Essays on Asset Pricing: The role of liquidity in asset pricing within Stocks and Real Estate Investment Trusts

Mohammad Sharik Essa

PhD

School of Business and Management, Royal Holloway, University of London

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<u>Declaration of Authorship</u>

I, Mohammad Sharik Essa, 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: *Sharik Essa*

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Abstract

This thesis looks to study asset pricing, exploring the role of traditional risk factors in contributing to the trading price of financial assets, along with exploring the role of illiquidity, in terms of its influence on pricing, its significance as an investment style, its impact on premiums that are based on traditional risk factors, along with its effect on behavioural traits such as herding, which could result in asset prices moving away from their fundamental value. Owing to the fact that the Real Estate Investment Trust (REIT) market is an under-researched segment of financial markets, the thesis looks to develop an in-depth understanding of the role illiquidity within this market, and segments this assessment based on potentially varying market conditions, distinguishing between recessionary and non-recessionary states.

Chapter three is the first empirical chapter which looks to assess the existence of illiquidity premiums (return on illiquid-minus-liquid stocks) in US stocks, along with assessing the impact of oil price, oil price volatility and other macroeconomic factors, on realised illiquidity premiums. Based on a data set that runs from 2007 to 2018, and incorporating for a structural break, we find that illiquidity premiums are positive and significant. During the non-recessionary phase, oil price has a positive impact, while during the recessionary state, we find that the impact is reversed and oil price has a negative relationship, with realised illiquidity premiums. These results are driven by the impact oil price has on investor sentiments, and on market liquidity via its effect on the import bill of the US. We also find that oil price volatility has significant explanatory power on realised illiquidity premiums in the non-recessionary state, and the direction of this influence is negative. Chapter four uses daily data from 2001 to 2020, to examine the presence, magnitude and significance of size, value, profitability, investment, and momentum premiums within US REITs, establishing if these premiums are associated with a higher risk, along with assessing the impact of financial distress and liquidity crisis on these premiums during recessionary and non-recessionary phases, including covid-19. The results indicate that premiums associated with all five factors are positive and significant, but in contradiction to the Efficient Market Hypothesis, we find that value and momentum portfolios provide superior returns without exposing investors to

higher risk. Furthermore, in contradiction to the risk based explanation of Fama–French/Carhart (2015/1997), we find significant evidence of a fall in profitability and momentum premiums with an uptick in financial distress and liquidity crisis. Given the lack of evidence we find in terms of conventional risk factors, illiquidity, and financial distress, being priced within certain premiums in the US REIT market, chapter five looks to test out herding as a contributor to mispricing, on a sub-sector level (health, hotel mortgage, residential, retail and warehouse) within the US REIT market, along with assessing the impact of expected/unexpected sector/market-wide illiquidity shocks on sub-sector herding, under two Markov-switching regimes. Using daily data from January 2014 to February 2022, along with identifying a structural break corresponding to the outbreak of covid-19, and consistent with noise trader risk theory (De Long, Shleifer, Summers and Waldmann, 1990), the research confirms the existence of herding behaviour within US REITs on a sub-sector level along with finding evidence that herding behaviour is relatively more intense during the crash regime. Using the VIX index as a sentiment indicator, the research also confirms that herding behaviour rises with an increase in investors' fear and uncertainty. When assessing illiquidity, our results confirm the significance of unexpected sector-wide illiquidity in enhancing herding within All REITs and all sub-sectors barring health, during the crash regime. An interesting result, given the crash regime is instigated by the outbreak of the covid-19 pandemic. During the expansionary phase, we find that only expected sector-wide illiquidity shocks are significant, and they enhance herding within residential, retail and warehouse sectors. Once we also incorporate for market-wide illiquidity, our results confirm that i) during the expansionary phase only expected illiquidity (market and sector-wide) enhances sub-sector herding within US REITs while ii) during the crash phase only unexpected illiquidity (market and sector-wide) enhances sub-sector herding within US REITs.

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List of Abbreviations

Abbreviation	Meaning
OVX	The Chicago Board of Exchange Crude Oil ETF Volatility Index
OLS	Ordinary Least Squares
VAR	Vector auto-regression
REIT	Real Estate Investment Trust
CAPM	Capital Asset Pricing Model
NAREIT	National Association of Real Estate Trusts
US	United States of America
Market Cap	Market Capitalisation
ARDL	Autoregressive Distributed Lag
ECM	Error Correction Model
CSAD	Cross-sectional absolute deviation
VIX	Chicago Board Options Exchange's Volatility Index
GARCH	Generalized Auto-Regressive Conditional Heteroskedasticity
MLE	Maximum Likelihood Estimation
MA	Moving Average
AR	Auto Regressive
G7	Group of seven
Fed	Federal Reserve
CBRE	Coldwell Banker Richard Ellis
SMB	Small Minus Big
HML	High Minus Low
RMW	Robust Minus Weak
CMA	Conservative Minus Aggressive
WML	Winners Minus Losers
B/M	Book-to-market
ILLIQ	Amihud (2002) Illiquidity Measure
S&P 500	Standard and Poor’s 500
NYSE	New York Stock Exchange
ETF	Exchange Traded Funds
ADR	American Depository Receipt
CSSD	Cross-sectional standard deviation

