ESSAYS ON VOLATILITY MODELLING, MARKET UNCERTAINTY, HERDING AND LIQUIDITY

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DECLARATION OF AUTHORSHIP

I, Abdulilah Ibrahim Alsheikhmubarak, 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: _____September 2019_____

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ABSTRACT

The expected future volatility captured by the implied volatility (IV) index, plays a significant role in finance theory in terms of asset pricing and volatility. While prior research typically relied on historical data and past behaviour in determining outlook, introducing the concept of IV for estimating future volatility has become very useful for several concepts. The objective of this PhD thesis is to answer several questions and explore new areas where IV could play a significant role. First, we model the volatility (or kurtosis) of the IV and determine its explanatory factors, then continue with investigating the impact of the IV on commonality in liquidity and herding behaviour.

Chapter one presents the objectives of this PhD thesis and its contributions, while chapter two reviews related literature about IV, commonality in liquidity and herding behaviour. Chapter three is the first empirical chapter. In this chapter, we evaluate the ability of symmetric and asymmetric GARCH systems to model the volatility of the FTSE 100 Implied Volatility Index (IV). We use GARCH, EGARCH, GJR-GARCH and GARCH-MIDAS to model variance. We also introduce FTSE 100 returns and several macroeconomic variables (UK industrial production, 3M London interbank offered rate (LIBOR), GBP effective exchange rate and unemployment rate) to investigate whether they explain variance. The results show that market returns are a major explanatory factor in addition to macroeconomic variables. Moreover, GARCH(1,1) outperforms other asymmetric models unless there is exceptionally high volatility, such as during the crisis of 2008, in which case EGARCH performs better. GJR-GARCH is outperformed by all other models. GARCH-MIDAS shows both macroeconomic variables and market returns are useful for estimating IV.

Chapter four is the second empirical chapter; it examines the role of market uncertainty [measured by the IV index (VIX)], and average market and industry liquidity pertaining

to individual stock liquidity using several measures of liquidity. We use daily data ranging from January 2007 to December 2017 for index-listed stocks from UK, Japan, and Eurozone stock markets. We first employ market uncertainty alone as a determinant of individual stock liquidity, and then add average market and industry liquidity to the model. The results show no significant impact from market uncertainty on the liquidity of individual stocks. Market and industry illiquidity show significant coefficients in more than half the sample countries, creating co-movement and eliminating any role associated with market uncertainty.

Chapters five and six are the third and fourth empirical chapters. The main purpose of these chapters is to establish a link between herding and the conditional variance [using GARCH(1,1)] associated with several global factors. We examined herding behaviour in the G7 countries in chapter five, and selected several oil-exporting countries in chapter six, employing daily data from May 2007 to December 2018. We first tested for herding using a static model incorporating oil price and oil fear (OVX) indices, the market fear index, and cross-market US factors (VIX index, stock returns dispersion and market index returns). Signs of herding were only found in Japan and Saudi Arabia. Furthermore, oil-exporting countries were found to be sensitive to changes in the OVX in terms of herding behaviour, while G7 countries prove to be sensitive to oil price changes. Regarding US cross-market factors, we found a significant effect from returns dispersion (in all markets), stock market returns (in G7 countries, Russia and Mexico), and the VIX index (in G7 countries). Additionally, we applied a time-varying approach using a Kalman filter to investigate the dynamic nature of herding and its components. A significant interaction was found between market returns and the conditional volatility of the OVX, the oil price index, stock market fear index (VIX), and market volatility. The dynamic nature of herding suggests the static model cannot precisely detect herding behaviour, and thus, the incorporation of these factors is vital to understand the causes of herding.

Chapter seven outlines the empirical findings of the PhD thesis, stressing the importance of IV in the financial markets and discussing the limitations and implications of the research. IV is a significant deterministic function in asset pricing, and understanding it is crucial for researchers and practitioners.

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LIST OF ABBREVIATIONS

ADF	Augmented dickey fuller stationarity test
ADX	A stock market index that measures the stock performance of companies listed in Abu Dhabi Securities Exchange in United Emirates
AIC	Akaike information criterion test
AMH	Amihud Illiquidity Measure
ARCH	Autoregressive conditional heteroscedasticity model
BIC	Bayesian information criteria
CA	Canada
CAC	A stock market index that measures the stock performance of companies listed on Euronext Paris Stock Exchange in France
CBOE	Chicago Board Options Exchange
CHF	Swiss franc - Currency of Switzerland
CLARM	Classical linear auto regression models
CPI	Consumer price index
CSAD	Cross-sectional absolute deviation
CSSD	Cross-sectional standard deviation
DAX	A stock market index that measures the stock performance of companies listed on Frankfurt stock exchange in Germany
DFM	Dubai Financial Market
EEX	Effective exchange rate
EGARCH	Exponential generalized autoregressive conditional heteroskedasticity
ETF	Exchange-traded fund
EUR	Euro - Currency of the European Union

EURO STOXX	A stock market index that measures the stock performance of companies listed in the Eurozone stock market
FR	France
FTSE	A stock market index of companies listed on the London Stock Exchange in the United Kingdom
FW	Fixed window
G7	Group of seven countries - Consisting of Canada, France, Germany, Italy, Japan, UK and US
GARCH	Generalized autoregressive conditional heteroskedasticity
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
GJR-GARCH	Threshold generalized autoregressive conditional heteroskedasticity
GR	Germany
Herd	Herding
HLS	Bid-ask spread estimator
IL	Industry average liquidity
ILLIQ	Illiquidity measure
IP	Industrial Production
IPC	A stock market index that measures the stock performance of companies listed on Mexico stock exchange
IT	Italy
IV	Implied volatility
JP	Japan

JPY	Japanese yen - Currency of Japan
KU	Kuwait
KWSEDIX	A stock market index that measures the stock performance of companies listed in Kuwait Stock Exchange
LIBOR	London Interbank Offered Rate
LLF	log-likelihood function
LSE	London Stock Exchange
MIDAS	Mixed data sampling
MINA	Middle Eastern and North African countries
ML	Market average liquidity
MOEX	A stock market index that measures the stock performance of companies listed on Moscow stock exchange in Russia
MX	Mexico
NASDAQ	National Association of Securities Dealers Automated Quotations
NIKKEI 225	A stock market index of companies listed on the Tokyo Stock Exchange in Japan
NO	Norway
NYSE	New York Stock Exchange
Obs	Observations
OLS	Ordinary least squares
OSE	A stock market index that measures the stock performance of companies listed in Oslo Stock Exchange in Norway
OVX	Oil implied volatility index
PhD	Doctor of Philosophy
PP	Phillips Perron stationarity test

QA	Qatar
QE	A stock market index that measures the stock performance of companies listed in Qatar Stock Exchange
QS	Quoted spread
RU	Russia
RVI	Implied volatility index based on Moscow Stock Exchange in Russia
RW	Rolling window
S&P	A stock market index that measures the stock performance of companies listed on Standard and Poor's stock exchange in the United States
SA	Saudi Arabia
SIC	Schwarz information criterion test
TASI	Tadawul All Share Index- A stock market index that measures the stock performance of companies listed in Saudi Stock Exchange
TED	the difference between the risk-free T-Bill rate and the London Interbank Offered Rate
UAE	United Arab Emirates
UK	United Kingdom
UR	Unemployment rate
US	United States
USD	United States Dollar – Currency of United States
VAR	Vector Autoregression
VCAC	Implied volatility index based on Euronext Paris Stock Exchange in France
VDAX	Implied Volatility index based on Frankfurt Stock Exchange index in Germany

VFTSE	Implied volatility index based on the London Stock Exchange index in the United Kingdom
VIF	Variance inflation factor
VIMEX	Implied volatility index based on Mexico Stock Exchange
VIX	Standard and Poor's 500 implied volatility index in the United States
VOL	Stocks volume
VOLA	Stocks volatility
VSTOXX	Implied volatility index based on Eurozone Stock Exchange index
VVIX	Volatility of the Standard and Poor's 500 implied volatility index implied volatility index
VXJ	Implied volatility index based on Tokyo Stock Exchange index in Japan
VXN	Nasdaq implied volatility index in the United States

CHAPTER 1: INTRODUCTION

Market uncertainty, also known as the fear index or fear gauge, is a measure of implied volatility (IV) as derived from stock index option prices. Modelling and forecasting IV is of great importance in empirical finance. A growing body of literature is emerging to examine the informational content of IV indices and their forecasting ability. These indices contain critical information about the forward-looking aspects of actual volatility in the underlying index, and have been used as a key measure of risk (Hentschel, 2003). IV indices are more informative than the historical realised volatility of stock market index returns when forecasting (Fernandes et al., 2014). IV indicates financial instability revealing when the market is reaching an extreme level of sentiment; therefore, high IV levels coincide with high levels of market stress (Whaley, 2000). IV also serves as an estimation tool for market participants, since many trading strategies rely on the fear index for hedging and speculative purposes (Sarwar, 2012).

Many studies have examined the properties of the daily time series of the IV index and its predictability power. Early studies have shown that IV is a significant predictor of realised future volatility (Beckers, 1981, Chiras and Manaster, 1978, Latane and Rendleman Jr, 1976). Furthermore, in relation to equity markets, studies by Fleming et al. (1995), Christensen and Prabhala (1998), and Blair et al. (2010) have shown that IV (VIX) provides more accurate forecasts of future volatility than the historical standard deviation of daily returns. Nevertheless, in more recent studies, the benefits of combining the VIX, as an asset within portfolio allocation, with long-term equity investments has been highlighted (see Daigler and Rossi (2006), Moran and Dash (2007), and Sloyer and Tolkin (2008)). The combination of VIX and long-term equity helps mitigate risk exposure and is beneficial for the purpose of returns.

Conversely, another thread in the literature sought to identify those factors that have a significant impact on IV's movements and volatility. Previous studies examined IV movements based on several determinants, particularly stock market returns and macroeconomic announcements. Several studies documented the asymmetric relationship between market returns and IV indices. Whaley (2000) and Giot (2005) analysed the effect of aggregate stock market returns on IV in the US market, and showed a significant response in terms of IV to negative market shocks. Elsewhere, the impact of macroeconomic announcements on IV has been documented. While Ederington and Lee (1996) focused on the impacts of scheduled and unscheduled announcements, other studies have tried to identify which types of scheduled announcement significantly impact IV (Nofsinger and Prucyk, 2003, Clements, 2007, Vähämaa, 2009).

A recent direction in the literature has been to examine the volatility (kurtosis) of the IV index. The importance of modelling the volatility of IV proceeds from the need for market participants to be clear about market sentiment towards the expectation of future values of IV. Yang-Ho Park (2015) explored the effects of VVIX[1] on tail risk hedging returns, while Wang et al. (2013) focused on the effects of VVIX on equity premia. However, research on the volatility of volatility remains limited and is specific to the US, with several areas pertinent to IV literature remaining unexplored. In addition, the study of the volatility of IV was excluded in prior research investigating the relationship between market returns, macroeconomic variables and IV. In chapter 3 we take research on the volatility (kurtosis) of IV a step further, by using GARCH models to investigate the effect of several exogenous factors, macroeconomic variables and stock market returns on the volatility of the IV in the UK. To the best of our knowledge, this approach has not been explored in the literature and it is predicted that it will improve the estimation of IV.

[1] The VVIX is a volatility of the IV measure, which represents the expected volatility of the 30-day forward price of the CBOE volatility index.

The scope of market uncertainty research has extended dramatically since the global financial crisis of 2007–2008, and now covers several areas.

Research into market uncertainty has rapidly extended since the global financial crisis of 2007–2008 and now covers several additional areas. The literature focusing on commonality as an explanatory factor for market illiquidity has recognized the importance of implied volatility as firstly, a forward-looking measure of market realised volatility and secondly, one of the most important determinants of an asset's risk. This is due to the extent to which systematic liquidity variations constitute a priced factor, while the ability to understand the causes of liquidity covariations have the potential to improve the capability of investors and traders to deal with such risks. Moreover, changes in market liquidity during periods of market stress are significantly related to changes in market uncertainty (Bao et al., 2011). The fourth chapter (i.e. the second empirical chapter) therefore investigated the importance of implied volatility as an explanatory factor in the commonality of liquidity

The role of IV has also been extended to the herding literature. The information asymmetry hypothesis (along with an assumption that investors are risk averse) indicates that a substantial increase in implied volatility could potentially represent a substantial increase in market risk. This has the potential to prompt risk-averse investors to exhibit irrational behaviour, including following others in making investment decisions that result in herding behaviour patterns in the market. Hence, the fifth and the sixth chapters of this thesis (i.e. the third and the fourth empirical chapters) examine the role of implied volatility in forming herding patterns in financial markets.

Herding studies seek out determinants and sources of herding behaviour styles. When traders and market participants ignore their beliefs and follow a collective approach, this causes herding behaviour. This then results in prices deviating from economic fundamentals potentially subsequently causing market stress and shocks. A large body of literature has investigated herding behaviour since the creation of the cross-sectional standard deviation for stock returns by Christie and Huang (1995), followed by the cross-sectional absolute deviation (CSAD) by Change et al. (2000). Studies have tested for herding in both developed and developing countries (Caparrelli et al., 2004; Chiang and Zheng, 2010; Economou et al., 2011). Research into herding has recently transferred from the attempt to identify herding patterns in stock markets to exploring its causes and determinants Recent studies of herding behaviour have incorporated market sentiment and return volatility. The US fear index (VIX) has been investigated as a potential source of herding in several studies (Philippas et al., 2013, Chiang et al., 2013, Economou et al., 2016, Economou et al., 2018). These studies have identified the significant role of the US VIX in generating herding patterns, noting that this is not confined to the US market but also influences international markets.

Nevertheless, to date herding estimation models have been limited to market returns and the VIX index as an independent determinant. Therefore, in chapters 5 and 6 we extend herding research by including oil prices, the oil fear index (OVX)[2], the historical volatility of market returns, and several cross-market US factors[3]. The impact of oil prices and the OVX on stock market returns is recognised but has never been used in herding estimation. We also test for herding by applying a dynamic approach using a Kalman filter-based model. The main purpose of using Kalman filters in herding research is to overcome any issues caused by structural changes owing to periods of market stress when using the average values estimated over a specific sample of data. Chapter 5 tests for herding in the G7 countries using specific explanatory factors, while chapter 6 uses the same

[2] OVX is the CBOE Crude Oil ETF IV index. It measures the market's future expectation of 30-day volatility of crude oil prices. The OVX is obtain by applying the VIX methodology.
[3] We use the US VIX, stock market returns and the cross-sectional absolute deviation from the mean.

methodology but covers seven selected oil-exporting countries (Russia, Mexico, Saudi Arabia, Kuwait, UAE, and Qatar).

In summary, this thesis aims to: i) model the volatility of IV based on several macroeconomic variables in the UK by using several forms of GARCH model; ii) examine the role of IV on individual stock liquidity alongside market and industry liquidity in the UK, Japan and the Eurozone; and iii) test for herding behaviour in the G7 countries and seven selected oil-exporting countries by incorporating the IV index, oil price index, OVX and several cross-market US factors using the CSAD approach with modifications and by further applying the Kalman filter approach to investigate the time-varying nature of herding behaviour.

When it comes to the issue of data selection, the UK market was selected for analysis in the first empirical chapter in response to the strong research potential of the UK market. This is due to the UK stock market being generally considered one of the largest stock markets by capitalisation and a globally attractive destination for investors. In addition, this study was conducted in the UK. The analysis was expanded in the second empirical chapter to include other G7 countries. The Eurozone stock market is one of the largest markets in the world, while the combined stock markets of Europe offer beneficial opportunities for any investor, even during periods of political and financial turmoil. The Eurozone stock market includes three G7 countries, i.e. Germany, France and Italy. The inclusion of this area in the analysis offers considerable opportunity for comparison, due to similarities of location and regulation. I also included the Japanese (Tokyo) Stock Exchange as part of the G7 and highly developed free-market economies. The Japanese Stock Exchange is also an important destination for global investors, making its inclusion in the analysis beneficial for the purposes of comparison, in particular due to differences of location, culture, and regulation. Canada was excluded from the analysis as there was a lack of data relating to the implied volatility index initiated in 2010. The US was also excluded, due to the existence of similar research concerning the US stock market.

The data selection was expanded to include all G7 countries in the third empirical chapter, due to their stock markets being the most sophisticated and advanced world economies and, as such, the main destination for investors. Moreover, these countries are the most importing oil countries and this chapter examined herding behaviour primarily in relation to oil prices. The fourth empirical chapter therefore focused on the main oil exporting countries for purposes of comparison, as well as to determine the impact of oil prices on both importing and exporting countries.

The main contributions of this thesis to the literature are as follows:

1- Prior research has tried to investigate the role of the IV index on stock market returns, and as a cross-market factor in international stock markets. However, it has never explained the volatility of the IV index relative to exogenous variables. This thesis also shows that implementing the volatility of the IV in symmetric and asymmetric GARCH models, using macroeconomic factors and stock market returns as explanatory factors, significantly helps with the estimation of IV movements. Moreover, by using the GARCH-MIDAS approach, this thesis justifies how macroeconomic variables and market returns affect the movements of the IV.
2- Research into common sources of liquidity, examining the role of IV are limited to the US market. This thesis examines the effect of IV alongside aggregate the market and industry liquidity in the UK, Japan and Eurozone markets. It also shows that using different liquidity and illiquidity measures (never before used in such an approach) reveals the impact of the IV index and market and industry aggregate liquidity during and after the financial crisis of 2007–2008.

3- Historically, herding research has been limited to examining herding behaviour instead of identifying its causes. While previous research has only used the IV index in herding estimations, this thesis states that an approach incorporating several factors (IV index, oil price, OVX, returns volatility and cross-market US factors) provides a clearer understanding of herding patterns and sources. This approach will provide a definitive answer to the mixed findings of previous research. It also shows the importance of using a dynamic approach to understand herding behaviour.

The thesis is structured as follows: Chapter two presents an overall review of the existing literature covering several topics, including the role of the IV index, volatility modelling, liquidity and herding in stock markets. The literature review chapter aims to provide the theoretical foundations for the thesis' main concepts, and shed light on previous empirical research to highlight key empirical findings, reveal potential research streams and identify current research limitations. Relevant literature specific to each of the topics studied is also presented in each chapter for clarity.

Chapter three is the first empirical chapter, and it aims to model the volatility of the IV index in the UK, the FTSE 100 IV index with 30-day expiration, and IV. While the available research on the volatility of the IV is limited to the US, there is strong research potential in the UK market, since it is considered one of the largest stock markets globally in terms of market capitalisation. To conduct this research, several explanatory factors are used, namely i) realised (historical) volatility, ii) stock market index returns for the FTSE 100, and iii) four macroeconomic variables for the UK, namely industrial production (IP), the London 3 months interbank offered rate (LIBOR), the GBP effective exchange rate (EEX) and the unemployment rate (UR). We use symmetric and asymmetric forms of GARCH models and GARCH mixed data sampling (GARCH-MIDAS) to enhance the credibility of the estimated results and to improve forecasting ability. Our results show the exogenous explanatory factors evaluated play a significant role in defining variations in the volatility of the IV index. As for GARCH models, GARCH(1,1) outperformed the other asymmetric models. Moreover, using GARCH-MIDAS confirmed the importance of macroeconomic variables and market returns when modelling the volatility of IV.

Chapter four investigates potential sources of common liquidity based on the effect of IV, industry and market average liquidity and individual stock liquidity. Prior research is limited and specific to the US stock market, and so the chapter extends a previous study by Chung and Chuwonganant (2014) to include the IV index covering the London Stock Exchange (FTSE 100), the Japanese stock market (Nikkei 225), and the Eurozone stock market (EURO STOXX50). We use three liquidity measures to justify the results: i) the Amihud (2002) illiquidity measure, ii) the Corwin & Schultz bid–ask estimator, and iii) the quoted spread. We split the data into two temporal groupings: i) during the financial crisis (from January 2007 to December 2009), and ii) after the financial crisis (from January 2010 to December 2017) to examine the effects of the financial crisis on liquidity commonality. The findings from this chapter suggest the average industry liquidity plays a significant role in explaining the variation in individual assets in all the examined regions. Nonetheless, average market liquidity is significant only in the Eurozone stock market, while the IV indices show no significant effect across all the examined markets.

Chapter five explores herding behaviour in the stock markets of the G7 countries using both static and dynamic models. The majority of the existing research focuses on identifying herding behaviour in stock markets rather than understating what factors create herding patterns among traders. We provide novel evidence of herding behaviour by incorporating several variables, namely: i) the oil price index, ii) the OVX, iii) the IV index (IV) and iv) cross-market global effects[4]. When using a static, constant-coefficient model we found no existence of herding behaviour in any of the G7 countries, with the exception of Japan. Furthermore, the oil price was found to have a significant effect on the dispersion of market returns in Japan, Germany, France and Italy, while the OVX produces insignificant coefficients in all countries. This finding suggests these countries are affected by the current oil price and not by future expectations of oil volatility. Moreover, the cross-market global effect represented by US factors is absorbed by all G7 countries, creating herding behaviour in these markets during periods of US market stress. These results are consistent with those reported in previous studies by Chang et al. (2000), Chiang and Zheng (2010), and Economou et al. (2018).

The conventional static model does not capture the possible dynamic nature of herding behaviour. Chiang et al. (2013) were the first to employ a time-varying approach to examine herding's dynamic nature using a Kalman filter-based model, although they only included the conditional variance of market returns. Following this approach, we used Kalman filter steps to generate herding coefficients to examine the dynamic nature of herding behaviour under the evaluated factors. We found significant interactions between market returns and the conditional volatility of all factors, suggesting herding has a dynamic nature and that static models cannot precisely detect herding patterns within the markets.

Chapter six uses the same methodology as that used in chapter five by examining herding behaviour under static and dynamic models in several selected oil-exporting countries[5] (Russia, Mexico, Saudi Arabia, UAE, Norway, Qatar and Kuwait). Using the static model, we only found herding behaviour in the Saudi stock market. Unlike oil prices, which have a significant effect on several G7 countries, the OVX has a significant impact

[4] To test for the effect of major foreign factors in the model, we include US factors such as US fear index (CBOE VIX), and US price index returns (S&P500), and the stock market cross sectional absolute deviation (CSAD of S&P500)
[5] We have selected these countries because they are the largest oil exporters with adequate data availability.

on several oil-exporting countries. This indicates that oil-exporting countries pay more attention to the future expectation of oil prices than current prices. Testing for dynamic herding using the Kalman filter approach, we document dynamic herding behaviour in most countries, in G7 and in oil exporting countries. The interaction between market returns and the conditional variances of oil prices, oil and market fear indices, and US cross-market factors result in a significant herding tendency in all of the countries examined.

Finally, chapter seven concludes and summarises the main ideas set out in the thesis, the results and findings, limitations and potential future research, as well as implications.

CHAPTER 2: LITERATURE REVIEW

2.1. INTRODUCTION

This chapter provides an overall review of existing research and findings deemed relevant to the topic discussed in this PhD thesis. We discuss various strands of literature, including: i) IV indices and their relationship with several variables, ii) commonality in liquidity, industry and market liquidity, and the role of market uncertainty, and iii) the impact of IV and global factors on herding behaviour. The aim of this chapter is to discuss previous research and empirical findings to identify potential research gaps.

This chapter is structured as follows: since IV is the main theme of this PhD thesis, sections 2 and 3 introduce the literature on IV, including its construction and forecasting ability. Section 4 discusses the literature relevant to the first empirical chapter, the research on IV modelling and its relationship with stock market returns, macroeconomic variables and macroeconomic announcements. It also discusses the volatility (or kurtosis) of the IV index and research potential in this area.

Section 5 presents the literature covering the second empirical chapter, discussing the role of several determinants informing correlated movements in liquidity. This section reviews the literature, involving commonality in terms of liquidity and its sources. We mainly show the role of IV indices as a source driving variation in liquidity across stock markets, as well as the aggregate impact of industry and market average liquidity on market-wide liquidity. We also discuss other determinants as suggested by supply and demand sides when explaining liquidity movements across individual stocks.

Sections 6 discusses the literature covering the third and fourth empirical chapters. This section explains herding behaviour and presents prior research. examining herding in financial markets. It also discusses herding models and the existence of herding behaviour in several regions, in particular in both developed and developing countries. It provides a review of the importance of IV among other variables (oil price and fear indices and the US cross-market effect) in forming herding patterns among investors in financial markets.

Finally, a review of relevant literature is presented at the beginning of each empirical chapter to make it easier for the reader to relate the findings of our empirical investigation to prior research.

2.2. IMPLIED VOLATILITY AND VOLATILITY FORECASTING

In the empirical and theoretical finance literature, volatility is recognised as one of the most important determinants of asset risk. The ability to predict volatility in market stocks is of great importance to market participants and regulators, since it enables them to predict the risks they will encounter and appropriately implement hedging strategies (Frijns et al., 2010). Any asset valuation procedure includes assessment of the level of risk to future payoffs (Busch et al., 2011). IV is the market's forecast of future volatility and is believed to be more informative than historical volatility (Canina and Figlewski, 1993). I consider that Implied Volatility (IV), as calculated by the Black–Scholes model, can be seen as an effective predictor of future volatility. This is particularly so as it is computed from the market price of stock options. Furthermore, I found a number of researchers employing IV in volatility models as a measure of perceived future price risk in relation to assets. IV as extracted by the Black–Scholes formula is a unique volatility parameter and the formula recovers from the price of an option contract (Lee, 2005). In other words, the Black–Scholes formula calculates IV from the current option's current market price, solving the pricing model for volatility by setting model and the current market prices as equal (Canina and Figlewski, 1993).

Aside from its use as a forward-looking measure of market realised volatility, IV has also been used to explain and estimate stock market returns (Frijns et al., 2010). After examining the relationship between the US IV index (VIX)[6] and the stock market returns index, many studies have reported a significant negative relationship (Whaley, 1993; Fleming et al., 1995; 1999; Hibbert et al., 2008). The relationship between the VIX and stock returns is asymmetric, where negative stock returns are associated with an increase in VIX. Hence, it is often referred to as the investor fear index or gauge, as it causes investors to expect higher stock market volatility in the future (Frijns et al., 2010) and a price decline (Whaley, 2000). It has also been referred to as a measure of investor sentiment (Baker and Wurgler, 2006). I feel that these studies offer an in-depth deep analysis of the characteristics of the negative and asymmetric relationship between implied volatility and stock market returns, as discussed below in relation to differing measures of implied volatility.

2.3. IMPLIED VOLATILITY INDEX CONSTRUCTION

The US S&P 500 index option, commonly known as the VIX index, was the first IV index developed by a reporting authority. The VIX is financial benchmark index, in which a market estimate of expected volatility is calculated using the midpoint of S&P 500 index option bid–ask quotes. Subsequently, many countries developed their own IV index to establish the expected volatility of their stock markets. For example, the FTSE 100 VIX index (VFTSE) in the UK, the Nikkei 225 index options (VXJ) in Japan, and the DAX

[6] The Chicago Board Options Exchange (CBOE) developed a volatility index (VIX) based on the IV of the S&P 100 index options in 1993. In 2003, the CBOE calculated the volatility index with underlying S&P 500 index options. The S&P500 VIX depends on the in-the-money and out-the-money options of the S&P 500 index. VIX calculation was based on the Model-Free IV by Britten-Jones and Neuberger (2000). VIX is computed on a real time basis on each trading day, and it is based on the IV of both call and put option contracts. Several methodologies preceded the development of VIX by CBOE; e.g. Gastineau (1977) constructed an average volatility index by IV of in-the-money call options of 14 stocks in the US market. Later, Cox and Rubistein (1985) created a new method for calculating IV including more options of the same stocks, thereby using and improving Gastineau's method for weighting volatility related to option's expiration time. Also, Whaley (1993) constructed an IV index based on the IV of numerous near the money options on the S&P 100 index.

volatility index (VDAX) in Germany. In the white paper presented by the CBOE[7], the generalized formula used for the VIX index calculation is defined as follows:

$$\sigma^2 = \frac{2}{T}\sum_i \frac{\Delta K_i}{K_i^2}\, e^{RT} Q(K_i) - \frac{1}{T}\left[\frac{F}{K_0} - 1\right]^2 \qquad (2.1)$$

Where σ^2 is the VIX index divided by 100, T is the option's time to expiration, F if the forward index level calculated as F = strike price + e^{RT}(Call Price – Put Price), derived from index option prices, K_0 is the first strike below the forward index level F, K_i is the strike price of the i^{th} out-of-the-money options (a call if $K_i > K_0$, and a put if $K_i < K_0$, and both call and put if $K_i = K_0$), ΔK_i is the interval between strike prices calculated as $\Delta K_i = \frac{K_{i+1} - K_{i-1}}{2}$, R is the risk-free interest rate to expiration, and $Q(K_i)$ is the average of the bid quote and ask quote for each option with strike K_i.

2.4. RESEARCH ON IMPLIED VOLATILITY

This section reviews the research conducted examining the IV index and its relationship with stock market returns, macroeconomic factors and macroeconomic announcements, as well as the GARCH models adopted for the modelling process.

2.4.1. IMPLIED VOLATILITY AND STOCK MARKET RETURNS

A number of studies have examined the informational content of IV when forecasting conditional volatility of market returns. Day and Lewis (1992) modelled the volatility of S&P100 index, using the implied content of index options, an exogenous variable using

[7] CBOE refers to the Chicago Board Options Exchange, which was originally created in 1973, expanding the Chicago Board of trade (CBOT) to offer standardized options trading.

GARCH and EGARCH, to conduct symmetric and asymmetric analysis. Their results showed that the information content of the IV, and the conditional volatility from GARCH and EGARCH do not completely characterize conditional stock market volatility, in terms of both in and out-of-sample estimation and forecasting in the US. Canina and Figlewski (1993) and Fleming et al. (1995), also found that IV, as represented by S&P100 index option, produces weak forecasts of subsequent realized volatility. However, I consider these studies to be limited, due to being undertaken over a short period of time, along with the use of low frequency data (i.e. employed within four to six years of the composition of the S&P 100, rather than in relation to the whole market). I therefore view these as resulting in a judgement relating to only a small portion of the market, while the S&P index, by contrast, consists of a larger number of companies within the stock market. However, unlike previous studies, Christensen and Prabhala (1998) used monthly frequency and a longer volatility time series span of the S&P 100 index and its corresponding index option, finding strong evidence that IV can predict future realized volatility. Furthermore, Blair et al. (2010) compared the informational content of the implied S&P 100 volatility index and the corresponding stock returns in the context of forecasting volatility in the short term. Their findings show a significantly accurate forecast by the implied index over incremental forecasting information either in low or high frequencies of stock market returns. Similarly, Corrado and Miller (2005) examined the forecast ability of the IV indices of the S&P 100, S&P 500 and Nasdaq 100 from 1988 to 2003, and found these indices dominate historical index volatility when providing future market forecasts. l view these studies as confirming that implied volatility is capable of ensuring improved estimates of the volatility of future returns, in comparison to ex post standard deviations of returns' historical data. I therefore feel that the information concerning the forecasting capabilities of implied volatility are vital for future research into this subject

In contrast, several studies examined the empirical link between changes in stock returns and the impact of this on IV indices. Whaley (2000) investigated the CBOE's Volatility Indices (VIX and VXN), wherein VIX and VXN correspond to the S&P 500 and the NASDAQ 100 respectively. Whaley has documented a negative and significant relationship between market returns and IV indices. In other words, positive stock returns reduce IV and vice versa. Giot (2005), analysed the relationship between S&P 100 and NASDAQ 100 returns, and their IV indices (VIX and VXN respectively). The VIX shows a significant, asymmetric relationship, and a stronger response to negative market shocks than positive market returns. However, there is a weaker and asymmetric response from VXN on market returns changes. I feel that the literature tends to examine the influence of IV on returns, suggesting that this is extracted from the stock market, particularly in relation to stock market option prices and future expectations of market movements, i.e. investors view such aspects as a risk proxy of any decision making. This was confirmed by the fact that, during my research, I only identified two studies relevant to this strand in the literature

Since volatility indices have become increasingly popular among scholars and practitioners as a measure of uncertainty and a new asset of derivative instruments, research into volatility jumps has gained more attention. Volatility jumps are widely recognised as salient features of volatility, and modelling of the dynamics of the IV series has received growing interest (Psychoyios et al., 2010). Bakshi et al. (2006) examined the role of volatility jumps and return jumps as approximated by reverting to logarithmic diffusion with jumps when forecasting individual return distributions using a sample of the most active firms on the CBOE. Their findings suggest return jumps are a more significant source of modelling returns kurtosis than volatility jumps. In contrast, Wagner and Szimayer (2004) examined the behaviour of IV indices in the US and Germany using a mean reversion model, and documented significant positive jumps that identified stress market jumps. Additionally, Dotsis et al. (2007) explored the ability of continuous-time-diffusion and jump-diffusion to model IV indices from European and US markets over time. They indicated the importance of the addition of jumps to market volatility estimations. I found implied volatility jump to be essential for both accurate pricing and effective risk management. Implied volatility estimation under jump specifications turned to be more accurate in describing the dynamics of implied volatility under different construction specifications of the VIX (e.g., VIX, VXO, VXD).

However, despite various research methodologies having been used to determine the forecasting ability of IV indices, the models most widely used to examine the role of IV in forecasting market returns are symmetric and asymmetric GARCH models, which are reviewed in the next section.

2.4.2. IMPLIED VOLATILITY, MARKET RETURNS, AND MACROECONOMIC VARIABLES

With regard to conditional volatility, Flannery and Protopapadakis (2002) analysed the impact of several macroeconomic series on both returns and returns' conditional volatility over the period 1980-1996 using GARCH. Six risk factors yielded a significant effect: consumer and producer price indices, balance of trade, unemployment rate, housing starts and monetary aggregate.

Engle and Rangel (2008), reviewed the macroeconomic effects on returns in about 50 countries using spline-GARCH, and found evidence that GDP and interest rates were the principal causes of market volatility. Similarly, Engle et al. (2013) used GARCH-MIDAS to investigate the link between returns and macroeconomic determinants. Their core finding was to confirm the accuracy of the model when calculating the influence of long-term macroeconomic variables. These variables are tested in terms of pseudo out-of-sample predictions over long horizons, and were proven to outperform traditional statistical models. The long components refer to macroeconomic variables (inflation and industrial production) sampled over longer periods, for example monthly and quarterly. The short component is represented by daily stock returns. The data set used in this new class model ranges from 1890 to 2010, and is relevant to the US market.

Several studies also applied different forms of GARCH model to study the effect of macroeconomic factors on returns. Sariannidis et al. (2009) and Cho and Elshahat (2014) use different approaches to GARCH models, and state that GDP, changes in oil prices, 10-year bond returns and exchange rates influence US aggregate stock market volatility. Using the VAR-GARCH-M style, Pelloni and Polasek (2003) showed that unemployment rate has an effect on the US, UK and German stock markets. Mangani (2009) also claimed that discount rates (Bank/repo rate) and gold prices affect returns in South Africa, while Oseni and Nwosa (2011) followed an EGARCH model when analysing Nigeria's stock market, demonstrating that GDP affects returns.

To estimate the volatility of US stock returns, Asgharian et al. (2013) introduced 'embedded principle components' into GARCH-MIDAS to combine several macroeconomic factors: interest rate, unemployment rate, term premium, inflation rate, exchange rate, default rate, industrial production and growth rate. GARCH-MIDAS with principal components outperforms other GARCH models and forecasting specifications. Girardin and Joyeux (2013) also used GARCH-MIDAS to successfully relate CPI to China's market volatility. I found that previous studies had identified the importance of macroeconomic indicators on stock market returns. This was due to macroeconomic variables being an essential aspect of stock market performance and thus being employed to assess the general state of an economy

2.4.3. THE EFFECT OF MACROECONOMIC ANNOUNCEMENTS ON IMPLIED VOLATILITY

The impact of information releases on market uncertainty as measured by IV has been investigated in many studies, suggesting IV can be predicted by macroeconomic announcements (Heuson and Su, 2003). Ederington and Lee (1996), investigated the influence of scheduled and unscheduled macroeconomic announcements on market uncertainty, as captured by the IV of option prices. They discovered that scheduled announcements lead to lower levels of implied standard deviation (ISD), and vice versa concerning unscheduled announcements.

Nofsinger and Prucyk (2003) examined reaction in terms of the trading volume on the S&P 500 option index (OEX) following scheduled economic news in 1993 and 1994. They found that of the many types of announcements, consumer confidence, new home sales, factory orders and construction spending directly affected option trading volume. Vähämaa (2009) used different methodologies and a large set of macroeconomic announcements to demonstrate an effect on S&P 500 option index (VIX) using data from 1999 to 2003. Clements (2007) examined the role of monetary policy announcements on the (VIX), and found that meetings of the Federal Open Market committee had a major effect. Several studies have also investigated the effect of announcements on IV in other countries, and have identified a strong link. For example Äijö (2008) used FTSE-100 index options in the UK, and Füss et al. (2011) measured the effect of macroeconomic announcements on the German IV index (VDAX) and (VIX). Also, Shaikh and Padhi (2013) used the Indian (VIX) and Tanha et al. (2014) undertook research investigating Australian index options, yielding similar results. I consider that the use of explanatory factors, in addition to macroeconomic pronouncements, identified the movements of implied volatility. I also view the contradictory findings in the literature concerning their effectiveness as primarily arising from differences between the research methodologies employed.

2.4.4. RESEARCH QUESTIONS REGARDING VOLATILITY OF THE IMPLIED VOLATILITY, STOCK MARKET RETURNS, AND MACROECONOMIC FACTORS.

In the previous sections, we discussed research patterns in the area of market returns, conditional/implied volatilities and macroeconomic variables. Research in the area of ‘volatility of volatility’ is limited, being specific to the US concentrating on the effect of VVIX on tail risk hedging returns (Yang-Ho Park, 2015) and their effect on the equity premium (Wang et al., 2013). Having identified relations between macroeconomic variables, implied/conditional volatilities and returns, we are now venturing into a new area, investigating the effect of macroeconomic variables and market returns on volatility (or kurtosis) of IV, which is worthy of exploration given the absence of literature describing the UK market[8].

Therefore, the following research questions are posed:

1- Do stock market returns and macroeconomic variables play a significant role in modelling the volatility of the IV index?
2- Are symmetric and asymmetric GARCH models beneficial for modelling the examined relationship?
3- How does using a mixed data frequency assist the estimation process?

The following section examines the literature concerning commonality in liquidity and its major determinant, i.e. market uncertainty. The illiquidity of individual assets has

[8] To the best of our knowledge, there is no other study that investigates the effect of macroeconomic variables and returns on the volatility of volatility for the UK or any other country.

captured the interest of researchers, while market uncertainty became one of the major sources of commonality in liquidity.

2.5. COMMONALITY IN LIQUIDITY

IV plays an important role in liquidity commonality. Commonality in liquidity refers to the responses of individual stocks to market-wide or industry-wide movements of liquidity (Fabre and Frino, 2004). A number of studies have focused on this (e.g. Hasbrouck and Seppi, 2001; Huberman and Halka, 2001; Chordia et al., 2000). The motivation for investigating this issue is its implications for financial economics. Commonality in liquidity can present a portfolio risk, i.e. a non-diversifiable priced risk, when investors require high returns from assets that are sensitive to industry-wide and market-wide liquidity shocks (Chordia et al., 2000). Understanding the sources of commonality in liquidity is important to market participants, since systematic variation in liquidity is considered a priced source of risk (Brennan and Subrahmanyam, 1996).

Commonality in liquidity is generally a result of variations in liquidity demand and supply. Demand for liquidity can arise as a variation stimulated by the desire to transact, while supply-generated commonality could be caused by systematic variations in the costs of providing liquidity (Coughenour and Saad, 2004). For example, interest rate shocks could stimulate a systematic increase in demand for liquidity and could alter the cost and the risk when supplying liquidity (Pástor and Stambaugh, 2003). In general, liquidity co-variations typically arise from interactions between liquidity demanders, liquidity suppliers and market makers (Brennan and Subrahmanyam, 1996).

Commonality in liquidity can also be triggered by several factors. General price swings in the market influence the market-wide liquidity response. Price swings can also result from changes in trading volume, which is a principal determinant of investors’ inventory, and any volume variation will most likely result in co-movements in optimal inventory levels, bringing about co-movements in the bid–ask spread of individual assets (Chordia et al., 2000). Volatility is also a determinant of commonality in liquidity. Large orders from dealers' inventories or institutional funds with similar investing styles cause correlated trading patterns, which thereby induce changes in inventory levels across market sectors. Therefore, liquidity can be expected to create similar co-movements across individual assets, since it is correlated with inventory fluctuations (Chordia et al., 2000).

The implications of commonality have been widely investigated in prior research documenting commonality in liquidity by providing some evidence of sources. In the following sections, we review empirical work devoted to investigating the determinants of liquidity commonality, mainly the role of IV indices, average industry and market liquidity, liquidity premia and expected market returns, and the demand and supply sides of liquidity commonality.

2.5.1. IMPLIED VOLATILITY INDEX, A MEASURE OF UNCERTAINTY

The IV index has been used widely in the literature as a measure of uncertainty. Chung and Chuwonganant (2014) studied the impact of market uncertainty on stock liquidity in the US market. They presented strong evidence that the fear index exerts a market-wide impact on liquidity, while the liquidity of individual stocks is not only related to internal risk, but also to wider market uncertainty. The impact of the fear index is greater than the combined effects of all the other determinants of stock liquidity[9].

[9] Chung and Chuwonganant (2014) used several determinants of stock liquidity with VIX, which are market and industry liquidity, stock returns, stock returns volatility at time t, t_{-1} and t_{+1}. They also used individual stock price, stock volume, and four dummy variables for the effect of trading days on Tuesday, Wednesday, Thursday and Friday.

In relation to equity markets and asset-pricing theories, many studies have used the VIX[10] and its impact as a measure of future volatility. Bao et al. (2011) examined the level of liquidity of the corporate bond market and the resultant link to asset pricing implications in the US. They showed a positive relationship between the illiquidity of individual bonds and changes in VIX. This link has not been established based only on the financial crisis in 2008, it was also found throughout the data sample, which ranges from 2003 to 2009. Pan and Singleton (2008) studied the sovereign credit spreads of Mexico, Turkey and Korea, finding a strong common relation to the US VIX. They explained how common global factors could cause significant correlations.

Similarly, Longstaff (2010) related sovereign credit spreads, using a large set of credit default swaps, to the market volatility risk premium, also measured by the US VIX index. Graham and Harvey (2015) also presented evidence of cases where the level of the risk premium is affected by credit spreads and market volatility, the VIX index, in the US market. According to Brunnermeier et al. (2008) there are instances where currency crashes correlate positively to an increase in the TED[11] spread and the VIX. In addition, TED and VIX were found to have explanatory power with regard to determining the future returns of carry trades[12]. Likewise, Ranaldo and Söderlind (2007) documented, by using a set of currency pairs from 1999 to 2006, that when stock market volatility increases safe-haven currencies[13] appreciate and appear to be stronger, since carry trade is correlated with the VIX.

Recently, there is also a tendency to use VIX as a measure of financial market risk. Adrian and Shin (2010) found evidence of where high prices of VIX reduce the risk tolerance of

[10] VIX is the IV index of the S&P 500, which is traded at the CBOE. It shows the expected future outlook for 30-day volatility.

[11] TED is the difference between the risk-free T-Bill rate and the London Interbank Offered Rate (LIBOR).

[12] A currency carry trade is a strategy that enables investors to borrow a low yielding currency to fund the purchase of another, high yielding currency.

[13] The safe-haven currencies are the British pound (GBP), euro (EUR), Japanese yen (JPY), and Swiss franc (CHF) against the U.S. dollar (USD).

market makers due to strictures on risk management. Bekaert et al. (2013) linked market uncertainty and monetary policy in a vector-autoregressive framework. Their findings suggest that a lax monetary policy is negatively correlated with risk aversion and uncertainty. Conversely, it has not been statistically proven that when the VIX and risk aversion are higher, monetary policy is laxer. Since the VIX is decomposed into risk aversion and uncertainty, the main component driving the co-movement between monetary policy and VIX is risk aversion[14]. I recognize the significant implications of the relationship between implied volatility index, asset markets, and monetary policy. I therefore view an analysis of the relationship between monetary policy and the IV as clarifying the relationship between stock market and monetary policy due to it significantly affects risk aversion and uncertainty.

2.5.2. COMMONALITY IN LIQUIDITY, MARKET AND INDUSTRY LIQUIDITY CO-VARIATION

A growing body of literature appears to find commonality in liquidity, specifically the size of interactions at the microstructure level of cross-stock liquidity, where stock liquidity appears to be defined by market and industry liquidity. For instance, Hasbrouck and Seppi (2001), examined the role of the systematic cross-stock liquidity effect using several liquidity proxies[15]. They highlighted that the liquidity of individual assets' is not the principal common component, but broader common determinants of liquidity could have a greater impact.

Chordia et al. (2000) demonstrated that liquidity movements display a market-wide intertemporal response to price changes. The variation in trading volume is a source of

[14] Bekaert et al. (2013) also documented that market uncertainty reacts also to lax monetary policy. However, the response of certainty to monetary policy effect is weaker than the immediate responses of risk aversion.
[15] Hasbrouck and Seppi (2001) used bid-ask spreads and bid-ask quotes as an alternative to other determinants of liquidity, such as price, volume and volatility.

co-movements in inventory levels, and therefore leads to co-movements in liquidity measures. Volume on the other hand can serve as a common factor describing liquidity, as common trading styles, such as institutional funds and market makers with similar trading strategies, exhibit the same trading patterns. Hence, variations in inventory could be correlated across individual stock in the market or within the same industry and exhibit a similar co-movement pattern. Moreover, asymmetric occasional information could influence many firms to fluctuate in the same direction, causing covariation and a similar co-movement in terms of liquidity, influencing both market and industry liquidity.

Huberman and Halka (2001) also documented the existence of a symmetric component to liquidity. They used four measures of liquidity: quantity depth, dollar depth, spread and spread/price ratio. Their findings indicated the existence of common, and systematic cross-stock liquidity factors. In many cases, liquidity allocation was contingent on the cost of equity riskiness level, and on the interest rate perceived by the market participants. Meanwhile in other cases, several factors could guide the behaviour of market makers, such as volatility of equity prices and returns, volatility of interest rates, and market turmoil. Accordingly, the average inventory levels held by market participants could be correlated across stock and cause co-movement in liquidity. I consider that that liquidity has thus been confirmed as more than an attribute of any single factor, particularly as there is a significant impact exerted on liquidity by volume, volatility, stock price, inventory risks and asymmetric information. I further view the commonality of liquidity as assisting in an understanding of the impact of inventory risks and asymmetric information on individual stock liquidity.

2.5.3. LIQUIDITY PREMIA AND EXPECTED RETURNS

Liquidity is a major aspect of consideration when pricing common stocks, and it is commonly acknowledged in several studies that expected returns increase in response to market illiquidity (e.g. Amihud and Mendelson, 1986; Brennan and Subrahmanyam, 1996; Datar et al., 1998; and Jones, 2002). Amihud (2002) showed that stock excess return is a form of compensation, a risk premium on illiquid stocks. I conclude that the use of a new measure of illiquidity (ILLIQ[16]) determines the expected returns across stocks, where over a period of time, expected market illiquidity influences the predicted stock excess return.. Acharya and Pedersen (2005) presented evidence of illiquid assets having a high commonality with market liquidity. However, Korajczyk and Sadka (2008) found that only across-measure systematic liquidity involves a risk premium, whereas return shocks correlate with liquidity shocks.

Similarly, Bekaert et al. (2007) presented results for 18 emerging countries using several liquidity measures[17]. Their results proved consistent with previous studies in which liquidity had a strong effect, and was a determinant of expected returns. Goyenko (2006) discovered that illiquidity is a source of systematic risk in the US Bond market, and that excess returns compensate for asset illiquidity risk. I observed considerable agreement within the literature concerning the importance of systematic liquidity, due to its ability to predict future market returns. Current research appears to focus on the US market as being the most liquid global market, leading me to identify a need for further in-depth consideration of the significance of liquidity in both emerging and frontier markets.

2.5.4. DEMAND AND SUPPLY SIDES THEORIES OF LIQUIDITY COMMONALITY

[16] The illiquidity measure used by Amihud (2002) consists of the ratio of the absolute value of a stock daily return over its daily volume, averaged over a period of time.
[17] Bekaert et al. (2007) used the transformation of the proportion of daily zero asset returns averaged over a period of a month, then they applied Amidhud (2002) measure into a panel VAR model.

Prior research provided empirical evidence of the importance of both supply and demand side theories and liquidity co-variation. Demand-side theory is concerned with the financial behaviour of investors, institutional trading, and trading activities. On the other hand, supply-side theory relates to liquidity funding activities carried out by financial intermediaries (Brennan and Subrahmanyam, 1996).

In terms of the demand-side of liquidity commonality, Kamara et al. (2008) documented that an increase in institutional ownership by investment companies and investment advisors promotes increased liquidity. Also, the increase in institutional ownership can explain the variation in liquidity commonality in the US market. Furthermore, Karolyi et al. (2012) examined time-series variation in commonality in liquidity across 40 international stock markets. Their findings suggest commonality in liquidity is highly affected by market shocks, the high presence of international investors, and high correlated trading activities. Koch et al. (2016) identified another important factor causing commonality in liquidity. They argued that the stocks held by mutual funds and large investors move together in the same direction, producing a correlation in trading across stocks, and therefore a co-movement in liquidity.

