by Ibbotson et al. (2013).

Khorana, Servaes, and Tufano (2009) believe that fees differ from fund to fund, as the characteristics of the funds can result in lower costs. It is important to study costs as Carhart (1997) highlights that the investment costs of expense ratios, transaction costs, and load fees all have a direct, negative impact on funds' performance.

Furthermore, Kaplan and Schoar (2005) highlight that although private equity partnerships earn returns (gross of fees) exceeding the S&P 500 over the entire sample period (1980–1997), average fund returns net of fees are roughly equal to those of the S&P 500, signifying the negative impact of fees.

Malkiel (2005) finds evidence to indicate that professional investment managers, both in the US and abroad, do not outperform their index benchmarks while French (2008) mentions that under reasonable assumptions, the typical investor would have increased his average annual return by 67 basis points over the 1980–2006 period if he had switched to a passive market portfolio signifying that investors are better off investing into passive funds.

Ibbotson et al. (2013) highlight that illiquidity has a cost as the stocks may take longer to trade and even have higher transaction costs but trading costs can be mitigated through longer horizons and less trading, which translates into higher returns for the less liquid

stocks. Nevertheless, less liquid portfolios may involve the risk of needing to quickly liquidate positions in a crisis, for which more passively held portfolios can largely mitigate this risk. Therefore, studying migration of the portfolio will also allow us to understand if any of the portfolios can be managed at a low cost or passively.

5.4.5.1. MIGRATION OF STOCKS OF VARIOUS INVESTMENT STYLES

Table 5.13 shows the migration of stocks from each quartile in *year (t)* (sorting year) to other quartiles in *year (t+1)* (performance year) for all investment styles. As before, the quartiles are only rebalanced annually meaning that the stocks are held for at least one year while diagonal results (underlined & *italics)* represent stocks that remain in their respective quartiles after one year.

Panel A of table 5.13 shows that overall 78.45% of the illiquid stocks remain in the same quartile. For the "*high illiquid quartile"* (Quartile 1), 76.99% remain in their quartile while the rest migrate to other quartiles, with the next quartile (Q2) receiving the most stocks (21.32%). However, the most stable quartile is the "*high liquid quartile"* (Quartile 4) as 93.60% of stocks remain within their quartile.

In comparison to other investment styles, size is considered the most stable as overall 84.16% of stocks remain within their quartile while momentum results in the lowest stability of only 30.35%. Value quartiles are also relatively stable, whereby overall 67.62% remain in the same quartile.

Generally, table 5.13 signifies that the transaction costs in maintaining illiquidity based portfolios are relatively low. Therefore, along with the stable returns and risks reported earlier, illiquidity styles can be regarded as a stable strategy. Moreover, table 5.13 shows that the "*high liquid portfolio"* (Quartile 4) is the most stable (lower transaction costs) although the portfolio still generates positive returns with lower risks (table 5.2).

Table 5.13: Migration of stocks one year after portfolio construction for all investment styles: January 1991 to December 2014

The table shows the migration of stocks from each quartile in *year (t)* (sorting year) to other quartiles in *year (t+1)* (performance year) for all investment styles. The sample uses companies with complete relevant data that are listed on *FTSE All-Share index* between January 1991 and December 2014. As before, the quartiles are only rebalanced annually meaning that the stocks are held for at least one year. Diagonal results (underlined & *italics)* represent stocks that remains in its respective quartiles after one year. The last column shows that all rows sum to 100%. All data are obtained from DataStream.

Panel A

Illiquidity migration (Overall 78.45% remains in the same quartile)

Year t	*Year t+1 (Illiquidity)*				
(Illiquidity)	*Q1*	*Q2*	*Q3*	*Q4*	**Total**
Quartile 1	***76.99%***	21.32%	1.60%	0.10%	100.00%
Quartile 2	18.09%	***65.01%***	16.62%	0.29%	100.00%
Quartile 3	0.69%	12.03%	***78.20%***	9.07%	100.00%
Quartile 4	0.12%	0.40%	5.89%	***93.60%***	100.00%

Panel B

Value migration (Overall 67.62% remains in the same quartile)

Year t	*Year t+1 (Value)*				
(Value)	*Q1*	*Q2*	*Q3*	*Q4*	**Total**
Quartile 1	***65.21%***	28.68%	3.37%	2.74%	100.00%
Quartile 2	30.91%	***56.82%***	11.69%	0.57%	100.00%
Quartile 3	3.46%	12.24%	***68.72%***	15.59%	100.00%
Quartile 4	2.12%	1.20%	16.97%	***79.71%***	100.00%

Panel C

Size migration (Overall 84.16% remains in the same quartile)

Year t	*Year t+1 (Size)*				
(Size)	*Q1*	*Q2*	*Q3*	*Q4*	**Total**
Quartile 1	***86.41%***	13.34%	0.18%	0.07%	100.00%
Quartile 2	11.64%	***75.40%***	12.67%	0.29%	100.00%
Quartile 3	0.34%	10.57%	***81.35%***	7.73%	100.00%
Quartile 4	0.06%	0.23%	6.24%	***93.48%***	100.00%

Panel D

Momentum migration (Overall 30.35% remains in the same quartile)

Year t	*Year t+1 (Momentum)*				
(Momentum)	*Q1*	*Q2*	*Q3*	*Q4*	**Total**
Quartile 1	***32.41%***	22.40%	21.02%	24.17%	100.00%
Quartile 2	24.01%	***29.34%***	26.24%	20.41%	100.00%
Quartile 3	19.81%	28.66%	***29.28%***	22.26%	100.00%
Quartile 4	25.74%	21.33%	22.55%	***30.37%***	100.00%

5.4.5.2. RETURNS AND RISKS ASSOCIATED WITH MIGRATION IN ILLIQUIDITY PORTFOLIOS

Table 5.14 shows equally-weighted, annualised return and risks for quartile portfolios based on illiquidity migration as highlighted in Panel A of Table 5.13. As before, the prior year *(t-1)* is used to construct the quartiles and are then used to calculate the stock performance for a given year *(t)*. Quartiles are rebalanced annually.

Due to the limited number of stocks and to ensure that the results are robust, we only consider portfolios that meet our diversification requirements of at least 12 stocks in average. Diagonal results (underlined & *italics)* in table 5.14 represent stocks that remain in their respective quartiles after one year.

Table 5.14 shows that in quartile 3 (row 3), the returns of stocks migrating from more liquid (Q3) quartiles to less liquid (Q2) actually increase, while illiquid stocks (Q1) migrating to more liquid quartile (Q2) in quartile 1 (row 1) returns actually reduce.

However, this is not always the case, as in quartile 2 (row 2), stocks which migrated from Q2 to the more liquid quartile (Q3), actually shown increased returns, which is similar to the findings of Ibbotson et al. (2013). Similarly, risk profiling is also less consistent as moving from less liquid quartiles to the more liquid quartiles do not necessary decrease the quartiles' riskiness.

The findings are different to Ibbotson et al. (2013) since their results show that as less liquid migrate to more liquid, returns increase dramatically while migrating the other way results in the opposite, which is consistent to Fama and French (2007) evidence on value and size. Thus, Ibbotson et al. (2013) show that changes in liquidity are associated with changes in valuation.

Nevertheless, an interesting finding of table 5.14 is that the average returns of the remaining stocks in "*high illiquid quartile"* (quartile 1 in Q1) and "*high liquid quartile"* (quartile 4 in Q4) have actually increased in comparison to the original portfolio as reported earlier in table 5.2. It is particularly noticeable for the "*high liquid quartile"* (Q4) whose returns increase from 8.69% (table 5.2) to 10.11% (table 5.14), signifying that the stocks which migrated have a negative impact on the initial portfolio. Therefore, if there is a method in which we can just keep the stable stocks, we can construct a passive portfolio that can generate higher returns with lower transaction costs. Even if this is not possible, table 5.13 highlights that 93.60% of stocks will not have moved anyway, indicating the savings that investors can make on transaction costs.

Table 5.14: Annualized returns and risks associated with migration in illiquidity portfolios: January 1992 to December 2014

This table shows equally-weighted, annualised returns (in percentage format) for quartile portfolios based on illiquidity migration as highlighted in Panel A of Table 5.13. As before, the prior year *(t-1)* is used to construct the quartiles and are then used to calculate the quartile returns and risks for a given year *(t)*. The quartiles are also rebalanced annually. Therefore, the sorting sample period is from January 1991 to December 2013 whilst *table 5.14* sample period is from January 1992 to December 2014 and the stocks are held for at least one year. The table also shows the unsystematic and systematic risks of the portfolio based on standard deviation and beta respectively. Beta is calculated based on *FTSE All-share index*. Due to the limited number of stocks and to ensure that the results are significant, we only consider portfolios that meet our diversification requirements of at least 12 average stocks. Thus, acceptable portfolios with 12 or more average stocks are in **bold**. Diagonal results (underlined & *italics)* represent stocks that remains in its respective quartiles after one year. All data are obtained from DataStream.

	Year t+1 (Illiquidity)			
Year t (Illiquidity)	***Q1***	***Q2***	***Q3***	***Q4***
Quartile 1				
Arithmetic mean	***19.00%***	**12.07%**	13.98%	-3.96%
Standard deviation	***26.64%***	**29.76%**	15.89%	42.82%
Beta (FTSE All Share)	***1.30***	**1.52**	0.54	3.01
Average no. of stocks	***74***	**19**	2	1
Quartile 2				
Arithmetic mean	**15.99%**	***11.49%***	**13.34%**	-2.94%
Standard deviation	**26.43%**	***21.76%***	**26.20%**	38.39%
Beta (FTSE All Share)	**1.32**	***1.18***	**1.41**	1.49
Average no. of stocks	**18**	***66***	**15**	2
Quartile 3				
Arithmetic mean	7.98%	**15.72%**	***10.02%***	11.88%
Standard deviation	28.91%	**37.12%**	***22.24%***	20.46%
Beta (FTSE All Share)	1.48	**1.69**	***1.23***	1.02
Average no. of stocks	2	**12**	***79***	9
Quartile 4				
Arithmetic mean	-12.99%	29.28%	15.65%	***10.11%***
Standard deviation	27.69%	30.79%	37.38%	***22.63%***
Beta (FTSE All Share)	0.93	0.23	1.69	***1.22***
Average no. of stocks	1	1	6	***90***

Overall the results in table 5.13 indicates that the portfolio based on illiquidity can be managed at *"low in cost",* meeting the fourth and final benchmark criterion. This means that illiquidity has met all 4 of Sharpe (1992) benchmark criteria signifying that it can be made into a benchmark portfolio and can be categorised as a viable investment style in line with the other more tradition styles such as value style.

5.4.6. COVARIANCE VERSUS CHARACTERISTICS

Since we have now established that illiquidity can be regarded as a viable investment style, we will now look at different ways of constructing portfolios. Interestingly, most finance research seems to focus on using stock sensitivity such as Fama-French 3 factor model to explain results. Pastor and Stambaugh (2003) follow a similar approach with

illiquidity. Therefore, it will be fascinating to investigate whether a stock sensitivity measure based on "*covariance"* can construct portfolios that generate results that are comparable to portfolios constructed based on the "*characteristics"* of the stocks such as P/B ratio (value) and Amihud (illiquidity).

5.4.6.1. COVARIANCE PORTFOLIO RETURNS AND RISKS

Similar to before, construction of table 5.15, uses the prior year *(t-1)* illiquidity measure to build the quartiles and calculate the returns and risks for a given year *(t)*. However, instead of using Amihud, we will be using covariance which is the sensitivity of the stocks to the illiquidity factor. Following Ibbotson et al. (2013), the covariance of each stock is obtained by regressing[88] the 12-months excess returns of each stock over the market returns (stock returns minus market returns) on the illiquidity factor, whereby market return is represented by *FTSE All-Share index* while the illiquidity factor[89], which is calculated earlier, is based on Amihud.

The quartile (or portfolio) ranks in table 5.15 are determined by the value of the covariance or illiquidity beta (β), whereby stocks with high covariance values (β) are considered to be correlated to "*high illiquid portfolio"* whereas low covariance value (β) companies are related to "*high liquid portfolio"*. The prior year *(t-1)* value (β) is used to sort (construct) the quartiles, which are then used to calculate the quartile results for a given year *(t)*. The quartiles are also rebalanced annually.

Table 5.15 shows that constructing portfolio based on *"covariance model"* generates results consistent to *"characteristic model"*, as "*high covariance portfolio" (Q1)* produced higher returns compared to "*low covariance portfolio" (Q4)* and the covariance (illiquidity) premium is found to be positive and significant at least at 10% level. Moreover, it is established that the "*high covariance portfolio"* has both the highest systematic and unsystematic risk, justifying the portfolio's higher returns. Nevertheless, the portfolio returns do not increase monotonically with increase in stock illiquidity (covariance).

[88] Please bear in mind that the 12 months period may not be ideal for the regression period but to be consistent with our current research of using monthly data as well as our comparison to characteristics later that also uses monthly data, we decide to continue using the shorter than ideal regression. The method is used by Ibbotson et al (2013).
[89] Illiquidity factor = illiquid portfolio minus liquid portfolio

Table 5.15: Annualized returns and risks of the covariance portfolio: January 1992 to December 2014

This table shows equally-weighted, annualised returns (in percentage format) for quartile portfolios based on the covariance of the stocks. The covariance of each stock is obtained by regressing the 12-months excess returns of each stock over the market returns (Stock returns minus market returns) on the illiquidity factor. As before, market return is represented by *FTSE All-Share index* while the illiquidity factor is calculated using Amihud. Quartile portfolio ranks are determined by the value of the covariance or illiquidity beta (β), whereby stocks with high values (β) are considered to be correlated to *high illiquid* portfolio whereas low value (β) companies are related to *high liquid* portfolio. The prior year *(t-1)* value (β) is used to sort (construct) the quartiles, which are then used to calculate the quartile returns and risk for a given year *(t)* and the quartiles are also rebalanced annually. Therefore, the sorting sample period is from January 1991 to December 2013 whilst *table 5.15* (performance) sample period is from January 1992 to December 2014 and the stocks are held for at least one year. The "Q1 – Q4" takes a long position in the quartile of high covariance (β) stocks (Q1) and a short position in the quartile of low covariance (β) companies. The table also shows the unsystematic and systematic risks of the portfolio based on standard deviation and beta respectively. Beta is calculated based on *FTSE All-share index*. Newey-West p-value are reported in brackets for the arithmetic mean of the "Q1 – Q4" portfolio, whereby **bold** figures denote statistically significance coefficient at least at 10% level. The bandwidth parameter for the Newey-West p-value is calculated using the Newey-West automatic lag selection. All data are obtained from DataStream.

Cross Section	Result	Q1	Q2	Q3	Q4	Q1 - Q4
*High covariance vs Low covariance	Arithmetic mean	16.32%	11.62%	11.24%	12.38%	3.94%
						(0.0865)
(Q1 = High Covariance, Q4 = Low Covariance)	Standard deviation	28.09%	20.86%	19.58%	21.92%	11.93%
	Beta (FTSE All Share)	1.45	1.14	1.14	1.22	0.23
	Average no. of stocks	112	112	112	112	

Note:
*High covariance for a stock means the stock correlates more with *High illiquid portfolio*, whilst low covariance means the stock correlates more with *High liquidity portfolio.*

5.4.6.2. INTERSECTION OF COVARIANCE AND CHARACTERISTICS

To investigate the effectiveness of either "*covariance model"* or "*characteristics model"* as an illiquidity measure to construct portfolios, we will be using independent double sorting as before, whereby 16 portfolios of the intersection between characteristics (Amihud) and covariance[90] (illiquidity beta) will be generated.

Table 5.16 reports that across rows the portfolio returns of *"characteristic model",* increases with illiquidity consistently. Some of the returns across columns *("covariance model")* also increases with illiquidity but it is less consistent and weaker. In fact, under *"mid-illiquidity portfolio"* column, the "*low covariance portfolio"* is seen to generate higher returns relative to "*high covariance portfolio"*.

[90] High covariance for a stock means the stock correlates more with *High illiquidity*, whilst low covariance means the stock correlates more with *High liquidity.*

Nevertheless as Ibbotson et al. (2013) and Daniel and Titman (1998) mention that the off-diagonal portfolios demonstrate the relative importance of *"covariance model"* versus *"characteristics model"*. The off-diagonal (underlined & *italics* in table 5.16) reveals that "*Low Covariance &* ***High Illiquid*** *portfolio"* performs better than the "***High Covariance*** *& High Liquid portfolio"* which is most likely due to the *characteristics* of the stocks. Figure 5.6 confirms this by comparing the two off-diagonal cumulative returns, whereby the growth of the *"Low Covariance &* ***High Illiquid*** *portfolio"* is higher compared to "***High Covariance*** *& High Liquidity portfolio".*

Table 5.16: Annualized returns and risks of covariance (illiquidity beta (β)) and illiquidity (characteristics - Amihud) intersection portfolios: January 1991 to December 2014

This table shows the results of intersection quartiles between covariance (illiquidity beta (β)) and illiquidity (characteristics) investment styles. The quartiles are constructed by independently sorting the portfolios into quartiles based on the illiquidity as well as covariance of the stocks and then by taking the intersection sets of quartiles to produce 16 intersection groups as below. As before, the prior year *(t-1)* intersection measure is used to construct the quartiles, which are then used to calculate the quartile returns and risk for a given year *(t)* and the quartiles are also rebalanced annually. Therefore, the sorting sample period is from January 1991 to December 2013 whilst the sample period of the returns & risks, as in table 5.16 below, are from January 1992 to December 2014 and the stocks are held for at least one year. The table also shows the unsystematic and systematic risks of the portfolio based on standard deviation and beta respectively. Beta is calculated based on *FTSE All-share index*. Due to the limited number of stocks and to ensure that the results are significant, we only consider portfolios that meet our diversification requirements of at least 12 average stocks. Thus, acceptable portfolios with 12 or more average stocks are in **bold**. All data are obtained from DataStream

Cross Section	High Illiquid	Mid Illiquid	Mid Liquid	High Liquid
High Covariance (Beta)				
Arithmetic mean	**19.84%**	**14.63%**	**14.12%**	***12.99%***
Standard deviation	**28.27%**	**29.72%**	**30.61%**	***28.24%***
Beta (FTSE All Share)	**1.36**	**1.58**	**1.51**	***1.35***
Average no. of stocks	**41**	**29**	**19**	***12***
Mid-High Covariance (Beta)				
Arithmetic mean	**15.28%**	**11.65%**	**10.59%**	**6.85%**
Standard deviation	**24.11%**	**22.37%**	**22.07%**	**16.97%**
Beta (FTSE All Share)	**1.18**	**1.19**	**1.24**	**0.99**
Average no. of stocks	**27**	**29**	**25**	**21**
Mid-Low Covariance (Beta)				
Arithmetic mean	**18.92%**	**11.99%**	**9.27%**	**7.84%**
Standard deviation	**33.08%**	**19.75%**	**19.69%**	**17.16%**
Beta (FTSE All Share)	**1.60**	**1.06**	**1.14**	**0.98**
Average no. of stocks	**20**	**25**	**29**	**28**
Low Covariance (Beta)				
Arithmetic mean	***18.36%***	**15.26%**	**11.28%**	**8.92%**
Standard deviation	***24.21%***	**27.08%**	**25.10%**	**18.68%**
Beta (FTSE All Share)	***1.13***	**1.42**	**1.30**	**1.06**
Average no. of stocks	***15***	**19**	**29**	**42**

Note:

*High covariance for a stock means the stock correlates more with *High illiquidity*, whilst low covariance means the stock correlates more with *High liquidity.*

The off-diagonal (underlined & *italics*) shows the relative importance of covariance vs characteristic, as it reveals ***High Illiquid* *Low Covariance* minus ***High Liquidity*** *High Covariance* produce positive returns regardless of the intervention of covariance, whereas ***High Covariance*** *High Liquidity* minus ***Low Covariance*** *High Illiquid* produces negative returns, which is most likely due to the characteristics of the stocks. Moreover, the returns across columns (characteristics) is consistent to past results whereby returns increase with illiquidity, but is not consistent across rows (covariance) signifying that that the returns are not significantly dependent on covariance.

Figure 5.5: Comparison of the growth of £100 across the covariance (illiquidity beta (β)) and illiquidity (characteristics - Amihud) intersection portfolios: January 1992 to December 2014
This figure shows the growth of £100 invested in selected covariance (illiquidity beta (β)) and illiquidity intersection portfolios over the 23 years study period. The intersection portfolios used are *High Covariance High Illiquid* and *Low Covariance High Liquid*. For comparison purpose, the dollar growth for investing in the *High Covariance quartile*, *Low Covariance quartile* and benchmark of *FTSE All-share* and *3 months LIBOR* are also included in figure 5.5. All data are obtained from DataStream.

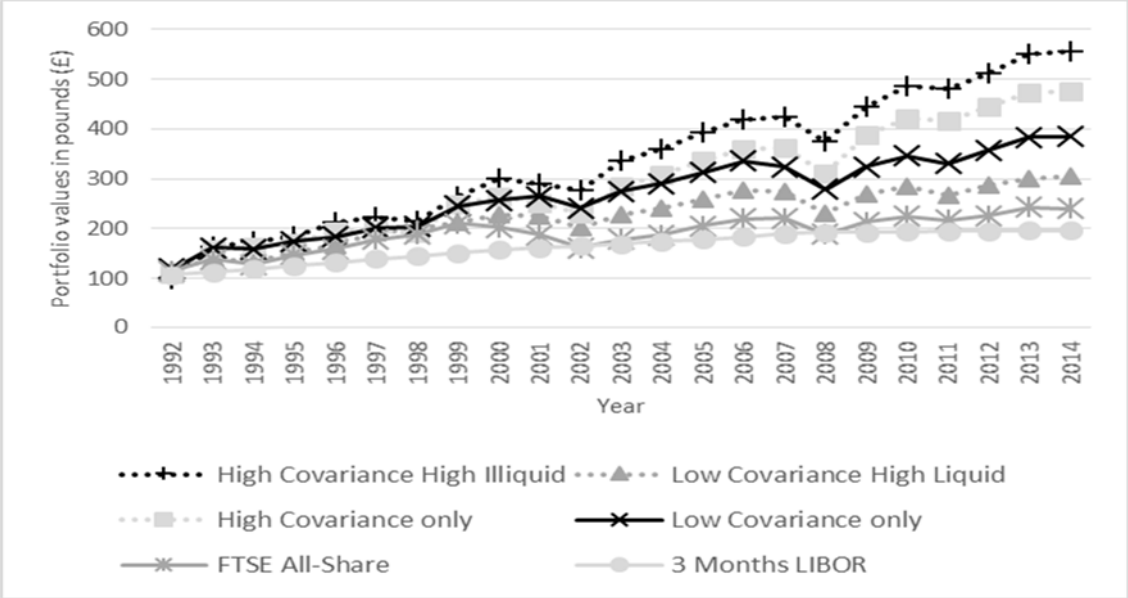
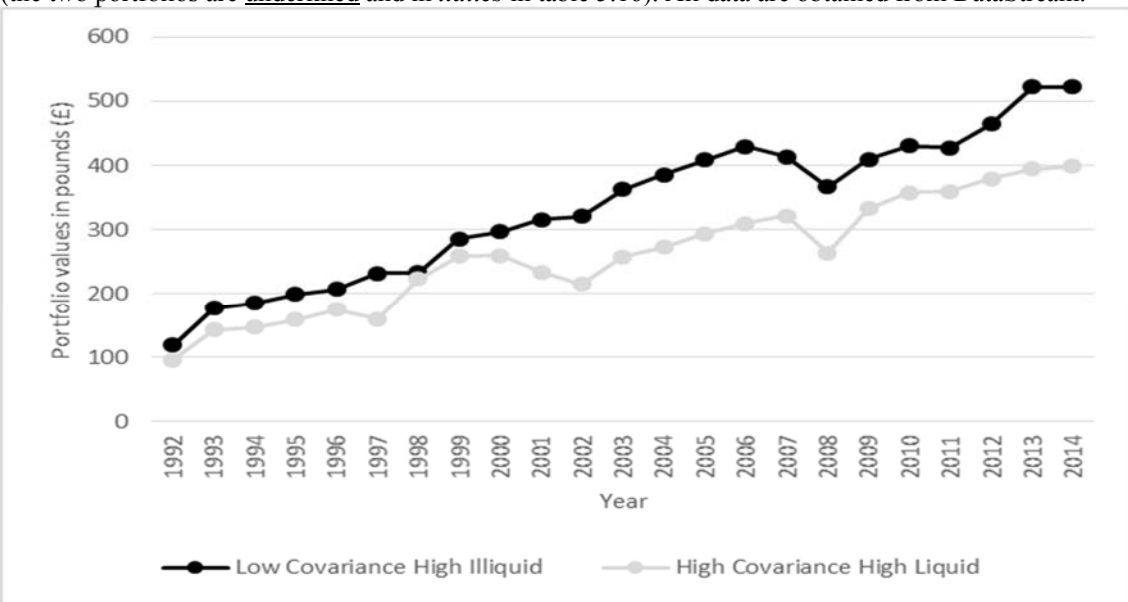


Figure 5.6: Comparison of the growth of £100 in relation to Covariance (illiquidity beta (β)) versus Characteristics (Amihud): January 1992 to December 2014
This figure shows the growth of £100 invested in selected covariance (illiquidity beta (β)) and illiquidity intersection portfolios over the 23 years study period. In order to investigate the historical performance of Covariance versus Characteristic, the intersection portfolios used are *Low Covariance High Illiquid* and *High Covariance High Liquid*, which are the southwest and northeast portfolios respectively in table 5.16 (the two portfolios are <u>underlined</u> and in *italics* in table 5.16). All data are obtained from DataStream.



The simple performance measurement in table 5.17 reports that the best portfolio is shown by the "*Low Covariance & **High illiquid** portfolio"*, further confirming the strength and significance of the *"characteristics model"* over *"covariance model"*. Therefore, along with the consistent results of *"characteristics model"* across its row in table 5.16, this indicates that returns are not significantly dependent on *"covariance model"* but more on *"characteristics model"*. Our results coincide with Ibbotson et al. (2013) as well as Daniel and Titman (1998), who investigate *"value versus growth styles"* instead of illiquidity.

Table 5.17: Simple performance measurements (risk-adjusted returns) of the covariance (illiquidity beta (β)) and illiquidity (characteristics - Amihud) intersection portfolios: January 1992 to December 2014

This table shows the simple performance measurements of the covariance and illiquidity intersection quartiles describe in table 5.16. The measurement allows for further analysis of the portfolios performance by scaling the returns. Three performance measurements are used namely Sharpe ratio (SR), Treynor's ratio (TR) and information ratios (IR). Description of the simple performance measurements is found in table 5.3. Due to the limited number of stocks and to ensure that the results are significant, we only consider portfolios that meet our diversification requirements of at least 12 average stocks. Thus, acceptable portfolios with 12 or more average stocks are in **bold.** The sample period is from January 1992 to December 2014. All data are obtained from DataStream.

Cross Section	High Illiquid	Mid Illiquid	Mid Liquid	High Liquid
High Covariance (Beta)				
Sharpe Ratio	**55.30%**	**35.08%**	**32.39%**	***31.09%***
Treynor Ratio	**11.51%**	**6.59%**	**6.56%**	***6.49%***
Information Ratio	**70.90%**	**45.60%**	**38.30%**	***35.47%***
Average number of stocks	**41**	**29**	**19**	***12***
Mid-High Covariance (Beta)				
Sharpe Ratio	**45.92%**	**33.25%**	**28.92%**	**15.59%**
Treynor Ratio	**9.37%**	**6.27%**	**5.13%**	**2.66%**
Information Ratio	**58.61%**	**43.59%**	**40.93%**	**11.11%**
Average number of stocks	**27**	**29**	**25**	**21**
Mid-Low Covariance (Beta)				
Sharpe Ratio	**44.46%**	**39.42%**	**25.73%**	**21.16%**
Treynor Ratio	**9.21%**	**7.33%**	**4.44%**	**3.72%**
Information Ratio	**54.48%**	**55.60%**	**37.69%**	**22.45%**
Average number of stocks	**20**	**25**	**29**	**28**
Low Covariance (Beta)				
Sharpe Ratio	***58.47%***	**40.84%**	**28.18%**	**25.24%**
Treynor Ratio	***12.56%***	**7.76%**	**5.44%**	**4.43%**
Information Ratio	***73.71%***	**55.06%**	**33.70%**	**33.60%**
Average number of stocks	***15***	**19**	**29**	**42**

Table 5.18 also shows that overall only 33.95% of stocks remained in the same quartile for *covariance model*, which is quite low in comparison to "*characteristic model"* stability of 78.45% (panel A of table 5.13). Thus, we show that *"characteristics model"* is the best way to construct illiquidity or passive portfolios as it provides consistent results.

Table 5.18: Migration of stocks one year after portfolio construction for covariance: January 1991 to December 2014

The table shows the migration of stocks from each quartile in *year (t)* (sorting year) to other quartiles in *year (t+1)* (performance year) for portfolios based on covariance (illiquidity beta (β)). The sample uses companies with complete relevant data that are listed on *FTSE All-Share index* between January 1991 and December 2014. As before, the quartiles are only rebalanced annually meaning that the stocks are held for at least one year. Diagonal results (underlined & *italics)* represent stocks that remains in its respective quartiles after one year. The last column shows that all rows sum to 100%. All data are obtained from DataStream.

Covariance migration (Overall 33.95% remains in the same quartile)					
Year t	***Year t+1 (Covariance)***				
(Covariance)	***Q1***	***Q2***	***Q3***	***Q4***	**Total**
Quartile 1	***39.00%***	24.73%	17.09%	19.18%	100.00%
Quartile 2	24.04%	***30.50%***	24.23%	21.23%	100.00%
Quartile 3	16.32%	25.25%	***33.26%***	25.17%	100.00%
Quartile 4	19.20%	20.72%	27.02%	***33.06%***	100.00%

5.4.7. THE JANUARY EFFECT

5.4.7.1. JANUARY PREMIUMS OF FTSE ALL-SHARE INDEX AND VARIOUS INVESTMENT FACTORS

Another consistent findings of past literature are the appearance of a seasonal effect in the month of January. It appears that it relates to all investment styles such as Fama and French (1992) on value style, Keim (1983) on size effects, De Bondt and Thaler (1985) on momentum style and Eleswarapu and Reinganum (1993) on illiquidity premium. Thus, we believe that we should briefly cover the topic.

To investigate the January effect we will be applying Haug and Hirschey (2006) framework. Table 5.19 shows equally-weighted, monthly returns and risks (in % format) for the month of January, other months and the January premiums[91], which are based on the investment style factors (premiums) as well as the market. Wilcoxon signed rank test is used to test the significance of the results at least at 10% level.

Contrary to Reinganum and Shapiro (1987), table 5.19 shows that January premiums do not exist within the market, which is measured using *FTSE All Share index*. This is similar for momentum factor. Although January premiums seem to exist, they are not significant.

Nevertheless, it does exist within the other three investment styles namely value, size and illiquidity signifying that the earlier positive and significant investment style premiums may be due to the January returns or vice versa, which is similar to Haug and Hirschey (2006) study of US market even though they do not consider illiquidity.

[91] January premiums is the paired difference between the month of January and other months.

Table 5.19: Monthly returns and risks for the month of January, other months and January Premiums of the FTSE All-Share index and respective investment factors: January 1992 to December 2014

This table shows equally-weighted, monthly returns and risks (in percentage format) for the month of January, other months and the January premiums. The table is based on the investment factors (effects), which is described in table 5.2 as well as the FTSE All-Share market index. To test the significance of the results, a Wilcoxon signed rank test is used whereby the p-value of the tests are reported in brackets and **bold** figures denote statistically significance results at least at 10% level. The sample period is from January 1992 to December 2014. All data are obtained from DataStream.

Investment Factors	January	Other 11 months	January Premiums (Paired Difference)
FTSE All-Share			
N	23	**253**	23
Mean	-0.46%	**0.56%**	-1.03%
Standard deviation	4.36%	**4.02%**	4.56%
Median	0.04%	**0.94%**	-0.17%
Percent positive	52.17%	**61.26%**	43.48%
Wilcoxon signed rank test (P-Value)	(0.9636)	**(0.0020)**	(0.5531)
Size factor (Size effect)			
N	**23**	**253**	**23**
Mean	**3.82%**	**0.62%**	**3.19%**
Standard deviation	**3.44%**	**2.75%**	**3.44%**
Median	**2.97%**	**0.65%**	**2.80%**
Percent positive	**91.30%**	**59.29%**	**82.61%**
Wilcoxon signed rank test (P-Value)	**(0.0002)**	**(0.0010)**	**(0.0008)**
Value factor (Value effect)			
N	**23**	**253**	**23**
Mean	**1.99%**	**0.58%**	**1.41%**
Standard deviation	**2.67%**	**2.86%**	**2.88%**
Median	**2.26%**	**0.33%**	**2.51%**
Percent positive	**86.96%**	**55.73%**	**69.57%**
Wilcoxon signed rank test (P-Value)	**(0.0030)**	**(0.0061)**	**(0.0254)**
Momentum factor (Momentum effect)			
N	23	253	23
Mean	1.24%	0.06%	1.19%
Standard deviation	4.35%	4.14%	4.95%
Median	0.05%	0.45%	-0.37%
Percent positive	52.17%	56.52%	47.83%
Wilcoxon signed rank test (P-Value)	(0.2669)	(0.0678)	(0.3536)
Illiquidity factor (Illiquidity effect)			
N	**23**	**253**	**23**
Mean	**4.07%**	**0.49%**	**3.58%**
Standard deviation	**3.07%**	**2.74%**	**3.24%**
Median	**3.90%**	**0.67%**	**3.80%**
Percent positive	**95.65%**	**59.68%**	**91.30%**
Wilcoxon signed rank test (P-Value)	**(0.0001)**	**(0.0055)**	**(0.0002)**

5.4.7.2. JANUARY PREMIUMS OF ENHANCED PORTFOLIOS

To further investigate January return premiums, table 5.20 shows the January premiums of the enhanced portfolios that are described earlier in tables 5.4, 5.6, 5.8, and 5.15. As expected, January premiums are found to be positive and significant for all enhanced portfolios.

Nevertheless, interestingly, January premiums are also discovered within the *"momentum enhanced portfolio"*, which earlier is not significant for *momentum factor* in table 5.19. This discovery may be due to the introduction of illiquidity to momentum style.

Earlier research such as Ritter (1988) does highlight that low-capitalization stocks have unusually high average returns in early January compared to large-capitalization stocks, a phenomenon Ritter (1988) calls the turn-of-the-year effect. Also Haug and Hirschey (2006) highlight in their study that January premiums remain mainly a small-cap phenomenon although value factor also plays some role. This is expected as our earlier findings show that size and illiquidity factors are strongly correlated to each other.

Table 5.20: Monthly returns and risks for the month of January, other months and January Premiums of the enhanced portfolios: January 1992 to December 2014

This table shows equally-weighted, monthly returns and risks (in percentage format) for the month of January, other months and the January premiums of the enhanced portfolios, which are briefly described in table 5.4, 5.6, 5.8 and 5.16. To test the significance of the results, a Wilcoxon signed rank test is used whereby the p-value of the tests are reported in brackets and **bold** figures denote statistically significance results at least at 10% level. The sample period is from January 1992 to December 2014. All data are obtained from DataStream.

Enhanced portfolios	January	Other 11 months	January Premiums (Paired Difference)
Microcap, High illiquid			
N	**23**	**253**	**23**
Mean	**4.30%**	**1.39%**	**2.91%**
Standard deviation	**4.67%**	**5.56%**	**5.00%**
Median	**3.33%**	**1.45%**	**3.63%**
Percent positive	**82.61%**	**67.19%**	**78.26%**
Wilcoxon signed rank test (P-Value)	**(0.0007)**	**(0.0000)**	**(0.0184)**
High value, High illiquid			
N	**23**	**253**	**23**
Mean	**5.23%**	**1.50%**	**3.73%**
Standard deviation	**5.08%**	**5.99%**	**5.53%**
Median	**5.32%**	**1.34%**	**3.57%**
Percent positive	**91.30%**	**65.61%**	**78.26%**
Wilcoxon signed rank test (P-Value)	**(0.0002)**	**(0.0000)**	**(0.0037)**
High momentum, High illiquid			
N	**23**	**253**	**23**
Mean	**5.75%**	**1.50%**	**4.25%**
Standard deviation	**6.15%**	**5.94%**	**5.71%**
Median	**4.68%**	**1.64%**	**3.92%**
Percent positive	**86.96%**	**63.24%**	**82.61%**
Wilcoxon signed rank test (P-Value)	**(0.0004)**	**(0.0000)**	**(0.0013)**
High covariance, High illiquid			
N	**23**	**253**	**23**
Mean	**4.75%**	**1.37%**	**3.37%**
Standard deviation	**5.04%**	**5.85%**	**5.31%**
Median	**5.12%**	**1.75%**	**4.04%**
Percent positive	**86.96%**	**64.43%**	**78.26%**
Wilcoxon signed rank test (P-Value)	**(0.0007)**	**(0.0000)**	**(0.0102)**

5.4.7.3. JANUARY PREMIUMS OF THE ILLIQUIDITY AND VALUE/GROWTH INTERSECTIONS

Since illiquidity is the focus of the research, we will be concentrating on whether illiquidity plays any role on January premiums of the other styles.

Table 5.21 shows equally-weighted returns and risks for the January premiums of the Value/Growth and illiquidity intersection portfolios. The table shows that January premiums are present in the *"high illiquid"* portfolios (first column) while across *"high value"* portfolios (first row), there is no consistent pattern of significant January return premiums. Moreover, it can be observed that there are no January premiums for the *"high liquidity"* portfolios (last column). Thus, signifying that January premiums is more related to illiquidity than value style.

Table 5.21: Monthly returns and risks for the January return premiums of the value/growth and illiquidity intersection portfolios: January 1992 to December 2014
This table shows equally-weighted, monthly returns and risks (in percentage format) for the January return premiums of the Value/Growth and illiquidity intersection portfolios. To test the significance of the results, a Wilcoxon signed rank test is used whereby the p-value of the tests are reported in brackets and **bold** figures denote statistically significance results at least at 10% level. The sample period is from January 1992 to December 2014. All data are obtained from DataStream.

Cross Section	High Illiquid	Mid Illiquid	Mid Liquid	High Liquid
High Value Portfolio				
n	**23**	23	23	23
Mean	**3.73%**	0.93%	0.83%	0.65%
Standard deviation	**5.53%**	5.28%	5.87%	7.61%
Median	**3.57%**	2.08%	1.37%	1.34%
Percent positive	**78.26%**	60.87%	56.52%	60.87%
Wilcoxon signed rank test (P-Value)	**(0.0037)**	(0.1103)	(0.3229)	(0.4748)
Mid Value Portfolio				
n	**23**	23	23	23
Mean	**1.75%**	-0.11%	-0.22%	-1.28%
Standard deviation	**4.61%**	5.58%	4.58%	5.42%
Median	**3.42%**	0.98%	-0.33%	-0.40%
Percent positive	**73.91%**	56.52%	47.83%	43.48%
Wilcoxon signed rank test (P-Value)	**(0.0914)**	(0.8671)	(0.8911)	(0.3860)
Mid Growth Portfolio				
n	**23**	23	23	23
Mean	**2.40%**	1.42%	0.90%	-0.98%
Standard deviation	**5.54%**	5.51%	4.62%	5.33%
Median	**3.88%**	2.80%	1.49%	-0.12%
Percent positive	**69.57%**	65.22%	65.22%	43.48%
Wilcoxon signed rank test (P-Value)	**(0.0658)**	(0.2541)	(0.3536)	(0.6373)

High Growth Portfolio				
n	23	**23**	**23**	23
Mean	0.61%	**1.49%**	**0.84%**	-1.07%
Standard deviation	5.18%	**4.89%**	**4.36%**	4.38%
Median	3.21%	**2.41%**	**1.78%**	0.29%
Percent positive	60.87%	**69.57%**	**69.57%**	56.52%
Wilcoxon signed rank test (P-Value)	(0.3229)	**(0.0752)**	**(0.2416)**	(0.4562)

5.4.7.4. JANUARY PREMIUMS OF THE ILLIQUIDITY AND SIZE INTERSECTIONS

To confirm the results in table 5.21, we will investigate the intersection between the size and illiquidity portfolios in table 5.22, which is also the equally-weighted returns and risks for the January premiums of the intersection.

Interestingly, although size and illiquidity are earlier found to be highly correlated to each other, table 5.22 shows that January premiums are present in the *"high illiquid"* portfolios (first column) while across *"micro only"* portfolios (first row), there is no significant January premiums other than the first column, which is probably due to the high illiquidity. Moreover, it can be observed that there are also no January premiums for the *"high liquid"* portfolios (last column). Therefore, demonstrating that January premiums is also more associated to illiquidity than size.

Table 5.22: Monthly returns and risks for the January return premiums of the size and illiquidity intersection portfolios: January 1992 to December 2014

This table shows equally-weighted, monthly returns and risks (in percentage format) for the January return premiums of the size and illiquidity intersection portfolios. To test the significance of the results, a Wilcoxon signed rank test is used whereby the p-value of the tests are reported in brackets and **bold** figures denote statistically significance results at least at 10% level. The sample period is from January 1992 to December 2014. All data are obtained from DataStream.

Cross Section	High Illiquid	Mid Illiquid	Mid Liquid	High Liquid
Micro Portfolio				
n	**23**	23	13	3
Mean	**2.91%**	0.01%	2.49%	-1.86%
Standard deviation	**5.00%**	5.90%	10.89%	6.57%
Median	**3.63%**	0.46%	1.13%	-1.06%
Percent positive	**78.26%**	56.52%	69.23%	33.33%
Wilcoxon signed rank test (P-Value)	**(0.0184)**	(0.6373)	(0.4420)	(0.7893)

Small Portfolio				
n	**23**	23	22	7
Mean	**2.08%**	0.94%	1.32%	-1.00%
Standard deviation	**5.08%**	4.71%	5.87%	9.63%
Median	**2.56%**	0.95%	1.78%	1.16%
Percent positive	**78.26%**	69.57%	63.64%	71.43%
Wilcoxon signed rank test (P-Value)	**(0.0534)**	(0.3229)	(0.1832)	(0.3525)
Medium Portfolio				
n	**23**	23	23	19
Mean	**1.84%**	1.40%	0.46%	-0.47%
Standard deviation	**4.89%**	4.88%	4.61%	7.12%
Median	**0.98%**	2.68%	0.96%	-0.49%
Percent positive	**69.57%**	73.91%	65.22%	47.37%
Wilcoxon signed rank test (P-Value)	**(0.0974)**	(0.1759)	(0.4380)	(0.8248)
Big Portfolio				
n	9	15	23	23
Mean	6.56%	-0.52%	-0.45%	-1.07%
Standard deviation	11.60%	9.70%	4.82%	4.80%
Median	1.25%	-2.47%	-0.44%	0.10%
Percent positive	66.67%	33.33%	47.83%	56.52%
Wilcoxon signed rank test (P-Value)	(0.2863)	(0.5509)	(0.9394)	(0.7495)

5.4.7.5. JANUARY PREMIUMS OF THE ILLIQUIDITY AND MOMENTUM/CONTRARIAN INTERSECTIONS

Table 5.23 shows the equally-weighted returns and risks for the January premiums of the intersections of momentum/ contrarian and illiquidity portfolios. As expected and similar to before, table 5.23 shows that January premiums is more related to illiquidity, as positive and significant results can be found under *"high illiquid"* portfolios (first column) while the *"high liquid"* portfolios (last column) does not show any January return premiums.

Obviously, since the momentum factor is the only investment factor that does not show any January premiums in table 5.19, we do not expect for it to show any significant patterns across the high momentum portfolios (row) in table 5.23. Nevertheless, it does report positive and significant results under *"mid-illiquidity portfolio"* as well but

compared to illiquidity, the January premiums for momentum is less consistent, further confirming that January premium is an illiquidity phenomenon.

Table 5.23: Monthly returns and risks for the January return premiums of the momentum/contrarian and illiquidity intersection portfolios: January 1992 to December 2014
This table shows equally-weighted, monthly returns and risks (in percentage format) for the January return premiums of the momentum/contrarian and illiquidity intersection portfolios. To test the significance of the results, a Wilcoxon signed rank test (or sign test) is used whereby the p-value of the tests are reported in brackets and **bold** figures denote statistically significance results at least at 10% level. The sample period is from January 1992 to December 2014. All data are obtained from DataStream.

Cross Section	High Illiquid	Mid Illiquid	Mid Liquid	High Liquid
High Momentum Portfolio				
n	**23**	**23**	23	23
Mean	**4.25%**	**1.76%**	1.68%	-0.11%
Standard deviation	**5.71%**	**4.57%**	5.13%	5.36%
Median	**3.92%**	**2.33%**	1.34%	0.27%
Percent positive	**82.61%**	**73.91%**	60.87%	52.17%
Wilcoxon signed rank test (P-Value)	**(0.0013)**	**(0.0703)**	(0.1664)	(0.8671)
Mid Momentum Portfolio				
n	**23**	23	23	23
Mean	**1.95%**	0.35%	0.48%	-1.25%
Standard deviation	**4.33%**	4.83%	4.29%	4.71%
Median	**2.66%**	1.53%	1.14%	-0.29%
Percent positive	**73.91%**	65.22%	60.87%	43.48%
Wilcoxon signed rank test (P-Value)	**(0.0372)**	(0.5132)	(0.5132)	(0.3536)
Mid Contrarian Portfolio				
n	23	23	23	23
Mean	1.35%	0.63%	-0.12%	-2.14%
Standard deviation	4.75%	5.58%	4.69%	5.68%
Median	2.44%	0.95%	0.67%	-0.74%
Percent positive	65.22%	60.87%	52.17%	39.13%
Wilcoxon signed rank test (P-Value)	(0.1858)	(0.6373)	(0.6158)	(0.2180)
High Contrarian Portfolio				
n	**23**	23	23	23
Mean	**3.08%**	0.68%	0.05%	-0.11%
Standard deviation	**5.50%**	6.90%	5.81%	7.14%
Median	**3.41%**	2.47%	0.15%	1.41%
Percent positive	**78.26%**	52.17%	60.87%	52.17%
Wilcoxon signed rank test (P-Value)	**(0.0156)**	(0.3536)	(0.7038)	(0.8196)

5.5. CONCLUSION

Investors have always wanted to find ways to beat the market and thus various investment styles have been established and some of the popular ones are value (Fama & French, 1992) and momentum (Jegadeesh & Titman, 1993). Recently, illiquidity has gained importance probably due to the financial crisis but its classification as an investment style has not been recognised even though researchers such as Amihud and Mendelson (1986) find evidence to suggest that returns are an increasing function of illiquidity. Moreover, Ibbotson et al. (2013) state that illiquidity has the most obvious connection to valuation, as investors will pay more for more liquid stocks and less for less liquid stocks and thus there should be an illiquidity premium. Therefore, we feel that it is time to conduct such a research on the UK market using Ibbotson et al. (2013) framework which is based on Sharpe (1992) benchmark criteria of *1) identifiable before the fact, 2) not easily beaten, 3) a viable alternative,* and *4) low in cost.*

The first criterion of *"identifiable before the fact"* is met by using the prior year (*t-1)* related style measure to construct and calculate the results of the quartiles (or portfolio) for a given year *(t)*. For the traditional style measures, we have decided to use P/B ratio (value), MV (size) and annualised returns (momentum). For measuring illiquidity, we have decided to use *Amihud illiquidity measure* (Amihud, 2002) because it is simple and provides the most consistent results when we compare against other liquidity measures.

The second criterion is *"not easily beaten"* and we compare the results of the 3 investment styles with illiquidity. The investigation also provides us with the opportunity to revisit whether the different investment styles perform well within UK. Our results show that value premium, size premium and even illiquidity have positive and significant results while momentum style performs better than contrarian style but the results are insignificant.

Nevertheless, our primary objective is to investigate whether illiquidity meets the second criterion. An illiquidity premium does exist and it is only smaller to size premium. The top illiquid portfolio is also able to beat the benchmarks of *FTSE All Share index* and *3 months LIBOR*.