CHAPTER 1: INTRODUCTION

Over the past two decades, asset pricing has gained significant prominence, in-part due to market downturns resulting from incorrect assessments regarding the fundamental value of assets. In actuality, asset prices are not only determined by fundamental factors such as expected future cash flows, growth rate and discount rate, but forces of demand and supply within the market play an integral part in impacting prices, which in-turn impacts return on assets. A rise in demand within an asset would raise its price, and hence would offer a higher potential realised return for investors currently holding onto the asset.

During the decade that preceded the 2001 dot-com crash, investor sentiments were highly positive regarding tech stocks, injecting significant demand towards these stocks and resulting in an inflated price. Furthermore, low levels of interest rates also attracted more investors towards these stocks, relative to interest bearing bonds. The creation of an asset bubble was a consequence of this, that is, asset prices going beyond their fundamental value. Eventually, as news started to spread that these tech companies were running out of cash, or were having liquidity issues, investors started selling their stocks, and this soon turned into panic selling, resulting in a sharp fall in the price of tech stocks. Prior to the 2007/08 recession, the federal reserve had an extended period of interest rate cuts starting at 6.5% in May 2000 to 1% in June 2003. The idea being, to inject demand and enhance spending within the economy. Based on the idea that an injection of demand would enhance asset prices, an extended period of interest rate cuts could potentially over inflate asset prices beyond their fundamental value. This was also the case with prices within the real estate market. The federal reserve started increasing rates in June 2004, and two years later the Federal funds rate had reached 5.25%, where it remained until August 2007. The rise in interest rates spiralled a cycle of default within the economy, and financial lenders authorised foreclosures with respect to collaterals. The sheer rise in supply of these collaterals, significantly reduced their prices, to a point where the initial leveraged amounts could no longer be recovered. Both of these scenarios explain the importance of demand and investor sentiments on asset prices, and the notion of how changes in prices based on these sentiments, could potentially result in asset prices swaying away from their fundamental value, and this could have far reaching consequences for the rest of the economy.

Conventional asset pricing models have generally not incorporated for liquidity (Paul, Walther and Kuster-Simic, 2021), but the 2007/08 global financial crisis has shown that asset prices react significantly to liquidity effects (Crotty, 2009). Illiquidity impacts how easily assets can be sold, posing a threat to financial stability, and making illiquidity a risk. Amihud and Mendelson (1986) introduce illiquidity as being an essential factor in stock pricing, theoretically concluding that stock price or value is higher as illiquidity falls. This would imply a potential rise in capital gains or realised returns for investors holding on to these securities prior to the fall in illiquidity, and then having the opportunity to sell their securities at the current inflated prices, once a fall in illiquidity has been realised.

Brunnermeier (2009) and Crotty (2009) conclude that illiquidity and illiquidity risk was a major source of the 2007/08 financial crisis. Furthermore, they believe that this liquidity tightening impacted investor sentiments towards a 'flight-to-safety' with regards to their investments, in-turn impacting asset prices via a shift in investor demand. Acharya and Pedersen (2005) discussed the idea that liquidity is not only risky but also has commonality. This would imply that liquidity has far reaching consequences in terms of its impact on the whole financial system. Based on the idea put forward by Amihud and Mendelson (1986) of liquidity as a risk, investors would expect a higher relative return for investing in relatively illiquid stocks, as a compensation or exposing themselves to a relatively higher risk. The difference in returns of illiquid and liquid stocks is referred to as the illiquidity premium, and has given rise to liquidity as an investment style.

Owing to the significance of liquidity in terms of impacting asset prices, along with its importance as an investment style, extensive research within the stock market has been conducted on the relationship between liquidity and stock returns, but the empirical evidence is mixed. Research such as Acharya and Pedersen (2005), Li et al. (2011), Amihud et al. and (2015) find a positive relationship between illiquidity and returns. On the other-hand, studies such as Huang (2003), Lo et al. (2004), Novy-Marx (2004) and Ben-Rephael et al. (2015) argue that there is no evidence that the return differential between illiquid and liquid stocks is significantly positive. Based on this contradictory evidence, chapter three of this thesis firstly looks to assess the presence of an illiquidity premium in US stocks between 2007 and 2018. For this purpose, the research utilises the Amihud illiquidity measure (Amihud, 2002) to divide stocks into five equally weighted monthly portfolios. The return differential between the most illiquid and least illiquid portfolios is then defined as the illiquidity premium.