Other studies have explored supply-side theory, and its major role in contributing to commonality in liquidity. Coughenour and Saad (2004) found support for the supply-side of liquidity commonality sources. They argued that specialist portfolio liquidity[18] co-varies with stock liquidity, causing a co-variation with market liquidity. Chordia et al. (2005) found that the impact of monetary policy shocks and money flows, are significantly and positively related to liquidity commonality across stock and bond markets. Comerton-Forde et al. (2010) also provided evidence, after consulting 11 years of NYSE specialist trading activities, that the balance sheet and income statements of

[18] NYSE specialist liquidity providers firms.

market makers play a significant role in explaining variations in liquidity. Hameed et al. (2010) found that commonality in liquidity increases in the presence of large negative returns shocks, affecting both industry and market stocks. This study has led me to conclude that liquidity responds asymmetrically to changes in asset market value. This view is supported by the majority of theories related to the issue of supply and demand being consistent with the theoretical models, thus indicating that a decrease in liquidity has a greater impact on negative market returns than the increase resulting from positive returns. However, I feel that a variation in supply and demand is unable to identify the contagion between illiquidity and liquidity commonality. This is due to a decline in the value of aggregate assets values providing only indirect evidence of a decreasing supply of liquidity, with a direct impact on all stock within the market.

2.5.5. RESEARCH QUESTIONS REGARDING COMMONALITY IN LIQUIDITY, THE ROLE OF IMPLIED VOLATILITY, AND AVERAGE INDUSTRY AND MARKET LIQUIDITY

Previous studies have examined the probable causes of commonality in liquidity. However, limited attention has been devoted to explaining the role of IV index. Chung and Chuwonganant (2014) were the first to study the impact of fear indices on liquidity co-movements in the US market during the financial crisis of 2007-2008. In addition, other studies examined the impact of VIX on the level of liquidity in the corporate bond market (Bao et al., 2011) on sovereign credit spreads (Pan and Singleton, 2008), credit spreads (Graham and Harvey, 2015), and the currency markets (Brunnermeier et al., 2008).

Most of the research to date has examined the role of IV during periods of market stress. Moreover, studies of the effect of IV as a source of liquidity commonality are specific to the US market and were only related to the financial crisis. Thus, the research questions for the second empirical chapter are:

1- Is the IV index a source of liquidity commonality in stock markets?
2- Is the impact of IV on liquidity co-movements affected by other liquidity determinants and average industry and market liquidity?

The final section of the literature review discusses herding behaviour in financial markets, based on implied volatility indices alongside a number of other determinants that are discussed in depth. A number of studies have examined the relationship between herding and market uncertainty, indicating that an increase in implied volatility is more likely to represent higher levels of market risk, resulting in both rational and irrational investors to form herding patterns in the market.

2.6. HERDING

IV has also been extended to explaining herding behaviour in stock markets. Several definitions of herding behaviour are offered in the literature, and it is often used to describe correlations in trading activities arising from interactions between market participants (Chiang and Zheng, 2010). According to Tan et al. (2008), herding is a behavioural tendency involving following the trading actions of other market participants owing to collective information that might cause prices to deviate from their fundamental value. Herding behaviour in financial markets holds significant interest in the literature for scholars and practitioners. Bikhchandani and Sharma (2000) identified the chief reasons for herding to be false information (informational cascades), and concern for reputation and compensation structures. Herding behaviour is more likely to arise in financial markets during periods of large market movement, while investors rely on their own beliefs and access to private information. I observed that herding behaviour tends to contradict the Efficient Market Hypothesis (EMH), which states that stocks are traded within the market at a fair price, due to herding behaviour being found in stock markets worldwide.

The importance of herding arises from it being used as an explanation of stock return volatility (Christie and Huang, 1995). Consideration of the effect of herding on returns and risk has become a component of asset pricing models, as it drives prices away from their fundamental values (Tan et al., 2008). Indeed, the occurrence of several financial crises has intensified interest in the existence of herding behaviour, since they resulted from extensive herding behaviour among market participants (Chari and Kehoe, 2004). However, several researchers have argued for a lack of evidence to suggest that institutional herding removes prices from fundamental values (Lakonishok et al., 1992; Wermers, 1999; Sias, 2004). As market participants, institutions can be seen to herd if they simultaneously react to fundamental information made public at a specific time. This does not necessarily result in such herding destabilizing stock prices, since these can increase the efficiency of the market by speeding up the adjustment of prices to the new fundamentals. Alternatively, institutions can be found to herd if market participants encounter the same irrational moves in individual investor sentiment that is capable of exerting a stabilizing effect.

Prior research has identified herding behaviour according to different measures. Bikhchandani et al. (1992) explained herding as a cascade using a theoretical model. The basic cascade model is applied when actions, rather than private information, are publicly visible and when there are limits to accessing private information and potential actions. Later, Romer (1992) created a model of trading patterns, showing the quality of other investors' information as potentially leading to a market crash. Furthermore, while Trueman (1994) examined investors' behaviour to evaluate prior analysts' recommendations to capture herding, Maug and Naik (1995) modelled how takeover activity produces public information that will in turn lead to herding. Later, Chang et al. (2000) extended work by Christie and Huang (1995) designed to produce a non-linear regression specification thar would identify herding behaviour by examining the relationship between equity return dispersions (measured by the cross-sectional absolute deviation for returns, CSAD) and market returns. Since then, herding research has mostly employed CSAD to measure herding in stock markets, bonds market and mutual funds. Finally, Hwang and Salmon (2004) have proposed a new approach to measuring herding, based on the cross-sectional dispersion of the factor sensitivity of assets. This measures herding through observation of deviations from beliefs concerning equilibrium expressed in CAPM prices. This separates the adjustment to news concerning fundamentals from herding caused by market sentiment, thus extracting the underlying herding component in observed asset returns.

The evidence of previous studies has led me to conclude that most research focussing on herding behaviour has been based on the models of Christie and Huang (1995) and Chang et al. (2000). In addition, I found that the models most frequently employed in herding behaviour research consist of CSSD and CSAD, which are built on the basis of capital asset pricing model, i.e. the expected returns on a security related to the potential level of risk. In the following sections, we review the literature covering research on herding behaviour according to stock market returns, the IV index and several global factors.

2.6.1. EXAMINATION OF HERDING BEHAVIOUR

Herding behaviour has been examined in a number of studies. One aspect of the literature examines herding in relation to changes of institutional ownership within (or across) periods of time (Lakonishok et al., 1992, Sias, 2004, Avramov et al., 2006, Liao et al., 2011, Huang et al., 2016). The second path started with Christie and Huang (1995) who applied a cross-sectional standard deviation of stock returns to test herding behaviour relative to market consensus. Later, Chang et al. (2000) used the cross-sectional absolute deviation (CSAD) to measure dispersion of returns using a non-linear specification to measure the significance of herding. They both examined the trading behaviour of market participants in several advanced and developing countries, and reported on herding behaviour, especially during periods of extreme market movements.

Further, several studies have been designed to test for herding in developed markets. Chiang and Zheng (2010) provided extensive evidence of several countries that include advanced markets, Latin American markets, and Asian markets. During the period of 1988-2009, they tested for herding in different contexts and found evidence of herding in all countries, except for the US and Asian markets. Moreover, Caparrelli et al. (2004) proposed several modifications to CSAD to study herding in the Italian market. They indicated that herding is present under extreme market conditions, specifically during persistent growth rate and in bull markets. Economou et al. (2011) tested for the existence of herding in Portuguese, Italian, Spanish and Greek markets from 1998 to 2008. They also used the CSAD approach, and found a high degree of co-movement in the dispersion of cross-sectional returns among these markets, indicating the power of herding forces in the region. However, they only found strong evidence of herding in Greek and Italian markets.

Notably, several recent studies using the herding approaches set out by Christie and Huang (1995) and Chang et al. (2000), have focused mostly on emerging markets. Tan et al. (2008), Hsieh et al. (2011), Andersson et al. (2006), and Yao et al. (2014), all found evidence of herding under different market conditions in emerging markets[19] including China. Furthermore, several studies examined the Taiwanese stock market (Lin and

[19] The emerging markets examined in these studies are Bangladesh, India, Indonesia, Malaysia, Pakistan, Philippines, Sri Lanka, and Thailand.

Swanson, 2003, Chen et al., 2012) and found contradictory results. However, an extensive study by Demirer et al. (2010) employed different herding models and reported evidence of herding across all sectors of the Taiwan Stock Exchange. Moreover, Huang et al. (2015) investigated the impact of idiosyncratic volatility on herding in Taiwan. They found that herding behaviour exists in the market, showing distinct patterns in response to idiosyncratic volatility.

More recently, herding research has concentrated on Arab and GCC countries. Balcilar et al. (2017) proposed a dynamic herding approach, with a modification that makes it possible to examine herding styles under different market regimes in the UAE, Saudi Arabia, Kuwait and Qatar. They provided initial evidence of herding in three market regimes (low, high and crash volatility regimes).

My research has led to conclude that previous studies have tended to consider herding behaviour in relation to data samples of between two and four years in length. In addition, they have also favoured the employment of CSAD, i.e. the conventional static herding model. However, I consider that an examination of herding behaviour under different market conditions requires longer data samples, including robustness tests. Furthermore, my analysis has led me to view previous studies of herding as being limited by their use of a constant coefficient model. This results in the estimated coefficients reflecting an average value of a functional relation over a specific sample period, with herding behaviour being assumed to remain unchanged. This aspect is discussed in detail in chapters five and six.

2.6.2. OIL, FEAR INDEX AND STOCK MARKET HERDING

Crude oil is one of the most closely observed commodities in the world, as it is an important driver of economic activity. A considerable number of empirical studies have examined the link between oil prices and economic activity in both developed and emerging nations (Hamilton, 2003, Hammoudeh and Choi, 2006, Kilian, 2008, Chiou and Lee, 2009, Arouri et al., 2011). In addition, some empirical papers have studied the impact of oil shocks' on emerging markets (Basher and Sadorsky, 2006, Park and Ratti, 2008) and in GCC countries (Hammoudeh and Aleisa, 2004, Zarour, 2006, Hammoudeh and Choi, 2006, Akoum et al., 2012). However, limited effort has been directed towards producing empirical models that connect oil price shocks to fluctuations in returns (Balcilar et al., 2017) and herding dynamics. Nevertheless, there has been considerable focus on the effect of oil prices on stock prices. Specifically, Mohanty et al. (2014) and Demirer et al. (2015a) identified significant evidence of the effect of oil on the US economy in general, and on stock prices.

In contrast, alternative channels were proposed in several studies to examine the different factors that might affect herding behaviour. Philippas et al. (2013) incorporated the fear index, while testing for herding in US Real Estate investment trusts (REITs) from 2004 to 2011. They documented that market herding can be associated with the deterioration of investors' sentiment about current and future market conditions, leading to an increase in the fear index. Chiang at al. (2013) also incorporated the US IV index (VIX) to detect dynamic herding behaviour with stock market returns and market returns' experiencing conditional volatility in Pacific-Basin markets. They identified strong evidence that VIX influences herding behaviour in several markets, suggesting that a higher level of VIX tends to increase observed market herding. Economou et al. (2018) investigated herding in the US, UK and German stock markets, also citing the impact of the fear index, from 2004 to 2014. They further reported a significant effect from local and cross-market fear indices on herding.

Concentrating on oil exporting countries, which play a significant role in world energy markets, multiple studies have explored the relationship between oil prices and macroeconomic variables. Arouri and Rault (2012) reported a positive relationship between stock prices and oil prices in GCC countries, with the exception of Saudi Arabia. In contrast, other studies suggest a decline in the influence of crude oil on economic activities (Hammoudeh and Choi, 2006). Akoum et al. (2012) examined co-movements between oil prices and aggregate stock prices in the GCC region, and suggested the market is not strongly linked to oil shocks. I feel these findings indicate that GCC countries can be considered as forming frontier markets, resulting in becoming less integrated into (and influenced by) global economic indicators.

I found that the majority of these studies added a number of factors that enhanced CSAD (i.e. the conventional herding behaviour model) in relation to the herding patterns of stock markets. I consider that their primary contribution consisted of the addition of the fear index, with only a few adding variables such as cross market slipover. I therefore concluded that my own research should focus on firstly, macroeconomic variables and secondly, global factors, i.e. commodity prices and exchange rates.

2.6.3. CROSS-MARKET HERDING

Until recently, herding research focused on factors within a single country, and hence, empirical results suffered from several problems. From an economic perspective, excluding important global factors leads to bias in the estimation process (Kennedy, 2003). The existence of herding behaviour has been documented in several countries, but the results available do not reflect the broader effect of the global spill overs among financial markets (Chiang and Zheng, 2010). I feel that there is now an increased interdependence between financial markets, particularly across global regions and during stressful market conditions. Likewise, Chiang and Zheng (2010) presented evidence of herding in developed countries in the context of the US market. Economou et al. (2018)

tested for cross-market herding in the US, the UK ,and the German markets incorporating their respective IV indices. Cross-market herding eliminates any benefits from global diversification, because it causes inevitable exposure to international risk.

I found that the majority of previous research has tended to focus on herding behaviour in terms of stock market returns. I identified few studies incorporating additional variables, including the fear index and the cross-market effect of these variables. Furthermore, Chiang et al. (2013) was the first to use a time-varying coefficient model, which was a major improvement over constant coefficient models. However, they were also limited in terms of the explanatory factors used previously. The contribution of this study is to incorporate global factors, Oil price and fear indices in time varying coefficient models to explain market herding patterns. Oil price and the OVX have never before been investigated alongside one another in the literature as control variables when exploring herding. Using the Kalman-filter allows us to overcome the issue of structural changes caused by market stress that arises when referring to the average value of relationships over a specified time range. The Kalman-filter involves a transition equation which allows estimation of state variables when actual results are disrupted by noise (Athans, 1974).

Further, Chiang et al. (2007) documented significant correlations across several Asian markets. Since Asian markets' stocks are exposed to systematic risk, the gain from forming diversified portfolios of stocks from these countries declines, which manifests as a high correlation in turbulent markets. Likewise, Chiang and Zheng (2010) showed evidence of herding in Latin America markets in response to the US market. Additional evidence of cross-market herding emerges in GCC markets. For instance, Hammoudeh and Li (2008) focused on the integration of GCC countries toward sudden changes in volatility. They noted that the majority of these countries are sensitive to global change; for example, the 1997 Asian crisis, the collapse in oil prices in 1998, and the Russian crisis in 1998. In contrast, Yu and Hassan (2008) analysed correlations between MENA[20] markets and global markets and reported mixed results. Arabic MENA markets report a lesser response to global market factors. However, as these tend to be frontier countries, I viewed them as being influenced to a lesser extent by the global financial system. Thus, I consider that there is a potential for inaccurate results arising from a study of herding behaviour based on the cross-market effect.

2.6.4. RESEARCH QUESTIONS ON HERDING

Major studies on herding focus on identifying the existence of herding behaviour rather than on investigating its determinants. While the research referenced in the previous section has examined herding behaviour in several regions, the evidence documented is variable. The incorporation of the fear index as a determinant of herding behaviour has been proposed in several studies alongside overall market returns and cross-market factors. However, no attention has been given to other important global factors, such as the oil price index and the OVX.

Since the oil price affects stock market returns (Sadorsky, 1999), it possibly plays a role in forming herding behaviour. The OVX could also influence stock markets and herding behaviour, since it indicates buyers' expectations about future oil prices. In contrast, since the US economy has a significant impact on global markets, its herding determinants might have a cross-market effect.

Moreover, previous studies examined herding based on static models, ignoring the possible dynamic nature of herding behaviour. Chiang et al. (2013) were the first to investigate the dynamic nature of herding behaviour using a Kalman filter-based model.

[20] Middle Eastern and North African countries. This study examined the behaviour of equity markets in Bahrain, Egypt, Israel, Jordan, Kuwait, Morocco, Oman and Saudi Arabia.

They also incorporated the fear index and the US cross-market effect in determining herding behaviour.

Therefore, our research questions for the third and fourth empirical chapters are:

1- Does herding behaviour exist in the G7 countries and several selected oil-exporting countries?
2- Do IV, the oil price, fear indices, and cross-market factors play roles in forming herding patterns in stock markets?
3- Does herding behaviour have a dynamic nature? And how is it identified based on the aforementioned determinants?

2.7. SUMMARY OF RESEARCH QUESTIONS

The literature demonstrates the importance of IV as a determinant of asset risk. The role of IV in financial markets is widely investigated when forecasting the future volatility of market returns. It has also been extended to cover several areas, such as commonality in liquidity and herding behaviour. However, a number of questions have arisen from the literature review, which will be answered in the following four empirical chapters.

The first empirical chapter is the third in this PhD thesis. It models the volatility (kurtosis) of the IV index based on internal volatility, market returns, and several macroeconomic variables using several symmetric and asymmetric GARCH models. Modelling the volatility of the volatility has previously only been investigated in the US market and as such is based on its historical data. Therefore, modelling the effect of macroeconomic variables and stock returns on the volatility of the IV has not been performed yet, and so we have decided to examine this relationship in the context of the UK market.

The second empirical chapter evaluates the role of IV as an influence on commonality in liquidity. We also employ data detailing average industry and market liquidity alongside IV to identify the effect on individual stock liquidity. Research in this area is US specific and has only focused on evidence collected during the financial crises in 2007-2008. In this chapter we aim to expand our investigation to cover more countries, and address the periods during and after the financial crises.

Our third and fourth empirical chapters investigate herding behaviour based on IV, stock market returns, and several global factors. We used static conventional models, and a dynamic based model (Kalman-filter) to establish a link between herding and the conditional variance of variables. Research on the dynamic nature of herding behaviour is limited in the literature, using only the conditional variance of stock market returns. In these chapters we examine the dynamic nature of herding according to the conditional variation in IV, Oil price and fear indices, and several cross-market US factors.

CHAPTER 3: A COMPARATIVE GARCH ANALYSIS OF MACROECONOMIC VARIABLES AND RETURNS ON MODELLING THE KURTOSIS OF FTSE 100 IMPLIED VOLATILITY INDEX

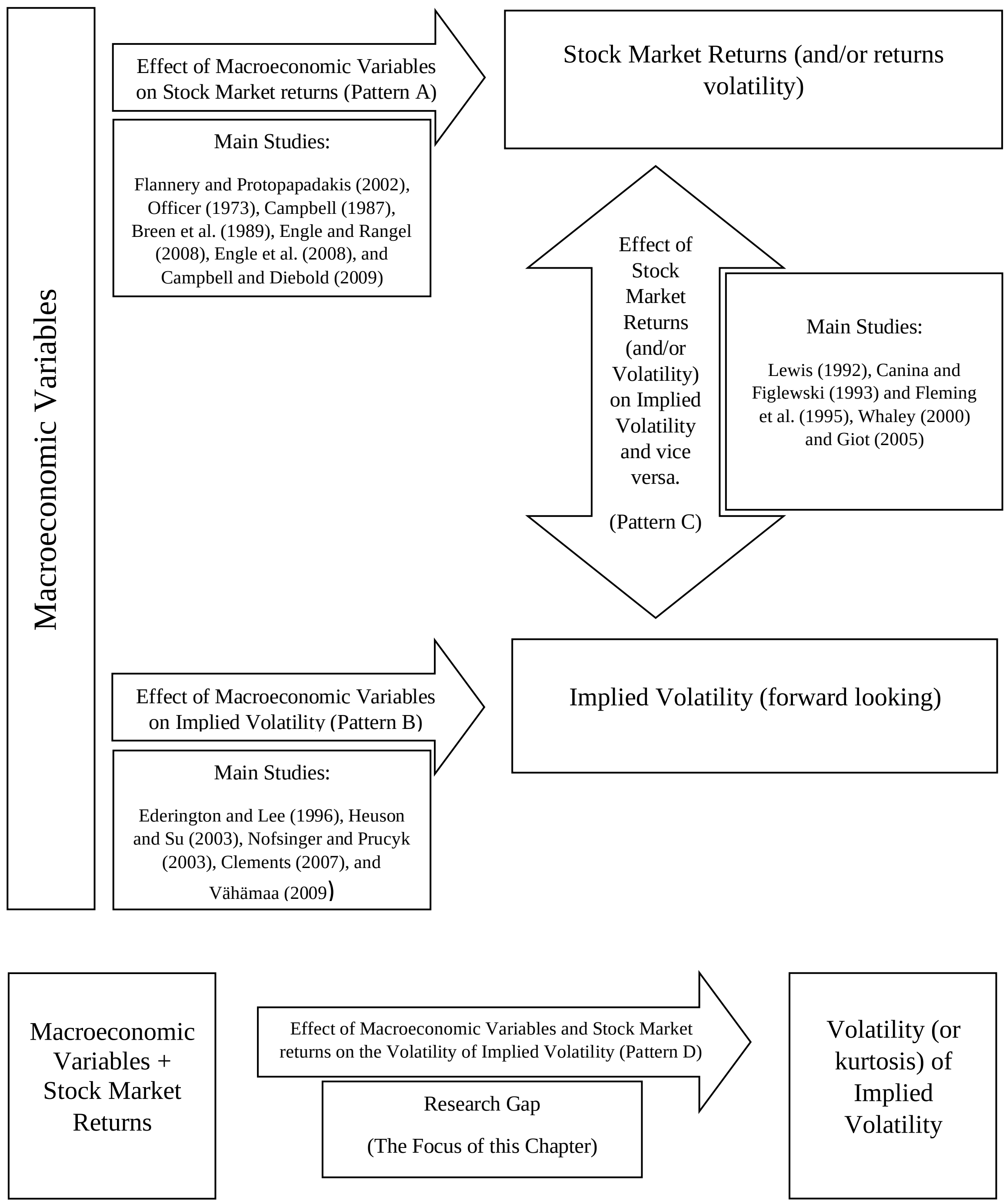
3.1. INTRODUCTION

Within financial markets, it is crucial to engage in volatility estimation and forecasting. This stems from the need to anticipate future fluctuations for risk management and investment purposes. To a certain degree, IV captures the future realized volatility of market returns and market expectations (Canina and Figlewski, 1993). IV indices capture different types of index options, thereby providing information about expected future returns. Modelling and explaining IV indices hold great importance in the literature. Previous studies have tended to explain movements in the IV indices using different methodologies, mainly focusing on realized volatility, or by including exogenous variables, such as market returns or macroeconomic factors. The relationship between IV, market returns, and macroeconomic variables has been investigated from many different perspectives (See figure 3.1). However, what remains unexplored is the relationship between the volatility (or kurtosis) of IV and exogenous variables, such as macroeconomic factors and market returns. We wish to take the 'volatility of IV' literature a step further employing a variety of GARCH systems to model the impact of exogenous variables on the 'volatility of the IV' index. Research in this area is virtually non-existent[21].

[21] Research in the area of volatility of volatility (captured by VVIX and created by CBOE, VVIX stands for volatility of the VIX) has concentrated on the effect of VVIX on tail risk hedging returns (Yang-Ho Park, 2015) and on expected stock returns & variance risk premiums (Wang et al., 2013). It is specific only to the US market.

Figure 3.1: Plot of research patterns between macroeconomic variables, stock market returns, volatility and implied volatility indices.

This figure shows research patterns between macroeconomic variables, stock market returns, volatility and IV. The first pattern studies how macroeconomic variables affect stock market returns (and/or volatility), as denoted by (A). The second pattern relates to measuring the effect of macroeconomic announcements on IV, as denoted by (B). The third research pattern focuses on measuring the effect of stock market returns (and/or volatility) on IV and vice versa, as denoted by (C). The last pattern, which is the focal point of this study, investigates the effect of both macroeconomic variables and stock market returns on the volatility (or kurtosis) of IV.



For the UK market, which is the focal point of this study, no index captures the 'volatility of the IV index'[22].

Identifying those factors that may (or may not) impact on 'the volatility of IV', will help market participants decide if there is a consensus (and which factors affect the formation of consensus) about future movements in the IV index[23] and the market itself. Most importantly, it will also help them to design their risk strategies to hedge tail risk returns[24] or capture the volatility risk premium.[25]

Research pattern (A) in figure 3.1 accounts for the largest body of literature; whereby a vast number of studies analyse the effect of macroeconomic variables (inflation, industrial production, GDP, exchange rate, interest rate, and unemployment rate) on stock market returns. Changes in those variables affect the existence of the available real investment opportunities, firm's cash flows and risk-adjusted discount rates (Flannery and Protopapadakis, 2002). Officer (1973), Campbell (1987), Breen et al. (1989), Engle and Rangel (2008), Campbell and Diebold (2009), and Engle et al. (2013) have explained and related the fluctuations in stock market returns according to several macroeconomic determinants.

The informational content of macroeconomic variables also plays a major role in defining IV movements (research pattern B). Ederington and Lee (1996), Heuson and Su (2003), Nofsinger and Prucyk (2003), Clements (2007), and Vähämaa (2009) indicated that macroeconomic announcements affect IV indices.

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[22] The CBOE in the US has created an index which captures the volatility of the IV index (VIX). This new index is called VVIX. See http://www.cboe.com/products/vix-index-volatility/volatility-on-stock-indexes/the-cboe-vvix-index/vvix-whitepaper

[23] Yang-Ho Park (2015) considers volatility of volatility as a proxy for uncertainty over volatility.

[24] Yang-Ho Park (2015) finds that the volatility of volatility or VVIX has strong predictability for tail risk hedging returns. Knowing which factors affect VVIX will help with hedging tail risk returns.

[25] The CBOE explains in their VVIX Whitepaper (See http://www.cboe.com/products/vix-index-volatility/volatility-on-stock-indexes/the-cboe-vvix-index/vvix-whitepaper) what strategies can be pursued to capture the volatility risk premium among other reasons regarding the usefulness of the VVIX. We elaborate further below. We wish to thank the reviewer for urging us to include reasons that market participants would be interested in modelling the volatility (kurtosis) of IV.

As far as the relationship between IV and market returns is concerned, the research pattern (C) in figure 3.1 shows a two-way relationship is present. The literature focuses on the effect of IV on stock market returns. Empirical evidence indicates there is a negative and asymmetric relationship between market returns and IV (Baillie and DeGennaro, 1990). Previous literature examined the role of IV in capturing the dynamics of market return volatility. For instance Day and Lewis (1992), Canina and Figlewski (1993) and Fleming et al. (1995), reported that IV does not entirely capture the dynamics of market return volatility in the US. On the other hand, the reciprocal relationship, more specifically the role of market returns in estimating IV, has received limited attention in the literature. This is due to the initial logic stating that, since implied volatility is extracted from the stock market, VIX reflects the option prices, with the most recent being constructed based on stocks in the market. Hence, investors consider VIX as a leading indicator for their decisions, due to it reflecting future expectations of the market's movement. However, there is limited number of studies, see Whaley (2000) and Giot (2005) who indicated a negative, significant relationship linking market returns indices such as the S&P100, S&P500 and NASDAQ 100 to IV indices. Different research methodologies were used when analysing these relationships, but the most prominent model for understanding the behaviour of IV is the GARCH model and its extended family.

In this paper, we are modelling the volatility of the log-returns FTSE 100 IV index, 30 days option expiration. Studying the volatility of the IV is tantamount to studying the kurtosis of the IV. A leptokurtic IV distribution means a high presence of outliers, which shows a lack of consensus and an unsettled market. It is important to model the kurtosis of the IV index (IV) because market participants require information about the degree of consensus the market itself has in terms of the future values of the IV index (IV). In other words, the market participants need to be clear about the strength of opinions formed regarding the future values of the IV index (IV). Yang-Ho Park (2015) perceives the volatility of volatility (VVIX) as a proxy for uncertainty over volatility and considers it a tail risk indicator in the US. High volatility of the IV clearly indicates there is no consensus about future movements and the stability of the IV itself. In addition, a high volatility of the IV could also indicate a looming crisis. Yang-Ho Park (2015) shows that in the US, an increase in the uncertainty measure (captured by VVIX or volatility of volatility) increases the current price of tail risk hedging options and lowers subsequent returns over the subsequent period. Our GARCH models will help identify which factors (returns, macroeconomic factors) might potentially play a role in predicting a looming crisis, first as captured by the volatility of the IV index itself (IV)[26]. Also modelling the volatility of the IV index (IV) will enable market participants to obtain a better understanding of the factors that determine the prices of IV index options and futures, as well as the IV itself.

According to the CBOE which have already developed a volatility index of the VIX called VVIX, trading strategies can be formed to assist with risk management[27]. This is achieved by forming a portfolio based on VVIX, which essentially captures the price of a portfolio of VIX options. Selling this VVIX portfolio captures the volatility risk premium. If market participants believe the VVIX is too high or too low at a particular point in time, they have the option to buy or sell the underlying portfolio. Specifically buying a VVIX portfolio returns the difference between realized and expected volatility less the volatility risk premium. Conversely selling a VVIX portfolio returns the difference between expected and realized volatility plus the volatility risk. To the extent that volatility expectations are unbiased, consistently selling a VVIX portfolio captures the volatility risk premium. By modelling the volatility of the IV irrespective of markets, we are able

[26] Even though there are no studies for the 'volatility of the IV index' (IV) in the UK, the CBOE presents evidence that the VIX (IV or fear index) and the VVIX (volatility of the VIX) are significantly correlated when the VIX (IV or fear index) itself gets extreme values. This indicates why it is important to model the volatility of the IV in the UK.
[27] See VVIX Whitechapter. http://www.cboe.com/products/vix-index-volatility/volatility-on-stock-indexes/the-cboe-vvix-index/vvix-whitepaper.

to identify factors that might have an impact on the volatility of the IV, and in this way market participants could gain better control over their risk.

To model the volatility of the IV index, we use several explanatory factors; namely, realized volatility, the FTSE 100 index log-returns (FTSE100R) and macroeconomic variables. This is research pattern (D) in figure 3.1. Using log-returns for both IV and FTSE 100 index yields better results, because IV indices and stock market returns are normally distributed (Bachelier, 2011). The macroeconomic variables that we used were: the UK industrial production (IP), the London 3 month interbank interest rate (LIBOR3M), GBP effective exchange rate (EEX), and unemployment rate (UR)[28].

The macroeconomic variables discussed above were selected in response to the considerable number of available studies into the impact of macroeconomic variables on stock markets. The first comprehensive research was conducted by Malkiel (1970) and Roll and Ross (1980). In theory, the interest rates, money supply, inflation, exchange rates and foreign currency reserves of macroeconomic variables impact on the stock index, leading to a fluctuation in stock market prices. Moreover, the Efficient Market Hypothesis (Malkiel, 1970) indicates that an efficient market fully reflects all the relevant information relating to changes in macroeconomic factors concerning current stock prices. In particular, changes in the Industrial Production index are considered to be indicators reflecting similar changes in overall economic activity. Thus, while an increase in industrial production raises the presumed level of future cash flows and the profitability of firms, the expected relationship between interest rates and stock prices remains negative, since any rise in interest rates increases the cost of investing in equities. Furthermore, this negative relationship is reflected in a reduction in both profits and dividends, as a result of rising interest expenses. In addition, the Discounted Cash Flow

[28] We have excluded the UK inflation rate (CPI) and UK GDP. CPI is excluded because it is highly correlated with the UK unemployment rate and the three months London interbank offered rate (LIBOR3M). GDP is excluded because it is sampled quarterly.

model indicates that rising interest rates can cause an increase in the discount factor of cash flows. Moreover, currency depreciation is expected to have a positive impact on the stock market, because it enables domestic firms to become more competitive. However, any depreciation in the value of a national currency will also increase import costs, while currency depreciation can also damage balance sheets by increasing the value of debt stated in foreign currency, causing a deterioration in the financial positions of firms (Aghion et al., 2001; Bleakley and Cowan, 2002). Finally, the rate of employment illustrates the development and strength of the economy, while unemployment rates form a critical measure of an economy's overall health. Thus, having a greater proportion of the population in employment equates to higher levels of economic output, retail sales, savings and corporate profits. Stocks therefore tend to rise or fall in response to employment reports, as investors digest the potential changes in these areas.

We apply symmetric and asymmetric forms of GARCH models, using different estimation methods. As a benchmark, we first analyse the conditional variance of the IV, and its own volatility. Afterwards, we add the FTSE100R and other macroeconomic variables individually with IV to study their effect on variability. We try different combinations of these variables to produce the best results. We finally use GARCH-MIDAS [(MIDAS): mixed data **s**ampling][29] to capture the impact of the FTSE100R and of other macroeconomic variables, sampled with a monthly frequency, on the daily volatility of IV. GARCH-MIDAS is a univariate model that allows us to include only one variable at a time.

[29]GARCH-MIDAS conditional volatility consists of a short-term component specified by realized volatility of returns, and a long-term component that reflects macroeconomic fluctuations. In many cases, researchers tend to eliminate data from large datasets in order to match frequencies between high and low frequency variables. GARCH-MIDAS allows us to overcome the problem of non-aligned frequencies between high and low frequency variables and gives the estimated results more credibility.

To the best of our knowledge, modelling the effect of macroeconomic variables and returns on the ‘volatility of the IV index’ has not been investigated before[30]. The IV reflects future market fluctuations in the FTSE100R, and enables investors to make better decisions in terms of investment and risk management. We believe these methods of evaluation, adding FTSE100R and other macroeconomic determinants as exogenous variables when analysing IV, could improve variance estimation and out-of-sample estimations of IV. Moreover, using the GARCH-MIDAS approach could either confirm the relationship between our chosen variables, or produce alternative results. The MIDAS approach could also improve our forecasting ability, since it allows us to analyse all the available data sampled at different frequencies. Macroeconomic variables are theoretically great candidates, since they create conditions under which financial assets are priced (Chen et al., 1986).

Our results show that FTSE100R and macroeconomic variables play a significant role in defining the volatility of IV. GARCH(1,1) outperformed other asymmetric models, EGARCH and GJR-GARCH. FTSE100 returns, IP, LIBOR 3M, EER, and UR helped explain IV volatility, and provided significant outputs using both symmetric and asymmetric GARCH models. The GARCH-MIDAS approach also confirmed the ability of macroeconomic variables when estimating IV’s volatility.

The remainder of the paper is organized as follows: Section 2 presents the literature review. Data and the volatility models are explained in sections 3 and 4. Section 5 contains the empirical results and analysis followed by the conclusion.

3.2. LITERATURE REVIEW

[30] Research in the area of ‘volatility of volatility’ is limited, specific to the US and has concentrated on the effect of VVIX on tail risk hedging returns (see Yang-Ho Park, 2015) and its effect on the equity premium (Wang et al., 2013).

The aim of the literature review section is to categorise empirical findings to explain research patterns that are demonstrated in Figure 3.1. Section 2.1 sheds light on studies that adopted GARCH models when modelling stock market returns based on macroeconomic variables, referred to as research pattern A. Section 2.2 presents empirical work on how macroeconomic announcements affect IV, referred to as research pattern B. Section 2.3 discusses the two-way relationship between IV, stock market returns and returns volatility, referred to as research pattern C.

3.2.1. THE USE OF MACROECONOMIC VARIABLES IN GARCH MODELS TO ESTIMATE MARKET RETURNS AND RETURNS VOLATILITY – PATTERN A

With regard to conditional volatility, Flannery and Protopapadakis (2002) analysed the impact of several macroeconomic series on both returns and returns' conditional volatility over the 1980-1996 period using GARCH. Six risk factors showed a significant effect: consumer and producer price indices, balance of trade, unemployment rate, housing starts and monetary aggregate.

Engle and Rangel (2008), observed macroeconomic effects on returns in about 50 countries using spline-GARCH, revealing that it was mainly GDP and interest rates that caused market volatility. Similarly, Engle et al. (2013) used GARCH-MIDAS to investigate the link between returns and macroeconomic determinants. Their core finding pertained to the high accuracy of the model when adding long-term macroeconomic variables. These variables were tested in terms of pseudo out-of-sample predictions across long horizons, and were proven to outperform traditional statistical models. The long components refer to macroeconomic variables (inflation and industrial production) which are sampled over longer periods, for example monthly and quarterly. The short component is represented by daily stock returns. The data set used in this new class model ranged from 1890 to 2010, and it was relevant to the US market.

Several studies also applied different forms of GARCH models to study the effect of macroeconomic factors on returns. Sariannidis et al. (2009) and Cho and Elshahat (2014) used different approaches to GARCH models, stating that GDP, changes in oil prices, 10-year bond returns and exchange rates do influence US aggregate stock market volatility. Pelloni and Polasek (2003), using the VAR-GARCH-M style, showed that unemployment rate has an effect on US, UK and German stock markets. Mangani (2009) also claimed that discount rates (Bank/repo rate) and gold prices affect returns in South Africa, while Oseni and Nwosa (2011) followed an EGARCH model when analysing Nigeria's stock market, showing that GDP does affect returns.

To estimate the volatility of US stock returns, Asgharian et al. (2013) used the 'embedded principle components' into GARCH-MIDAS to combine several macroeconomic factors: interest rate, unemployment rate, term premium, inflation rate, exchange rate, default rate, industrial production and growth rate. GARCH-MIDAS with principal components outperforms other GARCH models and forecasting specifications. Girardin and Joyeux (2013) also used GARCH-MIDAS, and succeeded in relating CPI to China's market volatility. I found that previous studies had identified the importance of macroeconomic indicators on stock market returns. This was due to macroeconomic variables being an essential aspect of stock market performance and thus being employed to assess the general state of an economy.

3.2.2. THE EFFECT OF MACROECONOMIC ANNOUNCEMENTS ON IMPLIED VOLATILITY – PATTERN B

The impact of information releases on market uncertainty as measured by IV were investigated in many studies, suggesting that IV can be predicted by macroeconomic announcements (Heuson and Su, 2003). Ederington and Lee (1996) investigated the impact of scheduled and unscheduled macroeconomic announcements on market uncertainty, as captured by the IV of option prices. They discovered that scheduled announcements lead to lower levels of implied standard deviation (ISD), and vice versa concerning unscheduled announcements.

Nofsinger and Prucyk (2003) examined the reaction of the trading volume on the S&P 500 option index (OEX) following scheduled economic news in 1993 and 1994. From many types of announcements, consumer confidence, new home sales, factory orders and construction spending directly affected option trading volume. Vähämaa (2009) used different methodologies, and a large set of macroeconomic announcements to show there is an effect on the S&P 500 option index (VIX) when using data from 1999 to 2003. Clements (2007) examined the role of monetary policy announcements on the (VIX), and found that meetings of the Federal Open Market committee had a major effect on (VIX). Several studies also investigated the effect of announcements on IV in other countries, and also found a strong link. For example Äijö (2008) used FTSE-100 index options in the UK, and Füss et al. (2011) measured the effect of macroeconomic announcements on the German IV index (VDAX) and (VIX). Also, Shaikh and Padhi (2013) studied the Indian (VIX) and Tanha et al. (2014) undertook research in Australian index options, yielding similar results. I consider that the use of explanatory factors, in addition to macroeconomic pronouncements, identified the movements of implied volatility. I also view the contradictory findings in the literature concerning their effectiveness as primarily arising from differences between the research methodologies employed.

3.2.3. IMPLIED VOLATILITY (FORWARD LOOKING), STOCK MARKET RETURNS AND CONDITIONAL VOLATILITY: A TWO WAY RELATIONSHIP – PATTERN C

A number of studies examined the informational content of IV when forecasting the conditional volatility of market returns. Day and Lewis (1992) model the volatility of the S&P100 index, using the implied content of index options, an exogenous variable using GARCH and EGARCH, to conduct symmetric and asymmetric analysis. Their results showed the information content of the IV and that the conditional volatility from GARCH and EGARCH do not completely characterize conditional stock market volatility, in terms of both in and out-of-sample estimation and forecasts in the US. Canina and Figlewski (1993) and Fleming et al. (1995), also found that IV, represented by the S&P100 index option, produces weak forecasts of subsequent realized volatility. However, unlike previous studies, Christensen and Prabhala (1998) used monthly frequency and a longer volatility time series span of S&P 100 index and its corresponding index option, finding strong evidence that IV can predict future realized volatility.

In contrast, a few studies examined the empirical link between changes in stock returns and how this affects IV indices. Whaley (2000) investigated the Chicago Board Options Market Exchange’s Volatility Indices (VIX and VXN), where the VIX and the VXN, correspond to the S&P 500, and the NASDAQ 100 respectively. Whaley documented a negative and significant relationship between market returns and IV indices. In other words, positive stock returns reduce IV and vice versa. Giot (2005), analysed the relationship between S&P 100 and NASDAQ 100 returns, and their IV indices (VIX and VXN respectively). The VIX shows a significant, asymmetric relationship, and a stronger response to negative market shocks than positive market returns. However, there is a weaker and asymmetric response from VXN to market returns changes. I feel that the literature tends to examine the influence of IV on returns, suggesting that this is extracted from the stock market, particularly in relation to stock market option prices and future expectations of market movements, i.e. investors view such aspects as a risk proxy of any decision making. This was confirmed by the fact that, during my research, I only identified two studies relevant to this strand in the literature.

In the previous sections, we discussed research patterns in the area of market returns, conditional/implied volatilities and macroeconomic variables. Research in the area of the 'volatility of volatility' is limited, specific to the US and focuses on the effect of VVIX on tail risk hedging returns (Yang-Ho Park, 2015) and its effect on equity premiums (Wang et al., 2013)[31]. Having identified relations between macroeconomic variables, implied/conditional volatilities and returns, we are now venturing into a new area, namely the effect of macroeconomic variables and market returns on the volatility (or kurtosis) of IV, which is worthy of exploration given the absence of literature about the UK market[32].

3.3. DATA AND METHODOLOGY

The data in this study is derived from two main sources. The log-returns of the FTSE100 IV index, 30 days expiration, (IV), and observations obtained from FTSE Russell, covering a period from 4/1/2000 to 31/12/2015. We used the following samples in the analysis: full sample (From 1/4/2000 to 31/12/2015), subsample 1 (From 4/1/2000 to 8/8/2007), and subsample 2 (From 9/8/2007 to 31/12/2015). The first subsample is the period from the start of the IV indices until the start of the financial crisis in 2007, where

[31] We do not include this research pattern in figure 3.1 because research is quite limited and not of direct interest to our study, even though it is useful for motivation purposes. Figure 3.1 is a graphical representation of relationships between macroeconomic variables, returns, conditional/implied volatilities, and volatility of volatility. The effect of 'volatility of volatility' on hedging and the equity premium is a different research area. Introducing a new separate research pattern in figure 3.1 and in the literature review would unnecessarily increase the size of the literature review without contributing value to the study itself.

[32] To the best of our knowledge, there is no other study that investigates the effect of macroeconomic variables and returns on volatility of volatility for the UK or any other country.

the sub-prime mortgage bubble was acknowledged for the first time and the consequences first became obvious. The second subsample represents the period after the financial crisis to the end of 2015. Splitting the sample into before/after the financial crisis that started in August 2007, will allow us to examine whether the financial crisis had a detrimental effect on the ability of the financial models to predict volatility.

Regarding IV, there are several IV indices with different interpolated annualised IV dates on the underlying FTSE100 index, namely 30, 60, 90, 180 and 360 days. We chose the 30 days expiration index, since it has the highest volume of trades. We used daily and monthly data regarding IV in the analysis, due to the requirements of GARCH models in terms of frequencies. The IV index is calculated from out-of-the money options prices using the following formula:

$$\sigma^2{}_{IV} = \frac{2}{T}\left(1 + log\frac{F}{K_*} - \frac{F}{K_*} + e^{-rT}\int_0^{K_*}\frac{P(K)}{K^2}dK + e^{rt}\int_{K_*}^{\infty}\frac{C(K)}{K^2}dK\right), \qquad (3.1)$$

Where $\sigma^2{}_{IV}$, is the FTSE 100 IV index (IV), and *r* is the free risk interest rate. K_* is the strike immediately below F, the forward price, and *P(K)* and *C(K)* are the put and call prices at strike K.

Monthly observations relating to the FTSE100 index log-returns (FTSE100R), and the first differences of the macroeconomic variables, namely: industrial production (IP), London interbank 3 months offered rate (LIBOR3M), effective exchange rate (EEXR), and unemployment rate (UR), were collected from Datastream over the same period.

3.3.1. VOLATILITY MODELS

Modelling time series represents a big challenge due to statistical irregularities, such as non-stationarity and non-normal distribution. Classical linear regression models (CLRM) follow several assumptions, mainly the homoscedasticity assumption, in which the variance of error terms is constant over time (Francq and Zakoian, 2011). CLRM also assumes that the volatility forecast is equal to current estimates, since the expected value of the error terms is the same at any given time when squared (Engle, 2001). These assumptions are unrealistic, since the volatility of financial assets changes over time. Volatility can be exceptionally high or low over different periods (Alexander, 2008). Data in which the variances of the error terms are unequal (i.e. the error terms may reasonably be expected to be larger for some points or ranges of data than for others) are said to suffer from heteroskedasticity. The standard warning consists of the regression coefficients for an ordinary least squares regression remaining unbiased in the presence of heteroskedasticity, while standard errors and confidence intervals estimated by conventional procedures will be too narrow, thus giving a false sense of precision. Both ARCH and GARCH models treat heteroskedasticity as a variance to be modelled, rather than a problem in need of correction. This results in firstly, the deficiencies of least three squares being corrected and secondly, a prediction being computed for the variance of each error term. This aspect is of considerable interest in relation to finance, resulting in the choice of GARCH models for this study, due to the employment of economic, stationary and clustered data. Engle (1982) introduced an autoregressive conditional heteroscedasticity model (ARCH) model and its extension, the generalized ARCH (GARCH) by Bollerslev (1986), to capture the volatility of the heteroscedastic data. There are three main GARCH family assumptions: (1) stationarity; (2) conditional heteroscedasticity; and (3) volatility clustering. (1) A stationary process assumes that the mean, variance, autocorrelations and autocovariance structure of the time series do not change over time. (2) Heteroscedasticity implies that variances in the error terms of a model are not constant over different sample observations. (3) Volatility clustering denotes the tendency towards rapid change in the prices within financial time series to cluster together, resulting in the persistence of this magnitude of price variation. Thus, large price changes tend to be followed by large changes, and vice versa.

In our comparative analysis, we will apply several specifications and forms of GARCH models to estimate the conditional variance of IV, based on both daily and monthly frequencies.

3.3.1.1. SYMMETRIC GARCH MODELS

3.3.1.1.1. GARCH MODELS

The classic GARCH(1,1) model uses its own lags to generate conditional variance, and its specification is given below:

$$r_t = \mu + \epsilon_t, \tag{3.2}$$

$$\sigma_{t\ IV}^2 = \omega + \alpha_1 \epsilon^2{}_{t-1} + \beta_1 \sigma_{t\ IV_{t-1}}^2, \tag{3.3}$$

The mean equation (3.2) is specified and written as a function of a constant and an error term, where $\epsilon_t = \sigma_t\, z_t$, and z_t describes standardized residual returns. In the conditional variance equations, $\sigma_{t\ IV}^2$ represents conditional variance, and ω is the constant GARCH term. The ARCH error term in equation (3.3), $\epsilon^2{}_{t-1}$ captures volatility news for the last period, and the GARCH term, $\sigma_{t\ IV_{t-1}}^2$ is the forecasted variance for the last period.

To add exogenous variables, regressors, Xs, in the variance equation, equation number (3.3) is extended to:

$$\sigma^2_{t\,IV} = \omega + \sum_{j=1}^{1} \beta_j \sigma^2_{t\,IV\,t-1} + \sum_{i=1}^{1} \alpha_j \epsilon^2{}_{t-i} + Z_t^{'} \pi \qquad (3.4)$$

The parameter constraints $\omega > 0$, $\alpha, \beta \geq 0$, and $\alpha + \beta \leq 1$ are proposed by Bollerslev (1986) to ensure conditional variance is positive and finite. However, many authors, mainly Nelson and Cao (1992) and Alexander (2008), have reported several violations of these constraints, without indications of any statistical or sampling errors. They state that it is a practitioner's choice to impose any of these parameters as constraints (Alexander, 2008).

3.3.1.2. ASYMMETRIC GARCH MODELS

Asymmetric volatility suggests there are higher volatility levels in the downswings of the market than in the upswings. Symmetric forms of GARCH models cannot deal with asymmetries. It is important that conditional variance captures this asymmetry, as a means to explain the behaviour of market returns and its leveraging effect[33]. We will use two asymmetric GARCH models, the exponential GARCH (EGARCH), and the threshold GARCH (GJR-GARCH) models.

3.3.1.2.1. EGARCH

The exponential GARCH model was developed by Nelson (1991) to detect the presence of shocks, while the log function imposes positive results upon the conditional variance

[33] The leverage effect outlines the negative relationship between volatility and the market value of assets. In addition, market volatility experiences a greater increase than market positive shocks of equal size during negative shocks and market turmoil (Black, 1976). The hypothesis of the leverage effect consists of the following: a fall in stock price results in a decrease in equity, while the debt is constant. The consequent higher debt-to-equity ratio renders the firm riskier and more sensitive to negative shocks (Christie, 1982). The increased risk associated with a higher debt-to-equity ratio is consistent with corporate finance theories, i.e. that a company's default risk increases with its debt-to-equity ratio (Black, 1976; Ogden et al., 2003)

parameter. Since EGARCH attaches more importance to negative shocks than positives ones, it will provide a different interpretation of IV conditional volatility. IV displayed exceptional spikes especially in 2002, and between 2007 and 2008. Therefore, depending only on symmetric GARCH models can provide ambiguous results. The model specification is:

$$\log\left(\sigma_{t\,IV}^{2}\right) = \omega + \sum_{j=1}^{q} \beta_j \log\left({\sigma^2}_{t-j}\right) + \sum_{i=1}^{p} \alpha_i \left(\left| \frac{\epsilon_{t-i}}{\sigma_{t-i}^{2}} \right| - E\left| \frac{\epsilon_{t-i}}{\sigma_{t-i}^{2}} \right| \right) + \sum_{k=1}^{r} \gamma_k \left| \frac{\epsilon_{t-k}}{\sigma_{t-k}^{2}} \right| \tag{3.5}$$

The leverage effect in the model is exponential, as implied by the log function of the conditional variance, and therefore it is always positive. γ represents the asymmetric response parameter, and the impact is asymmetric when $\gamma_i \neq 0$. The positive effect, good news, has an impact of α_i, and the negative effect, bad news, has an impact of α_i and γ_k.