Similar to Ibbotson et al. (2013), we also decide to conduct further analysis by looking at the risk factors of the styles using financial models namely CAPM, Fama-French 3 factor model and Carhart 4 factor model. The results show that the long only "*illiquid portfolio"*

is able to generate positive and significant alpha based on all three models. Therefore, we consider the illiquidity portfolio as *"not easily beaten"*, meeting the second criterion of Sharpe (1992) benchmark requirement.

"A viable alternative" is the third criterion of benchmark requirement. In fact, illiquidity can even be considered as meeting the third criterion as illiquidity is able to outperform the benchmarks and momentum style. However, the illiquidity premium can also be due to the other investment styles. To shed light on this, we decide to construct double sorted illiquidity portfolios with the other styles. Illiquidity is able to enhance the returns of both value and momentum styles. Actually, the enhanced momentum portfolio of "*high momentum & high illiquid portfolio"* moves from the weakest to the best performing, after being intersected with illiquidity. Furthermore, the enhanced momentum portfolio also outperforms the other portfolios based on risk-adjusted measures of Sharpe ratio, Treynor ratio and Information ratio.

Moreover, using the three financial models, the results show that all enhanced portfolios are able to generate positive and significant alpha based on the CAPM but only the "*high momentum & high illiquid portfolio"* is able to generate positive significant monthly alpha for all three models. Therefore, further confirming that illiquid have met the third benchmark criterion of *"a viable alternative"*.

"Low in cost" is the fourth and last benchmark criteria of Sharpe (1992) and our results show that 78.45% of illiquid stocks remain in their quartile which is better than value and momentum portfolios, while the *top "high illiquid portfolio"* have around 76.99% of stocks staying in their quartile. This is evidence that illiquid portfolios can be managed at a low cost and consequently meeting the fourth criterion. Moreover, it also signifies that the portfolios can be managed passively and investors can gain higher net returns as they can save on the additional transaction costs[92] especially since Carhart (1997) mentions that transaction costs have a negative impact on fund's performance.

[92] As highlighted in the previous chapter, it is important to consider costs as Carhart (1997) signifies that investment costs of expense ratios, transaction costs and load fees all have a direct, negative impact on funds' performance. For instance, a study by S&P Dow Jones Indices in 2016 shows that about 90 percent of active stock managers failed to beat their index targets over various periods, of which fees explain a significant part of the underperformance (Stein, 2017). This is not surprising, as a typical active fund and passive fund at Fidelity Investments may charge 70 cents and 5 cents respectively for every $100 invested (Stein, 2017). However, trading costs can be mitigated through longer horizons and less trading (Ibbotson et al., 2013). Therefore, the stability of our illiquidity portfolios suggests that the negative impact from transaction (trading) costs can be reduced and there is profitability potential of our portfolios for investors.

Nevertheless, our *"high momentum & high illiquid portfolio*" is the best strategy for fund managers to utilize in the UK, which is different from Ibbotson et al. (2013) whose evidence indicate that *"high value & high illiquid portfolio*" will be better for fund managers in the US.

We also find evidence to suggest that although using financial models (or *"covariance model"*) are common in finance, it is discovered that "*characteristics model"* (e.g. financial ratios) may be the best way to construct illiquidity portfolios as it provides consistent results.

A brief study on January premiums is also conducted since past literature consistently indicates the existence of a seasonal effect for all investment styles. Our results show that the January effect is not present on the market level and momentum factor but it does exist under the other styles, while our double sorted portfolios on the three styles signify that the January premium is mainly an illiquidity phenomenon.

Overall, our results do prove that illiquidity, as represented by *Amihud Illiquidity measure*, meets all four criteria of Sharpe (1992) benchmark requirements. Therefore, we fully agree with Ibbotson et al. (2013) that illiquidity can be considered as an alternative investment style in equal standing with the other investment styles and it appears to reward investors who particularly have long horizons.

Nevertheless, similar to our study in the previous chapter, one finding that must be treated with caution is the strong positive correlation between size and illiquidity. Thus, using the longer period of 23 years does not improve results, as the strong relationship between size and illiquidity still remains. This comes into contrast with Ibbotson et al. (2013), signifying that the favourable performance of illiquidity may actually be due to size. Eleswarapu and Reinganum (1993) also highlight similar results but Elfakhani (2000) believes that the size premium may actually be due to illiquidity.

Moreover, our results are weaker in comparison to Ibbotson et al. (2013), probably due to the different liquidity measure used as well as the different characteristics of UK and US markets such as the lower volatility in the UK market relative to the US market (Bartram et al., 2012) since the lower level of volatility will definitely affect prices and

consequently individual and market liquidity (See Stoll (1978), Vayanos (2004), Hameed et al. (2010) and Amiram, Cserna, and Levy (2015))[93]

Further studies need to be conducted in different geographical areas but we believe that illiquidity still has its merits as an investment management tool and choosing an investment style actually depends on investors' preference. Since the latest crisis is partly attributed on the illiquidity of financial markets, it is anticipated that investors will expect more compensation for the illiquidity risk of holding stocks longer.

[93] Stoll (1978) shows that bid-ask spreads (liquidity) are positively affected by return volatility. Vayanos (2004) finds that during volatile times, investors reduce their willingness to hold illiquid assets, illiquidity premia increases followed by market betas of illiquid assets. Hameed et al (2010) mention that negative market returns decrease stock liquidity, with the effect being strongest for high volatility firms and during times of market funding tightness. Hameed et al (2010) also document that market volatility affect liquidity commonality positively. Amiram et al (2015) discover that the positive relationship between volatility and illiquidity is mainly due to 'a jump component' (infrequent, large isolated surprise price changes) while a negative relationship between illiquidity and diffusive volatility (smooth and expected small price changes) also exists, where the latter is commonly perceived as "volatility". Overall, it shows that there is a relationship between volatility and liquidity, which will obviously result in different findings for us compared to Ibbotson, Chen et al (2013), due to the difference in market volatility between the UK and the US.

CHAPTER 6 : MULTIPLE COUNTRIES RESPONSE TO OIL PRICE SHOCKS AND ILLIQUIDITY SHOCKS

6.1. INTRODUCTION

Due to the significance of crude oil, there are various studies that investigate its impact on financial markets, instruments and the economy. Hamilton (1983) studies its effect on the US economy while Sadorsky (1999) studies its relationship with stock markets. Hamilton (2011) highlights that out of eleven US recessions, ten US recessions are preceded by significant rises in oil price. Thus, it does indicate the importance of crude oil to the macro-economy.

There are also studies that highlight the relationship between illiquidity and the macro-economy such as Fujimoto (2004) who studies the US market and finds evidence that macroeconomic fundamentals appear to be significant determinants of liquidity. However, recently, some studies have emerged that show an inverse relationship. Liquidity appears to affect macroeconomic variables. For instance, Næs et al. (2011) mention that market liquidity contains useful information for estimating the current and future state of the US and Norwegian economy while Galariotis and Giouvris (2015) expand this line of research by studying G7 countries. Therefore, similar to oil, liquidity appears to have an impact on the economy.

Interestingly, both oil and liquidity are linked to the recent financial crisis of 2007-2008. In relation to oil, Taylor (2009) mentions that oil price increases have prolonged the financial crisis while Tverberg (2012) mentions that if the world oil supply continues to remain generally flat, a continuing financial crisis can be expected. With regards to liquidity, it is more obvious as some researchers even refer to the financial crisis as either liquidity crisis or crunch (Iyer et al., 2014). Crotty (2009) highlights that financial deregulation, complex financial products, liquidity dry-outs and investors running for liquidity and safety as some of the reasoning for the crisis. Cornett et al. (2011) mention that efforts to manage the liquidity crisis by banks led to a decline in credit supply. Nevertheless, Campello, Giambona, Graham, and Harvey (2011) indicate that credit lines on corporate spending ease the impact of the financial crisis. Generally, both oil and liquidity appear to have some connection to the recent financial crisis which require further investigation as to their ability to predict business cycles.

Furthermore, researchers have also acknowledged the connection of the two variables. For instance, Gupta (2008) assesses the relative oil vulnerability of 26 net oil-importing countries on the basis of various indicators such as exposure to geopolitical oil market concentration risks, as measured by a number of variables including market liquidity (size of domestic demand relative to world supply).

Alper and Torul (2008) show that for a small open economy such as Turkey, the inclusion of the global liquidity conditions (FFR and VIX)[94] is important when investigating the relationship between aggregate economic activity and oil price changes. Ratti and Vespignani (2013) research the effect of liquidity (measured by money supply, M2[95]) in China and in developed economies (US, Eurozone and Japan) on the real oil price and they find evidence that relative to developed economies, the cumulative impact of China's real M2 on the real price of crude oil is large and statistically significant, signifying the relative importance of China in the upsurge of the real price of crude oil.

Although Gupta (2008) Alper and Torul (2008) and Ratti and Vespignani (2013) define liquidity differently, their research shows the potential of conducting research using liquidity and oil variables. Moreover, since there are findings to link oil price and stock markets (Filis et al., 2011), it is expected that researching oil and market liquidity (based on stock markets) will provide meaningful results, which would be interesting for the readers, both academics and practitioners.

Moreover, we believe on the significance of researching asymmetric effects[96] on oil. Initially, research on oil such as Hamilton (1983) tends to focus only on oil price increases. Mork (1989) also investigates oil price decreases but his research finds statistically significant results only for oil price increases. Nevertheless, Engemann et al. (2014) study all 50 US states plus the District of Columbia (DC) and they discover that around 35 states are affected by positive oil price shocks only[97].

[94] The Fed Funds Rate (FFR) and the implied volatility of the S&P 500 index options (VIX) are used as measures of global liquidity.
[95] M2 is a measure of the money supply that includes all elements of M1 and "near money." M1 includes cash and checking deposits, while near money refers to savings deposits, money market securities, mutual funds and other time deposits. Near money assets are less liquid than M1 and not as suitable as exchange mediums, but they can be quickly converted into cash or checking deposits (M2, n.d.).
[96] Similar to Engemann, Owyang et al. (2014), we define an asymmetric effect when a country responds to either positive or negative oil price shocks while a symmetric effect occurs when a country responds to both shocks (positive and negative) or does not respond at all.
[97] Oil price shocks are calculated by comparing the current oil price with where it has been over the previous one (1) year or previous four (4) quarters as proposed by Hamilton (1996). For instance, positive oil price shocks are calculated as below (Engemann, Owyang et al., 2014):

$$\Delta x_t^+ = max\left\{0, 100 \times ln\frac{x_t}{max(x_{t-1}, x_{t-2}, x_{t-3}, x_{t-4})}\right\} \quad (6.1)$$

Where x_t is crude oil Brent price at quarter t and $x_{t-1}, x_{t-2}, x_{t-3}, x_{t-4}$ are the crude oil Brent price of the previous four (4) quarters.

Similar to oil, we feel that there are potential asymmetric effects as far as illiquidity is concerned. In their UK market study, Said and Giouvris (2017) discover that the reaction of liquidity after restrictive monetary shifts appears to be less noticeable compared to expansive monetary shifts. This signifies potential asymmetric effects of positive and negative illiquidity shocks [98] on the economy. Even though research on liquidity asymmetries will be interesting and beneficial within the current environment, surprisingly, there is actually limited research available. We aim to close this gap.

One important findings of Engemann et al. (2014) is that the most energy intensive US states appear to respond only to negative oil price shocks. Hence, it appears that the characteristics of the states or countries are also important in relation to oil price shocks research. However, for some reason, past studies seldom differentiate between oil exporting countries and oil importing countries, which is also highlighted by Wang et al. (2013). Due to this, we feel that it will be beneficial to investigate the effect of oil price shocks on the economies of net oil exporting countries and net oil importing countries.

We decide to use Engemann et al. (2014) framework, as it is closely related to our intended research. However, instead of using US states, we will be using eleven countries as part of our data sample, which is categorised as net oil exporting and net oil importing countries. Based on our analysis, five countries are categorised as net oil exporters and six as net oil importers. Furthermore, instead of using payroll employment, we decide to use *Gross Domestic Products (GDP)* as a proxy of macroeconomic activity because it is readily available for the countries in our sample.

We also briefly cover national oil price shocks, which is the specific country's currency conversion of USD[99] crude oil prices, as Cunado and De Gracia (2005) highlight that the significant effect of oil price shocks on macroeconomic variables becomes more significant when the shocks are defined in local currencies.

Overall, categorising the chosen countries into net oil exporting countries and net oil importing countries does provide some valuable insights, as net oil exporters (e.g. Brazil) and net oil importers (e.g. Germany) appear to benefit from positive oil price shocks and negative oil price shocks respectively. However, our results for asymmetric effects is

Please refer to data and variables section for more information.

[98] Hamilton (1996) equation for calculating oil price shocks appears to be simple enough and we feel that it can be applied to measure the shocks of other variables including illiquidity shocks.

[99] United States Dollar

contradictory to past research such as Engemann et al. (2014), as most countries in our sample respond to negative oil price shocks instead of positive oil price shocks. Furthermore, nationalising oil price shocks does not appear to provide any obvious improvement in results when testing for asymmetric effects while illiquidity shocks seem to exhibit clearer results.

The remainder of this paper is organised as follows. Section 6.2 presents the literature review while section 6.3 describes the data and variables. In section 6.4, the methodology, empirical results and analysis of the research are discussed followed by our conclusion in section 6.5.

6.2. LITERATURE REVIEW

6.2.1. OIL PRICE SHOCKS AND ECONOMY

In relation to oil and macroeconomic research, one of the earliest key studies is conducted by Hamilton (1983) who highlights that there is a significant increase in the price of crude petroleum prior to seven of the eight post world-war II recessions in the US. Nonetheless, although this does not automatically signify that oil price shocks cause the recessions, oil price shocks are found to be at least a contributing factor, as evidence indicates that over the period between 1948 and 1972, this correlation is statistically significant and non-spurious.

Hamilton (1996) reiterates his research on US data and the evidence has actually strengthened since Hamilton (1983), as his recent data is consistent with the historical correlation between oil price shocks and recessions. This is further confirmed in his more recent research also on the US economy (see Hamilton (2003) and Hamilton (2009)). In fact, Hamilton (2011) updates the count to ten out of eleven US recessions being preceded by significant rises in oil price. With the additional three rises occurring in the fall of 1990, 1999-2000 period and 2007–2008 period. As also highlighted in Hamilton (1983), the only exceptional recession is between 1960 and 1961, as there is no preceding rise in oil prices.

As observed, Hamilton's studies are more focused on the US economy and hence, it is important to explore other countries as well such as Cuñado and de Gracia (2003) who study fifteen European countries. Using quarterly data for the period between 1960 and

1999, Cuñado and de Gracia (2003) find a relationship between oil price shocks and macroeconomic variables such as inflation and industrial production indexes. However, they also find differential evidence of the effects of oil price shocks on each of the European countries.

Cunado and De Gracia (2005) conduct similar research on six Asian countries namely Japan, Singapore, South Korea, Malaysia, Thailand and the Philippines between 1975(Q1) and 2002(Q2). Their research suggests that oil prices have a significant effect on both economic activity and price indexes, especially when oil price shocks are in national currencies. Farzanegan and Markwardt (2009) also show the expected vulnerability of the Iranian economy to oil price fluctuations. Nevertheless, Chang and Wong (2003) highlight that the impact of oil price shocks on the Singapore economy is marginal but should not be considered negligible even though it is small.

Research is not limited to the impact of oil on the macro-economy but also on financial markets. For instance, Jones and Kaul (1996) highlight that changes in oil prices have a detrimental effect on output and real stock returns in the US, Canada, Japan and the UK during the post-war period but for both the UK and Japan results are less rational compared to US and Canada. Moreover, Sadorsky (1999) finds evidence that oil price and oil price volatility both play important roles in affecting real stock returns by studying the US market while Cunado and de Gracia (2014) who study twelve oil importing European countries suggest the existence of a negative and significant impact of oil price changes on most European stock market returns.

However, by examining the dynamic linkages between crude oil price shocks and stock market returns in 22 emerging economies, Maghyereh (2006) finds evidence inconsistent with prior research on developed economies, as their findings imply that oil price shocks have no significant impact on stock index returns. Furthermore, their results also suggest that stock market returns in these economies do not rationally signal shocks in the crude oil market.

Overall, past literature appears to show that crude oil does impact the economy of countries as well as financial markets. However, the degree of development of each country seems to show that there are some differences on how countries react towards crude oil. Even the classification of a country as an oil importer/exporter appears to be

important. For instance Singapore is only marginally impacted (Chang & Wong, 2003) while Iran is highly vulnerable to oil price fluctuations (Farzanegan & Markwardt, 2009).

6.2.1.1. ASYMMETRY DUE TO OIL SHOCKS

Nowadays, research is focusing on the asymmetric effects of oil price shocks on the economy and the financial markets. One of the prominent earlier studies is conducted by Mork (1989), as an extension of Hamilton (1983) studies on the US economy. Unlike Hamilton (1983), Mork (1989) also looks into oil price decreases. His research highlights that positive oil price changes have a significant negative effect on the US macro-economy measured using GNP, while oil price declines tend to have a small positive but statistically insignificant effect, indicating an asymmetric effect.

Mork et al. (1994) expand their research by covering seven *Organisation for Economic Co-operation and Development (OECD)* countries namely US, Canada, Japan, Germany (West), France, UK and Norway. Their results indicate that the correlations between *oil price increases* and growth are negative and significant for their sample (with the exception of Norway), while *oil price decreases* are mostly positively correlated with growth. Oil price reductions appear to have adverse effects on the business cycle for oil exporters. However, the adverse effect from an oil price decrease is only significant for the US and Canada which are oil exporters. Mork et al. (1994) highlight that asymmetry is not confined to the US, as most countries show evidence of asymmetric effects, with the exception of Norway. This is not surprising as the oil producing sector of Norway is large relative to the economy as a whole. Their results also confirm that oil-price fluctuations are important for the shaping of business cycles of the leading market economies.

Mork (1994) further reaffirms this by surveying oil market events and their relation to macroeconomic variables. He concludes that by considering sectoral imbalance, oil price increases seem to hurt aggregate activity while price declines do not appear to help. Other studies that focus on the asymmetric effects of oil price shocks on the macro-economy are conducted by Lee et al. (1995) and Ferderer (1996). They both study US data while also considering oil price variability and volatility respectively. Cuñado and de Gracia (2003) also consider asymmetric effects of oil price shocks but on fifteen European countries.

Recently, more research has been conducted on other regions focusing also on developing countries. Cunado and De Gracia (2005) study six Asian countries, finding evidence of asymmetric effects in the *oil prices–macro economy relationship* for some of the Asian countries. In relation to the *oil price changes–inflation rate relationship*, Japan, Thailand, South Korea and Malaysia show an asymmetric effect, while for *oil price changes–economic growth rate relationship*, only South Korea is impacted.

Farzanegan and Markwardt (2009) study Iran, one of the largest oil producers and a net oil exporting country, whose economy depends significantly on oil exports. By investigating the dynamic relationship between oil price shocks and major macroeconomic variables, Farzanegan and Markwardt (2009) highlight the asymmetric effects of oil price shocks. Interestingly, one of their findings indicates that both positive and negative oil price shocks significantly increase inflation.

Nevertheless, using US data between 1973 (Q2) and 2007 (Q4), Kilian and Vigfusson (2011) show empirically that there is no statistically significant evidence of asymmetry in the response functions of real GDP towards unanticipated changes in the real oil price. They highlight that both symmetric and asymmetric models correctly compute impulse responses of roughly the same magnitude in either positive or negative shocks.

Using US employment growth as a macroeconomic variable, Engemann et al. (2014) show some contradictory results to asymmetric effects. Their study of fifty US states (plus DC) discover that although most states are affected by positive shocks only, ten states experience symmetric responses, five states respond to both shocks and another five states respond to neither shocks. They also find evidence that five states show an asymmetric effect of responding only to negative oil price shocks.

Overall, the literature above shows that there are instances where symmetric responses do actually exist. Kilian and Vigfusson (2011) show a symmetric effect in their study of the US economy while Engemann et al. (2014) find symmetric effect evidence on some of the US states. Furthermore, Mork et al. (1994) highlight that only Norway shows evidence of symmetric effects, which is probably due to Norway's large oil-producing sector. Therefore, the classification of a country as oil exporter/importer may have some impact on the asymmetric effect results.

6.2.1.2. CHARACTERISTICS OF THE COUNTRY'S OIL INDUSTRY AND THE MACRO ECONOMY.

Although there appear to be some differences in the relationship between net oil exporting countries and net oil importing countries, such studies are still limited. For instance, Cunado and De Gracia (2005) find evidence that Malaysia's *oil prices–macro economy relationship* seems to be less significant compared to five other Asian economies, as Malaysia is the only oil-exporting country in their sample. However, Cunado and De Gracia (2005) mention that further research is needed to obtain a more reliable conclusion, even though their results seem to suggest that there are different responses between oil exporters and oil importers.

Mork et al. (1994) obtain results which show that although the US is less dependent on imported oil compared to countries like Germany, France and Japan, US is more vulnerable to oil price increases. Nonetheless, Norway, an oil-exporting country, behaves differently, as its economy benefits significantly from oil price increases and seems to be hurt by price declines but somewhat less significantly. The different behaviour for Norway[100] suggests that the domestic oil sector is large enough relative to the size of the economy, resulting in the country's net oil exporting position to influence the *oil price-GDP correlation* substantially (Mork et al., 1994). Furthermore, Engemann et al. (2014) highlight that apparently the US states that only respond to negative oil-price shocks are generally energy-intensive US states.

It appears that the characteristics of the countries or states are important in relation to the impact of oil price shocks but past studies seldom differentiate between oil exporting countries and oil importing countries, which is highlighted by Wang et al. (2013). Even though they differentiate between oil exporting and importing countries, their research focuses on the relationship between oil price shocks and stock markets, not the macro-economy. This is clearly a gap in the literature, highlighting the potential of conducting research that concentrates on the macro-economy.

[100] Furthermore, the reason that Norway is affected less when the oil price declines even though it is an oil exporter is because the government uses all wealth accumulated in previous years to boost the macro economy of the country when revenue from selling oil diminishes.

6.2.2. MARKET LIQUIDITY AND THE MACRO-ECONOMY

As highlighted earlier, our research looks into the effect of liquidity shocks on the macro-economy. There are various studies that investigate the relationship between market liquidity and the macro-economy of countries. However, the initial common theme is how macroeconomic variables affect market liquidity. Chordia et al. (2001) discover that market liquidity increases prior to major macroeconomic announcements by studying the effects of several explanatory variables (including macroeconomic announcements[101]) on aggregate market spreads, depths and trading activity for US stocks from 1988 to 1998. Fujimoto (2004) who also studies the US market obtains similar results as macroeconomic fundamentals are significant determinants of liquidity and their effects are stronger prior to the mid 1980's when business cycle dynamics are more volatile.

There is also similar research conducted on other markets. Söderberg (2008) tests the ability of fourteen macroeconomic variables' such as monthly inflation rate to forecast changes in market liquidity in the Scandinavian order-driven stock exchanges[102]. Said and Giouvris (2017) study the UK market by focusing on the impact of monetary conditions (measured using interest rates) on market liquidity.

Nevertheless, recently, more studies have emerged on the reverse relationship that is the impact of liquidity on macroeconomic variables. Næs et al. (2011) highlight that market liquidity contains useful information for estimating the current and future state of the US and Norway economy. Galariotis and Giouvris (2015) expand this line of research by studying G7 countries and they show that liquidity may contain some information for predicting the current and future state of the economies but it is found to be more country specific and liquidity-variable dependent.

Sung and Giouvris (2016) also conduct a similar study on Asia-Pacific countries but they segregate their data into developed and developing markets. Sung and Giouvris (2016) finds that some of their liquidity variables are able to predict macroeconomic variables but are not consistent over the 6 countries in their sample. Additionally, they find no causality between macro-variables and global liquidity in developed markets but a one-

[101] Their study focuses on macroeconomic variables such as Gross Domestic Product (GDP), the unemployment rate and the Consumer Price Index (CPI).
[102] Söderberg (2008) studies three Scandinavian order-driven stock exchanges namely Copenhagen (Denmark), Oslo (Norway) and Stockholm (Sweden) stock exchanges.

way causality from macro-variables to global liquidity in developing markets, signifying that the two markets react differently to liquidity variables.

6.2.2.1. ILLIQUIDITY SHOCKS AND THE ECONOMY

So far the literature does confirm that there is a relationship between macroeconomic variables and liquidity, indicating that there should also be a relationship between business cycles and liquidity. Nevertheless, unlike oil price shocks which have been linked to the state of the economy, there is less literature available regarding illiquidity shocks. Ellington et al. (2016) highlight that to the best of their knowledge, there is no empirical investigation on the effects of liquidity shocks on the real economy, as most literature focus on explanatory and forecasting performance (See Næs et al. (2011)). However, a few studies have emerged over the years such as Choi and Cook (2006) which cover the Japanese market. They discover that liquidity shocks significantly affect macroeconomic variables. Bali et al. (2014) find that liquidity shocks are positively associated with contemporaneous stock returns in the US. However, their research covers stock market returns and not macroeconomic variables.

China has been a major contributor to global liquidity over the past twenty years. Kang, Ratti, and Vespignani (2016) study the influence of liquidity shocks in China on the US economy and their findings confirm that China's liquidity expansion has a spill-over effect on the US through the effects of world commodity markets (oil and commodities prices) and China's exchange rate regime. Kang et al. (2016) show that liquidity shocks may not only affect a country's economy but also have a spill-over effect on other countries, signifying the importance of liquidity on the state of a country's economy.

Moreover, using US data from 1970 to 2014, Ellington et al. (2016) examine the dynamic impact of liquidity shocks of stock and housing markets on real GDP growth. They find that GDP is more resilient to stock market liquidity shocks throughout time but as disruptions in the property sector start to emerge, GDP becomes highly sensitive to house market liquidity shocks. Therefore, their study shows that liquidity shocks based on other variables can also impact the economy, further demonstrating the influence of liquidity shocks on macroeconomic variables.

6.2.2.2. POTENTIAL ASYMMETRIC EFFECTS DUE TO MARKET ILLIQUIDITY

Unlike oil price shocks, there is not much research available in relation to the asymmetric effects of illiquidity shocks on the economy. Thus, we feel that there is potential in researching the asymmetric effects of illiquidity shocks.

Chordia et al. (2001) have conducted some asymmetric effect research but it is in relation to bid-ask spreads (liquidity) response to market movements. They find that both quoted and effective spreads increase dramatically in down markets, but decrease only marginally in up markets.

Bali et al. (2014) find that liquidity shocks are positively related to stock returns, indicating that positive liquidity shocks are linked to higher stock returns while negative liquidity shocks are associated with lower stock returns. Although Bali et al. (2014) conduct research closer to our intentions by covering positive and negative liquidity shocks, unfortunately, their study does not directly explore asymmetry effects. Moreover, as highlighted earlier, their research explores stock market returns and not macroeconomic variables.

Brunnermeier and Pedersen (2009) mention flight-to-quality, whereby when funding becomes scarce speculators cut back on the market liquidity provision especially for capital intensive assets. This indicates that when market liquidity decreases, the state of the economy may potentially worsen due to fewer investment projects. Rajan (2006) mentions that in times of ample liquidity supplied by the central banks, investors tend to engage in riskier investments to earn higher returns. Thus, during expansive monetary condition periods where market liquidity is expected to increase, it is likely that investors will increase their investments in riskier projects, potentially increasing economic growth. The two events of constrain and ample liquidity potentially show a symmetric effect.

Nevertheless, there appear to be contradictory results. Ellington et al. (2016) provide evidence of asymmetric effect in the response of GDP to house market liquidity shocks, as the response is stronger during the great recession than non-recessionary period. However, the asymmetric effect involves house market liquidity shocks instead of stock market liquidity shocks and the liquidity shock is actually a sudden decline of market liquidity only.

Jensen and Moorman (2010) study on the US market finds that liquidity price adjusts substantially around expansive monetary policy shifts but maintains consistency around shifts to a restrictive monetary policy. Similarly, Said and Giouvris (2017) research on UK appears to show that market liquidity increases after expansive monetary shifts but it is less noticeable during restrictive periods, indicating that investors are less concerned with liquidity. Thus, providing more evidence of potential asymmetry effect of liquidity in the US and UK.

6.3. DATA AND VARIABLES

6.3.1. DATA

Our sample consists of 11 countries namely Brazil, Canada, Denmark, France, Germany, Japan, Mexico, Norway, Singapore, UK and US for the period from January 1997 to December 2015. The time period is determined by the availability of financial markets and economic data of the respective countries.

To determine economic growth, we use *Gross Domestic Product (GDP)* of the chosen countries while oil price shocks are based on the crude oil Brent prices. We decide to use crude oil Brent because at the point of our data collection, it is considered as the most widely used oil reference (Kurt, 2015). In comparison to other benchmarks such as WTI (West Texas Intermediate), around two thirds of global crude contracts use crude oil Brent (Kurt, 2015).

Since we are also covering liquidity of stock markets, we use the main available stock indices of our chosen eleven countries. The indices that are chosen are Oslo All Share index (Norway), TSX Composite index (Canada), OMXC Index (Denmark), IPC index (Mexico), Bovespa index (Brazil), STI Index (Singapore), FTSE All Share index (UK), Prime All Share Index (Germany), Nikkei 225 (Japan), SBF120 index (France) and S&P 500 (US).

We mainly use daily data to calculate quarterly illiquidity measures. GDP is available quarterly. Before the calculation of the illiquidity measures and construction of the portfolios, the sample is initially analysed for any unsuitable data to avoid the emergence of biased results. All the data use in this paper are obtained from DataStream, Bloomberg, World Bank website and US Energy Information Administration (EIA) website.

6.3.2. HAMILTON'S SHOCK EQUATIONS

Initially, Hamilton (1983) describes oil shocks as the log change in oil prices. However, Hamilton (1996) highlights fluctuation issues, as since 1986 most of the oil price increases happen immediately after even larger oil price decreases. Thus, Hamilton (1996) proposes that it appears more appropriate to compare the current price of oil with where it has been over the previous one year (or previous four quarters) rather than the previous one quarter alone.

This is appropriate as it will only cover significant increases or decreases in oil price, which can easily be described as an oil shock. In fact, Hamilton (2003) even suggests using a three years horizon instead of one year horizon. However, for our research we will use one year horizon similar to Engemann et al. (2014), as using three years horizon will further reduce our data span. According to Engemann et al. (2014), a positive (negative) oil price shock is defined as an increase (decrease) in the current price of oil above (below) the maximum (minimum) oil price over the previous four quarters.

Therefore, positive oil price shocks are given by:

$$\Delta x_t^+ = max\left\{0, 100 \times ln\frac{x_t}{max(x_{t-1}, x_{t-2}, x_{t-3}, x_{t-4})}\right\} \quad (6.1)$$

Where $x_t$is crude oil Brent price at quarter t and $x_{t-1}, x_{t-2}, x_{t-3}, x_{t-4}$ are the crude oil Brent price of the previous four quarters.

While for negative oil price shock, Engemann et al. (2014) describe it as:

$$\Delta x_t^- = min\left\{0, 100 \times ln\frac{x_t}{min(x_{t-1}, x_{t-2}, x_{t-3}, x_{t-4})}\right\} \quad (6.2)$$

Where $x_t$is crude oil Brent price at quarter t and $x_{t-1}, x_{t-2}, x_{t-3}, x_{t-4}$ are the crude oil Brent price of the previous four quarters.

Our original sample data is between January 1997 and December 2015. Our final data for analysis will be from January 1998 to December 2015. Over the 18 years period, table 6.1 shows that there are a total of 46 oil price shocks whereby 29 are positive oil price shocks and 17 are negative oil price shocks.

Table 6.1: Number of oil price shocks after applying Hamilton's shock equations.
This table reports the number of oil price shocks from the following equations:

1. Positive oil price shocks

$$\Delta x_t^+ = max\left\{0, 100 \times ln\frac{x_t}{max(x_{t-1}, x_{t-2}, x_{t-3}, x_{t-4})}\right\} \quad (6.1)$$

2. Negative oil price shocks

$$\Delta x_t^- = min\left\{0, 100 \times ln\frac{x_t}{min(x_{t-1}, x_{t-2}, x_{t-3}, x_{t-4})}\right\} \quad (6.2)$$

Where $x_t$is crude oil Brent price at quarter t and $x_{t-1}, x_{t-2}, x_{t-3}, x_{t-4}$ are the crude oil Brent price of the previous four (4) quarter. The original sample data is between January 1997 and December 2015 but after applying Hamilton's shock equations, our final data for analysis is from January 1998 to December 2015, consisting of 72 quarterly observations. All data are obtained from DataStream, Bloomberg, World Bank and US Energy Information Administration (EIA) website.

	Positive shocks	Negative shocks	Total shocks
Oil price	29	17	46

6.3.3. ILLIQUIDITY MEASURE

For illiquidity, we have decided to choose the *Amihud Illiquidity measure* (Amihud, 2002) as it is a recognisable measure, simple to calculate and has been extensively used in past literature. Amihud is calculated for each stock, s, every quarter as follows

$$Amihud_{sq} = \frac{1}{q}\sum_t \frac{1{,}000{,}000 \times |return_t|}{price_t \times volume_t} \quad (6.3)$$

Where t is each trading day.

6.4. METHODOLOGY, EMPIRICAL RESULTS AND ANALYSIS

6.4.1. OIL PRICE SHOCKS AND BUSINESS CYCLES

Table 6.2 provides more information on our chosen eleven countries. It shows that five countries are net oil exporting countries and the other six are net oil importing countries including the US. This table is constructed using the most recently available data of 2012

and it reports *"oil exports", "oil imports"* and *"net oil exports"* of the countries in our sample. The table also reports the *"annual oil revenue (expenditure) to GDP ratios"* of the countries, which are calculated using Wang et al. (2013) framework. *The "annual revenue (expenditure)"* of a country's net oil exports (imports) is calculated using the following formula:

Annual revenue (expenditure) of a country's net oil exports (imports) = Daily oil exports (imports) x number of days in a year x the annual average oil price. (6.4)

Where the annual average oil price of USD112.02 is the average price per barrel for Crude oil Brent in the year 2012 obtained from DataStream and the number of days in the year 2012 is 366 days because it is a leap year.

The table indicates that Canada is a major net oil exporting country whereas US is the main net oil importing country. The *"annual oil revenue to GDP ratio"* appears to be important for Norway while Singapore's *"annual oil expenditure to GDP ratio"* is the highest in comparison to the other countries.

Table 6.2: Description of countries in our sample in the year 2012.
This table reports the oil exports, oil imports and net oil exports of oil exporting and importing countries in our sample of 11 countries based on the most recently available data of the year 2012. The table also reports the countries annual oil revenue (expenditure) to GDP ratios, which are calculated using the average Brent oil price in 2012 of US$112.02 per barrel obtained from DataStream. We calculate the revenue (expenditure) of a country's net oil exports (imports) by the following formula: Daily oil exports (imports) x number of days in a year (366 days) x the average Brent oil price (USD112.02). The calculation technique for oil revenue to GDP ratio is similar to Wang et al (2013) framework. We have also reported the GDP (US$ billion) and GDP per capita (US$) of the countries in our sample. All data are obtained from DataStream, Bloomberg, World Bank and US Energy Information Administration (EIA) website.

Countries	Crude oil			Annual oil Revenue to GDP ratio	GDP per capita (US$)	MSCI Market Classification
	Exports	Imports	Net exports			
	(Thousand Barrels per day)					
Norway	1324	28	1296	10.42%	101,563.70	Developed
Canada	2470	736	1734	3.90%	52,495.30	Developed
Denmark	137	87	50	0.63%	58,125.40	Developed
Mexico	1280	10	1270	4.39%	9,720.60	Emerging
Brazil	526	375	151	0.25%	12,157.30	Emerging
United Kingdom	710	1222	-512	-0.79%	41,538.30	Developed
Singapore	0.1	1078	-1077.9	-15.28%	54,451.20	Developed
France	1.3	1159	-1157.7	-1.77%	40,838.00	Developed
Germany	3.8	1888	-1884.2	-2.18%	44,065.20	Developed
Japan	0	3724	-3724	-2.56%	48,629.20	Developed
United States	399	9812	-9413	-2.39%	51,433.00	Developed
World (Average)					10,499.50	

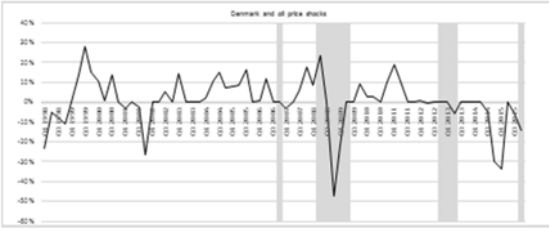
Figure 6.1: Business cycle and the oil price shocks.

The figure shows time series plots of the oil price shocks for all countries in our sample. The black lines are Hamilton-type oil-price shock variable based on oil Brent prices. A positive (negative) oil shock is defined as when the current (quarterly) oil price is above (below) the maximum (minimum) oil price over the last year (4 previous quarters). Shaded grey are recession periods and a recession period is identified as a period for which there is negative GDP growth for at least two consecutive terms. Sample range Q1 1998 to Q4 2015, 72 quarterly observations. All data are obtained from DataStream, Bloomberg, World Bank and US Energy Information Administration (EIA) website.

Norway

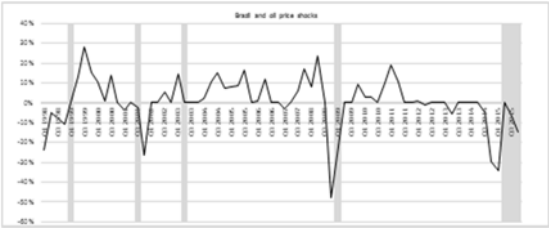
Canada

Denmark

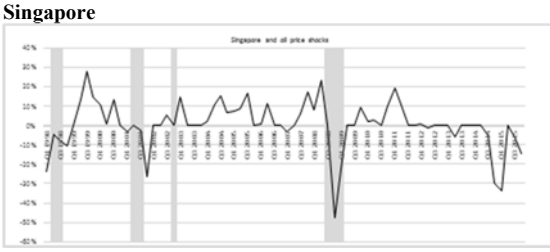


Mexico

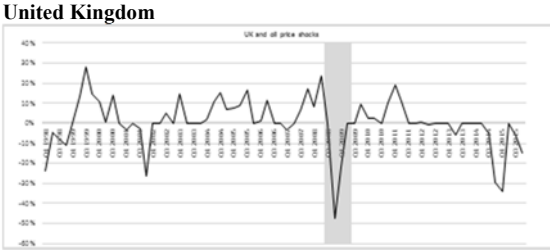
Brazil



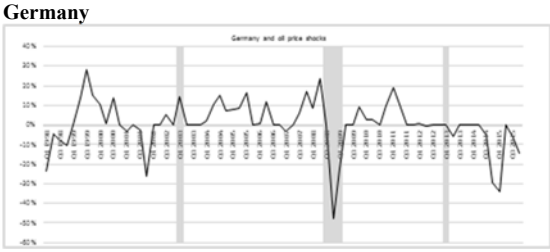
Singapore



United Kingdom



Germany



Japan

France

United States

Figure 6.1 shows time series plots of the Hamilton type oil price shocks for our chosen countries and the recession periods in our sample. We define a recession period as a period for which there is negative GDP growth for two consecutive terms. Since Engemann et al. (2014) use the *National Bureau of Economic Research (NBER)* recession periods for the US, our recession periods are different from them. However, to ensure consistency with other countries in our sample, we feel that the method of observing negative GDP growth for two consecutive terms is sufficient[103].

As expected, the figure shows that over the years, various countries have different periods of recessions. Nevertheless, although the duration period can be different, the recession period that all the countries face in our sample is the financial crisis of 2007-2008. Therefore, we will initially investigate the relationship between oil price shocks and recessions during this period.

The figure shows that generally net oil importing countries such as Singapore, UK, Germany, Japan, France and US go into recession immediately after enduring a positive oil price shock (or oil price increase). This is consistent to past studies such as Hamilton (1983), as countries tend to react to an increase in oil price. Our findings are also similar to Engemann et al. (2014) study on US states.

Interestingly, we observe that with the exception of Denmark and Mexico, recession hits net oil exporting countries with a delay. In fact, for Norway, Canada and Brazil, recession periods only happen after a negative oil price shock, which is expected to be detrimental for oil exporting countries.

Denmark and Mexico, two net oil exporting countries are probably affected earlier due to other factors. The economy of Denmark may not be too dependent on oil as among the net oil exporting countries, it exports the lowest amount of crude oil and its *"annual oil revenue to GDP ratio"* is the second lowest. Although Mexico is one of the major net oil exporters, its close proximity to the US may be the reason for the early recession period. Furthermore, US is Mexico's main trade partner for both exports and imports (World_Bank).

During other recession periods, the patterns are less noticeable for most countries. Canada and Brazil seem to confirm that negative oil shocks precede recession periods for net oil

[103] Galariotis and Giouvris (2015) also determine recession periods by observing negative GDP growth for two consecutive terms.

exporters. This pattern can be observed during the post-2015 recession period. However, Mexico appears to be the most unfortunate, as it is affected by both positive and negative oil price shocks, which seem to cause the recessions. This is also observed by Engemann et al. (2014) for the US state of New Mexico, which is classified as an energy producing state and rank among the top eight states in terms of both oil and gas production (Snead, 2009).

6.4.1.1. OIL PRICE SHOCKS COEFFICIENT

To further investigate the effect of oil price shocks, we use the model suggested by Engemann et al. (2014) where aggregate growth is determined by lags of itself and past innovations to oil prices. However, unlike Engemann et al. (2014) who use payroll employment, we use GDP as it is available for all our sample countries. Similarly, we model the growth rate of the countries' GDP, Δy_{it}, as an AR (4)[104]. Nevertheless, we omitted other variables such as the control for post-Hurricane Katrina because it is irrelevant to us.

$$\Delta y_{it} = \alpha_i + \sum_{j=1}^{4} \beta_{ij} \Delta y_{i,t-j} + \sum_{j=1}^{4} \gamma_{ij} \Delta x_{t-j}^{+} + \sum_{j=1}^{4} \delta_{ij} \Delta x_{t-j}^{-} + \varepsilon_{it} \qquad (6.5)$$

Where Δy_{t-j} is the GDP growth, Δx_{t-j}^{+} is Positive oil price shocks, Δx_{t-j}^{-} is Negative oil price shocks.

Our regression in table 6.3 shows that there is a relationship between GDP and oil price shocks but compared to Engemann et al. (2014) study on US, our results are less obvious. Engemann et al. (2014) results show that economic growth, proxied by payroll employment, is negative and statistically significant after a positive oil price shock at second, third and fourth quarter but our results show a response only at the fourth quarter. Nevertheless, in response to negative oil price shocks, our results are more similar to them as we also do not find any responses to negative oil price shocks for the US.

[104] The lag length K for the above equation are determine by 5 tests namely Likelihood Ratio (LR), Final Prediction Error (FPE), Akaike information criterion (AIC), Schwarz information criterion (SIC) and Hannan-Quinn information criterion (HQ). If there are any conflicts, the lag length with the highest number of significant tests is chosen and if there are still conflicts, the shortest lag length is chosen. However, due to the different countries (markets) involved, the tests provide conflicting lag length. Therefore, we decide to use four lags because most countries show similar results and it is consistent to Engemann et al. (2014) research.

With regards to other countries in our sample, the table appears to show that when there is a negative oil price shock, a few countries experience a positive and significant increase in GDP after the first quarter. This result is understandable for Japan and Germany because both countries are considered as big manufacturers and major oil importers. Thus, a reduction in oil prices should improve economic growth for the two countries.

However, for Norway, Canada and Mexico, it is less straightforward, as table 6.2 shows that they are net oil exporting countries and it is expected that they will benefit more from an increase in oil prices. The results of positive response towards negative oil price shocks, may merely indicate that oil is not a major part of their economic growth[105]. This is obviously contradictory to Mork et al. (1994) who comment that the oil producing sector of Norway is large relative to its economy as a whole. Surprisingly, Norway also obtain a negative and significant response towards positive oil price shocks, even though our earlier results in the previous section find otherwise.

As expected, Brazil, another net oil exporting country, achieves economic growth when there is a positive oil price shock after the first quarter. This is not surprising because as a net oil exporter, Brazil will benefit more from an increase in oil price. Denmark also shows similar results but it happens only after the third quarter. Denmark also has a negative response at the second and fourth quarter signifying that maybe Denmark is just not a major net oil exporting country, which is consistent to our results in the previous section.

Overall, table 6.3 shows that categorising the countries into net oil exporting countries and net oil importing countries does provide some valuable insights, as net oil exporters such as Brazil appears to benefit from positive oil price shocks while net oil importers such as Germany benefits from negative oil price shocks. However, there are mixed responses as well and some results are not as expected. For instance, Norway, a net oil exporter, responds positively towards a decrease in oil price. This could be a result of the financial and monetary policy of the Norwegian government[106]. Even for the US, the response to positive oil price shock comes later in comparison to Engemann et al. (2014) but this could be merely due to the difference in time periods and variables used.

[105] The Norwegian government is also known to use previously accumulated wealth from oil sales to counter balance reductions in oil revenue and a subsequent decline in GDP. Perhaps this is the reason for the positive results obtained here.
[106] The Norwegian government is known to increase spending when there is a decrease in oil price to cancel out any negative effects.

Table 6.3: Regression results of oil price shocks.

This table reports the coefficients from the following regression:

$$\Delta y_{it} = \alpha_i + \sum_{j=1}^{4} \beta_{ij} \Delta y_{i,t-j} + \sum_{j=1}^{4} \gamma_{ij} \Delta x_{t-j}^{+} + \sum_{j=1}^{4} \delta_{ij} \Delta x_{t-j}^{-} + \varepsilon_{it} \qquad (6.5)$$

Where Δy_{it} is the GDP growth at quarter *t*. The other variables are positive oil price shocks (Δx_{t-j}^{+}), negative oil price shocks (Δx_{t-j}^{-}) and also the GDP growth (Δy_{t-j}) at quarterly lags of t-j, for which we use up to 4 quarterly lags for our regressions. Based on oil Brent prices, a positive (negative) oil shock is defined as when the current (quarterly) oil price is above (below) the maximum (minimum) oil price over the last year (4 previous quarters). The sample period is from January 1998 to December 2015, consisting of 72 quarterly observations. Newey-West p-value are reported in brackets whereby **bold** figures denote statistically significance coefficient at least at 10% level. The bandwidth parameter for the Newey-West p-value is calculated using the Newey-West automatic lag selection. All data are obtained from DataStream, Bloomberg, World Bank, IMF and US Energy Information Administration (EIA) website.