The chapter then goes on to assess the impact of oil price, oil price volatility (using the US Oil Fund options implied volatility OVX index) and various other macroeconomic factors, on realised illiquidity premiums within US stocks, under recessionary and non-recessionary phases. The rationale of assessing the impact of oil stems from not only the importance of oil as a significant resource for the global economy, but also mixed evidence in literature regarding the impact of oil price movements on stocks. A rise in oil prices could increase cost of production for firms and have a negative impact on stock prices (Chen 2010; Cunado and Perez de Gracia 2014), on the other hand higher oil prices can boost earnings of energy firms which can then spiral down to the overall economy and have a positive impact on stocks (Tsai 2015; Foroni et al. 2017). Utilising an OLS model to assess coefficient magnitudes, direction and significance, along with using VAR modelling to construct impulse response functions, the results indicate that realised illiquidity premiums have a significantly positive relationship with oil price and a significantly negative relationship with OVX, in the non-recessionary period. During the recessionary phase, oil price has a negative impact on realised illiquidity premiums. The robustness of these results is confirmed using Auto-regressive distributed lag (ARDL) modelling and Error Correction Modelling (ECM) as short- and long-run elasticities are determined. The relationships are potentially driven by market sentiments and market liquidity. Lastly, in assessing asymmetry in impact, Illiquidity premiums do not show any asymmetric responses to oil price changes but our results do indicate significant evidence of asymmetric response to OVX changes.

The origins for chapter four lie within the Efficient Market Hypothesis, along with moving the asset market under focus to the Real Estate Investment Trust (REIT) market in the US.

Efficient Market Hypothesis states that all asset prices represent all available information, at the present point of time. This implies that the expected return on an any risky asset within the economy, is a compensation to investors for exposing themselves to the risk associated with that asset. This argument is further solidified by empirical asset pricing models, starting from the univariate Capital Asset Pricing Model (CAPM) which establishes that expected returns on an asset is only dependent on the market risk associated with that asset. Fama and French (1992) add two further risk factors to the CAPM model, namely size and value factors, to define expected return. This Fama and French three factor model has been seen to empirically outperform the CAPM model. Carhart (1997) extends on the Fama–French three factor model by adding a fourth factor called momentum, to explain cross-section of asset returns. Titman et al. (2004), and Novy-Marx (2013) conclude that the Fama–French three factor model is an incomplete model in explaining expected asset returns, and in 2015, Fama and French (2015) added two further risk factors to the model, namely, profitability and investment.

REITs are seen as a liquid way of incorporating real estate within an investors' portfolio, at relatively lower costs (Zhang and Hansz, 2022). There are two key elements to studying the REIT sector; i) Stephen and Simon (2005) report on the uniqueness of REITs as an asset class, concluding that their returns cannot be replicated by other asset classes, ii) Clayton and Mackinnon (2003) and Glascock et al. (2000) find a significant long-term relationship between REITs and the private real estate sector. These two key features ensure that REITs have a significant role in optimal portfolio creation and diversification, along with the role of REITs as a substitute for conventional real estate investments. Furthermore, according to the National Association of Real Estate Trusts (NAREIT), the 2021 REIT market cap was $1.74 trillion, which translates to 3.3% of the $53 trillion US stock market cap (NAREIT 2022b). This increased prominence of the REIT sector adds more relevance to this study for practitioners and academics.

Each risk factor such as size, value, profitability, investment and momentum, drives a specific risk premium. Investors capture the premium associated to these factors by going long on assets with positive factor exposure, and shorting assets with negative factor exposure

(Idzorek and Kowara 2013). Given that these factor based investment strategies or style investment strategies can be used to generate higher returns, therefore, they have gathered prominence amongst investors. Most empirical evidence of the benefits of these factor based strategies, specifically strategies based on size, value and momentum, comes from the stock market. But these results have been mixed not only in terms of the existence of these premiums but also the risk associated with them (Eun et al. 2010). The two new factors introduced by Fama and French (2015) namely, investment and profitability are still under-researched segments in terms of their ability to generate excess returns, and the risk associated with investment strategies based on these two premiums. Furthermore, given most of the empirical research comes from conventional stocks, that leaves a significant gap within academic literature. Hence, the first part of chapter four looks to examine the presence, magnitude and significance of size, value, profitability, investment and momentum premiums within the US REIT market between 2001 and 2020.