3.3.1.2.2. GJR-GARCH

Since we are using the log-returns data for IV, using the log function when estimating conditional variance can affect the significance level of the estimated parameters. Hence, we are using different forms of asymmetric models. GJR-GARCH, or the threshold GARCH, was presented by Zakoian (1994) and Glosten et al. (1993). GJR-GARCH is a model that introduces a threshold effect into volatility by specifying that conditional variance is a function of the positive and negative components of the residuals (Francq and Zakoian, 2011). GJR-GARCH conditional variance can be estimated with the following formula:

$$\sigma_{t\,IV}^{2} = \omega + \sum_{j=1}^{q} \beta_j {\sigma^2}_{t-j} + \sum_{i=1}^{p} \alpha_j {\epsilon^2}_{t-i} + \sum_{k=1}^{r} \gamma_k {\epsilon^2}_{t-k}\, I_{t-k} \tag{3.6}$$

Where I_t is a function, that is I_t=1 if ϵ_t < 0, and 0 otherwise.

3.3.1.3. THE GARCH-MIDAS MODEL

Engle et al. (2013) developed a new GARCH model with mixed data sampling GARCH-MIDAS, which decomposes short- and long run components. The model was used to measure the effect of the low frequency, long term component specified by macroeconomic variables, on a high frequency, short term component, the market returns. GARCH-MIDAS model is described by equations (3.7) to (3.11):

$$r_{i,t} = \mu + \sqrt{\tau_t g_{IV_{i,t}} \varepsilon_{i,t}}, \tag{3.7}$$

The $r_{i,t}$ is the daily returns i, and monthly t observations. The conditional variance is represented by the short-run component $g_{i,t}$, and the long-run component τ_t. The conditional variance of the short-term component, follows a daily GARCH(1,1) process, which is:

$$g_{IV_{i,t}} = (1 - \alpha - \beta) + \alpha \frac{(r_{i-1,t} - \mu)^2}{\tau_t} + \beta g_{IV_{i-1,t}}, \tag{3.8}$$

While the conditional variance of the long-term component is determined by the realized volatility of returns and macroeconomic variables, and implemented in the MIDAS equation:

$$\tau_t = m + \theta \sum_{k=1}^{K} \varphi_k(\omega) V_{t-k}, \tag{3.9}$$

The next equation represents the average of the monthly realized volatility of an exogenous variable:

$$V_t = \frac{1}{N} \sum_{i=1}^{N} x_{i,t}, \tag{3.10}$$

The macroeconomic variables, x_i are fixed value for i= 1, …, N, and long-term volatility is captured by beta polynomials for $V_{t-1}, V_{t-2}, \dots, V_{t-k}$:

$$\varphi_k(\omega) \propto \left(1 - \frac{k}{K}\right)^{c1-1} \left(\frac{k}{K}\right)^{c2-1}. \tag{3.11}$$

3.3.2. MODEL SPECIFICATIONS

We specified four different types of equations when estimating the IV using daily and monthly data, based on realized volatility, the FTSE100R$_t$, and the following macroeconomic variables: IP$_t$, LIBOR3M$_t$, EEX$_t$, and UR$_t$. Below we discuss our model's specifications:

1- For our benchmark case, we use only IV, into univariate, symmetric and asymmetric GARCH models (see equations (3.3), (3.5), and (3.6)). The reason we use different frequencies is because we would like to investigate whether different frequencies from the same index produce different results.
2- The second stage involves introducing FTSE 100$_t$, using multivariate GARCH models with equal data frequencies, when estimating IV, described by equations (3.4), (5), and (6). This will allow us to determine whether FTSE 100$_t$ alone can improve the estimation results as an exogenous determinant.

3- Thirdly, we add the first difference in macroeconomic variables at time *t* to identify their effect on IV, along with FTSE 100_t, also using equations (3.4), (3.5), and (3.6). Our purpose is to find an optimal combination of these variables to produce the best results.

4- Lastly, GARCH-MIDAS will be applied to determine whether mixed data frequency, daily and monthly, will produce different results in terms of the significance of the estimation parameters. We will use IV, with FTSE 100_t and other macroeconomic factors, one at a time as an exogenous variable, using equations (3.7) to (3.11).

3.4. RESULTS AND ANALYSIS

3.4.1. DESCRIPTIVE ANALYSIS

3.4.1.1. CORRELATION MATRIX ANALYSIS

Table 3.1 shows correlations between monthly observations of the independent variables, which are the FTSE100 index log-returns, and macroeconomic variables.

Based on Table 3.1, LIBOR3M is positively correlated (0.430) with EER and negatively correlated with UR (-0.346) at 1%. EER on the other hand, has a negative (-0.170) correlation with UR at 5%. Furthermore, IP is positively correlated with LIBOR30 (0.194) at 1%, and negatively correlated (0.123) with EER at 10%. To test for possible multicollinearity among the independent variables, we conducted variance inflation factor tests (VIF)[34], (see John et al., 1996). Table 3.1 shows the VIF values between the independent variables, which indicate no multicollinearity. VIF results are below 4, which

[34] The (VIF), an indicator of multicollinearity, is calculated as: VIF= 1/ (1-R^2). It is the reciprocal of tolerance. R^2 is obtained by regressing each independent variable on the remaining independent variables using OLS. This is given by $X_1 = \alpha_2 X_2 + \alpha_3 X_3 + \ldots + \alpha_k X_k + e$.

Table 3.1: Correlation matrix: January 2000 to December 2015

The table below shows correlations between monthly observations of FTSE100 index log-returns (FTSE100R), and the first difference of macroeconomic variables. The macroeconomic variables are: industrial production measure (IP), London 3 months interbank rate (LIBOR3M), UK GBP sterling effective exchange rate (EER) and Unemployment rate (UR). It also displays the variance inflation factor (VIF), an indicator of multicollinearity. As a rule of thumb, and since none of the chosen independent variables exceed the value of 5, there is no evidence of multicollinearity. The (VIF) is calculated as: VIF= 1/ (1-R^2). It is the reciprocal of tolerance. R^2 is obtained by regressing each independent variable on the remaining independent variables using OLS. This is given by $X_1 = \alpha_2 X_2 + \alpha_3 X_3 + \ldots + \alpha_k X_k + e$.

Variables	FTSE100R	IP	LIBOR 3M	EER	UR	VIF
FTSE100 - Returns	1.000					1.038
IP	0.106	1.000				1.061
LIBOR 3M	-0.076	0.194***	1.000			1.391
EER	-0.072	0.123*	0.430***	1.000		1.233
UR	-0.088	-0.134*	-0.346***	-0.170**	1.000	1.158

Notes: ***Correlation is significant at 0.01 level (two-tailed); **Correlation is significant at 0.05 level (two-tailed); *Correlation is significant at 0.10 level (two-tailed).

is the cut off value recommended by several researchers (e.g., Rogerson (2001), and Pan and Jackson (2008)). Lastly, FTSE 100_t has no significant correlation with any other exogenous, macroeconomic variables in the UK market. This result contradicts some of the previous empirical research findings, for example Olawale et al. (2014). A possible explanation for this could be that we used the first difference of the macroeconomic factors and the log-returns of FTSE 100_t, while other studies applied levels for all factors.

3.4.1.2. DESCRIPTIVE STATISTICS

Table 3.2 depicts descriptive statistics. Looking at the results of IV, daily and monthly frequency, both have similar means but different maximum, minimum standard deviations. This is because the monthly data captures only the last day (value) of a month, and does not consider any values in-between the ends of consecutive months. The reason that the means and medians of our macroeconomic variables are close to zero is because we present initial differences.

Table 3.2: Descriptive statistics of the variables

This table shows summary statistics for the log-returns of FTSE100 implied volatility index, 30 days expiration (IV) based on the level of daily and monthly frequency from 4/1/2000 to 31/12/2015, the FTSE 100 log-returns index (FTSE100R) industrial production measure (IP), London 3 months interbank rate (LIBOR3M), UK GBP sterling effective exchange rate (EER) and Unemployment rate (UR).

Variables	Daily IV	Monthly IV	FTSE100R	IP	LIBOR 3M	EER	UR
Observations	4014	191	191	191	191	191	191
Mean	0.000	0.000	-0.001	-0.076	-0.003	-0.049	-0.008
Median	-0.004	-0.046	0.006	-0.100	0.000	0.006	0.000
Maximum	0.540	0.812	0.091	2.600	0.000	3.543	0.500
Minimum	-0.738	-0.677	-0.243	-5.300	-0.499	-5.816	-0.200
Std. Dev.	0.067	0.248	0.047	1.022	0.036	1.296	0.081
Skewness	0.356	0.472	-1.298	-0.935	-13.747	-0.768	1.670
Kurtosis	10.488	4.332	6.602	7.294	189.997	5.654	11.057
Jarque-Bera	9462.478	21.199	156.868	175.540	285790.900	75.242	608.523
Probability	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Figure 3.2 presents the plots of all the variables. Looking at IV log-returns and FTSE100R log-returns charts, we observe that significant spikes in FTSE100 returns coincide with high IV. These spikes represent incidents where IV increased and was accompanied by a decrease in FTSE 100 returns between 2001 and 2002, and in 2008; mainly during the global recessions in 2002 and 2008. These recessions were attributed to negative economic trends in the UK economy. IV also exhibits high volatility between 2010 and 2011, and in 2015, due to market expectations, but does not coincide with high spikes in the FTSE00R chart. The industrial production plot shows the negative effect of the recession in 2002 and also the negative shock effect in 2007, that appeared with a delay after approximately two years, in 2009. Moreover, in 2012 IP turned negative, due to spending cuts to reduce the government's long-term budgetary deficit. The LIBOR 3M, effective exchange rate, and unemployment rate were affected mainly by the 2008 recession. LIBOR 3M was high at the beginning of 2007, since many financial institutions

were in critical situation. This increased the perceived risk of lending among banks causing inadequate liquidity in the interbank market, which subsequently exerted pressure on the economy. In 2009, LIBOR 3M decreased considerably, since various central banks provided liquidity for financial institutions worldwide. Regarding the effective exchange rate, the largest decrease was in 2009. This fall can be attributed to problems in equities and the banking sector in the UK. Similarly, the unemployment rate showed a considerable spike in 2009 arising from the effect of the financial crisis.

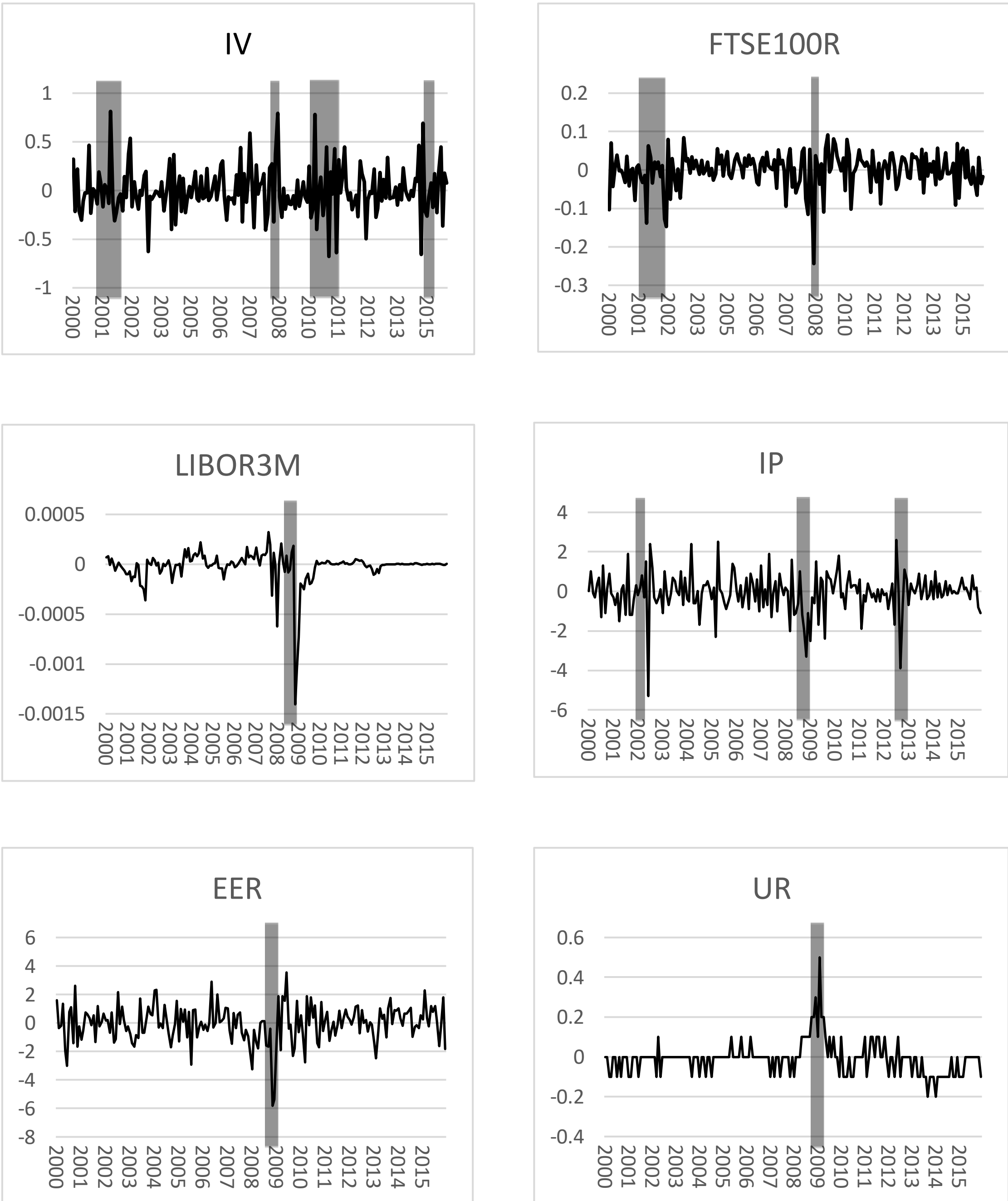
3.4.2. GARCH MODELS PARAMETERS EXPLANATION AND OPTIMAL CHOICE

Tables 3.3, 3.4, and 3.5 present detailed, daily and monthly data, and the results of IV, when regressed on FTSE 100_t returns and macroeconomic variables. GARCH parameter coefficients show a reaction to market shocks. These parameters, according to Alexander (2008), are I) the mean of the returns (μ), II) the GARCH constant parameter (ω), which measures volatility's reaction, III) The first ARCH error parameter (α_1), which measures the reaction of conditional volatility to market shocks (the higher the value of α, the more sensitive volatility is to market events), IV) the leverage effect (Υ_1), and V) the first GARCH parameter, the conditional variance (β_1), which measures the persistence of the conditional volatility regardless of the market volatility. When β is large (above 0.9), then volatility will persist for a long time after a market shock. The sum of α and β define the rate of convergence of the conditional volatility to the long term average volatility. When the sum of α and β is large, and closer to 1.00, the term structure of the GARCH model is relatively flat, and conditional volatility takes longer to converge to create average volatility.

The tables also present the parameters of independent variables, the FTSE 100_t log-

Figure 3.2: Plot of log-returns of FTSE100 implied volatility index, FTSE100 log-returns, and the first difference of macroeconomic variables.

This figure shows monthly data of FTSE100 implied volatility index log-returns, with 30 days expiration (IV), FTSE 100 log-returns (FTSE100R), and the first difference of the macroeconomic variables from January 2000, to December 2015. The macroeconomic variables are the Industrial Production (IP), London 3 months Inter Bank Rate (LIBOR 3M), Effective Exchange Rate (EER), and Unemployment Rate (UR). Shaded areas in the charts show the most volatile periods for each variable.



returns and macroeconomic variables. To decide which the best model is, we take into consideration the significance level of α and β, the Akaike Information Criterion (AIC), the Bayesian information criteria (BIC) and the log-likelihood function (LLF). To determine the best model, we use AIC and BIC, and of course decide which independent variables fit best the sample data. In case they provide contradictory information, we choose one with a higher LLF. The tables show five equations of IV, FTSE 100_t log-returns, and macroeconomic variables at time *t* for each of the GARCH models. The first two equations in each table show the estimation parameters for IV, based only on its realized volatility without the addition of independent variables. The last three equations in each table present the best fit models, and the best combination of variables in the variance equation after adding our independent variables. Since there are 33 possible combinations when adding independent variables, we included only the three best combinations respectively.

We used the classic order of ARCH term (q)=1, and the autoregressive order of GARCH term (p)=1, for GARCH, EGARCH and GJR-GARCH estimations. Even though the lag structure suggests an order of 3 for the GARCH term, it is not certain that it will always produce better results. Hansen and Lunde (2005) found that a GARCH(1,1) model provides better estimations and forecasts. We also tested all possible lag structures, and the classic order for GARCH term (p)=1 produces the best results in our analysis.

3.4.3. GARCH MODELS ESTIMATION RESULTS

Table 3.3 shows the estimation results of GARCH(1,1). Considering the full sample, and except for IV, with daily frequency, μ is significant in all equations. When μ is positive the higher the value of IV, the higher the variance of IV is. Similarly, ω is positive and significant in all equations, indicating sensitive reactions to volatility, which also determines the change in the long-term volatility. The analysis of IV with monthly frequency, equation (3.2), based on realized volatility, produces the highest ω value due to high market volatility. This happens because IV is monthly based and it does not consider values in between like daily data, which can reduce the effect of market shocks through a gradual shift in returns. However, equations (3.3), (3.4) and (3.5) in table 3.3, are also based on monthly data, but adding independent variables reduced sensitivity of ω to market volatility, since there are now several determinant and explanatory factors. Moreover, α is also positive and significant in all cases, confirming the existence of ARCH effects, the clustering patterns in the series. Since α is higher than 0.10 in all equations, except for subsample 1, this indicates a highly volatile and nervous market. Regarding subsample 1, α is lower than 0.10 in all equations, indicating a period of low volatility. Also, the GARCH persistence parameter β is significant in most equations, also lower than 0.90, specifying that volatility relatively quickly converges with average volatility. The lower the β, the faster convergence is achieved in the direction of average volatility. The sum of α and β becomes lower when adding independent variables, indicating that conditional volatility does not take a longer time to return to the average level of volatility. Adding the independent variables assisted with making conditional volatility more reactive to market shocks, and improved the significance of the estimation parameters. When evaluating models based on BIC, AIC, and LLF, equation (3.3) surpasses all other equations combining FTSE 100_t, $LIBOR3M_t$, and EEX_t. This means that adding market returns combined with macroeconomic variables enhances the estimation process for the full sample.

Results for subsamples 1 and 2 are almost similar to those in the full sample in terms of the significance of parameters, and the convergence rate of conditional volatility.

Table 3.3: GARCH(1,1) estimation results with Normal distribution (Gaussian)

This table presents the estimation results of GARCH(1,1) given below:

Mean equation: $$r_t = \mu + \epsilon_t, \qquad (3.2)$$

Variance equation: $$\sigma_{t\ IV_t}^2 = \omega + \sum_{j=1}^{1} \beta_j \sigma_{t\ IV_{t-1}}^2 + \sum_{i=1}^{1} \alpha_j \epsilon^2_{t-i} + Z_t' \pi \qquad (3.4)$$

This estimation is based on FTSE100 implied volatility index log-returns, 30 days expiration, using daily and monthly frequency of IV. In the variance equation, we have the FTSE 100 log-returns ($FTSE100R_t$), and our macroeconomic variables namely: Industrial Production (IP_t), London 3 months Inter Bank Rate ($LIBOR3M_t$), Effective Exchange Rate (EER_t), and Unemployment Rate (UR_t). The Full sample is from 4/1/2000 to 31/12/2015, subsample 1 is from 4/1/2000 to 8/8/2007, and subsample 2 is form 9/8/2007 to 31/12//2015. The parameters estimated are: the mean of the returns (μ), the first order of the GARCH constant parameters (ω), the first order of ARCH error term (α), and the first order of the GARCH term, (β). LLF is the value of the maximized likelihood function, BIC is the Bayesian information criterion, and AIC is the Akaike information criterion. IV index data is obtained from FTSE Russell, macroeconomic variables are obtained from Datastream. *** indicate significance at 1%, ** indicate significance at 5%, * indicate significance at 10%. The numbers in parentheses are t-statistics.

N	Samples	Variable in mean Equation	Variables in Variance Equation	*Mean Equation*	*Variance Equation*								α + β	LLF	BIC	AIC
				(μ)	(ω)	(α)	(β)	FTSE 100R	IP	LIBOR 3M	EEX	UR				
1	*Full sample*	Daily IV	-	-0.001	0.000***	0.100***	0.827***	-	-	-	-	-	0.927	5368.200	-2.666	-2.673
				(-0.576)	(9.970)	(13.254)	(63.262)									
2		Monthly IV	-	18.149***	26.944***	0.752***	-0.071***	-	-	-	-	-	0.681	-649.217	6.872	6.804
				(35.504)	(6.361)	(6.828)	(-0.786)									
3		Monthly IV	FTSE 100R, LIBOR3M, EER	-0.056***	0.020***	0.139**	0.511***	-0.455***	-	-29.694	-0.008***	-	0.650	16.083	0.024	-0.095
				(-3.459)	(4.149)	(1.964)	(7.922)	(-4.882)		(-1.745)	(-4.532)					
4		Monthly IV	FTSE 100R, LIBOR3M, EER, UR	-0.054***	0.023***	0.154**	0.459***	-0.443***	-	-17.009	-0.008***	0.033***	0.613	16.982	0.042	-0.094
				(-3.947)	-(4.827)	(2.228)	(5.518)	(-5.617)		(-0.720)	(-2.621)	(0.772)				
5		Monthly IV	FTSE 100R, EER	-0.056***	0.022***	0.105*	0.509***	-0.338***	-	-	-0.007***	-	0.614	14.636	0.012	-0.090
				(-3.068)	(3.758)	(1.725)	(-6.554)	(-5.245)			(-6.053)					

(Continued)

N	*Samples*	*Variable in mean Equation*	*Variables in Variance Equation*	*Mean Equation*	*Variance Equation*									*α +β*	LLF	BIC	AIC
				(*μ*)	(*ω*)	(*α*)	(*β*)	FTSE 100R	IP	LIBOR 3M	EEX	UR					
6		Daily IV	-	-0.001	0.000***	0.097***	0.817***	-	-	-	-	-		0.914	2850.493	-2.967	-2.979
				(0.658)	(4.636)	(7.177)	(29.188)										
7		Monthly IV	-	-0.007	0.001	-0.097***	1.069***	-	-	-	-	-		0.972	17.912	-0.198	-0.309
				(0.273)	(0.827)	(4.210)	(3321.267)										
8	*Sub1*	Monthly IV	FTSE 100R, IP, UR	-0.057***	0.022***	-0.075	0.574***	-0.467***	-0.006	-	-	-0.160		0.499	21.969	-0.138	-0.333
				(2.705)	(3.122)	(5.361)	(5.740)	(3.228)	(0.925)			(1.224)					
9		Monthly IV	FTSE 100R, LIBOR3M, UR	-0.057***	0.019***	-0.070***	0.635***	-0.516*	-	-7.207	-	-0.132		0.564	23.009	-0.161	-0.356
				(2.634)	(3.265)	(4.791)	(9.345)	(2.826)		(0.244)		(0.980)					
10		Monthly IV	FTSE 100R, EER, UR	-0.088***	0.023***	-0.077***	0.601***	-0.630***	-	-	-0.006	-0.171		0.524	23.162	-0.165	-0.359
				(3.897)	(3.060)	(3.713)	(5.764)	(4.489)			(1.242)	(1.282)					

(Continued)

N	Samples	Variable in mean Equation	Variables in Variance Equation	Mean Equation (μ)	Variance Equation (ω)	(α)	(β)	FTSE 100R	IP	LIBOR 3M	EEX	UR	$\alpha+\beta$	LLF	BIC	AIC
11		Daily IV	-	0.000	0.001***	0.118***	0.745***	-	-	-	-	-	0.862	2549.277	-2.410	-2.421
				(0.078)	(7.792)	(10.228)	(28.178)									
12		Monthly IV	-	-0.008	0.036**	0.504**	0.068	-	-	-	-	-	0.572	-6.207	0.306	0.202
				(0.383)	(2.018)	(2.241)	(0.278)									
13	*Sub2*	Monthly IV	FTSE 100R, IP, LIBOR3M, EER	-0.011	0.033***	0.484**	0.034***	-0.287*	0.010	-35.291	0.002	-	0.519	4.831	0.270	0.063
				(0.530)	(3.711)	(2.256)	(4.975)	(1.923)	(1.563)	(0.488)	(0.325)					
14		Monthly IV	FTSE 100R, IP, LIBOR3M, UR	0.020	0.035***	0.328**	0.210***	-0.081	0.014***	69.180***	-	0.146**	0.538	4.444	0.278	0.070
				(0.875)	(2.745)	(2.111)	(3.917)	(0.782)	(3.116)	(3.153)		(2.006)				

(Continued)

However, the combination of independent variables differs in terms of the variance equations. For subsample 1, equation 8, the combination of $FTSE100R_t$, IP_t, and UR_t generates the best fit; while in equation 13, the group of $FTSE100R_t$, IP_t, $LIBOR3M_t$, and UR_t provides the best results for subsample 2. Furthermore, only two combinations of independent variables showed significant values of α and β, due to the highly volatile market, since subsample 2 includes data drawn from the beginning of financial crisis in 2007.

Some of the exogenous coefficients in the variance equations are negative, which could be a consequence of sampling error and misspecification. With the introduction of the (ARCH) model by Engel (1982) and (GARCH) by Bollerslev (1986), parameter constraints were set out to ensure nonnegative conditional variance, more specifically: $\omega \geq 0$, $\beta_i \geq 0$ for all $i = 1$ to p, $\beta_j \geq 0$ for all $j = 1$ to q. Negative coefficients in GARCH models could result from non-stationary data or residual serial correlation in the mean equation. However, Nelson and Cao (1992) and Alexander (2008), indicated that imposing constraints is a practitioner's choice, and such constraints are generally difficult to enforce, since several violations have been reported in the ARCH literature. Nelson and Cao (1992) claim that violations of Bollerslev's inequality constraints could not be due to statistical errors or sampling problems. They documented several violations of Bollerslev's constraints, specifically negative values of ARCH and GARCH terms α's and β's respectively, when estimating daily data of S&P 500, and daily exchange rates for several currencies[35].

[35]Nelson and Cao (1992) encountered several violations of GARCH parameters constraints in their study. They reported several incidences of negative α_2 values in ARCH terms, in their subsamples when estimating the volatility of the daily returns of S&P500. They also reported negative α values for different orders of GARCH terms when estimating the conditional variance of three currencies against the US dollar, namely the British pound, the Japanese yen, and the Italian lira. Even though, they had not reported any negative β values in all cases of their empirical study, their decision, based on the Akaike information criterion (AIC), includes selecting the best fit models with negative α values.

Adding exogenous variables to the variance equation is tantamount to including a high order of GARCH terms in our estimation. Adding a covariate improves volatility estimations and mean negative coefficients could not be due to misspecification. In addition, we used the log returns from the volatility index, and the first difference in exogenous variables, and the variables are stationary as indicated by our stationarity tests. Additionally, no serial correlation is present in the residuals. Considering the absence of pathological effects (no misspecification, stationary data and no serial correlation in the residuals), we believe that our models do not 'misbehave', since negative values have been reported in the literature previously.

Table 3.4 shows the results of IV with market returns alongside macroeconomic factors using EGARCH(1,1). The parameter coefficients are mostly significant, and the information criteria, BIC and AIC are lower than those provided by GARCH(1,1) results in the majority of cases. However, the rates for the convergence of conditional volatility to long term average level measured by the sum of α and β is increasing (above 1.00), therefore it provides unrealistic estimations for most models. This could be explained by the specification of $EGARCH_t$, which considers the log of the variance, to guarantee positive variance values are produced. This could cause non-stationarity in most equations. In other words, the $EGARCH_t$ asymmetric feature, which includes the leverage effect, created a trending pattern in the results. In equations (3.2), (3.7) and (3.11), the convergence rate is below 1.00. The first two equations include IV in the full sample and IV in subsample 1, but are outperformed by other specifications using GARCH(1,1). The only meaningful equation using $EGARCH_t$ (1,1), is equation 11 in subsample 2, which provided fewer information criterion values. $EGARCH_t$ does not adequately capture the qualities of the data set in this case, because the log variance potentially introduces non-stationarity, unless there is exceptionally high volatility.

Table 3.4: EGARCH(1,1) estimation results with Normal distribution (Gaussian)

This table present the estimation results of EGARCH(1,1) model from the following the equation below:

Mean equation: $$r_t = \mu + \epsilon_t, \qquad (3.2)$$

Variance equation: $$log(\sigma_{t\ IV_t}^2) = \omega + \sum_{j=1}^{q} \beta_j \log(\sigma_{t\ IV_{t-j}}^2) + \sum_{i=1}^{p} \alpha_i \left(\left| \frac{\epsilon_{t-i}}{\epsilon_{t-i}} \right| - E \left| \frac{\epsilon_{t-i}}{\epsilon_{t-i}} \right| \right) + \sum_{k=1}^{r} \gamma_k \left| \frac{\epsilon_{t-k}}{\sigma_{t-k}} \right| \qquad (3.5)$$

This estimation is based on FTSE100 implied volatility index log-returns, 30 days expiration, using daily and monthly frequency of IV. In the variance equation, we have the FTSE 100 log-returns (FTSE100R$_t$), and our macroeconomic variables namely: Industrial Production (IP$_t$), London 3 months Inter Bank Rate (LIBOR3M$_t$), Effective Exchange Rate (EER$_t$), and Unemployment Rate (UR$_t$). The Full sample is from 4/1/2000 to 31/12/2015, subsample 1 is from 4/1/2000 to 8/8/2007, and subsample 2 is form 9/8/2007 to 31/12//2015. The parameters estimated are: the mean of the returns (μ), the first order of the GARCH constant parameters (ω), the first order of ARCH error term (α), first order of the leverage effect (γ), and the first order of the GARCH term, (β). LLF is the value of the maximized likelihood function, BIC is the Bayesian information criterion, and AIC is the Akaike information criterion. IV index data is obtained from FTSE Russell, macroeconomic variables are obtained from Datastream. *** indicate significance at 1%, ** indicate significance at 5%, * indicate significance at 10%. The numbers in parentheses are t-statistics.

N	*Samples*	*Variable in mean Equation*	*variables in the Variance Equation*	*Mean Equation*	*Variance Equation*									$\alpha+\beta$	LLF	BIC	AIC
				(μ)	(ω)	(α)	(γ)	(β)	FTSE 100R	IP	LIBOR 3M	EEX	UR				
1	Full sample	Daily IV	-	0.002**	-0.209***	0.068***	0.125***	0.971***	-	-	-	-	-	1.039	5416.604	-2.689	-2.696
				(2.28)	(10.99)	(8.41)	(18.70)	(353.47)									
2		Monthly IV	-	17.621***	2.395***	0.757***	0.533***	0.209	-	-	-	-	-	0.967	-646.780	6.874	6.789
				(37.74)	(3.80)	(3.25)	(2.75)	(1.36)									
3		Monthly IV	FTSE 100R, IP, UR	-0.039***	-5.570***	0.729***	0.104*	-0.596***	-10.266***	0.208***	-	-	4.795***	1.325	29.456	-0.088	-0.225
				(3.22)	(21.16)	(5.48)	(1.65)	(8.29)	(5.69)	(3.34)			(5.44)				
4		Monthly IV	FTSE 100R, IP, EER, UR	-0.033***	-5.538***	0.735***	0.108	-0.583***	-10.071***	0.210***	-	0.043	4.980***	1.318	29.670	-0.063	-0.216
				(2.59)	(19.91)	(5.30)	(1.55)	(7.77)	(5.42)	(3.32)		(0.66)	(5.50)				
5		Monthly IV	FTSE 100R, IP, LIBOR3M, UR	-0.039***	-5.559***	0.721***	0.104	-0.596***	-10.279***	0.206***	194.750	-	4.772***	1.317	0.887	-0.061	-0.214
				(3.24)	(20.00)	(5.36)	(1.62)	(8.17)	(5.65)	(3.15)	(0.22)		(5.38)				

(Continued)

N	Samples	Variable in mean Equation	Variables in the Variance Equation	Mean Equation (μ)	Variance Equation (ω)	(α)	(γ)	(β)	FTSE 100R	IP	LIBOR 3M	EEX	UR	α +β	LLF	BIC	AIC
6		Daily IV	-	0.001	-0.460***	0.118***	0.112***	0.937***	-	-	-	-	-	1.054	2864.750	-2.978	-2.993
				(1.054)	(5.581)	(6.053)	(7.652)	(74.006)									
7		Monthly IV	-	0.003	-1.210***	-0.393**	0.521***	0.521***	-	-	-	-	-	0.915	14.818	-0.079	-0.218
				(0.123)	(2.839)	(2.309)	(2.601)	(3.132)									
8	Sub1	Monthly IV	FTSE 100R, LIBOR3M	-0.033***	-0.263***	-0.846***	0.207**	0.735***	-10.642***	-	1440.465***	-	-	1.581	32.269	-0.367	-0.562
				(2.804)	(13.966)	(722.260)	(1.966)	(4.1E+103)	(4.340)		(3.408)						
9		Monthly IV	FTSE 100R, IP, LIBOR3M, UR	-0.035***	-0.400***	-0.998***	0.359***	0.683***	-7.122	-0.265	1398.517***	-	-4.301***	1.681	34.035	-0.306	-0.556
				(5.529)	(13513.209)	-1.0E+103	(3.443)	(5.7E+103)	(2.566)	(1.404)	(2.916)		(3.939)				
10		Monthly IV	FTSE 100R, LIBOR3M, UR	-0.035***	-0.375***	-0.954***	0.274***	0.692***	-8.104***	-	1173.317**	-	-2.816***	1.645	32.708	-0.327	-0.549
				(4.924)	(43.388)	(883288.889)	(2.666)	(5.8E+103)	(2.746)		(2.527)		(2.825)				

(Continued)

N	Samples	*Variable in mean Equation*	*Variables in the Variance Equation*	Mean Equation	*Variance Equation*										*α +β*	LLF	BIC	AIC
				(*μ*)	(*ω*)	(*α*)	(*γ*)	(*β*)	FTSE 100R	IP	LIBOR 3M	EEX	UR				
11	Sub2	Daily IV	-	0.003**	-0.197***	0.029***	0.153***	0.966***	-	-	-	-	-	0.996	2581.589	-2.437	-2.450
				(2.002)	(8.455)	(3.671)	(18.052)	(249.181)									
12		Monthly IV	-	0.007	-1.820**	0.636**	0.221	0.527*	-	-	-	-	-	1.163	-4.341	0.314	0.185
				(0.283)	(2.189)	(2.268)	(1.310)	(1.915)									
13		Monthly IV	FTSE 100R, LIBOR3M	-0.037	-1.986**	0.598**	0.136	0.476*	-8.802***	-	605.839	-	-	1.074	2.880	0.263	0.082
				(1.476)	(2.414)	(2.121)	(0.589)	(1.760)	(2.933)		(0.871)						
14		Monthly IV	FTSE 100R, LIBOR3M, EER	-0.041*	-1.745**	0.497*	0.098	0.528**	-8.478***	-	1214.355	-0.113	-	1.026	3.307	0.300	0.093
				(1.706)	(2.408)	(1.842)	(0.477)	(2.170)	(2.682)		(1.197)	(0.633)					
15		Monthly IV	FTSE 100R, LIBOR3M, EER, UR	-0.034	-1.764**	0.511**	0.123	0.520**	-7.890**	-	1481.759	-0.107	1.137	1.031	3.572	0.341	0.107
				(1.376)	(2.572)	(1.982)	(0.600)	(2.255)	(2.506)		(1.403)	(0.594)	(0.537)				

(Continued)

Table 3.5 shows GJR-GARCH(1,1) estimation results, following the same approach to GARCH and EGARCH. For the full sample, the results of IV, equations 1 and 2, show high rates of convergence of conditional volatility to the long term average, but later broke the parameter constraints, since the sum of α and β exceeded 1.00, indicating unrealistic results. However, adding the exogenous variables resulted only in two equations with significant ARCH and GARCH effects in the full sample, namely equations 3 and 4. The first combination was presented by equation 3, which includes $FTSE100R_t$ with EER_t, and the second was equation 4, which includes $FTSE100R_t$ with IP_t and UR_t. We eliminated the GJR-GARCH estimation results for subsample 1, since we could not find any possible combination of variables that provided significant ARCH and GARCH effects. As for subsample 2, except for IV, with monthly data, analysis shown in equation 6, the GJR-GARCH model provided significant parameters using only IV's daily realized volatility in equation 5, and also when adding exogenous variables, as described by equations 7, 8 and 9. However, all the GJR-GARCH results and equations were outperformed by GARCH and EGARCH.

To summarize, Table 3.6 presents the best fit equations that model the conditional volatility of IV. We cannot compare the daily and the monthly results of IV, with or without independent variables, because of the different data frequencies. When analysing IV based on its daily realized volatility, GARCH(1,1) outperformed other models for the full sample and subsample 1. The symmetric GARCH(1,1) model was more accurate over the low volatility period. However, EGARCH was able to capture existent volatility in a more volatile set of data, as was the case with subsample 2, where the market was highly volatile (especially between 2007 and 2008) due to the financial crisis. This was especially true when adding exogenous variables. So overall when IV is regressed on its monthly realized volatility, market returns and macroeconomic variables, GARCH(1,1)

Table 3.5: GJR-GARCH(1,1) estimation results with Normal distribution (Gaussian)

This table present the estimation results of GJR-GARCH(1,1) model from the following the equation below:

Mean equation: $$r_t = \mu + \epsilon_t, \tag{3.2}$$

Variance equation: $$\sigma^2_{t\ IV\,t} = \omega + \sum_{j=1}^{q} \beta_j \sigma^2_{t\ IV\,t} + \sum_{i=1}^{p} \alpha_j \epsilon^2{}_{t-i} + \sum_{k=1}^{r} \gamma_k \epsilon^2{}_{t-k}\, I_{t-k} \tag{3.6}$$

This estimation is based on FTSE100 implied volatility index log-returns, 30 days expiration, using daily and monthly frequency of IV. In the variance equation, we have the FTSE 100 log-returns ($FTSE100R_t$), and our macroeconomic variables namely: Industrial Production (IP_t), London 3 months Inter Bank Rate ($LIBOR3M_t$), Effective Exchange Rate (EER_t), and Unemployment Rate (UR_t). The Full sample is from 4/1/2000 to 31/12/2015, subsample 1 is from 4/1/2000 to 8/8/2007, and subsample 2 is form 9/8/2007 to 31/12//2015. The parameters estimated are: the mean of the returns (μ), the first order of the GARCH constant parameters (ω), the first order of ARCH error term (α), first order of the leverage effect (γ), and the first order of the GARCH term, (β). LLF is the value of the maximized likelihood function, BIC is the Bayesian information criterion, and AIC is the Akaike information criterion. IV index data is obtained from FTSE Russell, macroeconomic variables are obtained from Datastream. *** indicate significance at 1%, ** indicate significance at 5%, * indicate significance at 10%. The numbers in parentheses are t-statistics.

N	Samples	*Variable in mean Equation*	*Variables in the Variance Equation*	Mean Equation	*Variance Equation*										*α +β*	LLF	BIC	AIC
				(*μ*)	(*ω*)	(*α*)	(*γ*)	(*β*)	FTSE 100R	IP	LIBOR 3M	EEX	UR					
1	Full sample	Daily IV	-	0.001	0.000***	0.123***	-0.118***	0.881***	-	-	-	-	-		1.003	5399.548	-2.680	-2.688
				(1.333)	(11.450)	(13.336)	(11.657)	(99.872)										
2		Monthly IV	-	17.753***	29.474***	0.948***	-0.915**	-0.068	-	-	-	-	-		1.015	-645.458	6.860	6.776
				(33.530)	(6.171)	(5.590)	(2.123)	(0.760)										
3		Monthly IV	FTSE 100R, EER	-0.018	0.020***	0.247**	-0.269	0.494***	-0.333***	-	-	-0.003	-		0.741	14.321	0.043	-0.077
				(0.988)	(3.506)	(2.015)	(1.730)	(4.704)	(4.791)			(1.202)						
4		Monthly IV	FTSE 100R, IP, UR	-0.010	0.037*	0.030***	-0.150***	0.575**	-0.166	0.018***	-	-	0.051		0.604	0.374	0.216	0.080
				(0.358)	(1.861)	(5.247)	(4.244)	(2.316)	(1.389)	(4.199)			(0.814)					

(Continued)

N	*Samples*	*Variable in mean Equation*	*Variables in the Variance Equation*	Mean Equation (μ)	*Variance Equation* (ω)	(α)	(γ)	(β)	FTSE 100R	IP	LIBOR 3M	EEX	UR	$\alpha+\beta$	LLF	BIC	AIC
5		Daily IV	-	0.002	0.000***	0.122***	-0.124***	0.866***	-	-	-	-	-	0.988	2565.364	-2.422	-2.435
				(1.132)	(8.399)	(9.275)	(8.906)	(60.860)	-	-	-	-	-				
6		Monthly IV	-	0.011	0.037***	0.838*	-0.654	0.065						0.903	-4.887	0.325	0.196
				(0.437)	(2.609)	(1.808)	(1.315)	(0.315)									
7	Sub2	Monthly IV	FTSE 100R, LIBOR3M, UR	0.019	0.030***	0.353*	-0.317	0.402**	-0.234	-	100.294**	-	0.130***	0.756	3.870	0.289	0.082
				(0.750)	(5.261)	(1.817)	(1.332)	(2.530)	(1.542)		(2.243)		(2.787)				
8		Monthly IV	FTSE 100R, LIBOR3M, EER, UR	0.019	0.030**	0.354***	-0.313	0.417**	-0.233	-	102.405*	0.000	0.129**	0.771	3.744	0.337	0.104
				(0.761)	(2.237)	(21.440)	(2.388)	(2.018)	(1.299)		(1.801)	(0.044)	(2.193)				
9		Monthly IV	FTSE 100R, IP, EER	0.021	0.049**	0.027***	-0.186	0.571**	-0.174	0.021***	-	0.002	-	0.598	-8.183	0.528	0.320
				(0.510)	(2.077)	(2.786)	(3.081)	(2.500)	(1.333)	(3.078)		(0.593)					

(Continued)

models outperformed other models. This indicate that asymmetric models do not provide better estimations in such volatile environment, especially when adding exogenous variables. So overall GARCH(1,1) appears to be the best fit model unless there is exceptionally high volatility in which case EGARCH would perform better. In the next section, we take the analysis further by using GARCH-MIDAS, which enables us to analyse the effect of the chosen exogenous variables on IV using a mixed data approach.

3.4.4. GARCH-MIDAS ESTIMATION RESULTS

Table 3.7 displays GARCH-MIDAS output using six equations, the IV is regressed here on its realized monthly volatility alongside five independent variables namely $FTSE100R_t$, IP_t, $LIBOR3M_t$, EEX_t, and UR_t, which are introduced one at a time. We used 24 lags, covering two years of realized volatility (24 and 416 observations for the long, and the short components consecutively). The lags are averaged by the MIDAS equation to estimate long run conditional variance. Aside from using a fixed window approach (FW), we also used a rolling window (RW) specification to determine if it produces different results. A rolling analysis allows for the model parameters to change overtime to capture any instability in economic determinants over time.

According to table 3.7, it is evident that the mean of returns, μ is insignificant in all equations, thereby specifying that the mean does not explain volatility of returns. However, as indicated before, we rely on the significance of the ARCH error term α, and GARCH conditional volatility β, parameters in the model selection. In most cases, these parameters are significant, showing the existence of conditional heteroscedasticity and autocorrelation. Based on the results, a rolling window approach provides the most significant outputs, lower information criterion values, and higher LLF. For the entire

Table 3.6: Most fitted equations based on GARCH models estimation.

The table below presents the best fit equations for all samples based on the analysis of IV. Our explanatory factors are: FTSE 100 log-returns (FTSE100R_t), industrial production (IP_t), the London three months Inter Bank Interest Rate (LIBOR3M_t), GBP Effective Exchange Rate (EER_t), and Unemployment Rate (UR_t). The analysis in conducted using several GARCH models, GARCH(1,1), EGARCH(1,1), and GJR-GARCH(1,1). The tables present the best fit equations for all samples by taking into account the parameters of: (μ) the mean coefficients of the returns, (ω) the unconditional variance, (α) the ARCH term, (γ) the leverage effect, and (β) the GARCH term, the conditional variance. Models with significant parameters were ranked based on the lowest values of the Bayesian information criterion (BIC), and the Akaike information criterion (AIC).

Analysis results of only daily data of IV

Samples	Model ranking	Model	Variables	
			Mean Equation	Variance Equation
Full sample	1	GARCH	Daily IV	-
Subsample (1)	1	GARCH	Daily IV	-
Subsample (2)	1	EGARCH	Daily IV	-

Analysis results of monthly data of IV with exogenous variables

Samples	Model ranking	Model	Variables	
			Mean Equation	Variance Equation
Full sample	1	GARCH	Monthly IV	FTSE 100R, LIBOR3M, EER
Subsample (1)	1	GARCH	Monthly IV	FTSE 100R, IP, UR
Subsample (2)	1	GARCH	Monthly IV	FTSE 100R, IP, LIBOR3M, EER

sample, in equation 2, IV was regressed on its monthly realized volatility using a rolling window, producing the best model fit. It generates significant α and β terms, and produces the lowest information criterion. The ARCH term α in equation 2, reaches the highest value for all the full sample equations in the GARCH-MIDAS analysis (0.105) at the 1% significant level, indicating a high sensitivity to market shocks. Conditional variance, on the other hand, reaches a minimum value, showing the lowest convergence rate for conditional volatility to average volatility. For subsample 1, when regressing IV on its monthly realized volatility, using a rolling window (equation 4) produces the best fit model. We obtained the lowest values for AIC and BIC but not the highest α or the lowest

β. As for subsample 2, and due to the high volatility observed, regressing IV on UR_t, equation 36, using a rolling window provided the best fit model. It is an ARCH term, where α has the highest value, showing a high reaction to market volatility. It also has the lowest AIC and BIC values, but not the lowest β term, meaning it does not have the highest convergence rate.

GARCH-MIDAS clearly pointed out the significance of the ARCH error term α, and the conditional volatility effect β, in our results. It is apparent that modelling the variance of the equation with AR (p), using MIDAS for analysing IV has considerable benefits in several cases. In other words, GARCH-MIDAS provides further support for the effect that exogenous factors have on IV. For the whole sample, and for subsample 1, regressing IV according to its realized volatility, equations 2 and 4, provide the best fit. However, for subsample 2, adding UR_t as an independent variable and equation 36, outperformed the results produced by IV only and realized volatility. However, adding $FTSE100R_t$ to the IV regression did not generate a significant α. Equations from 7 to 12, indicate that volatility is not sensitive to market shocks. In the case of macroeconomic determinants, adding $LIBOR3M_t$ to IV (equations 19 to 24) and UR_t to IV (equations 31 to 36), provided significant α and β parameters in all samples when using FW and RW. The other two variables, when added as explanatory factors, specifically IP_t in equations 13 to 18, and $EEXR_t$ in equations 25 to 30, mostly provided significant results, but not for all the samples when using FW and RW.

The GARCH-MIDAS results support symmetric and asymmetric GARCH models, since adding macroeconomic variables to market returns assists with the estimation of daily and monthly data relating to IV. Also, in terms of mixed frequency, it sometimes provides

Table 3.7: GARCH-MIDAS estimation results with maximum likelihood

This table present the estimation results of GARCH-MIDAS model with 2 MIDAS lag years, following equations below:

Mean equation:

$$r_{i,t} = \mu + \sqrt{\tau_t g_{IV\,i,t}}\ \varepsilon_{i,t}, \tag{3.7}$$

conditional variance of the short-term component equation:

$$g_{IV\,i,t} = (1 - \alpha - \beta) + \alpha \frac{(r_{i-1,t} - \mu)^2}{\tau_t} + \beta g_{IV\,i-1,t}, \tag{3.8}$$

conditional variance of the long-term component equation:

$$\tau_t = m + \theta \sum_{k=1}^{K} \varphi_k(\omega)\, V_{t-k} \tag{3.9}$$

This estimation is based FTSE100 implied volatility index log-returns, 30 days expiration, with daily monthly frequency of IV. In the variance equations are the FTSE 100 log-returns (FTSE100R$_t$), and our macroeconomic variables namely: Industrial Production (IP$_t$), London 3 months Inter Bank Rate (LIBOR3M$_t$), Effective Exchange Rate (EER$_t$), and Unemployment Rate (UR$_t$). Full sample is from 4/1/2000 to 31/12/2015, subsample 1 is from 4/1/2000 to 8/8/2007, and subsample 2 is form 9/8/2007 to 31/12//2015. The parameters are the mean coefficients of the mean of the returns (μ), the first order of the GARCH constant parameters (ω), first of GARCH error term (α), first order of GARCH term, the conditional volatility (β), and the moving average variance (m). LLF is the value of the maximized likelihood function, BIC is the Bayesian information criterion, and AIC is the Akaike information criterion. IV index data is obtained from FTSE Russell, macroeconomic variables obtained from Datastream. *** indicate significance at 1%, ** indicate significance at 5%, * indicate significance at 10%. The numbers in parentheses are t-statistic values.