Variable		Δy_{t-j}				Δx_{t-j}^{+}				Δx_{t-j}^{-}			
Lag		$j=1$	$j=2$	$j=3$	$j=4$	$j=1$	$j=2$	$j=3$	$j=4$	$j=1$	$j=2$	$j=3$	$j=4$
Coefficient	α	β_1	β_2	β_3	β_4	γ_1	γ_2	γ_3	γ_4	δ_1	δ_2	δ_3	δ_4
Norway	**0.008**	**-0.240**	**-0.266**	-0.005	-0.162	-0.008	0.024	**-0.039**	0.027	**0.031**	-0.006	0.029	-0.009
	(0.001)	**(0.015)**	**(0.027)**	(0.962)	(0.139)	(0.712)	(0.341)	**(0.081)**	(0.357)	**(0.012)**	(0.852)	(0.101)	(0.533)
Canada	**0.003**	**0.455**	-0.101	0.091	0.031	0.006	-0.002	0.000	-0.016	**0.024**	-0.006	-0.001	-0.012
	(0.010)	**(0.004)**	(0.560)	(0.523)	(0.790)	(0.561)	(0.917)	(0.964)	(0.209)	**(0.084)**	(0.512)	(0.955)	(0.212)
Denmark	**0.003**	0.196	0.167	0.018	-0.038	0.002	**-0.039**	**0.045**	**-0.033**	0.022	0.003	-0.001	0.005
	(0.019)	(0.197)	(0.192)	(0.871)	(0.763)	(0.945)	**(0.080)**	**(0.039)**	**(0.079)**	(0.174)	(0.785)	(0.935)	(0.665)
Mexico	**0.004**	**0.402**	-0.017	0.015	-0.086	0.012	0.002	-0.002	-0.017	**0.040**	-0.026	-0.010	0.002
	(0.008)	**(0.036)**	(0.904)	(0.916)	(0.399)	(0.297)	(0.920)	(0.865)	(0.226)	**(0.049)**	(0.102)	(0.482)	(0.894)
Brazil	**0.006**	**0.426**	-0.240	0.123	-0.206	**0.044**	-0.047	0.016	-0.003	0.027	-0.006	0.005	0.009
	(0.029)	**(0.019)**	(0.149)	(0.180)	(0.118)	**(0.024)**	(0.182)	(0.438)	(0.899)	(0.197)	(0.804)	(0.810)	(0.573)
Singapore	**0.050**	0.180	-0.080	0.122	-0.173	0.177	-0.081	-0.138	0.135	0.128	-0.199	0.098	-0.047
	(0.033)	(0.192)	(0.608)	(0.517)	(0.186)	(0.380)	(0.776)	(0.334)	(0.363)	(0.278)	(0.146)	(0.525)	(0.780)
United Kingdom	**0.003**	**0.600**	**0.234**	-0.260	0.033	0.005	-0.014	-0.010	-0.001	0.002	-0.004	0.002	0.000
	(0.012)	**(0.022)**	**(0.097)**	(0.106)	(0.664)	(0.739)	(0.280)	(0.284)	(0.914)	(0.758)	(0.568)	(0.832)	(0.899)
Germany	**0.002**	**0.389**	0.021	0.060	0.003	0.010	-0.002	-0.023	0.002	**0.039**	-0.033	0.008	-0.012
	(0.080)	**(0.000)**	(0.851)	(0.593)	(0.968)	(0.409)	(0.925)	(0.173)	(0.837)	**(0.081)**	(0.150)	(0.569)	(0.350)
Japan	**0.005**	0.176	-0.150	**-0.215**	-0.103	0.009	-0.011	0.000	-0.024	**0.057**	-0.037	0.037	-0.009
	(0.007)	(0.261)	(0.279)	**(0.047)**	(0.397)	(0.658)	(0.733)	(0.989)	(0.260)	**(0.006)**	(0.119)	(0.120)	(0.702)
France	0.001	**0.493**	**0.267**	-0.045	-0.032	0.002	-0.007	-0.003	-0.001	0.011	-0.014	0.000	-0.002
	(0.150)	**(0.000)**	**(0.066)**	(0.719)	(0.767)	(0.862)	(0.614)	(0.700)	(0.902)	(0.132)	(0.233)	(0.935)	(0.800)
United States	**0.013**	0.201	**0.226**	0.017	0.045	0.003	-0.012	0.029	**-0.093**	0.042	-0.055	0.021	-0.024
	(0.024)	(0.190)	**(0.084)**	(0.916)	(0.707)	(0.964)	(0.881)	(0.637)	(0.029)	(0.393)	(0.267)	(0.458)	(0.519)

6.4.1.2. SPATIAL/ DIRECTIONAL ASYMMETRY OF OIL PRICE SHOCKS

In the previous section, we show that the countries in our sample respond differently towards either positive or negative oil price shocks. Therefore, in order to investigate this further, we study the asymmetric effects of the countries by exploring the spatial/directional asymmetry from two complementary perspectives which is similar to Engemann et al. (2014). The two perspectives involve using the *"estimated coefficients on the oil-price shock variables"* and the *"impulse responses to oil-price shocks"*.

6.4.1.2.1. SPATIAL/ DIRECTIONAL ASYMMETRY I: OIL PRICE SHOCKS COEFFICIENT

The aggregate directional asymmetries of the countries in table 6.4 are obtained using Wald tests. Table 6.4 will allow an investigation of the aggregate directional asymmetries in oil price shocks from the perspective of the oil price shocks' estimated coefficients that are highlighted in table 6.3.

Unlike Engemann et al. (2014), our results in table 6.4 appear to indicate that negative oil price shocks cause more responses than positive oil price shocks. Nevertheless, only Denmark and Japan exhibit statistically significant results. Both countries display positive responses towards negative oil price shocks, signifying that the two countries benefit from it. Due to Japan's characteristics as an oil importer, this is expected and consistent with earlier results. As an oil exporter, the result is surprising for Denmark but it can be seen as a confirmation that oil is not a major part of Denmark's economic growth. Table 6.2 does show that Denmark exports the lowest amount of crude oil and its *"annual oil revenue to GDP ratio"* is the second lowest among net oil exporting countries.

Our results also show that all the countries, with the exception of Japan, failed to reject the null hypothesis of directional symmetry meaning that their responses are symmetrical to both positive and negative oil price shocks.

Overall, our findings show that only Japan and Denmark appear to exhibit asymmetric effects, which is inconsistent to past studies such as Mork (1994). Furthermore, in contrast to Engemann et al. (2014) study, we find no evidence of asymmetric effect for the US. Kilian and Vigfusson (2011) who also use GDP like we do, also find no

significant evidence of an asymmetric effect. The difference in results could be due to the different sample period and variables used.

Table 6.4: Tests of aggregate directional symmetry of oil price shocks.
The table shows the aggregate directional symmetry of oil price shocks based on the coefficients of table 6.3 using Wald test. The variables below represent coefficients in relation to positive oil price shocks ($\sum \gamma_j$) and negative oil price shocks ($\sum \delta_j$). $\sum \gamma_j = \sum \delta_j$ is the tests for aggregate directional symmetry for the oil price shocks. The sample period is from January 1998 to December 2015, consisting of 72 quarterly observations. Newey-West p-value are reported in brackets whereby **bold** figures denote statistically significance coefficient at least at 10% level. The bandwidth parameter for the Newey-West p-value is calculated using the Newey-West automatic lag selection. All data are obtained from DataStream, Bloomberg, World Bank and US Energy Information Administration (EIA) website.

H_0	$\sum \gamma_j = 0$	$\sum \delta_j = 0$	$\sum \gamma_j = \sum \delta_j$
	$\sum \gamma_j$	$\sum \delta_j$	
Norway	0.003 (0.927)	0.046 (0.118)	-0.043 (0.436)
Canada	-0.012 (0.546)	0.005 (0.691)	-0.017 (0.508)
Denmark	-0.025 (0.440)	**0.028** **(0.092)**	-0.053 (0.179)
Mexico	-0.004 (0.891)	0.005 (0.786)	-0.010 (0.800)
Brazil	0.011 (0.703)	0.034 (0.517)	-0.024 (0.694)
Singapore	0.093 (0.718)	-0.020 (0.930)	0.113 (0.743)
United Kingdom	-0.020 (0.210)	-0.001 (0.951)	-0.020 (0.263)
Germany	-0.013 (0.596)	0.002 (0.860)	-0.015 (0.632)
Japan	-0.026 (0.417)	**0.048** **(0.050)**	**-0.074** **(0.095)**
France	-0.009 (0.529)	-0.005 (0.617)	-0.004 (0.818)
United States	-0.073 (0.469)	-0.016 (0.757)	-0.057 (0.617)

6.4.1.2.2. SPATIAL/ DIRECTIONAL ASYMMETRY II: IMPULSE RESPONSE FUNCTIONS OF OIL PRICE SHOCKS

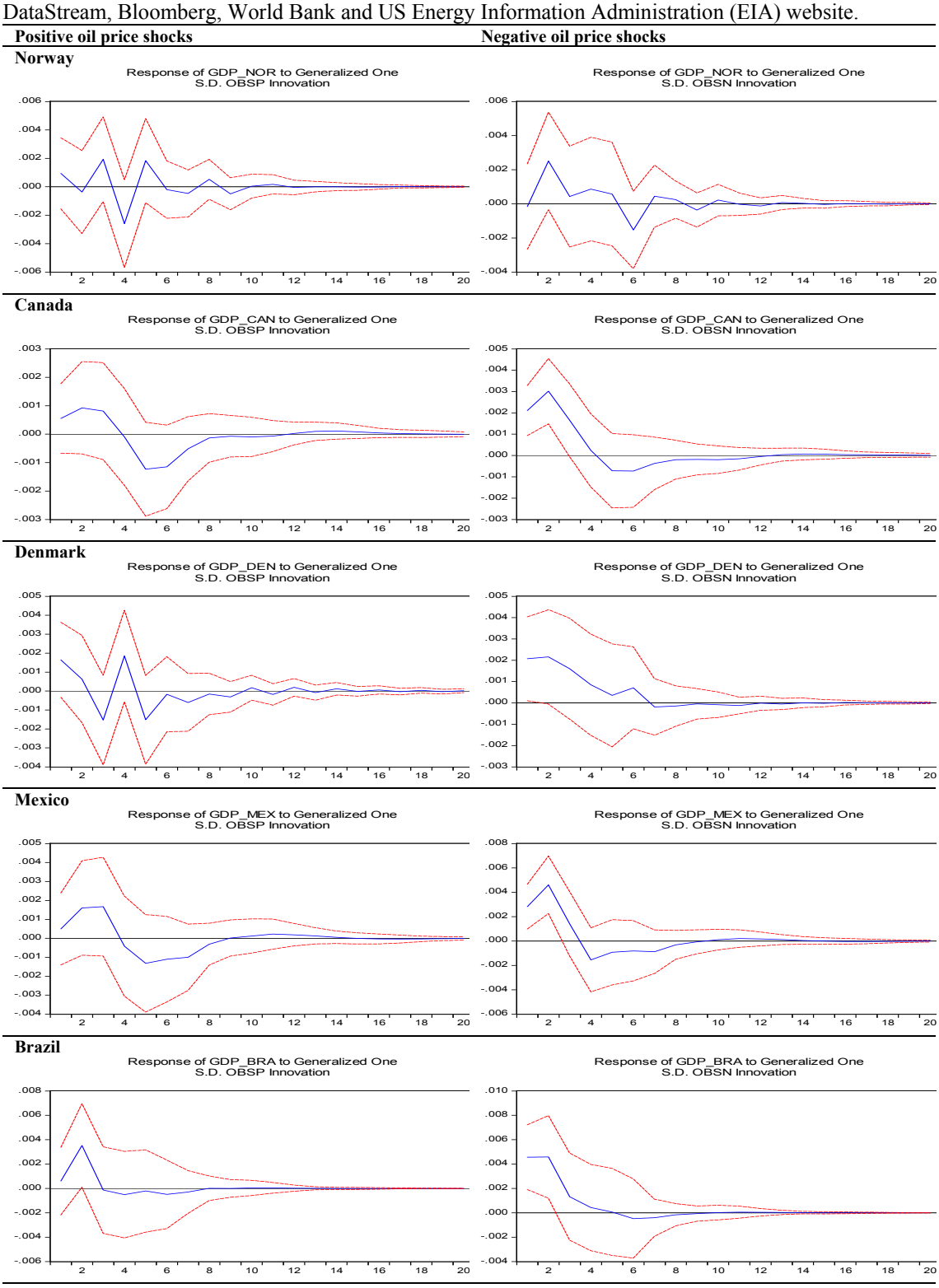
As highlighted earlier, we have also conducted impulse response functions on the eleven countries, as it may be able to provide a different viewpoint of directional asymmetry, following Engemann et al. (2014).

Table 6.5: Summary of spatial/ directional asymmetry of oil price shocks: Impulse response function. The table provides a summary of the results of the impulse response function of oil price shocks from figure 6.2. A country is considered to experience a shock if its response is statistically significant (different from zero) for at least one quarter. The sample period is from January 1998 to December 2015, consisting of 72 quarterly observations. All data are obtained from DataStream, Bloomberg, World Bank and US Energy Information Administration (EIA) website.

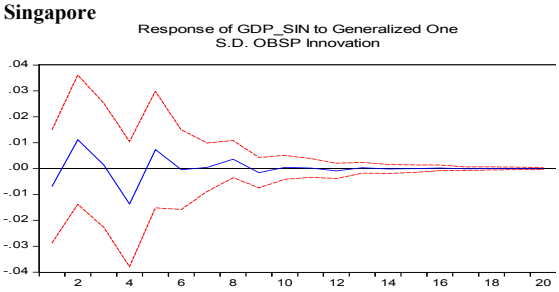
Positive oil shocks only	Negative oil shocks only	Both positive and negative oil shocks	Neither positive nor negative oil shocks
	Canada	Brazil	Norway
	Denmark		
	Mexico		
	Singapore		
	United Kingdom		
	Germany		
	Japan		
	France		
	United States		

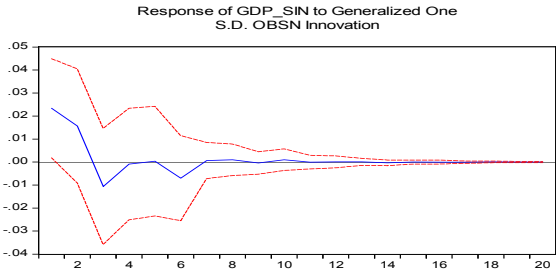
Figure 6.2: GDP and oil price shocks impulse response function.

This figure shows the impulse response function of the GDP to a generalised one standard deviation of either positive or negative oil price shocks. The VAR lag length is kept at four. The sample period is from January 1998 to December 2015, consisting of 72 quarterly observations. All data are obtained from DataStream, Bloomberg, World Bank and US Energy Information Administration (EIA) website.

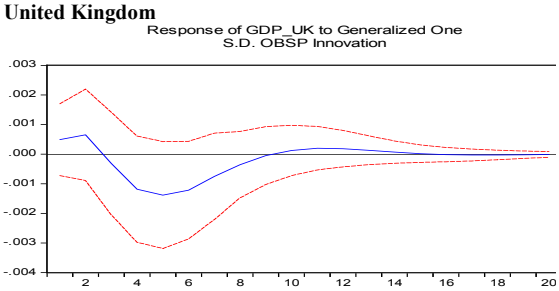


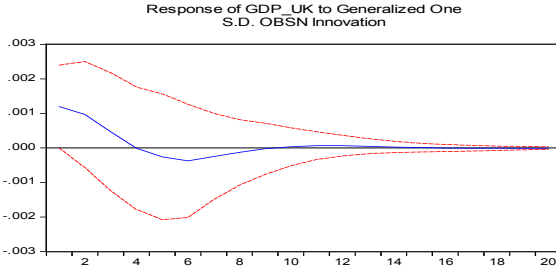
Singapore



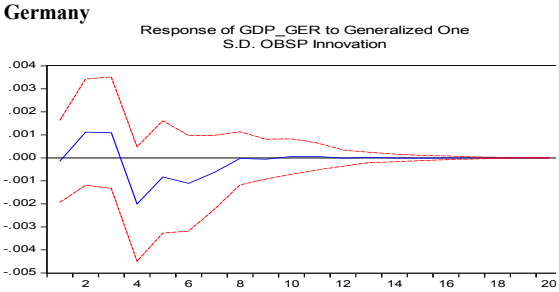


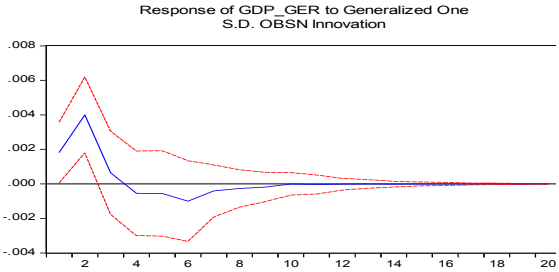
United Kingdom



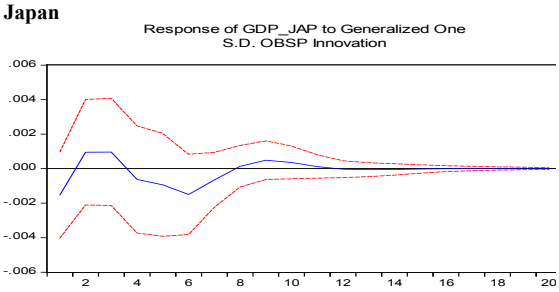


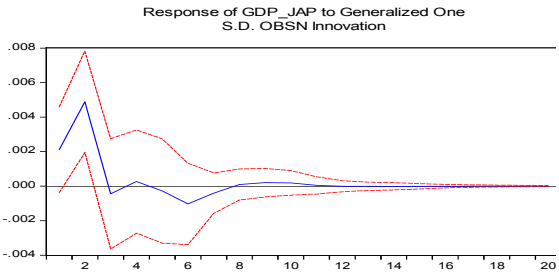
Germany



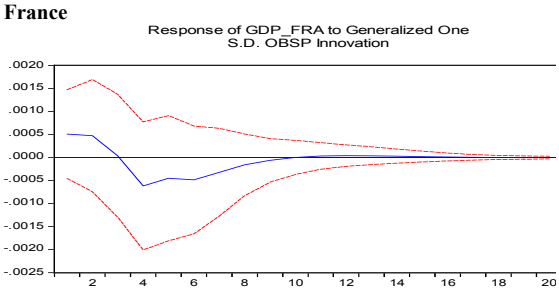


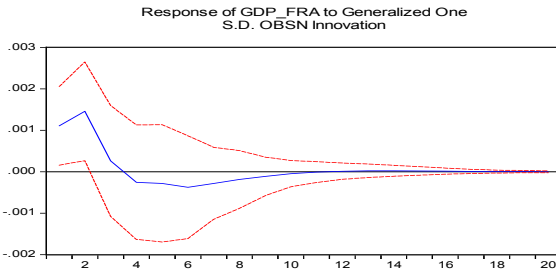
Japan



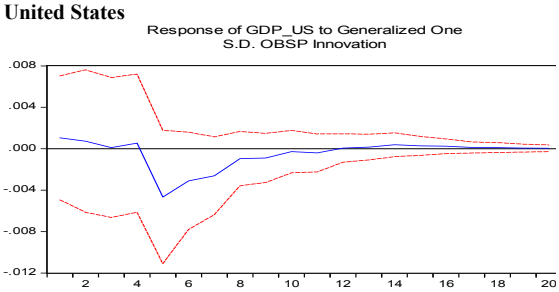


France





United States



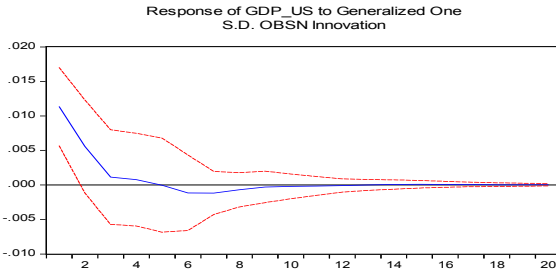


Table 6.5 presents a summary of results of directional asymmetry based on impulse response functions. The countries in table 6.5 are segregated according to their response to positive and negative oil price shocks. If a country's response is statistically different from zero for at least one quarter, then we consider the country to be responsive to the respective shock. Moreover, similar to Engemann et al. (2014) we define an asymmetric effect when a country responds to either positive or negative oil price shocks. A symmetric effect occurs when a country responds to either both shocks (negative and positive) or does not respond at all.

Unlike Engemann et al. (2014) who find that most states respond only to positive oil price shocks, table 6.5 shows that most countries respond to negative oil price shocks, which is consistent to our earlier results. Only Norway, a net oil exporting country shows symmetrical response to neither shocks. Brazil, another net oil exporter, is the only country that responds to both shocks. Surprisingly, based on impulse response functions, none of the countries in our sample respond only to positive oil price shocks. We will now investigate this further by looking at the individual countries impulse response functions as shown in figure 6.2.

As expected, figure 6.2 provides more evidence that the countries respond differently to either positive or negative oil price shocks. Norway appears to show a bouncy response towards both positive and negative oil price shocks but are not significant.

Denmark and Canada responses are only significant to negative oil price shocks, signifying that the GDP of Denmark and Canada grew when there is a negative oil price shock. Mexico's response, another net oil exporter, is also similar to Canada. Mexico responds positively towards both oil price shocks but it is only significant to negative oil price shock. Since Canada, Denmark and Mexico are net oil exporters, positive responses to negative oil price shocks are not expected as it indicates that the net oil exporters are benefiting from decreases in oil prices[107].

As highlighted earlier in table 6.5, Brazil is the sole country that responds to both positive and negative oil price shocks. Brazil's response is positive and significant to both shocks

[107] The results of positive response towards negative oil price shocks for net oil exporters, may merely indicate that oil is not a major part of their economic growth such as in table 6.2, Denmark's "annual oil revenue to GDP ratio" is actually less than 1%. Another reason, may be due to a close trade relationship between a net oil exporter and importer. For instance, Mexico is the main trade partner of the US and a negative oil price shock will allow US to trade more with Mexico causing Mexico to have a positive response regardless of oil revenue. Moreover, some net oil exporters may have other policies (or tools) to counter any unexpected negative oil price shocks. For example, Norway is known to use previously accumulated wealth from oil sales to counter balance reductions in oil revenue and a subsequent decline in GDP.

before decreasing in the next few quarters. As a net oil exporter, it is expected that GDP for Brazil will improve with an increase in oil price, which can be observed in figure 6.2. However, Brazil also responds positively to negative oil price shocks, which is unexpected.

In relation to net oil importing countries, it is more consistent as all the countries respond significantly towards negative oil price shock. The negative responses are not surprising for net oil importers, as it is expected that they will benefit from a decrease in oil price. However, as shown in table 6.5, none of the net oil importing countries responds to positive oil price shock significantly.

Regarding asymmetric effects, our results are consistent to past studies. However, in contrast to previous literature such as Hamilton (1983), Mork et al. (1994) and Engemann et al. (2014), our findings show that most countries respond to negative oil price shocks instead of positive oil price shocks[108]. Although Brazil responds to both shocks, researchers such as Farzanegan and Markwardt (2009) consider the responds asymmetrical as it responds to both shocks positively. Nevertheless, according to Engemann et al. (2014), it is considered symmetrical and hence along with Norway, Brazil exhibit symmetrical effect.

6.4.2. ILLIQUIDITY SHOCKS AND BUSINESS CYCLES

As mentioned in the literature, there is evidence of a two-way relationship between illiquidity and macroeconomic variables. Næs et al. (2011) and Galariotis and Giouvris (2015) highlight that liquidity may contain some information for estimating the current and future state of the economies. Also Choi and Cook (2006) discover that liquidity shocks significantly affect macroeconomic variables by studying the Japanese market. Hence, it will be interesting to study the relationship between illiquidity shocks and the macro-economy as Ellington et al. (2016) highlight that most literature concentrates on explanatory performance and none on the effects of liquidity shocks on the real economy.

[108] The financial crisis may have cause the market to react differently and also the strength of the oil price shocks may matter more. Although there are more positive shocks during our sample period, the maximum shock (strength) in negative oil price shock is 47% whereas for positive oil price shock, the maximum shock is 28% only. Furthermore, during this period, there are six occasions where negative oil price shock is more than 20% while for positive oil price shocks, it only occurs twice. Also investors may be more concerned with negative oil price shocks due to the crisis period. Thus, resulting in macro-economies responding to negative oil price shocks instead of positive oil price shocks.

Furthermore, there is also evidence of a potential asymmetric effect of liquidity variables, as Said and Giouvris (2017) show that market liquidity increases after expansive monetary shifts but the relationship is not clear during restrictive periods in the UK. This drives us to conduct research on the asymmetric effects of illiquidity variables.

We believe that Hamilton's formula of comparing the current value of a variable with the previous four values of the same variable is a simple and logical technique for determining a variable's shock. Thus, we feel that it can also be applied to measure the shocks of other variables, including illiquidity shocks.

We calculate positive and negative illiquidity shocks using Hamilton's shock equations (6.1) and (6.2) respectively but by replacing the crude oil Brent price with *Amihud illiquidity measure* values. Based on this, a positive illiquidity shock will indicate an increase in market illiquidity (or decline in market liquidity) while a negative illiquidity shock signifies a decrease in market illiquidity (or rise in market liquidity).

Table 6.6 shows that the countries in our sample have a different number of illiquidity shocks with Germany having the most illiquidity shocks while Canada and UK jointly face the lowest number of illiquidity shocks. Denmark has the highest number of positive illiquidity shocks while US endure the highest number of negative illiquidity shocks. In relation to the other countries, only Norway and Denmark have more positive illiquidity shocks than negative illiquidity shocks, signifying that the two countries suffer more decline in market liquidity during the sample period.

Table 6.6: Number of illiquidity shocks (Amihud) after applying Hamilton's shock equations.
This table reports the number of illiquidity shocks from the following equations:

1. Positive illiquidity shocks

$$\Delta x_t^+ = max\left\{0, 100 \times ln\frac{x_t}{max(x_{t-1}, x_{t-2}, x_{t-3}, x_{t-4})}\right\} \quad (6.6)$$

2. Negative illiquidity shocks

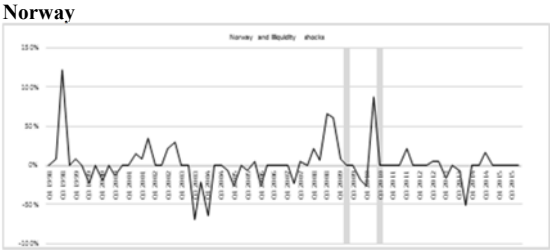
$$\Delta x_t^- = min\left\{0, 100 \times ln\frac{x_t}{min(x_{t-1}, x_{t-2}, x_{t-3}, x_{t-4})}\right\} \quad (6.7)$$

Where x_t is Amihud illiquidity measure values at quarter t and $x_{t-1}, x_{t-2}, x_{t-3}, x_{t-4}$ are the Amihud illiquidity measure values of the previous four (4) quarter. The original sample data is between January 1997 and December 2015 but after applying Hamilton's shock equations, our final data for analysis is from January 1998 to December 2015, consisting of 72 quarterly observations. All data are obtained from DataStream, Bloomberg, World Bank and US Energy Information Administration (EIA) website.

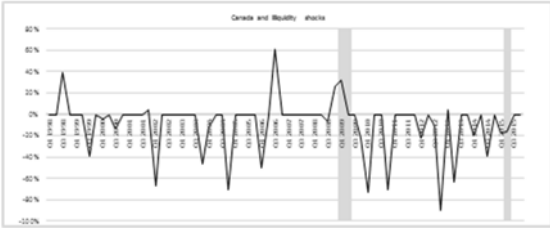
Countries	**Amihud illiquidity measure**		
	Positive shocks	**Negative shocks**	**Total shocks**
Norway	20	16	36
Canada	6	22	28
Denmark	21	18	39
Mexico	14	20	34
Brazil	10	20	30
Singapore	15	25	40
United Kingdom	13	15	28
Germany	19	24	43
Japan	8	27	35
France	11	18	29
United States	10	32	42

Figure 6.3: Business cycle and the illiquidity shocks (Amihud).
The figure shows time series plots of the illiquidity shocks for all countries in our sample. The black lines are Hamilton type illiquidity shock variable based on Amihud illiquidity measure. A positive (negative) illiquidity shock is defined as when the current (quarterly) Amihud value is above (below) the maximum (minimum) Amihud value over the last year (4 previous quarters). Shaded grey are recession periods and a recession period is identified as a period for which there is negative GDP growth for at least two consecutive terms. The sample period is from January 1998 to December 2015, consisting of 72 quarterly observations. All data are obtained from DataStream, Bloomberg, World Bank and US Energy Information Administration (EIA) website.

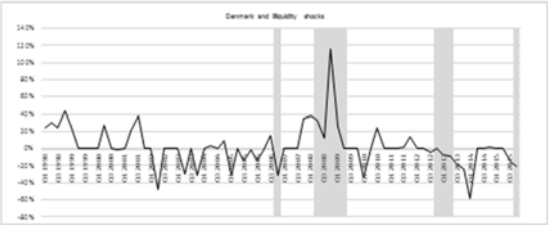
Norway



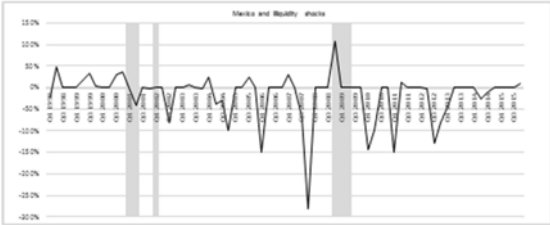
Canada



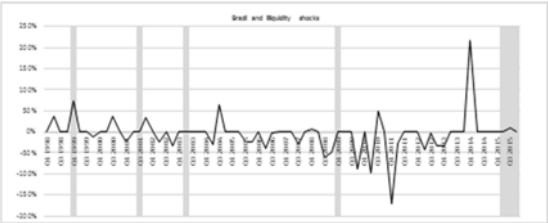
Denmark



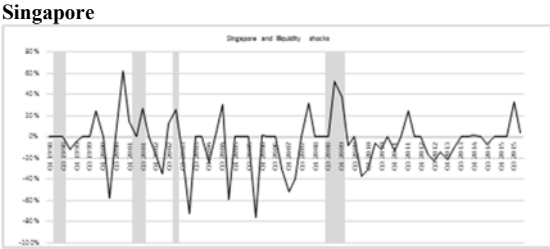
Mexico



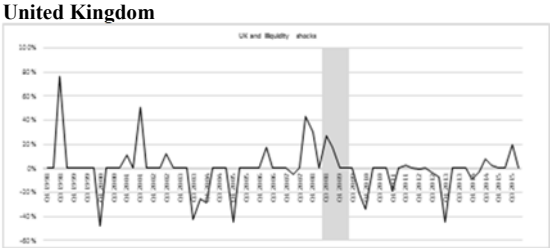
Brazil



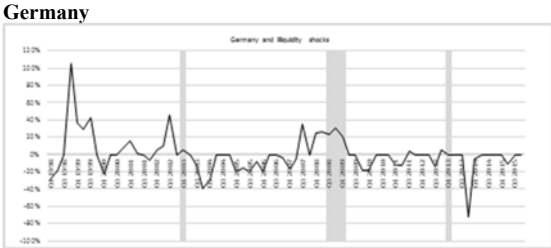
Singapore



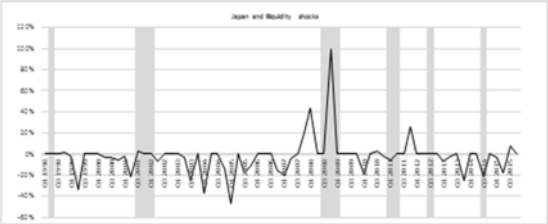
United Kingdom



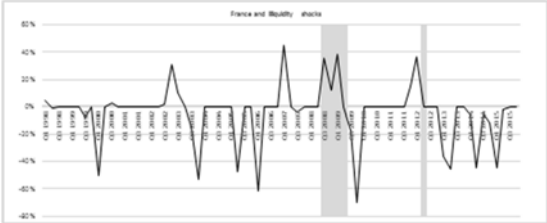
Germany



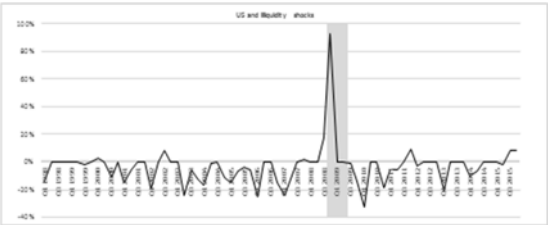
Japan



France



United States



We will initially focus on the financial crisis of 2007-2008 as there are simultaneous recessions in our sample countries allowing for easier comparison. Figure 6.3 shows that Norway, Canada, Denmark, Germany and US suffer positive illiquidity shocks prior to a recession, signifying that market illiquidity increases before a recession. Out of the five countries, three are net oil exporters while the other two are net oil importers. Thus, there is no feasible justification based on their categorisation as either net oil exporters or importers.

UK, Mexico and France also show positive illiquidity shocks but they occur at the same time with the recession while for Singapore and Japan, the positive illiquidity shocks occur one quarter after the beginning of the recession. Such results can imply that recessions have actually caused the positive illiquidity shock (or decrease in market liquidity) and not vice-versa.

Brazil shows some unexpected results during the crisis. There is actually a negative illiquidity shock prior to the recession, signifying that market liquidity has actually increased before the recession. Thus, signifying that market illiquidity may not be an important factor for the Brazilian economy[109]. Nevertheless, among the countries in our sample, Brazil has the second lowest GDP per capita and along with Norway have the shortest recession period during the financial crisis of 2007-2008. Moreover, Brazil is one of two countries categorised as an emerging market in table 6.2 by MSCI and as Sung and Giouvris (2016) comment developed and developing markets can respond differently to liquidity variables.

Other than the financial crisis period, countries such as Norway, Mexico, Singapore and Germany show consistent positive illiquidity shocks around recession periods while the UK and the US do not show any other recession periods within our sample periods.

Similar to Brazil during the crisis, Denmark, Japan and Canada also face both positive and negative illiquidity shocks around other recession periods. Nonetheless, Brazil and Japan show the most consistent results of negative illiquidity shocks prior to recession

[109] Brazil is one of two emerging countries in our sample and hence it may be less integrated to the global financial markets compared to the other countries in our sample. However, Sung and Giouvris (2016) highlight that relative to national liquidity, global liquidity has extra explanatory power in developing markets. Since we use national liquidity for this chapter, the reaction for Brazil is probably less because it is an emerging country.

periods. The two countries have the highest number of recession periods, as Brazil and Japan endure five and six recessions respectively in our sample[110].

6.4.2.1. ILLIQUIDITY SHOCKS COEFFICIENTS

Our regression results in table 6.7 are obtained using the previous equation (6.4) but the oil price shocks are replaced by illiquidity shocks. The table shows that there is a clear relationship between GDP and illiquidity shocks. In fact, the regression results on illiquidity shocks are clearer compared to oil price shocks, as the results are more consistent and statistically significant.

Table 6.7 generally shows that during the first quarter, most countries experience a negative and significant decrease in GDP when there is a positive illiquidity shock (or increase in market illiquidity), with the US obtaining the highest negative coefficient. Only Canada, Germany, France and Singapore do not react to positive illiquidity shocks. However, with the exception of Singapore, the other three countries show a similar negative coefficient but it is not statistically significant. After the first quarter, Norway, Denmark, Brazil, Japan and UK continue to show that positive illiquidity shocks affect their economies in a negative way[111].

Mexico and the US show mixed coefficients as higher lags show positive responses to positive illiquidity shocks. Only Canada experiences a positive response, instead of a negative response, to positive illiquidity shocks over the four lags, signifying that the GDP of Canada increases following an increase in market illiquidity. Furthermore, Singapore, Germany and France do not show any reaction to positive illiquidity shocks.

---

[110] The 1997 Asian financial crisis may have effected Japan due to its close economic relationship within the Asian region. Although later, Brazil is also effected by the Asian financial crisis (Frontline, n.d.). Nevertheless, Japan has been known to be in perpetual recession while the low GDP per capita for Brazil and being categorised as an emerging market may be the reason why Brazil is less integrated with foreign markets. Therefore, these may have increased the number of recessions for the two countries, resulting in the unique results. However, further investigations provide more consistent results as Japan is found to be negatively affected by positive illiquidity shocks while Brazil is not affected by either shocks, which is better explained in sub-chapter *6.4.2.2.2. Spatial/ Directional Asymmetry II: Impulse Response Functions of Illiquidity Shocks*.

[111] The results are anticipated because market illiquidity is expected to coincide with poor economy. Past research such as Brunnermeier and Pedersen (2009) highlights that when liquidity becomes scarce, speculators cut back on the provision for assets, potentially affecting the economy due to fewer projects. Moreover, Galariotis and Giouvris (2015) mention that there is a negative relationship between illiquidity and GDP, signifying that as market illiquidity increases, the economy will shrink. Thus, if market illiquidity decreases, the economy is expected to improve. Central banks use interest rates as a monetary policy instrument. By keeping interest rates low, banks will encourage economic growth. Said and Giouvris (2017) mention that low interest rates appear to increase market liquidity.

Reactions to negative illiquidity shocks are less convincing as there are fewer statistically significant coefficients. Among the statistically significant coefficients, only Mexico shows a positive response at first and third lags after a negative illiquidity shock, as it is expected that the economy will grow with an increase in market liquidity. Canada, Singapore and Germany unexpectedly experience negative responses at different quarters. By looking at the first quarter, nine countries exhibit negative instead of positive responses to negative illiquidity shocks but it is generally not statistically significant.

Overall, it appears that investors are more concerned when there is less liquidity available, which is consistent to past research.

Table 6.7: Regression results of illiquidity shocks.

This table reports the coefficients from the following regression:

$$\Delta y_{it} = \alpha_i + \sum_{j=1}^{4} \beta_{ij} \Delta y_{i,t-j} + \sum_{j=1}^{4} \gamma_{ij} \Delta x_{t-j}^{+} + \sum_{j=1}^{4} \delta_{ij} \Delta x_{t-j}^{-} + \varepsilon_{it} \qquad (6.8)$$

Where Δy_{it} is the GDP growth at quarter *t*. The other variables are positive illiquidity shocks (Δx_{t-j}^{+}), negative illiquidity shocks (Δx_{t-j}^{-}) and also the GDP growth (Δy_{t-j}) at quarterly lags of t-j, for which we use up to 4 quarterly lags for our regressions. Based on Amihud illiquidity measure, a positive (negative) illiquidity shock is defined as when the current (quarterly) Amihud value is above (below) the maximum (minimum) Amihud value over the last year (4 previous quarters). The sample period is from January 1998 to December 2015, consisting of 72 quarterly observations. Newey-West p-value are reported in brackets whereby **bold** figures denote statistically significance coefficient at least at 10% level. The bandwidth parameter for the Newey-West p-value is calculated using the Newey-West automatic lag selection. All data are obtained from DataStream, Bloomberg, World Bank and US Energy Information Administration (EIA) website.

Variable		Δy_{t-j}				Δx_{t-j}^{+}				Δx_{t-j}^{-}			
Lag		$j=1$	$j=2$	$j=3$	$j=4$	$j=1$	$j=2$	$j=3$	$j=4$	$j=1$	$j=2$	$j=3$	$j=4$
Coefficient	α	β_1	β_2	β_3	β_4	γ_1	γ_2	γ_3	γ_4	δ_1	δ_2	δ_3	δ_4
Norway	**0.012**	**-0.450**	**-0.402**	**-0.195**	**-0.228**	**-0.028**	-0.003	**-0.012**	-0.004	-0.002	-0.013	0.006	-0.005
	(0.000)	**(0.003)**	**(0.011)**	**(0.084)**	**(0.034)**	**(0.001)**	(0.557)	**(0.040)**	(0.607)	(0.796)	(0.277)	(0.354)	(0.588)
Canada	0.001	**0.586**	-0.250	0.172	0.009	-0.013	0.009	**0.011**	0.009	-0.003	-0.002	**-0.006**	-0.002
	(0.767)	**(0.000)**	(0.144)	(0.289)	(0.950)	(0.184)	(0.101)	**(0.012)**	(0.378)	(0.416)	(0.346)	**(0.061)**	(0.346)
Denmark	0.003	0.032	0.163	0.054	-0.017	**-0.012**	**-0.011**	0.002	-0.001	-0.006	-0.001	-0.001	-0.001
	(0.160)	(0.762)	(0.301)	(0.536)	(0.903)	**(0.001)**	**(0.028)**	(0.738)	(0.922)	(0.509)	(0.925)	(0.841)	(0.906)
Mexico	**0.005**	**0.520**	-0.076	0.028	-0.054	**-0.023**	0.001	**0.015**	-0.009	**0.002**	0.000	**0.002**	0.002
	(0.003)	**(0.002)**	(0.614)	(0.862)	(0.588)	**(0.007)**	(0.755)	**(0.000)**	(0.348)	**(0.049)**	(0.930)	**(0.008)**	(0.583)
Brazil	0.005	**0.468**	-0.166	0.074	-0.155	**-0.006**	0.000	0.000	**-0.008**	0.003	-0.002	-0.003	-0.006
	(0.138)	**(0.004)**	(0.355)	(0.489)	(0.268)	**(0.073)**	(0.908)	(0.920)	**(0.057)**	(0.553)	(0.685)	(0.511)	(0.356)
Singapore	**0.043**	0.104	-0.192	0.093	-0.199	0.017	-0.053	0.030	-0.045	**-0.162**	-0.021	-0.074	-0.014
	(0.048)	(0.337)	(0.236)	(0.664)	(0.123)	(0.835)	(0.718)	(0.779)	(0.666)	**(0.017)**	(0.691)	(0.109)	(0.845)
United Kingdom	**0.003**	**0.552**	0.171	-0.198	0.040	**-0.015**	**-0.007**	**-0.009**	0.005	-0.001	0.003	0.004	0.000
	(0.005)	**(0.001)**	(0.258)	(0.124)	(0.670)	**(0.046)**	**(0.071)**	**(0.089)**	(0.563)	(0.698)	(0.349)	(0.318)	(0.964)
Germany	0.001	**0.387**	-0.014	0.046	-0.126	-0.005	-0.007	0.004	0.004	-0.007	0.003	-0.006	**-0.015**
	(0.483)	**(0.085)**	(0.878)	(0.681)	(0.289)	(0.489)	(0.194)	(0.509)	(0.428)	(0.204)	(0.499)	(0.252)	**(0.047)**
Japan	**0.005**	0.106	-0.173	**-0.329**	-0.112	**-0.039**	0.004	**-0.034**	-0.007	-0.007	0.002	0.009	-0.004
	(0.007)	(0.481)	(0.141)	**(0.010)**	(0.297)	**(0.000)**	(0.632)	**(0.005)**	(0.505)	(0.399)	(0.821)	(0.386)	(0.631)
France	0.001	**0.522**	0.158	-0.016	-0.003	-0.005	-0.003	0.011	0.001	-0.002	0.001	-0.003	-0.001
	(0.655)	**(0.001)**	(0.344)	(0.895)	(0.977)	(0.340)	(0.429)	(0.191)	(0.813)	(0.303)	(0.808)	(0.275)	(0.732)
United States	0.009	0.079	**0.237**	0.161	0.065	**-0.075**	0.011	0.024	**0.047**	-0.037	-0.003	-0.015	0.055
	(0.474)	(0.560)	**(0.099)**	(0.463)	(0.578)	**(0.001)**	(0.620)	(0.391)	**(0.058)**	(0.311)	(0.914)	(0.631)	(0.203)

6.4.2.2. SPATIAL/ DIRECTIONAL ASYMMETRY OF OIL PRICE SHOCKS

Similar to oil price shocks, in order to scrutinise illiquidity shocks further, we study the asymmetry effects of the countries by exploring the spatial/directional asymmetry using two complementary perspectives namely the *"estimated coefficients on the illiquidity shock variables"* and the *"impulse responses to illiquidity shocks"*.

6.4.2.2.1. SPATIAL/ DIRECTIONAL ASYMMETRY I: ILLIQUIDITY SHOCKS COEFFICIENT

To obtain the aggregate directional asymmetry tests of the illiquidity shocks coefficients, we use Wald tests. This section will allow an investigation of directional asymmetries in illiquidity shocks from the perspective of the shocks' estimated coefficients reported earlier in table 6.7. Table 6.8 shows that when there is a positive illiquidity shock, only Norway, UK and Japan show a negative and statistically significant response, which is consistent to the previous section. Most of the other countries also have a negative response but it is not statistically significant. US is a bit of a surprise because it provides the highest statistically significant negative response in table 6.7 for the first lag but then again the fourth lag is positive and significant.

In relation to negative illiquidity shocks, the results are less convincing. Table 6.8 shows that there are statistically significant results but the responses are negative, signifying that as market liquidity increases, GDP actually decreases. Countries that show such a significant negative response are Canada, Singapore and Germany. Moreover, the rest of the countries also show negative responses but results are not statistically significant with the exception of Mexico, UK and US. Although the latter three countries show positive responses, results are not statistically significant.

The last column shows that other than Japan, all the countries in our sample failed to reject the null hypothesis of directional symmetry signifying that all the other countries are symmetrical to their response to positive and negative illiquidity shocks. This is unexpected as past literature shows that investors react differently to either an increase or decrease in market liquidity.

Table 6.8: Tests of aggregate directional symmetry of illiquidity shocks.
The table shows the aggregate directional symmetry of illiquidity shocks based on the coefficients of table 6.7 using Wald test. The variables below represent coefficients in relation to positive illiquidity shocks ($\sum \gamma_j$) and negative illiquidity shocks ($\sum \delta_j$). $\sum \gamma_j = \sum \delta_j$ is the tests for aggregate directional symmetry for the illiquidity shocks. The sample period is from January 1998 to December 2015, consisting of 72 quarterly observations. Newey-West p-value are reported in brackets whereby **bold** figures denote statistically significance coefficient at least at 10% level. The bandwidth parameter for the Newey-West p-value is calculated using the Newey-West automatic lag selection. All data are obtained from DataStream, Bloomberg, World Bank and US Energy Information Administration (EIA) website.

H_0	$\sum \gamma_j = 0$	$\sum \delta_j = 0$	$\sum \gamma_j = \sum \delta_j$
	$\sum \gamma_j$	$\sum \delta_j$	
Norway	**-0.047**	-0.014	-0.034
	(0.003)	(0.311)	(0.113)
Canada	0.016	**-0.013**	0.029
	(0.268)	**(0.037)**	(0.100)
Denmark	-0.021	-0.008	-0.013
	(0.145)	(0.544)	(0.556)
Mexico	-0.015	0.006	-0.021
	(0.224)	(0.168)	(0.179)
Brazil	-0.013	-0.008	-0.005
	(0.102)	(0.444)	(0.723)
Singapore	-0.051	**-0.271**	0.221
	(0.817)	**(0.057)**	(0.358)
United Kingdom	**-0.026**	0.005	-0.031
	(0.075)	(0.539)	(0.105)
Germany	-0.003	**-0.025**	0.022
	(0.784)	**(0.056)**	(0.213)
Japan	**-0.076**	-0.001	**-0.075**
	(0.001)	(0.958)	**(0.006)**
France	0.004	-0.005	0.010
	(0.684)	(0.418)	(0.534)
United States	0.006	0.000	0.006
	(0.935)	(0.999)	0.9638

6.4.2.2.2. SPATIAL/ DIRECTIONAL ASYMMETRY II: IMPULSE RESPONSE FUNCTIONS OF ILLIQUIDITY SHOCKS

To provide a different viewpoint of the directional asymmetry, as before, we have also conducted impulse response function on the eleven countries.

Table 6.9: Summary of spatial/ directional asymmetry of illiquidity shocks: Impulse response function.
The table provides a summary of the results of the impulse response function of the illiquidity shocks from figure 6.4. A country is considered to experience a shock if its response is statistically significant (different from zero) for at least one quarter. The sample period is from January 1998 to December 2015, consisting of 72 quarterly observations. All data are obtained from DataStream, Bloomberg, World Bank and US Energy Information Administration (EIA) website.

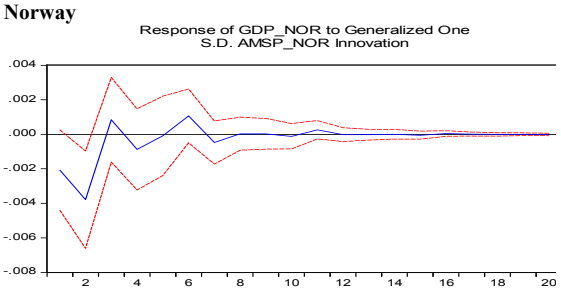
Positive shocks only	Negative shocks only	Both positive and negative shocks	Neither positive nor negative shocks
Norway		Mexico	Brazil
Canada		Singapore	Germany
Denmark			
United Kingdom			
Japan			
France			
United States			

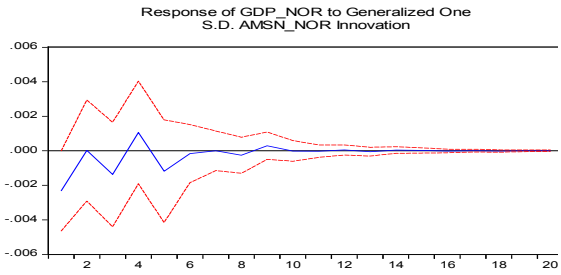
Figure 6.4: GDP and illiquidity shocks Impulse Response Function.

This figure shows the impulse response function of the GDP to a generalised one standard deviation of either positive or negative illiquidity shocks. The VAR lag length is kept at four. The sample period is from January 1998 to December 2015, consisting of 72 quarterly observations. All data are obtained from DataStream, Bloomberg, World Bank and US Energy Information Administration (EIA) website.

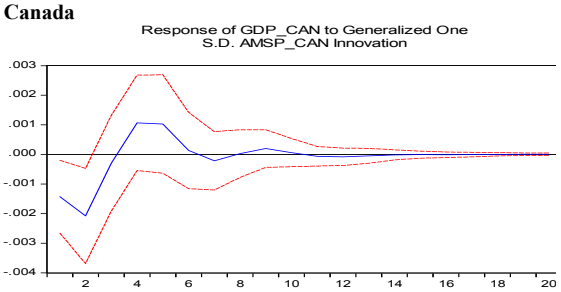
Positive illiquidity shocks | **Negative illiquidity shocks**

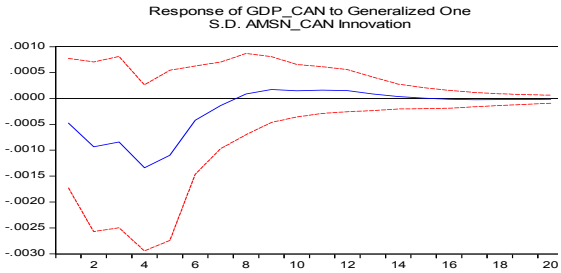
Norway



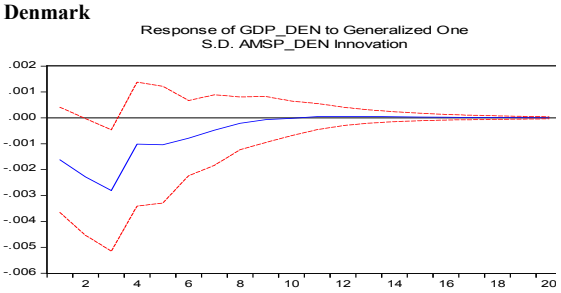


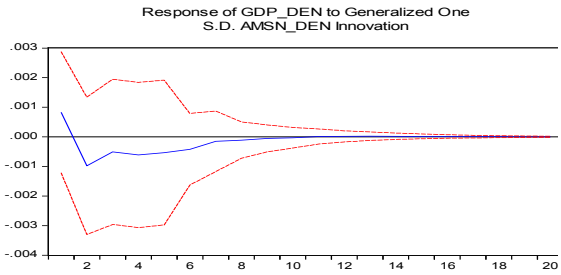
Canada



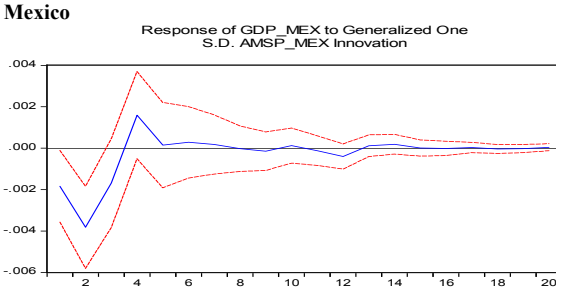


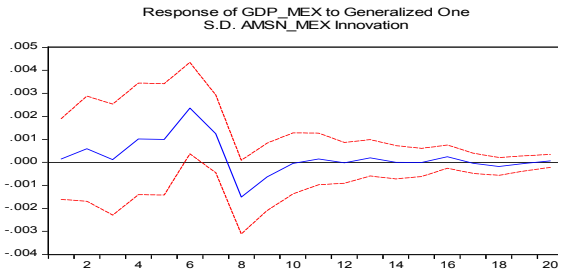
Denmark



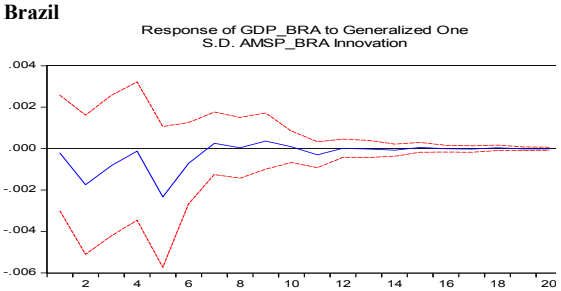


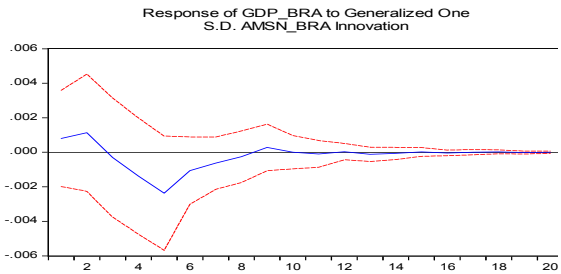
Mexico



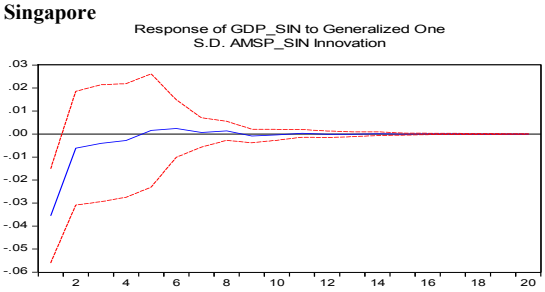


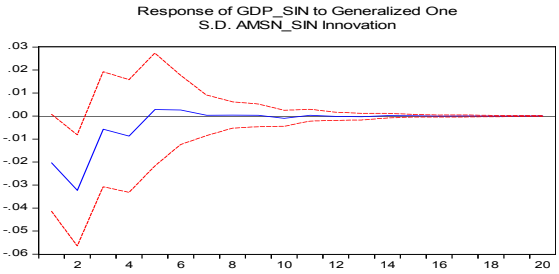
Brazil



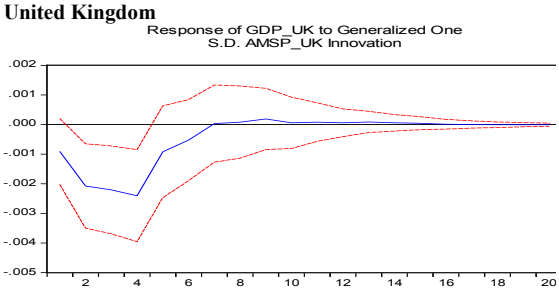


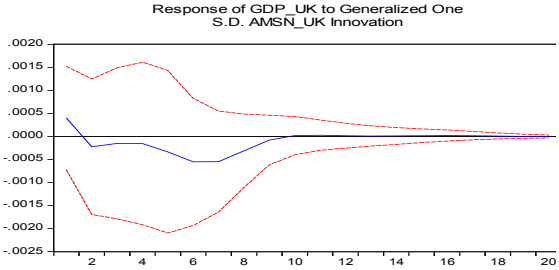
Singapore



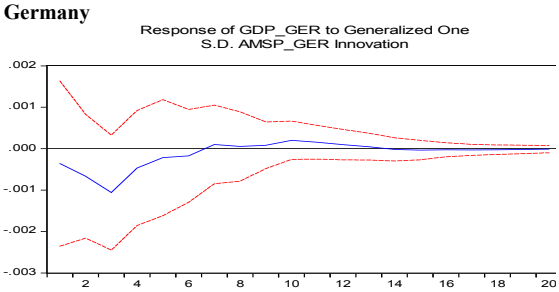


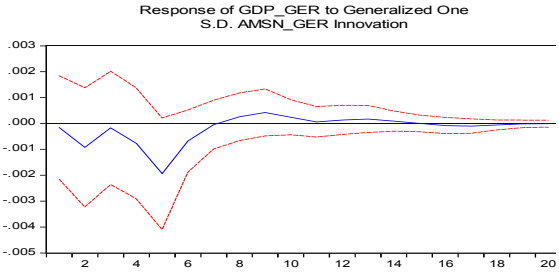
United Kingdom



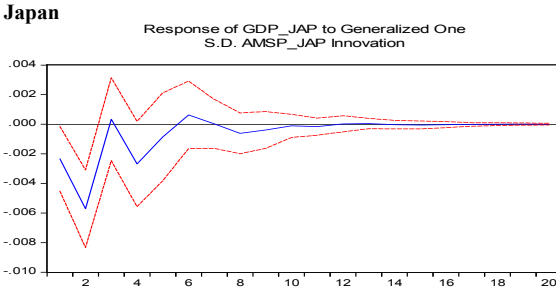


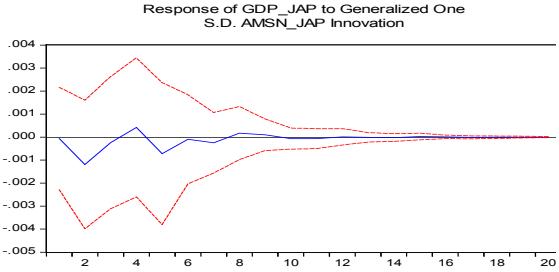
Germany



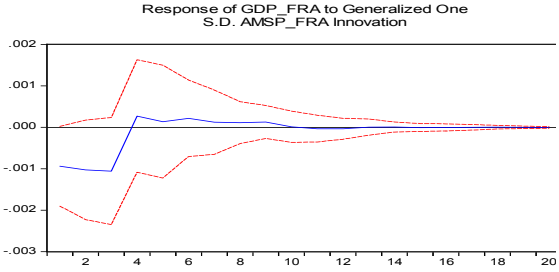


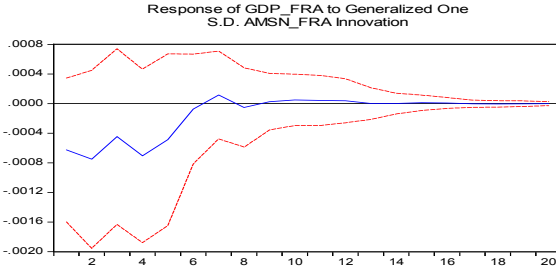
Japan



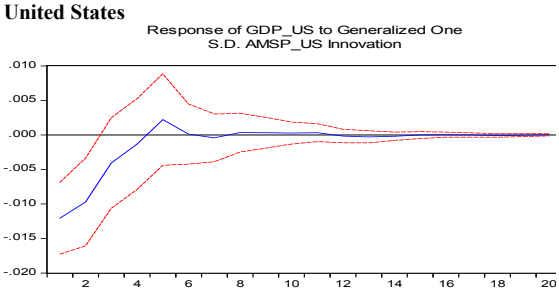


France





United States



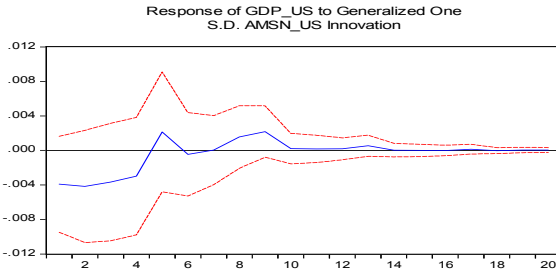


Table 6.9 shows the summary of the impulse response functions to positive and negative illiquidity shocks, whereby we consider the country to be responsive to an illiquidity shock if the country's response is statistically different from zero for at least one quarter.

Even though table 6.8 shows that only Japan rejects the null hypothesis of directional symmetry, table 6.9 indicates that seven of the countries in the sample are experiencing directional asymmetry by responding to positive illiquidity shocks only. Mexico and Singapore are the only two countries that respond to both positive and negative illiquidity shocks while Brazil and Germany respond to neither shock. Since our previous section shows inconsistent results to negative illiquidity shocks, it is not a surprise that table 6.9 shows similar results that none of the countries respond only to negative shocks. To investigate this further, we will now look at the individual countries' impulse response functions as shown in figure 6.4.

Figure 6.4 shows that Norway and Japan experience bouncy responses to both positive and negative illiquidity shocks but only responses to positive illiquidity shocks are statistically significant. As expected, the two countries' response to positive illiquidity shock started off negatively indicating that an increase in market illiquidity has caused the GDP of Norway and Japan to fall.

Canada show less bouncy graphs but similar to Norway and Japan, Canada also responds negatively to positive illiquidity shocks only. Such graphs can also be observed for Denmark and UK whereby GDP responds negatively to positive illiquidity shocks during the second quarter followed by a GDP increase in the following quarter. US and France also respond to positive illiquidity shocks only but the graph is slightly different as it is negative in the first quarter before gradually increasing in the next quarters.

Although Mexico experiences a similar negative response to a positive illiquidity shock, Mexico also experiences a statistically significant positive response to a negative illiquidity shock. This indicates that the GDP of Mexico is increasing when there is a negative illiquidity shock (or an increase in market liquidity). Therefore, Mexico appears to exhibit a genuine symmetrical effect as positive and negative illiquidity shocks causes the GDP of Mexico to move in the opposite direction respectively.

Singapore is the other country that responds to both positive and negative illiquidity shocks. As expected, Singapore responds negatively to positive illiquidity shocks and it occurs immediately during the first quarter which is similar to the US. However, unlike

Mexico, Singapore's response to negative illiquidity shocks is also negative signifying that when market liquidity increases, the GDP of Singapore decreases instead. Although the reaction of Singapore to negative illiquidity shocks is surprising, this is actually consistent to our findings in table 6.8 as Singapore has a statistically significant negative aggregate coefficient. Therefore, although Singapore responds to both shocks, it does not have a genuine symmetrical effect similar to Mexico, as it responds to both shocks negatively. However, based on Engemann et al. (2014), it is considered as symmetrical.

Brazil and Germany show no statistically significant responses to both positive and negative illiquidity shocks. Nevertheless, the pattern of the graphs for Brazil follow closely those of Mexico as there are negative and positive responses to positive and negative illiquidity shocks respectively, which is interesting as both Mexico and Brazil have the lowest GDP per capita and they are the only countries categorised as emerging markets in our sample. Germany shows a pattern of negative responses to negative illiquidity shocks that is more in line with the other countries in our sample. Since there are no statistically significant results for the two countries, the two countries exhibit symmetrical effect. The results could mean that illiquidity shocks do not actually impact the GDP of Brazil and Germany.

Overall, according to Engemann et al. (2014) description, four countries exhibit symmetrical effect to illiquidity shocks namely Mexico, Singapore, Brazil and Germany.

6.4.3. NATIONAL OIL PRICE SHOCKS AND BUSINESS CYCLES

Since Cunado and De Gracia (2005) study of six Asian countries suggests that the significant effect of oil price shocks on macroeconomic variables becomes more significant when the shocks are defined in local (or national) currencies, we decide to briefly investigate this.

As we are aware, the crude oil Brent price is in *USD*. In order to convert the price to national crude oil Brent price, we simply multiply the specific country's foreign exchange rate against USD with the crude oil Brent price (e.g. For the UK = GBP/USD x crude oil Brent price).

Table 6.10 shows the number of oil price shocks of the countries over the 18 years period after converting the oil price shocks to national oil price shocks. Obviously, US is not

affected as it is already in USD but the other countries are affected in different ways, shown in table 6.11.

Table 6.11 shows that the total number of oil shocks for Denmark has reduced by more than 10% while the total shocks for Canada have increased by 8.7%. However, in terms of positive oil price shocks, Brazil is the most affected as its positive oil price shocks increase by more than 24% while its negative oil price shocks are reduced by almost 30% after currency conversion. Considering this, Brazil is in fact more affected in comparison to Denmark.

Table 6.11 also shows that Singapore, UK and Japan appear to exhibit significant movement of both positive and negative shocks after currency conversation. Moreover, the table also shows that the number of negative oil price shocks for Norway, Mexico, Germany and France are not affected by it. Other than that, France and Germany which use the Euro (EUR) understandably have the same number of shocks.

As a result of currency conversion, figure 6.5 doesn't actually show any substantial changes that would change our earlier viewpoints as shown in figure 6.1. Other than oil price shocks becoming more or less pronounced, the relationship between oil price shocks and business cycles (or recessions) appears to be the same.

Table 6.10: Number of national oil price shocks after applying Hamilton's shock equations.
This table reports the number of national oil price shocks from the following equations:

1. Positive national oil price shocks

$$\Delta x_t^+ = max\left\{0, 100 \times ln\frac{x_t}{max(x_{t-1}, x_{t-2}, x_{t-3}, x_{t-4})}\right\} \quad (6.9)$$

2. Negative national oil price shocks

$$\Delta x_t^- = min\left\{0, 100 \times ln\frac{x_t}{min(x_{t-1}, x_{t-2}, x_{t-3}, x_{t-4})}\right\} \quad (6.10)$$

Where $x_t$is national crude oil Brent price at quarter t and $x_{t-1}, x_{t-2}, x_{t-3}, x_{t-4}$ are the national crude oil Brent price of the previous four (4) quarter. Since the crude oil Brent price is in USD, the national crude oil Brent price is obtained by multiplying the specific country's foreign exchange rate with the crude oil Brent price (e.g. for the UK = GBP/USD x Oil price). The original sample data is between January 1997 and December 2015 but after applying Hamilton's shock equations, our final data for analysis is from January 1998 to December 2015, consisting of 72 quarterly observations. All data are obtained from DataStream, Bloomberg, World Bank and US Energy Information Administration (EIA) website.

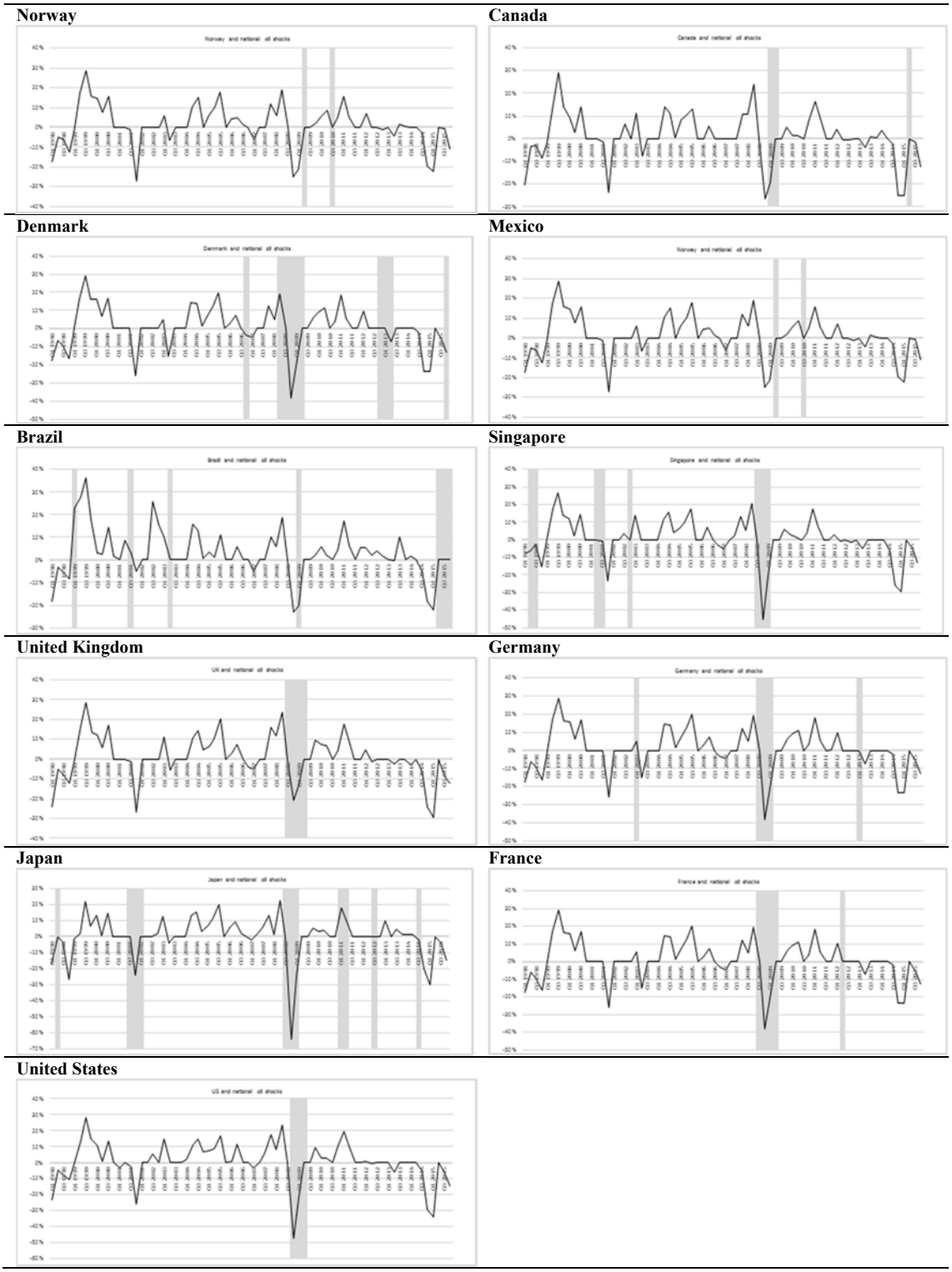
Countries	National oil price		
	Positive shocks	Negative shocks	Total shocks
Norway	28	17	45
Canada	30	20	50
Denmark	25	16	41
Mexico	31	17	48
Brazil	36	12	48
Singapore	27	21	48
United Kingdom	25	21	46
Germany	26	17	43
Japan	33	14	47
France	26	17	43
United States	29	17	46

Table 6.11: Percentage change in number of national oil price shocks compared to oil price shocks.
This table reports the percentage change in the number of national oil price shocks (table 6.10) in comparison to the number of oil price shocks (table 6.1). Since the crude oil Brent price is in USD, the national crude oil Brent price is obtained by multiplying the specific country's foreign exchange rate with the crude oil Brent price (e.g. for the UK = GBP/USD x Oil price). The sample is from January 1998 to December 2015, consisting of 72 quarterly observations. All data are obtained from DataStream, Bloomberg, World Bank and US Energy Information Administration (EIA) website.

Countries	Percentage change		
	Positive shocks	Negative shocks	Total shocks
Norway	-3.4%	0.0%	-2.2%
Canada	3.4%	17.6%	8.7%
Denmark	-13.8%	-5.9%	-10.9%
Mexico	6.9%	0.0%	4.3%
Brazil	24.1%	-29.4%	4.3%
Singapore	-6.9%	23.5%	4.3%
United Kingdom	-13.8%	23.5%	0.0%
Germany	-10.3%	0.0%	-6.5%
Japan	13.8%	-17.6%	2.2%
France	-10.3%	0.0%	-6.5%
United States	0.0%	0.0%	0.0%

Figure 6.5: Business cycle and the national oil price shocks.

The figure shows time series plots of the national oil price shocks for all countries in our sample. The black lines are Hamilton-type oil-price shock variable based on national crude oil Brent prices, obtained by multiplying the specific country's foreign exchange rate with the crude oil Brent price (e.g. for the UK = GBP/USD x Oil price). A positive (negative) oil shock is defined as when the current (quarterly) oil price is above (below) the maximum (minimum) oil price over the last year (4 previous quarters). Shaded grey are recession periods and a recession period is identified as a period for which there is negative GDP growth for at least two consecutive terms. Sample range Q1 1998 to Q4 2015, 72 quarterly observations. All data are obtained from DataStream, Bloomberg, World Bank and US Energy Information Administration (EIA) website.



6.4.3.1. NATIONAL OIL PRICE SHOCKS COEFFICIENT

Although figure 6.5 in the previous section seems to show minimum changes, we also conduct more regressions as shown in table 6.12 to investigate the issue further. In comparison to table 6.3, table 6.12 shows some significant changes in the relationship between GDP and oil price shocks after converting to national currencies.

Norway now shows a significant positive response instead of a negative response to positive national oil price shocks, which is expected for net oil exporting countries. Denmark still shows both positive and negative responses to positive national oil price shocks but relative to table 6.3, the negative response at lag four is now not significant.

Brazil appears to be affected the most by the currency conversion. Its response to positive national oil price shocks is now negative especially at lag 2, which is not expected for a net oil exporter. The UK also now responds negatively to positive national oil price shocks at the third lag and as a net oil importer, it is expected that the UK will be adversely affected by the positive shock.

Nevertheless, Canada, Mexico, Singapore, Germany, Japan and France response to positive oil shocks are not affected by converting to local currencies, even though some countries such as Germany and Japan show substantial changes in the number of shocks, as shown in table 6.11. The changes in responses for Denmark, UK and Brazil are consistent to table 6.11, as the three countries have endured the most changes in the number of positive shocks due to the conversion. However, although the number of positive oil shocks for Norway does not change much, it does result in significant responses.

In relation to negative oil price shocks, the original results in table 6.3 for Canada and Mexico appear to be affected by currency conversion, as now the two countries do not significantly and positively respond to negative shocks. Japan now shows a positive response to a negative oil price shock at the third lag but it also shows a negative response at the second lag. Moreover, Singapore exhibits negative responses to negative oil shocks which are also not expected for a net oil importer, while Germany is found not to be positively affected by the negative oil price shock anymore.

Table 6.11 highlights that due to currency conversion, there are changes to the number of negative oil shocks for Canada, Singapore and Japan, while there are no changes for

Norway and France. Mexico and Germany do not display any changes to the number of oil shocks but as highlighted earlier their response to negative oil price shocks have changed, which is surprising. This indicates that the timing as well as the strength of the shocks and not the number of shocks may have caused the changes of the two countries response to negative oil price shocks.

Table 6.12: Regression results of national oil price shocks.

This table reports the coefficients from the following regression:

$$\Delta y_{it} = \alpha_i + \sum_{j=1}^{4} \beta_{ij} \Delta y_{i,t-j} + \sum_{j=1}^{4} \gamma_{ij} \Delta x_{t-j}^{+} + \sum_{j=1}^{4} \delta_{ij} \Delta x_{t-j}^{-} + \varepsilon_{it} \qquad (6.11)$$

Where Δy_{it} is the GDP growth at quarter *t*. The other variables are positive national oil price shocks (Δx_{t-j}^{+}), negative national oil price shocks (Δx_{t-j}^{-}) and also the GDP growth (Δy_{t-j}) at quarterly lags of t-j, for which we use up to 4 quarterly lags for our regressions. National crude oil Brent price = Country's FX rate X crude oil Brent price. Based on national crude oil Brent prices, a positive (negative) oil shock is defined as when the current (quarterly) oil price is above (below) the maximum (minimum) oil price over the last year (4 previous quarters). The sample period is from January 1998 to December 2015, consisting of 72 quarterly observations. Newey-West p-value are reported in brackets whereby **bold** figures denote statistically significance coefficient at least at 10% level. The bandwidth parameter for the Newey-West p-value is calculated using the Newey-West automatic lag selection. All data are obtained from DataStream, Bloomberg, World Bank and US Energy Information Administration (EIA) website.

Variable		Δy_{t-j}				Δx_{t-j}^{+}				Δx_{t-j}^{-}			
Lag		$j=1$	$j=2$	$j=3$	$j=4$	$j=1$	$j=2$	$j=3$	$j=4$	$j=1$	$j=2$	$j=3$	$j=4$
Coefficient	α	β_1	β_2	β_3	β_4	γ_1	γ_2	γ_3	γ_4	δ_1	δ_2	δ_3	δ_4
Norway	**0.008**	**-0.204**	**-0.246**	-0.001	**-0.202**	-0.033	**0.047**	-0.028	0.013	**0.051**	-0.020	0.039	-0.021
	(0.001)	**(0.023)**	**(0.033)**	(0.990)	**(0.055)**	(0.277)	**(0.068)**	(0.168)	(0.567)	**(0.000)**	(0.451)	(0.116)	(0.272)
Canada	**0.003**	**0.518**	-0.140	0.103	0.015	0.013	-0.001	-0.012	-0.010	0.021	-0.007	-0.004	-0.010
	(0.031)	**(0.002)**	(0.391)	(0.494)	(0.901)	(0.243)	(0.940)	(0.381)	(0.340)	(0.263)	(0.634)	(0.756)	(0.485)
Denmark	0.002	0.233	0.126	0.061	-0.085	0.030	**-0.049**	**0.050**	-0.024	0.017	-0.001	-0.006	0.003
	(0.296)	(0.119)	(0.426)	(0.516)	(0.473)	(0.161)	**(0.017)**	**(0.045)**	(0.201)	(0.304)	(0.958)	(0.620)	(0.840)
Mexico	**0.005**	**0.435**	-0.067	-0.010	-0.111	0.012	0.002	-0.003	-0.015	0.047	-0.023	-0.014	0.014
	(0.004)	**(0.023)**	(0.648)	(0.941)	(0.284)	(0.311)	(0.896)	(0.860)	(0.243)	(0.104)	(0.279)	(0.428)	(0.494)
Brazil	**0.007**	**0.457**	-0.245	0.154	**-0.262**	**0.034**	**-0.060**	0.027	0.000	0.046	-0.010	0.010	0.022
	(0.016)	**(0.009)**	(0.160)	(0.160)	**(0.054)**	**(0.061)**	**(0.058)**	(0.174)	(0.982)	(0.178)	(0.776)	(0.798)	(0.437)
Singapore	**0.048**	0.182	-0.077	0.141	-0.178	0.167	-0.104	-0.065	0.110	0.128	**-0.250**	0.121	-0.057
	(0.042)	(0.182)	(0.635)	(0.467)	(0.153)	(0.406)	(0.722)	(0.670)	(0.432)	(0.315)	**(0.078)**	(0.481)	(0.756)
United Kingdom	**0.002**	**0.619**	0.221	-0.237	0.012	0.004	-0.011	**-0.015**	0.006	-0.002	0.003	-0.006	0.001
	(0.024)	**(0.016)**	(0.115)	(0.101)	(0.868)	(0.817)	(0.456)	**(0.044)**	(0.553)	(0.834)	(0.729)	(0.555)	(0.842)
Germany	0.001	**0.391**	0.012	0.100	-0.027	0.010	0.004	-0.020	0.012	0.035	-0.034	0.002	-0.015
	(0.421)	**(0.001)**	(0.920)	(0.348)	(0.698)	(0.482)	(0.832)	(0.275)	(0.288)	(0.160)	(0.154)	(0.891)	(0.258)
Japan	**0.004**	0.210	-0.190	**-0.218**	-0.088	0.015	-0.007	-0.014	-0.009	**0.054**	**-0.035**	**0.037**	-0.016
	(0.019)	(0.177)	(0.105)	**(0.033)**	(0.415)	(0.327)	(0.849)	(0.465)	(0.564)	**(0.000)**	**(0.036)**	**(0.010)**	(0.220)
France	0.000	**0.490**	**0.269**	-0.010	-0.065	0.006	-0.001	0.001	-0.005	0.004	-0.015	-0.007	-0.001
	(0.638)	**(0.001)**	**(0.039)**	(0.932)	(0.549)	(0.464)	(0.931)	(0.935)	(0.594)	(0.640)	(0.240)	(0.178)	(0.936)
United States	**0.013**	0.201	**0.226**	0.017	0.045	0.003	-0.012	0.029	**-0.093**	0.042	-0.055	0.021	-0.024
	(0.024)	(0.190)	**(0.084)**	(0.916)	(0.707)	(0.964)	(0.881)	(0.637)	**(0.029)**	(0.393)	(0.267)	(0.458)	(0.519)

6.4.3.2. SPATIAL/ DIRECTIONAL ASYMMETRY OF NATIONAL OIL PRICE SHOCKS

We will also investigate the effect of currency conversion on the asymmetry effects of the countries by exploring the spatial/directional asymmetry from two complementary perspectives. As before, this will be conducted by looking at *"estimated coefficients on the national oil price shock variables"* and the *"impulse responses to national oil price shocks"*.

6.4.3.2.1. SPATIAL/ DIRECTIONAL ASYMMETRY I: NATIONAL OIL PRICE SHOCKS COEFFICIENT

This section will allow an investigation of directional asymmetries in national oil price shocks from the perspective of the shocks' estimated coefficients reported earlier in table 6.12. Table 6.13 shows that the currency conversion has caused none of the countries to have significant responses to either positive or negative national oil price shocks.

Table 6.13: Tests of aggregate directional symmetry of national oil price shocks.
The table shows the aggregate directional symmetry of national oil price shocks based on the coefficients of table 6.12 using Wald test. The variables below represent coefficients in relation to positive oil price shocks ($\sum \gamma_j$) and negative oil price shocks ($\sum \delta_j$). $\sum \gamma_j = \sum \delta_j$ is the tests for aggregate directional symmetry for the national oil price shocks. The sample period is from January 1998 to December 2015, consisting of 72 quarterly observations. Newey-West p-value are reported in brackets whereby **bold** figures denote statistically significance coefficient at least at 10% level. The bandwidth parameter for the Newey-West p-value is calculated using the Newey-West automatic lag selection. All data are obtained from DataStream, Bloomberg, World Bank, IMF and US Energy Information Administration (EIA) website.

H_0	$\sum \gamma_j = 0$	$\sum \delta_j = 0$	$\sum \gamma_j = \sum \delta_j$
	$\sum \gamma_j$	$\sum \delta_j$	
Norway	0.000 (0.992)	0.048 (0.206)	-0.049 (0.446)
Canada	-0.010 (0.680)	0.000 (0.993)	-0.010 (0.753)
Denmark	0.007 (0.764)	0.012 (0.598)	-0.005 (0.873)
Mexico	-0.004 (0.906)	0.023 (0.447)	-0.027 (0.584)
Brazil	0.001 (0.960)	0.067 (0.417)	-0.066 (0.446)
Singapore	0.108 (0.645)	-0.058 (0.815)	0.166 (0.618)
United Kingdom	-0.016 (0.232)	-0.003 (0.734)	-0.013 (0.470)
Germany	0.006 (0.740)	-0.012 (0.504)	0.018 (0.547)
Japan	-0.014 (0.692)	0.040 (0.101)	-0.055 (0.186)
France	0.001 (0.916)	-0.018 (0.148)	0.020 (0.261)
United States	-0.073 (0.469)	-0.016 (0.757)	-0.057 (0.617)

6.4.3.2.2. SPATIAL/ DIRECTIONAL ASYMMETRY II: IMPULSE RESPONSE FUNCTIONS OF NATIONAL OIL PRICE SHOCKS

We have also conducted impulse response functions on the eleven countries, in order to provide a different perspective of the directional asymmetry. Table 6.14 shows that two countries are affected by currency conversion namely Brazil and UK.

As shown in table 6.11, Brazil has the most changes in the number of positive oil price shocks and this may have caused Brazil's response to positive oil price shocks to become insignificant. Nevertheless, Brazil's response to negative oil price shocks is not affected even though Brazil has the most changes in the number of negative oil price shocks. On the other hand, UK's response to negative oil price shocks has become insignificant. In order to further analyse the effect of currency conversion, we will also check the impulse response functions of the individual countries.

Figure 6.6 shows that there are some changes to the responses but the pattern appears to be similar. For example, although not significant Brazil and Mexico exhibit negative response to positive oil price shocks at the first quarter, which is not the case in figure 6.2. This is contrary to our understanding because as a net oil exporter, Brazil is expected to exhibit positive response to positive oil price shocks. This can also be seen for Germany, which now exhibits a positive response to a positive oil price shock also at the first quarter, which again is contrary to our findings, as Germany is a net oil importer. In relation to negative oil price shocks, only Norway shows changes relative to figure 6.2. Nonetheless, none of the responses are considered to be significant, indicating that the changes do not really matter.

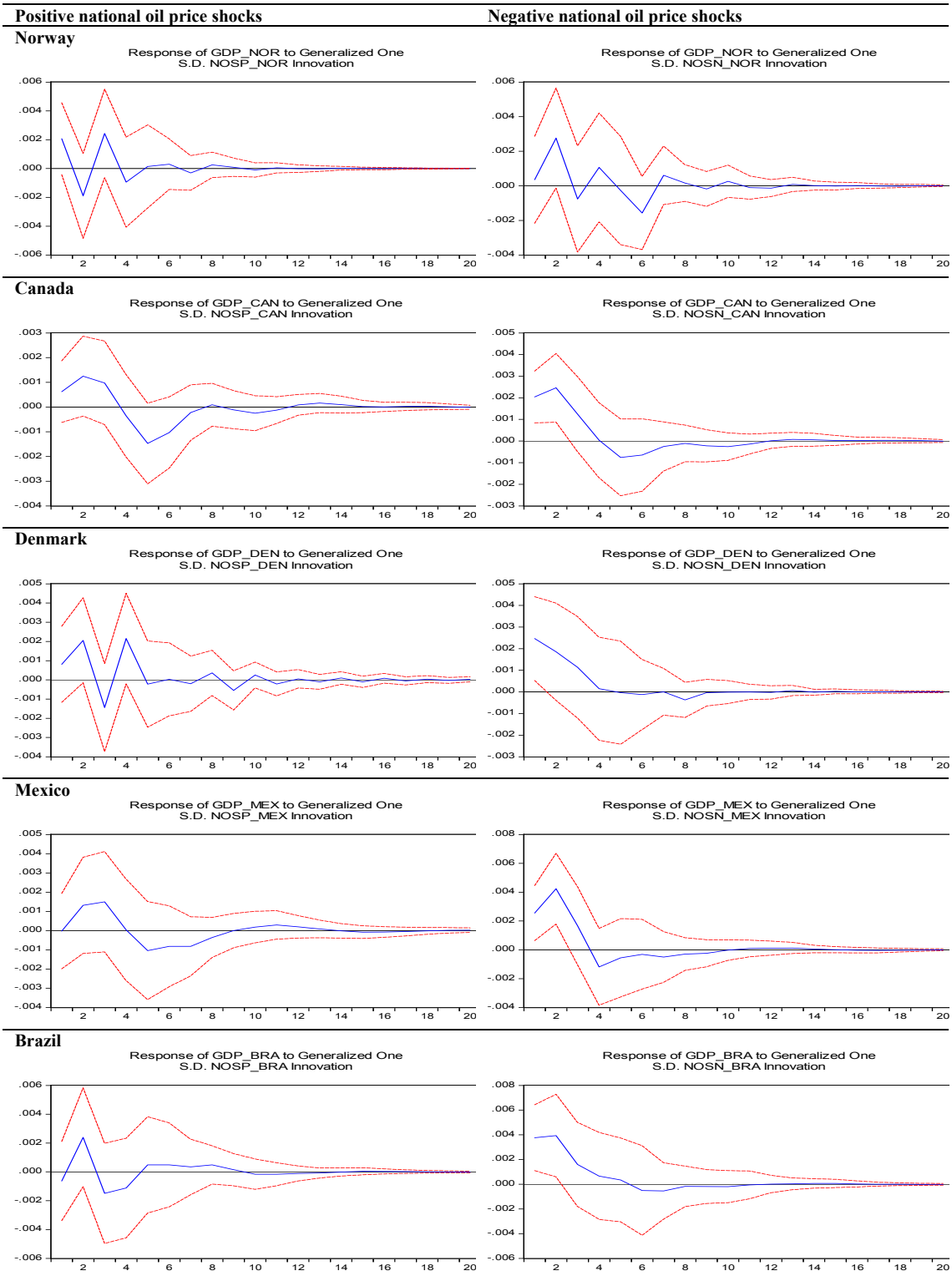
Table 6.14: Summary of spatial/ directional asymmetry of national oil price shocks: Impulse response function.

The table provides a summary of the results of the impulse response function of the national oil price shocks from figure 6.6. A country is considered to experience a shock if its response is statistically significant (different from zero) for at least one quarter. The sample period is from January 1998 to December 2015, consisting of 72 quarterly observations. All data are obtained from DataStream, Bloomberg, World Bank and US Energy Information Administration (EIA) website.

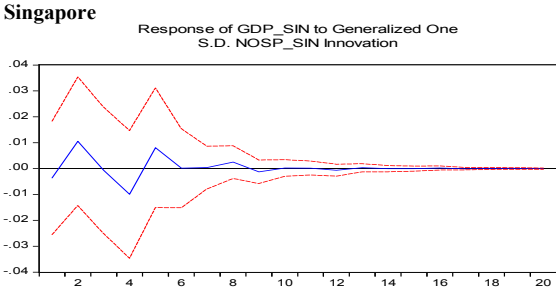
Positive oil shocks only	Negative oil shocks only	Both positive and negative oil shocks	Neither positive nor negative oil shocks
	Canada		Norway
	Denmark		United Kingdom
	Mexico		
	Brazil		
	Singapore		
	Germany		
	Japan		
	France		
	United States		

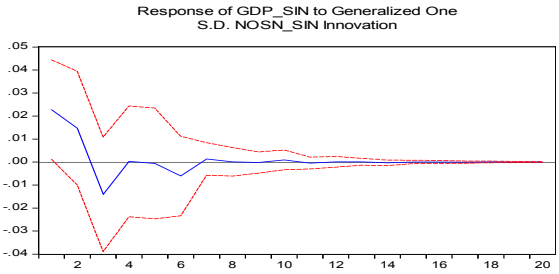
Figure 6.6: GDP and national oil price shocks impulse response function.

This figure shows the impulse response function of the GDP to a generalised one standard deviation of either positive or negative national oil price shocks. Since the crude oil Brent price is in USD, the national crude oil Brent price is obtained by multiplying the specific country's foreign exchange rate with the crude oil Brent price (e.g. for the UK = GBP/USD x Oil price). The VAR lag length is kept at four. The sample period is from January 1998 to December 2015, consisting of 72 quarterly observations. All data are obtained from DataStream, Bloomberg, World Bank and US Energy Information Administration (EIA) website.

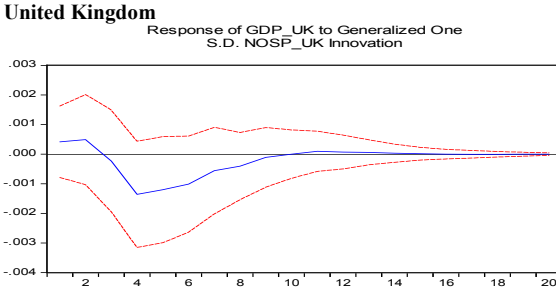


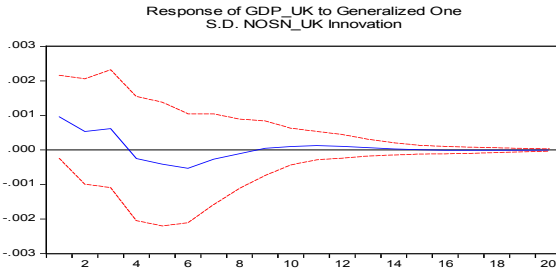
Singapore



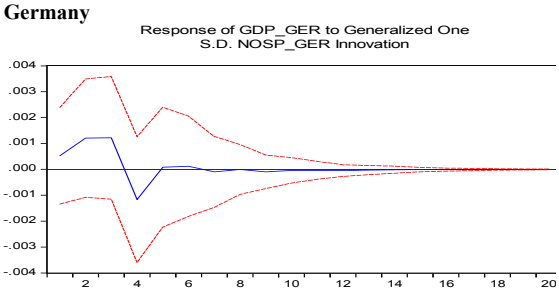


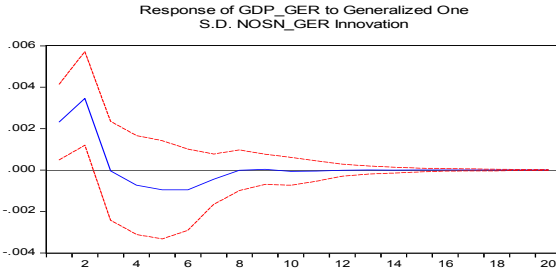
United Kingdom



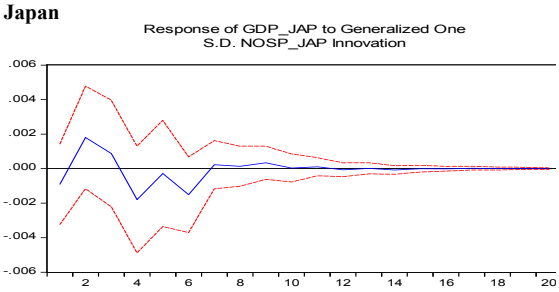


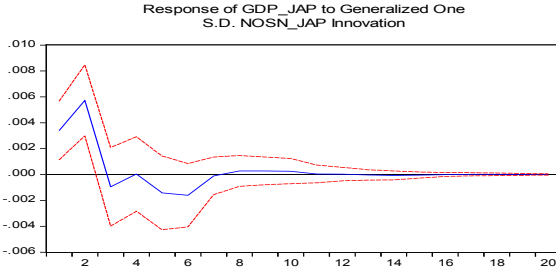
Germany



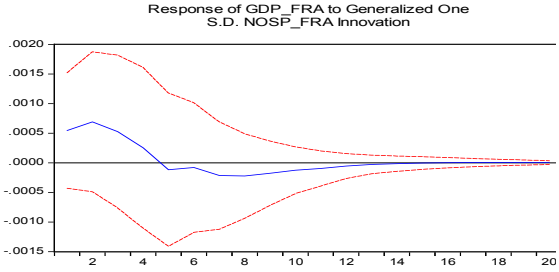


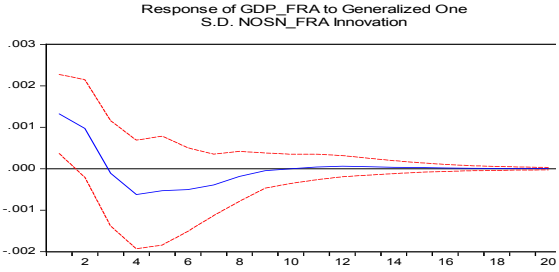
Japan



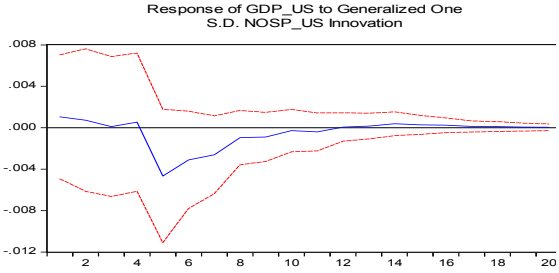


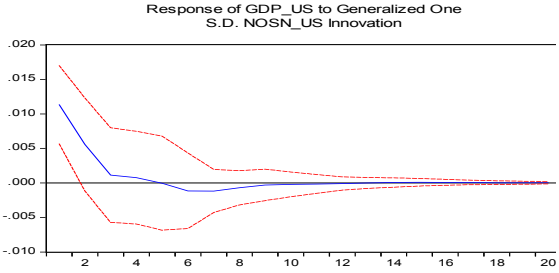
France





United States





6.5. CONCLUSION

This study looks at the impact of oil price shocks on eleven countries, consisting of five net oil exporting countries and six net oil importing countries. Our research starts off with the investigation of the relationship between oil price shocks and our sample countries.

During the financial crisis, our research initially shows that generally net oil importing countries such as Singapore, UK, Germany, Japan, France and US appear to go into recession immediately after a positive oil price shock, which is consistent to past studies such as Hamilton (1983). Whilst for net oil exporting countries such as Norway, Canada and Brazil, the recession only happens after a negative oil price shock.

Further investigation appears to indicate that Brazil, a net oil exporter, benefits from positive oil price shocks while net oil importers such as Germany benefits from negative oil price shocks. Nevertheless, there are mixed responses as well, such as for the US, the response to positive oil price shocks is delayed in comparison to Engemann et al. (2014) but this may merely be due to the differences in time periods and variables use.

Our first asymmetry effect exercise shows that all countries with the exception of Japan failed to reject the null hypothesis of directional symmetry. This means that all other countries exhibit a symmetrical response to both positive and negative oil price shocks. However, using impulse response functions, two countries exhibit symmetrical effect while most countries show significant asymmetry effects. However, most countries respond to negative oil price shocks instead of positive oil price shocks. This makes drawing a conclusion difficult regarding the effect of oil price shocks on macro-economies.

We also investigate the relationship between illiquidity shocks and the macro-economy of our sample countries. During the financial crisis period, some countries such as Norway, Canada, Denmark, Germany and the US endure positive illiquidity shocks prior to a recession period signifying that a market illiquidity increase (or market liquidity decrease) is followed by a recession. Further investigation by regression models reveals a clear relationship between illiquidity shocks and GDP in relation to positive illiquidity shocks. Moreover, the results on illiquidity shocks seem to be much clearer in comparison to oil price shocks.