N	*Variables*	*Sample*	*Specification*	(μ)	(α)	(β)	(θ)	(ω)	(m)	$\alpha + \beta$	LLF	BIC	AIC
1	Independent variable: ***IV*** Dependent Variable: -	Full sample	FW	0.000	0.102***	0.820***	0.002	19.932	0.001***	0.922	21311.700	-42573.700	-42611.500
				(-0.388)	(11.899)	(45.985)	(0.003)	(0.999)	(27.579)				
2			RW	0.000	0.105***	0.787***	0.174	1.002***	0.000***	0.892	21325.600	-42601.400	-42639.200
				(-0.303)	(11.754)	(43.764)	(13.463)	(6.396)	(5.615)				
3		Subsample 1	FW	0.000	0.098***	0.812***	0.004	4.890	0.000***	0.910	9104.190	-18163.000	-18196.400
				(-0.392)	(5.997)	(23.560)	(0.003)	(0.001)	(8.036)				
4			RW	0.000	0.102***	0.801***	0.125***	1.001**	0.000***	0.903	9104.660	-18164.000	-18197.300
				(-0.375)	(6.130)	(23.088)	(2.579)	(2.114)	(3.992)				
5		Subsample 2	FW	0.000	0.135***	0.716***	0.003	30.649	0.000***	0.851	9783.180	-19520.500	-19554.400
				(-0.249)	(9.691)	(24.232)	(0.010)	(0.002)	(27.395)				
6			RW	0.000	0.133***	0.711***	0.076**	2.273	0.000***	0.844	9783.680	-19521.500	-19555.400
				(-0.237)	(3.527)	(23.402)	(2.452)	(0.495)	(15.997)				

(Continued)

N	*Variables*	*Sample*	*Specification*	(μ)	(α)	(β)	(θ)	(ω)	(m)	α + β	LLF	BIC	AIC
7	Independent variable: ***IV*** Dependent Variable: ***FTSE 100R***	Full sample	FW	0.000	0.050	0.900***	0.079***	5.000***	0.000***	0.951	15688.400	-31327.100	-31364.900
				(-0.547)	(0.241)	(11.614)	(2.749)	(5.326)	(3.030)				
8			RW	0.000	0.050	0.900***	0.100	5.000***	0.000	0.950	15307.300	-30564.900	-30602.700
				(0.012)	(0.732)	(7.966)	(1.581)	(6.908)	(1.640)				
9		Subsample 1	FW	0.000	0.050	0.900***	0.39**	5.000***	0.000**	0.950	7212.980	-14380.600	-14414.000
				(0.057)	(0.349)	(9.087)	(1.999)	(4.433)	(2.454)				
10			RW	0.000	0.050	0.900***	0.100	5.000***	0.000	0.951	6641.540	-13237.700	-13271.100
				(0.222)	(0.543)	(5.848)	(1.406)	(6.690)	(1.473)				
11		Subsample 2	FW	0.000	0.050	0.900***	0.100*	5.000***	0.000*	0.950	8023.550	-16001.200	-16035.100
				(-0.017)	(0.818)	(8.992)	(1.903)	(31.322)	(1.953)				
12			RW	0.000	0.050	0.900***	0.100	5.000***	0.000	0.950	7628.190	-15210.500	-15244.400
				(-0.002)	(0.474)	(5.285)	(0.758)	(6.184)	(0.758)				

(Continued)

N	*Variables*	*Sample*	*Specification*	(μ)	(α)	(β)	(θ)	(ω)	(m)	$\alpha + \beta$	LLF	BIC	AIC
13	Independent variable: ***IV*** Dependent Variable: ***IP***	Full sample	FW	0.000	0.102***	0.818***	0.000	36.129	0.000***	0.920	21312.100	-42574.500	-42612.300
				(-0.378)	(12.750)	(56.911)	(-0.956)	(0.275)	(26.174)				
14			RW	0.000	0.050	0.900***	0.100	5.000***	0.002	0.950	9768.120	-19486.500	-19524.200
				(-0.003)	(0.327)	(4.131)	(0.904)	(13.009)	(0.913)				
15		Subsample 1	FW	0.000	0.076***	0.908***	0.000	49.039	0.000***	0.984	9098.450	-18151.600	-18184.900
				(-0.126)	(6.916)	(60.591)	(0.263)	(0.048)	(6.129)				
16			RW	0.000	0.252***	0.748***	0.131	2.571***	0.001*	0.999	9059.680	-18074.000	-18107.400
				(-0.172)	(11.103)	(32.901)	(1.588)	(2.606)	(1.675)				
17		Subsample 2	FW	0.000	0.131***	0.685***	0.000***	1.845***	0.000***	0.816	9792.200	-19538.500	-19572.400
				(-0.088)	(9.246)	(18.923)	(7.867)	(5.455)	(24.336)				
18			RW	0.000	0.050	0.900***	0.100	5.000***	0.000	0.950	5013.150	-9980.390	-10014.300
				0.000	(0.161)	(3.952)	(0.180)	(17.939)	(0.180)				

(Continued)

N	*Variables*	*Sample*	*Specification*	(μ)	(α)	(β)	(θ)	(ω)	(m)	$\alpha + \beta$	LLF	BIC	AIC
19	Independent variable: ***IV*** Dependent Variable: ***LIBOR 3M***	Full sample	FW	0.000	0.050***	0.900***	0.100***	5.000***	0.000	0.950	21251.900	-42454.000	-42491.800
				(-0.095)	(10.326)	(79.493)	(9.300)	(6.917)	(26.140)				
20			RW	0.000	0.050***	0.900***	0.100***	5.000***	0.000***	0.950	21259.900	-42470.000	-42507.800
				(-0.096)	(10.514)	(80.592)	(9.726)	(7.094)	(26.738)				
21		Subsample 1	FW	0.000	0.050***	0.900***	0.100***	5.000*	0.000***	0.951	9092.560	-18139.800	-18173.100
				(-0.126)	(5.825)	(41.977)	(3.637)	(1.846)	(15.781)				
22			RW	0.000	0.050***	0.900***	0.100***	5.000*	0.000***	0.950	9092.950	-18140.600	-18173.900
				(-0.126)	(5.807)	(41.619)	(3.593)	(1.810)	(15.706)				
23		Subsample 2	FW	0.000	0.050***	0.900***	0.100***	5.000**	0.000***	0.950	9776.990	-19508.100	-19542.000
				(-0.042)	(9.085)	(66.468)	(7.507)	(2.246)	(22.085)				
24			RW	0.000	0.050***	0.900***	0.100***	5.000**	0.000***	0.951	9776.650	-19507.400	-19541.300
				(-0.042)	(9.088)	(66.497)	(7.052)	(2.380)	(22.013)				

(Continued)

N	*Variables*	*Sample*	*Specification*	(μ)	(α)	(β)	(θ)	(ω)	(m)	$\alpha + \beta$	LLF	BIC	AIC
25	Independent variable: ***IV*** Dependent Variable: ***EEXR***	Full sample	FW	0.000	0.050	0.900***	0.100	5.000***	0.003	0.950	8841.700	-17633.600	-17671.400
				(-0.008)	(0.684)	(4.872)	(1.170)	(48.095)	(1.171)				
26			RW	0.000	0.107***	0.893***	0.000	5.152	0.000**	0.950	21249.700	-42449.700	-42487.400
				(-0.263)	(16.686)	(139.170)	(0.179)	(0.123)	(2.414)				
27		Subsample 1	FW	0.000	0.050	0.900***	0.100	5.000***	0.000	0.951	4479.230	-8913.130	-8946.460
				(-0.012)	(0.410)	(5.018)	(1.133)	(7.066)	(1.134)				
28			RW	0.000	0.050	0.900***	0.100	5.000***	0.001	0.950	4506.440	-8967.550	-9000.880
				(-0.003)	(0.335)	(4.219)	(0.921)	(14.135)	(0.937)				
29		Subsample 2	FW	0.000	0.231***	0.769***	0.029	4.962***	0.000	0.951	9718.760	-19391.600	-19425.500
				(-0.118)	(14.581)	(48.518)	(0.757)	(5.138)	(0.842)				
30			RW	0.000	0.050	0.900***	0.100	5.000***	0.001	0.951	4637.080	-9228.250	-9262.150
				0.000	(0.102)	(3.791)	(0.106)	(8.448)	(0.011)				

(Continued)

N	*Variables*	*Sample*	*Specification*	(μ)	(α)	(β)	(θ)	(ω)	(m)	$\alpha + \beta$	LLF	BIC	AIC
31	Independent variable: ***IV*** Dependent Variable: ***UR***	Full sample	FW	0.000	0.050	0.901***	0.020***	5.000***	0.000***	0.951	17164.000	-34278.200	-34316.000
				(1.176)	(1.248)	(12.120)	(3.467)	(9.233)	(3.576)				
32			RW	0.000	0.124***	0.876***	0.122**	1.056***	0.000***	0.999	21243.200	-42436.700	-42474.500
				(-0.564)	(23.609)	(167.500)	(2.443)	(78.401)	(2.443)				
33		Subsample 1	FW	0.000	0.050	0.900***	0.100**	5.000***	0.000**	0.950	6932.990	-13820.600	-13854.000
				(-0.022)	(1.360)	(10.849)	(2.287)	(8.391)	(2.411)				
34			RW	0.000	0.050	0.9000***	0.100	5.000***	0.000	0.950	6916.240	-13877.100	-13910.500
				(-0.009)	(0.501)	(5.677)	(1.298)	(6.966)	(1.310)				
35		Subsample 2	FW	0.000	0.050	0.900***	0.020***	5.000***	0.000***	0.950	3598.000	-34278.200	-34316.000
				1.176	(1.248)	(12.120)	(3.467)	(9.233)	(3.576)				
36			RW	0.000	0.124***	0.876***	0.123**	1.056***	0.000**	0.999	21243.200	-42436.700	-42474.500
				(-0.564)	(23.609)	(167.500)	(2.442)	(78.401)	(2.443)				

(Continued)

a better estimation than depending solely on monthly and daily realized volatility. However, it is impossible to compare the GARCH-MIDAS approach to other GARCH symmetric and asymmetric models, due to the different data frequencies used. The selection criteria AIC and BIC, which determines the best models, cannot be compared in this case, because a mixed data frequency provides higher values for these criterions, due to the greater number of observations used in the analysis.

3.5. CONCLUSION

In this study, we investigated the volatility and the conditional variance of the FTSE100 IV index with a 30 day expiration, IV, using daily and monthly data. We employed several GARCH models, the symmetric GARCH(1,1), and asymmetric GARCH models, such as EGARCH(1,1) and GJR-GARCH(1,1). We also investigated the capacity of the mixed data analysis approach namely GARCH-MIDAS to improve our modelling. We used several explanatory factors in the analysis, FTSE 100 index log-returns (FTSE100R) and macroeconomic determinants. The macroeconomic variables we used represented the first difference in terms of industrial production (IP), LIBOR three-month rate (LIBOR3M), GBP effective exchange rate (EEX), and unemployment rate (UR). Our sample covers a 15-year period from January 4, 2000 to December 31, 2015. In addition to analysing the whole sample, we also divided the sample into two subsamples, pre and post financial crisis.

GARCH(1,1) outperformed the other models for the full sample and for subsample 1 when daily IV was regressed according to its realized volatility. However, due to the highly volatile period from the middle of 2007 onwards, which is included in subsample 2, EGARCH(1,1) was able to model the volatility of daily IV much better and thereby outperform all other models. Adding macroeconomic factors into the analysis namely FTSE100R, IP, LIBOR 3M, EER, and UR improved the modelling process. Unlike other models, GJR-GARCH(1,1) did not produce any significant results with or without exogenous variables. However, GARCH(1,1) outperformed all the other models with different specification lags, starting from (1,1) and ending with (10,10) as explained in table 3.7.

Using GARCH-MIDAS, showed the usefulness of the selected exogenous variables when modelling daily IV. Monthly realized volatility returned the best results for the full sample and subsample 1. For subsample 2, which was characterised by highest average volatility, adding UR provided a better estimation than realized volatility. Other independent variables also displayed a clear effect on the estimation of daily IV, but this was not the case for both fixed window (FW), and rolling window (RW).

The implication of examining the volatility of the VIX for investors is that it will assist market participants to firstly, decide whether a consensus exists and secondly, to identify the factors influencing the formation of any consensus concerning future movements of both the implied volatility index and the market itself. More significantly, it will also help in the design of risk strategies, in order to hedge tail risk returns, or capture the volatility risk premium, by acknowledging the most likely negative relationship between the high levels of volatility related to VIX and stock market returns. Furthermore, VIX forms an important gauge for financial markets. Investors generally use a variety of tools when assessing economic conditions, rather than relying on any single measure. However, using this tool to monitor market uncertainty can enable policymakers improve their anticipation of short-term market volatility. This will maintain market stability through the use of monetary policies, including: (1) the control of money supply within stock markets; (2) placing additional restrictions on mutual funds and (3) investing in companies and brokers. Moreover, researchers can benefit from the chapter's findings through an improved understanding of the factors influencing the implied volatility. This will enable them to apply this aspect to further research, in areas including the impact of volatility on: (1) stock markets; (2) mutual funds; (3) international markets; (4) herding behaviour; and (5) market liquidity.

The following chapter examines the impact of the implied volatility index on commonality in liquidity. The global financial crisis of 2007-2008 has led to a dramatic increase in research into market uncertainty, resulting in this becoming a major factor in the discussion of commonality in liquidity

CHAPTER 4: INDVIDUAL STOCK LIQUIDITY: THE ROLE OF IMPLIED VOLATILITY, MARKET AND INDUSTRY LIQUIDITY. A MULTI-COUNTRY APPROACH

4.1. INTRODUCTION

Historically, the illiquidity of individual assets has captured the interest of researchers and market participants. The importance of market uncertainty as a source of commonality has also attracted researchers' attention. Chung and Chuwonganant (2014) were the first to study the impact of fear indices on liquidity in the US market; specifically, how they cause co-movements among individual stocks. The financial crisis of 2008 intensified the importance of illiquidity pricing factors bringing greater attention to the impact of market uncertainty (Brunnermeier, 2009). Interestingly, changes in market illiquidity are related strongly to changes in market uncertainty, and this relationship is significant during calm periods and when the market is in turmoil, such as during the 2008 financial crisis[36] (Bao et al., 2011). Prior studies also indicate that the liquidity of individual stocks have strong tendencies towards moving harmoniously, causing commonality in liquidity between individual assets, with both, market and industry liquidity (see, Hasbrouck and Seppi, 1998; Chordia et al., 2000; Hasbrouck and Seppi, 2001; and Huberman and Halka, 2001).

Many studies have aimed to identify the probable causes of liquidity co-movements, and its relationship with expected returns and risk premia. They have demonstrated that illiquidity is a source of systematic risk, and an explanatory factor of expected returns. Amihud (2002), Acharya and Pedersen (2005), and Korajczyk and Sadka (2008) revealed a positive correlation between illiquid assets and risk premiums, in which systematic risk

[36] According to Brunnermeier (2009), the financial crisis in 2007 and 2008 is the most sever market turmoil since the Great Depression, and it is caused mainly by illiquidity.

demands high-risk. Likewise, there is a positive correlation and variation in stock returns and liquidity turmoil. Prior studies also investigated various sources and theories of liquid commonality that relied on both demand and supply sides factors. Kamara et al. (2008), Karolyi et al. (2012), and Koch et al. (2016) provided evidence supporting demand side theory, where the financial behaviour of investors and institutional trading causes co-movement in market assets liquidity. While Coughenour and Saad (2004), Chordia et al. (2005), Comerton-Forde et al. (2010), and Hameed et al. (2010) examined supply-side theory, their findings suggest that the activities of liquidity providers explain liquidity commonality and variation. Chapter 3 modelled the implied volatility index, including the causes of its fluctuation based on its realized volatility and other macroeconomic factors. This chapter further investigates its impact (alongside other determinants) on stock market liquidity

Hence, in this paper we investigate sources of liquidity commonality by examining the effect of market uncertainty, and industry and market average liquidity on individual stocks liquidity. We extend the study by Chung and Chuwonganant (2014) to cover several markets, using data samples during the financial crisis (From January 2007 to December 2009) and after the financial crisis (From January 2010 to December 2017). This study includes data from the London Stock Exchange (FTSE100), the Japanese stock market (Nikkei225), and the Eurozone stock market (EURO STOXX50). Our methodology is based on the models used by Chordia et al. (2000), Coughenour and Saad (2004), and Chung and Chuwonganant (2014). We calculate individual stocks, and market and industry average liquidities using three different measures of liquidity, the Amihud (2002) illiquidity measure, the Corwin & Schultz bid-ask spread estimator, and the quoted spread. To determine market uncertainty, we use the corresponding IV indices of the chosen markets, the VFTSE, VXJ, and VSTOXX.

Our findings suggest that average industry illiquidity plays a significant role in determining the variation in illiquidity across individual assets, which in turn causes a co-movement of liquidity across the market. While average market illiquidity showed only an explanatory power in the Eurozone stock market, IV indices did not exhibit any significant parameters as independent variables in our models in the examined markets.

The remainder of the paper is organized as follows: Section 2 presents the literature review. Data and the regression models are explained in sections 3. Section 4 contains the empirical results and analysis followed by the conclusion.

4.2. LITERATURE REVIEW

4.2.1. IMPLIED VOLATILITY INDEX, A MEASURE OF UNCERTAINTY

The IV index has been used widely in the literature as a measure of uncertainty. Chung and Chuwonganant (2014) studied the impact of market uncertainty on stock liquidity in the US market. They presented strong evidence that the fear index exerts a market-wide impact on liquidity, while the liquidity of individual stocks is not only related to own risk, but also to market uncertainty. The impact of the fear index is greater than the combined effects of all other determinants of stock liquidity[37].

In relation to equity markets and asset-pricing theories, many studies have also used the VIX[38], focusing on its impact as a measure of future volatility. Bao (2011) examined the level of liquidity in the corporate bond market and its link to asset pricing implications in the US. They reported a positive relationship between the illiquidity of individual bonds and changes in VIX. This link has not only been established in relation to the financial

[37] Chung and Chuwonganant (2014) used several determinants of stock liquidity with VIX, which are market and industry liquidity, stock returns, stock returns volatility at time t, t_{-1} and t_{+1}. They also used individual stock price, stock volume, and four dummy variables for the effect of trading days on Tuesday, Wednesday, Thursday and Friday.

[38] VIX is the IV index of the S&P 500, which is traded at the Chicago Board Options Exchange (CBOE). It shows the expected future look of 30-day volatility.

crisis of 2008, it is found throughout the data sample, from 2003 to 2009. Pan and Singleton (2008) studied the sovereign credit spreads of Mexico, Turkey and Korea. They identified a strong common relationship to the US VIX. They explained how global common factors might cause significant correlations.

Similarly, Longstaff (2010) related sovereign credit spreads, using a large set of credit default swaps, to market volatility risk premium also measured by the US VIX index. Graham and Harvey (2015) also presented evidence of incidences where the level of the risk premium is affected by credit spreads and market volatility, the VIX index in US market. Brunnermeier et al. (2008) found evidence that currency crashes are correlated positively to an increase in the TED[39] spread and the VIX. In addition, TED and VIX were found to have explanatory power for determining future returns of the carry trades[40]. Likewise, Ranaldo and Söderlind (2007) documented, by using a set of currency pairs from 1999 to 2006, that when stock market volatility increases, safe-haven currencies[41] appreciate and appear stronger, since carry trade is correlated with the VIX.

Recently, there has also been a tendency to use the VIX as a measure of financial market risk. Adrian and Shin (2010) found evidence of the high prices of VIX reducing the risk tolerance of market makers due to risk management constrictions. Bekaert et al. (2013) linked market uncertainty and monetary policy, as held in a vector-autoregressive framework. Their findings suggest that lax monetary policy is negatively correlated with risk aversion and uncertainty. Contrariwise, it is not statistically proven that when VIX and risk aversion are higher, monetary policy is necessarily laxer. Since the VIX is decomposed into risk aversion and uncertainty, the main component that drives co-

[39] TED is the difference between the risk-free T-Bill rate and the London Interbank Offered Rate (LIBOR).
[40] A currency carry trade is a strategy that enables investors to borrow a low yielding currency to fund the purchase of another, high yielding currency.
[41] The safe-haven currencies are the British pound (GBP), the euro (EUR), Japanese yen (JPY), and the Swiss franc (CHF) against the U.S. dollar (USD).

movement between monetary policy and the VIX is risk aversion[42]. I recognize the significant implications of the relationship between implied volatility index, asset markets, and monetary policy. I therefore view an analysis of the relationship between monetary policy and the IV as clarifying the relationship between stock market and monetary policy due to it significantly affects risk aversion and uncertainty.

4.2.2. COMMONALITY IN LIQUIDITY, MARKET AND INDUSTRY LIQUIDITY CO-VARIATION

A growing body of literature appears to find commonality in liquidity, specifically the size of interactions at the microstructural level of cross-stock liquidity, where stock liquidity appears to be defined by market and industry liquidity. For instance, Hasbrouck and Seppi (2001), examined the role of the systematic cross-stock liquidity effect using several liquidity proxies[43]. They highlighted that individual assets' liquidity is not the main common component, as broader common determinants of liquidity potentially have a greater impact.

Chordia et al. (2000) demonstrated that liquidity movements display market-wide intertemporal response to price changes. The variation in trading volume is a source of co-movements in inventory levels, and therefore leads to co-movements in liquidity measures. Volume on the other hand, could represent the common factor in liquidity, where common trading styles, such as institutional funds and market makers with similar trading strategies, exhibit the same trading patterns. Hence, inventory variations could be correlated across individual stock in the market, or in the same industry, and exhibit a similar co-movement pattern. Moreover, asymmetric occasional information could

[42] Bekaert, Hoerova, and Duca (2013), also documented that market uncertainty also reacts to lax monetary policy. However, the response of certainty to monetary policy effect is weaker than the immediate responses of risk aversion.
[43] Hasbrouck and Seppi (1998) used the bid-ask spreads and bid-ask quote as an alternative of other determinants of liquidity such as price, volume and volatility.

influence firms to fluctuate in the same direction, causing a covariation and a similar co-movement in liquidity with both market and industry liquidity.

Huberman and Halka (2001) also documented the existence of a symmetric component of liquidity. They used four measures of liquidity: quantity depth, dollar depth, spread and spread/price ratio. Their findings indicate the existence of a common, systematic cross-stock liquidity factor. In many cases, liquidity allocation would be contingent on the cost of equity riskiness level, and on the interest rate perceived by market participants. While in other cases, several factors might guide the behaviour of market makers, such as the volatility of equity prices and returns, the volatility of interest rates, and market turmoil. Accordingly, inventory average levels held by market participants are correlated across stock and cause co-movement in liquidity. I consider that that liquidity has thus been confirmed as more than an attribute of any single factor, particularly as there is a significant impact exerted on liquidity by volume, volatility, stock price, inventory risks and asymmetric information. I further view the commonality of liquidity as assisting in an understanding of the impact of inventory risks and asymmetric information on individual stock liquidity.

4.2.3. LIQUIDITY PREMIA AND EXPECTED RETURNS

Liquidity is a major aspect of pricing with common stocks, and it is commonly acknowledged in several studies that expected returns increase due to market illiquidity (see, Amihud and Mendelson, 1986; Brennan and Subrahmanyam, 1996; Datar et al., 1998; and Jones, 2002). Amihud (2002), showed that stock excess return is a form of compensation, a risk premium, that occurs due to illiquid stocks. I conclude that the use of a new measure of illiquidity (ILLIQ[44]) determines the expected returns across stocks, where over a period of time, expected market illiquidity influences the predicted stock excess return. Acharya and Pedersen (2005) presented evidence of where illiquid assets have high commonality in liquidity with market liquidity. However, Korajczyk and Sadka (2008) found that only across-measure systematic liquidity involves a risk premium, whereas return shocks are correlated with liquidity shocks.

Similarly, Bekaert et al. (2007) presented results for 18 emerging countries using several liquidity measures[45]. Their results proved consistent with previous studies in which liquidity has a strong effect, and is a determinant of expected returns. Goyenko (2006) found out that illiquidity is a source of systematic risk in the US Bond market, and excess return compensates for the asset illiquidity risk. I observed considerable agreement within the literature concerning the importance of systematic liquidity, due to its ability to predict future market returns. Current research appears to focus on the US market as being the most liquid global market, leading me to identify a need for further in-depth consideration of the significance of liquidity in both emerging and frontier markets.

4.2.4. DEMAND AND SUPPLY SIDES THEORIES OF LIQUIDITY COMMONALITY

Prior research has provided empirical evidence concerning the importance of both supply- and demand side theories and liquidity co-variation. Demand-side theory is concerned with the financial behaviour of investors, institutional trading, and trading activities. On the other hand, supply-side theory relates to liquidity funding activities performed by financial intermediaries (Brennan and Subrahmanyam, 1996).

[44] The illiquidity measure used by Amihud (2002) consists of the ratio of the absolute value of a stock daily return over its daily volume, averaged over a period of time.
[45] Bekaert et al. (2007) used the transformation of the proportion of daily zero asset returns averaged over a period of a month, and then applied the Amidhud measure (2002) into a panel VAR model.

In terms of demand-side liquidity commonality, Kamara et al. (2008) documented that an increase in institutional ownership by investment companies and investment advisors bring about an increase in liquidity. In addition, the increase in institutional ownership explains the variation of liquidity commonality in the US market. Furthermore, Karolyi et al. (2012) examined the time-series variation in commonality in liquidity across 40 international stock markets. Their findings suggest that commonality in liquidity is highly affected by market shocks, the high presence of international investors, and high correlated trading activities. Koch et al. (2016) found another important factor that causes commonality in liquidity. They argued that stocks held by mutual funds and large investors move together in the same direction, producing a correlation in trading across stocks, thereby causing a co-movement in liquidity.

Other studies have explored supply-side theory, as playing a major role in explaining commonalty in liquidity. Coughenour and Saad (2004) found support for the supply-side of liquidity commonality sources. They argue that specialist portfolio liquidity[46] co-varies with stock liquidity, causing a co-variation with market liquidity. Chordia et al. (2005) found that the impact of monetary policy shocks and monetary flows, are significantly and positively related to liquidity commonality across stock and bond markets. Comerton-Forde et al. (2010) also provided evidence, using 11 years of NYSE specialist trading activities, that the balance sheets and income statements of market makers play a significant role in explaining variations in liquidity. Hameed et al. (2010) found that commonality in liquidity increases in the presence of large negative return shocks to both, industry and market stocks. This study has led me to conclude that liquidity responds asymmetrically to changes in asset market value. This view is supported by the majority of theories related to the issue of supply and demand being consistent with the theoretical models, thus indicating that a decrease in liquidity has a greater impact on negative market

[46] NYSE specialist liquidity providers firms.

returns than the increase resulting from positive returns. However, I feel that a variation in supply and demand is unable to identify the contagion between illiquidity and liquidity commonality. This is due to a decline in the value of aggregate assets values providing only indirect evidence of a decreasing supply of liquidity, with a direct impact on all stock within the market.

4.3. DATA AND LIQUIDITY MEASURES

4.3.1. DATA

This chapter includes a number of further G7 countries in the analysis, alongside the UK market. I included the Eurozone stock market due to it being one of the largest in the world, with the combined stock markets of Europe offering attractive opportunities for investors wishing to ensure the performance of their investments, even during times of turmoil. The Eurozone stock market includes three G7 countries, i.e. Germany, France and Italy. The inclusion of an area similar in both its location and regulations within the analysis facilitated the use of effective comparisons. I also included the Japanese (Tokyo) Stock Exchange as part of the G7, due to it being a highly developed free-market economy. In addition, the Japanese Stock Exchange is an important destination for global investors. Thus, it was a significant inclusion in the analysis for the purposes of comparison, in particular in recognition of differences of location, culture and regulation. Canada was, however, excluded from the analysis due to the lack of available data relating to the implied volatility index commencing in 2010. In addition, the US was excluded due to similar research having been previously been undertaken in relation to the US stock market.

In our sample, we use stocks listed on the London Stock Exchange (LSE) FTSE 100, the Nikkei 225, the Eurozone stock market (EURO STOXX 50), and their corresponding IV indices (VFTSE), (VXJ), and (VSTOXX). Our daily data was divided into two samples, during the financial crisis (from January 5, 2007 to December 28, 2009) and after (from January 5, 2010 to December 28, 2017) for all markets. All data was obtained from Datastream. The composition of the selected indices (FTSE100; NIKKEI225; EURO STOXX50) has been updated on an annual basis, due to the expected changes over time in response to the addition (and deletion) of constituents.

4.3.2. LIQUIDITY MEASURES

Choosing the ideal liquidity measure can be a challenging task since a single liquidity measure scarcely captures all aspects of liquidity (Goyenko et al., 2009). Therefore, we use three measures of liquidity to avoid any issues highlighted by Amihud et al. (2006)[47]. The measures we use are the Amihud (2002), Corwin and Schultz (2012), and the quoted spread. I have employed a separate combination of inputs for each measure, consisting of: (1) stock prices; (2) stock returns; (3) volume; and (4) bid-ask spread. I acknowledge that none of these form a perfect measure of liquidity, but the majority are highly positively correlated, thus according additional credibility to the overall results.

4.3.3. THE AMIHUD ILLIQUIDITY MEASURE (AMH)

The Amihud (2002) measure of stock illiquidity is widely used in the literature. It is an ideal measure when data is widely available and can be calculated for a large set of stocks

[47] Amihud et al. (2006) highlighted the following issues: (1) researchers require a large amount of data (long time series) in order to increase the power of their tests. This raises various concerns, due to the short duration of high-frequency data, in particular the lack of availability of high frequency data outside the US market. This forces researchers to estimate liquidity from daily return data, as well as any available from volume data. (2) Liquidity measures have been found to incur errors: firstly, due to a single measure being unable to capture all the different dimensions of liquidity and secondly, the empirically-derived measure forming a noisy estimate of the true parameter.

based on daily frequency (Koch et al., 2016). Moreover, the Amihud measure is significantly correlated with other liquidity measures (Hasbrouck, 2009).

The Amihud illiquidity measure (AMH) is calculated daily for all stock from our chosen countries and indices, and is extracted as follows:

$$\text{AMH}_{i,t} = \frac{1{,}000{,}000 \times |\, return_t|}{price_t \times volume_t} \tag{4.1}$$

Where the value of stock *i*'s absolute returns at time *t* is divided by stock volume, multiplied by price. We also multiplied the Amihud measure by 1,000,000.00, due to the resulting small values.

4.3.4. THE CORWIN & SCHULTZ BID-ASK SPREAD ESTIMATOR (HLS$_w$, HLS$_r$)

Another important measurement of liquidity is the bid-ask spread estimator with (HLS$_w$), and without (HLS$_r$) overnight returns as developed by Corwin and Schultz (2012). This bid-ask estimator measure is developed from high and low daily prices to calculate the bid-ask spread of stocks. The Corwin & Schultz bid-ask spread estimator relies on two assumptions: 1) Buyers (Sellers) initiate the low (high) prices of stock x in the market, 2) The high-to-low volatility component price ratio rises alongside the length of trading times, while the component caused by bid-ask spreads does not. It is calculated using the following equations:

$$HLS_{i,t} = \frac{2(e^{\alpha} - 1)}{1 + e^{\alpha}} \tag{4.2}$$

Where e is the mathematical basis, the constant of x, and α is calculated as following:

$$\alpha = \frac{\sqrt{2\beta} - \sqrt{\beta}}{3 - 2\sqrt{2}} - \sqrt{\frac{\gamma}{3 - 2\sqrt{2}}} \tag{4.3}$$

β and γ are calculated as:

$$\beta = E\left\{\sum_{j=0}^{1}\left[ln\left(\frac{H_{t+j}^{0}}{L_{t+j}^{0}}\right)\right]^{2}\right\} \quad (4.4)$$

$$\gamma = E\left\{\sum_{j=0}^{1}\left[ln\left(\frac{H_{t,t+1}^{0}}{L_{t,t+1}^{0}}\right)\right]^{2}\right\} \quad (4.5)$$

H_t^0 is the observed actual high stock price at time *t*, and L_t^0 is the actual observed low stock price for day at time *t.*

4.3.5. THE QUOTED SPREAD (QS)

The third measure of liquidity is the Quoted Spread (QS), which is calculated as follows:

$$\text{Quoted spread}_{i,t} = (\text{Ask}_{i,t} - \text{Bid}_{i,t})/M_{i,t} \quad (4.6)$$

Where $\text{Ask}_{i,t}$ is the market national best ask price of stock *i* at time *t*, and the $\text{Bid}_{i,t}$ is the market best bid price of stock *i* at time *t*. $M_{i,t}$ is the midpoint of the quote, and calculated as $((\text{Ask}_{i,t} - \text{Bid}_{i,t})/2)$ of stock *i* at time *t.*

4.4. METHODOLOGY AND MODEL SPECIFICATION

The model was initially suggested by Chordia et al. (2000), who calculated simple market model regressions by regressing the percentage of daily changes in liquidity for individual stock employing market measures liquidity. They subsequently added industry average liquidity to market liquidity, with trading activity and volatility being found within, rather than across, industry commonality. This resulted in industry specific inventory risks (Coughenour and Saad, 2004). Furthermore, cross-sectional variation in liquidity is known to depend on individual stock attributes including trading volume, volatility and price level.

The leads and lags for industry and market liquidity are designed to capture any lagged adjustment in commonality. Moreover, the market return is intended to remove any spurious dependence induced by an association between returns and spread measures (Chordia et al., 2000). Since they are functions of the transaction price, this contains potential relevance for the effective spread of measures. The changes are thus functions of individual returns, known to be significantly correlated with broad market returns (Chordia et al., 2000). I concluded that this model was the most appropriate for this current investigation as it had been previously used in several studies (Hasbrouck and Seppi, 2001; Coughenour and Saad, 2005; Chung and Chuwonganant, 2014).

Following Chung and Chuwonganant (2014), we estimate the following regression models for all stocks listed in the chosen countries (UK, Japan and Eurozone). We investigate the effect of VIXs on AMH, HLS, and QS liquidity measures before and after using market liquidity (ML), industry liquidity (IL), stocks volatility (VOLA), and stocks volume (VOL), as control variables:

$$\mathrm{DLM}_{i,t} = \alpha_{i0} + \alpha_{i1}\mathrm{DVIX}_t + \alpha_{i2}\mathrm{DVIX}_{t-1} + \alpha_{i3}\mathrm{DVIX}_{t+1} + \alpha_{i4}\mathrm{DML}_t + \alpha_{i5}\mathrm{DML}_{t-1} + \alpha_{i6}\mathrm{DML}_{t+1} + \alpha_{i7}\mathrm{DIL}_t + \alpha_{i8}\mathrm{DIL}_{t-1} + \alpha_{i9}\mathrm{DIL}_{t+1} + \alpha_{i10}\mathrm{DVOL}_t + \alpha_{i11}\mathrm{DVOLA}_t + \alpha_{i12}\mathrm{DVOLA}_{t-1} + \alpha_{i13}\mathrm{DVOLA}_{t+1} + \varepsilon_{1i,t} \tag{4.7}$$

and

$$\mathrm{Log}(\mathrm{LM}_{i,t}) = \alpha_{i0} + \alpha_{i1}\,\mathrm{Log}(\mathrm{VIX}_t) + \alpha_{i2}\mathrm{Log}(\mathrm{VIX}_{t-1}) + \alpha_{i3}\mathrm{Log}(\mathrm{VIX}_{t+1}) + \alpha_{i4}\mathrm{Log}(\mathrm{ML}_t) + \alpha_{i5}\mathrm{Log}(\mathrm{ML}_{t-1}) + \alpha_{i6}\mathrm{Log}(\mathrm{ML}_{t+1}) + \alpha_{i7}\mathrm{Log}(\mathrm{IL}_t) + \alpha_{i8}\mathrm{Log}(\mathrm{IL}_{t-1}) + \alpha_{i9}\mathrm{Log}(\mathrm{IL}_{t+1}) + \alpha_{i10}\,\mathrm{Log}(\mathrm{VOL}_t) + \alpha_{i11}\,\mathrm{Log}(\mathrm{VOLA}_t) + \alpha_{i12}\,\mathrm{Log}(\mathrm{VOLA}_{t-1}) + \alpha_{i13}\,\mathrm{Log}(\mathrm{VOLA}_{t+1}) + \varepsilon_{2i,t} \tag{4.8}$$

Where LM stands for ‘liquidity measures’, and is captured by the Amihud illiquidity ($AMH_{i,t}$), the Corwin & Schultz bid-ask spread estimator ($HLS_{i,t}$), and the quoted spread ($QS_{i,t}$) for each stock *i* at day *t* VIX_t, VIX_{t-1}, VIX_{t+1} are the implied market volatility index VIX at time *t*, t_{-1}, and t_{+1}; ML_t, ML_{t-1}, ML_{t+1} are the average market liquidity across all stocks at time *t*, *t*-1, and *t*+1; IL_t, IL_{t-1}, IL_{t+1} are the average quoted industry liquidity for all stocks in the same industry at time *t*, *t*-1, and *t*+1; VOL_t is the stock volume of stock *i* at day *t*; $VOLA_t$, $VOLA_{t-1}$, $VOLA_{t+1}$ are the standard deviation of stock *i* at time *t*, t_{-1}, and t_{+1}. D is the percentage change from the previous day, for all variables in Panel A, as calculated by: $DX_{it} = (X_{it} - X_{it-1})/ X_{it-1}$. Panel A exhibits the results of equation (4.7), while Panel B exhibits the results of equation (4.8). We run the regression models by excluding stock *i* when calculating both market and industry liquidity. All the coefficients reported in the tables represent the caused change percentage by the independent variables to each liquidity measure when they change by 1%.

We are also reporting the regression coefficients, the *t*-value of the average regression coefficient, the median *t*-value of all individual stock regression, and the median *t*-value for all individual stock regression. We also test for the independence of residuals from equation (4.7) and (4.8), because the reliability of the t-statistics is associated with cross-section dependence and the estimation error. We use the method set out in Chordia et al. (2000) and Coughenoour and Saad (2004). We also tested for the significance of other possible independent variables, such as stock volume, and stock volatility but they showed no significant effect from individual stock liquidity measures. The results are not presented to keep the tables smaller.

4.5. DESCRIPTIVE STATISTICS

Table 4.1 shows the descriptive statistics of individual stocks' liquidity, as measured by the Amihud illiquidity measure (AMH), the Corwin & Schultz bid-ask spread estimator with/without overnight returns, (HLS_r)/ (HLS_w)), as well as the quoted spread (QS) results for the UK, London Stock Exchange (LSE) FTSE 100, the Japanese stock market (Nikkei 225), and the Eurozone stock market (EURO STOXX 50). We are reporting the mean, the median, the standard deviation, and the percentiles at 5%, 25%, 50%, 75%, and 95% of the liquidity measures across the stocks of all the chosen countries. All the liquidity measures show consistent values (less than 0.01) in terms of the mean, the median and the standard deviation, except for AMH.

The FTSE100 market has the highest AMH values with a mean of 0.131 and a standard deviation of 0.329. Nikkei225 and EURO STOXX50 are very liquid, and have the lowest standard deviations. They have means of 0.008 and 0.017, and their standard deviations are 0.018 and 0.102 respectively. However, the other liquidity measures, HLS_w, HLS_r and QS, provide more stable results in all countries with mean values lower than 0.006, and standard deviation values lower than 0.07. In comparison with other liquidity measures, it is clear that the AMH measure produces the highest values for the mean, the median, and the standard deviation in all countries. An explanation of these high values could be related to the AMH calculation. Unlike the other liquidity measures, it includes stock volume and stocks absolute average daily returns, making it highly sensitive to trading sizes and expected returns (Lou and Shu, 2014).

Table 4.2 shows a correlation in the results between the four liquidity measures. The results indicate that all liquidity measures are positively correlated with one another as expected. The correlation between HLS_w and HLS_r is very high due to the very small difference between them, i.e. the second includes overnight returns in its calculation. Instead, the correlation parameters between liquidity measures are positive and significant at least at the 1% level of p-values. It is usual to find strong correlations

Table 4.1: Descriptive Statistics.

The table below shows descriptive statistics of the individual stocks liquidity measures (The Amihud illiquidity measure (AMH), the Corwin & Schultz bid-ask spread estimator with and without overnight returns, (HLS_r) and (HLS_w)) results of the UK, London Stock Exchange (LSE) FTSE 100, the Japan, stock market (Nikkei 225), and the Eurozone stock market (EURO STOXX 50). The date sets are the closing daily prices that range from January 5, 2010 to December 28, 2017. All data are obtained from Datastream.

Variable	Liquidity Measure	Mean	Median	Standard Deviation	Percentile				
					5	25	50	75	95
FTSE 100	*AMH*	0.131	0.074	0.329	0.006	0.033	0.074	0.145	0.368
	HLS_w	0.005	0.003	0.007	0.000	0.000	0.003	0.009	0.018
	HLS_r	0.006	0.003	0.007	0.000	0.000	0.003	0.009	0.019
	QS	0.001	0.001	0.016	0.000	0.000	0.001	0.001	0.016
Nikkei225	*AMH*	0.008	0.003	0.018	0.000	0.001	0.003	0.009	0.028
	HLS_w	0.005	0.000	0.007	0.000	0.000	0.000	0.008	0.018
	HLS_r	0.006	0.003	0.007	0.000	0.000	0.003	0.009	0.020
	QS	0.003	0.002	0.030	0.001	0.001	0.002	0.003	0.007
EURO STOXX50	*AMH*	0.017	0.004	0.102	0.000	0.001	0.004	0.010	0.049
	HLS_w	0.005	0.002	0.007	0.000	0.000	0.002	0.008	0.018
	HLS_r	0.005	0.003	0.007	0.000	0.000	0.003	0.009	0.019
	QS	0.001	0.000	0.068	0.000	0.000	0.000	0.001	0.003
S&P/TSX 60	AMH	*0.211*	0.044	0.310	0.002	0.003	0.024	0.145	0.208
	HLSw	*0.004*	0.001	0.008	0.001	0.000	0.003	0.003	0.016
	HLSr	*0.006*	0.005	0.009	0.000	0.000	0.001	0.004	0.017
	QS	*0.001*	0.001	0.021	0.000	0.000	0.001	0.001	0.013

between measures since all measures are used to calculate liquidity for the same countries and periods. However, since the correlations are not very close to perfect, each measure shows it uniqueness when capturing different aspects of liquidity (Goyenko et al., 2009).

Figure 4.1 presents the plots for market uncertainty in the London Stock Exchange (VFTSE), Nikkei225 (VXJ), and the Eurozone stock market (VSTOXX). Notice the high spikes during the financial crisis between 2007 and 2008, which appear within the shaded area. Market uncertainty indices are more stable after 2010.

Table 4.2: Correlation among average individual stocks liquidity measures.

The table below shows the correlation between average individual stocks liquidity measures (The Amihud illiquidity measure (AMH), the Corwin & Schultz bid-ask spread estimator with and without overnight returns, (HLS_r) and (HLS_w)) results of the UK, London Stock Exchange (LSE) FTSE 100, the Japan, stock market (Nikkei 225), and the Eurozone stock market (EURO STOXX 50). The date sets are the closing daily prices from January 5, 2007 to December 28, 2017. Number in parentheses are the p-values. All data are obtained from Datastream.

Variable	Liquidity Measure	Correlation			
		AMH	HLS_w	HLS_r	*QS*
FTSE 100	*AMH*	1.000			

	HLS_w	0.518	1.000		
		(0.000)	------		
	HLS_r	0.522	0.901	1.000	
		(0.000)	(0.000)	------	
	QS	0.622	0.614	0.620	1.000
		(0.001)	(0.009)	(0.008)	------
Nikkei225	*AMH*	1.000			

	HLS_w	0.710	1.000		
		(0.003)	------		
	HLS_r	0.704	0.921	1.000	
		(0.003)	(0.000)	------	
	QS	0.617	0.603	0.603	1.000
		(0.000)	(0.000)	(0.000)	------
EURO STOXX50	*AMH*	1.000			

	HLS_w	0.553	1.000		
		(0.000)	------		
	HLS_r	0.577	0.878	1.000	
		(0.007)	(0.000)	------	
	QS	0.488	0.527	0.533	1.000
		(0.003)	(0.002)	(0.002)	------

4.6. THE EFFECT OF IMPLIED VOLATILITY INDICES ON INDIVIDUAL STOCKS LIQUIDITY.

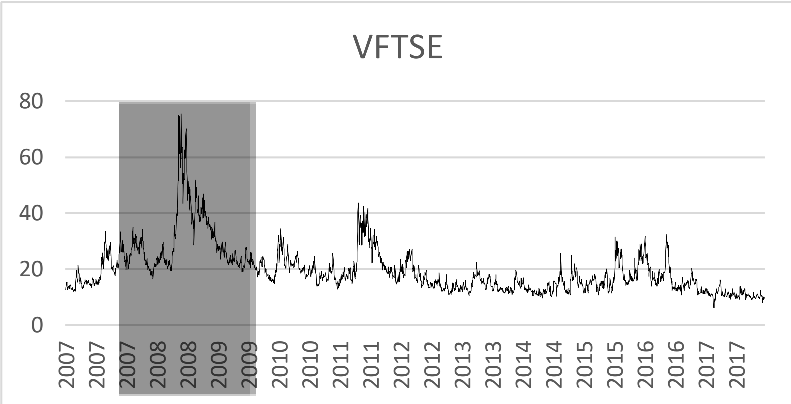
Tables 4.3 to 4.5 show the results of the average individual stocks liquidity measures (AMH, HLS_w, HLS_r and QS) of the London Stock Exchange (FTSE100), Japan stock market (Nikkei225), and Eurozone stock market (EURO STOXX50) responses to their corresponding IV indices, VFTSE, VXJ, and VSTOXX. The data is divided into two samples, that collected during the financial crisis (from January 5, 2010 to December 28, 2009) and after (from January 5, 2010 to December 28, 2017). The mean coefficients of all fear indices for all measures of liquidity at times t, t_{-1}, and t_{+1} are not significant in either model (7) and (8), when we include the market and industry liquidity averages. Even when we regress individual stock liquidity on their fear indices only at time t, t_{-1}, and t_{+1}, they did not yield any significant effects, and therefore were not reported in the tables.

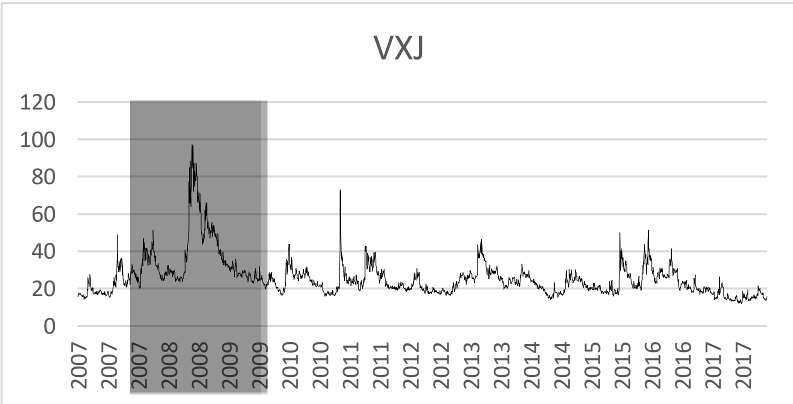
Our results differ from the findings of Nagel (2012), Adrian and Shin (2010) and Chung and Chuwonganant (2014), whose studies are pertinent to the US market. They provided strong evidence that individual assets are affected by the uncertainty level of their own risk and the uncertainty of the market as a whole. They related changes in liquidity to variation in the fear index. Furthermore, market uncertainty could be capturing additional risks, other than individual asset risk, such as the costs of liquidity providers and inventory risk.

In our sample, the coefficients of fear indices do not define changes in individual average stocks liquidity. A possible explanation is that investors and market participants are not guided by the actual level of the fear index during and after the financial crisis. Our findings for the UK, Japan, and European markets vary from the findings in the past literature, which is focused mainly on the US market. Most evidence showed a strong impact from VIX on market participant in the US market only during the crisis and at no other point in time (Neffelli and Resta, 2018). Similar results were reported by Chandorkar and Brzeszczyński (2018) using a sample size from January 1990 to June 2017. They indicated that fear indices failed to predict future market movements in the US, the UK, and the European markets in the long run. In short, market participants pay little attention as their responses toward fear indices are weaker. Fear indices do not appear to determine the outlook of the markets.

Figure 4.1: Plot of the market uncertainty in the UK, Japan, and the Eurozone markets.

This figure shows the daily data of market uncertainty of the London Stock Exchange (VFTSE), Nikkei225 (VXJ), and the Eurozone stock market (VSTOXX). The date sets are the closing daily prices that range from January 5, 2010 to December 28, 2017. All data are obtained from Datastream.





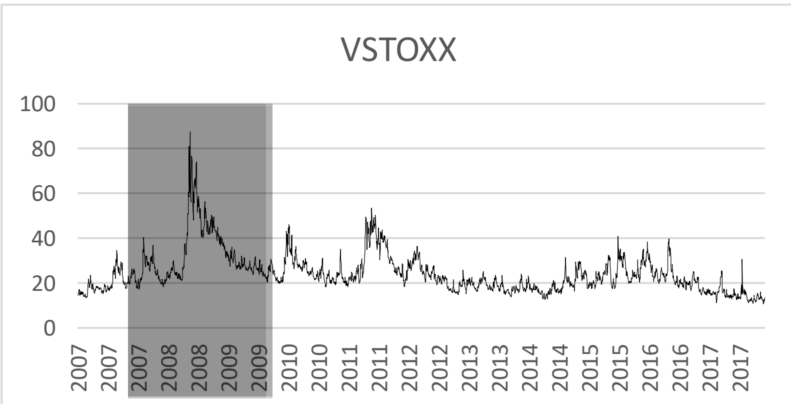


Table 4.3: Effect of the London Stock Exchange (LSE) FTSE 100 implied volatility index (VFTSE), market and industry liquidity on individual stock illiquidity ($LM_{i,t}$).

This table presents the regression estimation results of the following models for each of the FTSE 100 companies using daily data divided into two samples: 1) sample (1), during the financial crisis from January 5, 2007 to December 5, 2009; 2) sample (2) after the financial crisis, from January 5, 2010 to December 28, 2017, to investigate the effect of VFTSE on $LM_{i,t}$, captured by three liquidity measures (AMH, HLS, and QS), before and after using market liquidity as a controlling variable:

$$DLM_{i,t} = \alpha_{i0} + \alpha_{i1} DVFTSE_t + \alpha_{i2} DVFTSE_{t-1} + \alpha_{i3} DVFTSE_{t+1} + \alpha_{i4}DML_t + \alpha_{i5}DML_{t-1} + \alpha_{i6}DML_{t+1} + \alpha_{i7}DIL_t + \alpha_{i8}DIL_{t-1} + \alpha_{i9}DIL_{t+1} + \varepsilon_{1i,t} \quad (4.7)$$

and

$$Log(LM_{i,t}) = \alpha_{i0} + \alpha_{i1} Log(VFTSE_t) + \alpha_{i2}Log(VFTSE_{t-1}) + \alpha_{i3}Log(VFTSE_{t+1}) + \alpha_{i4}Log(ML_t) + \alpha_{i5}Log(ML_{t-1}) + \alpha_{i6}Log(ML_{t+1}) + \alpha_{i7}Log(IL_t) + \alpha_{i8}Log(IL_{t-1}) + \alpha_{i9}Log(IL_{t+1}) + \varepsilon_{1i,t} \quad (4.8)$$

Where LM stands for liquidity measure, and is captured by: 1) $AMH_{i,t}$, the Amihud illiquidity measure calculated for each company, every day as following: $AMH_{i,t} = \frac{1,000,000 \times |return_t|}{price_t \times volume_t}$ of stock i at day t. 2) $HLS_{i,t}$, is the Corwin & Schultz bid-ask spread estimator for each stock calculated by: $HLS_{i,t} = \frac{2(e^a-1)}{1+e^a}$. 3) $QS_{i,t}$, the quoted spread for each company, daily, by using: $QS_{i,t} = (Ask_{i,t} - Bid_{i,t})/M_{i,t}$. $VFTSE_t$, $VFTSE_{t-1}$, $VFTSE_{t+1}$ are the implied market volatility index VFTSE at time *t*, *t*-1, and *t*+1; ML_t, ML_{t-1}, ML_{t+1} are the average quoted market liquidity across all stocks at time *t*, *t*-1, and *t*+1; IL_t, IL_{t-1}, IL_{t+1} are the average quoted industry liquidity, the average quoted spread across all stocks in the same industry at time *t*, *t*-1, and *t*+1. D is the percentage change from the previous day, for all variables in Panel A, calculated by: $DX_{it} = (X_{it} - X_{it-1})/X_{it-1}$. Panel A exhibit the results of equation (4.1), while Panel B exhibits the results of equation (4.2). We're reporting the regression coefficients, the *t*-value of the average regression coefficient, the median *t*-value of all individual stock regression, and the median *t*-value of all individual stock regression. We also test for the independence of the residuals from equation (4.1) and (4.2), because the reliability of the t-statistics depends on the cross-section dependence in estimation error. We use the method in Chordia, Roll, and Subrahmanyam (2000) Coughenoour and Saad (2004). After estimating 100 FTSE stocks, we sort the residuals alphabetically based on their industries and assign each stock a serial number *i*(*i*=1, …, 100) and then we estimate the following regression: $\varepsilon_{1i+1,t} = \delta_0 + \delta_1\varepsilon_{1i,t} + \mu_{1i,t}$ and $\varepsilon_{2i+1,t} = \delta_0 + \delta_1\varepsilon_{2i,t} + \mu_{1i,t}$ where ε_{1i}, ε_{2i}, ε_{1i+1}, ε_{1i+1} are residuals from equation (4.1) and (4.2), $\mu_{1i,t}$ and $\mu_{1i,t}$ are the disturbance terms. Panel C exhibits the cross-section dependence in estimation error, and the correlation coefficient between ε_{1i+1t} and ε_{1it}, and between ε_{2i+1t} and ε_{2it}. All data are obtained from Datastream.

Panel A: Regression coefficients from model (1)												
LM	Sample	Variable	*c*	*VIX*	VIX_{-1}	VIX_{+1}	*ML*	ML_{-1}	ML_{+1}	*IL*	IL_{-1}	IL_{+1}
AMH	Sample (1) (2007-2009)	Coefficients	1.835	2.175	-2.933	-0.285	0.001	-0.002	-0.002	0.170	-0.041	-0.063
		Average t-value	**5.036**	0.438	-0.596	-0.058	0.054	-0.137	-0.100	1.579	-0.388	-0.605
		Mean t-value	**6.189**	0.777	-0.722	-0.118	0.033	-0.172	-0.172	0.869	-0.028	-0.369
		Median t-value	**6.342**	0.703	-0.638	-0.163	-0.062	-0.195	-0.272	0.455	-0.323	-0.302
	Sample (2) (2010-2017)	Coefficients	0.016	-0.023	0.017	-0.009	0.002	0.000	-0.001	0.001	-0.003	-0.002
		Average t-value	**11.921**	-1.593	1.132	-0.589	1.207	0.009	-0.604	0.495	**-1.978**	-1.190
		Mean t-value	0.130	-0.017	0.012	-0.006	0.013	0.000	-0.007	0.005	-0.022	-0.013
		Median t-value	**9.539**	0.178	0.009	0.263	0.912	-0.656	-0.318	0.927	-0.657	-0.245
QS	Sample (1) (2007-2009)	Coefficients	0.360	0.113	-0.065	0.101	1.027	-0.082	-0.084	0.470	0.107	0.014
		Average t-value	**4.240**	0.093	-0.054	0.084	1.280	-0.342	-0.353	0.990	0.692	0.093
		Mean t-value	**5.852**	0.029	-0.199	0.253	1.759	-0.778	-0.778	0.707	0.774	0.504
		Median t-value	**6.581**	-0.006	-0.322	0.206	0.325	-0.252	-0.457	0.747	0.327	0.245
	Sample (2) (2010-2017)	Coefficients	0.003	0.002	0.001	0.000	0.002	0.000	0.000	0.005	0.001	0.001
		Average t-value	**9.839**	0.455	0.347	0.090	0.198	0.415	-0.204	0.905	1.524	0.752
		Mean t-value	0.107	0.005	0.004	0.001	0.024	0.005	-0.002	0.053	0.017	0.008
		Median t-value	**9.359**	-0.206	0.171	0.238	1.678	-0.369	-0.699	0.119	0.752	0.342

(Continued)

Panel A: Regression coefficients from model (1)												
LM	Sample	Variable	*c*	*VIX*	VIX_{-1}	VIX_{+1}	*ML*	ML_{-1}	ML_{+1}	*IL*	IL_{-1}	IL_{+1}
HLS_w	Sample (1) (2007-2009)	Coefficients	2.283	-23.352	-3.844	-0.751	0.031	-0.189	-0.435	-0.007	-0.012	-0.027
		Average t-value	1.253	-0.948	-0.158	-0.031	0.018	-0.114	-0.262	-0.046	-0.077	-0.167
		Mean t-value	**2.304**	0.100	-0.020	0.095	-0.026	-0.486	-0.486	0.413	-0.103	-0.171
		Median t-value	**2.419**	0.078	-0.141	0.088	-0.199	-0.203	-0.491	-0.050	-0.096	-0.156
	Sample (2) (2010-2017)	Coefficients	0.004	0.001	0.006	-0.007	0.000	0.000	0.000	0.000	0.000	0.000
		Average t-value	**4.540**	0.065	0.526	-0.620	-0.450	-0.340	-0.512	0.013	1.256	-0.352
		Mean t-value	0.049	0.001	0.006	-0.007	-0.005	-0.004	-0.006	0.000	0.014	-0.004
		Median t-value	**3.016**	0.143	-0.233	-0.001	-0.211	-0.107	-0.438	-0.076	-0.115	-0.166
HLS_r	Sample (1) (2007-2009)	Coefficients	2.331	-22.885	-4.042	-2.528	0.022	0.000	-0.225	-0.041	-0.043	-0.061
		Average t-value	1.272	-0.915	-0.163	-0.103	0.011	0.000	-0.121	-0.109	-0.115	-0.161
		Mean t-value	**2.362**	0.120	0.017	-0.083	-0.070	-0.288	-0.288	0.341	0.011	-0.210
		Median t-value	**2.393**	0.108	-0.112	-0.039	-0.114	-0.230	-0.368	-0.039	-0.099	-0.220
	Sample (2) (2010-2017)	Coefficients	0.009	-0.008	-0.023	0.013	0.001	0.000	-0.001	0.000	0.000	0.000
		Average t-value	**3.093**	-0.215	-0.595	0.344	0.807	-0.039	-0.305	0.647	-0.298	-0.246
		Mean t-value	0.034	-0.002	-0.006	0.004	0.009	0.000	-0.003	0.007	-0.003	-0.003
		Median t-value	**3.093**	0.001	-0.172	0.044	-0.036	-0.063	-0.305	-0.073	-0.137	-0.141

(Continued)

Panel B: Regression coefficients from model (1)												
LM	Sample	Variable	*c*	*VIX*	VIX_{-1}	VIX_{+1}	*ML*	ML_{-1}	ML_{+1}	*IL*	IL_{-1}	IL_{+1}
AMH	Sample (1) (2007-2009)	Coefficients	-6.387	0.739	0.010	0.093	0.099	0.045	0.035	**0.157**	0.021	0.036
		Average t-value	**-7.578**	0.755	0.014	0.125	1.564	0.719	0.561	**2.369**	0.313	0.544
		Mean t-value	**-8.109**	0.781	0.005	0.121	1.533	0.476	0.476	**2.279**	0.283	0.562
		Median t-value	**-8.420**	0.738	0.019	0.133	1.458	0.708	0.576	**2.679**	0.504	0.871
	Sample (2) (2010-2017)	Coefficients	-0.033	-0.006	0.005	0.001	**0.003**	0.000	0.001	**0.001**	0.000	0.000
		Average t-value	**-6.101**	-1.288	1.663	0.193	**5.437**	0.486	1.237	**2.122**	-0.383	-0.402
		Mean t-value	-0.066	-0.014	0.018	0.002	**4.059**	0.005	0.013	**2.023**	-0.004	-0.004
		Median t-value	**-13.704**	0.230	-0.064	0.280	**9.116**	-0.489	-0.220	**2.023**	1.450	0.346
QS	Sample (1) (2007-2009)	Coefficients	-2.396	0.106	-0.129	-0.083	**0.205**	0.093	0.085	**0.177**	0.028	0.049
		Average t-value	**-4.249**	0.231	-0.372	-0.239	**2.448**	1.115	1.012	**2.077**	0.334	0.579
		Mean t-value	**-4.820**	0.262	-0.406	-0.248	**2.582**	0.996	0.996	**2.462**	0.477	0.663
		Median t-value	**-4.746**	0.139	-0.602	-0.329	**2.482**	1.034	0.903	**2.137**	0.235	0.673
	Sample (2) (2010-2017)	Coefficients	-0.063	0.000	-0.003	0.000	**0.002**	-0.001	0.000	0.001	0.000	0.000
		Average t-value	**-12.040**	0.178	-1.567	-0.036	**3.398**	-1.622	-0.560	**1.844**	1.093	0.069
		Mean t-value	-0.131	0.002	-0.017	0.000	**3.037**	-0.018	-0.006	0.020	0.012	0.001
		Median t-value	**-9.963**	-0.199	0.236	0.230	**3.719**	1.498	1.032	**2.619**	0.682	0.667

(Continued)

Panel B: Regression coefficients from model (1)												
LM	Sample	Variable	*c*	*VIX*	VIX_{-1}	VIX_{+1}	*ML*	ML_{-1}	ML_{+1}	*IL*	IL_{-1}	IL_{+1}
HLS_w	Sample (1) (2007-2009)	Coefficients	-10.610	0.289	-0.182	1.249	**-0.963**	0.089	0.165	-0.101	0.028	0.040
		Average t-value	**-3.808**	0.171	-0.141	0.973	**-4.317**	0.399	0.742	-0.947	0.267	0.372
		Mean t-value	**-3.880**	0.205	-0.147	0.958	**-4.406**	0.755	0.755	-0.431	0.263	0.307
		Median t-value	**-3.924**	0.225	-0.232	0.808	**-4.247**	0.334	0.858	-0.794	0.285	0.229
	Sample (2) (2010-2017)	Coefficients	-0.053	-0.015	0.006	0.018	-0.003	0.002	0.001	-0.002	0.001	0.000
		Average t-value	**-8.357**	-1.467	0.753	**2.311**	**-3.799**	**2.612**	**1.859**	-1.123	1.722	0.433
		Mean t-value	-0.091	-0.016	0.008	0.025	-0.041	0.028	0.020	-0.045	0.019	0.005
		Median t-value	**-7.235**	-0.026	0.176	0.969	**-5.004**	**2.948**	**2.476**	-1.436	0.304	0.429
HLS_r	Sample (1) (2007-2009)	Coefficients	-10.329	0.243	-0.124	1.211	-0.916	0.125	0.220	-0.143	0.004	0.033
		Average t-value	**-3.578**	0.145	-0.097	0.950	**-3.702**	0.503	0.889	-1.140	0.031	0.261
		Mean t-value	**-3.637**	0.177	-0.111	0.944	**-3.811**	0.895	0.895	-0.722	0.048	0.239
		Median t-value	**-3.828**	0.115	-0.154	0.942	**-3.703**	0.454	0.830	-0.948	0.030	0.247
	Sample (2) (2010-2017)	Coefficients	-0.056	-0.017	0.006	0.019	-0.001	0.002	0.000	-0.003	0.000	0.000
		Average t-value	**-8.705**	-1.617	0.822	**2.453**	-0.596	1.765	0.302	-1.109	0.532	0.601
		Mean t-value	-0.095	-0.018	0.009	0.027	-0.006	0.019	0.003	-0.045	0.006	0.007
		Median t-value	**-7.205**	-0.294	0.197	1.214	**-3.273**	**1.813**	1.153	-1.105	0.136	0.660

(Continued)

Panel C: Check for cross-section dependence in estimation error

	LM	Sample	Average Correlation	Average t-statistics	Median t	|t|>1.645 %	|t|>1.96 %
Results from regression model (1)	*AMH*	(1)	0.036	1.565	0.599	0.534	0.500
		(2)	0.013	0.588	0.243	0.056	0.047
	QS	(1)	0.000	0.062	-0.255	0.362	0.328
		(2)	-0.005	-0.209	-0.297	0.085	0.075
	HLS_w	(1)	-0.001	-0.044	-0.164	0.034	0.017
		(2)	0.000	-0.014	-0.105	0.005	0.005
	HLS_r	(1)	0.003	0.108	-0.144	0.103	0.069
		(2)	0.002	0.088	-0.117	0.009	0.009

Panel C: Check for cross-section dependence in estimation error

	LM	Sample	Average Correlation	Average t-statistics	Median t	|t|>1.645 %	|t|>1.96 %
Results from regression model (2)	*AMH*	(1)	0.073	0.172	0.043	0.948	0.948
		(2)	0.028	1.389	0.997	0.16	0.136
	QS	(1)	0.029	1.250	0.722	0.621	0.603
		(2)	0.001	0.056	0.271	0.113	0.094
	HLS_w	(1)	0.065	0.874	0.043	0.845	0.776
		(2)	0.052	0.347	0.313	0.258	0.235
	HLS_r	(1)	0.065	0.839	0.061	0.828	0.776
		(2)	0.039	0.758	1.593	0.207	0.178

(Continued)

Additionally, Chung and Chuwonganant (2014) showed that market uncertainty had a great impact on individual stocks liquidity during the financial crisis, only in the US market. A further potential explanation of this aspect is that the US VIX constitutes a global proxy for investor sentiment. The US economy currently forms the central point for other economies in the world as a result of its highly integrated global trading system. The ease of information spillover could result in a greater impact of the US VIX on the UK, Eurozone and Japan markets, than their own implied volatility.

To the best of our knowledge, we are unaware of any other studies examining the effect of index fears on market-wide liquidity following the financial crisis for the US or any other markets; therefore, complicating direct comparison.

4.7. THE EFFECT OF AVERAGE MARKET LIQUIDITY ON INDIVIDUAL STOCK LIQUIDITY.

Tables 4.3 to 4.5 also depict the results of the individual stocks liquidity measures (AMH, HLS_w, HLS_r and QS) of the London Stock Exchange (FTSE100), Japan's stock market (Nikkei225), and the Eurozone stock market (EURO STOXX50) as responses to their corresponding average market liquidity, during and after the financial crisis. According to model (7), the AMH mean of the ML coefficients for the average, the mean and the median t-values[48] at times t, t_{-1}, and t_{+1}, in sample (1) and (2) for FTSE100, and Nikkei225 are not significant. On the other hand, the mean of the ML coefficients only at time t of Euro STOXX50 are significant and consistent in sample (2). When ML at time t increases (decreases) by 1% this will lead to an increase (decrease) in average AMH of 1.95%.

[48] The average t-value is calculated by extracting the t-value from the average coefficients of all calculated regressions of all stocks in the market, while the mean t-values is the average t-values from the calculated regressions across all stocks in the market. The median t-value is the median of all t-values from the all regressions applied for all stocks in the market.

Table 4.4: Effect of the Tokyo Stock Exchange (Nikkei 225) implied volatility index (VXJ), market and industry liquidity on individual stock illiquidity ($LM_{i,t}$).

This table presents the regression estimation results of the following models for each of the Nikkei 225 companies using daily data divided into two samples: 1) sample (1), during the financial crisis from January 5, 2007 to December 5, 2009; 2) sample (2) after the financial crisis, from January 5, 2010 to December 28, 2017, to investigate the effect of VXJ on $LM_{i,t}$, captured by three liquidity measures (AMH, HLS, and QS), before and after using market liquidity as a controlling variable:

$$DLM_{i,t} = \alpha_{i0} + \alpha_{i1}\,DVXJ_t + \alpha_{i2}\,DVXJ_{t-1} + \alpha_{i3}\,DVXJ_{t+1} + \alpha_{i4}DML_t + \alpha_{i5}DML_{t-1} + \alpha_{i6}DML_{t+1} + \alpha_{i7}DIL_t + \alpha_{i8}DIL_{t-1} + \alpha_{i9}DIL_{t+1} + \varepsilon_{1i,t} \quad (4.7)$$

and

$$Log(LM_{i,t}) = \alpha_{i0} + \alpha_{i1}Log(VXJ_t) + \alpha_{i2}Log(VXJ_{t-1}) + \alpha_{i3}Log(VXJ_{t+1}) + \alpha_{i4}Log(ML_t) + \alpha_{i5}Log(ML_{t-1}) + \alpha_{i6}Log(ML_{t+1}) + \alpha_{i7}Log(IL_t) + \alpha_{i8}Log(IL_{t-1}) + \alpha_{i9}Log(IL_{t+1}) + \varepsilon_{1i,t} \quad (4.8)$$

Where LM stands for liquidity measure, and is captured by: 1) $AMH_{i,t}$, the Amihud illiquidity measure calculated for each company, every day as following: $AMH_{i,t} = \frac{1{,}000{,}000 \times |return_t|}{price_t \times volume_t}$ of stock i at day t. 2) $HLS_{i,t}$, is the Corwin & Schultz bid-ask spread estimator for each stock calculated by: $HLS_{i,t} = \frac{2(e^a - 1)}{1 + e^a}$. 3) $QS_{i,t}$, the quoted spread for each company, daily, by using: $QS_{i,t} = (Ask_{i,t} - Bid_{i,t})/M_{i,t}$. VXJ_t, VXJ_{t-1}, VXJ_{t+1} are the implied market volatility index VXJ at time t, t-1, and t+1; ML_t, ML_{t-1}, ML_{t+1} are the average quoted market liquidity across all stocks at time t, t-1, and t+1, t-1, and t+1; IL_t, IL_{t-1}, IL_{t+1} are the average quoted industry liquidity, the average quoted spread across all stocks in the same industry at time t, t-1, and t+1. D is the percentage change from the previous day, for all variables in Panel A, calculated by: $DX_{it} = (X_{it} - X_{it-1})/ X_{it-1}$. Panel A exhibit the results of equation (4.1), while Panel B exhibits the results of equation (4.2). We're reporting the regression coefficients, the t-value of the average regression coefficient, the median t-value of all individual stock regression, and the median t-value of all individual stock regression. We also test for the independence of the residuals from equation (4.1) and (4.2), because the reliability of the t-statistics depends on the cross-section dependence in estimation error. We use the method in Chordia, Roll, and Subrahmanyam (2000) Coughenoour and Saad (2004). After estimating 225 Nikkei stocks, we sort the residuals alphabetically based on their industries and assign each stock a serial number i(i=1, …, 225) and then we estimate the following regression: $\varepsilon_{1i+1,t} = \delta_0 + \delta_1\varepsilon_{1i,t} + \mu_{1i,t}$ and $\varepsilon_{2i+1,t} = \delta_0 + \delta_1\varepsilon_{2i,t} + \mu_{1i,t}$ where ε_{1i}, ε_{2i}, ε_{1i+1}, ε_{1i+1} are residuals from equation (4.1) and (4.2), $\mu_{1i,t}$ and $\mu_{1i,t}$ are the disturbance terms. Panel C exhibits the cross-section dependence in estimation error, and the correlation coefficient between ε_{1i+1t} and ε_{1it}, and between ε_{2i+1t} and ε_{2it}. All data are obtained from Datastream.

Panel A: Regression coefficients from model (1)												
LM		Variable	*c*	*VIX*	VIX_{-1}	VIX_{+1}	*ML*	ML_{-1}	ML_{+1}	*IL*	IL_{-1}	IL_{+1}
AMH	Sample (1) (2007-2009)	Coefficients	0.848	0.816	-0.040	-0.184	1.016	-0.010	0.105	0.593	-0.010	-0.034
		Average t-value	**5.145**	0.395	-0.020	-0.089	1.811	-0.019	0.202	1.422	-0.025	-0.087
		Mean t-value	**5.360**	0.475	-0.055	-0.063	1.016	0.146	0.146	1.542	-0.154	-0.153
		Median t-value	**5.504**	0.531	-0.133	-0.123	1.854	0.065	0.231	1.323	-0.208	-0.125
	Sample (2) (2010-2017)	Coefficients	0.005	-0.001	-0.018	0.000	0.002	-0.001	-0.045	**1.015**	0.054	-0.001
		Average t-value	**6.594**	-0.140	**-1.763**	-0.046	0.916	-0.582	-0.147	**2.760**	0.155	-0.314
		Mean t-value	0.031	-0.001	-0.008	0.000	0.004	-0.003	-0.131	**3.123**	0.095	-0.001
		Median t-value	**8.267**	0.074	-0.353	-0.061	0.097	-0.327	-0.107	**2.911**	0.097	0.202
QS	Sample (1) (2007-2009)	Coefficients	-0.202	23.412	-6.320	-4.761	-0.546	-0.020	0.039	0.489	-0.268	0.075
		Average t-value	-0.261	1.150	-0.579	-0.438	-1.426	-0.123	0.242	**2.106**	-1.149	0.320
		Mean t-value	**2.606**	2.077	-0.263	-0.289	-1.675	0.150	0.150	1.587	-0.905	0.086
		Median t-value	1.144	1.044	-0.183	-0.198	0.088	0.000	0.112	0.946	-0.163	0.161
	Sample (2) (2010-2017)	Coefficients	0.001	0.002	0.001	0.003	0.000	0.000	0.016	0.118	0.020	0.000
		Average t-value	**9.384**	**1.970**	0.774	**3.115**	**2.618**	**-2.544**	0.092	1.501	0.251	-1.393
		Mean t-value	0.044	0.009	0.004	0.015	0.012	-0.012	-0.440	1.033	0.017	-0.007
		Median t-value	**9.077**	1.332	0.478	-0.145	1.253	-0.060	-0.427	0.080	-0.016	-0.013

(Continued)

Panel A: Regression coefficients from model (1)													
LM		Variable	*c*	*VIX*	VIX_{-1}	VIX_{+1}	*ML*	ML_{-1}	ML_{+1}	*IL*	IL_{-1}	IL_{+1}
HLS_w	Sample (1) (2007-2009)	Coefficients	1.779	1.344	4.295	-1.052	0.039	-0.010	-0.018	-0.026	0.017	-0.029
		Average t-value	1.326	0.072	0.233	-0.057	0.115	-0.028	-0.051	-0.114	0.078	-0.129
		Mean t-value	**1.989**	-0.017	-0.042	-0.206	-0.058	-0.078	-0.078	-0.026	0.152	-0.194
		Median t-value	**1.898**	-0.118	-0.089	-0.175	-0.056	-0.037	-0.069	-0.115	-0.082	-0.161
	Sample (2) (2010-2017)	Coefficients	0.000	0.000	0.000	0.000	0.000	-0.464	-5.928	1.735	0.000	0.000
		Average t-value	**30.964**	-1.549	**-2.294**	-1.230	0.166	-0.964	-0.346	1.899	-1.187	-0.688
		Mean t-value	0.145	-0.007	-0.011	-0.006	0.001	0.075	-0.868	1.497	-0.006	-0.003
		Median t-value	1.630	-0.073	-0.018	0.619	0.080	-0.211	-0.587	1.414	-1.365	0.205
HLS_r	Sample (1) (2007-2009)	Coefficients	2.312	2.219	4.297	-0.906	-0.093	0.082	0.030	0.179	-0.239	-0.190
		Average t-value	1.405	0.101	0.198	-0.042	-0.215	0.190	0.068	0.171	-0.228	-0.182
		Mean t-value	**2.037**	0.086	-0.050	-0.089	-0.037	-0.051	-0.051	-0.118	0.124	-0.264
		Median t-value	**1.912**	-0.010	-0.115	-0.095	-0.032	-0.054	-0.057	-0.139	-0.121	-0.265
	Sample (2) (2010-2017)	Coefficients	0.010	0.003	0.027	0.067	-0.003	-0.002	3.243	1.336	-2.976	0.000
		Average t-value	**2.619**	0.061	0.514	1.300	-0.856	-0.714	0.244	0.768	-0.465	-0.086
		Mean t-value	0.012	0.000	0.002	0.006	-0.004	-0.003	-0.416	-0.055	-0.067	0.000
		Median t-value	**2.443**	-0.057	0.024	-0.090	-0.104	-0.210	-0.430	-0.076	-0.091	-0.100

(Continued)

Panel B: Regression coefficients from model (1)

LM		Variable	*c*	*VIX*	VIX_{-1}	VIX_{+1}	*ML*	ML_{-1}	ML_{+1}	*IL*	IL_{-1}	IL_{+1}
AMH	Sample (1) (2007-2009)	Coefficients	-0.852	0.104	0.082	-0.278	0.482	0.060	0.035	0.290	-0.021	0.011
		Average t-value	-0.577	0.104	0.110	-0.369	1.759	0.218	0.127	1.270	-0.091	0.048
		Mean t-value	-0.511	0.099	0.103	-0.345	1.622	0.144	0.144	1.353	-0.124	0.027
		Median t-value	-0.807	0.150	0.166	-0.319	1.732	0.282	0.160	1.385	-0.185	0.066
	Sample (2) (2010-2017)	Coefficients	-0.003	0.004	-0.003	-0.001	**0.003**	0.001	0.040	**0.367**	0.028	-0.001
		Average t-value	-0.951	1.237	-1.481	-0.436	**4.562**	**1.794**	0.288	**2.409**	0.189	-1.983
		Mean t-value	-0.004	0.006	-0.007	-0.002	**3.021**	0.008	0.249	**2.784**	0.098	-0.009
		Median t-value	-0.951	0.053	-0.055	-0.035	**3.600**	0.104	0.309	**2.300**	0.104	-0.004
QS	Sample (1) (2007-2009)	Coefficients	-6.229	0.494	-0.132	0.016	0.009	-0.001	0.006	**0.087**	0.028	0.027
		Average t-value	**-17.843**	1.251	-0.441	0.052	0.683	-0.094	0.482	**3.074**	0.997	0.968
		Mean t-value	**-20.296**	1.337	-0.333	0.044	0.572	0.351	0.351	**2.738**	0.963	0.993
		Median t-value	**-19.297**	1.411	-0.310	0.051	0.582	-0.256	0.382	**2.369**	0.902	1.049
	Sample (2) (2010-2017)	Coefficients	-0.012	0.000	0.001	0.000	0.000	0.000	0.005	**0.213**	**0.136**	0.001
		Average t-value	**-8.619**	0.151	1.517	0.143	1.788	1.183	0.350	**7.531**	**4.871**	6.135
		Mean t-value	-0.040	0.001	0.007	0.001	0.008	0.006	0.379	**7.088**	**4.745**	0.029
		Median t-value	**-18.957**	**2.217**	-0.563	-0.624	0.643	0.072	0.407	**6.947**	**4.846**	4.739

(Continued)

Panel B: Regression coefficients from model (1)												
LM		Variable	*c*	*VIX*	VIX_{-1}	VIX_{+1}	*ML*	ML_{-1}	ML_{+1}	*IL*	IL_{-1}	IL_{+1}
HLS_w	Sample (1) (2007-2009)	Coefficients	-6.363	-0.791	-0.393	1.876	**-0.338**	0.162	0.162	**-0.335**	0.007	-0.003
		Average t-value	**-4.665**	-0.455	-0.299	1.426	**-2.968**	1.608	1.620	**-3.140**	0.064	-0.026
		Mean t-value	**-4.660**	-0.468	-0.298	1.443	**-3.074**	1.662	1.662	**-2.937**	0.103	-0.043
		Median t-value	**-4.899**	-0.425	-0.275	1.464	**-2.888**	1.581	1.657	**-3.062**	0.032	0.005
	Sample (2) (2010-2017)	Coefficients	-0.053	0.007	0.000	0.008	**-0.366**	-0.001	0.167	**-0.159**	0.015	0.000
		Average t-value	**-8.713**	0.080	0.058	**1.892**	**-8.056**	-1.142	1.484	**-2.225**	0.211	-0.121
		Mean t-value	-0.041	0.006	0.000	0.009	**-3.359**	-0.005	1.482	**-1.980**	0.282	-0.001
		Median t-value	**-7.757**	0.269	0.019	0.580	**-8.471**	1.261	1.424	**-2.536**	0.235	0.480
HLS_r	Sample (1) (2007-2009)	Coefficients	-7.594	-0.825	-0.216	1.753	**-0.210**	0.100	0.110	**-0.568**	0.027	0.045
		Average t-value	**-4.430**	-0.484	-0.166	1.351	**-2.519**	0.812	0.895	**-3.917**	0.190	0.324
		Mean t-value	**-4.401**	-0.484	-0.164	1.355	**-2.573**	0.908	0.908	**-3.727**	0.213	0.317
		Median t-value	**-4.466**	-0.485	-0.150	1.357	**-2.404**	0.905	0.969	**-4.051**	0.162	0.287
	Sample (2) (2010-2017)	Coefficients	-0.053	0.007	0.000	0.008	**-0.366**	-0.001	0.167	**-0.159**	0.015	0.000
		Average t-value	**-8.713**	0.080	0.058	**1.892**	**-8.056**	-1.142	1.484	**-2.225**	0.211	-0.121
		Mean t-value	-0.041	0.006	0.000	0.009	**-3.359**	-0.005	1.482	**-1.980**	0.282	-0.001
		Median t-value	**-7.757**	0.269	0.019	0.580	**-8.471**	1.261	1.424	**-2.536**	0.235	0.480

(Continued)

Panel C: Check for cross-section dependence in estimation error								
	LM	Sample	Average Correlation	Average t-statistics	Median t	|t|>1.645 %	|t|>1.96 %
Results from regression model (1)	*AMH*	(1)	0.017	0.724	0.137	1.052	0.983
		(2)	0.009	0.402	0.070	0.052	0.028
	QS	(1)	0.076	0.071	0.866	1.379	1.241
		(2)	0.048	0.136	0.248	0.034	1.948
	HLS_w	(1)	-0.001	-0.022	-0.173	0.086	0.069
		(2)	0.755	0.888	0.240	0.138	3.103
	HLS_r	(1)	-0.002	-0.093	-0.168	0.052	0.052
		(2)	0.005	0.227	-0.091	0.862	0.862

Panel C: Check for cross-section dependence in estimation error							
	LM	Sample	Average Correlation	Average t-statistics	Median t	|t|>1.645 %	|t|>1.96 %
Results from regression model (2)	*AMH*	(1)	0.007	0.302	0.306	0.862	0.672
		(2)	0.007	0.316	0.085	0.047	0.033
	QS	(1)	0.220	0.895	0.773	0.241	3.224
		(2)	0.133	0.211	0.934	0.621	2.500
	HLS_w	(1)	0.072	0.093	0.672	0.569	2.310
		(2)	0.328	0.010	0.080	0.586	2.414
	HLS_r	(1)	0.067	0.881	0.605	0.483	2.362
		(2)	0.328	0.010	0.080	0.586	2.414

(Continued)

Finally, when using HLS_w, and HLS_r, average market liquidity shows no sign of a significant effect on individual stock liquidity in any of the countries.

Our results differ from findings for the US market that have indicated a co-movement among the liquidity of individual assets in the market[49]. The impact of industry liquidity, IL (which will be explained in the next section), eliminates the power of ML at time t, t_{-1}, and t_{+1}; in many cases indicating that strong attention is directed by market participants towards IL rather than ML. According to model (8)'s results, 60% of all ML coefficients of sample (1) and (2) of FTSE100, Nikkei225, and Euro STOXX50 appear to be significant, and have a strong impact on individual asset liquidity. Taking logs in model (2) smoothed out the data and enabled the liquidity measures to capture the effect of ML on individual stocks' liquidity.

Using AMH in sample (1), MLs at time t are significant in the Nikkei225 and Euro STOXX50 markets. For instance, when MLs at time t increases (decreases) by 1% in Euro STOXX50, this will lead to an increase (decrease) in AMH average individual stock liquidity by 0.48% and 0.14% respectively. Furthermore, in sample (2), Nikkei225, and Euro STOXX50 markets, show significant ML_t coefficients. When using QS in Sample (1), ML has significant coefficients in the FTSE100 market, while in sample (2), ML is significant only in the FTSE100.

With regard to HLS_w and HLS_r in sample (1), using logs in model (2), ML was significant in all countries, and in sample (2) all aspects were significant except in the FTSE100 market. One interpretation of the different outcomes between models (1) and (2) could be related to the inputs used in HLS_w and HLS_r calculations, and the closing, the high, and the low prices of stocks. Again, using the log function smoothed out the data and enabled HLS_w and HLS_r to capture the effect of ML on the liquidity of individual stocks.

[49] See for example Hasbrouck and Seppi (1998), and Huberman and Halka (2001).

However, the effect of ML using HLS_w and HLS_r measures was found to be negative, which was not expected. In sample (1), when HLS_w (HLS_r) increases by 1% in FTSE100, Nikkei225, and Euro STOXX50 markets, it will cause a decrease by -0.96% (-0.91%), -0.34% (-0.21%), and -0.53% (-0.53%) respectively. Similarly, regarding the analysis of sample (2), when HLS_w (HLS_r) increases by 1% in the Nikkei225, and Euro STOXX50 markets, it will cause a fall of -0.37% (-0.37%), and -0.64% (-0.92%) respectively.

In summary, using equation (4.8), 60% of the mean coefficients of ML t-values at time *t* indicate that ML explains commonality in liquidity, and produces the same results for both samples. While the Amihud measure exhibits significant values for ML in Japan and the Eurozone, the quoted spread has no significant effect in any country, and the Corpwin and Schultz high-low spread estimator has a significant negative effect in Japan, and the Eurozone. These results are consistent with several studies (see, Chung and Chuwonganant (2014), and Adrian and Shin (2010)), where positive correlations between individual assets and market-wide liquidity exist.

4.8. THE EFFECT OF AVERAGE INDUSTRY LIQUIDITY ON ILLIQUIDITY MEASURES.

The mean coefficients of IL at time *t*, from models (7) and (8) are significant and capable of explaining variations in individual stocks' liquidity when using AMH in 56% of results. Similarly, the QS shows several significant outputs in the UK. However, the HLS_w and HLS_r measures produce no significant outputs for any stock markets.

In sample (1), and by using equation (4.7), all the coefficients of IL are insignificant in all cases. Though, in sample (2), AMH and QS at time *t* have significant outputs only in the FTSE100. However, in sample (2), with regard to AMH, in model (1) when IL at time *t* increases by 1%, this causes an increase of 1.02%, and 0.54% in the Nikkei225, and

5: The effect of the Eurozone stock market (EURO STOXX 50) implied volatility index (VSTOXX), market and industry liquidity on individual stock illiquidity ($LM_{i,t}$).

This table present the regression estimation results of the following models for each of the Euro STOXX 50 companies using daily data divided into two samples: 1) sample (1), during the financial crisis from January 5, 2007 to December 5, 2009; 2) sample (2) after the financial crisis, from January 5, 2010 to December 28, 2017, to investigate the effect of VSTOXX on $LM_{i,t}$, captured by the three liquidity measures (AMH, HLS, and QS), before and after using market liquidity as a controlling variable:

$$DLM_{i,t} = \alpha_{i0} + \alpha_{i1}\,DVSTOXX_t + \alpha_{i2}\,DVSTOXX_{t-1} + \alpha_{i3}\,DVSTOXX_{t+1} + \alpha_{i4}DML_t + \alpha_{i5}DML_{t-1} + \alpha_{i6}DML_{t+1} + \alpha_{i7}DIL_t + \alpha_{i8}DIL_{t-1} + \alpha_{i9}DIL_{t+1} + \varepsilon_{1i,t} \quad (4.7)$$

and

$$Log(LM_{i,t}) = \alpha_{i0} + \alpha_{i1}Log(VSTOXX_t) + \alpha_{i2}Log(VSTOXX_{t-1}) + \alpha_{i3}Log(VSTOXX_{t+1}) + \alpha_{i4}Log(ML_t) + \alpha_{i5}Log(ML_{t-1}) + \alpha_{i6}Log(ML_{t+1}) + \alpha_{i7}Log(IL_t) + \alpha_{i8}Log(IL_{t-1}) + \alpha_{i9}Log(IL_{t+1}) + \varepsilon_{1i,t} \quad (4.8)$$

Where LM stands for liquidity measure, and is captured by: 1) $AMH_{i,t}$, the Amihud illiquidity measure calculated for each company, every day as following: $AMH_{i,t} = \frac{1{,}000{,}000 \times |return_t|}{price_t \times volume_t}$ of stock i at day t. 2) $HLS_{i,t}$, is the Corwin & Schultz bid-ask spread estimator for each stock calculated by: $HLS_{i,t} = \frac{2(e^{a}-1)}{1+e^{a}}$. 3) $QS_{i,t}$, the quoted spread for each company, daily, by using: $QS_{i,t} = (Ask_{i,t} - Bid_{i,t})/M_{i,t}$. $VSTOXX_t$, $VSTOXX_{t-1}$, $VSTOXX_{t+1}$ are the implied market volatility index VSTOXX at time *t*, *t*-1, and *t*+1; ML_t, ML_{t-1}, ML_{t+1} are the average quoted market liquidity across all stocks at time *t*, *t*-1, and *t*+1, *t*-1, and *t*+1; IL_t, IL_{t-1}, IL_{t+1} are the average quoted industry liquidity, the average quoted spread across all stocks in the same industry at time *t*, *t*-1, and *t*+1. D is the percentage change from the previous day, for all variables in Panel A, calculated by: $DX_{it} = (X_{it} - X_{it-1})/X_{it-1}$. Panel A exhibit the results of equation (4.1), while Panel B exhibits the results of equation (4.2). We're reporting the regression coefficients, the *t*-value of the average regression coefficient, the median *t*-value of all individual stock regression, and the median *t*-value of all individual stock regression. We also test for the independence of the residuals from equation (4.1) and (4.2), because the reliability of the t-statistics depends on the cross-section dependence in estimation error. We use the method in Chordia, Roll, and Subrahmanyam (2000) Coughenoour and Saad (2004). After estimating 50 Euro STOXX stocks, we sort the residuals alphabetically based on their industries and assign each stock a serial number *i*(*i*=1, …, 5) and then $\varepsilon_{1i+1,t} = \delta_0 + \delta_1\varepsilon_{1i}$ we estimate the following regression: $\varepsilon_{1i+1,t} = \delta_0 + \delta_1\varepsilon_{1,t} + \mu_{1i,t}$ and $\varepsilon_{2i+1,t} = \delta_0 + \delta_1\varepsilon_{2i,t} + \mu_{1i,t}$ where ε_{1i}, ε_{2i}, ε_{1i+1}, ε_{1i+1} are residuals from equation (4.1) and (4.2), $\mu_{1i,t}$ and $\mu_{1i,t}$ are the disturbance terms. Panel C exhibits the cross-section dependence in estimation error, and the correlation coefficient between ε_{1i+1t} and ε_{1it}, and between ε_{2i+1t} and ε_{2it}. All data are obtained from Datastream.

Panel A: Regression coefficients from model (1)												
LM		Variable	*c*	*VIX*	VIX_{-1}	VIX_{+1}	*ML*	ML_{-1}	ML_{+1}	*IL*	IL_{-1}	IL_{+1}
AMH	Sample (1) (2007-2009)	Coefficients	1.205	6.409	-2.873	-1.442	0.117	-0.115	-0.124	0.221	-0.063	-0.086
		Average t-value	**3.966**	1.606	-0.720	-0.361	0.719	-0.700	-0.768	1.239	-0.370	-0.505
		Mean t-value	**2.896**	0.700	-0.342	-0.114	0.242	-0.072	-0.072	0.931	-0.226	-0.233
		Median t-value	**5.269**	1.499	-0.752	-0.332	0.140	-0.259	-0.166	1.524	-0.501	-0.648
	Sample (2) (2010-2017)	Coefficients	1.469	-0.210	-0.461	0.442	**1.949**	0.104	-0.107	**0.540**	-0.056	-0.040
		Average t-value	**6.453**	-0.078	-0.172	0.164	**4.473**	0.258	-0.266	**2.295**	-0.249	-0.179
		Mean t-value	**6.806**	-0.056	-0.152	0.100	**4.928**	0.194	-0.261	**1.955**	-0.303	-0.153
		Median t-value	**6.744**	-0.084	-0.177	0.231	**4.938**	0.340	-0.340	**2.481**	-0.561	-0.232
QS	Sample (1) (2007-2009)	Coefficients	0.561	-1.462	0.461	-0.912	-0.007	-0.015	-0.001	-0.016	-0.023	-0.065
		Average t-value	**3.069**	-0.553	0.175	-0.345	-0.072	-0.149	-0.008	-0.101	-0.152	-0.429
		Mean t-value	**3.395**	0.121	0.466	0.105	-0.039	-0.084	-0.084	0.175	-0.013	0.044
		Median t-value	**6.818**	0.279	0.690	0.202	-0.219	-0.214	-0.391	0.057	-0.024	0.001
	Sample (2) (2010-2017)	Coefficients	0.577	2.343	22.851	-3.862	2.439	1.045	-0.316	-2.384	-0.943	-1.052
		Average t-value	0.107	0.037	0.360	-0.061	0.235	0.109	-0.033	-0.415	-0.172	-0.192
		Mean t-value	**4.411**	0.740	0.335	0.362	0.303	0.356	0.095	-0.274	-0.122	0.075
		Median t-value	**3.758**	0.490	0.346	0.350	0.136	0.280	0.287	-0.244	-0.170	-0.065

(Continued)

Panel A: Regression coefficients from model (1)													
LM		Variable	*c*	*VIX*	VIX_{-1}	VIX_{+1}	*ML*	ML_{-1}	ML_{+1}	*IL*	IL_{-1}	IL_{+1}
HLS_w	Sample (1) (2007-2009)	Coefficients	0.395	0.405	-1.481	-1.074	-0.001	-0.001	-0.002	0.058	0.000	-0.005
		Average t-value	1.652	0.113	-0.415	-0.301	-0.067	-0.034	-0.103	**1.907**	-0.003	-0.153
		Mean t-value	1.394	0.012	-0.013	0.004	-0.052	-0.084	-0.084	0.841	0.043	-0.110
		Median t-value	**2.590**	0.019	-0.058	-0.231	-0.084	-0.099	-0.165	-0.048	-0.136	-0.314
	Sample (2) (2010-2017)	Coefficients	1.778	-5.932	-3.908	-2.042	0.000	0.000	-0.001	-0.002	0.002	-0.003
		Average t-value	**1.697**	-0.398	-0.263	-0.137	0.010	-0.033	-0.065	-0.038	0.045	-0.075
		Mean t-value	**2.892**	0.055	-0.071	0.232	-0.094	0.004	-0.124	0.032	-0.038	-0.129
		Median t-value	**2.636**	0.030	-0.166	0.037	-0.132	-0.070	-0.117	-0.103	-0.112	-0.136
HLS_r	Sample (1) (2007-2009)	Coefficients	0.577	1.397	0.294	-1.501	-0.002	0.001	-0.003	0.026	-0.002	-0.005
		Average t-value	**1.874**	0.299	0.063	-0.322	-0.068	0.027	-0.148	0.915	-0.056	-0.171
		Mean t-value	1.441	0.079	0.064	0.051	-0.055	-0.090	-0.090	0.592	0.040	-0.119
		Median t-value	**2.574**	0.081	0.082	-0.140	-0.095	-0.099	-0.179	-0.087	-0.157	-0.269
	Sample (2) (2010-2017)	Coefficients	2.159	-2.006	-3.408	-0.275	-0.001	-0.001	-0.001	-0.004	-0.002	-0.003
		Average t-value	1.655	-0.108	-0.184	-0.015	-0.058	-0.045	-0.068	-0.075	-0.030	-0.061
		Mean t-value	**2.811**	0.200	-0.025	0.301	-0.106	-0.074	-0.118	-0.003	0.004	-0.002
		Median t-value	**2.630**	0.135	-0.083	0.113	-0.100	-0.094	-0.116	-0.074	-0.105	-0.121

(Continued)

Panel B: Regression coefficients from model (1)													
LM		Variable	*c*	*VIX*	VIX_{-1}	VIX_{+1}	*ML*	ML_{-1}	ML_{+1}	*IL*	IL_{-1}	IL_{+1}
AMH	Sample (1) (2007-2009)	Coefficients	-1.515	0.466	-0.174	-0.047	**0.140**	0.002	0.001	**0.199**	0.007	0.008
		Average t-value	**-3.726**	0.992	-0.517	-0.139	**3.185**	0.040	0.016	**5.617**	0.202	0.226
		Mean t-value	**-2.108**	0.547	-0.291	-0.072	**1.741**	0.011	0.011	**3.103**	0.089	0.103
		Median t-value	**-3.575**	1.071	-0.565	0.034	**2.841**	0.148	0.008	**5.581**	0.281	0.076
	Sample (2) (2010-2017)	Coefficients	-0.776	0.054	-0.109	0.085	**0.655**	-0.086	-0.088	**0.321**	0.022	0.025
		Average t-value	**-1.728**	0.123	-0.338	0.262	**9.181**	-1.191	-1.216	**6.258**	0.421	0.486
		Mean t-value	**-1.749**	0.137	-0.344	0.256	**9.183**	-1.235	-1.285	**6.278**	0.367	0.502
		Median t-value	**-1.699**	0.232	-0.362	0.177	**8.783**	-1.265	-1.233	**6.401**	0.411	0.442
QS	Sample (1) (2007-2009)	Coefficients	-3.408	0.066	0.086	0.015	0.068	0.038	0.045	0.010	0.006	0.005
		Average t-value	**-5.520**	0.183	0.329	0.057	1.262	0.712	0.830	0.265	0.159	0.128
		Mean t-value	**-3.695**	0.085	0.239	0.064	0.622	0.409	0.409	0.133	0.033	0.043
		Median t-value	**-6.470**	0.137	0.381	0.244	1.022	0.352	0.677	0.303	0.115	0.189
	Sample (2) (2010-2017)	Coefficients	-6.775	0.047	-0.071	-0.019	0.068	0.053	0.069	0.025	0.029	0.040
		Average t-value	**-17.267**	0.124	-0.253	-0.066	1.100	0.850	1.107	0.559	0.649	0.896
		Mean t-value	**-21.366**	0.450	-0.277	0.151	0.837	0.651	0.920	0.154	0.175	0.427
		Median t-value	**-20.445**	0.121	-0.445	0.191	0.694	0.173	0.826	0.066	-0.234	0.636

(Continued)

Panel B: Regression coefficients from model (1)													
LM		Variable	c	VIX	VIX_{-1}	VIX_{+1}	ML	ML_{-1}	ML_{+1}	IL	IL_{-1}	IL_{+1}
HLS_w	Sample (1) (2007-2009)	Coefficients	-6.500	0.373	0.127	0.288	**-0.525**	0.010	0.021	0.022	-0.004	0.005
		Average t-value	**-7.013**	0.348	0.164	0.375	**-6.625**	0.263	0.530	0.708	-0.120	0.159
		Mean t-value	**-3.885**	0.195	0.089	0.206	**-3.676**	0.294	0.294	0.636	-0.064	0.063
		Median t-value	**-6.860**	0.385	0.124	0.190	**-6.432**	0.509	0.504	0.295	-0.127	0.042
	Sample (2) (2010-2017)	Coefficients	-8.380	-0.240	1.134	0.096	**-0.643**	0.027	0.073	0.088	-0.002	0.009
		Average t-value	**-7.511**	-0.213	1.356	0.116	**-9.874**	0.413	1.121	0.834	-0.075	0.276
		Mean t-value	**-7.549**	-0.220	1.369	0.121	**-9.942**	0.409	1.130	0.392	-0.088	0.244
		Median t-value	**-7.581**	-0.188	1.433	0.122	**-9.682**	0.321	1.087	0.347	-0.122	0.185
HLS_r	Sample (1) (2007-2009)	Coefficients	-5.975	0.114	0.238	0.382	**-0.534**	0.051	0.069	0.015	-0.002	0.012
		Average t-value	**-4.694**	0.106	0.309	0.499	**-6.425**	0.616	0.835	0.444	-0.061	0.344
		Mean t-value	**-2.610**	0.060	0.172	0.276	**-3.567**	0.457	0.457	0.511	-0.020	0.151
		Median t-value	**-4.650**	-0.041	0.445	0.369	**-6.383**	0.536	0.786	0.290	-0.110	0.142
	Sample (2) (2010-2017)	Coefficients	-10.493	0.030	1.068	0.014	**-0.915**	0.018	0.097	0.032	0.010	0.013
		Average t-value	**-8.342**	0.027	1.296	0.017	**-11.437**	0.226	1.215	0.923	0.290	0.369
		Mean t-value	**-8.417**	0.022	1.309	0.024	**-11.530**	0.219	1.213	1.571	0.277	0.395
		Median t-value	**-8.434**	0.065	1.221	0.073	**-11.247**	0.070	1.159	0.167	0.351	0.190

(Continued)

Panel C: Check for cross-section dependence in estimation error							
	LM	Sample	Average Correlation	Average t-statistics	Median t	|t|>1.645 %	|t|>1.96 %
Results from regression model (1)	*AMH*	(1)	0.019	0.836	0.067	0.190	0.155
		(2)	-0.001	-0.05	-0.519	0.12	0.1
	QS	(1)	0.004	0.183	-0.129	0.121	0.103
		(2)	0.034	1.560	0.457	0.260	0.240
	HLS_w	(1)	-0.011	-0.526	-0.184	0.052	0.034
		(2)	0.001	0.032	-0.048	0.000	0.000
	HLS_r	(1)	0.004	0.193	-0.089	0.034	0.034
		(2)	0.002	0.075	-0.038	0.020	0.020

Panel C: Check for cross-section dependence in estimation error							
	LM	Sample	Average Correlation	Average t-statistics	Median t	|t|>1.645 %	|t|>1.96 %
Results from regression model (2)	*AMH*	(1)	0.027	1.153	0.746	0.397	0.397
		(2)	0.011	0.513	-0.114	0.36	0.34
	QS	(1)	0.115	0.246	0.965	0.638	0.603
		(2)	0.037	0.281	0.336	0.300	0.280
	HLS_w	(1)	0.067	0.899	0.333	0.483	0.466
		(2)	0.085	0.964	0.076	0.720	0.660
	HLS_r	(1)	0.064	0.791	0.079	0.448	0.414
		(2)	0.066	0.064	0.535	0.620	0.580

(Continued)

EURO STOXX50 respectively. Similarly, in model (2), when IL at time t increases by 1% it causes an increase by 0.37%, and 0.32% in Nikkei225, and EURO STOXX50 respectively. However, according to the FTSE100 stock market results in table 4.4, and similarly to market uncertainty and liquidity, IL at time t has no effect on variations in the stocks liquidity of the individual AMH markets. The insignificant signs of IL at times t_{-1} and t_{+1} indicate that the market is efficient, and market participants observe information immediately. Lastly, HLS_w, HLS_r, and QS measures produce no significant IL results in any country.