Similar to oil price, the first asymmetry effect test is less convincing but when using impulse response functions results are more consistent. Results indicate that seven of our sample countries experience directional asymmetry by responding to positive illiquidity shocks only, while four countries show symmetrical effect. However, Mexico seems to exhibit a genuine symmetrical effect as positive and negative illiquidity shocks cause the GDP of Mexico to move in the opposite direction respectively.

We also study national oil price shocks briefly as Cunado and De Gracia (2005) show that the significant effect of oil price shocks on macroeconomic variables becomes more significant when the shocks are defined in national currencies. Unfortunately, our results are mixed, as earlier tests appear to show improvement in the results but later tests show results that contradict past literature.

In conclusion, we obtain contradictory results regarding the effect of oil price shocks on national economies. Although national oil price shocks show mixed results, our initial tests show some encouraging results due to currency conversion, signifying potential for future research. In addition illiquidity shocks appear to provide much clearer results (asymmetry is present) even though the Hamilton (1996) equation is actually meant for oil price shocks. Overall our study shows that illiquidity shocks[112] appear to be at least an equally important determinant of the state of the economy compared to oil price shocks which are thought to be one of the most important factors for a number of years.

[112] Market capitalisation may be an important variable for liquidity because by comparing the market capitalization of a specific country's stock market relative to another, stock markets with high market capitalisation is expected to be more liquid as it is more globally integrated. Another criterion that we should consider is foreign investor as Sung and Giouvris (2016) signifies its importance particularly for developing countries. Sung and Giouvris (2016) highlight that foreign direct investment is increasingly sought by developing countries and it could increase liquidity as well as macroeconomic indicators in the host country. In our research, we have not considered market capitalization because one of the variables of our illiquidity measure namely *Amihud illiquidity measure* is market value (or capitalization). Even though we have also not included foreign investors, we feel that including market value and foreign investors may be good for our future research.

CHAPTER 7 : OIL, BALTIC DRY INDEX, MARKET LIQUIDITY AND BUSINESS CYCLES: EVIDENCE FROM NET OIL EXPORTING COUNTRIES AND NET OIL IMPORTING COUNTRIES

7.1. INTRODUCTION

Due to the recent financial crisis of 2007-2008, liquidity research has gained importance, as Crotty (2009) highlights that the crisis happened when investors run for liquidity and safety. Brunnermeier (2009) mentions that the crisis has led to the most severe financial crisis since the great depression and threatens to have large repercussions on the real economy, indicating the significance of market liquidity on the economy.

Nevertheless, along with liquidity we believe that the price of oil is an important part of macroeconomic activity. Basher and Sadorsky (2006) highlight that countries' demand for oil increases significantly due to urbanization and modernization, indicating that oil is considered the lifeblood of modern economies. Furthermore, similar to illiquidity, oil is also linked to the financial crisis as Taylor (2009) mentions that oil price increases have prolonged the crisis. Tverberg (2012) also suggests that if world oil supply should remain the same (low), then there is the possibility of a continuing financial crisis similar to the 2008-2009 recession. Although both liquidity (Crotty, 2009) and oil prices (Tverberg, 2012) are related to present/past crises and economic growth, there is no research available that investigates the combined effect of the two variables.

Galariotis and Giouvris (2015) find evidence that market liquidity may contain some information for predicting the current and future state of the economy. We believe that oil price may be more important for conducting a similar estimation. Thus, we decide to conduct research on the effect of both oil and market liquidity on economic growth using their framework.

Since we are conducting research on oil, we also include *national foreign exchange rate (NFX)* as part of our variables because oil is usually priced in *United States Dollar (USD)*. Furthermore, Cunado and Gracia (2005) highlight that the effect of oil on economic activity becomes more significant when oil is defined in local currencies. We also include *Baltic Dry index (BD)*, as it is commonly used as an indicator of economic activity reflecting on the global demand for raw materials (Bakshi et al., 2011). BD has also been

linked to oil as Tett (2016) mentions that the behaviour of Baltic Dry index (BD) is almost as dramatic as oil prices when viewing the global economy.

Although there are various studies on oil available, Wang et al. (2013) highlight that past studies seldom differentiate between oil exporting countries and oil importing countries. Wang et al. (2013) have conducted such research but their study is not between oil and macroeconomic activity. We undertake original research by covering ten countries grouped into five net oil exporting countries (Norway, Canada, Denmark, Mexico and Brazil) and five net oil importing countries (Singapore, United Kingdom (UK), Germany, Japan and France). Our grouping is based on the latest data available on US Energy Information Administration and DataStream.

Overall, this paper contributes to the current literature of macroeconomics forecasting. Næs et al. (2011) mention that a larger cross-section of stock markets should be investigated to test the predictive power of liquidity on the state of the economy. We expand this line of research by focusing on ten countries, of which four are new countries in comparison to Næs et al. (2011) and Galariotis and Giouvris (2015). Even though some of the countries are similar, we provide original results by including extra predictive variables such as oil (OB), Baltic Dry index (BD) and national foreign exchange (NFX), in addition to the illiquidity variables[113] which have not been used before. Moreover, by segregating our sample into net oil exporters and net oil importers, we will be able to investigate which predictive variables affect macroeconomic activity[114] of the two groups of countries. Finally, we also split our net oil exporting countries into developed and emerging countries in order to further enhance our study.

The remainder of this paper is organised as follows. Section 7.2 presents the literature review while section 7.3 describes the data and variables. In section 7.4, the methodology, empirical results and analysis are discussed followed by our conclusion in section 7.5.

[113] The paper uses the *Amihud illiquidity measure* to construct two illiquidity variables namely *national illiquidity (NAM)* and *global illiquidity (GAM)*. National illiquidity (NAM) relates to the illiquidity of the companies of a specific country while global illiquidity (GAM) excludes the companies of the specific country and hence consisting of international companies only. Further details of the illiquidity variables can be found in the *Data and variables section*.

[114] The paper uses Gross Domestic Product (GDP) as a proxy for macroeconomic activity.

7.2. LITERATURE REVIEW

7.2.1. OIL PRICES AND THE MACRO-ECONOMY

One of the earliest key studies on oil and macroeconomic variables is conducted by Hamilton (1983) who finds that there is a significant increase in the price of crude petroleum prior to seven of the eight post world war II recessions in the US. Nonetheless, although this does not automatically signify that oil shocks cause the recessions, oil shocks can be seen at least as a contributing factor. Hamilton (2011) in fact updates the count to ten out of eleven US recessions being preceded by significant rises in oil price. Mork (1989) investigates both increases and decreases in oil price and finds that positive oil price changes have a negative and significant relationship with changes in the US macro-economic activity while oil price decreases tend to have a positive impact on macro-economic activity, but it is small, and not statistically significant.

Mork et al. (1994) expand their research by covering seven *Organisation for Economic Co-operation and Development (OECD)*[115] countries and their results indicate that with the exception of Norway, *oil price increases* are significant and negatively correlated with macroeconomic indicators (GDP) of the other countries. Surprisingly, Mork et al. (1994) also find that *oil price decreases* are significant and positively correlated to macroeconomic activity for the US and Canada[116], suggesting that an oil price reduction may also have adverse effects on the business cycle regardless of the degree to which the country depends on oil. Cuñado and de Gracia (2003) study fifteen European countries and find evidence of oil price shocks affecting macroeconomic variables such as inflation and industrial production indexes. Furthermore, Cunado and De Gracia (2005) undertake similar research on six Asian countries and highlight that oil prices have a significant effect on both economic activity and price indexes. Nevertheless, they show that the effects of oil price shocks on each of the European countries can be different.

All studies above concentrate on the relationship between oil prices and macroeconomic activity. There is also research on the impact of oil on financial markets. For instance, Jones and Kaul (1996) highlight that changes in oil prices have a detrimental effect on output and real stock returns in the US, Canada, Japan and the UK post-war. Sadorsky

[115] Mark, Olsen et al. (1994) OECD sample is consisting of US, Canada, Japan, Germany (West), France, UK and Norway
[116] Mork, Olsen et al. (1994) highlight that Canada switches from a position of net oil importer to net oil exporter over time while we classify Canada as a net oil exporter based on the latest available data (2012) that we obtained from US EIA website.

(1999) finds evidence that oil price and *oil price volatility* both play important roles in affecting real stock returns by studying the US market.

Using Toda and Yamamoto (1995) version of Granger causality tests on the Indian market, Ghosh and Kanjilal (2016) reveal that there exists a unidirectional Granger causality running from oil price to exchange rate in phase I while in phase II, causality runs from oil price to stock market as well as stock market to exchange rate. In phase III[117], the causality runs from crude oil price to stock market with no feedback effect, indicating that global oil price is exogenously determined.

There is also a comparable unidirectional effect when looking at the relationship between energy consumption and GDP. Lee (2005) finds evidence that long-run and short-run causalities run from energy consumption to GDP, but not vice versa using their sample of eighteen developing countries. Wolde-Rufael (2004) finds a similar unidirectional causality in Shanghai, China from 1952 to 1999. Moreover, Narayan and Smyth (2008) highlight that energy consumption Granger causes real GDP positively in the long run for the G7 countries. They also mention that the results are consistent with the energy dependent hypothesis, suggesting that energy consumption is a major factor influencing economic growth for energy dependent countries.

Nevertheless, we believe that there may also be an inverse relationship between energy and economic growth whereby economic growth can influence oil price. The logic behind this is as follows. As economies improve, it is expected that the energy consumption of those economies will also increase resulting in an increasing demand for oil causing the oil price to also increase. For instance, Kraft and Kraft (1978) find evidence in the US that causality is unidirectional, running only from GNP to energy[118] for the post-war period between 1947 and 1974. Al-Iriani (2006) also finds unidirectional causality running from GDP to energy consumption by studying six *Gulf Cooperation Council (GCC)*[119] countries. Interestingly, since Al-Iriani (2006) result is unidirectional, any changes to energy consumption (e.g. energy consumption policies) will not have negative effects on their economic growth. Similarly, Mehrara (2007) also shows unidirectional

[117] Ghosh and Kanjilal (2016) use data from January 2, 2003 to July 29, 2011, which are chosen based on the fact that oil price starts rising once again from 2003 onwards after the oil price crises in 1973 and 1979/1980. In order to get a better understanding, the entire data span is further divided into three sub-phases of prior (phase I) and post (phase III) to the most volatile phase (phase II) that spans from July 2, 2007 to Dec 29, 2008.

[118] Energy is represented by Gross energy inputs which include the total of inputs into the economy of primary fuels plus the generation of hydro and nuclear power converted to equivalent energy inputs (BTU's). The primary fuels include both domestic and imports of coal, natural gas and petroleum (Kraft & Kraft, 1978)

[119] Gulf Cooperation Council (GCC) countries are: Bahrain, Kuwait, Oman, Qatar, Saudi Arabia and United Arab Emirates (UAE).

strong causality from economic growth to energy consumption for eleven oil exporting countries.

However, there are also studies that find a bidirectional causality such as Oh and Lee (2004). They find a long run bidirectional relationship between energy and GDP by studying Korea for the 1970–1999 period. However, Oh and Lee (2004) also find evidence of short run unidirectional causality running from energy to GDP. Soytas and Sari (2003) obtain mixed results. They find bidirectional causality in Argentina, while for Italy and Korea, the causality runs from GDP to energy consumption and inversely for Turkey, France, Germany and Japan.

There are also studies that find contradictory results of no causality between economic growth and energy consumption such as Eden and Hwang (1984) research on US, using data between 1947 and 1979. A more important point is highlighted by Al-Iriani (2006) who mention in their research of GCC countries that energy consumption is based on aggregate data, so oil consumption may only be a portion of other more relevant energy variables[120]. Wolde-Rufael (2004) actually dis-aggregated the energy series, finding evidence to suggest that there is no Granger causality running in any direction between oil consumption and real GDP but there is only a unidirectional Granger causality running from coal, electricity and total energy consumption to real GDP. This indicates that other energy variables have a stronger effect on economic growth and hence energy consumption may not be appropriately captured by oil.

Basher et al. (2012) investigate the dynamic relationship between oil prices, exchange rates and emerging market stock prices and show that positive shocks to oil prices tend to depress emerging market stock prices. However, a positive oil production shock lowers oil prices while a positive shock to real economic activity increases oil prices. They also show that increases in oil prices are due to increases in emerging market stock prices.

Clements and Fry (2008) highlight that commodity exporting countries through their exchange rate can have an impact on commodity prices. This situation can arise if a country is a large producer of a commodity or if a group of commodity exporting countries have the combined market power to influence the world prices of commodities. This can relate to oil as oil can be classified as part of commodities. In fact, Clements and

[120]Energy consumption for the World Bank (Global Consumption Database) consists of Electricity, Gas and other fuels.

Fry (2008) give examples of Saudi Arabia which has the ability to influence oil price while Australia is a price maker for wool. Moreover, Saudi Arabia is part of *OPEC (Organization of the Petroleum Exporting Countries)*, a group of oil exporting countries, which should have the combined market power to influence oil prices. In fact, Kaufmann et al. (2004) find evidence that *OPEC*[121] Granger cause real oil prices but there is no inverse relationship (causality), implying that OPEC is able to influence real oil price.

Sheppard et al. (2016) report that due to poor performance of oil companies and big oil producing countries going into recession, OPEC led by Saudi Arabia decides to cut oil production to help the oil market recover. This is consistent with the findings of Fan and Xu (2011) who highlight that one of three main drivers[122] affecting oil prices are the supply–demand relationship of oil market. However, it should be pointed out that the main drivers of oil price changes are distinct during different structural periods.

Overall, past literature shows that there is a relationship between oil and economic growth. Cunado and De Gracia (2005) highlight that oil affects economic activity while it is less obvious in the other direction. Kaufmann et al. (2004) and Sheppard et al. (2016) shows that OPEC can influence real oil prices to benefit their economies if required. Thus, the literature appears to suggest the possibility of bidirectional relationship between oil and economic growth.

7.2.1.1. NET OIL EXPORTING COUNTRIES VERSUS NET OIL IMPORTING COUNTRIES

We believe that the degree to which oil is important to a specific country's economy may result in the specific country to react differently to oil price movements. For instance, a country that is less dependent on oil is expected to react less to any movement in oil prices.

Earlier research tends to focus on the US economy, an oil importer, and the results show that there is a significant increase in the price of crude petroleum prior to recession periods (Hamilton, 1983). However, an oil exporter is expected to benefit from an oil

[121] The variables of OPEC: include capacity utilization, OPEC production quotas, the degree to which OPEC exceeds these production quotas, and crude oil stocks in OECD nations.

[122] The other two main drivers of oil price are relevant *"market fundamentals"* and *"episodic events"*. *"Market fundamental"* includes the US dollar exchange rate, stock market, gold market and oil futures. "Episodic events" include market wars and terrorist attacks. Fan & Xu (2011) mention two episodic events namely the US terrorist attack (11th September 2001) and invasion of Iraq (20th March 2003).

price increase, as shown by Saudi Arabia's willingness to cut oil production in order to improve revenue and their economy (Sheppard et al., 2016). Wang et al. (2013) mention that the influence of oil price shocks on the national economies of oil-exporting countries can be different from those of oil-importing countries, as oil price increases may bring positive effects on the national economies of oil-exporting countries.

Mork et al. (1994) obtain results which show that Norway, an oil-exporting country, behaves differently from the other countries in their sample, as Norway's economy benefits significantly from oil price increases. Moreover, Mork et al. (1994) highlight that Norway seems to be hurt by oil price declines but less significantly. Mork et al. (1994) mention that if the domestic oil sector is large enough relative to the size of the economy, a country's net oil exporting position appears to influence the *oil-price-GDP correlation* substantially. Nevertheless, UK[123], another oil-exporting country in their research, exhibits similar results to oil-importing countries such as US, Germany, France, and Japan.

Cunado and De Gracia (2005) find that Malaysia's *oil price–economy relationship* seems to be less significant compared to other five Asian economies, as Malaysia is the only oil-exporting country in their sample. Cunado and De Gracia (2005) stress that more research is required to obtain a more reliable conclusion but their results seem to suggest that there are different responses between oil exporters and oil importers.

Moreover, Wang et al. (2013) highlight the different reaction between oil-exporting countries and oil-importing countries, as positive aggregate and precautionary demand oil shocks are shown to result in a higher degree of co-movement among the stock markets in oil-exporting countries but not among stock markets in oil-importing countries. Engemann et al. (2014) highlight that apparently the most energy-intensive US states are the states that only respond to negative oil-price shocks.

Overall, it seems that the classification of whether a country is an oil exporter or importer is important when undertaking research on oil. However, past studies seldom differentiate between oil exporting countries and oil importing countries, which is also highlighted by Wang et al. (2013). Although they differentiate between oil importing/exporting countries, their focus is on the relationship between oil price shocks and stock markets instead of

[123] In this paper, we classify UK as a net oil importer based on the latest available data as of 2012 that we obtained from US EIA website.

macroeconomic activity. This indicates the importance of investigating the effect of oil prices on economic activity differentiating between oil importing and exporting countries.

7.2.2. LIQUIDITY AND THE MACRO-ECONOMY

Chordia et al. (2001) study the effect of several explanatory variables on aggregate market spreads, depths and trading activity for US stocks from 1988 to 1998 and confirm that short-term interest rates significantly affect market liquidity as well as trading activity. Fujimoto (2004) who also studies the US market presents similar findings as macroeconomic fundamentals appear to be significant determinants of liquidity and their effects are stronger prior to the mid 1980's when business cycle dynamics are more volatile. Furthermore, Said and Giouvris (2017) study the UK market and find evidence that expansive monetary conditions (measured using interest rates) increase market liquidity. Generally, past literature finds evidence that macroeconomic variables affect market liquidity. Söderberg (2008) finds evidence that some of the fourteen macroeconomic variables in his sample are able to forecast market liquidity of the Scandinavian stock exchanges including Copenhagen (Denmark), Oslo (Norway) and Stockholm (Sweden).

Recently, more studies have emerged on the inverse relationship that is the impact of liquidity on macroeconomic variables. Chordia et al. (2001) indicate that market liquidity increases prior to major macroeconomic announcements but it concentrates mostly on speculative trading activity and competition among informed traders[124] (Admati & Pfleiderer, 1988). Næs et al. (2011) mentions that at least since WWII, market liquidity contains useful information for estimating the current and future state of the US and Norway economy. Galariotis and Giouvris (2015) expand this line of research by studying G7 countries. Even though results are mixed, Galariotis and Giouvris (2015) also find evidence that liquidity variables are generally negatively related to GDP, signifying that economic growth increases following a reduction in market illiquidity (or increase in

[124] Chordia, Roll et al. (2001) study focuses on macroeconomic variables such as Gross Domestic Product (GDP), the unemployment rate and the Consumer Price Index (CPI) but only finds significant results for GDP and the unemployment rate. Although Chordia, Roll et al. (2001) appear to highlight that market liquidity impact macroeconomics, their study is actually in relation to speculative trading activity by uninformed trading causing depth measure to increase. However, it decreases back to normal level, as the announcement dates approaches, signifying that there is an increase in the number of informed traders. Furthermore, during periods when liquidity trading is concentrated, competition among informed traders can bring additional liquidity (Admati & Pfleiderer 1988). Please refer to Chordia, Roll et al (2001) and Admati & Pfleiderer (1988) for more information.

market liquidity). Sung and Giouvris (2016) also conduct a similar study but on four developed and two emerging Asia-Pacific countries and they find that some of their liquidity variables are able to predict macroeconomic variables but are not consistent over the six countries. Moreover, Sung and Giouvris (2016) find that relative to national liquidity, global liquidity has extra explanatory power in developing markets.

So far the literature appears to show that there is a potential two-way relationship between illiquidity and macroeconomic variables, as Fujimoto (2004) mentions that macroeconomic fundamentals seem to be significant determinants of liquidity while Næs et al. (2011) highlight the inverse relationship. Pereira and Zhang (2010) do find a bidirectional relationship but their study involves stock market and liquidity while Chordia et al. (2001) find indirectly that there is a potential two-way relationship between macroeconomic variables and liquidity.

Galariotis and Giouvris (2015) have found evidence that there is a two-way causality between macroeconomic indicators and liquidity variables for the six countries in their sample but it is more consistent for global liquidity.

When considering both developed and developing markets, Sung and Giouvris (2016) also find that there is a two-way causality between macroeconomic variables and national liquidity but not for global liquidity. Moreover, they find no causality between macroeconomic variables and global liquidity in developed markets but mainly a one-way causality from macroeconomic variables to global liquidity in developing markets, signifying that the two markets react differently to liquidity variables. Dey (2005) finds that turnover is significant for emerging market portfolios only, while it is insignificant for developed market portfolios, indicating that due to the high liquidity of developed markets, liquidity is not a concern for investors. Thus, providing further evidence that the two markets respond differently. This is interesting as our sample consists of two (2) countries that are categorised as emerging markets while the others are developed markets.

Overall, the literature shows that there is potentially a two-way causality between liquidity and macroeconomic variables but the causality depends on the liquidity measure used. For instance Galariotis and Giouvris (2015) find a two-way causality for global liquidity whereas Sung and Giouvris (2016) obtain similar results for national liquidity.

7.2.3. BALTIC DRY INDEX AND THE MACRO-ECONOMY

The Baltic Dry Index (BD) is a shipping and trade proxy created by the Baltic Exchange and it reflects the rates that freight carriers charge to haul solid raw materials such as iron ore, coal, cement, and grain (Rothfeder, 2016). Lin and Sim (2013) highlight that BD has become one of the most important indicators of the cost of shipping and an important barometer of the volume of worldwide trade and manufacturing activity. Essentially, BD captures trade activity. A decrease in BD usually means that shipping prices and commodities sales are dropping (Rothfeder, 2016).

Although the predictive ability of BD has recently waned, BD still shows some potential. In the past, a dip in the BD foretold IndyMac's bankruptcy which is one of the first major bank failures during the financial crisis of 2007-2008 (Rothfeder, 2016). Bakshi et al. (2011) find evidence of positive association between a BD increase and growth on stock/commodity returns as well as in global economic activity by studying the industrial production of 20 countries. Furthermore, using daily data spanning from 1985 to 2012, Apergis and Payne (2013) show the predictive capacity of the BD for both financial assets and industrial production, whereby the relationship is found to be positive. Thus, revealing the role of the BD in predicting the future course of the real economy.

Another reason that we consider Baltic Dry Index (BD) as part of our research is due to its apparently close relationship with oil. Tett (2016) mentions that recently, the behaviour of the BD is almost as dramatic as oil prices due to the current sluggish trade environment. Kilian (2009) introduces a new measure of monthly global real economic activity based on dry cargo bulk freight rate data that is used to disentangle demand and supply shocks in the global crude oil market. Although the dry cargo bulk freight rate is not actually BD, its concept is the same as the dry cargos consist of grain, oilseeds, coal, iron ore, fertilizer, and scrap metal. A similar technique is also applied by Wang et al. (2013) in order to estimate the scale of global economic activity as a proxy for global oil demand.

There also appears to be an inverse relationship between macroeconomic variables and Baltic Dry Index (BD). Klovland (2002) shows that cycles in economic activity are major determinants of the short-run behaviour of shipping freight rates in the years between 1850 and World-War I. Moreover, since Apergis and Payne (2013) indicate that there is a relationship between commodities and BD, a change in demand for commodities should

have an effect on BD as well. For example, due to economic growth, an increase demand for commodities will eventually affect BD. Bloch et al. (2012) mention that China's demand for coal is surging because of China's strong economic growth. Hence, there is potentially a two-way relationship between BD and economic growth. In fact, Bloch et al. (2012) find that there is a bidirectional causality between coal consumption and GDP using demand-side analysis. Thus, since coal is part of BD, it should be expected that economic growth may also affect BD.

On a separate note, Lin and Sim (2013) investigate 48 *Least Developed Countries (LDC)* designated by the United Nations using BD as an instrument for trade and they find that a 1% expansion in trade raises GDP per capita by approximately 0.5% on average, emphasizing the importance of trade towards the economic development of LDCs or low income countries. Since we have two emerging countries in our sample, it may be interesting to investigate whether developed and emerging countries will react differently to the predictive variables including BD. However, Mexico and Brazil are not part of Lin and Sim (2013) LDCs.

Overall, BD appears to have some relationship with economic growth as highlighted by Bakshi et al. (2011) since it has the ability to predict economic growth. Bloch et al. (2012) find evidence of a potential two-way causality. Moreover, BD's close relationship with oil is one of the main reasons that we decide to include BD in our research since BD is used as a proxy for global oil demand (Wang et al., 2013).

7.2.4. FOREIGN EXCHANGE AND THE MACRO-ECONOMY

We have included *national foreign exchange (NFX) rate* as part of our predictive variables because oil is usually priced in *United States Dollars (USD)*. Moreover, there appears to be a relationship between oil and NFX as Basher et al. (2012) mention that lower USD coincides with higher oil prices and vice versa. Moreover, Basher et al. (2012) highlight that positive oil shocks tend to depress USD in the short run, which is consistent with Krugman (1980) research that exchange rate movements are determined primarily by current account movements. Therefore, for a net oil importer like the US, rising oil prices lead to a current account deterioration causing exchange rates to fall.

The mechanism behind the relationship between NFX and the economy of countries appears simple. It is expected that as NFX rate change, the prices of goods and services will affect exports and imports. This is a simple policy that is commonly reported in the mainstream media. For instance in 2015, China's central bank has purposely devalued the Yuan relative to the USD because a cheaper Yuan will make Chinese exports less expensive, potentially boosting overseas sales (exports) that have been among the main drivers of economic growth for China's remarkable rise over the past 30 years (Inman, 2015).

There are studies on the impact of NFX on exports. Cashin et al. (2004) investigate 58 commodity exporting countries between 1980 and 2002. They find evidence of a long-run relationship between national real exchange rate and real commodity prices for about one-third of the commodity exporting countries. They do not actually show the effect of NFX on the economy but they show that NFX is an important aspect of trade (exports and imports). Since oil is also considered to be a commodity, it is expected that the impact will be similar. Moreover, oil appears to have some relationship with the economy. For example Hamilton (2011) highlights that ten out of eleven US recessions have been preceded by significant rises in oil price.

Farzanegan and Markwardt (2009) study on the relationship between the Iranian economy and oil, highlights the "Dutch Disease" syndrome. For instance, due to significant real effective NFX rate appreciation, the price of imports reduces while the price of exports increases, resulting in an inflationary effect which can affect the economy of Iran. Therefore, it will be expected that the NFX rate has at least an indirect effect on the economic growth or decline of the countries.

Furthermore, as mentioned earlier, it is common for studies of oil to be connected to NFX. In addition to Farzanegan and Markwardt (2009), Jiménez-Rodríguez and Sánchez (2005) highlight that changes in oil price influence NFX markets and inflation, giving rise to indirect effects on real activity while Cunado and De Gracia (2005) research on six Asian countries mention that the significant effect of oil price shocks on both economic activity and price indexes becomes more significant when the shocks are defined in local currencies. Nandha and Hammoudeh (2007) examine the relationship between beta risk and realized stock index return in the presence of oil and exchange rate sensitivities for fifteen countries in the Asia-Pacific region and they highlight that no country shows

sensitivity to oil price when measured in USD but find that the Philippines and South Korea are oil-sensitive when oil is expressed in local currencies.

The impact of NFX rate is not just limited to exports and imports, as it can also relate to financial markets. Dumas and Solnik (1995) investigate whether NFX rate risks are priced in international asset markets and their findings support the existence of NFX risk-premia for equities and currencies by covering the world's four largest equity markets namely Germany, UK, Japan and US. Nandha and Hammoudeh (2007) also find evidence that 8 out of 15 countries show a significant relationship between the changes in the exchange rate and domestic stock index returns.

However, Park and Ratti (2008) indicate that using real world oil price (USD) to measure real oil price shocks provides more cases of statistically significant impact on real stock returns in comparison to using national real oil price. Hussin, Muhammad, Abu, and Razak (2012) highlight that oil price is valid for the purpose of predicting changes in Islamic share prices in Malaysia but NFX rate is not. Moreover, Jorion (1991) presents evidence that the relationship between stock returns and the value of the dollar differs systematically across industries but their findings do not suggest that NFX risk is priced in the US stock market, contradicting firms decision to hedge.

Interestingly, Lizardo and Mollick (2010) study on the relationship between oil and NFX rate shows that increases in real oil prices lead to a significant depreciation of the USD against net oil exporter currencies such as Canada, Mexico, and Russia while the opposite can be seen for the NFX rate of oil importers such as Japan. Thus, signifying that the NFX of oil exporters and importers react differently to oil price movements.

Finally, we feel that economic growth can also affect NFX rate, as Inman (2015) highlights that the main reason that China devalue the Yuan is due to its flagging economy. This is also reported by Ryan and Farrer (2015) indicating that the state of the economy of a country can also impact NFX rate.

Overall, the literature shows a potential connection between NFX rate and economic growth as well as the possibility of a two-way relationship between the two variables. Cunado and De Gracia (2005) highlight that the impact of oil price shocks on economic activity becomes more significant when shocks are defined in national currencies but Park and Ratti (2008) find contradictory evidence when investigating stock returns. Nevertheless, Lizardo and Mollick (2010) different observations for oil exporters and

importers motivate us to include NFX rate in our study as we are exploring net oil exporters and importers.

7.3. DATA AND VARIABLES

7.3.1. DATA

We have chosen ten (10) countries for our data sample expanding from January 1998 to December 2015. Using the most recent data obtained from the US *Energy Information Administration (EIA)* website, we have equally segregated our countries into five (5) net oil exporting countries and five (5) net oil importing countries. The net oil exporting countries are Norway, Canada, Denmark, Mexico and Brazil while the net oil importing countries are Singapore, UK, Germany, Japan and France. The countries and periods are selected based on the availability of financial markets and economic data of the respective countries. Unfortunately, due to limited data availability, we are unable to include any members of the OPEC. Please refer to Table 7.1 for more information.

7.3.2. MACROECONOMIC, MARKET AND ILLIQUIDITY DATA

We use the main available stock indices of our chosen ten (10) countries to calculate market data such as our illiquidity measure. The indices that we chose are *Oslo All Share index (Norway), TSX Composite index (Canada), OMXC Index (Denmark), IPC index (Mexico), Bovespa index (Brazil), STI Index (Singapore), FTSE All Share index (UK), Prime All Share Index (Germany), Nikkei 225 (Japan)* and *SBF120 index (France).*

Gross Domestic Product (GDP) is used to determine economic growth. For *financial variables (FV)* and as control variables, we use the *risk free rate (RF), standard deviation* or market volatility *(SD), excess market returns (XS)* and *Dividend yield (DY)*. Risk free rate (RF) is the quarterly risk free rate of the respective countries[125] while Standard deviation or market volatility (SD) is the standard deviation of daily average returns for

[125] The risk free rates that we have chosen for our ten (10) countries are 3 months *Norwegian Interbank Offered Rate (NIBOR) (Norway), 28 days Mexican Federal Treasury Certificate (CETE) Rate (Mexico), 3 months Canada Treasury Bills (Canada), Brazil Money Market Rate (Brazil), 3 months Denmark Interbank Offered Rate (Denmark), 3 months Singapore Interbank Offer Rate (SIBOR) (Singapore), 3 months UK Treasury Bills (United Kingdom), 3 months Frankfurt Interbank Offer Rate (FIBOR)* (Germany), 3 months Japan interbank bank rate (Japan)* and *3 months Paris Interbank Offer Rate (PIBOR)* (France).* *FIBOR and PIBOR are eventually merged into *Euro Interbank Offered Rate (Euribor).*

all stocks over each quarter. Dividend yield (DY) is calculated as the cross sectional quarterly average for all stocks of the respective countries. Excess market returns (XS) is the cross sectional average returns for all stocks of the respective countries in excess of the risk free rate of the respective countries also over each quarter. Unfortunately, due to the limited number of stocks available for certain countries, certain financial variables that are used by Galariotis and Giouvris (2015) are not available for us such as size premium (SMB) and value premium (HML).

Our five (5) predictive variables are national foreign exchange (NFX), national illiquidity (NAM), global illiquidity (GAM), crude oil Brent (OB) and Baltic Dry Index (BD). *National foreign exchange (NFX)* is the specific country's *currency foreign exchange*[126] *relative to USD* and hence an increase in value will signify that USD has strengthened while the respective country's currency has weakened. For instance, for UK (GBP), an increase in the GBP/USD value means that GBP has weakened while USD has strengthened. The opposite scenario will be observed if the NFX value reduces. We include NFX because the crude oil Brent (OB) is normally priced in USD and Cunado and De Gracia (2005) study of six (6) Asian countries suggests that the significant effect of oil price shocks on macroeconomic variables becomes more significant when oil prices are defined in local currencies.

In comparison to the other variables, choosing the right illiquidity measure is not as straightforward because as highlighted by Goyenko et al. (2009), different illiquidity measures capture different aspects of liquidity. There are various measures available such as *Bid-Ask spread (Amihud & Mendelson, 1986)* and *High-Low Spread* (Corwin & Schultz, 2012). However, since Amihud et al. (2005) mention that there is hardly a single liquidity measure that can capture all aspects of estimating the effect of liquidity on asset prices, we have decided to choose the *Amihud illiquidity measure (Amihud, 2002)*. We have chosen the *Amihud illiquidity measure* because it is a recognisable measure which has been extensively used in the past literature and it is simple to calculate. More importantly, since we are investigating ten countries, it is essential as we have the inputs for the Amihud illiquidity measure (Amihud) for all the countries in our sample.

[126] The NFX consists of Norway (Norwegian Krone - NOK), Canada (Canadian Dollar - CAD), Denmark (Danish Krone - DKK), Mexico (Mexican Peso - MXN), Brazil (Brazilian Real - BRL), Singapore (Singapore Dollar - SGD), UK (UK Pound Sterling - GBP), Germany (Euro - EUR), Japan (Japanese Yen - JPY) and France (Euro - EUR).

Our *Amihud illiquidity measure* is calculated for each stock, s, in all countries for every quarter as follows:

$$Amihud_{sq} = \frac{1}{q}\sum_t \frac{1{,}000{,}000 \times |return_t|}{price_t \times volume_t} \tag{7.1}$$

Where t is each trading day.

We believe that using one illiquidity measure is sufficient because we will be considering two aspects of illiquidity namely national and global illiquidity for all the countries in our sample. *National illiquidity (NAM)* is simply the cross sectional average of *Amihud illiquidity measure* for all stocks of the respective countries in our sample. *Global illiquidity (GAM)* is created using the equally weighted average of the *Amihud illiquidity measure* across all stocks for the nine (9) countries, with the exception of the stocks belonging to a specific country nominated for the analysis which is similar to Brockman, Chung, and Pérignon (2009) and Galariotis and Giouvris (2015) technique. For instance, the global illiquidity (GAM) for UK is the equally weighted average of all sample stocks of the nine (9) countries, with the exception of stocks that are part of the UK FTSE All Share index.

Oil is based on the *crude oil Brent prices (OB)* and we chose to use it because at the point of our data collection, crude oil Brent (OB) is considered as the most widely used oil reference (Kurt, 2015). In comparison to other benchmarks such as the WTI (West Texas Intermediate), around two thirds of global crude contracts use crude oil Brent (Kurt, 2015).

Lastly, *Baltic Dry index (BD)* is an index that tracks the cost of shipping commodities, such as coal, iron ore, steel, cement, and grain, around the world (Apergis & Payne, 2013). Thus, it can be an indicator of global demand for raw materials as well as a predictor of growth in global economic activity (Bakshi et al., 2011). Moreover, BD appears to be closely related to oil. Tett (2016) remarks that the behaviour of the BD is almost as dramatic as oil prices when viewing the global economy.

We mainly use daily data to calculate our quarterly variables except for GDP which is already in quarterly. Before the calculation of the illiquidity measures and construction of the portfolios, the sample is initially scrutinised for any unsuitable data to avoid biased

results. All the data used in this paper are obtained from DataStream, Bloomberg, World Bank website and US *Energy Information Administration (EIA)* website.

7.3.3. DETAILS OF COUNTRIES AND VARIABLES

Table 7.1 provides more information of our chosen ten (10) countries, which is constructed using the most recently available data of the year 2012, obtained from US EIA website. The table reports the *"oil exports"* and *"oil imports"* of the countries in our sample as well as the *"net oil exports (imports)",* which is merely the difference of oil exports and imports. Using the net oil exports, the ten (10) countries are then segregated into five (5) net oil exporting countries and net oil importing countries respectively. The net oil exporters are Norway, Canada, Denmark, Mexico and Brazil while net oil importers consist of Singapore, UK, Germany, Japan and France. The table also reports the *"annual oil revenue (expenditure) to GDP ratios"* of the countries, which are calculated using Wang et al. (2013) framework. *The "annual revenue (expenditure)"* of a country's net oil exports (imports) is calculated using the following formula:

Annual revenue (expenditure) of a country's net oil exports (imports) = Daily oil exports (imports) x number of days in a year x the annual average oil price. (7.2)

Where the annual average oil price of USD112.02 is the average price per barrel for Crude oil Brent in the year 2012 obtained from DataStream and the number of days in the year 2012 is 366 days because it is a leap year.

Since we are investigating Baltic Dry index, we have also included information for "*liner shipping connectivity index"* because it captures how well countries are connected to global shipping networks and it is computed by the *United Nations Conference on Trade and Development (UNCTAD).* Other information that we include in the table are the countries' "*exports, imports and net exports for goods and services (as a percentage of GDP)"* as well as "*GDP per capita"* and "*MSCI market classification"*. With the exception of MSCI market classification, all the information is obtained from the World Bank website and it is more updated in comparison to our oil information, as we manage

to obtain information as of 2015. The MSCI market classification categorises the countries in our sample as either developed or emerging markets/ countries as of 2016 and it is obtained directly from MSCI website.

Table 7.1 shows that Canada is a major net oil exporting country whereas Germany is the main net oil importer. The *"annual oil revenue to GDP ratio"* appears to be the highest for Norway while Singapore's *"annual oil expenditure to GDP ratio"* is the highest in comparison to the other countries. The table also shows that only Mexico and Brazil are classified as emerging markets/ countries by MSCI while Singapore is the highest net exporter of goods and services as a percentage of GDP. Interestingly, the *liner shipping connectivity index* for the five (5) net oil importing countries is higher in comparison to the five (5) net oil exporters with Singapore having the highest index value.

In table 7.2, panel A shows descriptive statistics (mean, median, standard deviation, maximum and minimum) of the GDP for the ten (10) countries while panel B exhibits descriptive statistics for crude oil Brent (OB) and Baltic dry index (BD). In Panel C of table 7.2, we present descriptive statistics of the *national foreign exchange (NFX)* rate of the ten (10) countries relative to the USD. The last two (2) panels (panel D and Panel E respectively) exhibit descriptive statistics of the two (2) liquidity measures namely national (NAM) and global illiquidity (GAM).

Table 7.1: Details of the ten (10) countries in our sample.
This table reports the exports, imports and net exports of crude oil as well as goods and services of the ten (10) countries in our sample. The data is based on the most recently available data whereby the data for crude oil is from the year 2012 while the other data are from the year 2015 and 2016. The ten (10) countries are segregated into net oil exporting countries and net oil importing countries according to the countries latest net oil exports data. The table also reports the countries annual oil revenue (expenditure) to GDP ratios, which are calculated using the average crude oil Brent price in 2012 of USD112.02 per barrel. We calculate the revenue (expenditure) of a country's net oil exports (imports) by the following formula:

Annual revenue (expenditure) of a country's net oil exports (imports) = Daily oil exports (imports) x number of days in a year (366 days) x the average crude oil Brent price (USD112.02) (7.2)

The calculation technique for oil revenue to GDP ratio is similar to Wang et al (2013) framework. We have also reported the Liner shipping connectivity index, GDP per capita (USD) and MSCI Market classification of the countries in our sample. All data are obtained from DataStream, Bloomberg, World Bank, MSCI and US Energy Information Administration (EIA) website.

Countries	2012				2015					2016
	Crude oil Brent (Thousand Barrels per day)			Annual oil revenue (expenditure) to GDP ratio (%)	Goods and services (% of GDP)			Liner shipping connectivity index	GDP per capita (USD)	MSCI Market Classification
	Exports	Imports	Net exports (imports)		Exports	Imports	Net Exports			
Net oil exporters										
Norway	1324	28	1296	10.42%	37.4%	32.0%	5.4%	4.8	74,481.8	Developed
Canada	2470	736	1734	3.90%	31.6%	34.0%	-2.4%	42.9	43,315.7	Developed
Denmark	137	87	50	0.63%	55.2%	47.8%	7.4%	52.3	53,014.6	Developed
Mexico	1280	10	1270	4.39%	35.4%	37.5%	-2.1%	43.0	9,005.0	Emerging
Brazil	526	375	151	0.25%	12.9%	14.1%	-1.2%	41.0	8,677.8	Emerging
Net oil importers										
Singapore	0.1	1078	-1077.9	-15.28%	176.5%	149.6%	26.9%	117.1	52,888.7	Developed
United Kingdom	710	1222	-512	-0.79%	27.6%	29.2%	-1.6%	95.2	43,929.7	Developed
Germany	3.8	1888	-1884.2	-2.18%	46.8%	39.2%	7.6%	97.8	41,178.5	Developed
Japan	0	3724	-3724	-2.56%	17.6%	18.0%	-0.4%	68.8	34,523.7	Developed
France	1.3	1159	-1157.7	-1.77%	30.0%	31.4%	-1.4%	77.1	36,352.5	Developed
World (Average)					29.5%	28.7%	0.8%	96.7	10,098.2	

Table 7.2: Descriptive statistics of the chosen variables of the ten (10) countries in our sample.

Panel A shows descriptive statistics (mean, median, standard deviation, maximum and minimum) of the Gross Domestic Products (GDP) for the ten (10) countries while panel B exhibit the descriptive statistics for crude oil Brent and Baltic dry index. Panel C shows the descriptive statistics of the national foreign exchange (NFX) rate of the countries in our sample relative to United States Dollars (USD). Panel D and panel E shows the descriptive statistics of national and global illiquidity (Amihud) measures for the relevant quarters respectively. Panel F and panel G show the descriptive statistics of the market value (millions) of the countries' chosen indices in their respective currencies and in USD respectively. The sample period is from January 1998 to December 2015, consisting of 72 quarterly observations. All data are obtained from DataStream, Bloomberg, World Bank and US Energy Information Administration (EIA) website.

	Panel A: Gross Domestic Product (GDP)										**Panel B: Oil and Baltic Dry**	
	Norway	**Canada**	**Denmark**	**Mexico**	**Brazil**	**Singapore**	**UK**	**Germany**	**Japan**	**France**	**Oil**	**Baltic Dry**
Mean	0.417%	0.579%	0.258%	0.587%	0.598%	1.341%	0.489%	0.322%	0.151%	0.363%	60.753	2442.264
Median	0.300%	0.625%	0.300%	0.655%	0.895%	1.363%	0.600%	0.400%	0.300%	0.400%	57.685	1541.500
Std. Dev.	1.106%	0.637%	0.887%	0.912%	1.264%	2.226%	0.643%	0.851%	1.099%	0.499%	34.825	2098.322
Maximum	3.500%	1.550%	2.900%	2.140%	2.490%	9.250%	1.800%	2.100%	2.700%	1.300%	122.060	10228.000
Minimum	-2.500%	-2.280%	-2.400%	-3.850%	-3.970%	-3.375%	-2.300%	-4.500%	-4.100%	-1.700%	11.480	617.000

Panel C: National foreign exchange relative to United States Dollars (USD)										
	Norway	**Canada**	**Denmark**	**Mexico**	**Brazil**	**Singapore**	**UK**	**Germany**	**Japan**	**France**
Mean	6.852	1.241	6.285	11.488	2.206	1.528	0.610	0.844	107.559	0.844
Median	6.566	1.207	5.944	11.004	2.093	1.545	0.622	0.798	109.218	0.798
Std. Dev.	1.113	0.206	0.996	1.836	0.585	0.198	0.056	0.134	15.087	0.134
Maximum	9.258	1.594	8.580	16.762	3.848	1.834	0.704	1.151	139.879	1.151
Minimum	5.084	0.968	4.775	8.422	1.127	1.223	0.489	0.640	77.331	0.640

Panel D: National illiquidity (Amihud)										
	Norway	**Canada**	**Denmark**	**Mexico**	**Brazil**	**Singapore**	**UK**	**Germany**	**Japan**	**France**
Mean	769.285	250.049	1172.796	82.614	293.854	27.057	2.531	3135.614	0.021	20.579
Median	659.688	170.281	809.699	61.600	245.384	6.787	2.190	2930.160	0.012	14.030
Std. Dev.	479.259	231.279	935.942	88.548	292.291	39.599	1.244	1810.116	0.017	15.991
Maximum	1882.618	858.993	3568.500	339.392	1341.593	194.620	6.073	8500.649	0.069	66.339
Minimum	123.574	3.317	163.083	0.152	0.390	0.696	0.764	88.869	0.004	1.749

Panel E: Global illiquidity (Amihud)										
	Norway	**Canada**	**Denmark**	**Mexico**	**Brazil**	**Singapore**	**UK**	**Germany**	**Japan**	**France**
Mean	498.570	550.494	458.219	567.237	546.113	572.793	575.246	261.937	575.497	573.441
Median	477.785	517.163	429.353	550.467	512.172	561.465	566.422	253.547	566.588	564.668
Std. Dev.	228.986	257.903	219.861	257.269	260.301	257.563	258.915	115.769	258.992	258.537
Maximum	1048.510	1207.902	1158.321	1216.468	1177.493	1231.602	1236.298	504.251	1236.703	1230.518
Minimum	118.793	89.373	122.953	140.753	124.352	141.902	143.932	80.292	144.098	137.470

Panel F: Market value (millions) in the respective national currencies										
	Norway NOK	**Canada CAD**	**Denmark DKK**	**Mexico MXN**	**Brazil BRL**	**Singapore SGD**	**UK GBP**	**Germany EUR**	**Japan JPY**	**France EUR**
Mean	11,096.240	5,412.093	10,247.557	83,151.336	18,647.683	10,854.897	3,060.525	3,975.110	1,114,927.875	11,446.907
Median	1,283.815	1,401.250	689.615	32,427.300	7,272.040	6,491.160	405.985	285.375	508,874.805	4,541.700
Std. Dev.	41,707.368	10,845.973	36,658.792	133,740.967	32,315.015	11,734.605	10,656.610	11,631.946	1,995,805.407	18,549.008
Maximum	594,579.470	115,924.790	786,397.570	992,079.050	301,720.990	68,402.790	182,388.730	248,650.900	36,880,843.080	163,556.850
Minimum	3.200	0.040	0.870	149.940	15.740	3.310	0.960	0.310	12,064.360	21.760

Panel G: Market value (millions) in USD										
	Norway USD	**Canada USD**	**Denmark USD**	**Mexico USD**	**Brazil USD**	**Singapore USD**	**UK USD**	**Germany USD**	**Japan USD**	**France USD**
Mean	1,753.672	4,743.675	1,720.015	6,684.349	8,971.786	7,624.667	5,057.328	4,867.006	10,456.410	14,169.776
Median	193.982	1,191.664	112.451	2,858.528	3,484.788	4,435.872	674.505	348.738	4,749.940	5,502.411
Std. Dev.	6,812.642	9,802.044	6,176.118	10,510.816	16,207.038	8,537.873	17,665.177	14,092.001	18,281.989	23,254.931
Maximum	116,958.937	106,092.550	116,798.596	80,083.811	165,281.560	50,922.592	279,202.036	245,145.322	344,766.485	213,992.328
Minimum	0.453	0.036	0.130	15.780	6.230	1.813	1.502	0.272	103.514	23.558

7.4. METHODOLOGY, EMPIRICAL RESULTS AND ANALYSIS

7.4.1. PREDICTIVE VARIABLES AND BUSINESS CYCLES

Figure 7.1 to 7.5, exhibits time series of the five (5) predictive variables in our research in relation to recession periods. Our five (5) predictive variables consist of national illiquidity (NAM), global illiquidity (GAM), national foreign exchange (NFX), oil (OB) and Baltic Dry index (BD). We define a period as a recession period when there is negative GDP growth for at least two consecutive quarters.