Using model (8), in sample (1) AMH and QS produces IL's coefficients in the UK market only. Additionally, in sample (2), the AMH measure, except for the mean t-values of the FTSE100, IL at time t is significant in all countries for the average, the mean and the median t-values. The QS has similar results to AMH, except that in the eurozone, IL does not have a significant effect on individual stocks liquidity. Finally, the HLS_w and HLS_r measures show a significant effect only in Japan and Eurozone markets. AMH is the most powerful measure of liquidity in our analysis in terms of its significant responses to IL at time t. The mean, the average, and the median of the t-values for all countries, except in the UK, are all significant and consistent. Industry liquidity appears to be an important determinant of stock liquidity.

4.9. CHECK FOR CROSS-SECTION DEPENDENCE IN ESTIMATION ERROR.

Since the reliability of t-statistics depends on cross-section independence in estimation error, we test for the independence of the residuals from equation (4.7) and (4.8). We use the method set out in Chordia et al. (2000), and Coughenour and Saad (2004). After estimating individual stocks liquidity measures for the FTSE 100, Nikkei 225, and EURO STOXX 50, we sort the residuals alphabetically, for each market separately, based on their industries, and assign each stock a serial number $i(i=1, \ldots, n)$, and then $\varepsilon_{1i+1,t} = \delta_0 + \delta_1\varepsilon_{1i}$ we estimate the following regression: $\varepsilon_{1i+1,t} = \delta_0 + \delta_1\varepsilon_{1,t} + \mu_{1i,t}$ and $\varepsilon_{2i+1,t} = \delta_0 + \delta_1\varepsilon_{2i,t} + \mu_{1i,t}$ where ε_{1i}, ε_{2i}, ε_{1i+1}, ε_{1i+1} are residuals from equation (4.1) and (4.2), $\mu_{1i,t}$ and $\mu_{1i,t}$ are the disturbance terms. Panel C exhibits cross-section dependence in the case of estimation error, and the correlation coefficient between ε_{1i+1t} and ε_{1it}, and between ε_{2i+1t} and ε_{2it}. For all markets, and for model (1) and (2) using all measures of liquidity, the average t-statistics for the correlation coefficients are very small and insignificant, indicating that there is no dependence between the residuals of the regression models. Therefore, we can depend on the results shown in the tables.

4.10. CONCLUSION

Recent studies have examined co-movement of liquidity across individual assets in the markets, highlighting probable factors that cause liquidity commonality in stock markets. Many theories have been used to identify sources of commonality, the main ones being demand-side theories based on the behaviour of liquidity demanders, and supply-side theories, which suggest that common information causes similar patterns in activities. Furthermore, researchers are increasingly using the IV index as a measure of market uncertainty to investigate how its variability affects illiquidity.

In this study, by examining the effect of VIX, market liquidity and industry liquidity, we have shown that market and industry average liquidity exerts a market-wide impact, causing individual assets to exhibit co-movement during the financial crisis (between 2007 to 2009) and after (from 2010 to 2017) across several markets (the London Stock Exchange (FTSE100), Japan stock market (Nikkei225), and Eurozone stock market (EURO STOXX50)). Analysing the VIX, we found no sign of any effect on individual stock liquidity as measured by AMH, HLS_w, HLS_r, and QS. It is clear that market participants direct no importance towards the VIX in the UK, Japanese, and Eurozone market. Moreover, our results differ from those of Chung and Chuwonganant (2014) and Brunnermeier and Pedersen (2009), who showed that market liquidity decreases when market uncertainty increases. In other words, they indicated a significant effect from VIX on the US market during the financial crisis (between 2007 and 2009).

We investigated both periods, during and after the financial crisis, and found that VIX does not exhibit any significant results. Similar results were reported in the US, the UK, and the European market after the financial crisis in 2007-2008, by Neffelli and Resta (2018) and Chandorkar and Brzeszczyński (2018), showing market uncertainty does not predict the future movement of market returns in the longer term, five years and more.

Chapters five and six explore the influence of implied volatility on herding behaviour. This relationship has been examined in many studies, thus indicating a significant correlation between implied volatility (i.e. market uncertainty) as a proxy of market risk and patterns of herding behaviour in the market.

CHAPTER 5: THE IMPACT OF OIL, VOLATILITY AND FEAR GAUGE ON RETURNS DISPERSION AND DYNAMIC HERDING BEHAVIOUR

5.1. INTRODUCTION

Research into herding behaviour holds a special place in the literature, and expanded rapidly after the global financial crisis in 2007. The idea of herding behaviour emanates from the tendency of individual participants to suppress their beliefs, intuition, and convictions to adopt a collective approach. They also follow 'majority decisions' in their investment decisions and choices, regardless of prevailing disagreements regarding predictions about the market (Christie and Huang, 1995). Herding behaviour is characterized by the convergence of investors' decisions ignoring personal signals, involving making decisions by following the observed trend. Herding behaviour has been examined in diverse contexts in the US market, as well as in international markets as reported in empirical literature. If investors attempt to follow market consensus, and trade in the same direction for a specified period, this leads to specific behaviour patterns in the market (Chiang and Zheng, 2010). Consequently, this then causes a price deviation from economic fundamentals, which could potentially lead to market shocks and crashes (Demirer et al., 2014).

On one hand, a number of research papers have focused on investors herding in international markets (Christie and Huang, 1995, Chang et al., 2000, Economou et al., 2011). Whereas, on the other, researchers have focused on i) the bond market (Galariotis et al., 2016), ii) the US real estate market (Philippas et al., 2013), iii) the ETFs market (Gleason et al., 2004), iv) the Commodities market (Demirer et al., 2015), and finally (v) the foreign exchange market (Kaltwasser, 2010). However, the majority of studies concentrate on recognizing the existence of herding, instead of determining the causes of such behaviour among investors. Herding behaviour is examined in several regions, in both developed and developing countries, as well as exporting and importing countries. Mixed evidence has been provided for each region while employing different methodological approaches.

Herding studies have looked for herding determinants, by incorporating market sentiment and returns volatility in the estimation models. The IV index (VIX) was employed in several studies (Chiang et al., 2013; Economou et al., 2016; Economou et al., 2018; Philippas et al., 2013), which documented significant herding in response to the market fear index. The fear index, specifically the US VIX, has been widely recognized as a significant explanatory variable for a number of international markets (Siriopoulos and Fassas, 2009). The impact of oil price and OVX[50] has been examined according to market returns, but not herding behaviour. Similarly, market returns volatility has been used for determining dynamic herding behaviour in the market (Chiang et al., 2013), but there is no investigation of the combined explanatory power of the fear index, the oil index, or OVX.

In this paper we provide new evidence of herding behaviour by incorporating several factors through a dynamic approach using a Kalman-filter based model. We tested for herding examination in G7 countries from May 2007 to December 2018. We used the herding approach proposed by Chang et al. (2000) with a modification that allowed us to capture the dynamic, time-varying, nature of herding behaviour. Herein we provide new evidence for the existence of herding incorporating the fear indices of market and oil, oil price index, and cross-market global effect[51]. This paper contributes to the existing literature by having incorporated the volatility of the aforementioned factors in our tests to obtain a better understanding of herding causes. We hope that our approach will

[50] OVX is the CBOE Crude Oil ETF IV index. It measures the market's future expectations of 30-day volatility in crude oil prices. The OVX is obtained by applying the VIX methodology.

[51] To test for the effect of major foreign factors in the model, we include the US factors such as US fear index (CBOE VIX), and US price index returns (S&P500), and the stock market cross sectional absolute deviation (CSAD of S&P500)

provide a definitive answer to the mixed findings observed. We observed that, by using a static model, herding exists only in Japan. These results are consistent with previous findings concerning the existence of herding in Japan (Chang et al., 2000), and the absence of herding behaviour in the US (Chang et al., 2000; Chiang and Zheng, 2010; Economou et al., 2018), Germany, France, and Italy (Mobarek et al., 2014), in the UK (Economou et al., 2018). Unlike the OVX, oil prices appear to have a high impact on herding in Japan, Germany, France and Italy. The same results have been documented during periods of market stress. We also show that investors are highly affected by market fear, causing herding patterns. Similar results in different countries were obtained by Chiang et al. (2013)[52], and Economou et al. (2018)[53]. Additionally, we tested for cross-market spill overs and found evidence that the dispersion of US market returns and stock market returns have a significant global effect. Chiang et al. (2013) also tested for herding using a dynamic model in Pacific-Basin markets and identified herding behaviour. However, unlike our approach they included only the conditional variance of market returns in the model. We document herding patterns in most countries with the help of the conditional variance of global explanatory factors, the oil price and oil fear indices, and the market fear index.

The remainder of the paper is organized as follows: Section 2 presents the literature review. Data and herding models are explained in sections 3 and 4. Section 5 contains the empirical results and analysis followed by the conclusion.

5.2. LITERATURE REVIEW

[52] Chiang et al. (2013) did not include the local market fear index within each market, but instead, they indicated a great cross-market impact of the US market fear index (VIX) on several Pacific-Basin markets.

[53] Economou et al. (2018) also found a significant impact of local and cross-market effect of fear indices between the US, UK, and Germany.

5.2.1. EXAMINATION OF HERDING BEHAVIOUR

Herding behaviour has been examined in a number of studies. One major stream in the literature can be seen to explore herding based on changes of institutional ownership within (or across) periods of time (Lakonishok et al., 1992, Sias, 2004, Avramov et al., 2006, Liao et al., 2011, Huang et al., 2016). The second path started with Christie and Huang (1995), who apply the cross-sectional standard deviation of stock returns to test how herding behaviour moves towards market consensus. Later, Chang et al. (2000) used cross-sectional absolute deviation (CSAD) to measure returns dispersion using a non-linear specification to measure the significance of herding. They both examined the trading behaviour of market participants in several advanced and developing countries, and reported the existence herding behaviour, especially in periods of extreme market movements.

Further, several studies have tested for herding in developed markets. Chiang and Zheng (2010) provided extensive evidence of several countries that include advanced markets; i.e. Latin American markets, and Asian markets. During the period of 1988-2009, they tested for herding in different contexts and found evidence of herding in all countries, except in US and Asian markets. Moreover, Caparrelli et al. (2004) proposed several modifications of CSAD to study herding in the Italian market. They indicated that herding is present under extreme market conditions, specifically during periods of persistent growth rate and in bull markets. Economou et al. (2011) tested for the existence of herding in Portuguese, Italian, Spanish and Greek markets from 1998 to 2008. They also used the CSAD approach and found a high degree of co-movement in the cross-sectional returns' dispersion among these markets, indicating the power of herding forces in the region. However, they found strong herding evidence in the Greek and Italian markets only.

5.2.2. OIL, FEAR INDEX AND STOCK MARKET HERDING

Crude oil is one of the most closely watched commodities in the world, and an important driver of economic activity. Changes in oil price tend to impact on economic activity by differing transmission mechanisms, including channels of supply and demand. (1) The supply side is impacted when a rise in oil price leads to an increase in production cost (i.e. crude oil forms a basic input of a production process), thus leading to firms reducing their output. (2) The demand side is impacted when increased oil prices leads to a reduction in both consumption and investment. Firstly, consumption is impacted incidentally through its positive relationship to disposable income (Jiménez-Rodríguez and Sánchez, 2005). Secondly, investment is influenced by an increase in a firm's costs as a result of an increase in the price of oil. Higher production costs result in a lower rate of return on investments, which then have an adverse impact on levels of investment. Moreover, increased changeability in the oil price may have an influence on investment, by increasing uncertainty pertaining to future movements of price levels (Rafiq et al., 2009). Hamilton (1983) sought to evaluate the relationship between the aggregate economy and the OP by formulating three hypotheses considering the correlation between OP shock and output. He concluded that oil shocks played a significant role in slowing down the macroeconomic activity in the US.

A large body of empirical studies has examined the link between oil prices and economic activities in several developed and emerging countries (Hamilton, 2003, Hammoudeh and Choi, 2006, Kilian, 2008, Chiou and Lee, 2009, Arouri et al., 2011). In addition, other empirical papers have studied the impact of oil shocks and spills on emerging markets (Basher and Sadorsky, 2006, Park and Ratti, 2008) and in GCC countries (Hammoudeh and Aleisa, 2004, Zarour, 2006, Hammoudeh and Choi, 2006, Akoum et al., 2012). However, little effort has been directed towards producing empirical models and connecting oil price shocks and returns fluctuations (Balcilar et al., 2017) and herding dynamics. However, there has been more focus on the effect of oil prices on stock prices. Specifically, Mohanty et al. (2014) and Demirer et al. (2015a) found significant evidence of the effect of oil on the US economy in general, and on stock prices.

On the other hand, alternative channels were proposed in several studies to examine the different factors that might affect herding behaviour. Philippas et al. (2013) incorporated the fear index while testing for herding in the US Real Estate investment trust (REITs) between 2004 and 2011. They documented that market herding is associated with the deterioration of investors' sentiment about current and future market conditions and the increase in the fear index. Chiang et al. (2013) also incorporated the US IV index (VIX) to detect dynamic herding behaviour with stock market returns and market returns' conditional volatility in Pacific-Basin markets. They identified strong evidence that the VIX influences herding behaviour in several markets, suggesting that a higher level of VIX typically increases observed market herding. Economou et al. (2018) investigated herding in the US, UK and Germany stock markets including with regard to the impact of the fear index, from 2004 to 2014. They also documented a significant effect from the local and cross-market fear index impact on herding.

5.2.3. CROSS-MARKET HERDING

Until recently, herding research had focused on factors within a single country, and hence, empirical results had suffered from several problems. From an economic perspective, excluding important global factors creates bias in the estimation process (Kennedy, 2003). I feel that there is now an increased interdependence between financial markets, particularly across global regions and during stressful market conditions. In their research, Chiang and Zheng, 2010 presented evidence of herding in developed countries in the direction of the US market. Similarly, Economou et al. (2018) explored the impact of the dynamics of membership on cross-border exchange groups in relation to herding behaviour within the context of the Euronext exchange group. Their results revealed a significant impact of various domestic and international markets on herding in Belgium, France, the Netherlands and Portugal. Furthermore, Guney et al. (2017) documented the significant impact of the returns from the US and South African markets on herding in eight African frontier stock markets, documenting a number of significant results. Economou et al. (2018) tested for cross-market herding among the US, the UK and the German markets, incorporating their respective IV indices. Cross-market herding eliminates any benefits from global diversification, which then causes inevitable international risk exposure.

Furthermore, Chiang et al. (2013) was the first to use a time-varying coefficient model, which was a major improvement relative to constant coefficient models. However, they were also limited as to the explanatory factors used previously. The contribution of this study is to incorporate global factors, Oil price and fear indices in time varying coefficient models which can explain market herding patterns. The incorporation of Oil price and OVX was never investigated before in the literature as a control variable in herding examination. The use of the Kalman-filter allows us to overcome the issue of structural change, as caused by market stress, which exists when using the average value of relationships over a specified time range. The Kalman-filter involves a transition equation, which allows the estimation of state variables when actual results are disrupted by noise (Athans, 1974). I found that the majority of these studies added a number of factors that enhanced CSAD (i.e. the conventional herding behaviour model) in relation to the herding patterns of stock markets. I consider that their primary contribution consisted of the addition of the fear index, with only a few adding variables such as cross market slipover. I therefore concluded that my own research should focus on firstly, macroeconomic variables and secondly, global factors, i.e. commodity prices and exchange rates.

5.3. METHODOLOGY

5.3.1. DETECTING HERDING MODELS

Different methods of testing for the presence of herding behaviour are widely discussed in the literature. Christie and Huang (1995), and Chang et al. (2000) were the first to propose herding measures based on cross-sectional stock returns. They suggested that market participants' trading activities depend on overall market conditions ,and observed momentum. The rational asset-pricing models under normal market conditions, state that dispersion in cross-sectional returns is positively related to the absolute value of market returns. However, it is commonly believed that investors follow market consensus in highly volatile periods, and herding will also be present due to the individuals' collective market actions. Christie and Huang (1995) suggested that testing for the statistical significance of returns dispersion in response to extreme market returns is measured by the $CSSD_t$ formula, which can be expressed as:

$$CSSD_t = \sqrt{\frac{\sum_{i=1}^{N}(R_{i,t} - R_{m,t})^2}{(N-1)}} \tag{5.1}$$

Where $R_{i,t}$ is the observed returns of stock i at time t, and $R_{m,t}$ is the equally weighted realized returns of market stocks N at time t. The $CSSD_t$ measure tends to be sensitive to outliers, since it is defined as squared return-deviations. In a later study, Chang et al. (2000) propose cross-sectional absolute deviation $CSAD_t$, calculated as follows:

$$CSAD_t = \frac{\sum_{i=1}^{N}\left|R_{i,t} - R_{m,t}\right|}{N} \tag{5.2}$$

While $R_{i,t}$ in this model is the equity's log difference return on day t. Chang et al. (2000), suggested that during periods of large price swings, market participants tend to follow average market consensus. This relationship between $CSAD_t$ and average market returns are more likely to be nonlinear. Therefore, they propose a nonlinear regression model that will capture herding activity by detecting the relationship between $CSAD_t$ and market returns:

$$CSAD_t = \alpha + \gamma_1 |R_{m,t}| + \gamma_2 R^2_{m,t} + \varepsilon_t \tag{5.3}$$

In cases of a significant negative coefficient in squared market returns γ_2, herding behaviour is present, since during times of market stress, returns dispersions decline. The evidence of previous studies has led me to conclude that most research focussing on herding behaviour has been based on the models of Christie and Huan (1995) and Chang et al. (2000). In addition, I found that the models most frequently employed in herding behaviour research consist of CSSD and CSAD, which are built on the basis of capital asset pricing model, i.e. the expected returns on a security related to the potential level of risk.

In this study, we aim to include several explanatory factors to establish whether they have a significant effect on herding behaviour and to help determine if herding is more sensitive towards certain variables. We employ i) the market fear index, ii) oil price, iii) OVX, and iv) the US cross-market effect. The impact of Fear index captured by the IV index (VIX) on herding is documented in recent studies (Chiang et al., 2013; Economou et al., 2016; Economou et al., 2018; Philippas et al., 2013). During turbulent market periods, herding can be more prevalent as a result of increased uncertainty. The response of stock market volatility to oil price shocks is broadly documented in the literature (Hamilton, 2009, Kilian and Park, 2009, Jung and Park, 2011, Abhyankar et al., 2013, Kang and Ratti, 2013, Güntner, 2014). Stock market volatility depends on oil price shocks. These finding are not only limited to the stock market. Existing literature has documented that oil price shocks are critical to explaining the responses of many other economic variables[54] (Bastianin and Manera, 2018). However, there is a missing link between oil price shocks and herding behaviour. Similarly, the OVX has never been investigated in the context of herding. It will be of great interest to examine the impact of oil price and oil fear indices on herding behaviour in the G7 markets.

Global financial markets are highly integrated, and this is facilitated by quick information transfer, therefore trading and behaviour spill overs are highly interconnected between markets (Chiang and Zheng, 2010). The importance of the US market is also well recognized, due to its significant role in global financial transactions, and in international equity market co-movements (Connolly and Wang, 2003; Forbes and Rigobon, 2002). We include two US factors, market return squared and the cross-sectional absolute deviation.

5.3.2. AUGMENTED HERDING TESTING MODEL

We adopt the herding model proposed by Chang et al. (2000), further our argument using equation (5.3). Our new model is as follows:

$$CSAD_t = \alpha + \gamma_1|R_{m,t}| + \gamma_2 R_{m,t}^2 + \gamma_3 OVX_t + \gamma_4 Oil_t + \gamma_5 VIX_{m,t} + \gamma_6 VIX_{US,t} + \gamma_7 CSAD_{US,t} + \gamma_8 R_{US,t}^2 + \varepsilon_t \tag{5.4}$$

Where *OVX* is the daily log returns of the CBOE crude oil volatility index at time *t*, and *Oil* is the daily log returns of the Brent crude oil price at time *t*. *VIX* is the daily log returns of the IV index of market *m*, at time *t*. VIX_{US}, $CSAD_{US}$, R_{US}^2 are US cross-market factors,

[54] Such as GDP and inflation (Kilian, 2009), bond returns (Kang et al., 2014), macroeconomic variables (Kang and Ratti, 2013), in the US market.

namely, the daily log returns of CBOE volatility index, cross sectional absolute deviation of the SP500 market, and the log returns of the SP500 index, correspondingly

5.3.3. ASYMMETRIC AUGMENTED HERDING MODELS

Asymmetric behaviour has also been of special interest in many studies. These studies examine asymmetric characteristics under different market conditions. Longin and Solnik (2001), Tan et al. (2008), Chiang and Zheng (2010), Economou et al. (2011), observed investors' behaviour under rising and falling markets. To test whether traders behave differently under different market conditions, we employ a dummy variable that is associated with market returns squared alongside previous explanatory factors in equation (5.4). The equation is:

$$CSAD_t = \alpha + \gamma_1 D^{up}|R_{m,t}| + \gamma_2(1 - D^{up})|R_{m,t}| + \gamma_3 D^{up} R_{m,t}^2 + \gamma_4(1 - D^{up})R_{m,t}^2 + \gamma_5 OVX_t + \gamma_6 Oil_t + \gamma_7 VIX_{m,t} + \gamma_8 VIX_{US,t} + \gamma_9 CSAD_{US,t} + \gamma_{10} R_{US,t}^2 + \varepsilon_t \quad (5.5)$$

The D^{up} is a dummy variable that equals 1 on days when market returns are positive, and 0 on days when market returns are either zero or negative.

5.3.4. KALMAN FILTER HERDING MODELS

The previous constant regression models provide average estimates of coefficients over time. to detect the existence of herding. Therefore, estimated results are static in nature. In various applications, the driving forces of economic factors could be either immeasurable or not observable directly (Pichler, 2007). The estimation procedures could be extended and improved using a state space model driven by a stochastic process to measure time-varying convergence dynamics. Kalman (1960) suggested the Kalman linear filtering and prediction approach, which makes it possible to find the optimum averaging factor for each consequent state, and to update knowledge of state variables when a new data point becomes available (Tsay, 2005). There are several ways to derive the Kalman-filter, and to estimate the time-varying convergence dynamics of herding behaviour, as written in the following equations:

$$\hat{X}_t = \hat{X}_{t-1} + K_t(\gamma_t - \hat{X}_{t-1}), \tag{5.6}$$

Where $\hat{X}_t$ is the dynamic estimate of herding captured by γ_2 from equation (5.3), which follows a random walk process. K_t is the Kalman gain, calculated as follows:

$$K_t = \frac{P_{t-1}}{P_{t-1} + r}, \tag{5.7}$$

P_{t-1} is the prior error covariance, and r is the standard deviation for the measurement of noise. The error covariance is expressed as:

$$P_t = (1 - K_t)\, P_{t-1} \tag{5.8}$$

The results presented using the Kalman-filter process have important implications for estimating and testing the dynamic nature of herding estimates. To identify its determinants, Chiang et al. (2013) stated that herding relates to two main hypotheses: the stock market performance hypothesis, and the volatility hypothesis. Firstly, several studies have related herding activities to stock market performance, where institutional investors trade excessively following irrational market momentum (Black, 1986, Trueman, 1988). Investors might also react to fluctuations in stock market prices (Grinblatt et al., 1995), and positive news might drive traders to invest in the same direction by buying stocks, and vice versa, leading to market destabilization (Shiller and Pound, 1989, Brennan and Thakor, 1990, De Long et al., 1990, Scharfstein and Stein, 1990, Banerjee, 1992, Sentana and Wadhwani, 1992). Secondly, a number of empirical studies have indicated that during highly volatile markets, traders follow similar trading patterns, which in turn causes cross-market correlations to increase (Butler and Joaquin, 2002, Corsetti et al., 2005). In other words, when expected market volatility rises due to market stress, feedback traders will experience a greater impact on prices, and existent returns dispersion will rise (Sentana and Wadhwani, 1992), and determining this to be an ideal model for the study.

The two theories are combined to determine their impact on the estimated herding time series produced by the Kalman-filter. We extract the conditional volatility of stock returns using the GARCH(1,1) process. We also add the conditional volatility of Oil_t, OVX_t, $VIX_{m,t}$, to the cross-market US conditional volatility $VIX_{us,t}$, and $R^2_{us,t}$. We include all these determinants in the following regression:

$$H_t = \beta_0 + \beta_1 R_{m,t} + \beta_2 \sigma^2_{OVX_t} + \beta_3 \sigma^2_{Oil_t} + \beta_4 \sigma^2_{VIX_{m,t}} + \beta_5 \sigma^2_{R_{m,t}} + \beta_6 \sigma^2_{VIX_{US,t}} + \beta_7 \sigma^2_{R_{US,t}} + \varepsilon_t \tag{5.9}$$

The dependent variable H describes the estimated herding values for time t, the values of γ_2 from equation (5.3), as derived from equation (5.6). σ^2 describes the conditional variance of our determinant factors. As for the $\sigma^2_{VIX_t}$, we employ the volatility (or kurtosis) of the IV indices[55] as explanatory variables. The use of volatility of the volatility index as a proxy of market uncertainty helps capture herding behaviour towards market consensus on future market expectations.

Finally, we test for the joint effect of returns and volatility for each of our explanatory factors, this is expressed as follows:

$$CSAD_t = \alpha + \gamma_1 |R_{m,t}| + \gamma_2 R^2_{m,t} + \gamma_3 R^3_{m,t} + \gamma_4 R^2_{m,t} * \sigma^2_{R_{m,t}} + \gamma_5 R^2_{m,t} * \sigma^2_{OVX_t} + \gamma_6 R^2_{m,t} * \sigma^2_{Oil_t} + \gamma_7 R^2_{m,t} * \sigma^2_{VIX_{m,t}} + \varepsilon_t \tag{5.10}$$

[55] Research on the area of volatility of volatility (also known as kurtosis) is limited to a few studies (see Yang-Ho Park, 2015; Wang et al., 2013; and Alsheikhmubarak and Giouvris, 2019). We obtain the conditional variance of the IV indices using an asymmetric GARCH(1,1) process for all IV indices. In order to unify the data across all countries, we excluded the US VVIX index created by the CBOE for the US market.

Where the product of each conditional volatility σ^2 with its corresponding index price captures the interaction of herding with other volatility determinants.

5.4. DATA

In this study, we use data from all the firms listed in the G7 markets (US, UK, Japan, Germany, France, Italy, and Canada). We also use their corresponding stock markets indices (SP500, FTSE100, Nikkei225, DAX30, CAC40, FTSEMIB40, and SPTSX60; and their market fear indices (CBOE VIX, VFTSE, VXJ, VDAX, VCAC)[56]. In addition, we also incorporated the Brent Crude Oil price, and the CBOE Crude Oil Volatility index (OVX) in the analysis. All the data was drawn from the Thomson-Reuters DataStream from January 2007 to December 2018. The composition of the selected indices (i.e. SP500; FTSE100; Nikkei225; DAX30; CAC40; FTSEMIB40; and SPTSX60) has been updated on an annual basis, in response to the expected changes over time resulting from the addition and deletion of constituents.

Table 5.1 presents a summary of descriptive statistics regarding the cross-sectional dispersion of individual assets' returns (CSAD) for all countries. The number of companies in each country ranges from 30 (Germany) to 500 (USA). The mean (standard deviation) values of CSADs are very close regionally; ranging from 0.010 to 0.012 (0.005 5o 0.006) except for Italy's stock market, which has a slightly higher value of 0.021 (0.014). Table 5.2 presents the correlation matrix of CSAD across all countries. Without exception, all the pairs are positively and highly significant, with the highest values

[56] In the interest of data consistency, we have excluded the impact of the market fear index on herding behaviour in Italy and Canada due to data availability. Italy's market VIX index (FTSE MIB IVI) was launched on 18 February 2013, while the Canadian S&P/TSX 60 VIX (VIXC) was launched on October 18, 2010. We do not believe this elimination will affect the results, because we tested for the VIXs effect using the available data by applying equations (4) and (5) and found no significant effect on herding behaviour in those markets.

Table 5.1: Descriptive statistics of *CSAD*$_t$.

This table show summary statistics of the equally weighted cross-sectional absolute deviations *(CSAD$_t$)* for the G7 countries: including the US, Japan (JP), Germany (GR), France (FR), Italy (IT), Canada (CA). The statistics are based on daily observations from May 2007 to December 2018. The calculation of *CSAD$_t$* is based on equation (5.2), stated as: $CSAD_t = \frac{1}{N}\sum_{i=1}^{N}\left|R_{i,t} - R_{m,t}\right|$.

Market	Minimum	Maximum	Mean	Median	Std. dev	Kurtosis	Skewness	Obs
$CSAD_{US}$	0.000	0.052	0.011	0.009	0.006	8.829	2.311	3037
$CSAD_{JP}$	0.000	0.046	0.012	0.011	0.005	4.836	1.030	3037
$CSAD_{GR}$	0.000	0.124	0.010	0.009	0.006	64.128	5.068	3037
$CSAD_{UK}$	0.000	0.064	0.011	0.010	0.006	9.745	2.349	3037
$CSAD_{FR}$	0.000	0.041	0.010	0.009	0.005	6.136	1.843	3037
$CSAD_{IT}$	0.000	0.136	0.021	0.017	0.014	9.789	2.443	3037
$CSAD_{CA}$	0.000	0.062	0.011	0.010	0.006	8.876	2.085	3037

reported between the US, the UK and Canada. Figure 5.1 presents plots of aggregate market indices.

5.5. EMPIRICAL RESULTS

5.5.1. EVIDENCE OF HERDING, AND THE IMPACT OF OIL PRICE AND OIL FEAR INDICES, MARKET FEAR INDICES, AND CROSS-MARKET EFFECT

Table 5.3 provides results based on equation (5.4) for the G7 countries. These regressions test for the existence of herding, while incorporating the market VIX, Oil price index, Oil VIX, and the cross-market US factors using Newey-West consistent estimators (1987)[57]. Panels A1, A2, and A3 provided estimates for the full sample (from May 2007 until December 2018), during the financial crisis (from May 2007 until December 2010) and following the financial crisis (from January 2010 until December 2017). The results of equation (5.4), as presented in Table 5.3 display high explanatory power in all samples, since the values of the adjusted R-squared vary from 0.214 to 0.958. Furthermore, the presence of herding behaviour is indicated by a negative significant coefficient of γ_2,

[57] The test was also run using a weighted least squared estimator for detecting herding based on equation (5.3). Since the results are similar, they are not reported in this study in the interest of brevity. The results are available upon request.

which is absent in the empirical estimates, as there is no observed herding behaviour evident in any of the countries described. These results are consistent with several studies; Christie and Huang (1995), Chang et al. (2000), Mobarek et al. (2014), and Economou et al. (2018) found no evidence of herding in the US, the UK, or Germany[58].

Table 5.3 also presents the coefficients of $OVX_{m,t}$, $Oil_{m,t}$, and $VIX_{m,t}$, in particular in reference to their impact on market returns dispersion. The $OVX_{m,t}$ coefficient (γ_3) shows no significant negative results in any country. In contrast, $Oil_{m,t}$ has significant negative values in Japan, Germany, France, and Italy in Panel 1, and no sign of an effect in Panels 2 and 3. It is relatively interesting that market returns in these countries are affected by the current level of Oil prices, and not by future expectations about Oil fluctuation. Oil returns play a major role in describing herding styles, and changes in the current oil price have an immediate impact on many companies in the market, causing a herding behaviour response.

As an additional control variable, the market fear index effect on returns dispersion is also reported in Table 5.3. The $VIX_{m,t}$ had a significant negative effect on the US, Japan, Germany and UK markets in Panels 1-3, as represented by γ_5 coefficients. Although, there is no significant herding towards market returns in these countries, it is apparent that the market fear index plays a major role not only in determining the movement of market stock prices[59], but also in its effect on investors' herding behaviour. Similar results were also reported in the US, UK, and Germany by Economou et al. (2018)[60].

[58] In contrast to these studies, Chiang and Zheng (2010) reported on herding behaviour in the UK and Germany using industrial returns instead of individual stock returns from April 1989 to April 2009. Also, Chiang et al. (2013), documented herding evidence in the US market from February 1987 to November 2009.
[59] Previous studies documented a significant negative and asymmetric link between the fear index and market returns (see, Schwert, 1989; Schwert, 1990, Fleming et al., 1996; Pan, Giot, 2005; Dennis et al., 2006; Bollerslev and Zhou, 2006; Ederington and Guan, 2010; Frijns et al., 2010)
[60] Economou el al. (2018) used similar approach by applying daily data from January 2004 to July 2014. They also found the same results during the global financial crisis.

Table 5.2: Correlation matrix of *CSAD*

This table reports the correlations of the cross-sectional absolute deviation $CSAD_t$ of individual stock returns among the G7 countries: including the US, Japan (JP), Germany (GR), France (FR), Italy (IT), Canada (CA). The statistics are based on daily observations from May 2007 to December 2018. The calculation of $CSAD_t$ is based on equation (5.2), stated as: $CSAD_t = \frac{1}{N}\sum_{i=1}^{N}\left|R_{i,t} - R_{m,t}\right|$.

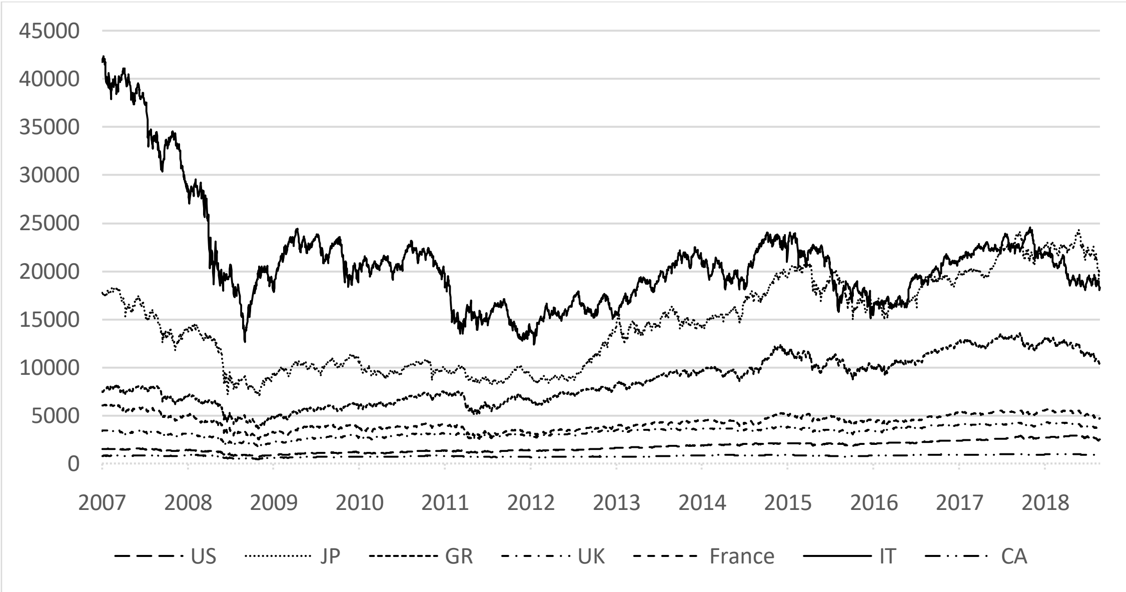
	US	JP	GR	UK	FR	IT	CA
US	1.00						

JP	0.53	1.00					
	(34.25)	-----					
GR	0.72	0.51	1.00				
	(56.68)	(31.88)	-----				
UK	0.80	0.55	0.74	1.00			
	(72.09)	(35.2)	(60.05)	-----			
FR	0.75	0.51	0.78	0.82	1.00		
	(61.57)	(32.28)	(67.56)	(76.97)	-----		
IT	0.35	0.21	0.35	0.39	0.45	1.00	
	(20.19)	(11.76)	(20.45)	(22.91)	(27.17)	-----	
CA	0.79	0.51	0.62	0.73	0.67	0.32	1.00
	(70.84)	(32.09)	(42.91)	(58.17)	(48.36)	(18.49)	-----

The role of the US market is integrated into equation (5.4) by adding $VIX_{US,t}$, $CSAD_{US,t}$, $R^2_{us,t}$ factors as incremental, control variables. Without any exception, the values of the γ_6, $VIX_{US,t}$ coefficients are positive and significant across all countries and panels. Since only negative, significant coefficients of fear index would confirm that herding increases during periods of uncertainty, these results suggest that high values of $VIX_{US,t}$ only stimulate significant herding behaviour in the US, having no international cross market influence on herding. In contrast, the values of γ_7, $CSAD_{US,t}$, coefficients are positive and significant in all the countries under examination, and throughout all the samples. Cross-market herding suggests a dominant effect from dispersions in US market returns, and spill over into international markets. The cross-sectional absolute deviation of returns for the control market (i.e. the US) suggests the dominant influence of cross-market dispersions of spillovers from US market returns over international markets.

Figure 5.1: Plot of aggregate market indices.

This figure shows daily data of market indices in the G7 markets, US (SP500), UK (FTSE100), Japan (Nikkei225), Germany (DAX30), France (CAC40), Italy (FTSEMIB40), and Canada (SPTSX60). All data are drawn from Thomson-Reuters DataStream from May 2007 to December 2018.



As for the cross-sectional market returns effect of the US, $R^2_{US,t}$, γ_8 displays significant and negative coefficients across all G7 countries in Panels 1 and 3, with the exception of Germany, France, and Italy in Panel 2. The squared US market returns is a gauge of extreme market shocks, and its informational context is 'absorbed' by the G7 countries, which contributes to herding.

5.5.2. TEST FOR ASYMMETRIC RESPONSE

Tests of the asymmetric response based on equation (5.5) are reported in Table 5.4, showing herding behaviour during 'up' and 'down' market periods. The coefficients (γ_3 to γ_9) of the control variables $D^{up} R^2_{m,t}$, $(1\text{-}D^{up})R^2_{m,t}$, $OVX_{m,t}$, $Oil_{m,t}$, $VIX_{m,t}$, $VIX_{us,t}$, and $CSAD_{us,t}$, exhibit similar results, as shown in table 5.3, indicating similar behaviour under different market conditions. Herding towards these explanatory factors can arise from the flow of positive and negative information. Panel B1 in table 5.4, reports the test equality

Table 5.3: Estimates of herding equation incorporating Market Volatility Index, Oil price index, Oil Volatility index, and the US factors.

This table presents the estimation coefficients of the regression results using equation (5.4):

$$CSAD_t = \alpha + \gamma_1|R_{m,t}| + \gamma_2 R^2_{m,t} + \gamma_3 Oil_t + \gamma_4 OVX_t + \gamma_5 VIX_{m,t} + \gamma_6 VIX_{us,t} + \gamma_7 CSAD_{us,t} + \gamma_8 R^2_{us,t} + \varepsilon_t \tag{5.4}$$

Where $CSAD$ is the cross-sectional absolute deviation of returns; R is the log returns of the market m; Oil is the log returns of Brent Crude Oil price; OVX *is* the log returns CBOE Crude Oil Volatility; VIX is the log returns of the implied volatility index of market m; while the VIX, $CSAD_{us}$, R^2_{us}, are the US cross-market factors, the log returns of the CBOE implied volatility index, return dispersion, and the log returns of market index returns. All at time t using daily data for the US, Japan (JP), Germany (GR), France (FR), Italy (IT), Canada (CA) from May 2007 to December 2018. We test for the whole sample, during financial crisis from May 2007 to July 2009, and after the financial crisis from July 2009 to December 2018. All data are obtained from Thomson-Reuters DataStream. t-statistics are reported in protheses, and $\bar{R}^2$ is the adjusted R^2. *** indicate significance at 1%, ** indicate significance at 5%, * indicate significance at 10%.

Market	C	$\lvert R_{m,t}\rvert$	$R^2_{m,t}$	$OVX_{m,t}$	$Oil_{m,t}$	$VIX_{m,t}$	$VIX_{us,t}$	$CSAD_{us,t}$	$R^2_{us,t}$	$\bar{R}^2$
Panel A1 - Regression estimations										
US	0.008***	0.363***	0.420	0.000	-0.001	-0.004***				0.420
	(66.01)	(23.93)	(1.61)	(-0.06)	(-0.44)	(-3.76)				
JP	0.069***	-0.024***	-0.903***	-0.002	-0.001**	-0.000*	0.013***	0.039***	-0.503***	0.949
	(173.17)	(-7.15)	(-19.57)	(-1.24)	(-2.16)	(-1.93)	(158.6)	(7.83)	(-10.98)	
GR	0.017***	-0.027*	4.068***	0.005	-0.004**	-0.001***	0.003***	0.523***	-0.517***	0.601
	(12.47)	(-1.83)	(12.86)	(1.36)	(-2.57)	(-2.72)	(10.27)	(27.62)	(-2.63)	
UK	0.016***	0.147***	-0.008	-0.004	-0.001	-0.002***	0.003***	0.642***	-0.689***	0.689
	(13.97)	(10.51)	(-0.03)	(-1.18)	(-0.53)	(-2.56)	(12.36)	(40.11)	(-4.67)	
FR	0.015***	0.078***	0.992***	0.002	-0.004***	0.000	0.002***	0.443***	-0.081***	0.632
	(14.84)	(7.33)	(5.08)	(0.77)	(-3.09)	(-0.94)	(11.63)	(31.47)	(-9.62)	
IT	0.018***	0.506***	4.355***	-0.020	-0.011***		0.002***	0.403***	-2.127***	0.538
	(5.38)	(17.91)	(9.54)	(-1.09)	(-3.01)		(2.95)	(9.01)	(-5.19)	
CA	0.015***	0.279***	-0.189	-0.009	-0.001		0.002***	0.639***	-0.282*	0.739
	(12.46)	(18.29)	(-0.69)	(-1.45)	(-0.41)		(9.09)	(36.17)	(-1.88)	
Panel A2 - Regression estimations during the global financial crisis (2007-2009)										
US	0.011***	0.475***	1.377***	-0.006	0.000	-0.009**				0.492
	(23.71)	(11.69)	(2.58)	(-0.52)	(-0.03)	(-2.44)				
JP	0.091***	-0.007	-0.468***	0.000	-0.001***	0.001***	0.018***	0.022*	-0.440***	0.958
	(69.44)	(-0.84)	(-5.49)	(-0.13)	(-2.52)	(-4.98)	(62.95)	(1.99)	(-6.28)	
GR	0.039***	-0.147***	5.867***	0.035***	-0.004***	-0.002***	0.008***	0.467***	0.297	0.608
	(6.26)	(-2.76)	(7.41)	(2.76)	(-3.67)	(-8.70)	(5.65)	(7.94)	(0.73)	
UK	0.032***	0.140***	-0.055	0.004	0.000	-0.009**	0.006***	0.542***	-0.636**	0.665
	(6.95)	(3.35)	(-0.09)	(0.39)	(0.03)	(-2.56)	(6.09)	(12.69)	(-2.39)	
FR	0.029***	0.069**	0.518	0.014*	-0.007*	-0.005	0.005***	0.388***	0.147	0.705
	(8.40)	(2.31)	(1.26)	(1.96)	(-1.96)	(-1.13)	(7.26)	(12.04)	(0.74)	
IT	0.023***	0.451***	5.180***	-0.047	-0.021**		0.004**	0.587***	-0.273	0.741
	(2.74)	(7.17)	(6.18)	(-0.74)	(-2.39)		(2.23)	(7.55)	(-0.57)	
CA	0.026***	0.328***	-1.207	-0.001	-0.003		0.005***	0.641***	-0.087***	0.812
	(5.93)	(8.54)	(-1.32)	(-0.06)	(-0.66)		(5.11)	(15.24)	(-3.31)	

Market	C	$\lvert R_{m,t} \rvert$	$R^2_{m,t}$	$OVX_{m,t}$	$Oil_{m,t}$	$VIX_{m,t}$	$VIX_{us,t}$	$CSAD_{us,t}$	$R^2_{us,t}$	$\bar{R}^2$
Panel A3 - Regression estimations after the global financial crisis (2009-2018)										
US	0.008***	0.259***	-0.032	0.004	0.000	-0.002*				0.253
	(75.87)	(13.69)	(-0.05)	(1.14)	(-0.07)	(-1.82)				
JP	0.066***	-0.036***	1.170***	-0.001	0.000	0.001***	0.012***	0.014***	-0.164**	0.957
	(213.06)	(-12.18)	(19.61)	(-0.86)	(-0.26)	(2.76)	(191.87)	(2.95)	(-2.34)	
GR	0.005***	0.159***	1.756***	0.000	-0.003	-0.002**	0.001*	0.033*	-0.120***	0.214
	(3.45)	(8.12)	(3.33)	(-0.06)	(-1.27)	(-2.26)	(1.89)	(1.79)	(-8.74)	
UK	0.011***	0.139***	0.543	-0.006	-0.001	-0.001**	0.002***	0.591***	-0.990***	0.518
	(10.29)	(7.19)	(0.79)	(-1.76)	(-0.86)	(-2.19)	(7.82)	(32.02)	(-3.33)	
FR	0.013***	0.054***	2.292***	-0.002	-0.003	0.000	0.002***	0.455***	-0.835***	0.483
	(12.19)	(4.47)	(8.29)	(-0.76)	(-0.38)	(-0.52)	(8.90)	(25.09)	(-2.83)	
IT	0.022***	0.514***	4.065***	-0.010	0.005		0.003***	0.264***	-10.582***	0.474
	(6.15)	(16.38)	(7.19)	(-0.89)	(1.31)		(3.8)	(4.27)	(-11.82)	
CA	0.013***	0.365***	-2.954	-0.009	0.002		0.002***	0.570***	-2.189***	0.530
	(5.93)	(8.54)	(-1.32)	(-0.06)	(-0.66)		(5.11)	(15.24)	(-3.31)	

(Continued)

of herding coefficients (D^{up} $R^2_{m,t}$, (1-D^{up})$R^2_{m,t}$) using the Wald test, and examining asymmetry of herding coefficients under different market conditions, in rising and falling markets. Wald tests show significant asymmetry in Japan, and asymmetric results and herding exist only in falling markets. Moreover, it is evident that herding is more significant in periods of falling markets than in rising markets. However, several empirical studies have shown that positive shocks generate stronger herding effects than negative shocks (See Hellwig (1980), Campbell et al. (1993), Diks and Van Der Weide (2003)). The majority of these studies examined periods prior to the global financial crisis in 2007-2009, whereas asymmetric volatility increased during the crisis. This magnified the asymmetry in herding behaviour, which in return implies that asymmetry in herding is time-varying (Park and Sabourian, 2011).

Table 5.4: Estimates of herding equation in rising and declining stock market incorporating Market Volatility Index, Oil price index, Oil Volatility index, and the US factors.

This table presents the estimation coefficients of the regression results using equation (5.5):

$$CSAD_t = \alpha + \gamma_1 D^{up}|R_{m,t}| + \gamma_2(1 - D^{up})|R_{m,t}| + \gamma_3 D^{up} R^2_{m,t} + \gamma_4(1 - D)^{up} R^2_{m,t} + \gamma_5 OVX_t + \gamma_6 Oil_t + \gamma_7 VIX_{m,t} + \gamma_8 VIX_{us,t} + \gamma_9 CSAD_{us,t} + \gamma_{10} R^2_{us,t} + \varepsilon_t \quad (5.5)$$

Where *CSAD* is the cross-sectional absolute deviation of returns; *R* is the log returns of the market *m*; *OVX is* the log returns CBOE Crude Oil Volatility; *Oil* is the log returns of Brent Crude Oil price; $VIX_{m,t}$ is the log returns of the implied volatility index of market *m*; while the VIX_{US}, $CSAD_{US}$, R^2_{US}, are the US cross-market factors, the log returns of the CBOE implied volatility index, return dispersion, and the log returns of market index returns. D^{up} is a dummy variable that equals to 1 when market return is positive, and 0 when market returns are either negative or zero. All at time *t* using daily data for the US, Japan (JP), Germany (GR), France (FR), Italy (IT), Canada (CA) from May 2007 to December 2018. All data are obtained from Thomson-Reuters DataStream. t-statistics are reported in protheses, and $\bar{R}^2$ is the adjusted R^2. Panel B reports statistics for Wald test, with restrictions of $\gamma_3 = \gamma_4$, the difference in herding coefficients between up and down markets. *** indicate significance at 1%, ** indicate significance at 5%, * indicate significance at 10%.