The figures reveal that the countries in our sample have different recession periods. However, it is observed that all the countries have been affected by the financial crisis of 2007-2008 but the recession duration can be different. Thus, we will initially investigate the relationship between our predictive variables and the recent crisis period in order to ensure consistency.

Figure 7.1 shows that during the crisis period, national illiquidity (NAM) is able to predict the recession for three (3) net oil exporters namely Norway, Canada and Denmark, as NAM increases before the recession whereas among net oil importers, only Germany shows such a relationship. The other countries show less clear evidence, as NAM decreases prior to the recession. Interestingly, for net oil exporters, the two (2) countries for which NAM does not show predictive ability during the crisis are the only emerging countries in our sample namely Brazil and Mexico. Nevertheless, if we consider other recession periods, then some of the countries do show expected results such as Brazil and France. The NAM of the two (2) countries does increase before the other recession periods, signifying predictive ability.

Figure 7.2 results are more consistent, as global illiquidity (GAM) increases prior to the recession period for all the countries, indicating the predictive ability of GAM during the crisis. Although there are contradictory results during other recession periods, most GAM results continue to show an enhanced predictive ability.

With reference to oil (OB), figure 7.3 shows that all five (5) net oil importing countries go into recession immediately after an increase in oil price (OB) during the financial crisis, which is consistent with past studies such as Hamilton (1983), as countries tend to react to an increase in oil price. Fascinatingly, it is observed that with the exception of Denmark, there is a delay with which net oil exporting countries enter recession, as oil price (OB)

actually decreases prior to the recession period. This is actually expected for net oil exporters as a decrease in oil price is considered detrimental for such countries and is consistent to Mork et al. (1994) who finds that Norway, a net oil exporter, reacts differently to the oil importing countries in their sample. Among net oil exporters, Denmark is the only net oil exporter that reacts differently to oil (OB) during the crisis. Table 7.1 shows that Denmark exports the smallest amount of crude oil and have the second lowest *"annual oil revenue to GDP ratio",* indicating that probably the economy of Denmark may not be too dependent on oil.

Coincidentally, during the crisis, figure 7.4 also shows that there is an increase in the Baltic Dry index (BD) prior to a recession period for net oil importers, while for net oil exporters the BD exhibits an increase only in the case of Norway prior to recessions. The results are contradictory to past studies such as Bakshi et al. (2011) who highlight that increases in the Baltic Dry index growth rate could predict increases in economic growth, concurring with strengthening commodity prices and rising stock markets. Rothfeder (2016) reports that BD somehow predicts IndyMac's bankruptcy during the financial crisis of 2007-2008.

Nevertheless, Baltic Dry Index (BD) is also an indicator for global demand of raw materials and is related to commodities (Bakshi et al., 2011) and hence similar to oil, an increase in BD may benefit exporters of raw materials more, relative to importers. Moreover, Wang et al. (2013) has used BD as a proxy for global oil demand, signifying that BD may actually be a good indicator of oil prices. Net oil exporters (except for Norway) endure a recession after a decrease of BD. We observe a delayed recession since the BD drops two quarters prior to a recession.

Figure 7.5 is less consistent as Norway, Canada, Brazil and UK endure an increase in National foreign exchange (NFX) prior to recession periods while Mexico, Denmark, Singapore, Germany, Japan and France endure a recession period after a decrease in NFX.

Overall, in comparison to national illiquidity (NAM), global illiquidity (GAM) shows more consistent results as during the financial crisis, GAM is able to predict recessions for the majority of countries. With reference to oil (OB), all five (5) net oil importing countries go into recession immediately after an increase in oil price during the financial crisis while it is observed that oil price actually decreases prior to recessions for net oil exporters (with the exception of Denmark), which is expected. The Baltic Dry index (BD)

shows that there is also an increase in the index prior to a recession for net oil importers, while it decreases for net oil exporters (with the exception of Norway) prior to recessions, indicating that it may actually be a good proxy for oil. Moreover, it appears to show that oil may have a stronger effect on economic growth relative to BD. Further analysis is required to investigate this issue.

Figure 7.1: Business cycle and National illiquidity based on Amihud illiquidity measure.
The figure shows time series plots of the *national illiquidity based on Amihud illiquidity measure (NAM)* for all the countries in our sample, which are represented by the black lines. Shaded grey are recession periods and a recession period is identified as a period for which there is negative GDP growth for at least two consecutive terms. Sample range Q1 1998 to Q4 2015, 72 quarterly observations. All data are obtained from DataStream, Bloomberg, World Bank and US Energy Information Administration (EIA) website.

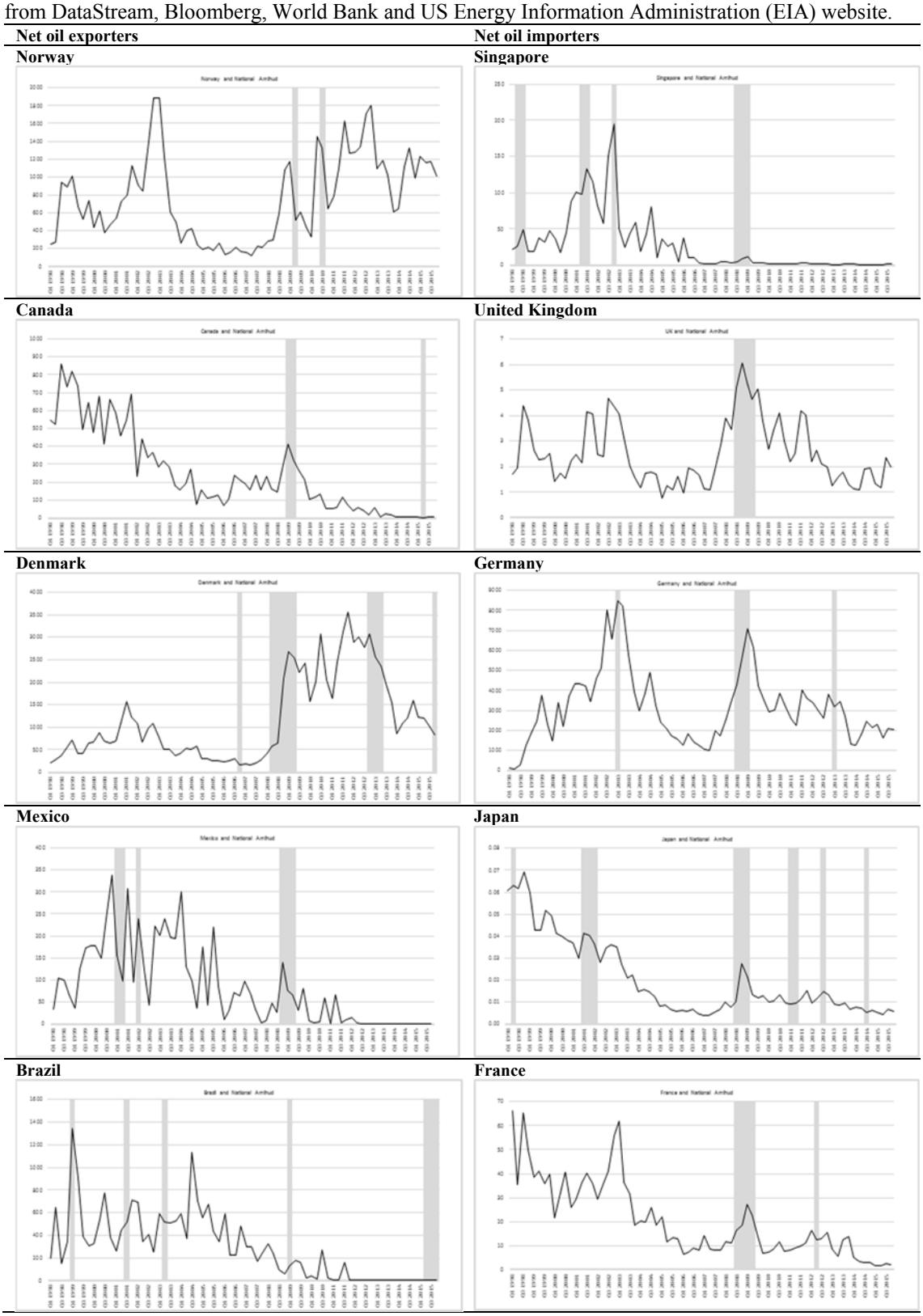


Figure 7.2: Business cycle and Global illiquidity based on Amihud illiquidity measure.
The figure shows time series plots of the *global illiquidity based on Amihud illiquidity measure (GAM)* for all the countries in our sample, which are represented by the black lines. Global illiquidity is constructed as in Brockman et al. (2009) and Galariotis and Giouvris (2015) whereby global illiquidity is created by combining all countries except the country nominated for the test. Shaded grey are recession periods and a recession period is identified as a period for which there is negative GDP growth for at least two consecutive terms. Sample range Q1 1998 to Q4 2015, 72 quarterly observations. All data are obtained from DataStream, Bloomberg, World Bank and US Energy Information Administration (EIA) website.

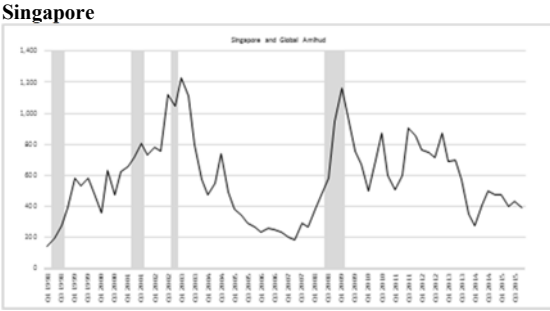
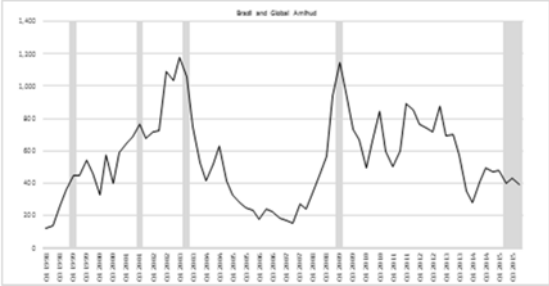
Net oil exporters	**Net oil importers**
Norway	**Singapore**
	
Canada	**United Kingdom**
	
Denmark	**Germany**
	
Mexico	**Japan**
	
Brazil	**France**
	

Figure 7.3: Business cycle and crude oil Brent price.

The figure shows time series plots of the crude oil Brent price, which are represented by the black lines. Shaded grey are recession periods and a recession period is identified as a period for which there is negative GDP growth for at least two consecutive terms. Sample range Q1 1998 to Q4 2015, 72 quarterly observations. All data are obtained from DataStream, Bloomberg, World Bank and US Energy Information Administration (EIA) website.

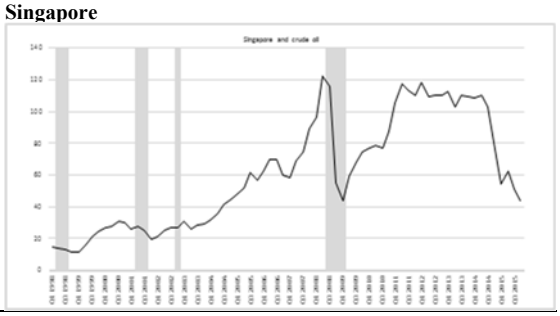
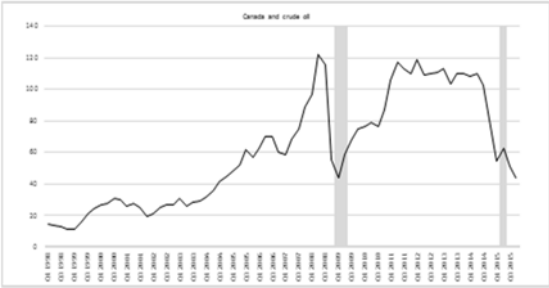
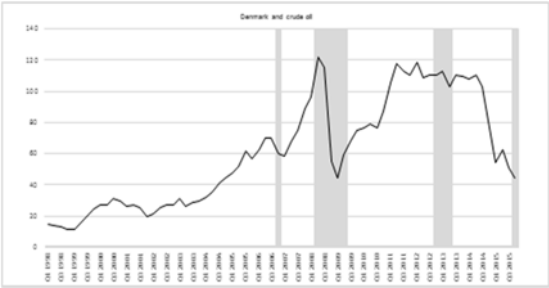
Net oil exporters	Net oil importers
Norway	**Singapore**
	
Canada	**United Kingdom**
	
Denmark	**Germany**
	
Mexico	**Japan**
	
Brazil	**France**
	

Figure 7.4: Business cycle and Baltic Dry Index.

The figure shows time series plots of the Baltic Dry index, which are represented by the black lines. Shaded grey are recession periods and a recession period is identified as a period for which there is negative GDP growth for at least two consecutive terms. Sample range Q1 1998 to Q4 2015, 72 quarterly observations. All data are obtained from DataStream, Bloomberg, World Bank and US Energy Information Administration (EIA) website.

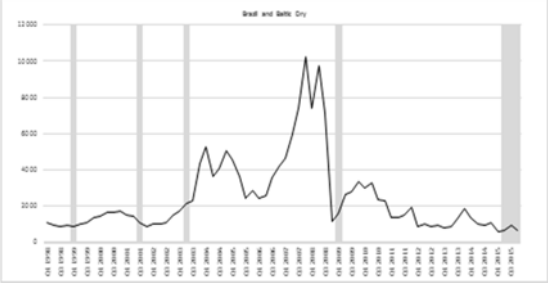
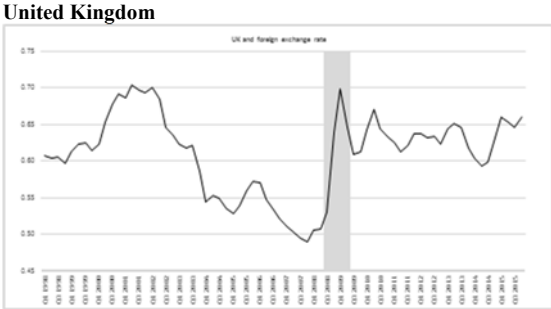
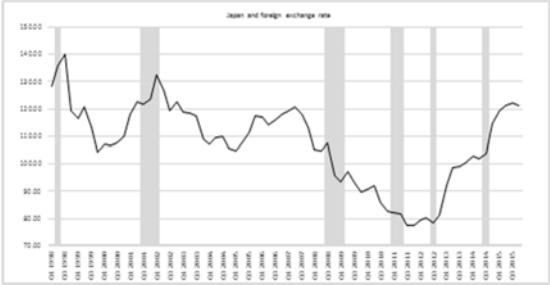
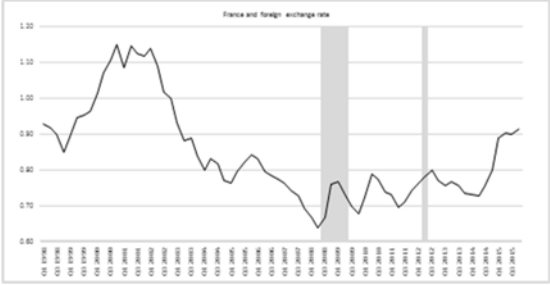
Net oil exporters	Net oil importers
Norway	**Singapore**
	
Canada	**United Kingdom**
	
Denmark	**Germany**
	
Mexico	**Japan**
	
Brazil	**France**
	

Figure 7.5: Business cycle and national foreign exchange.

The figure shows time series plots of the national foreign exchange (NFX) relative to United States Dollars (USD) for all the countries in our sample, which are represented by the black lines. Shaded grey are recession periods and a recession period is identified as a period for which there is negative GDP growth for at least two consecutive terms. Sample range Q1 1998 to Q4 2015, 72 quarterly observations. All data are obtained from DataStream, Bloomberg, World Bank and US Energy Information Administration (EIA) website.

Net oil exporters	Net oil importers
Norway	**Singapore**
	
Canada	**United Kingdom**
	
Denmark	**Germany**
	
Mexico	**Japan**
	
Brazil	**France**
	

7.4.2. CORRELATIONS

Correlations in table 7.3 use only raw data before any differencing and orthogonalization. The correlation analysis in table 7.3 shows the relationship of the different variables with each other and it is undertaken for all countries in our sample. Panel A to panel E show the correlation results for net oil exporters. The correlation results for net oil importers are presented in panel F to panel J. We will initially look at the relationship between *Gross Domestic Product (GDP)* and *financial variables (FV),* followed by the relationship between GDP and the predictive variables inclusive of *national foreign exchange (NFX), national illiquidity (NAM), global illiquidity (GAM), crude oil Brent (OB)* and *Baltic Dry index (BD).* We will then investigate the relationship between the financial variables and the predictive variables followed by a brief study of the correlations among the predictive variables.

Similar to Galariotis and Giouvris (2015), it appears that *standard deviation (or market volatility) (SD)* is negative and significantly correlated to GDP for most countries, with the exception of Norway and Canada. The significant results indicate that as standard deviation increase, GDP actually reduces. *Dividend yield (DY)* also shows consistent results as most countries except for Norway and Denmark show negative correlation to GDP. Six (6) countries have *excess market returns (XS)* that are positively correlated to GDP, signifying that as excess market returns increase GDP also improves. The *risk-free rate (RF)* shows less consistent results, as only two (2) countries are found to be negatively correlated to GDP while Canada shows a positive relationship. The negative correlation between the risk-free rate and GDP is expected since as the interest rate falls, investment increases and this results in an increase in GDP.

Correlations between GDP and the predictive variables show that out of the five (5) predictive variables, illiquidity variables appear to be more strongly correlated to GDP, as more countries display significant correlations. Between national (NAM) and global illiquidity (GAM), the latter seems to be more important as six (6) countries exhibit significant correlations to GDP while for national illiquidity (NAM) only four (4) countries show correlations. Moreover, Denmark, UK and Germany are found to be negatively correlated to both illiquidity variables. Galariotis and Giouvris (2015) also find such a relationship for the UK. As expected, the two (2) illiquidity variables consistently show negative correlations to GDP, indicating that GDP increases with a decrease in illiquidity (or increase in market liquidity).

Correlations are less noticeable for the other three predictive variables. For instance, only the GDP of Brazil shows a positive correlation to Baltic Dry index (BD), signifying that as BD increases, the GDP of Brazil also improves. In relation to Crude oil Brent (OB), only the GDP of UK and France show significant correlations to oil. Nevertheless, as net oil importers, the negative correlation for the two countries is justifiable, as it is expected that the GDP of net oil importers will deteriorate due to an increase in oil price. For national foreign exchange (NFX), only Brazil and France show significant correlations to GDP but the signs are opposite, as Brazil exhibit negative correlation while France positive correlation.

Correlations between financial variables and the predictive variables show that the *risk free rate (RF), standard deviation (SD)* and *dividend yield (DY)* are correlated with at least four (4) countries for all the predictive variables. Standard deviation is found to be positively correlated to *national illiquidity (NAM)* for all ten (10) countries while DY positively correlates to *global illiquidity (GAM)* for nine (9) countries with the exception of Singapore. DY also correlates with NAM for eight countries and hence DY appears to have the closest relationship with both illiquidity variables. RF, SD and DY appear to show a strong relationship with *national foreign exchange (NFX),* as all three (3) financial variables are significantly correlated for eight (8) countries. In relation to oil, both RF and SD are significantly correlated to *crude oil Brent (OB)* in nine countries with the exception of Japan and UK respectively, which are both net oil importing countries. For DY, the correlation with OB can only be observed in seven (7) countries except for Norway, UK and Singapore. The financial variables relationship with *Baltic Dry Index (BD)* is weaker. Both DY and RF correlate with BD in five (5) countries while SD shows a relationship in four countries. Nevertheless, the weakest correlation is shown by *excess market returns (XS)* as it is not significantly correlated with NFX, OB and BD. XS is only correlated to the illiquidity variables in only three (3) countries for NAM and one (1) country for GAM namely France.

Among the predictive variables, *national foreign exchange (NFX)* is significantly correlated with *crude oil Brent (OB)* for all countries and the relationship appears to be negative with the exception of Mexico. The negative relationship signifies that there may be a benefit for the economies of net oil exporters as an increase in oil prices will be boosted by the strengthening of their NFX. Mexico may not benefit from the positive relationship, as an increase in oil price will be offset by the weakening of Mexico's

NFX[127] relative to USD. Similarly, the negative relationship may not be beneficial for net oil importing countries, as oil price decreases, their NFX weakens relative to USD and there will be no opportunity to purchase oil at cheaper price. Oil (OB) is also found to be positively correlated to *Baltic Dry index (BD)* and in a way this somehow justifies some researchers' usage of the BD to estimate oil demand such as Wang et al. (2013) but bear in mind that the correlation is just over 0.2. *Global illiquidity (GAM)* is also found to be significantly correlated to BD for all countries but the correlation is negative. Surprisingly, *national illiquidity (NAM)* and GAM, which are used to measure illiquidity, are found to be positively correlated in only six (6) countries except for Canada, Mexico, Brazil and Japan[128].

Overall, financial variables have stronger correlations to GDP in comparison to predictive variables. *Standard deviation (SD)* appears to relate to GDP of most countries. Among the predictive variables, *global illiquidity (GAM)* is found to have the strongest relationship with countries' GDP, while *Baltic Dry Index (BD)* and *crude oil Brent (OB)* are found to be less correlated to GDP. Only the GDP of UK and France show significant correlations to OB and the negative correlation for the two (2) countries is expected, as the GDP of net oil importers will deteriorate due to an increase in oil price. For BD, only the GDP of Brazil shows positive correlation which is as expected. Financial variables and predictive variables appears to show some significant correlation to each other but *excess market returns (XS)* shows the weakest correlation, as it is not correlated with *national foreign exchange (NFX)*, OB and BD. Oil (OB) is found to be positively correlated to BD and this somehow justifies some researchers' usage of the BD to estimate oil demand.

[127] As highlighted earlier, an increase in NFX means USD strengthens while the specific country's currency weakens. In this case, Mexican Peso will weaken with the strengthening of USD.

[128] The national illiquidity (NAM) of Brazil and Mexico are probably not correlated to their respective global illiquidity (GAM) because the two countries are categorised as emerging countries by MSCI in table 7.1 and their financial markets may not be globally integrated. Although Canada and Japan are developed countries, the financial markets of the two countries may be more interrelated with certain countries such as the US and China which are not part of our sample. These may have resulted in the countries' national illiquidity (NAM) to not be correlated to their respective global illiquidity (GAM). Ultimately, our global illiquidity (GAM) variables are constructed using only countries available in our sample and by omitting countries such as the US, China, South Korea, India and Russia may have resulted in the variable to be less global.

Table 7.3: Correlations of the chosen variables for all ten (10) countries.

The table shows correlation coefficients between all variables use in our analysis. The associated p-values are reported in parentheses below each correlation coefficient. GDP is the macroeconomic variable and the respective country quarterly real Gross Domestic Product (GDP) growth. RF is the quarterly risk free rate of the respective countries. SD is the standard deviation/ market volatility and DY is the dividend yield, which are calculated as the cross sectional average for all stocks of the respective countries in our sample. XS is excess market returns, which is the cross sectional average returns for all stocks in excess of the RF of the respective countries. NFX is the national foreign exchange relative to United States Dollars (USD). Amihud (AM) is our illiquidity measure and the prefix 'N' in front of each illiquidity variable refers to national illiquidity based on Amihud (NAM) while the prefix 'G' refers to global illiquidity based on Amihud (GAM). Global illiquidity is constructed as in Brockman et al. (2009) and Galariotis and Giouvris (2015) whereby global illiquidity is created by combining all countries except the country nominated for the test. OB is crude oil Brent price while BD is the Baltic Dry index. Correlations presented below are for raw data. The sample period is from January 1998 to December 2015, consisting of 72 quarterly observations. All data are obtained from DataStream, Bloomberg, World Bank and US Energy Information Administration (EIA) website.

Panel A: Norway	GDP_NOR	RF_NOR	SD_NOR	XS_NOR	DY_NOR	NFX_NOR	NAM_NOR	GAM_NOR	OB	BD
GDP_NOR	1.0000									

RF_NOR	-0.0407	1.0000								
	(0.7345)	---								
SD_NOR	-0.1384	**0.2947**	1.0000							
	(0.2462)	**(0.0120)**	---							
XS_NOR	**0.2179**	**-0.3779**	**-0.3111**	1.0000						
	(0.0660)	**(0.0011)**	**(0.0078)**	---						
DY_NOR	-0.0852	0.0742	**0.7360**	**-0.2590**	1.0000					
	(0.4766)	(0.5357)	**(0.0000)**	**(0.0280)**	---					
NFX_NOR	0.0101	**0.5208**	**0.2080**	-0.0914	0.1020	1.0000				
	(0.9331)	**(0.0000)**	**(0.0795)**	(0.4450)	(0.3937)	---				
NAM_NOR	**-0.2283**	-0.0607	**0.4822**	**-0.2896**	**0.4061**	0.0126	1.0000			
	(0.0537)	(0.6126)	**(0.0000)**	**(0.0136)**	**(0.0004)**	(0.9164)	---			
GAM_NOR	-0.1917	0.1723	**0.6295**	-0.0524	**0.4536**	0.1065	**0.5625**	1.0000		
	(0.1067)	(0.1478)	**(0.0000)**	(0.6623)	**(0.0001)**	(0.3731)	**(0.0000)**	---		
OB	-0.0484	**-0.5226**	**-0.2048**	-0.0562	-0.0180	**-0.8101**	0.1936	-0.0965	1.0000	
	(0.6866)	**(0.0000)**	**(0.0844)**	(0.6394)	(0.8807)	**(0.0000)**	(0.1032)	(0.4201)	---	
BD	0.0311	0.0667	**-0.2804**	0.0605	**-0.2216**	**-0.4660**	**-0.5510**	**-0.2261**	**0.2163**	1.0000
	(0.7951)	(0.5777)	**(0.0171)**	(0.6136)	**(0.0614)**	**(0.0000)**	**(0.0000)**	**(0.0561)**	**(0.0680)**	---

Panel B: Canada	GDP_CAN	RF_CAN	SD_CAN	XS_CAN	DY_CAN	NFX_CAN	NAM_CAN	GAM_CAN	OB	BD
GDP_CAN	1.0000									

RF_CAN	**0.2927**	1.0000								
	(0.0126)	-----								
SD_CAN	-0.0948	**0.4652**	1.0000							
	(0.4285)	**(0.0000)**	-----							
XS_CAN	0.1354	-0.0449	-0.1797	1.0000						
	(0.2569)	(0.7082)	(0.1309)	-----						
DY_CAN	**-0.6532**	**-0.4663**	0.0113	-0.0787	1.0000					
	(0.0000)	**(0.0000)**	(0.9248)	(0.5113)	-----					
NFX_CAN	0.1717	**0.5956**	**0.6634**	0.1001	**-0.4433**	1.0000				
	(0.1493)	**(0.0000)**	**(0.0000)**	(0.4028)	**(0.0001)**	-----				
NAM_CAN	0.1553	**0.7138**	**0.7995**	-0.0028	**-0.3488**	**0.7716**	1.0000			
	(0.1928)	**(0.0000)**	**(0.0000)**	(0.9812)	**(0.0027)**	**(0.0000)**	-----			
GAM_CAN	**-0.3249**	**-0.3946**	0.1571	0.0688	**0.3492**	0.1035	0.0024	1.0000		
	(0.0054)	**(0.0006)**	(0.1877)	(0.5655)	**(0.0026)**	(0.3870)	(0.9844)	-----		
OB	-0.1348	**-0.6126**	**-0.6211**	-0.1637	**0.3234**	**-0.9211**	**-0.7522**	0.0178	1.0000	
	(0.2590)	**(0.0000)**	**(0.0000)**	(0.1695)	**(0.0056)**	**(0.0000)**	**(0.0000)**	(0.8822)	-----	
BD	-0.0250	0.1388	**-0.2155**	-0.0158	**0.3254**	**-0.3556**	-0.1844	**-0.2866**	**0.2163**	1.0000
	(0.8347)	(0.2450)	**(0.0691)**	(0.8955)	**(0.0053)**	**(0.0022)**	(0.1209)	**(0.0146)**	**(0.0680)**	-----

Panel C: Denmark	GDP_DEN	RF_DEN	SD_DEN	XS_DEN	DY_DEN	NFX_DEN	NAM_DEN	GAM_DEN	OB	BD
GDP_DEN	1.0000									

RF_DEN	-0.0408	1.0000								
	(0.7338)	-----								
SD_DEN	**-0.4696**	-0.0345	1.0000							
	(0.0000)	(0.7735)	-----							
XS_DEN	0.1714	**-0.3498**	**-0.3675**	1.0000						
	(0.1501)	**(0.0026)**	**(0.0015)**	-----						
DY_DEN	-0.0815	**0.4136**	0.0007	-0.0354	1.0000					
	(0.4961)	**(0.0003)**	(0.9957)	(0.7680)	-----					
NFX_DEN	0.1520	**0.3920**	**-0.2040**	0.0162	**0.4442**	1.0000				
	(0.2023)	**(0.0007)**	**(0.0857)**	(0.8929)	**(0.0001)**	-----				
NAM_DEN	**-0.2838**	**-0.4952**	**0.6591**	-0.1807	**-0.3344**	**-0.2872**	1.0000			
	(0.0157)	**(0.0000)**	**(0.0000)**	(0.1288)	**(0.0041)**	**(0.0144)**	-----			
GAM_DEN	**-0.3007**	0.1414	**0.2847**	-0.1953	**0.4188**	**0.3377**	**0.2425**	1.0000		
	(0.0103)	(0.2361)	**(0.0154)**	(0.1001)	**(0.0003)**	**(0.0037)**	**(0.0402)**	-----		
OB	-0.1627	**-0.4957**	**0.3399**	-0.0842	**-0.4746**	**-0.7426**	**0.5527**	**-0.2935**	1.0000	
	(0.1721)	**(0.0000)**	**(0.0035)**	(0.4819)	**(0.0000)**	**(0.0000)**	**(0.0000)**	**(0.0123)**	-----	
BD	0.0094	**0.3553**	-0.1796	-0.0618	-0.0904	**-0.4673**	**-0.3593**	**-0.2027**	**0.2163**	1.0000
	(0.9379)	**(0.0022)**	(0.1311)	(0.6060)	(0.4500)	**(0.0000)**	**(0.0019)**	**(0.0877)**	**(0.0680)**	-----

Panel D: Mexico	GDP_MEX	RF_MEX	SD_MEX	XS_MEX	DY_MEX	NFX_MEX	NAM_MEX	GAM_MEX	OB	BD
GDP_MEX	1.0000									

RF_MEX	-0.0309	1.0000								
	(0.7967)	-----								
SD_MEX	**-0.3202**	**0.6481**	1.0000							
	(0.0061)	**(0.0000)**	-----							
XS_MEX	0.1547	**-0.2847**	**-0.3996**	1.0000						
	(0.1946)	**(0.0154)**	**(0.0005)**	-----						
DY_MEX	**-0.3752**	**0.4866**	**0.3935**	-0.0573	1.0000					
	(0.0012)	**(0.0000)**	**(0.0006)**	(0.6326)	-----					
NFX_MEX	-0.0614	**-0.6409**	**-0.3208**	0.1803	**-0.3145**	1.0000				
	(0.6086)	**(0.0000)**	**(0.0060)**	(0.1297)	**(0.0071)**	-----				
NAM_MEX	-0.1215	**0.3278**	**0.2288**	-0.0538	**0.3863**	**-0.5757**	1.0000			
	(0.3093)	**(0.0049)**	**(0.0532)**	(0.6536)	**(0.0008)**	**(0.0000)**	-----			
GAM_MEX	**-0.3876**	**-0.2163**	0.0633	0.0305	**0.3309**	0.1220	0.1781	1.0000		
	(0.0008)	**(0.0680)**	(0.5973)	(0.7995)	**(0.0045)**	(0.3075)	(0.1344)	-----		
OB	0.1154	**-0.6273**	**-0.4285**	0.0940	**-0.4167**	**0.5468**	**-0.6438**	-0.0276	1.0000	
	(0.3342)	**(0.0000)**	**(0.0002)**	(0.4321)	**(0.0003)**	**(0.0000)**	**(0.0000)**	(0.8177)	-----	
BD	0.1167	-0.1396	**-0.1989**	0.1054	-0.0558	-0.1462	-0.0431	**-0.3024**	**0.2163**	1.0000
	(0.3288)	(0.2422)	**(0.0939)**	(0.3780)	(0.6417)	(0.2205)	(0.7193)	**(0.0098)**	**(0.0680)**	-----

Panel E: Brazil	GDP_BRA	RF_BRA	SD_BRA	XS_BRA	DY_BRA	NFX_BRA	NAM_BRA	GAM_BRA	OB	BD
GDP_BRA	1.0000									

RF_BRA	**-0.2435**	1.0000								
	(0.0393)	-----								
SD_BRA	**-0.2874**	**0.4819**	1.0000							
	(0.0144)	**(0.0000)**	-----							
XS_BRA	**0.2062**	0.1006	**-0.3056**	1.0000						
	(0.0822)	(0.4006)	**(0.0090)**	-----						
DY_BRA	**-0.3674**	**0.7321**	**0.4239**	0.0747	1.0000					
	(0.0015)	**(0.0000)**	**(0.0002)**	(0.5329)	-----					
NFX_BRA	**-0.2184**	0.0324	**-0.2244**	0.0679	**0.3602**	1.0000				
	(0.0653)	(0.7868)	**(0.0580)**	(0.5708)	**(0.0019)**	-----				
NAM_BRA	0.1510	**0.6634**	**0.2295**	**0.3305**	**0.5137**	0.1176	1.0000			
	(0.2056)	**(0.0000)**	**(0.0524)**	**(0.0046)**	**(0.0000)**	(0.3251)	-----			
GAM_BRA	-0.1463	-0.1217	-0.0747	-0.0303	**0.2355**	**0.2775**	-0.1008	1.0000		
	(0.2202)	(0.3086)	(0.5330)	(0.8007)	**(0.0464)**	**(0.0183)**	(0.3995)	-----		
OB	0.1246	**-0.7847**	**-0.4069**	-0.1116	**-0.6572**	**-0.2285**	**-0.6583**	0.0247	1.0000	
	(0.2972)	**(0.0000)**	**(0.0004)**	(0.3506)	**(0.0000)**	**(0.0535)**	**(0.0000)**	(0.8368)	-----	
BD	**0.4405**	-0.1828	-0.0139	0.0659	**-0.4006**	-0.0916	0.1057	**-0.3123**	**0.2163**	1.0000
	(0.0001)	(0.1244)	(0.9080)	(0.5824)	**(0.0005)**	(0.4443)	(0.3771)	**(0.0076)**	**(0.0680)**	-----

Panel F: Singapore	GDP_SIN	RF_SIN	SD_SIN	XS_SIN	DY_SIN	NFX_SIN	NAM_SIN	GAM_SIN	OB	BD
GDP_SIN	1.0000									

RF_SIN	-0.1441	1.0000								
	(0.2271)	-----								
SD_SIN	**-0.2042**	**0.6062**	1.0000							
	(0.0854)	**(0.0000)**	-----							
XS_SIN	**0.2836**	-0.0698	0.0776	1.0000						
	(0.0158)	(0.5603)	(0.5171)	-----						
DY_SIN	**-0.3161**	0.1182	**0.3437**	-0.0891	1.0000					
	(0.0068)	(0.3227)	**(0.0031)**	(0.4568)	-----					
NFX_SIN	0.0322	**0.4854**	**0.5891**	0.1118	**-0.2230**	1.0000				
	(0.7880)	**(0.0000)**	**(0.0000)**	(0.3499)	**(0.0597)**	-----				
NAM_SIN	-0.1825	0.1297	**0.3112**	-0.0801	-0.1887	**0.6999**	1.0000			
	(0.1249)	(0.2774)	**(0.0078)**	(0.5037)	(0.1124)	**(0.0000)**	-----			
GAM_SIN	-0.1667	**-0.5770**	0.0241	-0.0125	0.1275	0.0430	**0.3542**	1.0000		
	(0.1615)	**(0.0000)**	(0.8405)	(0.9168)	(0.2859)	(0.7198)	**(0.0023)**	-----		
OB	-0.0027	**-0.4825**	**-0.6441**	-0.1534	0.0406	**-0.9018**	**-0.5909**	-0.0407	1.0000	
	(0.9823)	**(0.0000)**	**(0.0000)**	(0.1984)	(0.7348)	**(0.0000)**	**(0.0000)**	(0.7345)	-----	
BD	0.0964	0.1014	-0.0650	-0.0418	**-0.2188**	0.0039	-0.1902	**-0.3007**	**0.2163**	1.0000
	(0.4207)	(0.3969)	(0.5876)	(0.7273)	**(0.0648)**	(0.9739)	(0.1095)	**(0.0103)**	**(0.0680)**	-----

Panel G: UK	GDP_UK	RF_UK	SD_UK	XS_UK	DY_UK	NFX_UK	NAM_UK	GAM_UK	OB	BD
GDP_UK	1.0000									

RF_UK	0.1702	1.0000								
	(0.1528)	-----								
SD_UK	**-0.6366**	-0.0023	1.0000							
	(0.0000)	(0.9845)	-----							
XS_UK	**0.2038**	**-0.2003**	**-0.3479**	1.0000						
	(0.0860)	**(0.0916)**	**(0.0028)**	-----						
DY_UK	**-0.6374**	-0.0999	**0.8611**	-0.1071	1.0000					
	(0.0000)	(0.4040)	**(0.0000)**	(0.3704)	-----					
NFX_UK	-0.0080	**-0.3669**	0.1863	0.0558	**0.3559**	1.0000				
	(0.9467)	**(0.0015)**	(0.1172)	(0.6418)	**(0.0022)**	-----				
NAM_UK	**-0.4964**	-0.0899	**0.8093**	**-0.2715**	**0.7738**	**0.2518**	1.0000			
	(0.0000)	(0.4526)	**(0.0000)**	**(0.0210)**	**(0.0000)**	**(0.0328)**	-----			
GAM_UK	**-0.2591**	**-0.3516**	**0.4343**	-0.0028	**0.6382**	**0.5580**	**0.6237**	1.0000		
	(0.0280)	**(0.0025)**	**(0.0001)**	(0.9815)	**(0.0000)**	**(0.0000)**	**(0.0000)**	-----		
OB	**-0.2585**	**-0.6490**	-0.0424	-0.0373	-0.1524	**-0.2168**	-0.0444	-0.0495	1.0000	
	(0.0284)	**(0.0000)**	(0.7236)	(0.7559)	(0.2011)	**(0.0674)**	(0.7110)	(0.6799)	-----	
BD	-0.1606	**0.3322**	0.0462	-0.1287	-0.1263	**-0.7778**	0.0063	**-0.3020**	**0.2163**	1.0000
	(0.1778)	**(0.0044)**	(0.7001)	(0.2813)	(0.2905)	**(0.0000)**	(0.9582)	**(0.0099)**	**(0.0680)**	-----

Panel H: Germany	GDP_GER	RF_GER	SD_GER	XS_GER	DY_GER	NFX_GER	NAM_GER	GAM_GER	OB	BD
GDP_GER	1.0000									

RF_GER	-0.0656	1.0000								
	(0.5843)	-----								
SD_GER	**-0.2988**	**0.5179**	1.0000							
	(0.0108)	**(0.0000)**	-----							
XS_GER	0.1853	**-0.3286**	**-0.2047**	1.0000						
	(0.1191)	**(0.0048)**	**(0.0845)**	-----						
DY_GER	**-0.6891**	**-0.2052**	**0.3188**	-0.1633	1.0000					
	(0.0000)	**(0.0838)**	**(0.0063)**	(0.1705)	-----					
NFX_GER	-0.0103	**0.4087**	**0.4604**	-0.1331	**-0.2179**	1.0000				
	(0.9318)	**(0.0004)**	**(0.0000)**	(0.2651)	**(0.0659)**	-----				
NAM_GER	**-0.4378**	0.0514	**0.4703**	-0.1578	**0.5303**	0.1901	1.0000			
	(0.0001)	(0.6682)	**(0.0000)**	(0.1855)	**(0.0000)**	(0.1097)	-----			
GAM_GER	**-0.3312**	**-0.3213**	**0.2603**	-0.1196	**0.4925**	0.1232	**0.4989**	1.0000		
	(0.0045)	**(0.0059)**	**(0.0272)**	(0.3169)	**(0.0000)**	(0.3026)	**(0.0000)**	-----		
OB	0.0814	**-0.4723**	**-0.5036**	-0.0481	**0.2495**	**-0.7444**	-0.1543	0.1307	1.0000	
	(0.4969)	**(0.0000)**	**(0.0000)**	(0.6884)	**(0.0345)**	**(0.0000)**	(0.1955)	(0.2740)	-----	
BD	0.0626	**0.4041**	-0.1430	-0.0600	-0.1335	**-0.4671**	-0.0852	**-0.5422**	**0.2163**	1.0000
	(0.6017)	**(0.0004)**	(0.2309)	(0.6166)	(0.2637)	**(0.0000)**	(0.4768)	**(0.0000)**	**(0.0680)**	-----

Panel I: Japan	GDP_JAP	RF_JAP	SD_JAP	XS_JAP	DY_JAP	NFX_JAP	NAM_JAP	GAM_JAP	OB	BD
GDP_JAP	1.0000									

RF_JAP	**-0.2882**	1.0000								
	(0.0141)	-----								
SD_JAP	**-0.3559**	**0.3929**	1.0000							
	(0.0022)	**(0.0006)**	-----							
XS_JAP	**0.2092**	**-0.3053**	**-0.2611**	1.0000						
	(0.0777)	**(0.0091)**	**(0.0267)**	-----						
DY_JAP	**-0.3041**	**0.2359**	0.1173	-0.1377	1.0000					
	(0.0094)	**(0.0461)**	(0.3264)	(0.2486)	-----					
NFX_JAP	-0.0203	0.0529	0.1410	0.0200	**-0.6886**	1.0000				
	(0.8653)	(0.6591)	(0.2375)	(0.8674)	**(0.0000)**	-----				
NAM_JAP	-0.1370	0.0685	**0.5411**	-0.0376	**-0.3452**	**0.4329**	1.0000			
	(0.2512)	(0.5677)	**(0.0000)**	(0.7537)	**(0.0030)**	**(0.0001)**	-----			
GAM_JAP	-0.0763	**-0.2265**	**0.2662**	-0.0820	**0.3894**	**-0.3094**	0.1316	1.0000		
	(0.5240)	**(0.0557)**	**(0.0238)**	(0.4934)	**(0.0007)**	**(0.0082)**	(0.2706)	-----		
OB	0.0099	0.1352	**-0.3455**	-0.0689	**0.6219**	**-0.7210**	**-0.7261**	-0.0495	1.0000	
	(0.9344)	(0.2576)	**(0.0030)**	(0.5653)	**(0.0000)**	**(0.0000)**	**(0.0000)**	(0.6799)	-----	
BD	0.0929	**0.5434**	-0.1380	-0.1426	-0.1420	0.0140	**-0.3783**	**-0.3019**	**0.2163**	1.0000
	(0.4376)	**(0.0000)**	(0.2478)	(0.2320)	(0.2340)	(0.9071)	**(0.0011)**	**(0.0100)**	**(0.0680)**	-----

Panel J: France	GDP_FRA	RF_FRA	SD_FRA	XS_FRA	DY_FRA	NFX_FRA	NAM_FRA	GAM_FRA	OB	BD
GDP_FRA	1.0000									

RF_FRA	0.0994	1.0000								
	(0.4059)	---								
SD_FRA	**-0.2889**	**0.4547**	1.0000							
	(0.0138)	**(0.0001)**	---							
XS_FRA	**0.2418**	**-0.2543**	**-0.3822**	1.0000						
	(0.0407)	**(0.0311)**	**(0.0009)**	---						
DY_FRA	**-0.7111**	**-0.2604**	**0.4804**	**-0.2140**	1.0000					
	(0.0000)	**(0.0271)**	**(0.0000)**	**(0.0710)**	---					
NFX_FRA	**0.2803**	**0.4090**	**0.3734**	-0.0217	-0.1638	1.0000				
	(0.0171)	**(0.0004)**	**(0.0012)**	(0.8565)	(0.1693)	---				
NAM_FRA	0.1498	**0.5085**	**0.5388**	-0.0081	0.0798	**0.6086**	1.0000			
	(0.2093)	**(0.0000)**	**(0.0000)**	(0.9464)	(0.5050)	**(0.0000)**	---			
GAM_FRA	**-0.4532**	-0.1119	**0.5046**	**-0.1994**	**0.8024**	0.1845	**0.2821**	1.0000		
	(0.0001)	(0.3493)	**(0.0000)**	**(0.0931)**	**(0.0000)**	(0.1208)	**(0.0163)**	---		
OB	**-0.3360**	**-0.4728**	**-0.3684**	-0.0973	**0.2393**	**-0.7444**	**-0.7176**	-0.0451	1.0000	
	(0.0039)	**(0.0000)**	**(0.0015)**	(0.4159)	**(0.0429)**	**(0.0000)**	**(0.0000)**	(0.7066)	---	
BD	-0.0400	**0.4036**	**-0.2041**	-0.1291	**-0.2311**	**-0.4671**	**-0.2573**	**-0.3008**	**0.2163**	1.0000
	(0.7390)	**(0.0004)**	**(0.0856)**	(0.2798)	**(0.0508)**	**(0.0000)**	**(0.0291)**	**(0.0102)**	**(0.0680)**	---

7.4.3. IN SAMPLE PREDICTION OF ECONOMIC GROWTH

7.4.3.1. STATIONARITY AND ORTHOGONALISATION

The last section on correlations shows that there are relationships between GDP and our predictive variables but since we plan to conduct regression analysis to forecast economic growth, the data may not be stationary, as the correlation analysis is performed using raw data. Thus, similar to Galariotis and Giouvris (2015) we initially test the data for stationarity before conducting any further analysis, as non-stationary data will result in potentially unreliable and biased outcomes. We conduct six (6) stationarity tests namely the *Augmented Dickey-Fuller (ADF) test, GLS detrended Dickey-Fuller (DFGLS) test, Phillips-Perron (PP) test, Kwiatkowski, Phillips, Schmidt, and Shin (KPSS) test, Elliot, Rothenberg, and Stock Point Optimal (ERS) test* and the *Ng and Perron (NP) test* on all the variables and if the variable examined satisfies at least four (4) of the stationarity tests, we consider the variable as stationary. The variables have been differenced to become stationary if the variable is deemed non-stationary. The variables that have been differenced, have a D in brackets at the back of the name of the variable in the tables.

The correlation analysis also shows that most independent variables are correlated to each other, signifying the possibility of biased results due to multicollinearity. Thus, in order to avoid multicollinearity, we have also orthogonalized[129] all the relevant variables using the same technique utilised by Galariotis and Giouvris (2015).

7.4.3.2. PREDICTING ECONOMIC GROWTH USING INDIVIDUAL PREDICTIVE VARIABLES

We estimate the following model to assess the predictive ability of our independent variables:

$$Y_{t+1} = \alpha + \beta' FV_t + \gamma' X_t + \varepsilon_{t+1} \qquad (7.3)$$

where Y_{t+1} is the realised growth of our macroeconomic variable, GDP, one quarter ahead (t+1); FV_t are the control variables at contemporaneous quarter t and contains the

[129] Similar to Galariotis & Giouvris (2015), we orthogonalize all explanatory variables. For example, in order to orthogonalise the explanatory variable X1, X2 and X3, we run the following regressions: X1=c+X2+X3+$residuals_{X1}$ and X2=c+X3+$residuals_{X2}$. Then, we use $residuals_{X1}$, $residuals_{X2}$ and X3. In this way, the variables should not be correlated to each other and there should not be any multi-collinearity.

following financial variables (FV): the risk free rate (RF), standard deviation or market volatility (SD), excess market returns (XS), dividend yield (DY), at least one lag of the dependent variable (GDP) and more lags of the GDP if autocorrelation remains in the residuals. X_t contains the following predictive variables: National foreign exchange (NFX), National illiquidity (NAM), Global illiquidity (GAM), Crude oil Brent (OB) and Baltic Dry index (BD). $\beta'$and γ' are the vector of coefficient estimates for the financial variables (or control variables) and predictive variables respectively and ε is the error term.

In table 7.4, we run six different regression models in order to identify the contribution of our predictive variables to economic growth. The first regression model includes one lag of the dependent variable and financial variables only. The following five regression models use the same variables as the first regression model but we add one predictive variable at a time. This is repeated for all countries. As highlighted earlier, if there is a D in brackets at the back of the name of the variable then it means that the variable has been differenced. Moreover, all variables are orthogonalised and the coefficients reported are standardised to allow comparison.

Table 7.4 shows that only France requires an additional lag of the dependent variable (GDP), as initially there is an autocorrelation in the residuals. We have reported both regressions in panel J and K respectively.

Although our correlation analysis indicates that standard deviation (SD) and dividend yield (DY) have the closest relationship with GDP, our first regression model which includes only financial variables appears to show that excess market returns (XS) is the most relevant coefficient as it is positive and significant for six (6) countries namely Norway, Denmark, Mexico, Brazil, Singapore and France. SD and DY are only significant for three countries (Norway, Singapore and UK) and one country respectively (Mexico). Similarly, risk free rate (RF) is positively significant to GDP in only one country namely Norway.

We will now investigate the effect of our predictive variables, adding one at a time. By adding national foreign exchange (NFX), only Brazil shows a significant result, indicating that NFX has the ability to predict the GDP of Brazil. The negative NFX sign signifies that USD weakens and *Brazilian Real (BRL)* has actually strengthened. Table 7.1 shows that Brazil's "*net exports of goods and services (% of GDP)"* is negative,

indicating that Brazil may be able to import goods and services at a cheaper price and hence somehow improve its GDP. Moreover, Brazil may benefit from a stronger NFX through its oil exports particularly since Brazil is a net oil exporter.

By comparison, we would expect NFX to be significant for Singapore as it has the highest *"annual oil expenditure to GDP ratio (%)"* and Singapore's *"exports and imports of goods and services (% of GDP)"* is more than 100% of its GDP, signifying that Singapore is less self-sufficient and trades more with other countries. However, the result is insignificant for Singapore.

Unlike Galariotis and Giouvris (2015), our findings indicate that global illiquidity (GAM) is less important in comparison to national illiquidity (NAM), as only two (2) countries' GDP are predicted by GAM while four (4) countries' economic growth can be predicted by NAM. Canada shows the only unexpected positive relationship for NAM while only Germany is affected by both illiquidity variables.

Interestingly, Crude oil Brent (OB) appears to be the most significant variable as the economic growth of nine (9) countries is positively predicted by it. Only UK, a net oil importer is not affected by OB. All the countries that are affected exhibit a positive coefficient, signifying that as oil price increases, the GDP of those countries also increases. Moreover, Mexico displays the highest positive coefficient, which is not surprising, as Mexico is a net oil exporter. The positive coefficient for net oil exporters is expected, as the higher oil price means higher revenue for those countries, which translates to higher GDP. However, for net oil importers we expect the opposite results whereby an oil price decrease, will increase GDP of those countries as they will be able to import oil cheaper for the development of their economy. Table 7.4 provides contradictory results for oil (OB) but Mork et al. (1994) do find evidence that US and Canada are positively related to a decrease in oil price even though the two (2) countries are oil importer and potential[130] oil exporter respectively. However, we will investigate this further in the next section when we include all variables.

Baltic Dry index (BD) is found to be significant for three (3) countries namely Canada, UK and France. The negative coefficients indicate that as BD increases, the economy of the three (3) countries shrinks. We notice that the three (3) countries' *"net exports of*

[130] Mork, Olsen et al. (1994) highlight that Canada switches from a position of net oil importer to net oil exporter over time while we classify Canada as a net oil exporter based on the latest available data (2012) that we obtain from US EIA website.

goods and services (% of GDP)" is negative and therefore one way to explain this is that as the BD increases (which indicates an increase in demand for raw materials as well as the price for those materials) this results in more expensive imports which leads to the GDP of those three countries to shrink.

The last panel L shows the summary of each country's adjusted R^2 after the addition of the individual predictive variables (one at a time) to our initial regression model which consists of the dependent variable (one lag or two lags) and financial variables only. *National foreign exchange (NFX)* provides extra explanatory power over the financial variables for three (3) countries only and as expected in the case of Brazil, the effect of NFX is the strongest. In relation to illiquidity, *national illiquidity (NAM)* provides greater explanatory power for four (4) countries over financial variables compared to *global illiquidity (GAM)* which provides greater explanatory power for three (3) countries only. Surprisingly, GAM and not NAM provides extra explanatory power in the case of Germany even though both illiquidity variables are significant.

As expected, oil (OB) exhibits the greatest explanatory power over financial variables, as there is improvement in nine (9) countries with the exception of UK. In the case of Japan, the addition of oil brings the highest improvement in explanatory power over financial variables. This may be due to Japan being a net importing country with the second highest *"Annual oil expenditure to GDP ratio"* after Singapore. Moreover, Japan is the only country that does not export any oil. Similar to NFX, the inclusion of Baltic Dry index (BD) provides extra explanatory power for only three (3) countries. The highest improvement is observed in the case of the UK, which is consistent to our earlier regression findings.

To summarize, excess market returns (XS) is the best predictor among financial variables as it is positively significant for six (6) countries, while among predictive variables, oil (OB) appears to be the best predictor as it is significant in nine (9) countries. Between illiquidity variables, national illiquidity (NAM) is found to be superior in comparison to global illiquidity (GAM). Similar to illiquidity, the Baltic Dry Index (BD) is found to be negatively related to economic growth, which is contradictory to Bakshi et al. (2011). NFX is the least important predictive variable, as we obtain a significant result only for Brazil.

Table 7.4: In sample prediction of economic growth using additional individual predictive variables for all ten (10) countries.
The table shows the results from predictive regression where we regress next quarter economic growth in macroeconomic variable (GDP_{t+1}) using different additional individual predictive variables. The regression model estimated is:

$$Y_{t+1} = \alpha + \beta' FV_t + \gamma' X_t + \varepsilon_{t+1} \qquad (7.3)$$

where Y_{t+1} is real GDP growth (GDP_{t+1}). We include one lag of the dependent variable (and we include more lags if there is autocorrelation in the residuals) and financial variables (FV_t) of RF (Risk free); SD (Standard deviation); XS (Excess market returns); DY (Dividend yield) as control variables. Predictive variables (X_t) are consisting of NFX (National foreign exchange), NAM (National illiquidity-Amihud), GAM (Global illiquidity-Amihud), OB (Crude oil Brent) and BD (Baltic Dry index). NFX is the national foreign exchange relative to United States Dollars (USD). Amihud (AM) is our illiquidity measure and the prefix 'N' in front of each illiquidity variable refers to national illiquidity-Amihud (NAM) while the prefix 'G' refers to global illiquidity-Amihud (GAM). Global illiquidity is constructed as in Brockman et al. (2009) and Galariotis and Giouvris (2015) whereby Global illiquidity is created by combining all countries except the country nominated for the test. OB is crude oil Brent price while BD is the Baltic Dry index. The coefficients reported are standardised. Adj. R2 presents Adjusted R^2 of the dependent variable (GDP) + financial variables (FV) + X (relevant additional predictive variable). Please note that panel L summarizes all results obtained from previous panels (countries) and are based on the methodology of Brockman et al (2009), Galariotis & Giouvris (2015) and Sung & Giouvris (2016). Newey-West p-value are reported in brackets whereby **bold** figures denote statistically significant coefficient at least at 10% level. The bandwidth parameter for the Newey-West p-value is calculated using the Newey-West automatic lag selection. The number in the last two columns are the probability values of the Ljung-Box test (Q Stat) and Breusch-Godfrey test (LM Test), for testing autocorrelation in the residuals. The null hypothesis is that there is no autocorrelation and a probability value above 0.05 indicates that there is no autocorrelation. Where there is autocorrelation, the regression is repeated and the final results are presented where the residuals are free from autocorrelation. Both the old and new Ljung-Box test (Q Stat) and Breusch-Godfrey test (LM Test) probability values are presented and the additional lagged variable is presented for as many lags as were necessary. The sample period is from January 1998 to December 2015, consisting of 72 quarterly observations. All data are obtained from DataStream, Bloomberg, World Bank and US Energy Information Administration (EIA) website.

Panel A: Norway										
	Cons	GDP	RF (D)	SD	XS	DY	X	Adj. R2	Q Stat	LM Test
GDPt+1 = FV	**0.0051**	**-0.2535**	**0.2311**	-0.1355	**0.2399**	-0.0038		0.1364	0.8170	0.6087
	(0.0000)	**(0.0044)**	**(0.0402)**	(0.1265)	**(0.0738)**	(0.9787)				
GDPt+1 = FV+FX (D)	**0.0052**	**-0.2663**	**0.2278**	-0.1353	**0.2423**	-0.0036	-0.1317	0.1415	0.6880	0.3815
	(0.0001)	**(0.0157)**	**(0.0332)**	(0.1249)	**(0.0751)**	(0.9788)	(0.3373)			
GDPt+1 = FV+NAM	**0.0053**	**-0.2833**	**0.2230**	-0.1354	**0.2448**	-0.0043	-0.1586	0.1494	0.7600	0.5067
	(0.0001)	**(0.0086)**	**(0.0402)**	(0.1614)	**(0.0651)**	(0.9776)	(0.1199)			
GDPt+1 = FV+GAM	**0.0052**	**-0.2576**	**0.2303**	-0.1351	**0.2412**	-0.0031	-0.0168	0.1230	0.8260	0.6258
	(0.0000)	**(0.0038)**	**(0.0299)**	(0.1450)	**(0.0822)**	(0.9825)	(0.8515)			
GDPt+1 = FV+OB (D)	**0.0051**	**-0.2514**	**0.2312**	-0.1361	**0.2387**	-0.0049	**0.1356**	0.1428	0.9840	0.9645
	(0.0002)	**(0.0240)**	**(0.0199)**	(0.1614)	**(0.0774)**	(0.9673)	**(0.0408)**			
GDPt+1 = FV+BD	**0.0054**	**-0.2531**	**0.2314**	**-0.1353**	**0.2402**	-0.0034	-0.0220	0.1232	0.8300	0.6333

Panel B: Canada										
	Cons	GDP	RF (D)	SD	XS	DY (D)	X	Adj. R2	Q Stat	LM Test
GDPt+1 = FV	**0.0022**	**0.6044**	-0.0947	0.0542	0.1608	-0.1155		0.3102	0.6280	0.4036
	(0.0760)	**(0.0001)**	(0.2628)	(0.6433)	(0.1510)	(0.4877)				
GDPt+1 = FV+FX (D)	**0.0022**	**0.6048**	-0.0948	0.0542	0.1608	-0.1156	0.0096	0.2993	0.6160	0.3872
	(0.0819)	**(0.0001)**	(0.2756)	(0.6448)	(0.1567)	(0.4853)	(0.9004)			
GDPt+1 = FV+NAM (D)	**0.0021**	**0.6337**	-0.1032	0.0546	0.1602	-0.1211	**0.1502**	0.3231	0.7960	0.6476
	(0.0920)	**(0.0000)**	(0.1726)	(0.6239)	(0.1350)	(0.4960)	**(0.0181)**			
GDPt+1 = FV+GAM	**0.0024**	**0.5761**	-0.0864	0.0535	0.1609	-0.1106	-0.0801	0.3055	0.6070	0.3568
	(0.0559)	**(0.0002)**	(0.3052)	(0.6362)	(0.1454)	(0.5404)	(0.3817)			
GDPt+1 = FV+OB (D)	**0.0032**	**0.4330**	-0.0447	0.0525	0.1666	**-0.0810**	**0.4754**	0.5185	0.7020	0.5983
	(0.0000)	**(0.0000)**	(0.5386)	(0.5852)	(0.1034)	**(0.0929)**	**(0.0000)**			
GDPt+1 = FV+BD	**0.0029**	**0.6024**	**-0.0940**	0.0539	**0.1603**	**-0.1157**	**-0.0846**	0.3070	0.7340	0.5572
	(0.0000)	**(0.0000)**	**(0.0001)**	(0.2703)	**(0.0000)**	**(0.0628)**	**(0.0011)**			

Panel C: Denmark										
	Cons	GDP	RF (D)	SD	XS	DY	X	Adj. R2	Q Stat	LM Test
GDPt+1 = FV	**0.0024**	0.0701	0.1431	**-0.2604**	**0.2997**	0.0504		0.1377	0.8120	0.5718
	(0.0326)	(0.6167)	(0.1145)	**(0.0200)**	**(0.0391)**	(0.7196)				
GDPt+1 = FV+FX (D)	**0.0024**	0.0634	0.1437	**-0.2625**	**0.2997**	0.0513	0.0710	0.1295	0.8910	0.7486
	(0.0411)	(0.6684)	(0.1039)	**(0.0179)**	**(0.0498)**	(0.7045)	(0.5748)			
GDPt+1 = FV+NAM (D)	**0.0024**	0.0811	**0.1420**	**-0.2571**	**0.2999**	0.0486	-0.0981	0.1345	0.8740	0.6878
	(0.0511)	(0.5606)	**(0.0434)**	**(0.0261)**	**(0.0751)**	(0.6640)	(0.3900)			
GDPt+1 = FV+GAM	**0.0026**	-0.0066	**0.1485**	**-0.2857**	**0.3021**	0.0583	**-0.2519**	0.1879	0.9800	0.9558
	(0.0319)	(0.9643)	**(0.0253)**	**(0.0052)**	**(0.0716)**	(0.5825)	**(0.0068)**			
GDPt+1 = FV+OB (D)	**0.0026**	-0.0271	**0.1512**	**-0.2910**	**0.3003**	0.0632	**0.2603**	0.1892	0.6760	0.3324
	(0.0101)	(0.8205)	**(0.0791)**	**(0.0033)**	**(0.0219)**	(0.6499)	**(0.0019)**			
GDPt+1 = FV+BD	**0.0036**	0.0723	**0.1426**	**-0.2601**	**0.3003**	0.0494	-0.1183	0.1394	0.6820	0.3386
	(0.0077)	(0.6164)	**(0.0287)**	**(0.0148)**	**(0.0675)**	(0.6583)	(0.1394)			

Panel D: Mexico										
	Cons	GDP	RF (D)	SD	XS	DY	X	Adj. R2	Q Stat	LM Test
GDPt+1 = FV	**0.0034**	**0.4185**	0.1083	0.0579	**0.2978**	**-0.1548**		0.2994	0.9250	0.8659
	(0.0339)	**(0.0049)**	(0.2023)	(0.6174)	**(0.0003)**	**(0.0185)**				
GDPt+1 = FV+FX (D)	**0.0034**	**0.4222**	0.1084	0.0583	**0.2975**	**-0.1539**	-0.1335	0.3077	0.8810	0.7889
	(0.0506)	**(0.0110)**	(0.3079)	(0.6428)	**(0.0022)**	**(0.0637)**	(0.1627)			
GDPt+1 = FV+NAM (D)	**0.0034**	**0.4167**	0.1083	0.0577	**0.2980**	**-0.1552**	-0.0443	0.2904	0.8960	0.8150
	(0.0260)	**(0.0023)**	(0.1669)	(0.6058)	**(0.0005)**	**(0.0173)**	(0.6882)			
GDPt+1 = FV+GAM	**0.0036**	**0.3806**	0.1077	0.0525	**0.3018**	**-0.1646**	-0.0993	0.2976	0.9950	0.9901
	(0.0139)	**(0.0030)**	(0.1297)	(0.5962)	**(0.0005)**	**(0.0136)**	(0.1667)			
GDPt+1 = FV+OB (D)	**0.0045**	**0.2262**	0.1046	0.0378	**0.3172**	**-0.1959**	**0.5002**	0.5247	0.8080	0.7355
	(0.0000)	**(0.0022)**	(0.1555)	(0.6167)	**(0.0000)**	**(0.0087)**	**(0.0032)**			
GDPt+1 = FV+BD	**0.0040**	**0.4265**	0.1085	0.0583	**0.2971**	**-0.1536**	-0.0641	0.2927	0.7970	0.6458
	(0.0049)	**(0.0009)**	(0.1094)	(0.5644)	**(0.0003)**	**(0.0181)**	(0.2314)			

Panel E: Brazil										
	Cons	GDP	RF (D)	SD	XS	DY	X	Adj. R2	Q Stat	LM Test
GDPt+1 = FV	**0.0039**	**0.3501**	-0.1723	-0.0232	**0.2434**	0.0240		0.1885	0.9470	0.8912
	(0.0203)	**(0.0059)**	(0.1316)	(0.8309)	**(0.0589)**	(0.7935)				
GDPt+1 = FV+FX (D)	**0.0039**	**0.3372**	-0.1735	-0.0209	**0.2453**	0.0201	**-0.1953**	0.2172	0.6920	0.4386
	(0.0105)	**(0.0072)**	(0.1601)	(0.8308)	**(0.0472)**	(0.8135)	**(0.0115)**			
GDPt+1 = FV+NAM (D)	**0.0039**	**0.3507**	-0.1721	-0.0232	**0.2434**	0.0241	0.0634	0.1800	0.9540	0.8986
	(0.0306)	**(0.0111)**	(0.2275)	(0.8194)	**(0.0522)**	(0.7836)	(0.3708)			
GDPt+1 = FV+GAM	**0.0038**	**0.3563**	-0.1708	-0.0219	**0.2430**	0.0245	0.1132	0.1896	0.9690	0.9378
	(0.0195)	**(0.0059)**	(0.1801)	(0.8198)	**(0.0522)**	(0.7779)	(0.3161)			
GDPt+1 = FV+OB (D)	**0.0046**	0.2415	-0.1894	-0.0222	**0.2554**	0.0015	**0.2490**	0.2316	0.7530	0.5556
	(0.0580)	(0.1006)	(0.2921)	(0.8381)	**(0.0430)**	(0.9883)	**(0.0002)**			
GDPt+1 = FV+BD	0.0025	**0.2931**	-0.1810	-0.0220	**0.2499**	0.0118	0.1228	0.1889	0.8130	0.6098
	(0.3010)	**(0.0291)**	(0.2469)	(0.8153)	**(0.0648)**	(0.8968)	(0.2774)			

Panel F: Singapore										
	Cons	GDP	RF (D)	SD (D)	XS	DY	X	Adj. R2	Q Stat	LM Test
GDPt+1 = FV	**0.0130**	0.0955	0.1346	**-0.2399**	**0.3113**	0.0302		0.1272	0.8060	0.5499
	(0.0001)	(0.3999)	(0.1422)	**(0.0514)**	**(0.0195)**	(0.7356)				
GDPt+1 = FV+FX (D)	**0.0130**	0.0961	0.1346	**-0.2399**	**0.3112**	0.0303	0.0157	0.1136	0.8280	0.5902
	(0.0002)	(0.3971)	(0.1376)	**(0.0494)**	**(0.0211)**	(0.7358)	(0.8871)			
GDPt+1 = FV+NAM (D)	**0.0130**	0.0945	0.1346	**-0.2398**	**0.3115**	0.0300	-0.0061	0.1134	0.7970	0.5303
	(0.0002)	(0.4109)	(0.1494)	**(0.0542)**	**(0.0180)**	(0.7388)	(0.9245)			
GDPt+1 = FV+GAM	**0.0128**	0.1051	**0.1335**	**-0.2403**	**0.3092**	0.0318	0.0474	0.1157	0.7800	0.4963
	(0.0000)	(0.2860)	**(0.0906)**	**(0.0484)**	**(0.0232)**	(0.6953)	(0.5321)			
GDPt+1 = FV+OB (OB)	**0.0138**	0.0321	0.1357	**-0.2333**	**0.3252**	0.0166	**0.2156**	0.1603	0.9140	0.8017
	(0.0000)	(0.7597)	(0.1031)	**(0.0206)**	**(0.0258)**	(0.8180)	**(0.0001)**			
GDPt+1 = FV+BD	**0.0131**	0.0962	0.1346	**-0.2400**	**0.3112**	0.0303	-0.0069	0.1134	0.7980	0.5321
	(0.0001)	(0.3542)	(0.1152)	**(0.0533)**	**(0.0219)**	(0.7183)	(0.9459)			

Panel G: UK										
	Cons	GDP	RF (D)	SD	XS	DY	X	Adj. R2	Q Stat	LM Test
GDPt+1 = FV	0.0015	**0.6893**	0.0104	**-0.1587**	0.0110	0.0682		0.4330	0.7210	0.5995
	(0.2699)	**(0.0003)**	(0.9143)	**(0.0014)**	(0.8764)	(0.4233)				
GDPt+1 = FV+FX (D)	0.0016	**0.6688**	0.0098	**-0.1584**	0.0116	0.0617	-0.0879	0.4320	0.7750	0.6749
	(0.2295)	**(0.0003)**	(0.9192)	**(0.0015)**	(0.8583)	(0.5068)	(0.3293)			
GDPt+1 = FV+NAM	0.0017	**0.6496**	0.0094	**-0.1582**	0.0121	0.0556	**-0.1283**	0.4404	0.8520	0.7732
	(0.1945)	**(0.0003)**	(0.9112)	**(0.0031)**	(0.8724)	(0.5667)	**(0.0990)**			
GDPt+1 = FV+GAM	0.0015	**0.6849**	0.0105	**-0.1588**	0.0112	0.0668	-0.0132	0.4241	0.7450	0.6187
	(0.2958)	**(0.0011)**	(0.8970)	**(0.0002)**	(0.8645)	(0.5348)	(0.8339)			
GDPt+1 = FV+OB (D)	0.0015	**0.6875**	0.0104	**-0.1587**	0.0110	0.0676	0.0037	0.4240	0.7210	0.5998
	(0.3528)	**(0.0044)**	(0.9060)	**(0.0002)**	(0.8693)	(0.5149)	(0.9750)			
GDPt+1 = FV+BD	**0.0039**	**0.6416**	0.0120	**-0.1601**	0.0131	0.0530	**-0.2738**	0.5038	0.3310	0.1594
	(0.0000)	**(0.0000)**	(0.8858)	**(0.0035)**	(0.8340)	(0.4660)	**(0.0421)**			

Panel H: Germany										
	Cons	GDP	RF (D)	SD	XS	DY	X	Adj. R2	Q Stat	LM Test
GDPt+1 = FV	0.0018	**0.4719**	-0.1809	-0.0849	0.0686	0.0367		0.1527	0.7170	0.4098
	(0.1851)	**(0.0081)**	(0.3791)	(0.5251)	(0.4285)	(0.7489)				
GDPt+1 = FV+FX (D)	0.0018	**0.4722**	-0.1810	-0.0849	0.0686	0.0369	-0.0127	0.1394	0.7140	0.4023
	(0.1890)	**(0.0088)**	(0.3840)	(0.5290)	(0.4311)	(0.7506)	(0.9009)			
GDPt+1 = FV+NAM	**0.0020**	**0.4079**	-0.1644	-0.0868	0.0710	0.0079	**-0.1150**	0.1505	0.8050	0.5122
	(0.0302)	**(0.0108)**	(0.4449)	(0.4959)	(0.4109)	(0.9367)	**(0.0980)**			
GDPt+1 = FV+GAM (D)	0.0019	**0.4488**	-0.1734	-0.0864	0.0698	0.0287	**-0.2672**	0.2170	0.8220	0.6534
	(0.1531)	**(0.0076)**	(0.4090)	(0.5217)	(0.4451)	(0.8001)	**(0.0007)**			
GDPt+1 = FV+OB (D)	**0.0024**	**0.2480**	-0.1276	-0.0891	0.0759	-0.0711	**0.4886**	0.3614	0.7000	0.4805
	(0.0159)	**(0.0726)**	(0.2406)	(0.3715)	(0.3931)	(0.5172)	**(0.0077)**			
GDPt+1 = FV+BD	0.0022	**0.4769**	-0.1817	-0.0850	0.0685	0.0396	-0.0482	0.1417	0.5940	0.2265
	(0.1333)	**(0.0239)**	(0.3455)	(0.5069)	(0.4657)	(0.7335)	(0.5764)			

Panel I: Japan										
	Cons	GDP	RF (D)	SD	XS	DY (D)	X	Adj. R2	Q Stat	LM Test
GDPt+1 = FV	**0.0017**	0.1068	0.1517	-0.2113	-0.0039	-0.1164		0.0473	0.7980	0.4034
	(0.0948)	(0.3019)	(0.1835)	(0.1328)	(0.9790)	(0.2570)				
GDPt+1 = FV+FX (D)	0.0017	0.1035	0.1520	-0.2117	-0.0043	-0.1180	0.0410	0.0340	0.7220	0.2400
	(0.1492)	(0.3797)	(0.1978)	(0.1272)	(0.9748)	(0.3109)	(0.6331)			
GDPt+1 = FV+NAM (D)	**0.0017**	0.0926	0.1528	-0.2148	-0.0035	-0.1222	-0.1121	0.0457	0.7960	0.4289
	(0.0829)	(0.3578)	(0.1717)	(0.1241)	(0.9811)	(0.2384)	(0.4345)			
GDPt+1 = FV+GAM	0.0017	0.1096	0.1515	-0.2104	-0.0043	-0.1154	0.0208	0.0326	0.8030	0.4140
	(0.1017)	(0.2361)	(0.1794)	(0.1400)	(0.9776)	(0.2064)	(0.7928)			
GDPt+1 = FV+OB (D)	**0.0019**	0.0131	**0.1602**	**-0.2299**	-0.0061	**-0.1572**	**0.3575**	0.1647	0.7510	0.4874
	(0.0123)	(0.8999)	**(0.0897)**	**(0.0582)**	(0.9637)	**(0.0779)**	**(0.0048)**			
GDPt+1 = FV+BD	**0.0029**	0.1160	0.1506	-0.2104	-0.0027	-0.1119	-0.0980	0.0426	0.9870	0.9578
	(0.0335)	(0.2451)	(0.2027)	(0.1049)	(0.9861)	(0.2256)	(0.2356)			

Panel J: France										
	Cons	GDP	RF (D)	SD	XS	DY	X	Adj. R2	Q Stat	LM Test
GDPt+1 = FV	0.0012	**0.6375**	-0.1943	-0.0634	**0.1874**	-0.0847		0.4436	0.1230	0.0249
	(0.1035)	**(0.0001)**	(0.2092)	(0.5332)	**(0.0410)**	(0.3783)				
GDPt+1 = FV+FX (D)	0.0012	**0.6375**	-0.1943	-0.0634	**0.1874**	-0.0847	0.0097	0.4349	0.1220	0.0247
	(0.1075)	**(0.0001)**	(0.2122)	(0.5369)	**(0.0431)**	(0.3844)	(0.9115)			
GDPt+1 = FV+NAM (D)	**0.0013**	**0.6263**	-0.1917	-0.0627	**0.1874**	-0.0906	**-0.1702**	0.4664	0.1120	0.0252
	(0.0877)	**(0.0001)**	(0.2388)	(0.5228)	**(0.0295)**	(0.3317)	**(0.0126)**			
GDPt+1 = FV+GAM	0.0014	**0.5961**	-0.1844	-0.0617	**0.1884**	-0.1036	-0.0653	0.4381	0.1900	0.0294
	(0.1261)	**(0.0037)**	(0.2829)	(0.5738)	**(0.0513)**	(0.3176)	(0.4805)			
GDPt+1 = FV+OB (D)	**0.0017**	**0.5040**	-0.1630	-0.0565	**0.1885**	-0.1503	**0.2396**	0.4838	0.3140	0.1311
	(0.0026)	**(0.0002)**	(0.2014)	(0.5491)	**(0.0532)**	(0.1714)	**(0.0073)**			
GDPt+1 = FV+BD	**0.0022**	**0.6314**	-0.1927	-0.0636	**0.1883**	-0.0857	**-0.1540**	0.4607	0.0260	0.0014
	(0.0010)	**(0.0001)**	(0.1747)	(0.4795)	**(0.0362)**	(0.4096)	**(0.0268)**			

Panel K: France (Two lags for GDP)

	Cons	GDP	GDP-1	RF (D)	SD	XS	DY	X	Adj. R2	Q Stat	LM Test
GDPt+1 = FV	0.0009	**0.5287**	0.2140	-0.2426	-0.0858	**0.2007**	-0.0536		0.4611	0.5690	0.1205
	(0.3362)	**(0.0006)**	(0.1050)	(0.1224)	(0.3713)	**(0.0229)**	(0.5903)				
GDPt+1 = FV+FX (D)	0.0009	**0.5288**	0.2140	-0.2426	-0.0858	**0.2007**	-0.0536	0.0098	0.4526	0.5700	0.1195
	(0.3400)	**(0.0007)**	(0.1079)	(0.1269)	(0.3765)	**(0.0248)**	(0.5948)	(0.9021)			
GDPt+1 = FV+NAM (D)	0.0009	**0.5131**	**0.2220**	-0.2417	-0.0859	**0.2011**	-0.0586	**-0.1755**	0.4866	0.5190	0.1082
	(0.3127)	**(0.0010)**	**(0.0769)**	(0.1344)	(0.3510)	**(0.0153)**	(0.5397)	**(0.0215)**			
GDPt+1 = FV+GAM	0.0008	**0.5323**	**0.2181**	-0.2449	-0.0865	**0.2008**	-0.0504	0.0089	0.4525	0.5610	0.1048
	(0.3706)	**(0.0041)**	**(0.0234)**	(0.1765)	(0.3833)	**(0.0615)**	(0.6467)	(0.9373)			
GDPt+1 = FV+OB (D)	**0.0013**	**0.4079**	**0.1987**	-0.2090	-0.0776	**0.2007**	-0.1190	**0.2307**	0.4985	0.8300	0.6109
	(0.0550)	**(0.0005)**	**(0.0479)**	(0.1168)	(0.3593)	**(0.0256)**	(0.2542)	**(0.0133)**			
GDPt+1 = FV+BD	**0.0018**	**0.5156**	**0.2272**	**-0.2439**	-0.0875	**0.2024**	-0.0528	**-0.1636**	0.4821	0.1920	0.0010
	(0.0040)	**(0.0008)**	**(0.0154)**	**(0.0983)**	(0.2563)	**(0.0443)**	(0.6277)	**(0.0039)**			

Panel L: Summary of each countries Adj. R2 after adding the individual control variables

	Adj. R2						% Change of Adj. R2 relative to FV only				
	FV only	FV + FX	FV + NAM	FV + GAM	FV + OB	FV + BD	FV + FX	FV + NAM	FV + GAM	FV + OB	FV + BD
Norway	0.136	0.142	0.149	0.123	0.143	0.123	3.76%	9.49%	-9.83%	4.70%	-9.66%
Canada	0.310	0.299	0.323	0.305	0.519	0.307	-3.50%	4.17%	-1.51%	67.18%	-1.00%
Denmark	0.138	0.130	0.134	0.188	0.189	0.139	-5.96%	-2.37%	36.43%	37.35%	1.19%
Mexico	0.299	0.308	0.290	0.298	0.525	0.293	2.80%	-3.00%	-0.60%	75.29%	-2.23%
Brazil	0.189	0.217	0.180	0.190	0.232	0.189	15.25%	-17.13%	5.32%	22.16%	-18.46%
Singapore	0.127	0.114	0.113	0.116	0.160	0.113	-10.68%	-10.86%	-9.03%	26.02%	-10.85%
UK	0.433	0.432	0.440	0.424	0.424	0.504	-0.22%	1.73%	-2.04%	-2.08%	16.37%
Germany	0.153	0.139	0.150	0.217	0.361	0.142	-8.69%	-1.42%	42.11%	136.73%	-7.15%
Japan	0.047	0.034	0.046	0.033	0.165	0.043	-28.12%	-3.21%	-31.01%	248.58%	-9.90%
France (One lag)	0.444	0.435	0.466	0.438	0.484	0.461	-1.97%	5.14%	-1.24%	9.05%	3.86%
France (Two lags)	0.461	0.453	0.487	0.452	0.498	0.482	-1.86%	5.52%	-1.87%	8.09%	4.55%

7.4.3.3. PREDICTING ECONOMIC GROWTH USING ALL VARIABLES

Instead of adding one predictive variable at a time, we will now use a regression model[131] which incorporates all variables and is shown in table 7.5.

Table 7.5 shows that in addition to Norway, the GDP of Denmark is also now positively related to risk free rate (RF). Even standard deviation (SD) have two (2) additional countries showing significant negative coefficients namely Norway and Germany. There no changes for excess market returns (XS) as the same six (6) countries exhibit positive coefficients while for dividend yield (DY), Japan also displays a negative and significant coefficient.

In relation to the predictive variables, national foreign exchange (NFX) remains negative and significant only for Brazil, confirming that Brazil benefits from their cheaper imports. However, this appears to be in contrast to table 7.1, as its trade data for oil as well as goods services is one of the lowest as a percentage of GDP. Nevertheless, as highlighted earlier, Brazil have the lowest *"annual oil revenue to GDP ratio (%)"* and negative *"net exports of goods and services (% of GDP)"* signifying that NFX may have positively affect Brazil's economic growth through cheaper *"imports of goods and services (% of GDP)"* and exports of expensive oil (OB).

The results of illiquidity variables change slightly, as national illiquidity (NAM) of Norway as well as global illiquidity (GAM) of Canada and Mexico are now found to be negatively significant to GDP. NAM has more significant results compared to GAM but NAM of Canada remains positively related to its GDP which is unexpected. If we exclude Canada, the GDP of four (4) countries is correctly predicted by NAM and GAM respectively. Thus, similar to Galariotis and Giouvris (2015), this shows that market illiquidity does contain some information for estimating the current and future state of the economy of certain countries in our sample.

The GDP of the nine (9) countries (except UK) are still predicted by oil (OB) even after including all predictive variables. This indicates that the effect of oil (OB) on the economy of the nine (9) countries is quite significant as the additional variables do not change the relationship. The results also confirm that the GDP of all nine (9) countries

[131] The regression model estimate is similar to the previous equation (7.3) but is conducted by including all the predictive variables.

are positively predicted by oil (OB) which is not expected for net oil importers[132]. However, Mork et al. (1994) do find evidence that countries with different characteristics namely US and Canada[133], can have similar reaction to oil (OB).

Baltic dry index (BD) still predicts the GDP of three (3) countries even after including all variables. However, the composition of the three (3) countries actually changes, as Brazil's GDP is now significantly affected by BD while the GDP of Canada is not affected by the BD. However, out of the three countries, Brazil obtains a positive coefficient which is more consistent to past research such as Bakshi et al. (2011). They show the ability of the BD to predict the future course of the economy of Brazil. Since national foreign exchange (NFX) and BD for Brazil remains significant, the results show that the two variables combined can predict the economic growth of Brazil and trade is apparently important for the GDP of Brazil.

Panel B presents a summary of explanatory power for all countries in the sample by looking at the adjusted R^2 of the combined predictive variables over financial variables. After including all predictive variables into the regression, surprisingly results for two (2) countries namely Singapore and Norway do not show improvement. Singapore may have different characteristics in comparison to the other countries. Table 7.1 shows that it has the highest *Annual oil expenditure to GDP ratio* and it is the only country with *exports/imports of goods and services (% of GDP)* that exceeds 100%. Thus, Singapore may require different financial and predictive variables.

Norway has the highest *"Annual oil revenue to GDP ratio"* and the lowest *"liner shipping connectivity index"* but unlike Singapore, Norway is affected the most when all the variables are included, as two (2) variables namely standard deviation (SD) and NAM become significant. Predictive variables for Germany show the greatest explanatory power over financial variables, as the adjusted R^2 increases by more than 200%.

Overall, the results show that when including all variables, oil (OB) is able to predict economic growth for most countries in our sample while excess market returns (XS) is the best predictor among financial variables (FV). Results are less consistent for national

[132] For net oil importers, we expect negative coefficient whereby an oil price decrease, will increase the GDP of those countries as they will be able to import oil cheaper for the development of the countries' economy. However, the positive coefficient for net oil exporters is expected, as the higher oil price means higher revenue for those countries, which translates to higher GDP. For instance, Sheppard, Raval et al. 2016 reports of Saudi Arabia's willingness to cut oil production in order to improve revenue and their economy, signifies that oil exporters are expected to benefit from an oil price increase.

[133] Mork, Olsen et al. (1994) highlight that Canada switches from a position of net oil importer to net oil exporter over time while we classify Canada as a net oil exporter based on the latest available data (2012) that we obtain from US EIA website.

and global illiquidity as there are changes in the number of countries affected. National illiquidity (NAM) is significant for five (5) countries' GDP and global illiquidity (GAM) is significant for four (4) countries' GDP. However, NAM has a positive effect in the case of Canada's GDP which is not consistent to past research such as Galariotis and Giouvris (2015). Whilst Baltic Dry index (BD) has a positive effect on Brazil's GDP after the inclusion of all variables. With regards to explanatory power, Germany shows the highest improvement while Norway and Singapore are the only two (2) countries that do not show any improvement over financial variables after including all predictive variables. Finally, results for individual countries show that oil (OB) has greater explanatory power in comparison to other predictive variables such as BD and the illiquidity variables.

Table 7.5: In sample prediction of macroeconomic variable with all variables for the ten (10) countries.
The table shows the results from predictive regression where we regress next quarter economic growth in macroeconomic variable (GDP_{t+1}) using all the variables. Thus, the regression model estimated is similar to before but is inclusive of all variables as below:

$$Y_{t+1} = \alpha + \beta' FV_t + \gamma' X_t + \varepsilon_{t+1} \qquad (7.4)$$

where Y_{t+1} is real GDP growth (GDP_{t+1}). We include one lag of the dependent variable (and we include more lags if there is autocorrelation in the residuals) and financial variables (FV_t) of RF (Risk free); SD (Standard deviation); XS (Excess market returns); DY (Dividend yield) as control variables. Predictive variables (X_t) are consisting of NFX (National foreign exchange), NAM (National illiquidity-Amihud), GAM (Global illiquidity-Amihud), OB (Crude oil Brent) and BD (Baltic Dry index). NFX is the national foreign exchange relative to United States Dollars (USD). Amihud (AM) is our illiquidity measure and the prefix 'N' in front of each illiquidity variable refers to national illiquidity-Amihud (NAM) while the prefix 'G' refers to global illiquidity-Amihud (GAM). Global illiquidity is constructed as in Brockman et al. (2009) and Galariotis and Giouvris (2015) whereby global illiquidity is created by combining all countries except the country nominated for the test. OB is crude oil Brent price while BD is the Baltic Dry index. The coefficients reported are standardised. Adj. R2 presents Adjusted R^2 of the dependent variable (GDP) + financial variables (FV) + ALL (All predictive variables). Please note that panel B summarizes all results obtained from panel A and are based on the methodology of Brockman et al (2009), Galariotis & Giouvris (2015) and Sung & Giouvris (2016). Newey-West p-value are reported in brackets whereby **bold** figures denote statistically significant coefficient at least at 10% level. The bandwidth parameter for the Newey-West p-value is calculated using the Newey-West automatic lag selection. The number in the last two columns are the probability values of the Ljung-Box test (Q Stat) and Breusch-Godfrey test (LM Test), for testing autocorrelation in the residuals. The null hypothesis is that there is no autocorrelation and a probability value above 0.05 indicates that there is no autocorrelation. Where there is autocorrelation, the regression is repeated and the final results are presented where the residuals are free from autocorrelation. Both the old and new Ljung-Box test (Q Stat) and Breusch-Godfrey test (LM Test) probability values are presented and the additional lagged variable is presented for as many lags as are necessary. The sample period is from January 1998 to December 2015, consisting of 72 quarterly observations. All data are obtained from DataStream, Bloomberg, World Bank and US Energy Information Administration (EIA) website.

Panel A: All Countries

	Cons	GDP	GDP-1	RF (D)	SD	XS	DY	NFX (D)	NAM	GAM	OB (D)	BD	Adj. R2	Q Stat	LM Test
Norway	**0.0056**	**-0.3003**		**0.2186**	**-0.1351**	**0.2480**	-0.0041	-0.1350	**-0.1617**	-0.0229	**0.1355**	-0.0192	0.1353	0.8100	0.6033
	(0.0000)	**(0.0000)**		**(0.0578)**	**(0.0000)**	**(0.0000)**	(0.9309)	(0.1945)	**(0.0004)**	(0.6542)	**(0.0000)**	(0.5298)			
	Cons	GDP	GDP-1	RF (D)	SD	XS	DY (D)	NFX (D)	NAM (D)	GAM	OB (D)	BD	Adj. R2	Q Stat	LM Test
Canada	**0.0040**	**0.4032**		-0.0360	0.0514	0.1660	-0.0766	0.0018	**0.1107**	**-0.1316**	**0.4837**	-0.0877	0.5284	0.4450	0.2755
	(0.0000)	**(0.0000)**		(0.6010)	(0.5214)	(0.1142)	(0.2322)	(0.9769)	**(0.0295)**	**(0.0808)**	**(0.0001)**	(0.1007)			
	Cons	GDP	GDP-1	RF (D)	SD	XS	DY	NFX (D)	NAM (D)	GAM	OB (D)	BD	Adj. R2	Q Stat	LM Test
Denmark	**0.0041**	-0.1203		**0.1575**	**-0.3222**	**0.3037**	0.0721	0.0851	-0.0802	**-0.2825**	**0.2885**	-0.1176	0.2506	0.7740	0.5207
	(0.0050)	(0.3313)		**(0.0000)**	**(0.0001)**	**(0.0020)**	(0.4549)	(0.4733)	(0.3495)	**(0.0013)**	**(0.0001)**	(0.1893)			
	Cons	GDP	GDP-1	RF (D)	SD	XS	DY	NFX (D)	NAM (D)	GAM	OB (D)	BD	Adj. R2	Q Stat	LM Test
Mexico	**0.0053**	**0.1553**		0.1033	0.0275	**0.3246**	**-0.2144**	-0.1266	-0.0537	**-0.1761**	**0.5241**	-0.0327	0.5472	0.9730	0.9603
	(0.0001)	**(0.0581)**		(0.1999)	(0.7081)	**(0.0000)**	**(0.0061)**	(0.1019)	(0.5160)	**(0.0160)**	**(0.0003)**	(0.6460)			

	Cons	GDP	GDP-1	RF (D)	SD	XS	DY	NFX (D)	NAM (D)	GAM	OB (D)	BD	Adj. R2	Q Stat	LM Test
Brazil	0.0024	0.1158		-0.2076	-0.0160	**0.2703**	-0.0274	**-0.2150**	0.0613	0.1087	**0.3024**	**0.2044**	0.2837	0.7920	0.5996
	(0.2633)	(0.4896)		(0.1972)	(0.8273)	**(0.0265)**	(0.7763)	**(0.0045)**	(0.3742)	(0.3058)	**(0.0003)**	**(0.0227)**			
	Cons	GDP	GDP-1	RF (D)	SD (D)	XS	DY	NFX (D)	NAM (D)	GAM	OB (D)	BD	Adj. R2	Q Stat	LM Test
Singapore	**0.0137**	0.0379		0.1349	**-0.2335**	**0.3238**	0.0176	0.0139	-0.0144	0.0366	**0.2143**	-0.0004	0.1054	0.8850	0.7269
	(0.0003)	(0.7360)		(0.1041)	**(0.0208)**	**(0.0258)**	(0.8393)	(0.9015)	(0.8502)	(0.6434)	**(0.0005)**	(0.9976)			
	Cons	GDP	GDP-1	RF (D)	SD	XS	DY	NFX (D)	NAM	GAM	OB (D)	BD	Adj. R2	Q Stat	LM Test
UK	**0.0048**	**0.4875**		0.0091	**-0.1590**	0.0179	0.0041	-0.1248	**-0.1723**	-0.0742	0.0890	**-0.2975**	0.5148	0.6880	0.4591
	(0.0000)	**(0.0040)**		(0.9178)	**(0.0063)**	(0.7373)	(0.9660)	(0.1125)	**(0.0021)**	(0.2976)	(0.3297)	**(0.0071)**			
	Cons	GDP	GDP-1	RF (D)	SD	XS	DY	NFX (D)	NAM	GAM (D)	OB (D)	BD	Adj. R2	Q Stat	LM Test
Germany	**0.0033**	0.0547		-0.0763	-0.0955	0.0832	-0.1562	-0.0063	**-0.2559**	**-0.2915**	**0.5495**	-0.0197	0.4662	0.4970	0.2350
	(0.0014)	(0.5321)		(0.6265)	(0.2822)	(0.3219)	(0.1431)	(0.9276)	**(0.0007)**	**(0.0000)**	**(0.0015)**	(0.7869)			
	Cons	GDP	GDP-1	RF (D)	SD	XS	DY (D)	NFX (D)	NAM (D)	GAM	OB (D)	BD	Adj. R2	Q Stat	LM Test
Japan	**0.0030**	0.0033		0.1608	**-0.2328**	-0.0051	**-0.1608**	0.0476	-0.1203	0.0110	**0.3590**	-0.0880	0.1369	0.8550	0.6744
	(0.0433)	(0.9644)		(0.1013)	**(0.0388)**	(0.9694)	**(0.0409)**	(0.5745)	(0.2565)	(0.8790)	**(0.0003)**	(0.2854)			
	Cons	GDP	GDP-1	RF (D)	SD	XS	DY	NFX (D)	NAM (D)	GAM	OB (D)	BD	Adj. R2	Q Stat	LM Test
France	**0.0033**	**0.3319**		-0.1222	-0.0492	**0.1921**	**-0.2293**	0.0083	**-0.1831**	**-0.1840**	**0.3060**	**-0.1629**	0.5390	0.3090	0.0683
	(0.0000)	**(0.0352)**		(0.3784)	(0.4897)	**(0.0255)**	**(0.0722)**	(0.9108)	**(0.0229)**	**(0.0295)**	**(0.0047)**	**(0.0515)**			
	Cons	GDP	GDP-1	RF (D)	SD	XS	DY	NFX (D)	NAM (D)	GAM	OB (D)	BD	Adj. R2	Q Stat	LM Test
France	**0.0028**	**0.3051**	**0.1621**	-0.1719	-0.0687	**0.2011**	-0.1798	0.0087	**-0.1846**	-0.1197	**0.2787**	**-0.1674**	0.5443	0.4470	0.0827
	(0.0000)	**(0.0251)**	**(0.0893)**	(0.2815)	(0.2765)	**(0.0356)**	(0.1979)	(0.9037)	**(0.0248)**	(0.2238)	**(0.0069)**	**(0.0261)**			

Panel B: Summary of each countries Adj. R2

	Adj. R2		% Change of Adj. R2 relative to FV only
	FV only	FV + ALL	FV + ALL
Norway	0.136	0.1353	-0.84%
Canada	0.310	0.5284	70.38%
Denmark	0.138	0.2506	81.93%
Mexico	0.299	0.5472	82.81%
Brazil	0.189	0.2837	50.50%
Singapore	0.127	0.1054	-17.15%
UK	0.433	0.5148	18.89%
Germany	0.153	0.4662	205.39%
Japan	0.047	0.1369	189.58%
France (One lag)	0.444	0.5390	21.51%
France (Two lags)	0.461	0.5443	18.03%

7.4.3.4. SUMMARY OF THE AVERAGE ADJUSTED R^2

Table 7.6 presents the grand average of adjusted R^2. The first line shows the results when all countries are included. National foreign exchange (NFX) does not show any extra explanatory power over financial variables (FV). Global illiquidity (GAM) has extra explanatory power over national illiquidity (NAM) and Baltic Dry index (BD), but BD has more explanatory power in comparison to NAM. Nevertheless, the extra explanatory power of the three (3) variables dwarves by the extra explanatory power of oil (OB), signifying the importance of oil (OB) for predicting economic growth.

So far our study, shows the importance of oil (OB) for the countries in our sample. In order to research this further, we have categorised the ten (10) countries into net oil exporters and net oil importers. To recap, net oil exporters are: Norway, Canada, Denmark, Mexico and Brazil while net oil importers are: Singapore, UK, Germany, Japan and France.