Market	C	$D^{up}\lvert R_{m,t}\rvert$	$(1-D^{up})\lvert R_{m,t}\rvert$	$D^{up} R^2_{m,t}$	$(1-D^{up})R^2_{m,t}$	$OVX_{m,t}$	$Oil_{m,t}$	$VIX_{m,t}$	$VIX_{US,t}$	$CSAD_{US,t}$	$R^2_{US,t}$	$\bar{R}^2$
Panel A - Regression estimations												
US	0.008***	0.310***	0.426***	0.765**	-0.008	0.003	-0.001	-0.009***				0.423
	(66.02)	(15.87)	(18.64)	(2.4)	(-0.02)	(0.63)	(-0.58)	(-5.9)				
JP	0.069***	-0.014***	-0.038***	0.712***	-1.133***	0.002**	-0.001**	0.001**	0.013***	0.042***	-0.501***	0.952
	(173.24)	(-3.72)	(-8.82)	(12.32)	(-18.21)	(2.31)	(-2.02)	(-2.47)	(158.59)	(8.31)	(-10.99)	
GR	0.017***	-0.047***	0.045**	5.646***	1.276***	-0.002	-0.003*	-0.001***	0.003***	0.534***	-0.370*	0.615
	(12.52)	(-2.77)	(2.28)	(15.46)	(2.88)	(-0.41)	(-2.00)	(-3.82)	(10.44)	(28.58)	(-1.90)	
UK	0.016***	0.102***	0.194***	1.245***	-1.115***	-0.003	-0.001	-0.004***	0.003***	0.638***	-0.640***	0.691
	(14.01)	(5.85)	(10.59)	(3.17)	(-2.99)	(-0.93)	(-0.57)	(-3.65)	(12.37)	(39.91)	(-4.32)	
FR	0.015***	0.089***	0.071***	1.093***	0.771***	-0.001	-0.003**	0.000	0.002***	0.443***	-0.038	0.644
	(14.92)	(7.2)	(5.3)	(4.66)	(2.76)	(-0.34)	(-2.42)	(-0.02)	(11.72)	(31.47)	(-0.29)	
IT	0.018***	0.516***	0.494***	4.134***	4.641***	0.020**	-0.011***		0.002***	0.403***	-2.121***	0.538
	(5.37)	(15.55)	(14.49)	(7.32)	(7.29)	(-.08)	(-3.02)		(2.95)	(9.02)	(-5.18)	
CA	0.015***	0.314***	0.248***	-0.500	0.085	0.013***	0.001		0.002***	0.639***	-0.274	0.740
	(12.41)	(16.67)	(13.88)	(-1.36)	(0.25)	(3.44)	(0.55)		(9.05)	(36.22)	(-1.52)	

Market	$D^{up} R^2_{m,t}$	$(1-D^{up})R^2_{m,t}$	$\beta_3 - \beta_4$	Chi-square	P-value
Panel B1 – Test equality of herding coefficients of $R^2_{m,t}$ (Wald test $\beta_3 = \beta_4$)					
US	0.765	-0.008	0.774	1.112	1.056
JP	0.712	1.133	-0.421	162.198	0.036***
GR	5.646	1.276	0.164	229.695	15.156
UK	1.245	-1.115	1.278	7.046	2.654
FR	1.093	0.771	-0.002	18.409	4.291
IT	4.134	4.641	-0.401	40.147	6.336
CA	-0.500	0.085	-0.636	4.047	2.012

(Continued)

Table 5.5: Descriptive statistics of *Herd*.

This table show summary statistics of the herding coefficient, the γ_2 from equation (5.2), using Kalman-filter process, equation (5.6) to (5.8) for the G7 countries: including the US, Japan (JP), Germany (GR), France (FR), Italy (IT), Canada (CA). The statistics are based on daily observations from May 2007 to December 2018.

Market	Minimum	Maximum	Mean	Median	Std. dev	Kurtosis	Skewness	Obs
$HERD_{US}$	-0.026	0.088	0.047	0.022	0.033	2.440	-0.049	3037.000
$HERD_{JP}$	-0.311	-0.166	-0.005	0.132	0.040	2.990	-0.528	3037.000
$HERD_{GR}$	-0.440	0.040	-0.004	-0.012	0.056	3.078	-0.676	3037.000
$HERD_{UK}$	-0.409	-0.011	0.013	-0.076	0.052	2.435	-0.049	3037.000
$HERD_{FR}$	-0.341	-0.020	-0.030	-0.144	0.043	3.247	-0.639	3037.000
$HERD_{IT}$	-0.389	0.052	-0.158	-0.527	0.050	2.480	-0.296	3037.000
$HERD_{CA}$	-0.291	-0.014	-0.028	-0.025	0.037	3.947	-0.189	3037.000

5.5.3. DETERMINANT FACTORS OF HERDING DYNAMICS

Time-varying herding behaviour estimates are obtained by applying the Kalman-Filter approach, as based on equations (5.6) and (5.8), and herding descriptive statistics are reported in table 5.5. Herding time series for all countries are negative, stationary and time varying[61]. The negative values of the herding coefficient γ_5 indicate the presence of dynamic herding, as reported earlier[62]. Table 5.6 reports correlations between herding coefficients as derived by applying Kalman-Filter processes, while table 5.7 show correlations in the conditional volatility of market returns. In both tables, correlation coefficients are mostly high and significant.

The determinant factors of dynamic herding behaviour are reported in table 5.8. According to our hypotheses, combined with market returns, we can add the conditional variances of the Oil IV index, Oil index, market fear index, market returns index, and the

[61] We conducted several stationarity tests, mainly ADF and PP, and found no unit root in the herding time series. However, the series are time varying, since clustering exists where volatility changes over time and high (low) volatility periods are followed by high (low) volatility periods.

[62] These results were obtained using constant-coefficient regression estimations of herding using equation (5.4) as reported in table 5.3. It was confirmed that herding is present in Japan for the whole sample and during the global financial crises.

Table 5.6: Correlation matrix of *Herd*.

This table reports the correlations of herding coefficient, the γ_2, using Kalman-filter process, equation (5.6) to (5.8) among the G7 countries: including the US, Japan (JP), Germany (GR), France (FR), Italy (IT), Canada (CA). The statistics are based on daily observations from May 2007 to December 2018.

	$Herd_{US}$	$Herd_{JP}$	$Herd_{GR}$	$Herd_{UK}$	$Herd_{FR}$	$Herd_{IT}$	$Herd_{CA}$
$Herd_{US}$	1.00						

$Herd_{JP}$	0.58	1.00					
	(36.65)	-----					
$Herd_{GR}$	0.34	0.21	1.00				
	(43.64)	(31.88)	-----				
$Herd_{UK}$	0.80	0.55	0.74	1.00			
	(62.72)	(26.95)	(77.11)	-----			
$Herd_{FR}$	0.75	0.51	0.78	0.82	1.00		
	(90.5)	(41.76)	(45.26)	(45.37)	-----		
$Herd_{IT}$	0.35	0.21	0.35	0.39	0.45	1.00	
	(35.94)	(18.42)	(21.35)	(21.05)	(41.86)	-----	
$Herd_{CA}$	0.79	0.51	0.62	0.73	0.67	0.32	1.00
	(75.8)	(30.21)	(54.88)	(65.47)	(28.18)	(9.48)	-----

cross market US fear index and market returns ($\sigma^2_{OVX_{m,t}}, \sigma^2_{Oil_{m,t}}, \sigma^2_{VIX_{m,t}}, \sigma^2_{R_{m,t}}, \sigma^2_{VIX_{US,t}}$, and $\sigma^2_{R_{US,t}}$). Except for the UK and Canada, countries that displayed negative mean coefficients when using a dynamic approach as reported in table (5), also display significant and negative market returns coefficients, γ_1. Unlike the previous findings using constant estimates, where herding prevails in falling markets, dynamic herding estimates move in the opposite direction. Since herding estimates are negative, this relationship states that when the market is rising, the detected herding measure increases. OVX volatility, Oil prices volatility, market fear index volatility [63], and market returns volatility (γ_2 to γ_5) show a positive significant relationship with herding in all markets. Whereas, the coefficients of cross market volatility, spill overs of US factors, market returns and fear index volatility, are significantly positive in all G7 countries, except for Japan and France.

[63] The fear index is reported for each country (we excluded Italy and Canada due to data availability as indicated previously).

Table 5.7: Correlation matrix of conditional variances.

This table reports the correlations of the conditional variance of market returns, obtained by asymmetric GARCH(1,1) process, among the G7 countries: including the US, Japan (JP), Germany (GR), France (FR), Italy (IT), Canada (CA). The statistics are based on daily observations from May 2007 to December 2018.

	σ^2_{US}	σ^2_{JP}	σ^2_{GR}	σ^2_{UK}	σ^2_{FR}	σ^2_{IT}	σ^2_{CA}
σ^2_{US}	1.00						

σ^2_{JP}	0.80	1.00					
	(73.65)	-----					
σ^2_{GR}	0.91	0.80	1.00				
	(118.53)	(72.9)	-----				
σ^2_{UK}	0.80	0.55	0.74	1.00			
	(15.97)	(15.26)	(16.95)	-----			
σ^2_{FR}	0.75	0.51	0.78	0.82	1.00		
	(115.92)	(70.47)	(175.63)	(17.71)	-----		
σ^2_{IT}	0.35	0.21	0.35	0.39	0.45	1.00	
	(14.57)	(7.21)	(14.38)	(1.12)	(15.99)	-----	
σ^2_{CA}	0.79	0.51	0.62	0.73	0.67	0.32	1.00
	(175.95)	(77.2)	(111.18)	(12.14)	(100.62)	(14.72)	-----

5.5.4. ESTIMATES OF DYNAMIC HERDING BEHAVIOUR

Table 5.9 shows estimated results of equation (5.10), were the interaction between market volatility and herding is augmented with the implied volatilities of Oil price and fear indices, market fear and the US cross market factors, fear and returns indices. Herding is present in all countries since all γ_2 is negative and significant. The nonlinear elements represented by $R^3_{m,t}$[64], that captures the integration between market returns and herding is insignificant in all countries. However, the interaction of market returns and returns volatility, represented by γ_4 is significant in all countries, suggesting that the dynamic nature of herding is time-varying and mainly affected by market conditional volatility. This notion indicates that constant coefficients cannot be precise for determining herding

[64] $R^3_{m,t}$ is the product term of R^2_m and $R_{m,t}$, herding and stocks returns.

Table 5.8: Dynamic herding behaviour determinant factors.

This table presents the estimation coefficients of the regression results using equation (5.9):

$$H_t = \beta_0 + \beta_1 R_{m,t} + \beta_2 \sigma^2_{OVX_t} + \beta_3 \sigma^2_{Oil_t} + \beta_4 \sigma^2_{VIX_{m,t}} + \beta_5 \sigma^2_{R_{m,t}} + \beta_6 \sigma^2_{VIX_{US,t}} + \beta_7 \sigma^2_{R_{US,t}} + \varepsilon_t \quad (5.9)$$

Where H is the herding coefficient, the γ_2 from equation (5.2), using Kalman-filter process, equation (5.6) to (5.8); R is the log returns of the market m; $\sigma^2_{R_{m,t}}$ is the conditional volatility of market index of market m; σ^2_{OVX} *is* the conditional volatility of CBOE Crude Oil Volatility index; $\sigma^2_{Oil}$is the conditional volatility of Brent Crude Oil price; σ^2_{VIX} is conditional volatility of the implied volatility index of market m; while the $\sigma^2_{VIX_{US}}$, $\sigma^2_{R_{US}}$, are the US cross-market factors, the conditional volatility of the CBOE implied volatility index, and the conditional volatility of market index. All at time t using daily data for the US, Japan (JP), Germany (GR), France (FR), Italy (IT), Canada (CA) from May 2007 to December 2018. We test for the whole sample, during financial crisis from May 2007 to July 2009, and after the financial crisis from July 2009 to December 2018. All data are obtained from Thomson-Reuters DataStream. t-statistics are reported in protheses, and $\bar{R}^2$ is the adjusted R^2. *** indicate significance at 1%, ** indicate significance at 5%, * indicate significance at 10%.

Country	C	$R_{m,t}$	$\sigma^2_{OVX_{m,t}}$	$\sigma^2_{Oil_{m,t}}$	$\sigma^2_{VIX_{m,t}}$	$\sigma^2_{R_{m,t}}$	$\sigma^2_{VIX_{US,t}}$	$\sigma^2_{R_{US,t}}$	$\bar{R}^2$
US	0.007***	-0.013***	4.768***	0.110***	0.000***	9.853***			0.509
	(46.06)	(-2.28)	(18.72)	(2.58)	(8.02)	(30.57)			
JP	0.008***	-0.000	3.596***	0.150***	0.044***	5.615***	-0.006	-0.026	0.593
	(49.32)	(-3.02)	(13.33)	(3.14)	(3.99)	(19.83)	(-0.49)	(-0.90)	
GR	0.006***	-0.014*	4.076***	0.181***	0.000***	12.551***	0.059***	0.001***	0.423
	(32.64)	(-1.76)	(13.53)	(3.62)	(6.33)	(26.36)	(4.96)	(8.07)	
UK	0.008***	0.004	5.365***	0.164***	0.212***	13.378***	0.039***	0.022***	0.502
	(40.96)	(0.46)	(20.92)	(3.74)	(8.09)	(30.46)	(3.42)	(2.98)	
FR	0.007***	-0.009*	3.346***	0.152***	0.000***	7.829***	-0.003	-0.005	0.696
	(49.39)	(-1.82)	(14.8)	(3.88)	(6.84)	(26.22)	(-0.36)	(-0.73)	
IT	0.012***	-0.027**	5.562***	0.552***		16.946***	0.110***	0.033*	0.672
	(24.22)	(-2.00)	(8.2)	(4.25)		(18.9)	(3.57)	(1.85)	
CA	0.010***	-0.009	4.903***	0.175***		14.239***	0.021**	0.044***	0.627
	(54.17)	(-3.83)	(15.63)	(3.56)		(32.18)	(1.79)	(4.33)	

Table 5.9: Estimates of dynamic herding implications.

This table presents the estimation coefficients of the regression results using equation (5.10):

$$CSAD_t = \alpha + \gamma_1|R_{m,t}| + \gamma_2 R^2_{m,t} + \gamma_3 R^3_{m,t} + \gamma_4 R^2_{m,t}{*}\sigma^2_{R_{m,t}} + \gamma_5 R^2_{m,t}{*}\sigma^2_{OVX_t} + \gamma_6 R^2_{m,t}{*}\sigma^2_{Oil_t} + \gamma_7 R^2_{m,t}{*}\sigma^2_{VIX_{m,t}} + \varepsilon_t \quad (5.10)$$

Where *CSAD* is the cross-sectional absolute deviation of returns; *R* is the log returns of the market *m*; $\sigma^2_{R_{m,t}}$, σ^2_{OVX}, σ^2_{Oil}, σ^2_{VIX}, are the conditional volatilities of index market returns of market *m*, Brent Crude Oil price, CBOE Crude Oil Volatility index, and the implied volatility index of market *m*. All at time *t* using daily data for the US, Japan (JP), Germany (GR), France (FR), Italy (IT), Canada (CA) from May 2007 to December 2018. We test for the whole sample, during financial crisis from May 2007 to July 2009, and after the financial crisis from July 2009 to December 2018. All data are obtained from Thomson-Reuters DataStream. t-statistics are reported in protheses, and $\bar{R}^2$ is the adjusted R^2. *** indicate significance at 1%, ** indicate significance at 5%, * indicate significance at 10%.

Country	C	$\lvert R_{m,t} \rvert$	$R^2_{m,t}$	$R^3_{m,t}$	$R^2_{m,t} * \sigma^2_{R_{m,t}}$	$\gamma_6 R^2_{m,t}{*}\sigma^2_{OVX_t}$	$\gamma_5 R^2_{m,t}{*}\sigma^2_{Oil_t}$	$\gamma_7 R^2_{m,t}{*}\sigma^2_{VIX_{m,t}}$	$\bar{R}^2$
US	0.005***	0.302***	-1.182***	-2.425	8.694***	6.526***	0.157***	0.008***	0.570
	(36.69)	(19.17)	(-2.68)	(-1.61)	(4.58)	(31.37)	(3.98)	(3.86)	
JP	0.007***	0.298***	-2.463***	-1.655	7.881***	4.287***	0.075**	0.059***	0.602
	(41.2)	(22.17)	(-8.71)	(-0.78)	(8.36)	(18.91)	(1.72)	(6.29)	
GR	0.005***	0.197***	-1.506***	0.124	3.081***	6.572***	0.321***	0.000**	0.655
	(28.94)	(10.27)	(-2.76)	(0.06)	(9.24)	(26.4)	(6.74)	(2.34)	
UK	0.006***	0.297***	-1.664***	4.852	1.744***	7.503***	0.208***	0.093***	0.620
	(30.88)	(16.81)	(-3.39)	(0.11)	(6.57)	(33.91)	(4.89)	(3.98)	
FR	0.006***	0.157***	-0.586**	-1.049	0.947***	5.002***	0.197***	0.000*	0.553
	(42.09)	(11.86)	(-1.86)	(-0.73)	(2.88)	(26.31)	(5.39)	(1.73)	
IT	0.009***	0.545***	-2.936***	-2.841	1.896***	5.413***	0.497***	0.133***	0.695
	(21.92)	(18.08)	(-4.27)	(-0.97)	(2.70)	(10.53)	(4.90)	(5.50)	
CA	0.007***	0.551***	-5.282***	-0.628	2.895***	6.863***	0.140***	0.023**	0.644
	(44.57)	(28.42)	(-8.61)	(-0.29)	(9.84)	(29.75)	(3.29)	(2.31)	

behaviour, which is consistent with the findings in table 5.5, where all regions, except in the US, exhibit negative herding coefficients.

Table 5.9 display higher explanatory power, in comparison with the initial analysis reported in table 5.3, since the values of the adjusted R-squared vary from 0.553 to 0.695. Interestingly, the volatility of Oil fear and price indices' conditional volatilities dynamic interaction with herding are also significant in most countries. These results are consistent with earlier findings that recognized the impact of macroeconomic announcements on investors' behaviour and uncertainty (Ederington and Lee, 1996; Fleming and Remolona, 1999; Nikkinen and Sahlstrom, 2004). The existent spill over from the volatility of energy sector to the global financial markets implies the transmission of risk perception of oil market by investors (Nazlioglu et al., 2015).

5.6. CONCLUSION

In this study, we examine herding behaviour in G7 countries (US, UK, Japan, Germany, France, Italy and Canada). We use daily data from May 2007 until December 2018. Using a conventional static herding model, we found patterns of herding behaviour only in Japan. Our results are consistent with earlier studies that documented no herding signs in developed countries (Christie and Huang, 1995, Chang et al., 2000). We also test for herding under different market conditions and found similar results, indicating an asymmetric response in the Japanese market. Several explanatory factors were incorporated to understand herding behaviour movements. We used the Oil price index, OVX, and market sentiment, alongside the US factors. Unlike Oil IV, Oil prices showed significant effect on herding in all G7 countries. We also found evidence of the US cross-market spill overs across the regions we examined. The US CASD and square stock market returns exhibited significant results in all countries. However, there was no significant international spill over effect from the US fear index.

Further, we used Kalman-filter procedures to extract herding coefficients to identify the dynamic nature of herding in response to the effect of global factors. We use market sentiment, oil price and fear indices' and conditional volatilities' states as variables. The interaction between market returns and the conditional variance of these factors showed a significant tendency of herding towards them in all the countries examined. In accordance with Chiang et al. (2013), we indicate that herding is affected by the state of volatility conditions, and not just by extreme market swings. This suggests that herding could not be measured only by static market returns, and that empirical models should be adjusted to incorporate the conditional variances of several explanatory factors. These findings would help market participants and policy makers understand the dynamic nature of herding behaviour and its determinant factors. More attention should be paid toward the Oil market, especially during stress periods, where it is shown that it has an important role in generating herding patterns within the global financial markets. Also, in accordance with Economou et al. (2018), the US cross herding effect eliminates some of the global diversification benefits, specifically when allocating liquidity between the US and the other G7 countries.

The following chapter continues to explore the determinants of herding behaviour. The discussion demonstrates the pronounced critical impact of implied volatility during an examination of herding behaviour, alongside a number of other factors, in particular when applying a dynamic herding approach. An identical method is employed in relation to oil exporting countries of various regions.

CHAPTER 6: EMPIRICAL ANALYSIS OF DYNAMIC HERDING BEHAVIOUR IN OIL EXPORTING COUNTRIES

6.1. INTRODUCTION

There has been an increased interest in herding behaviour among scholars and traders and it has consequently been investigated comprehensively in the literature. Herding behaviour is a term used to describe how collective information causes market participants to follow one another. They adhere to 'majority decisions' regardless of individual disagreements over market predictions (Christie and Huang, 1995). Whether or not herding is driven by rational or irrational reasons, it is the main driver of volatility (Chari et al., 2003). Research into herding behaviour has been undertaken in a number of different contexts, both in the US market and in other international markets, as demonstrated in the empirical literature. If investors attempt to adhere to the market consensus and conduct trade in the same direction over a particular period of time, this will ultimately lead to particular behavioural patterns in the market (Chiang and Zheng, 2010). The consequence of this is price deviations from economic fundamentals, which might then cause market shocks and crashes (Demirer et al., 2014).

Several research papers have highlighted herding behaviour among investors in international markets (Christie and Huang, 1995; Chang et al., 2000; Economou et al., 2015). There has also been research focused on the bond market (Galariotis et al., 2016), the US real estate market (Philippas et al., 2013), the ETFs market (Gleason et al., 2004), the commodities markets (Gleason et al., 2003), and the foreign exchange markets (Kaltwasser, 2010). Nevertheless, most studies focus on identifying herding rather than attempting to discover the causes of this phenomenon amongst investors. Herding behaviour has been researched in several regions in both developing and developed countries and in importing and exporting countries. Each of the regions offer mixed evidence when a range of methodological approaches are applied. There is also a growing trend towards examining herding in oil exporting countries, specifically GCC[65] countries. Moreover, recent empirical studies suggest that an effect from cross-market spill overs is evident in global markets, indicating that these markets are relatively interdependent, especially during highly volatile periods Chiang et al. (2007). Spill overs might also be a potential cause of herding.

Research on herding behaviour has incorporated market sentiment and returns volatility into estimation models to identify herding determinants. The IV index (VIX) was used in several pieces of research (Philippas et al., 2013; Chiang et al., 2013; Economou et al., 2015; Economou et al., 2018). These studies noted that herding often occurred in response to the market fear index. The fear index, particularly the US VIX, is widely known as a significant explanatory variable in many global markets (Siriopoulos and Fassas, 2009). Oil price and the OVX have an impact on market returns, but not on herding behaviour. In a similar context, the volatility of market returns has been used to determine dynamic herding behaviour in the market (Chiang et al., 2013). However, there has been no research into the combined explanatory power of the fear index, the oil index and the OVX.

In this paper we provide new evidence on herding behaviour by incorporating several factors: OVX, oil price index, stock market fear index (VIX), the cross-market US returns dispersion, VIX, and stock index returns, using a dynamic approach based on the Kalman-filter model. Several oil exporting countries (Russia, Mexico, Saudi Arabia, Kuwait, UAE, and Qatar)[66] will be examined and tested for herding behaviour using the herding approach suggested by Chang et al. (2000), with a modification that allows for the capture

[65] GCC to the Gulf Cooperation Council for the Arab States of the Gulf, Saudi Arabia, Kuwait, Qatar, Bahrain, UAE, and Oman.
[66] These countries have been selected because they are the world's biggest oil exporting countries, and also on data availability.

of the dynamic and time-varying nature of herding behaviour. This paper contributes to the existing literature, and to the mixed findings reported regarding herding in oil exporting countries, by: i) providing new evidence incorporating the fear indices of market and oil, oil price index and the cross-market global effect[67] to obtain a better understanding of what causes herding, and ii) by applying the Kalman-filter process to examine the dynamic nature of herding behaviour in response to the effect of the conditional volatility of these variables.

Most of the aforementioned research has only focused on identifying herding behaviour in the examined regions based on stock market returns. Few studies have incorporated additional variables, such as the fear index and the cross-market effect of these variables. Furthermore, Chiang et al. (2013) were the first to use a time-varying coefficient model. However, their variables remained limited to the explanatory factors that had been investigated before. This study contributes to the literature by including global factors, such as oil price and fear indices, that can better explain patterns in market herding. The effects of oil price and the OVX have never been investigated as controlled variables as part of an examination of herding behaviour. The Kalman-filter enables this research to overcome the issue of structural changes caused by market stress when using the average value of relationships over a specified time range. The Kalman-filter involves a transition equation, which permits the estimation of state variables when actual results are disrupted by noise (Athans, 1974).

The results of using a static model show that herding only exists in Saudi Arabia. Unlike oil prices and the market fear index[68], the OVX appears to have a significant impact on several countries. The same results have been documented during periods of market

[67] Since the US market plays an important role in the global financial system (Chiang and Zheng, 2001), it is reasonable to add the US price index returns, (S&P500), following Masih and Masih (2001) approach, market fear index (CBOE VIX), and the stock market cross sectional absolute deviation (CSAD of S&P500).

[68] Testing the impact of market fear index on herding occurs only in countries that have a public IV market index; Russia and Mexico.

stress. Additional tests were undertaken to assess cross-market spill overs and the evidence showed that the US market returns dispersion and stock market returns have a significant global effect. Finally, by testing for herding using the Kalman-filter approach, the herding patterns of most countries were documented using global explanatory factors, oil price and oil fear indices, and the market fear index.

The remainder of the paper is organised as follows: Section 2 presents the literature review. Data and the herding models are explained in sections 3 and 4. Section 5 contains the empirical results and analysis, and is followed by the conclusion.

6.2. LITERATURE REVIEW

6.2.1. EXAMINATION OF HERDING BEHAVIOUR

Herding behaviour has been explored and examined in a variety of ways. Recent studies, using the herding approaches of Christie and Huang (1995) and Chang et al. (2000), have mostly focused on emerging markets. Tan et al. (2008), Hsieh et al. (2011), Lee et al. (2013), and Yao et al. (2014) all found evidence of herding under different market conditions in emerging markets[69] including China. Several other studies chose to examine the Taiwanese stock market (Lin and Swanson, 2003, Chen et al., 2012) and discovered contradictory results. However, an extensive study by Demirer et al. (2010) employed different herding models and reported evidence of herding on all sectors in the Taiwan Stock Exchange. Moreover, Huang et al. (2015) investigated the impact of idiosyncratic volatility on herding in Taiwan, and found that herding behaviour is evident in the market and demonstrates distinct patterns in response to idiosyncratic volatility.

[69] The emerging markets examined in these studies are Bangladesh, India, Indonesia, Malaysia, Pakistan, Philippine, Sri Lanka and Thailand.

Recent research on herding has concentrated on Arabic and GCC countries. Balcilar et al. (2017) proposed a dynamic herding approach with modifications that enable researchers to examine herding patterns under different market regimes in the UAE, Saudi Arabia, Kuwait and Qatar. They provided initial evidence of herding in three market regimes: low, high and crash volatility regimes.

6.2.2. OIL, IMPLIED VOLATILITY AND STOCK MARKET HERDING

Crude oil is a closely watched global commodity and a vital driver of economic activity. Many empirical studies have examined the link between economic activity and oil prices in a number of emerging and developed countries (Hamilton, 2003; Hammoudeh and Choi, 2006; Kilian, 2008; Chiou and Lee, 2009; Arouri et al., 2011). In addition, other empirical papers have researched the impact of oil shock spills on emerging markets (Basher and Sadorsky, 2006; Park and Ratti, 2008) and in GCC countries (Hammoudeh and Aleisa, 2004; Zarour, 2006; Hammoudeh and Choi 2006; Akoum et al., 2012). However, few empirical models have been produced that connect oil price shocks to fluctuations in returns (Balcilar et al., 2017) and reflect herding’s dynamic nature.

In relation to oil exporting countries that play a significant role in world energy markets, many studies have explored the relationship between oil prices and macroeconomic variables. Arouri and Rault (2012) reported a positive relationship between the stock prices in GCC countries, except for Saudi Arabia. Conversely, other studies indicate a decline in the influence of crude oil on economic activities (Hammoudeh and Choi, 2006). Akoum et al. (2012) examined co-movements between oil prices and aggregate stock prices in the GCC region, and found the market is not strongly linked to oil shocks. I feel these findings indicate that GCC countries can be considered as forming frontier markets, resulting in becoming less integrated into (and influenced by) global economic indicators.

6.2.3. CROSS-MARKET HERDING

To date, herding research has mainly focused on factors in a single country, creating many inherent problems for empirical results. From an economic perspective, ignoring important global factors can lead to bias in the process of estimation (Kennedy, 2003). Herding behaviour has been documented in many countries, yet these results do not reflect the wider effect of global spill over in the financial markets (Chiang and Zheng, 2010). Interdependence between financial markets has increased, and this is particularly evident in turbulent market conditions. Chiang et al. (2007) documented significant correlations across several Asian markets. Asian markets stocks are exposed to systematic risk, which means that there is a decline in profits when forming diversified portfolios of stocks in these countries. This is in turn shown as having a high correlation with herding in turbulent markets. Similarly, Chiang and Zheng. (2010) demonstrated evidence of herding in Latin American markets in the direction of the US market.

More evidence of cross-market herding is present in the GCC markets. For instance, Hammoudeh and Li (2008) concentrated on the integration of GCC countries toward sudden changes in volatility. They found most of these countries to be sensitive to global changes and used the 1997 Asian crisis, the collapse of oil prices in 1998 and the Russian crisis in 1998 as examples. Contrastingly, Yu and Hassan (2008) analysed the correlation between MENA[70] markets and global markets and obtained mixed results. Arabic MENA markets show a lesser response to global market factors. However, as these tend to be frontier countries, I viewed them as being influenced to a lesser extent by the global

[70] Middle Eastern and North African countries. This study examined the behaviour of equity markets in Bahrain, Egypt, Israel, Jordan, Kuwait, Morocco, Oman and Saudi Arabia.

financial system. Thus, I consider that there is a potential for inaccurate results arising from a study of herding behaviour based on the cross-market effect.

6.3. METHODOLOGY

6.3.1. DETECTING HERDING MODELS

Different testing methods have been implemented to determine the existence of herding behaviour, and are widely discussed in the literature. Christie and Huang (1995) and Chang et al. (2000) first proposed herding measures based on cross-sectional stock returns. They suggested that the trading activity of market participants depends on observed momentum and overall market conditions. The rational asset-pricing models in normal market conditions state that dispersion of cross-sectional returns is positively related to the absolute value of market returns. However, it is commonly believed that investors will follow market consensus during highly volatile periods, and thus, herding will be evident due to the collective market actions of individuals. Christie and Huang (1995) state that testing for the statistical significance of returns dispersion as a response to extreme market returns can be measured using the $CSSD_t$ formula, which is expressed as follows:

$$CSSD_t = \sqrt{\frac{\sum_{i=1}^{N}(R_{i,t} - R_{m,t})^2}{(N-1)}} \tag{6.1}$$

While $R_{i,t}$ in this model is the log difference return of the equity on day t, Chang et al. (2000) suggest that in periods of large price swings, market participants will usually follow the average market consensus. The relationship between $CSAD_t$ and average market returns will most likely be nonlinear. Consequently, a nonlinear regression model is suggested for capturing herding activity by detecting the relationship between $CSAD_t$ and market returns:

$$CSAD_t = \frac{\sum_{i=1}^{N} \left| R_{i,t} - R_{m,t} \right|}{N} \tag{6.2}$$

While $R_{i,t}$ in this model is the log difference return of the equity on day *t*. Chang et al. (2000) suggest that in periods of large price swings, market participants will usually follow the average market consensus. The relationship between $CSAD_t$ and the average market returns will most likely be nonlinear. Consequently, a nonlinear regression model is suggested for capturing herding activity by detecting the relationship between $CSAD_t$ and market returns:

$$CSAD_t = \alpha + \gamma_1 |R_{m,t}| + \gamma_2 R_{m,t}^2 + \varepsilon_t \tag{6.3}$$

Herding behaviour exists when there is a significant negative coefficient from squared market returns γ_2 , because there is a decline in returns dispersions in times of market stress. The evidence of previous studies has led me to conclude that most research focussing on herding behaviour has been based on the models of Christie and Huan (1995) and Chang et al. (2000). In addition, I found that the models most frequently employed in herding behaviour research consist of CSSD and CSAD, which are built on the basis of capital asset pricing model, i.e. the expected returns on a security related to the potential level of risk. At this point, this study intends to include several explanatory factors for testing, examining whether they significantly affect herding behaviour and assist with determining if herding has greater sensitivity towards particular variables: the market fear index, oil price, the OVX, and the US cross-market effect. The impact of the Fear index as captured by the IV index (VIX) on herding has been detailed in recent studies (Philippas et al., 2013; Chiang et al., 2013; Economou et al., 2015; Economou et al., 2018). It appears that herding might be more prevalent in turbulent market periods because of increased uncertainty. Stock market volatility responses to oil price shocks are widely documented in the literature (Hamilton, 2009; Kilian and Park, 2009; Jung and Park, 2011; Abhyankar et al., 2013, Kang and Ratti, 2013; Güntner, 2014). Stock market volatility relies on oil price shocks, but these findings are not only confined to the stock market. Existing literature has shown that oil price shocks are vital for explaining the responses to many other economic variables (Bastianin and Manera, 2018). However, there are missing links between herding behaviour and oil price shocks, and, similarly, the OVX has not been investigated in the context of herding. It will be interesting to examine the impact of oil price and the oil fear indices on herding behaviour in G7 markets. Global financial markets have a high level of integration, which is encouraged by the rapid transfer of information. As a consequence, trading and behaviour spill overs are highly related between markets (Chiang and Zheng, 2010). The importance of the US market is well documented because of its significant role in international equity market co-movements and in global financial transactions (Forbes and Rigobon, 2002; Connolly and Wang, 2003). Three US factors are included in this study: the fear index, cross-sectional absolute deviation and market returns squared.

6.3.2. AUGMENTED HERDING TESTING MODEL

For this study, the herding model suggested by Chang et al. (2000), and the further argument equation (6.3) were used. The new model is as follows:

$$CSAD_t = \alpha + \gamma_1|R_{m,t}| + \gamma_2 R_{m,t}^2 + \gamma_3 OVX_t + \gamma_4 Oil_t + \gamma_5 VIX_{m,t} + \gamma_6 VIX_{US,t} + \gamma_7 CSAD_{US,t} + \gamma_8 R_{US,t}^2 + \varepsilon_t \tag{6.4}$$

Where OVX is the daily log returns of the CBOE crude oil volatility index at time *t*, and oil is the daily log returns of the Brent crude oil price at time *t*. VIX is the daily log returns of the IV index of market *m*, at time *t*. VIX_{US}, $CSAD_{US}$, R_{US}^2 are the US cross-market factors, which are the daily log returns of the CBOE volatility index, the cross sectional absolute deviation of the SP500 market, and the log returns of the SP500 index correspondingly.

6.3.3. ASYMMETRIC AUGMENTED HERDING MODELS

Asymmetric behaviour is also of great interest to some researchers. They focus on asymmetric characteristics under varying market conditions. Longin and Solnik (2001), Tan et al. (2008), Chiang and Zheng (2010), and Economou et al. (2011) observed the behaviour of investors under falling and rising markets. The study applied a dummy variable linked to market returns squared together with previous explanatory factors in equation (6.4) to ascertain whether traders behave differently under various market conditions. The equation is as follows:

$$CSAD_t = \alpha + \gamma_1 D^{up}|R_{m,t}| + \gamma_2 (1 - D^{up})|R_{m,t}| + \gamma_3 D^{up} R^2_{m,t} + \gamma_4 (1 - D^{up}) R^2_{m,t} + \gamma_5 OVX_t + \gamma_6 Oil_t + \gamma_7 VIX_{m,t} + \gamma_8 VIX_{US,t} + \gamma_9 CSAD_{US,t} + \gamma_{10} R^2_{US,t} + \varepsilon_t \tag{6.5}$$

The D^{up} is a dummy variable, which equals 1 on days when market returns are positive, and 0 on days when market returns are zero or negative.

6.3.4. KALMAN FILTER HERDING MODELS

The abovementioned constant regression models provide an average estimate coefficient over time to detect herding. The estimated results are therefore static. In different applications, the driving forces of economic factors can be immeasurable or not directly observable (Pichler, 2007). The estimation procedures can be extended and improved with a state space model driving a stochastic process for measuring the dynamics of time-varying convergence. Kalman (1960) suggests that the Kalman linear filtering and prediction approach allows researchers to discover an optimum averaging factor for each of the consequent states, and to update the knowledge of state variables when new data points are available (Tsay, 2005). There are a number of ways to derive the Kalman-filter, and to estimate the dynamics of the time-varying convergence of herding behaviours. These are represented below:

$$\hat{X}_t = \hat{X}_{t-1} + K_t(\gamma_t - \hat{X}_{t-1}), \tag{6.6}$$

Where $\hat{X}_t$ is the dynamic estimate of herding captured by γ_2 from equation (6.3), followed by a random walk process. K_t is the Kalman gain, which is calculated as follows:

$$K_t = \frac{P_{t-1}}{P_{t-1} + r}, \tag{6.7}$$

P_{t-1} is the prior error covariance, and r is the standard deviation of the measurement noise. Error covariance is expressed as:

$$P_t = (1 - K_t)\, P_{t-1} \tag{6.8}$$

The results from the Kalman-filter process have crucial implications for testing and estimating the dynamic nature of herding estimates. To identify key determinants, Chiang et al. (2013) remarked that herding is linked to two main hypotheses: the volatility hypothesis and the stock market performance hypothesis. Several studies have related herding activities to stock market performance, as institutional investors trade excessively after an irrational bout of market momentum (Black, 1986, Trueman, 1988). Investors might react to fluctuations in stock market prices (Grinblatt et al., 1995), and positive news might drive traders to invest in similar ways by buying stocks and vice versa, leading to market destabilisation (Shiller and Pound, 1989, Brennan and Thakor, 1990, De Long et al., 1990, Scharfstein and Stein, 1990, Banerjee, 1992, Sentana and Wadhwani, 1992).

Some empirical studies have shown that in highly volatile markets, traders follow similar trading patterns, which leads to increases in cross-market correlation (Butler and Joaquin, 2002, Corsetti et al., 2005). This means that, when there is an increased expectation of market volatility because of market stress, feedback traders have a greater impact on prices and existing dispersion of returns will increase as a consequence (Sentana and Wadhwani, 1992).

Both theories are combined to determine the impact on the estimated herding time series, as produced by the Kalman-filter. An extraction of the conditional volatility of stock returns was conducted using the GARCH(1,1) process. The conditional volatility of Oil_t, OVX_t, $VIX_{m,t}$, was also added. Every determinant was included in the following regression:

$$H_t = \beta_0 + \beta_1 R_{m,t} + \beta_2 \sigma^2_{OVX_t} + \beta_3 \sigma^2_{Oil_t} + \beta_4 \sigma^2_{VIX_{m,t}} + \beta_5 \sigma^2_{R_{m,t}} + \beta_6 \sigma^2_{VIX_{US,t}} + \beta_7 \sigma^2_{R_{US,t}} + \varepsilon_t \tag{6.9}$$

The dependent variable H describes the estimated herding values on time t, the values of γ_2 from equation (6.3), as derived from equation (6.6). σ^2 is the conditional variance of the determinant factors. Regarding $\sigma^2_{VIX_t}$, the volatility (or kurtosis) of the IV indices[71] were employed as explanatory variables. The volatility of the volatility index was used as a market uncertainty proxy aided by capturing herding behaviour towards market consensus on future market expectations.

[71] Research on the area of volatility of volatility (also known as kurtosis) is limited to a few studies (see See Yang-Ho Park, 2015; Wang et al., 2013; and Alsheikhmubarak and Giouvris, 2019). The conditional variance of the IV indices were obtained using an asymmetric GARCH(1,1) process for all IV indices. In order to unify the data across all countries, the US VVIX index created by CBOE for the US market was excluded.

Finally, a test for the joint effect of returns and volatility for each explanatory factor was performed and is expressed as follows:

$$CSAD_t = \alpha + \gamma_1 |R_{m,t}| + \gamma_2 R_{m,t}^2 + \gamma_3 R_{m,t}^3 + \gamma_4 R_{m,t}^2 * \sigma_{R_{m,t}}^2 + \gamma_5 R_{m,t}^2 * \sigma_{OVX_t}^2 + \gamma_6 R_{m,t}^2 * \sigma_{Oil_t}^2 + \gamma_7 R_{m,t}^2 * \sigma_{VIX_{m,t}}^2 + \varepsilon_t \tag{6.10}$$

This describes where the product of each conditional volatility σ^2 with its corresponding index price captures herding interaction with other volatility determinants.

6.4. DATA

Data from all the listed firms in the selected oil exporting countries was used in this study. The countries selected were: Russia, Mexico, Saudi Arabia, UAE, Norway, Qatar, and Kuwait. Their corresponding stock markets indices (MOEX, IPC, TASI, ADX[72], OSE, QE, and KWSEIDX) were also used in conjunction with their market fear indices (RVI, and VIMEX)[73]. The composition of these indices has been updated on an annual basis, in order to reflect the expected change over time arising from the addition and deletion of constituents. Additionally, the Brent Crude Oil price was incorporated along with the CBOE Crude Oil Volatility index (OVX). Furthermore, US factors, such as the US fear index (CBOE VIX), the US price index returns (S&P500) and the stock market cross sectional absolute deviation (CSAD of S&P500) were included to test for the effect of major foreign factors in the model. All the data was drawn from Thomson-Reuters DataStream ranging from January 2007 to December 2018, except for the data from Kuwait which was obtained from publicly listed sources. The number of observations collated for each country is 3037.

[72] ADX is the Abu Dhabi Securities Exchange. There are three stock exchange markets in United Arab Emirates, the ADX and the DFM, Dubai Financial Market, and NASDAQ Dubai. However, we only choose ADX due to its high trading volume.

[73] Several countries under examination in this paper don't have IV indices (Saudi Arabia, Kuwait, UAE, and Qatar).

Table 6.1: Descriptive statistics of *$CSAD_t$*.

This table show summary statistics of the equally weighted cross-sectional absolute deviations *($CSAD_t$)* for Russia (RU), Mexico (MX), Saudi Arabia (SA), United Arab Emirates (AU), Norway (NO), Qatar (QA), and Kuwait (KU). The statistics are based on daily observations from May 2007 to December 2018. The calculation of *$CSAD_t$* is based on equation (6.2), stated as: $CSAD_t = \frac{1}{N}\sum_{i=1}^{N}\left|R_{i,t} - R_{m,t}\right|$.

Market	Minimum	Maximum	Mean	Median	Std. dev	Kurtosis	Skewness	Obs
$CSAD_{RU}$	0.000	0.105	0.012	0.011	0.008	22.450	3.439	3037.000
$CSAD_{MX}$	0.000	0.074	0.012	0.011	0.006	17.077	2.556	3037.000
$CSAD_{SA}$	0.000	0.084	0.012	0.010	0.006	16.627	2.462	3037.000
$CSAD_{AU}$	0.000	0.470	0.014	0.012	0.013	697.285	21.097	3037.000
$CSAD_{NO}$	0.000	0.071	0.024	0.020	0.008	4.954	0.784	3037.000
$CSAD_{QA}$	0.000	0.091	0.014	0.012	0.009	15.882	3.067	3037.000
$CSAD_{KU}$	0.000	0.256	0.017	0.016	0.009	165.153	7.367	2930.000

Table 6.1 presents a summary of descriptive statistics of the cross-sectional dispersion of individual assets' returns (CSAD) for all countries. The highest mean value of the CSAD standard deviation and Kurtosis are present in UAE. Balcilar et al. (2013) also found that the UAE has the highest mean value and standard deviation among the GCC countries, suggesting unusual variations across stocks, due to unexpected market shocks. Table 6.2 presents the correlation matrix of CSAD across all countries. All of the pairs are positively and highly significant without exception, with the highest values reported from Russia and Mexico. However, these correlation numbers are lower in comparison to the correlation matrix of CSAD concerning G7 countries as used in the previous chapter. A possible explanation is that the majority of these countries are frontier markets and therefore less integrated into the global financial system.

6.5. EMPIRICAL RESULTS

6.5.1. EVIDENCE OF HERDING

Table 6.3 provides results based on equation (6.4) for the selected oil exporting countries. These regressions test for the existence of herding, while incorporating the market VIX,

Table 6.2: Correlation matrix of *CSAD*$_t$.

This table reports the correlations of the cross-sectional absolute deviation *CSAD*$_t$ of individual stock returns among Russia (RU), Mexico (MX), Saudi Arabia (SA), United Arab Emirates (AU), Norway (NO), Qatar (QA), and Kuwait (KU). The statistics are based on daily observations from May 2007 to December 2018. The calculation of *CSAD*$_t$ is based on equation (6.2), stated as: $CSAD_t = \frac{1}{N}\sum_{i=1}^{N}|R_{i,t} - R_{m,t}|$.

	RU	MX	SA	AU	NO	QA	KU
RU	1.00						

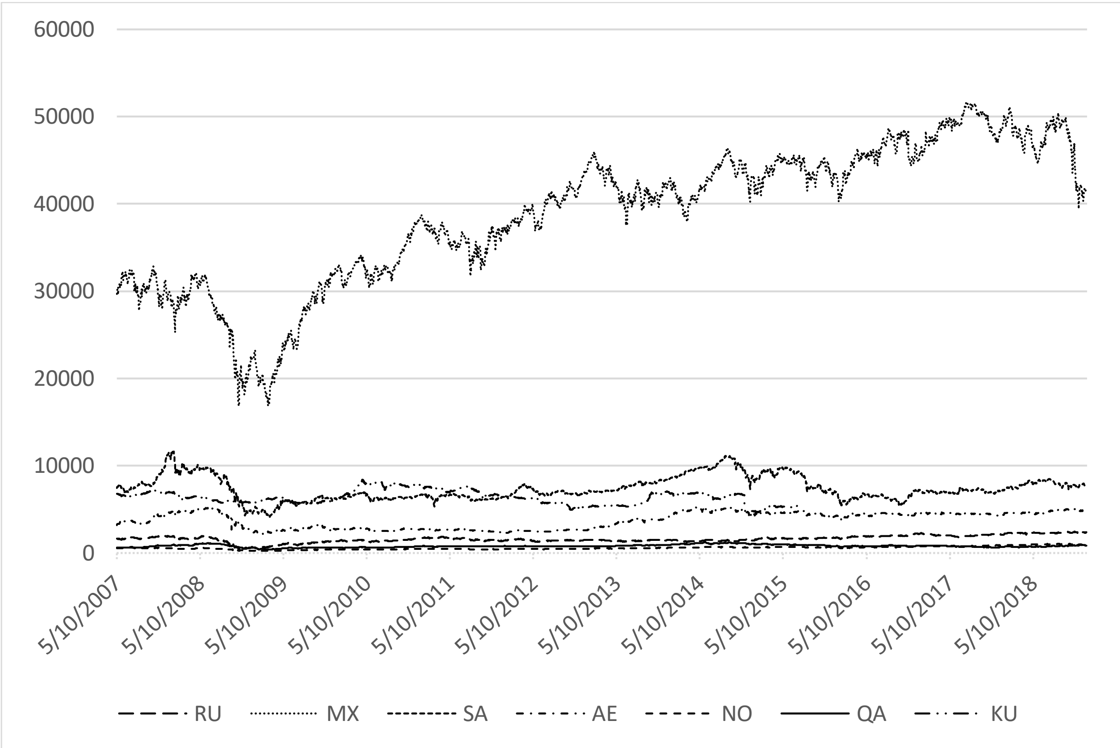
MX	0.48	1.00					
	(29.95)	-----					
SA	0.28	0.29	1.00				
	(15.56)	(16.26)	-----				
AU	0.26	0.18	0.25	1.00			
	(14.82)	(10.11)	(14.21)	-----			
NO	0.50	0.52	0.24	0.18	1.00		
	(31.47)	(32.59)	(13.43)	(9.85)	-----		
QA	0.40	0.34	0.38	0.30	0.28	1.00	
	(23.74)	(19.44)	(22.45)	(16.76)	(15.7)	-----	
KU	0.26	0.20	0.26	0.20	0.19	0.30	1.00
	(14.41)	(10.84)	(14.72)	(11.15)	(10.44)	(17.3)	-----

oil price index, Oil VIX and the US factors using the Newey-West consistent estimators (1987)[74]. Panels A1, A2, and A3 provide estimates for the full sample (from May 2007 until December 2018), during the financial crisis (from May 2007 until December 2010) and after the financial crisis (from January 2010 until December 2017). The results for equation (6.4), presented in table 6.3, display a high explanatory power in all the samples, since the values of the adjusted R-squared vary from 0.227 to 0.919. The presence of herding behaviour is indicated by a negative significant coefficient of γ_2. With the exception of Saudi Arabia[75], the empirical estimates in panels A1 and A2 do not demonstrate any negative significant values from γ_2 and the coefficients in the countries

[74] The analysis was also conducted using a weighted least squared estimator in detecting herding based on equation (6.3). Since the results are similar, they are not reported in this study in the interest of brevity. The results are available upon request.
[75] Youssef and Mokni (2018) also found evidence of herding behaviour in Saudi Arabia and Qatar. However, their results are obtained by using weekly data, instead of daily data, from 2003 to 2017.

Figure 6.1: Plot of aggregate market indices.