The adjusted R^2 for net oil exporters (line 2) shows that NFX now has extra explanatory power over financial variables but BD does not have extra explanatory power. In terms of illiquidity variables, GAM remains superior in comparison to NAM. Nonetheless, oil (OB) outperforms all other predictive variables. For net oil importers (line 3), results are similar whereby oil (OB) provides superior explanatory power. By comparing the three groups, it appears that oil (OB) is more important for net oil exporters as the explanatory power is higher in comparison to the other two groups, consistent with Wang et al. (2013).

Baltic Dry index (BD) is found to be more important for net oil importers probably since the countries are more focused on trading goods and services rather than oil (OB). Furthermore, net oil importers are on the top 5 *"liner shipping connectivity index"*, which captures how well countries are connected to global shipping networks.

With reference to illiquidity, global illiquidity (GAM) seems to be more important for net oil exporters while for net oil importers, national illiquidity (NAM) appears to be more important. National foreign exchange (NFX) also provides greater explanatory power for net oil exporters relative to net oil importers, signifying that NFX may be important for them for trading oil. Being an emerging country may play a role as well. Brazil is the only country that displays significant results for NFX. Therefore, we are going to investigate this later by comparing developed and emerging countries.

Overall, our results confirm the importance of the chosen predictive variables. Both illiquidity variables are able to provide greater explanatory power in comparison to financial variables but global illiquidity (GAM) variable is apparently superior. Baltic Dry index (BD) also provides some explanatory power while national foreign exchange (NFX) is the only variable that does not provide any benefits when all countries are included. However, it can be unanimously said that oil (OB) is the most important predictive variable, as it provides the greatest explanatory power especially for net oil exporters while BD appears to be more important for net oil importers.

Table 7.6: Summary of the average adjusted R^2 of the ten (10) countries as a group (All countries, net oil exporters and net oil importers).

The table shows the summary average adjusted R^2 results from the predictive regression of table 7.4 and table 7.5. FV only (financial variables) includes RF (Risk free); SD (Standard deviation); XS (Excess market returns); DY (Dividend yield) as well as one lag of the dependent variable (and we include more lags if there is autocorrelation in the residuals). The predictive variables are NFX (National foreign exchange), NAM (National illiquidity-Amihud), GAM (Global illiquidity-Amihud), OB (Crude oil Brent) and BD (Baltic Dry index), whereas ALL involves regression using all the variables. Thus, the Adj. R2 presents Adjusted R^2 of the dependent variable (GDP) + financial variables (FV) + X (relevant additional variables) or ALL (All variables). Please note that summarising by taking the average adjusted R^2 is based on the methodology of Brockman et al (2009), Galariotis & Giouvris (2015) and Sung & Giouvris (2016). All countries include all ten (10) countries in our sample. Net oil exporters are Norway, Canada, Denmark, Mexico and Brazil while net oil importers are Singapore, UK, Germany, Japan and France. For France, we use Adj. R2 of the regression with two lags of GDP, as it results in no autocorrelation in the residuals. NFX is the national foreign exchange relative to United States Dollars (USD). Amihud (AM) is our illiquidity measure and the prefix 'N' in front of each liquidity variable refers to national illiquidity-Amihud (NAM) while the prefix 'G' refers to global illiquidity-Amihud (GAM). Global illiquidity is constructed as in Brockman et al. (2009) and Galariotis and Giouvris (2015) whereby global illiquidity is created by combining all countries except the country nominated for the test. OB is crude oil Brent price while BD is the Baltic Dry index. The sample period is from January 1998 to December 2015, consisting of 72 quarterly observations. All data are obtained from DataStream, Bloomberg, World Bank and US Energy Information Administration (EIA) website.

Summary of each countries Adj. R2

	Average Adj. R2							% Change of Adj. R2 relative to FV only					
	FV only	FV + FX	FV + NAM	FV + GAM	FV + OB	FV + BD	FV + ALL	FV + FX	FV + NAM	FV + GAM	FV + OB	FV + BD	FV + ALL
X→GDP (All countries)	0.229	0.227	0.231	0.235	0.322	0.233	0.351	-1.154%	0.897%	2.271%	40.219%	1.808%	53.167%
X→GDP (Net oil exporters)	0.214	0.219	0.215	0.221	0.321	0.210	0.349	2.164%	0.481%	2.927%	49.874%	-1.956%	62.776%
X→GDP (Net oil importers)	0.244	0.234	0.247	0.248	0.322	0.257	0.353	-4.068%	1.263%	1.694%	31.743%	5.112%	44.731%

7.4.4. CAUSALITY

So far our research has focused on the relationship and the effect of predictive variables on GDP. However, there is a possibility of an inverse relationship that is GDP may cause the predictive variables or even a two-way relationship. For instance, in relation to illiquidity, Fujimoto (2004) who studies the US market finds evidence that macroeconomic fundamentals are significant determinants of liquidity while for oil (OB), Sheppard et al. (2016) report that due to big oil producing countries going into recession, OPEC led by Saudi Arabia decides to cut oil production to help the oil market recover, signifying that there is a possibility for oil prices (OB) to be affected by GDP. With respect to national foreign exchange (NFX), Inman (2015) highlights that the main reason that China devalues its currency is due to its weakening economy while for Baltic Dry index (BD), Bloch et al. (2012) mentions that due to China's strong economic growth, China's demand for coal is surging and since coal is part of BD, it is expected that economic growth may also affect BD.

Furthermore, there is also evidence of a two-way or bidirectional relationship between the chosen predictive variables and macroeconomics. Galariotis and Giouvris (2015) find a two-way causality between global liquidity and macroeconomic variables in their study of G7 countries while Bloch et al. (2012) find a bidirectional causality between coal consumption and GDP, as coal is one of the raw materials captured by BD.

7.4.4.1. CAUSALITY RESULTS FOR ALL COUNTRIES, NET OIL EXPORTERS AND NET OIL IMPORTERS

In table 7.7, we use Galariotis and Giouvris (2015) methodology to investigate the possibility of an inverse or a two-way relationship between our predictive variables and GDP. Similarly, we use two causality tests namely the *'standard pairwise Granger causality panel data test'* and the *'Dumitrescu-Hurlin (D-H) panel data test'*. However, unlike them, we have two further panels of countries namely net oil exporters (panel B) and net oil importers (panel C), in addition to the panel data involving all countries (Panel A). We report the F-test and probability/p-value (in parenthesis) for the *standard pairwise Granger causality panel data test* and the W-stat, Z bar and probability/p-value (in parenthesis) for the *Dumitrescu-Hurlin (D-H) panel data test*. The null hypotheses for the *standard pairwise Granger causality panel data test* is that our predictive variables

do not Granger cause GDP and GDP does not Granger cause our respective predictive variables. For the *Dumitrescu-Hurlin (D-H) panel data test*, the null hypothesis is that our predictive variables do not homogeneously cause GDP and then we test the null hypothesis that GDP does not homogeneously cause our predictive variables.

Panel A in table 7.7 reports causality results between our predictive variables and macroeconomic variable for all ten (10) countries in our sample. The panel shows that there are no interactions between national foreign exchange (NFX) and the macroeconomic variable (GDP) while both illiquidity variables appear to cause GDP based on D-H panel data test for national illiquidity (NAM) and standard Granger causality panel data test for global illiquidity (GAM). However, GDP also Granger causes GAM signifying a two-way causality for GAM, which is close to the findings of Galariotis and Giouvris (2015).

A two-way relationship can also be observed for Baltic Dry index (table 7.7, panel A, lines 9-10) according to both standard Granger and D-H tests which is close to the bidirectional evidence that Bloch et al. (2012) find between coal consumption and GDP. Oil (OB) also shows a two-way causality but not for both tests. Oil (OB) homogenously causes GDP (D-H test) while GDP granger causes oil (standard granger test).

Next we will investigate causality results for net oil exporting countries in panel B of table 7.7. Panel B shows that GDP Granger causes NFX but there are no interactions between national illiquidity (NAM) and GDP as previously observed when using all countries. Moreover, for net oil exporters, GDP does not homogenously cause global illiquidity (GAM) based on D-H test but the two-way relationship between GAM and GDP remains according to the *standard Granger test*. In comparison to all countries, oil (OB) and Baltic dry index (BD) relationship with GDP remains the same, as there is still a two-way causality.

Panel C in table 7.7 shows causality tests for net oil importing countries which consist of Singapore, UK, Germany, Japan and France. Similar to net oil exporters, GDP of net oil importers also cause NFX according to *D-H test*. Surprisingly, there is no interaction between national illiquidity (NAM) and GDP for net oil importers. Global illiquidity (GAM) still appears to have a two-way relationship with GDP but it is slightly weaker compared to all countries and net oil exporters. Furthermore, there is no more a two-way

causality for both oil (OB) and Baltic Dry index (BD). GDP still Granger cause oil (OB) while BD Granger causes GDP (both tests) but not the other way round.

Overall, GDP is found to cause national foreign exchange (NFX) when our countries are segregated into net oil exporters and importers, signifying that GDP may be the reason that countries try to manipulate their currencies as reported by Inman (2015) for China. With regards to illiquidity, we obtain similar findings to Galariotis and Giouvris (2015), as there is a two-way relationship between global illiquidity (GAM) and our macroeconomic variable (GDP).

The Baltic Dry index (BD) and oil (OB) show a two-way relationship but it appears to be stronger for the former. Evidence for the BD is similar to Bloch et al. (2012) research which involves coal consumption as coal is part of the Baltic Dry index (BD). As expected oil (OB) does impact GDP as also highlighted by Mork et al. (1994). There is also inverse causality, signifying that a group of countries can affect oil prices as suggested by Kaufmann et al. (2004) in relation to OPEC countries but interestingly, our data does not include any OPEC countries. In relation to net oil exporters and importers, oil (OB) is apparently more important for net oil exporters as the two-way causality remains while for net oil importers, we observe a one-way causality from GDP to oil (OB). Wang et al. (2013) do find different reactions between oil-exporting and oil-importing countries, as positive aggregate and precautionary demand oil shocks are shown to result in a higher degree of co-movement among the stock markets in oil-exporting countries.

Table 7.7: Granger Causality Tests (Panel Data of all countries, net oil exporters and net oil importers).

The table shows Panel Granger causality tests between quarterly macroeconomic variable (GDP) and all relevant variables. The predictive variables are consisting of NFX (National foreign exchange), NAM (National illiquidity-Amihud), GAM (Global illiquidity-Amihud), OB (Crude oil Brent) and BD (Baltic Dry index). NFX is the national foreign exchange relative to United States Dollars (USD). Amihud (AM) is our illiquidity measure and the prefix 'N' in front of each illiquidity variable refers to national illiquidity-Amihud (NAM) while the prefix 'G' refers to global illiquidity-Amihud (GAM). Global illiquidity is constructed as in Brockman et al. (2009) and Galariotis and Giouvris (2015) whereby global illiquidity is created by combining all countries except the country nominated for the test. OB is crude oil Brent price while BD is the Baltic Dry index. All variables are orthogonalised. Besides the standard pairwise Granger causality panel data test, we also use the Dumitrescu-Hurlin (D-H) panel data test. We first test the null hypothesis that our variables do not Granger cause the macroeconomic variable in question and then we test the null hypothesis that our macroeconomic variable does not Granger cause the respective variables in question. The null for the D-H test is that that our variables do not homogeneously cause the macroeconomic variable in question and then we test the null hypothesis that our macroeconomic variable does not homogeneously cause the particular variables in question. We do this for all macroeconomic and predictive variables. We report the F-test and p-value (in parenthesis) for the standard panel Granger causality test and the W-stat, Z bar and probability (in parenthesis) for the D-H test. We use 2 and 4 lags for our tests. If in **bold**, figures denote statistically significant results at least at 10% level. Panels A, B and C present results for all countries, net oil exporters and net oil importers respectively. The sample period is from January 1998 to December 2015, consisting of 72 quarterly observations. All data are obtained from DataStream, Bloomberg, World Bank and US Energy Information Administration (EIA) website.

Panel A: All countries

		Standard pairwise Granger Causality Tests		Dumitrescu-Hurlin (D-H)	
		Std (2 lags)	Std (4 lags)	D-H (2 lags)	D-H (4 lags)
Line 1	H0: NFX does not →GDP	0.139 (0.871)	0.496 (0.739)	1.961 -0.154 (0.878)	3.160 -1.007 (0.314)
Line 2	H0: GDP does not → NFX	0.511 (0.600)	0.724 (0.576)	1.006 -1.570 (0.116)	4.346 0.208 (0.835)
Line 3	H0: NAM does not →GDP	1.017 (0.362)	0.788 (0.533)	**0.664** **-2.077** **(0.038)**	3.259 -0.905 (0.366)
Line 4	H0: GDP does not → NAM	0.543 (0.581)	1.115 (0.348)	2.148 0.124 (0.901)	4.146 0.003 (0.998)
Line 5	H0: GAM does not →GDP	**7.822** **(0.000)**	**4.977** **(0.001)**	2.877 1.205 (0.228)	4.147 0.005 (0.996)
Line 6	H0: GDP does not → GAM	**4.851** **(0.008)**	**5.912** **(0.000)**	2.298 0.346 (0.730)	**5.915** **1.815** **(0.070)**
Line 7	H0: OB does not →GDP	0.097 (0.907)	0.798 (0.527)	1.348 -1.062 (0.288)	**2.304** **-1.883** **(0.060)**
Line 8	H0: GDP does not → OB	**4.622** **(0.010)**	**4.335** **(0.002)**	2.174 0.163 (0.871)	4.551 0.418 (0.676)
Line 9	H0: BD does not →GDP	**26.420** **(0.000)**	**19.185** **(0.000)**	**16.756** **21.813** **(0.000)**	**22.729** **19.065** **(0.000)**
Line 10	H0: GDP does not → BD	1.401 (0.247)	**4.152** **(0.003)**	0.981 -1.608 (0.108)	**6.593** **2.516** **(0.012)**

Panel B: Net oil exporting countries

		Standard pairwise Granger Causality Tests		Dumitrescu-Hurlin (D-H)	
		Std (2 lags)	Std (4 lags)	D-H (2 lags)	D-H (4 lags)
Line 1	H0: NFX does not →GDP	1.255 (0.286)	1.017 (0.399)	1.672 -0.411 (0.681)	2.862 -0.928 (0.354)
Line 2	H0: GDP does not → NFX	**3.196** **(0.042)**	**3.442** **(0.009)**	1.698 -0.385 (0.701)	5.644 1.087 (0.277)

		0.416	0.462	0.709	1.940
Line 3	H0: NAM does not →GDP	(0.660)	(0.764)	-1.422	-1.595
				(0.155)	(0.111)
		0.149	0.385	2.450	3.985
Line 4	H0: GDP does not → NAM	(0.862)	(0.819)	0.404	-0.114
				(0.686)	(0.909)
		4.364	**2.632**	2.642	4.375
Line 5	H0: GAM does not →GDP	**(0.014)**	**(0.034)**	0.605	0.168
				(0.545)	(0.866)
		3.849	**4.924**	2.630	**7.295**
Line 6	H0: GDP does not → GAM	**(0.022)**	**(0.001)**	0.593	**2.283**
				(0.553)	**(0.022)**
		0.249	0.265	0.773	**1.561**
Line 7	H0: OB does not →GDP	(0.780)	(0.900)	-1.355	**-1.869**
				(0.175)	**(0.062)**
		3.502	**2.475**	2.382	4.588
Line 8	H0: GDP does not → OB	**(0.031)**	**(0.044)**	0.332	0.322
				(0.740)	(0.747)
		10.200	**9.349**	**12.183**	**15.306**
Line 9	H0: BD does not →GDP	**(0.000)**	**(0.000)**	**10.623**	**8.098**
				(0.000)	**(0.000)**
		0.384	**3.233**	0.897	**7.172**
Line 10	H0: GDP does not → BD	(0.682)	**(0.013)**	-1.225	**2.199**
				(0.221)	**(0.028)**

Panel C: Net oil importing countries

		Standard pairwise Granger Causality Tests		Dumitrescu-Hurlin (D-H)	
		Std (2 lags)	Std (4 lags)	D-H (2 lags)	D-H (4 lags)
		0.056	0.301	2.249	3.458
Line 1	H0: NFX does not →GDP	(0.946)	(0.878)	0.194	-0.496
				(0.846)	(0.620)
		0.333	0.666	**0.314**	3.049
Line 2	H0: GDP does not → NFX	(0.717)	(0.616)	**-1.836**	-0.792
				(0.066)	(0.428)
		0.803	0.877	0.619	4.578
Line 3	H0: NAM does not →GDP	(0.449)	(0.478)	-1.516	0.315
				(0.130)	(0.753)
		0.396	0.955	1.846	4.306
Line 4	H0: GDP does not → NAM	(0.673)	(0.432)	-0.229	0.118
				(0.819)	(0.906)
		3.919	**2.503**	3.112	3.919
Line 5	H0: GAM does not →GDP	**(0.021)**	**(0.042)**	1.098	-0.162
				(0.272)	(0.871)
		1.719	**2.040**	1.965	4.535
Line 6	H0: GDP does not → GAM	(0.181)	**(0.089)**	-0.104	0.284
				(0.917)	(0.777)
		0.120	0.788	1.924	3.047
Line 7	H0: OB does not →GDP	(0.887)	(0.533)	-0.147	-0.793
				(0.883)	(0.428)
		1.789	**2.385**	1.967	4.515
Line 8	H0: GDP does not → OB	(0.169)	**(0.051)**	-0.102	0.269
				(0.919)	(0.788)
		16.472	**11.120**	**21.330**	**30.152**
Line 9	H0: BD does not →GDP	**(0.000)**	**(0.000)**	**20.225**	**18.865**
				(0.000)	**(0.000)**
		1.427	1.604	1.064	6.014
Line 10	H0: GDP does not → BD	(0.241)	(0.173)	-1.049	1.359
				(0.294)	(0.174)

7.4.5. NET OIL EXPORTERS: DEVELOPED VERSUS EMERGING COUNTRIES

Sung and Giouvris (2016) finds that causality between macroeconomic variables and liquidity are different for developed and developing markets. Since our data consists of two (2) countries that are categorised as emerging markets/ countries by MSCI, we decide to investigate this briefly by further regrouping our net oil exporting countries into developed and emerging countries. Therefore, developed countries are consisting of Norway, Canada and Denmark while Mexico and Brazil will form part of emerging countries.

7.4.5.1. SUMMARY OF THE AVERAGE ADJUSTED R^2 FOR NET OIL EXPORTERS: DEVELOPED VS EMERGING COUNTRIES

As before, table 7.8 presents a summary of the grand average of adjusted R^2 of the relevant variables. According to table 7.8, national foreign exchange (NFX) has extra explanatory power over financial variables for emerging countries, which could probably be due to Brazil, as Brazil is the only country that shows significant results in the earlier sections. Both illiquidity variables provide extra explanatory power for developed countries which is probably due to the more established financial markets of developed countries. Nevertheless, global illiquidity (GAM) remains superior compared to national illiquidity (NAM) for developed countries. As expected, oil (OB) is more important for emerging countries, as oil (OB) provides superior explanatory power over financial variables, potentially due to emerging countries over-reliance on oil. Surprisingly, the Baltic dry index (BD) does not provide any extra explanatory power over financial variables for both developed and emerging markets. However, then again in table 7.1, our net oil exporting countries are in the bottom five *"liner shipping connectivity index"* of our sample.

Overall, table 7.8 shows that oil (OB) appears to be more significant for emerging countries while illiquidity variables provide superior explanatory power for developed countries.

Table 7.8: Summary of the average adjusted R^2 of the five (5) net oil exporting countries as a group of developed and emerging countries (Net oil exporters-Developed countries and Net oil exporters-Emerging countries).

The table shows the summary average adjusted R^2 results from the predictive regression of table 7.4 and table 7.5. FV only (financial variables) includes RF (Risk free); SD (Standard deviation); XS (Excess market returns); DY (Dividend yield) as well as one lag of the dependent variable (and we include more lags if there is autocorrelation in the residuals). The predictive variables are consisting of NFX (National foreign exchange), NAM (National Amihud), GAM (Global Amihud), OB (Crude oil Brent) and BD (Baltic Dry), whereas ALL involves regression using all the variables. Thus, the Adj. R2 presents Adjusted R^2 of the dependent variable (GDP) + financial variables (FV) + X (relevant additional variables) or ALL (All variables). Please note that summarising by taking the average adjusted R^2 is based on the methodology of Brockman et al (2009), Galariotis & Giouvris (2015) and Sung & Giouvris (2016). Net oil exporters - Developed countries are Norway, Canada, and Denmark while Net oil exporters – Emerging countries are Mexico and Brazil. NFX is the national foreign exchange relative to United States Dollars (USD). Amihud (AM) is our liquidity measure and the prefix 'N' in front of each illiquidity variable refers to national illiquidity-Amihud (NAM) while the prefix 'G' refers to global illiquidity-Amihud (GAM). Global illiquidity is constructed as in Brockman et al. (2009) and Galariotis and Giouvris (2015) whereby global illiquidity is created by combining all countries except the country nominated for the test. OB is crude oil Brent price while BD is the Baltic Dry index. The sample period is from January 1998 to December 2015, consisting of 72 quarterly observations. All data are obtained from DataStream, Bloomberg, World Bank and US Energy Information Administration (EIA) website.

Summary of developed versus emerging countries Adj. R2

	Average Adj. R2							% Change of Adj. R2 relative to FV only					
	FV only	FV + FX	FV + NAM	FV + GAM	FV + OB	FV + BD	FV + ALL	FV + FX	FV + NAM	FV + GAM	FV + OB	FV + BD	FV + ALL
X→GDP (Net oil exporters – Developed countries)	0.195	0.190	0.202	0.205	0.284	0.190	0.305	-2.383%	3.870%	5.488%	45.561%	-2.507%	56.474%
X→GDP (Net oil exporters – Emerging countries)	0.244	0.262	0.235	0.244	0.378	0.241	0.415	7.610%	-3.578%	-0.140%	55.041%	-1.296%	70.325%

7.4.5.2. CAUSALITY RESULTS FOR NET OIL EXPORTERS: DEVELOPED VS EMERGING COUNTRIES

We have also conducted casualty tests on net oil exporters (developed countries) and net oil exporters (emerging countries) to investigate if there is a two-way causality between GDP and the chosen predictive variables for the two group of countries (or markets).

Panel A in table 7.9 reports causality results between GDP and our predictive variables for net oil exporters (developed countries). The panel shows that national foreign exchange (NFX) Granger cause GDP but there is no interaction between national illiquidity (NAM) and GDP. Global illiquidity (GAM) Granger causes GDP and surprisingly there is two-way relationship between Baltic Dry index (BD) and GDP although in our last section BD apparently does not provide any extra explanatory power. More surprisingly there is no interaction between oil (OB) and GDP, probably due to insufficient amount of data after segregation of net oil exporting countries to developed and emerging countries.

Panel B of table 7.9 shows causalities for emerging countries among net oil exporters. Unlike developed countries, emerging countries do not show any interaction between GDP and NFX, which is unexpected as our earlier results appear to show that Brazil may be the reason that there is a relationship between GDP and NFX. However, GDP appears to cause both national illiquidity (NAM) and global illiquidity (GAM). There is also no two-way causality between GDP and Baltic Dry index (BD) but BD does cause GDP. Similar to developed countries, there are no interactions found between GDP and oil (OB) also for emerging countries, again probably due to insufficient data.

Overall, there is only two-way causality between Baltic Dry (BD) and GDP for developed countries. There is no causality between national illiquidity (NAM) and GDP for developed countries while for emerging countries there is a one-way causality from GDP to NAM. This is contradictory to Sung and Giouvris (2016) who finds that there is a two-way causality between macroeconomic variables and national liquidity. Nevertheless, our contradictory evidence is probably due to the high liquidity of developed markets. Dey (2005) highlights that liquidity is not a concern for investors, resulting in insignificant results for developed markets. Both markets (group of countries) obtain significant results for global illiquidity (GAM) but for developed countries, GAM caused GDP while the opposite is observed for emerging countries, which is similar to Sung and Giouvris (2016)

However, Sung and Giouvris (2016) find no causality for developed markets. Surprisingly, one-way causality for national foreign exchange (NFX) is found only in developed countries and not emerging countries. More surprisingly, there is no causality between oil (BD) and GDP for both developed and emerging countries, probably due to insufficient amount of data after segregation of net oil exporting countries to developed and emerging countries.

Table 7.9: Granger Causality Tests (Panel Data of Net oil exporters–Developed countries and Net oil exporters–Emerging countries).

The table shows Panel Granger causality tests between quarterly macroeconomic variable (GDP) and all relevant variables. The predictive variables are NFX (National foreign exchange), NAM (National illiquidity-Amihud), GAM (Global illiquidity-Amihud), OB (Crude oil Brent) and BD (Baltic Dry). NFX is the national foreign exchange relative to United States Dollars (USD). Amihud (AM) is our liquidity measure and the prefix 'N' in front of each illiquidity variable refers to national illiquidity-Amihud (NAM) while the prefix 'G' refers to global illiquidity-Amihud (GAM). Global illiquidity is constructed as in Brockman et al. (2009) and Galariotis and Giouvris (2015) whereby global illiquidity is created by combining all countries except the country nominated for the test. OB is crude oil Brent price while BD is the Baltic Dry index. All variables are orthogonalised. Besides the standard pairwise Granger causality panel data test, we also use the Dumitrescu-Hurlin (D-H) panel data test. We first test the null hypothesis that our variables do not Granger cause the macroeconomic variable in question and then we test the null hypothesis that our macroeconomic variable does not Granger cause the respective variables in question. The null for the D-H test is that that our variables do not homogeneously cause the macroeconomic variable in question and then we test the null hypothesis that our macroeconomic variable does not homogeneously cause the particular variables in question. We do this for all macroeconomic and liquidity variables. We report the F-test and p-value (in parenthesis) for the standard panel Granger causality test and the W-stat, Z bar and probability (in parenthesis) for the D-H test. We use 2 and 4 lags for our tests. If in **bold**, figures denote statistically significant results at least at 10% level. Panels A and B present results for Net oil exporters (Developed countries) and Net oil exporters (Emerging countries) respectively. The sample period is from January 1998 to December 2015, consisting of 72 quarterly observations. All data are obtained from DataStream, Bloomberg, World Bank and US Energy Information Administration (EIA) website.

Panel A: Net oil exporters (Developed countries)

		Standard pairwise Granger Causality Tests		Dumitrescu-Hurlin (D-H)	
		Std (2 lags)	Std (4 lags)	D-H (2 lags)	D-H (4 lags)
Line 1	H0: NFX does not →GDP	0.665 (0.515)	0.902 (0.464)	2.042 -0.018 (0.986)	3.367 -0.435 (0.664)
Line 2	H0: GDP does not → NFX	**2.483** **(0.086)**	**2.303** **(0.060)**	1.513 -0.448 (0.654)	4.599 0.256 (0.798)
Line 3	H0: NAM does not →GDP	0.106 (0.900)	0.205 (0.935)	0.474 -1.292 (0.196)	2.084 -1.155 (0.248)
Line 4	H0: GDP does not → NAM	0.964 (0.383)	0.499 (0.736)	0.856 -0.981 (0.326)	3.046 -0.615 (0.538)
Line 5	H0: GAM does not →GDP	**2.717** **(0.069)**	1.510 (0.201)	1.641 -0.344 (0.731)	3.221 -0.517 (0.605)
Line 6	H0: GDP does not → GAM	0.559 (0.573)	1.216 (0.305)	0.891 -0.954 (0.340)	4.588 0.250 (0.803)
Line 7	H0: OB does not →GDP	0.257 (0.773)	0.174 (0.952)	0.792 -1.033 (0.301)	1.873 -1.273 (0.203)
Line 8	H0: GDP does not → OB	1.625 (0.200)	1.457 (0.217)	2.438 0.303 (0.762)	4.520 0.212 (0.833)
Line 9	H0: BD does not →GDP	**9.047** **(0.000)**	**6.964** **(0.000)**	**13.155** **9.019** **(0.000)**	**15.399** **6.324** **(0.000)**
Line 10	H0: GDP does not → BD	0.475 (0.622)	**2.513** **(0.043)**	1.348 -0.582 (0.561)	**8.634** **2.524** **(0.012)**

Panel B: Net oil exporters (Emerging countries)

		Standard pairwise Granger Causality Tests		Dumitrescu-Hurlin (D-H)	
		Std (2 lags)	Std (4 lags)	D-H (2 lags)	D-H (4 lags)
Line 1	H0: NFX does not →GDP	0.610 (0.545)	0.324 (0.862)	1.117 -0.628 (0.530)	2.104 -0.934 (0.350)
Line 2	H0: GDP does not → NFX	1.031 (0.360)	1.715 (0.151)	1.975 -0.059 (0.953)	7.211 1.405 (0.160)

		0.558	0.549	1.061	1.725
Line 3	H0: NAM does not →GDP	(0.574)	(0.700)	-0.665	-1.107
				(0.506)	(0.268)
		3.018	1.632	**4.841**	5.394
Line 4	H0: GDP does not → NAM	**(0.052)**	(0.170)	**1.841**	0.573
				(0.066)	(0.567)
		2.078	1.391	4.143	6.107
Line 5	H0: GAM does not →GDP	(0.129)	(0.241)	1.378	0.899
				(0.168)	(0.369)
		4.185	**4.856**	**5.239**	**11.356**
Line 6	H0: GDP does not → GAM	**(0.017)**	**(0.001)**	**2.106**	**3.304**
				(0.035)	**(0.001)**
		0.657	0.468	0.743	1.093
Line 7	H0: OB does not →GDP	(0.520)	(0.759)	-0.877	-1.397
				(0.381)	(0.163)
		2.019	1.261	2.297	4.689
Line 8	H0: GDP does not → OB	(0.137)	(0.289)	0.154	0.250
				(0.877)	(0.803)
		8.113	**6.663**	**10.725**	**15.167**
Line 9	H0: BD does not →GDP	**(0.001)**	**(0.000)**	**5.751**	**5.058**
				(0.000)	**(0.000)**
		0.037	1.863	0.221	4.981
Line 10	H0: GDP does not → BD	(0.964)	(0.121)	-1.223	0.386
				(0.221)	(0.700)

7.5. CONCLUSION

This study looks into the relationship between macroeconomic growth (captured by GDP) and predictive variables namely national foreign exchange (NFX), national illiquidity (NAM), global illiquidity (GAM), oil (OB) and Baltic Dry index (BD). By investigating net oil exporting countries (Norway, Canada, Denmark, Mexico and Brazil) and net oil importing countries (Singapore, UK, Germany, Japan and France), our paper offers original results on the two groups of countries which have not been commonly segregated in the past as highlighted by Wang et al. (2013).

This paper shows that excess market returns (XS) is the most relevant financial variable, while among predictive variables, oil (OB) appears to be the most significant as the GDP of nine (9) countries is predicted by it. The coefficient obtained is positive. Between illiquidity variables, national illiquidity (NAM) is found to be superior in comparison to global illiquidity (GAM) but both variables mainly show a negative relationship with GDP, except for Canada's GDP which is found to be positively related with national illiquidity (NAM). National foreign exchange (NFX) is the least important predictive variable, as it is significant only in the case of Brazil. Baltic Dry index (BD) is found to be negatively related to economic growth, which is contradictory to past research. Nevertheless, when including all variables, Brazil obtains a positive coefficient revealing

the ability of the Baltic Dry index (BD) to predict the future course of the economy, consistent to past research such as Bakshi et al. (2011). Since NFX and BD remain significant in the case of Brazil, the results show that the two variables combine can predict the state of the economy of Brazil. Both illiquidity variables provide greater explanatory power in comparison to financial variables but global illiquidity (GAM) is apparently superior. BD also provides some explanatory power while NFX does not provide any benefits when all countries are included. However, it is found that overall oil (OB) is the most important predictive variable, as it provides the greatest explanatory power. Our results show that oil (OB) has higher explanatory power for net oil exporters while the BD seems to be more important for net oil importing countries. Moreover, NFX is also found to provide some explanatory power for the group of net oil exporters only.

With regards to causality, we obtain almost similar findings to Galariotis and Giouvris (2015), as there is two way causality between global illiquidity (GAM) and GDP. Unlike Galariotis and Giouvris (2015) who find evidence of a two way causality, our results show one way causality from national illiquidity (NAM) to GDP. However, it should be pointed out that Galariotis and Giouvris (2015) research involves G7 countries for different periods and hence it may not be directly comparable to our study.

GDP is found to cause NFX when the countries are segregated into net oil exporters and importers. Baltic Dry index (BD) and oil (OB) shows a two-way causality but it appears to be stronger for the former. Evidence for the BD is similar to Bloch et al. (2012) study which involves coal consumption, as coal is part of BD. As expected, oil (OB) does impact GDP as mentioned by Mork et al. (1994) and there is also an inverse causality, signifying that a group of countries can affect the price of oil (OB) as suggested by Kaufmann et al. (2004) although none of our countries are part of OPEC. In relation to net oil exporters and importers, oil (OB) is apparently more important for net oil exporters as the two-way causality remains, while for net oil importers, only causality from GDP to oil (OB) can be observed. GDP is found to cause NFX when the countries are segregated into net oil exporters and importers, signifying that macroeconomic inactivity (captured by GDP) may be the reason that countries try to manipulate their currencies as reported by Inman (2015) for China.

By further segregating net oil exporting countries into developed (Norway, Canada and Denmark) and emerging markets/ countries (Mexico and Brazil), our results show that NFX has extra explanatory power over financial variables for emerging countries while

both illiquidity variables provide extra explanatory powers for developed countries only. Nevertheless, global illiquidity (GAM) remains superior compared to national illiquidity (NAM) for developed countries. Oil (OB) appears to be more important for emerging countries, potentially due to emerging countries over-reliance on oil while Baltic dry index (BD) does not provide any extra explanatory power for both developed and emerging countries. We find a two-way causality between BD and GDP for developed countries. There is one way causality from GDP to NAM for emerging countries, which is contradictory to Sung and Giouvris (2016) who find that there is a two way causality between macroeconomic variables and national liquidity for emerging markets. We obtain significant results for GAM for both markets. However, for developed countries, GAM causes GDP while the opposite is observed for emerging countries. The findings on emerging countries is similar to Sung and Giouvris (2016) but they find no causality for developed markets. Surprisingly, a one-way causality for NFX is found only for developed countries and not for emerging countries. More surprisingly, there is no causality between oil (BD) and GDP for both developed and emerging countries of net oil exporters which may probably due to insufficient amount of data after segregation of the net oil exporting countries.

Overall, in relation to illiquidity variables, we find similar results but also some contradictory results to Galariotis and Giouvris (2015) and Sung and Giouvris (2016), probably due to different data and periods used. Nevertheless, we believe that further research is necessary in order to include OPEC countries especially when studying oil. One other issue that has arisen is the classification of the chosen countries based on the latest available data of 2012. For instance Mork et al. (1994) classify UK as an oil exporting country while we consider it as a net oil importing country. Moreover, Mork et al. (1994) highlight that the UK and Norway switch from a position of net importer to net exporter of oil in the 1970s while Canada also has moved back and forth between net exporter and net importer over time. Therefore, for future studies the classification of countries should probably be based on the average or total oil exports or imports over the sample periods.

CHAPTER 8 : CONCLUSION

At the start of this PhD thesis, we acknowledge that the financial crisis of 2007/ 2008 is an important event for the global financial markets and liquidity appears to be one of the reasons for the crisis, as some researchers even refer to the crisis as a liquidity crisis. Past liquidity research also provides evidence of the influence that liquidity has on asset pricing, signifying the importance of liquidity for firms, investors, regulators and financial markets. Hence, due to the financial crisis and financial sector developments, the study of liquidity has become more prominent. Even though the number of studies on liquidity have increased over the years, some questions remain unanswered as past research tends to focus on the US market. Therefore, we believe that further studies should be done on liquidity.

Chapter one provides an introduction as well as the aims of our PhD research while the second chapter reviews the literature that is relevant to our research. We have conducted five empirical studies. The third chapter is the first empirical chapter, which investigates the relationship between illiquidity and monetary conditions in the UK. Chapter four and five research the ability of illiquidity as an investment style in the UK. However, chapter four focuses on the financial crisis while chapter five employs a longer data period and conducts additional analysis such as the January effect. Chapter six and seven are the last two empirical chapters and both chapters investigate illiquidity and the energy markets by studying net oil exporters and importers. Chapter six investigates the asymmetric effect of oil price and illiquidity shocks on economic growth while chapter seven studies the relationship between economic growth and five predictive variables such as oil, national illiquidity, global illiquidity and the Baltic Dry index.

Our findings in chapter three show that in general, illiquid portfolios generate higher returns relative to liquid portfolios and changes to monetary conditions seem to have more effect on illiquid stocks relative to liquid stocks, signifying the sensitivity of the illiquid stocks. This chapter also shows that market liquidity increases after expansive shifts, but with some interruptions due to major events such as the financial crisis. However, it is less noticeable during restrictive periods, suggesting that investors are less concerned with liquidity, at least in the UK.

Chapter four investigates the potential of illiquidity as an investment style in the UK during the financial crisis, using Ibbotson et al. (2013) framework and Sharpe (1992) benchmark criteria of 1) *"identifiable before the fact",* 2) *"not easily beaten",* 3) *"a viable alternative",* and 4) *"low in cost".* Our results show that pre-crisis, illiquidity is able to meet the four criteria of Sharpe (1992) benchmark requirements or at least show its profitability as an investment style. Thus, we agree with Ibbotson et al. (2013) that illiquidity can be considered as an alternative investment style in equal standing with the other styles. However, as expected, the portfolios performance post-crisis is almost consistently worse relative to pre-crisis. Interestingly, although illiquidity is not as successful after the crisis, it does provide steady profits as it is able to perform better than the benchmarks. Furthermore, it is more stable, signifying profit opportunity potential.

Chapter five is similar to our study in the previous chapter but using a longer period of 23 years and the results shows that illiquidity still meets all four criteria of Sharpe (1992). However, using the longer period does not improve results, as the strong relationship between size and illiquidity still remains, signifying that the favourable performance of illiquidity may actually be due to size. The chapter also finds evidence to suggest that with regards to *"covariance model"* (e.g. financial models), "*characteristics model"* (e.g. financial ratios) may be the best technique to construct illiquidity portfolios as it provides consistent results. Finally, the January effect seems to be present on the investment styles (except for momentum), while our double sorted portfolios signify that the January effect of value and size investment styles appear to be an illiquidity phenomenon.

Chapter six investigates the impact of oil price shocks and illiquidity shocks on eleven (11) countries, consisting of five (5) net oil exporting countries (Brazil, Canada, Denmark, Mexico and Norway) and six (6) net oil importing countries (France, Germany, Japan, Singapore, UK and US). During the financial crisis, our research initially shows that generally net oil importing countries appear to go into recession immediately after a positive oil price shock, while the recession for net oil exporting countries only happen after a negative oil price shock. However, our results for asymmetric effect are contradictory to past research such as Engemann et al. (2014) who concentrate on the US states, as most countries in our sample respond to negative oil price shocks instead of positive oil price shocks. Our findings also show two countries exhibiting symmetrical effect. Furthermore, we *"nationalise"* the oil price shocks but it does not seem to provide any obvious improvement in results when testing for asymmetric effect.

We also investigate illiquidity shocks in chapter six and our evidence expectedly show that countries such as Norway, Canada, Denmark, Germany and the US endure positive illiquidity shocks prior to a recession period. Further investigation by regression models reveal a clear relationship between illiquidity shocks and GDP in relation to positive illiquidity shocks. Although most countries experience directional asymmetry in relation to illiquidity shocks, four countries show symmetrical effect, with Mexico displaying a genuine symmetrical effect as positive and negative illiquidity shocks cause the GDP of Mexico to move in the opposite direction respectively. Moreover, the results on illiquidity shocks seem to be much clearer in comparison to oil price shocks.

Chapter seven is the final empirical chapter and it looks into the relationship between macroeconomic growth (captured by GDP) and five (5) predictive variables. We split our sample into net oil exporting countries and net oil importing countries. This chapter provides original results by including extra predictive variables such as oil (OB), Baltic Dry index (BD) and national foreign exchange (NFX), in addition to the illiquidity variables[134] which have not been used before. Our findings show that excess market returns (XS) is the most relevant financial variable, while among predictive variables, oil (OB) appears to be the most significant as the GDP of nine (9) countries is positively predicted by it. Between illiquidity variables, national illiquidity (NAM) is found to be superior in comparison to global illiquidity (GAM). NFX is the least important predictive variable while BD is found to be negatively related to economic growth, which is contradictory to past research. Chapter seven also shows that oil (OB) has higher explanatory power for net oil exporters while the BD seems to be more important for net oil importing countries.

With regards to causality, chapter seven finds that there is two way causality between global illiquidity (GAM) and GDP but unlike Galariotis and Giouvris (2015), our results show only one way causality from national illiquidity (NAM) to GDP. Baltic Dry index (BD) and oil (OB) shows a two-way causality but it appears to be stronger for the former. Oil (OB) is apparently more important for net oil exporters as the two-way causality remains while for net oil importers, only causality from GDP to oil (OB) can be observed. By further segregating net oil exporting countries into developed (Norway, Canada and

[134] The paper uses the *Amihud illiquidity measure* to construct two illiquidity variables namely *national illiquidity (NAM)* and *global illiquidity (GAM)*. *National illiquidity (NAM)* relates to the illiquidity of the companies of a specific country while *global illiquidity (GAM)* excludes the companies of the specific country and hence consisting of international companies only. Further details of the illiquidity variables can be found in the *Data and variables section* of chapter seven.

Denmark) and emerging markets/ countries (Mexico and Brazil), our results show that oil (OB) appears to be more important for emerging countries, potentially due to emerging countries over-reliance on oil while BD does not provide any extra explanatory power for both developed and emerging countries. Surprisingly, there is no causality between oil (BD) and GDP for both developed and emerging countries of net oil exporters which may probably due to insufficient amount of data after segregation of the countries.

As a summary, the PhD thesis main findings are as follows:

- Firstly, the evidence generally shows that illiquid portfolios are found to supersede liquid stocks returns but different illiquidity measures capture different aspects of liquidity, thus there can be some divergence on the results obtained.

- Secondly, we find that market liquidity and the *"illiquid minus liquid stocks (IML) portfolio"* are affected by changes in monetary conditions. However, market liquidity and the IML portfolio have different reaction towards BOE base rate and LIBOR. It shows that investors who are concerned with market illiquidity and the IML portfolio should focus on LIBOR and BOE decisions respectively. Nevertheless, it can be deducted that when there is an intersection between the two monetary conditions, the reaction is stronger.

- Thirdly, our results show that illiquidity is able to meet the four criteria of Sharpe (1992) benchmark requirements or at least show its profitability, signifying its potential as an investment style. However, illiquidity is found to be strongly correlated to size for the UK market.

- Fourthly, most countries generally experience directional asymmetry in relation to both oil price shocks and illiquidity shocks but there are also countries that show symmetrical effect.

- Fifthly, illiquidity shocks appear to be at least an equally important determinant of the state of the economy compared to oil price shocks which is thought to be one of the most important factors for a number of years.

- Sixthly, among the five (5) predictive variables, oil (OB) appears to be the most significant as it is able to predict the GDP of 9 out of 10 countries, while excess market returns (XS) is the most relevant among the four (4) financial variables.

Even though illiquidity is less able to predict economic growth compared to oil, illiquidity still provides some explanatory power.

- Lastly, categorising the chosen countries into net oil exporting countries and net oil importing countries does provide some valuable insights, as net oil exporters (e.g. Brazil) and net oil importers (e.g. Germany) appear to benefit from positive oil price shocks and negative oil price shocks respectively. Furthermore, oil (OB) has higher explanatory power for net oil exporters while the Baltic Dry index (BD) seems to be more important for net oil importing countries.

There are also limitations to our research. For instance, our study on the relationship between illiquidity and monetary conditions obtain weaker evidence in comparison to Jensen and Moorman (2010), as our results are generally not always significant[135] particularly for restrictive conditions[136]. Furthermore, although our results appear to confirm illiquidity as a profitable style, there is a strong relationship between size and illiquidity which is in contrast with Ibbotson et al. (2013). Nevertheless, we believe that the different results in comparison to past researchers may simply be due to different periods and liquidity measures used. Another reason may be the different characteristics of UK and US markets such as the lower volatility in the UK market relative to the US market (Bartram et al., 2012), since the lower level of volatility will definitely affect asset prices and liquidity. Stoll (1978) does show that liquidity is positively affected by return volatility.

With regards to chapter three, four and five, we believe that further studies need to be conducted by including more countries and over longer periods. Although we include more countries for chapter six and seven, we feel that including OPEC countries is important especially when studying oil. One other issue that has arisen is the classification of the chosen countries based on the latest available data of 2012. For instance Mork et al. (1994) classify UK as an oil exporting country while we consider it as net oil importing

[135] We have also conducted a stock migration investigation using Amihud as a measure of liquidity but using quartiles instead of quintiles between January 1991 and December 2014. Basically, our investigation looks into stock migration from each quartile in year (t) (sorting year) to other quartiles in year (t+1) (performance year). The quartiles are only rebalanced annually meaning that stocks are held for at least one year. Our overall results show (not presented here to keep the number of tables as low as possible) that over the period, on average 78.45% of stocks remain in the same quartiles. This could be one of the reasons why our results are not always significant.

[136] Table 3.2 shows that there are more expansive periods compared to restrictive periods, which may be another reason for results that are not significant during restrictive periods.

country. Therefore, for future studies the classification of countries should probably be based on the average or total oil exports or imports over the sample periods.

The findings of the thesis also provide some implications for regulators, policymakers and investors as follows.

Our first empirical chapter shows that the IML portfolio returns increase following expansive monetary shifts, signifying profit opportunity for investors during expansive periods. As also shown in our first empirical chapter, regulators or policymakers such as central banks can use liquidity to stabilise the financial markets. It also shows that investors and regulators who are concerned with IML portfolio and market liquidity should focus on BOE decisions and LIBOR respectively. However, it can be concluded that when there is an intersection between the two monetary conditions, the reaction is stronger. Although market liquidity is less affected by the BOE base rate compared to LIBOR, the correlation between the two interest rates indicate that the decision by the BOE as regulator still plays a significant role in controlling the liquidity of financial markets.

Nevertheless, major events such as the financial crisis can still adversely influence market liquidity while monetary policies appear to be less effective during restrictive periods because investors are less concerned with liquidity. Therefore, during such events or periods, regulators and policymakers should probably use other financial tools to control market liquidity.

Our second empirical chapter signifies that pre-crisis, investors can use illiquidity as an alternative investment style in equal standing to the other styles, as it meets the four criteria of Sharpe (1992) benchmark requirements. Even though illiquidity is not as successful post-crisis, illiquidity is more stable and it is able to perform better than the benchmarks. Thus, signifying profit opportunities for investors with lower transaction costs.

Using a longer data sample, the third empirical chapter shows that investors can still use illiquidity as an investment style and investors should focus on “characteristics model” instead of “covariance model” when constructing investment portfolios. The January effect evidence for the investment styles indicates further profit potentials for investors in the month of January.

However, investors should keep in mind that there is a strong relationship between size and illiquidity as shown in our second and third empirical chapters. Nevertheless, we feel that illiquidity still has its merits as an investment management tool and choosing an investment style actually depends on the investors' preference.

With regards to the asymmetric effect study in our fourth empirical chapter, most countries in our sample respond to negative oil price shocks instead of positive oil price shocks, which is contradictory to past research. Therefore, policymakers such as government officials should anticipate that negative oil price shocks can also influence macro-economies. Moreover, policymakers should also consider illiquidity shocks, as our results on illiquidity shocks appear to be much clearer in comparison to oil price shocks.

Nevertheless, when five predictive variables including oil and illiquidity are investigated, our fifth empirical chapter highlights that policymakers, particularly policymakers of net oil exporters as well as emerging countries, should include oil when predicting economic growth. Moreover, policymakers should also acknowledge the importance of other variables such as excess market returns (XS) and for net oil importers, Baltic Dry index (BD).

In conclusion, the thesis shows that regulators (e.g. central banks) can use liquidity to stabilise the market while investors can use it as an investment style. Although liquidity is less able to predict economic growth compared to oil, liquidity still provides some explanatory power for researchers such as policymakers. Therefore, the PhD thesis shows the continued importance of liquidity for finance theory as well as for both academics and practitioners.

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