This figure shows daily data of market indices for Russia (RU), Mexico (MX), Saudi Arabia (SA), United Arab Emirates (AU), Norway (NO), Qatar (QA), and Kuwait (KU). All data are drawn from Thomson-Reuters DataStream from May 2007 to December 2018.



do not indicate any herding behaviour. However, in panel A3, Saudi Arabia, UAE, Qatar and Kuwait exhibit a negative and significant γ_3 coefficient, indicating herding following the global financial crisis. Balcilar et al. (2013) also found similar results in Saudi Arabia, Dubai, and Qatar and he relates herding in these countries to the level of market volatility, stating there is a negative relationship between herding behaviour and volatility in stock market returns. However, Saudi Arabia is the only market that demonstrated significant signs of herding behaviour in all periods, indicating that clear return dispersions decline during periods of market stress[76]. UAE, Qatar, and Kuwait also demonstrated similar herding signs, following the global financial crisis, indicating a similar situation to their

76 Rahman (2015) indicated several causes for the existence of herding in the Saudi Market, summarized as follows: 1) 80% of people who have direct access to stock trading has no formal or informal trading education. 2) More than 25% of traders acquire their related market knowledge from friends and forums.

neighbour, Saudi Arabia. These countries share a border with Saudi Arabia, have a similar culture and traditions, and, most importantly, have highly convergent economies that lead to close trading relations. Geographic proximity means there are less publicly released records, which causes correlated trading decision in the region. These factors offer possible explanations for the similarities in their herding patterns.

Table 6.3 also presents the coefficients of $OVX_{m,t}$, $Oil_{m,t}$, and $VIX_{m,t}$, and details their impact on the market returns dispersion. The $OVX_{m,t}$ coefficient (γ_3) shows significant negative results in Mexico, Saudi Arabia, Qatar, and Kuwait in panels 1 and 2, but no sign of having an effect in panel 3. In contrast, $Oil_{m,t}$, $VIX_{m,t}$ has no effect in any of the panels. The returns dispersion in oil exporting countries is affected by the future expectation of oil prices presented by the oil IV index and not the corresponding oil prices[77]. Oil exporting countries rely heavily on income generated from oil exports[78]. Since major stocks in these markets depend heavily on oil income and government expenditure, the expectations of future oil prices play a major role in defining trading habits during periods when there is an increase in fear and uncertainty among market participants. Some of the possible explanations for this are that the market activities of oil exporters are more affected by political news than macroeconomic news (Kutan and Yuan, 2002), when herding around the crude oil market is absent.

The role of the US market is investigated in equation (6.4) by adding $VIX_{US,t}$, $CSAD_{US,t}$, and $R^2_{US,t}$ as incremental controlled variables. Without exception, the values of γ_6, $VIX_{US,t}$ coefficients are positive and significant across all the countries and panels. Only negative,

[77] Opposing results were found in the G7 countries (Alsheikhmubarak and Evangelos, 2019). G7 countries are affected by the current level of Oil prices, where changes in Oil prices have an immediate impact on companies in these markets leading to a herding behaviour response.
[78] According to the oil exporting balance of trade, excluding Russia and Norway, where oil income accounts for less than 50% of their total income, in Mexico, Saudi Arabia, UAE, Qatar and Kuwait, oil exports account for more than 70% of total income.

Table 6.3: Estimates of herding equation incorporating Market Volatility Index, Oil price index, Oil Volatility index, and the US factors.

This table presents the estimation coefficients of the regression results using equation (6.4):

$$CSAD_t = \alpha + \gamma_1|R_{m,t}| + \gamma_2 R^2_{m,t} + \gamma_3 OVX_t + \gamma_4 Oil_t + \gamma_5 VIX_{m,t} + \gamma_6 VIX_{US,t} + \gamma_7 CSAD_{US,t} + \gamma_8 R^2_{US,t} + \varepsilon_t \qquad (6.4)$$

Where *CSAD* is the cross-sectional absolute deviation of returns; *R* is the log returns of the market *m*; *OVX* is the log returns CBOE Crude Oil Volatility; *Oil* is the log returns of Brent Crude Oil price; *VIX* is the log returns of the implied volatility index of market *m*; while the VIX_{US}, $CSAD_{US}$, R^2_{US}, are the US cross-market factors, the log returns of the CBOE implied volatility index, return dispersion, and the log returns of market index returns. All at time *t* using daily data for Russia (RU), Mexico (MX), Saudi Arabia (SA), United Arab Emirates (AU), Norway (NO), Qatar (QA), and Kuwait (KU) from May 2007 to December 2018. We test for the whole sample, during financial crisis from May 2007 to July 2009, and after the financial crisis from July 2009 to December 2018. All data are obtained from Thomson-Reuters DataStream, except for Kuwait, where the Kuwaiti data are collected from publicly listed data. t-statistics are reported in protheses, and $\bar{R}^2$ is the adjusted R^2. *** indicate significance at 1%, ** indicate significance at 5%, * indicate significance at 10%.

Market	*C*	$\lvert R_{m,t} \rvert$	$R^2_{m,t}$	$OVX_{m,t}$	$Oil_{m,t}$	$VIX_{m,t}$	$VIX_{USus,t}$	$CSAD_{USus,t}$	$R^2_{USus,t}$	$\bar{R}^2$
Panel A1 - Regression estimations										
RU	0.013***	0.224***	0.215***	-0.002	-0.003	-0.001	0.001***	0.261***	-1.648***	0.532
	(7.09)	(20.74)	(3.06)	(-0.40)	(-1.59)	(-0.41)	(3.89)	(10.43)	(-7.31)	
MX	0.010***	0.264***	1.243***	-0.004*	-0.004	0.000	0.001***	0.434***	-1.196***	0.588
	(7.96)	(16.52)	(3.35)	(-1.98)	(-0.48)	(-0.19)	(4.58)	(24.33)	(-6.00)	
SA	0.013***	0.471***	-3.383***	-0.013***	-0.002		0.002***	0.197***	-0.211	0.432
	(8.15)	(-27.77)	(-12.18)	(-2.88)	(-1.23)		(4.68)	(8.89)	(-1.04)	
AE	0.016***	0.621***	0.722***	0.006	0.001		0.002***	0.088***	0.431	0.825
	(8.09)	(46.78)	(19.81)	(1.05)	(0.34)		(4.07)	(3.32)	(1.80)	
NO	0.015***	0.421***	-0.604	0.008	-0.003		0.000	0.318***	0.647***	0.536
	(7.83)	(21.83)	(-1.36)	(1.44)	(-1.63)		(0.67)	(12.3)	(2.74)	
QA	0.020***	0.404***	0.335	-0.000***	0.003		0.003***	0.300***	0.085	0.440
	(7.99)	(18.29)	(0.99)	(-3.01)	(1.28)		(5.5)	(8.99)	(0.28)	
KU	0.027***	0.946***	0.073	-0.015**	-0.001		0.004***	0.250***	0.377	0.478
	(10.52)	(31.11)	(0.44)	(-2.03)	(-0.19)		(7.24)	(7.35)	(1.200)	
Panel A2 - Regression estimations during the global financial crisis (2007-2009)										
RU	0.028***	0.267***	-0.028	-0.005	0.001	-0.013	0.006***	0.280***	-1.606***	0.663
	(3.97)	(9.69)	(-0.19)	(-0.36)	(0.17)	(-0.63)	(3.53)	(4.25)	(-3.90)	
MX	0.016***	0.272***	1.716**	-0.105	-0.008	-0.003	0.003**	0.454***	-1.395***	0.677
	(3.39)	(6.63)	(2.32)	(-3.50)	(-1.59)	(-0.4)	(2.55)	(10.48)	(-4.10)	
SA	0.008*	0.488***	-4.674***	-0.031***	-0.002		0.000***	0.104**	0.332	0.312
	(1.45)	(11.24)	(-7.90)	(-2.66)	(-0.30)		(4.39)	(2.04)	(1.03)	
AE	0.026***	0.614***	0.741***	0.023	-0.001		0.004***	0.044	0.689	0.919
	(3.67)	(18.99)	(9.62)	(1.57)	(-0.13)		(2.59)	(0.66)	(1.66)	
NO	0.035***	0.343***	0.183	0.024***	-0.005		0.006***	0.457***	0.293	0.819
	(7.67)	(9.23)	(0.37)	(2.59)	(-1.07)		(6.10)	(10.95)	(1.12)	
QA	0.061***	0.256***	1.091	-0.001*	0.020		0.011***	0.017	0.302	0.408
	(6.32)	(3.99)	(1.41)	(-2.05)	(1.36)		(5.22)	(0.19)	(0.54)	
KU	0.050***	0.439*	10.056	-0.033*	0.006		0.009***	0.212***	0.064	0.227
	(6.00)	(1.70)	(0.70)	(-1.92)	(0.67)		(4.91)	(2.72)	(0.13)	

Market	C	$\lvert R_{m,t} \rvert$	$R^2_{m,t}$	$OVX_{m,t}$	$Oil_{m,t}$	$VIX_{m,t}$	$VIX_{us,t}$	$CSAD_{USus,t}$	$R^2_{USus,t}$	$\bar{R}^2$
Panel A3 - Regression estimations after the global financial crisis (2009-2018)										
RU	0.013***	0.224***	0.215***	-0.002	-0.003	-0.001	0.001***	0.261***	-1.648***	0.532
	(7.09)	(20.74)	(3.06)	(-0.40)	(-1.59)	(-0.41)	(3.89)	(10.43)	(-7.31)	
MX	0.009***	0.350***	-2.241	-0.006	-0.002	0.001	0.001***	0.381***	-1.932***	0.397
	(7.16)	(17.27)	(-0.63)	(-1.43)	(-1.45)	(0.54)	(3.51)	(17.02)	(-5.54)	
SA	0.010***	0.385***	-0.737***	-0.007	-0.001		0.001***	0.199***	-1.170***	0.416
	(6.49)	(20.96)	(-2.11)	(-1.48)	(-0.75)		(2.77)	(7.27)	(-2.96)	
AE	0.013***	0.799***	-4.212***	0.000	0.001		0.001***	0.083***	-0.597	0.511
	(6.79)	(32.36)	(-7.59)	(0.04)	(0.36)		(2.83)	(2.58)	(-1.28)	
NO	0.017***	0.578***	-5.139	0.005	-0.001		0.001*	0.279***	0.272	0.391
	(8.44)	(19.29)	(-0.86)	(0.83)	(-0.66)		(1.83)	(8.00)	(0.51)	
QA	0.008***	0.377***	-2.247***	0.002	0.001		0.000***	0.299***	0.273	0.399
	(3.65)	(15.30)	(-4.31)	(0.30)	(0.21)		(2.73)	(7.76)	(0.49)	
KU	0.023***	1.002***	-0.157***	-0.003	0.000		0.003***	0.168***	-0.711	0.545
	(9.02)	(33.90)	(-2.48)	(-0.42)	(0.13)		(5.45)	(3.77)	(-1.10)	

(Continued)

of the fear index would confirm that herding increases during periods of uncertainty, suggesting that the effect of $VIX_{US,t}$ is absent in all countries. Notwithstanding, the values of γ_7, $CSAD_{US,t}$, coefficients are positive and significant in all the countries under examination and across all samples. The cross-sectional absolute deviation of returns for the control market (i.e. the US) suggests the dominant impact of cross-market dispersions of the US market returns spillovers over international markets.

The appearance of cross-market herding suggests a dominant effect from dispersions in US market returns spill over into international markets. This co-varying movement is facilitated by information processing and transmitting methods that carry the effects of trade and investment activities globally. As for the effect of the US, $R^2_{US,t}$, γ_8 displays significant and negative coefficients in Russia and Mexico only in panels 1 and 3. However the spill over from US stock market returns does not appear to have an effect on GCC herding formation. A potential explanation for this aspect is that these markets exhibit strong herding behaviour. This is based on the squared market returns coefficient

Table 6.4: Estimates of herding equation in rising and declining stock market incorporating Market Volatility Index, Oil price index, Oil Volatility index, and the US factors.

This table presents the estimation coefficients of the regression results using equation (6.5):

$$CSAD_t = \alpha + \gamma_1 D^{up}|R_{m,t}| + \gamma_2(1-D^{up})|R_{m,t}| + \gamma_3 D^{up} R^2_{m,t} + \gamma_4(1-D)^{up} R^2_{m,t} + \gamma_5 OVX_t + \gamma_6 Oil_t + \gamma_7 VIX_{m,t} + \gamma_8 VIX_{US,t} + \gamma_9 CSAD_{US,t} + \gamma_{10} R^2_{US,t} + \varepsilon_t \quad (6.5)$$

Where *CSAD* is the cross-sectional absolute deviation of returns; *R* is the log returns of the market *m*; *OVX* is the log returns CBOE Crude Oil Volatility; *Oil* is the log returns of Brent Crude Oil price; $VIX_{m,t}$ is the log returns of the implied volatility index of market *m*; while the VIX_{US}, $CSAD_{US}$, R^2_{US}, are the US cross-market factors, the log returns of the CBOE implied volatility index, return dispersion, and the log returns of market index returns. D^{up} is a dummy variable that equals to 1 when market return is positive, and 0 when market returns are either negative or zero. All at time *t* using daily data for the Russia (RU), Mexico (MX), Saudi Arabia (SA), United Arab Emirates (AU), Norway (NO), Qatar (QA), and Kuwait (KU) from May 2007 to December 2018. All data are obtained from Thomson-Reuters DataStream, except for Kuwait, where the Kuwaiti data are collected from publicly listed data. t-statistics are reported in protheses, and $\bar{R}^2$ is the adjusted R^2. Panel B reports statistics for Wald test, with restrictions of $\gamma_3 = \gamma_4$, the difference in herding coefficients between up and down markets. *** indicate significance at 1%, ** indicate significance at 5%, * indicate significance at 10%.

Market	C	$D^{up}\lvert R_{m,t}\rvert$	$(1-D^{up})\lvert R_{m,t}\rvert$	$D^{up} R^2_{m,t}$	$(1-D^{up})R^2_{m,t}$	$OVX_{m,t}$	$Oil_{m,t}$	$VIX_{m,t}$	$VIX_{US,t}$	$CSAD_{US,t}$	$R^2_{US,t}$	$\bar{R}2$
Panel A - Regression estimations												
RU	0.013***	0.246***	0.199***	0.137	0.321**	-0.007	-0.003	0.001	0.001***	0.261***	-1.668***	0.532
	(7.08)	(19.12)	(13.15)	(1.76)	(2.37)	(-1.32)	(-1.43)	(0.70)	(3.88)	(10.44)	(-7.41)	
MX	0.010***	0.270***	0.281***	1.567***	0.269	-0.006*	-0.003**	0.000	0.001***	0.435***	-1.176***	0.590
	(7.90)	(14.63)	(13.08)	(3.76)	(0.49)	(-1.69)	(-2.17)	(0.23)	(4.56)	(24.43)	(-5.91)	
SA	0.013***	0.417***	0.518***	-2.308***	-4.300***	-0.010**	-0.002		0.002***	0.201***	-0.180	0.436
	(8.06)	(19.85)	(25.61)	(-6.05)	(-12.34)	(-2.20)	(-1.28)		(4.59)	(9.11)	(-0.89)	
AE	0.016***	0.609***	0.541***	0.667***	1.507***	0.005	0.001		0.002***	0.098***	0.425*	0.832
	(8.5)	(35.97)	(31.44)	(16.1)	(18.07)	(0.85)	(0.63)		(4.35)	(3.78)	(1.81)	
NO	0.014***	0.460***	0.375***	-0.643	-0.292	-0.005	-0.002		0.000	0.316***	0.674***	0.540
	(7.81)	(19.43)	(16.39)	(-1.29)	(-0.72)	(-0.87)	(-0.96)		(0.63)	(12.24)	(2.84)	
QA	0.019***	0.450***	0.352***	0.152	0.590	-0.003***	0.004		0.003***	0.300***	0.125	0.442
	(7.94)	(16.60)	(12.38)	(0.35)	(1.28)	(-3.50)	(1.39)		(5.44)	(9.02)	(0.41)	
KU	0.027***	1.046***	0.937***	-4.755	0.115	-0.015**	0.000		0.004***	0.249***	0.389***	0.479
	(10.53)	(13.75)	(25.09)	(-1.16)	(0.62)	(-2.01)	(-0.16)		(7.29)	(7.32)	(1.24)	

Market	$D^{up} R^2_{m,t}$	$(1-D^{up})R^2_{m,t}$	$\beta_3 - \beta_4$	Chi-square	P-value
Panel B1 – Test equality of herding coefficients of $R^2_{m,t}$ (Wald test $\beta_3 = \beta_4$)					
RU	0.137	0.321	0.000	0.556	0.745
MX	1.567	0.269	-0.001	9.291	3.048
SA	-2.308	-4.300	-0.200	53.491	7.314
AE	0.667	1.507	-0.096	6.821	2.612
NO	-0.643	-0.292	-0.316	4.068	2.017
QA	0.152	0.590	-0.297	0.201	0.449
KU	-4.755	0.115	-0.245	1.911	1.382

(Continued)

where these indices also have low correlation coefficients with the squared US market returns, i.e. due to these countries being frontier, and therefore less integrated within the global economy. In other words, herding is significant and eliminates any effect proceeding from US market's shocks.

6.5.2. ASYMMETRY OF HERDING BEHAVIOUR

Tests of asymmetric response based on equation (6.5) are reported in table 6.4, demonstrating herding behaviour during 'up' and 'down' market periods. The coefficients (γ_3 to γ_9) for the control variables $D^{up} R^2_{m,t}$, $(1\text{-}D^{up})R^2_{m,t}$, $OVX_{m,t}$, $Oil_{m,t}$, $VIX_{m,t}$, $VIX_{US,t}$, and $CSAD_{US,t}$ exhibit similar results, as shown in table 6.2, indicating similar behaviour under different market conditions[79]. These explanatory factors show herding can arise from the flow of both positive and negative information. Panel B1 in table 6.3, reports the test equality of herding coefficients ($D^{up} R^2_{m,t}$, $(1\text{-}D^{up})R^2_{m,t}$) using the Wald test and examining the asymmetry of herding coefficients under different market conditions in both rising and falling markets. Since asymmetric response was only tested for in Saudi Arabia, it is clearly absent, and herding appears to be more significant when there is a falling market rather than a rising market. However, several empirical results show that positive shocks generate stronger herding effects than negative shocks (Hellwig, 1980; Campbell et al., 1993; Diks and Van Der Weide, 2003). The majority of these studies examined periods prior to the global financial crisis in 2007-2009, during which asymmetric volatility increased. This magnified the asymmetry in herding behaviour, which in turn implies asymmetry in herding is time-varying (Park, 2011).

[79] Panel B1 in table 6.3, reports the test equality of herding coefficients using the Wald test, examining asymmetry of herding coefficients under different market conditions, and in rising and falling market. Wald tests show significant asymmetry among coefficients, and results are reported only for Saudi Arabia since they were the only markets for which significant herding was confirmed. Also, it is clear that herding is more significant in periods of falling markets than during rising markets.

Table 6.5: Descriptive statistics of *Herd*.

This table show summary statistics of the herding coefficient, the γ_2, using Kalman-filter process, equation (6.6) to (6.8) for Russia (RU), Mexico (MX), Saudi Arabia (SA), United Arab Emirates (AU), Norway (NO), Qatar (QA), and Kuwait (KU). The statistics are based on daily observations from May 2007 to December 2018.

Market	Minimum	Maximum	Mean	Median	Std. dev	Kurtosis	Skewness	Obs
$HERD_{RU}$	-0.327	-0.026	-0.007	-0.158	0.042	2.147	-0.229	3037.000
$HERD_{MX}$	-0.470	0.068	-0.026	-0.250	0.060	2.631	-0.526	3037.000
$HERD_{SA}$	-0.616	-0.019	-0.005	-0.266	0.078	2.709	-0.542	3037.000
$HERD_{AU}$	-0.481	-0.034	-0.006	-0.213	0.061	2.143	-0.437	3037.000
$HERD_{NO}$	-0.375	0.088	-0.009	-0.109	0.048	2.857	-0.547	3037.000
$HERD_{QA}$	-0.372	-0.024	-0.005	-0.108	0.047	2.182	-0.416	3037.000
$HERD_{KU}$	-0.393	-0.044	-0.007	-0.128	0.050	3.473	-0.615	2930.000

6.5.3. DETERMINANT FACTORS OF HERDING DYNAMICS

Time-varying herding behaviour estimates are obtained by applying the Kalman-Filter based on equation (6.6) to (6.8) and herding descriptive statistics are reported in table 6.5. The herding series are negative, stationery and time varying[80] for all countries. Negative values of herding coefficient γ_5 indicate the presence of dynamic herding activities[81]. Using the time varying estimation applying the Kalman filter helped to identify herding styles in additional countries. All countries displayed negative dynamic herding mean coefficients that mostly suggest inconsistent findings with the results, as reported earlier[82]. Table 6.6 reports correlations between herding coefficients as derived by applying the Kalman-Filter processes, while table 6.7 shows correlations among the conditional volatility of market returns. In both tables, correlation coefficients are mostly

[80] Several stationarity tests were conducted, mainly ADF and PP, and there is no unit root in the herding time series. However, the series are time varying since clustering exists where the volatility changes over time and high (low) volatility periods are followed by high (low) volatility periods.
[81] As explained earlier, significant negative herding coefficients suggest an existent herding behaviour where returns dispersion decrease during market stress.
[82] These results were obtained by using constant-coefficient regression estimation of herding using equation (6.4) and reported in table 6.3. It was confirmed that herding is present in Saudi Arabia for the whole sample and during the global financial crisis, and in Saudi Arabia, Qatar and Kuwait after the financial crisis.

Table 6.6: Correlation matrix of *Herd*.

This table reports the correlations of herding coefficient, the γ_2, using Kalman-filter process, equation (6.6) to (6.8) among Russia (RU), Mexico (MX), Saudi Arabia (SA), United Arab Emirates (AU), Norway (NO), Qatar (QA), and Kuwait (KU). The statistics are based on daily observations from May 2007 to December 2018.

	$Herd_{RU}$	$Herd_{MX}$	$Herd_{SA}$	$Herd_{AU}$	$Herd_{NO}$	$Herd_{QA}$	$Herd_{KU}$
$Herd_{RU}$	1.00						

$Herd_{MX}$	0.48	1.00					
	(13.36)	-----					
$Herd_{SA}$	0.28	0.29	1.00				
	(20.59)	(36.07)	-----				
$Herd_{AU}$	0.26	0.18	0.25	1.00			
	(12.63)	(4.46)	(5.52)	-----			
$Herd_{NO}$	0.50	0.52	0.24	0.18	1.00		
	(85.19)	(58.8)	(21.32)	(26.23)	-----		
$Herd_{QA}$	0.40	0.34	0.38	0.30	0.28	1.00	
	(14.72)	(16.37)	(16.64)	(6.43)	(5.3)	-----	
$Herd_{KU}$	0.26	0.20	0.26	0.20	0.19	0.30	1.00
	(16.87)	(40.02)	(47.81)	(24.13)	(19.89)	(44.34)	-----

high and significant. However, these correlation numbers are lower in comparison to the correlation matrix of CSAD concerning G7 countries as used in the previous chapter. A possible explanation is that the majority of these countries are frontier markets and therefore less integrated into the global financial system. Dynamic herding behaviour determinant factors are reported in table 6.8. According to the hypothesis of this study, the conditional variances of the oil IV index, the oil index, the market fear index, the market returns index and the cross market US fear index were combined with market returns ($\sigma^2_{OVX_{m,t}}, \sigma^2_{Oil_{m,t}}, \sigma^2_{Vix_{m,t}}, \sigma^2_{R_{m,t}}, \sigma^2_{Vix_{US,t}},$ and $\sigma^2_{R_{US,t}}$). Every country that displayed negative mean coefficients in the estimates of dynamic herding behaviour reported in table 6.5 also displayed significant negative market returns coefficients γ_1. Unlike the previous findings that used constant estimates, dynamic herding estimates move in the opposite direction when herding prevails in falling markets. Since herding estimates are negative, this relationship states that when the market is rising, detected herding measures increase. OVX, implied market volatility and market returns volatility (γ_2, γ_4 and γ_5) show a positive significant relationship with herding in all markets. Oil volatility γ_3 shows

Table 6.7: Correlation matrix of conditional variances.

This table reports the correlations of the conditional variance of market returns, obtained by asymmetric GARCH(1,1) process, among Russia (RU), Mexico (MX), Saudi Arabia (SA), United Arab Emirates (AU), Norway (NO), Qatar (QA), and Kuwait (KU). The statistics are based on daily observations from May 2007 to December 2018.

	σ^2_{RU}	σ^2_{MX}	σ^2_{SA}	σ^2_{AU}	σ^2_{NO}	σ^2_{QA}	σ^2_{KU}
σ^2_{RU}	1.00						

σ^2_{MX}	0.48	1.00					
	(92.23)	-----					
σ^2_{SA}	0.28	0.29	1.00				
	(57.98)	(64.56)	-----				
σ^2_{AU}	0.26	0.18	0.25	1.00			
	(26.53)	(15.25)	(15.54)	-----			
σ^2_{NO}	0.50	0.52	0.24	0.18	1.00		
	(111.81)	(125.46)	(70.56)	(18.32)	-----		
σ^2_{QA}	0.40	0.34	0.38	0.30	0.28	1.00	
	(89.79)	(79.14)	(64.54)	(20.57)	(79.9)	-----	
σ^2_{KU}	0.26	0.20	0.26	0.20	0.19	0.30	1.00
	(-0.55)	(-0.62)	(-0.13)	(-0.21)	(-0.49)	(-0.52)	-----

significant positive coefficients in Russia and Mexico only. However, the coefficients of cross market volatility spill overs from US factors, market returns and fear index volatility are not significant across all countries.

6.5.4. ESTIMATES OF DYNAMIC HERDING BEHAVIOUR

Table 6.9 shows the estimated results for equation (6.10), where the interaction between market volatility and herding is augmented with the implied volatilities of oil price and fear indices and market fear indices. Herding has been present in all countries, since γ_2 is negative and significant, except in the UAE and Qatar. The nonlinear elements represented by $R^3_{m,t}$[83] capture the evidence that integration between market returns and

[83] $R^3_{m,t}$ is the product term of R^2_m and $R_{m,t}$, herding and stocks returns.

Table 6.8: Dynamic herding behaviour determinant factors.

This table presents the estimation coefficients of the regression results using equation (6.9):

$$H_t = \beta_0 + \beta_1 R_{m,t} + \beta_2 \sigma^2_{OVX_t} + \beta_3 \sigma^2_{Oil_t} + \beta_4 \sigma^2_{VIX_{m,t}} + \beta_5 \sigma^2_{R_{m,t}} + \beta_6 \sigma^2_{VIX_{US,t}} + \beta_7 \sigma^2_{R_{US,t}} + \varepsilon_t \tag{6.9}$$

Where H is the herding coefficient, the γ_2 from equation (6.2), using Kalman-filter process, equation (6.6) to (6.8); R is the log returns of the market m; σ^2_{OVX} *is* the conditional volatility of CBOE Crude Oil Volatility index; $\sigma^2_{Oil}$is the conditional volatility of Brent Crude Oil price; σ^2_{VIX} is conditional volatility of the implied volatility index of market m; $\sigma^2_{R_{m,t}}$ is the conditional volatility of market index of market *m*; while the $\sigma^2_{VIX_{US}}$, $\sigma^2_{R_{US}}$, are the US cross-market factors, the conditional volatility of the CBOE implied volatility index, and the conditional volatility of market index. All at time *t* using daily data for Russia (RU), Mexico (MX), Saudi Arabia (SA), United Arab Emirates (AU), Norway (NO), Qatar (QA), and Kuwait (KU) from May 2007 to December 2018. We test for the whole sample, during financial crisis from May 2007 to July 2009, and after the financial crisis from July 2009 to December 2018. All data are obtained from Thomson-Reuters DataStream, except for Kuwait, where the Kuwaiti data are collected from publicly listed data. t-statistics are reported in protheses, and $\bar{R}^2$ is the adjusted R^2. *** indicate significance at 1%, ** indicate significance at 5%, * indicate significance at 10%.

Country	C	$R_{m,t}$	$\sigma^2_{OVX_{m,t}}$	$\sigma^2_{Oil_{m,t}}$	$\sigma^2_{VIX_{m,t}}$	$\sigma^2_{R_{m,t}}$	$\sigma^2_{VIX_{US,t}}$	$\sigma^2_{R_{US,t}}$	$\bar{R}^2$
RU	0.008***	-0.027***	5.119***	0.209***	0.020***	4.575***	0.039	-0.005	0.516
	(35.19)	(-4.64)	(14.48)	(3.41)	(3.63)	(28.9)	(1.66)	(-0.51)	
MX	0.009***	-0.005	1.683***	0.164***	0.050**	14.685***	0.013	0.013	0.556
	(48.65)	(-3.50)	(5.70)	(3.28)	(2.35)	(28.43)	(1.07)	(1.33)	
SA	0.009***	-0.046***	2.193***	0.151		8.584***	-0.007	-0.011	0.435
	(44.59)	(-6.16)	(6.78)	(0.67)		(20.97)	(-0.54)	(-1.38)	
AE	0.011***	-0.185***	8.004***	-0.003		0.852***	0.025	-0.013	0.423
	(24.17)	(-12.94)	(12.84)	(-0.03)		(7.60)	(0.86)	(-0.77)	
NO	0.016***	-0.018**	4.301***	0.333		9.644***	0.067	-0.026	0.439
	(67.55)	(-1.93)	(10.02)	(0.01)		(20.71)	(1.25)	(-0.46)	
QA	0.010***	-0.031***	1.445***	0.034		12.390***	0.048	-0.021	0.458
	(33.72)	(-2.98)	(2.75)	(0.41)		(23.16)	(1.44)	(-1.08)	
KU	0.014***	-0.374***	4.834***	0.139		0.130**	0.024	-0.022	0.423
	(42.32)	(-17.78)	(10.13)	(1.45)		(1.68)	(1.07)	(-1.60)	

Table 6.9: Estimates of dynamic herding implications.

This table presents the estimation coefficients of the regression results using equation (6.10):

$$CSAD_t = \alpha + \gamma_1|R_{m,t}| + \gamma_2 R^2_{m,t} + \gamma_3 R^3_{m,t} + \gamma_4 R^2_{m,t}{*}\sigma^2_{R_{m,t}} + \gamma_5 R^2_{m,t}{*}\sigma^2_{OVX_t} + \gamma_6 R^2_{m,t}{*}\sigma^2_{Oil_t} + \gamma_7 R^2_{m,t}{*}\sigma^2_{VIX_{m,t}} + \varepsilon_t \quad (6.10)$$

Where *CSAD* is the cross-sectional absolute deviation of returns; *R* is the log returns of the market *m*; $\sigma^2_{R_{m,t}}$, σ^2_{OVX}, σ^2_{Oil}, σ^2_{VIX}, are the conditional volatilities of index market returns of market *m*, Brent Crude Oil price, CBOE Crude Oil Volatility index, and the implied volatility index of market *m*. All at time *t* using daily data for Russia (RU), Mexico (MX), Saudi Arabia (SA), United Arab Emirates (AU), Norway (NO), Qatar (QA), and Kuwait (KU) from May 2007 to December 2018. We test for the whole sample, during financial crisis from May 2007 to July 2009, and after the financial crisis from July 2009 to December 2018. All data are obtained from Thomson-Reuters DataStream, except for Kuwait, where the Kuwaiti data are collected from publicly listed data. t-statistics are reported in protheses, and $\bar{R}^2$ is the adjusted R^2. *** indicate significance at 1%, ** indicate significance at 5%, * indicate significance at 10%.

Country	C	$\lvert R_{m,t} \rvert$	$R^2_{m,t}$	$R^3_{m,t}$	$R^2_{m,t} * \sigma^2_{R_{m,t}}$	$\gamma_6 R^2_{m,t}{*}\sigma^2_{OVX_t}$	$\gamma_5 R^2_{m,t}{*}\sigma^2_{Oil_t}$	$\gamma_7 R^2_{m,t}{*}\sigma^2_{VIX_{m,t}}$	$\bar{R}^2$
RU	0.006***	0.280***	-0.387***	-0.405	1.709***	6.680***	0.241***	0.018***	0.758
	(30.07)	(24.43)	(-2.59)	(-1.65)	(4.29)	(23.95)	(4.58)	(3.61)	
MX	0.007***	0.417***	-2.214***	-5.743	0.756***	3.687***	0.252***	0.043**	0.727
	(40.72)	(22.32)	(-4.2)	(-0.21)	(6.88)	(16.86)	(6.03)	(2.34)	
SA	0.007***	0.473***	-2.408***	-1.468	0.275***	2.910***	0.145***		0.606
	(36.37)	(25.89)	(-5.92)	(-0.83)	(3.33)	(11.14)	(2.92)		
AE	0.008***	0.611***	-0.182	-4.303	0.413***	4.054***	0.110**		0.832
	(42.13)	(37.36)	(-0.54)	(-0.87)	(3.97)	(14.51)	(2.02)		
NO	0.013***	0.543***	-4.216***	-7.087	0.085***	5.011***	0.290***		0.560
	(63.29)	(24.55)	(-6.94)	(-0.38)	(7.84)	(17.22)	(5.38)		
QA	0.008***	0.422***	0.524	4.492	0.284***	5.080***	0.084		0.720
	(29.41)	(19.29)	(1.27)	(0.56)	(5.46)	(13.21)	(1.15)		
KU	0.009***	1.082***	-7.050***	-25.626	0.533*	5.264***	0.268***		0.650
	(29.24)	(17.72)	(-2.56)	(-0.57)	(1.920)	(13.92)	(3.55)		

herding is insignificant in all countries. However, the interaction between market returns and returns volatility, represented by γ_4, is significant in all countries, suggesting that the dynamic nature of herding is time-varying and mainly affected by conditional market volatility. This notion indicates that constant coefficients lack precision as methods of determining herding behaviour, which is consistent with the findings in table 6.5, which shows all regions exhibit negative herding coefficients.

Interestingly, the volatility of oil fear and the conditional volatility of price indices have a dynamic interaction with herding, which is significant in most countries, γ_5 and γ_6. These results are consistent with earlier findings that recognised the impact of macroeconomic announcements on the behaviour and uncertainty of investors (Ederington and Lee, 1996; Fleming and Remolona, 1999; Nikkinen and Sahlstrom, 2004). The current spill over from the volatility of the energy sector to the global financial markets implies the transmission of risk perception by oil market by investors (Nazlioglu et al., 2015). However this is not significantly established in terms of oil exporters (Rodríguez and Sánchez, 2005). The volatility of the fear index's interaction with market returns 'γ_6' is significant in Russia and Mexico, with their established IV indices. Evidently, equation (6.10) increased the explanatory power of the model, since the values of the adjusted R-squared ($\bar{R}^2$) range from 0.560 to 0.832 when compared with previous results.

6.6. CONCLUSION

In this study, herding behaviour was examined in several selected oil exporting countries (Russia, Mexico, Saudi Arabia, Norway, Kuwait, Qatar, and UAE). We applied daily data from May 2007 to December 2018. Using a conventional static herding model, we only identified patterns of herding behaviour in Saudi Arabia. We also tested for herding under different market conditions and similar results were found, indicating no asymmetric response in Saudi Arabia. Several explanatory factors were incorporated to understand the movements common to herding behaviour. We used the Oil price index, OVX, and market sentiment, alongside the US factor. While oil prices had an insignificant effect on herding, the OVX exhibited significant results across all oil exporting countries. Similarly, there was significant evidence of US cross-market spill over in the examined regions. While the US returns cross-sectional dispersion shows a significant effect in all countries, the square stock market returns is significant only in Russia and Mexico. However, there are no significant international spill overs from the US fear index.

Additionally, the Kalman-filters were used to extract herding coefficients and to identify the dynamic nature of herding under the effects of global factors. We use the conditional variance of market sentiment, oil price and fear indices as state variables. Interactions between market returns and the conditional variance of these factors indicate a significant tendency of herding towards them in every country examined. In accordance with Chiang et al. (2013), the study showed that herding is affected by the state of volatility and not only by extreme swings in the market. This indicates that herding cannot be measured solely by static market returns, and empirical models need to be adjusted to include the conditional variances of several explanatory factors. Such findings allow policy makers and market participants to understand the dynamic nature of herding behaviour as determinant factors. Greater attention needs to be paid towards the oil market uncertainty index, particularly in turbulent periods, as it holds a vital role in generating herding patterns in global financial markets.

CHAPTER 7: CONCLUSION

The literature evidences the growing importance of the role of market uncertainty, the fear index; especially since the financial crisis of 2007–2008. The IV index (IV) gained in importance, owing to its ability to provide critical information about future expectations about underlying asset's volatility. The IV index represents a quick and important measure of market sentiment (Whaley, 2000) and mirrors investors' demand for hedging (Neffelli and Resta, 2018). Over the past decade the application of the IV as a measure of market risk has been widely examined in the literature. However, research on the IV is mainly focused on its relationship with the corresponding stock market index. We believe that the role of market uncertainty has an important impact on other areas, such as liquidity and herding, and that further studies should be conducted to address the remaining unanswered questions.

Chapter one is the introduction and provides an overview of the thesis and the aims of this research, while the second chapter provides a review of the literature that is relevant to this research. The third chapter is the first empirical chapter of the thesis and examines the impact of market returns and several macroeconomic factors on the volatility (or kurtosis) of the UK IV index. The fourth chapter is the second empirical chapter and aims to investigate the effect of the IV index and industry, and market-wide liquidity on the liquidity of individual assets in the UK, Japan and Eurozone markets. Chapters five and six are the third and the fourth empirical chapters, and both aim to examine herding behaviour and to establish a link between herding and the conditional variance of the IV index, the oil price and fear indices, and cross-market US factors. Chapter five investigates this relationship in G7 countries, while chapter six covers several oil-exporting countries (Russia, Mexico, Saudi Arabia, UAE, Norway, Qatar and Kuwait).

In chapter three, our results show that the volatility of the IV is significantly defined by UK stock market returns and macroeconomic variables. Stock market returns (FTSE 100), IP, 3 months London interbank offered rate (LIBOR), effective exchange rate (EER) and UR were shown to play a major role in defining the volatility of the IV index (IV) when using three symmetric and asymmetric forms of GARCH models. Analysing the volatility of IV based on its realised volatility, the results of GARCH(1,1) outperformed other models for the full sample and for sample 1 (from 4/1/2000 to 8/8/2007), while EGARCH(1,1) was better at modelling the volatility of the IV in sample 2 (from 9/8/2007 to 31/12/2015). The asymmetric GARCH(1,1) proved more accurate in periods of low volatility, while EGARCH performs better in periods of exceptionally high volatility.

When IV was modelled based on realised volatility, stock market returns, and macroeconomic variables, GARCH(1,1) outperformed the other models in all tested periods. These results show that the asymmetric models (EGARCH and GJR-GARCH) provide less significant results in a volatile market when adding exogenous variables. We also found that using mixed data sampling GARCH-MIDAS when adding market returns and macroeconomic variables supports the results provided by symmetric and asymmetric GARCH models, showing the value of the selected exogenous variables.

Chapter four investigates the effect of the IV index and average industry and market liquidity on the liquidity of individual market stocks during and after the financial crisis of 2007–2008. Our findings in chapter four show that individual stock liquidity is significantly affected by the average of industry illiquidity in the UK, Japan, and the Eurozone stock markets. Average market illiquidity showed significant results only in the Eurozone stock markets. More importantly, the corresponding IV indices showed no significant effect on individual stock liquidity in the markets before and after the financial crisis. The market participants paid no particular attention to the IV index in these countries.

Chapters five and six provide new evidence of herding behaviour by incorporating several variables using conventional static models and a dynamic approach using a Kalman filter-based model. While chapter five examines herding in G7 countries, chapter six covers several oil-exporting countries, which are Russia, Mexico, Saudi Arabia, the UAE, Norway, Qatar and Kuwait. We provide new evidence of the existence of herding in both chapters by incorporating market and oil fear indices, the oil price index, and cross-market global effects[84].

In chapter five, we show that by using a static model, as suggested by Chang et al. (2000), herding behaviour patterns only exist in Japan. Regarding the incorporated explanatory variables, we found that unlike the oil IV index (OVX), which shows no significant parameters in any of the countries, the oil prices had a significant effect on herding behaviour in all the G7 countries. These results suggest that stock market returns in the G7 countries are affected by the current oil price level and not by the market participants' future expectations about oil prices. However, in chapter 6, when using a static model, we only observed herding behaviour in Saudi's stock market. Unlike the G7 countries, oil-exporting countries are affected by the future expected volatility of oil prices, and not by the current oil price level, which showed an insignificant effect on herding behaviour.

Moreover, in chapter 5, the market fear index was shown to have a negative significant effect on herding behaviour in several countries (the US, Japan, Germany and the UK). Regarding the role of the US cross-market effect on herding, while the US VIX showed no effect on herding behaviour in the G7 countries, US stock market returns and the cross-sectional dispersion of returns displayed a significant coefficient, indicating a dominant effect over international markets when forming herding behaviour. In chapter 6, the market fear index, which was only provided in Russia and Mexico, showed no significant

[84] To test for the effect of major foreign factors in the model, we include the US factors such as the US fear index (CBOE VIX), and the US price index returns (S&P500), and the stock market cross sectional absolute deviation (CSAD of S&P500)

effect on herding. Regarding the US cross-market effect, unlike stock market returns, the US VIX and cross-sectional dispersion of returns had a significant effect on forming herding behaviour in oil-exporting countries.

Furthermore, by using a Kalman filter to test for the dynamic nature of herding behaviour, we were able to identify the determinants of herding dynamics by examining the effect of the conditional variance of our independent variables on herding coefficients. In both chapters 5 and 6, the interaction between market returns and the conditional variance of our variables showed a significant tendency in herding behaviour toward all these independent factors. This shows that herding behaviour has a dynamic rather than static nature over time and is affected by state of volatility conditions.

To summarise, the main findings of this PhD thesis can be stated as follows:

- By modelling the volatility of the UK IV index (IV), we identified several factors that explain variance, namely: 1) the index realised volatility, 2) stock market returns, 3) IP, 4) LIBOR, 5) GBP EER, and 6) UR. Adding these exogenous variables when analysing the volatility of the IV improved variance estimation.
- While modelling the volatility (or kurtosis) of the IV, we found that using a symmetric form of the GARCH model, specifically GARCH(1,1), led to results that outperformed other models asymmetric GARCH models, except during periods of exceptionally high volatility, such as during the financial crisis of 2007–2008. Furthermore, using GARCH mixed data sampling, GARCH-MIDAS, enables us to analyse data sets that are sampled at different frequencies, and, most importantly, confirmed the usefulness of stock market returns and other macroeconomic variables for estimating the volatility of the IV index.
- When analysing the causes of co-movement among individual assets liquidity in the UK, Japan, and Eurozone stock markets, we found that among the VIX index,

average industry liquidity, and market average liquidity, only industry liquidity plays a significant role in determining the variation of liquidity movements among individual stocks both during and after the financial crisis.

- Market average liquidity only has a significant effect on individual assets in the Eurozone stock market, showing an explanatory power when defining liquidity movements in this market. However, the IV indices did not exhibit a significant impact in the examined markets, indicating that market participants pay no attention to the liquidity allocation with regard to future market volatility expectations.
- When examining herding behaviour in G7 countries and several oil-exporting countries using the static conventional herding model proposed by Chiang and Zheng (2010), we only confirmed herding behaviour in Japan and Saudi Arabia.
- We provide new evidence of herding behaviour by incorporating several global factors. We found that while the OVX plays a significant role in forming herding behaviour in the G7 countries, current oil prices have a significant effect on herding in oil-exporting countries.
- We also found that the market fear index holds explanatory power in forming herding behaviour in several G7 countries, but not in the oil-exporting countries studied. By examining the role of the US cross-market factors, we showed that while the US stock market returns and cross-sectional returns dispersion affect herding behaviour in the G7 countries, the US VIX and stock market returns have an impact on herding behaviour in oil-exporting countries.
- Finally, by using a Kalman filter-based model, we generated herding coefficients and found that the conditional variances of all independent variables are determinant factors of the dynamic herding behaviour in all countries. Later, the interaction between market returns, which represent herding coefficients, and the

conditional variance of the other factors were found to indicate a significant tendency for herding in all countries under examination. These findings clearly show the importance of examining the dynamic nature of herding according to these global factors and eliminating them could lead to false judgment.

We also believe that further research needs to be conducted when modelling the volatility of the IV index, causes of commonality in liquidity, and finally herding behaviour. As far as modelling the volatility of the IV index; since the effect of stock market returns and macroeconomic variables has not been investigated before, except in this study, more research should be conducted in additional countries using a longer set of temporal data. In addition, the explanatory power of other factors could be investigated when modelling the volatility of the volatility, such as oil prices and cross-market factors; for example, the US factors. Moreover, when examining liquidity commonality, more countries should be covered in future research, such as the other G7 countries and developing countries. In addition, other models should be tested when examining this relationship, such as GARCH models. Finally, research into herding behaviour could be extended by employing local macroeconomic variables that could have a significant effect when forming herding patterns in stock markets.

The findings of this thesis suggest a number of significant implications that may prove beneficial for both policymakers and market participants. The modelling in Chapter 3 of implied volatility, irrespective of markets, enabled me to identify several factors exerting an impact on volatility, i.e. market returns and four macroeconomic variables. This was found to enable market participants (including investors, stakeholders and fund managers) to achieve greater control over risk, in particular by forming a portfolio based on the volatility of IV, thus highlighting the price of a portfolio of IV options. This study has therefore highlighted that market participants are able to buy or sell the underlying portfolio if they conclude that IV volatility is either too high or too low. If a portfolio based on the volatility of IV returns the difference between realised and expected volatility (minus the volatility risk premium), then selling the portfolio returns the difference between expected and realised volatility (along with the volatility risk).

I feel that future researchers will be able to benefit from the findings of the first empirical chapter, since it establishes a foundation in the literature for modelling the implied volatility based on several explanatory factors. In addition, researchers have the option to use further models of volatility and explanatory factors to examine their role in modelling the volatility of the volatility. I also consider that it may be beneficial for regulators and policy makers to consider these findings when promoting responsible investment practices among investors, particularly in understanding its importance in relation to trading decision making. Furthermore, this would allow policymakers to mitigate risk and potential negative outcomes during periods when high-stress in stock markets impacts on market stability, in particular by predicting these periods using the model established in the current research. They would subsequently be able to impose strict market mechanism to regulate market orders conducted by brokers, investment companies and individual traders, in order to prevent any potential market shocks.

Chapter 4 examined the factors resulting in a commonality of liquidity in financial markets in the countries selected for study, identifying that average industry liquidity has a significant impact on individual stock liquidity. I consider that investors will be able to benefit from the findings of this chapter by focusing on an industry's level of liquidity. High levels of liquidity flow in the average industry are combined with an increase in stock prices, and vice versa. An acknowledgment of this fact would assist investors and stakeholders to achieve a well-diversified portfolio, including paying closer attention to the variation of average industry liquidity when allocating liquidity in their portfolios. Regulators or policymakers are able to use liquidity to stabilise stock markets when periods of high market high volatility are indicated by the movements and the volume of the aggregate industry liquidity. This can be achieved by limiting the liquidity flow potentially resulting in market disorder and inflation, by imposing a specific limit of orders and liquidity amounts in each sector on all market participants.

Finally, this chapter lay the foundations for an examination of the commonality of liquidity, based on implied volatility, market and industry liquidity. Researchers could additionally benefit from these findings by being able to use methodologies other than OLS to further examine the role of implied volatility and market volatility on liquidity commonality. Moreover, several factors (i.e. market volatility and models) have been tested in this study, identifying no sign of any influence on the commonality of liquidity. Researchers could therefore benefit by being able to avoid these techniques and employ more effective methods and models.

The findings in chapters 5 and 6 highlight the importance of dynamic models for the investigation of herding behaviour. This could help policymakers and regulators in understanding the dynamic nature of herding behaviour under the influence of global factors, i.e. oil price, fear indices, the market fear index and US cross-market factors. Furthermore, additional attention should be paid to these herding determinants, particularly during periods of high volatility, due to these playing a vital role in herding behaviour in financial markets. Potential risks encountered in the stock market are indicated by applying the dynamic approach with the help of the above explanatory factors. This enables them to be managed and avoided through monitoring of the stock market and paying attention to stock prices deviating from their fundamental values in response to herding behaviour, as well as preventing such orders to buy being executed on either a small or large scale. On the other hand, both investors and stakeholders could avoid following identified herding patterns negatively impacting the efficiency of stock markets, so avoiding the under- or over-valuation of markets. This also would avoid issues arising with the level of portfolio risk when having either an under- or over-valuated asset, potentially resulting in financial losses.

Researchers can benefit from these findings based on the new methodology, including employing a dynamic Kalman filter approach in estimating herding and by adding new explanatory factors such as oil volatility and implied volatility, alongside other conventional factors, i.e. market returns, market implied volatility, and cross-market factors. This will enable researchers to progress their examination of herding by testing the impact of other explanatory factors and possible methodologies potentially offering valuable outcomes when testing for dynamic herding behaviour in the same or other countries.

However, this study contains a number of limitations. The major issue relates to data availability. Intraday data of most variables used in all this study's empirical chapters were found to be either unavailable or impractical to access. The use of intraday data (i.e. high frequency data) could have contributed additional precision to the results. Moreover, no available data could be accessed for research concerning herding behaviour with regard to oil exporting countries such as Venezuela, Nigeria, Iran and Kazakhstan. The ability to add such results to the analysis would have increased the value of the current research. Furthermore, the time limitations of this research prevented the use of several methodologies or models besides OLS in the second empirical chapter. These would have been beneficial in identifying the influence of implied volatility on commonality illiquidity, i.e. GARCH models and the Kalman filter dynamic approach.

In conclusion, the findings of this PhD thesis could be used by policymakers, regulators and market participants to stabilise financial markets by knowing and predicting periods of market stress. Periods of market stress can be indicated by the volatility of the IV index, commonality in liquidity caused by aggregate industry liquidity, and the dynamic herding behaviour caused by local and global factors. Furthermore, all the areas that have been studied in this thesis, namely the volatility of the IV, commonality in liquidity, and herding behaviour, reveal the continued importance of the IV index to scholars and regulators.

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