Chapter four then looks to test out Efficient Market Hypothesis and the risk based explanation of Fama and French (1996) by assessing if the excess returns on these strategies is a compensation in terms of exposing investors to a higher risk. The study incorporates for comprehensive risk indicators including standard deviation, beta from the CAPM model, factor loadings from the Fama-French three factor and five factor models, along with using risk adjusted performance measures such as the Sharpe and Treynor ratios. As a robustness measure, the research also analyses the factor loadings from the Carhart four factor model. Consistent with the Efficient Market Hypothesis, the results suggest that REIT strategies based on size, profitability and investment are associated with a significant rise in systematic risk. In contradiction to the Efficient Market Hypothesis, and consistent with Ooi et al. (2007), the results suggest that the value strategy provides significant positive returns without any significant evidence of exposing investors to a higher systematic risk. Additionally, the results also find a similar conclusion for the momentum strategy. This could potentially suggest systematic mispricing of these value and momentum REITs, or it could also suggest exclusion of relevant risk factors, that might be priced in to these premiums, but are excluded from traditional asset pricing models.

To assess the latter in more detail, chapter four then looks to test the impact of liquidity crisis, and default risk (or financial distress) within the economy, on these factor based premiums in the US REIT market. The rationale for including financial distress is two-fold, firstly, modern finance theory would suggest that investors would require a higher return on factor based strategies with enhanced vulnerability as a result of a rise in financial distress. Secondly, the addition of this factor is driven by mixed results in literature in terms of the impact of financial distress on factor based premiums (Vassalou and Xing, 2004; Penman et al. 2007; Mohanram, 2005; Huang et al. 2013). Exploring the impact of liquidity stems from the work of Caballero and Krishnamurthy (2009), who use the 2007 crisis to link changes in interest rates, credit conditions leverage, and risk premiums, with the liquidity crisis. Furthermore, REITs are regulated by the fact that they have to distribute 90% of their taxable earnings as dividends. This could make REITs more prone to default risk relative to similar firms in other sectors (Chung et al. 2016)

The study accounts for two non-recessionary phases, and three recessionary phases, and utilises Autoregressive Distributed Lag (ARDL) modelling and Error Correction Modelling (ECM) to construct short- and long-run equilibriums, when gauging the impact of financial distress and liquidity crisis on factor based premiums. The results suggest that both financial distress and liquidity crisis have a positive impact on size, value and investment premiums, during the recessionary state. This result is consistent with the risk based explanation of Fama and French (1996). During the non-recessionary state, this impact is insignificant. For momentum and profitability premiums, we do find significant evidence of a fall in these premiums corresponding to a rise in the probability of financial default and liquidity crisis. These results contradict Fama and French (1996), the Efficient Market Hypothesis, and the idea that the profitability and momentum factors represent systematic risk.

Following the lack of evidence, we find in terms of conventional risk factors, and illiquidity, and financial distress, being priced within certain premiums in the US REIT market, chapter five looks to assess if mispricing, as a product of herding, could contribute to the existence of these factor based premiums. Zhou and Anderson (2011) define herding as behavioural tendency of investors to follow the action of others rather than their own beliefs and private information, which could potentially drive asset prices away from their fundamental value, hence result in mispricing of assets. For academics, movement of asset prices away from fundamental value contradicts traditional asset pricing models and has theoretical implications (Christie and Huang, 1995). Shin (2010) argue that during economic downturns, herding could result in exponential negative shocks, which could in-turn pose a significant threat to financial stability, along with reducing investors' ability to reduce portfolio risk via diversification (Chiang and Zheng, 2010). Gavriilidis, Kallinterakis, Tsalavoutas (2016) study the impact of religion on financial decisions in seven Muslim majority countries, claiming that herding effects are more intense during Ramadan, relative to non-Ramadan months. This study also provides motivation to assess herding under various states of the world, by incorporating non-linearity and varying market conditions. Gavriilidis, Kallinterakis, and Ferreira (2013) study the Spanish market and claim that institutional herding intent is more relevant during down markets and periods of heightened volatility.

Nazlioglu, Gormus and Soytas (2016) argue that all REIT sub-sectors are unique, basing their argument on how market factors impact various REITs differently. The uniqueness of each REIT sub-sector has been widely reported in literature, in terms of varying premiums that exist within different sub-sectors (Capozza and Korean, 1995), the different correlation levels of various REIT sectors with the stock market (Peterson and Hsieh, 1997), along with varying risk-adjusted returns between REIT sub-sectors (Cho, 2017). For this reason, the research looks to assess the presence and significance of herding behaviour within US REITs on a sub-sector level. Furthermore, given the argument provided by Shin (2010), that herding effects are more significant during economic downturns, the research looks to investigate if sub-sector herding within US REITs is more intense on days with negative market returns, as compared to days with positive market returns, by utilising a dummy approach.

Christie and Huang (1995) wrote a fundamental paper in terms of utilising cross-sectional dispersion of asset returns as a measure to capture herding. Chang et. al (2000) extend on this study by introducing non-linearity, and using the cross-sectional absolute deviation (CSAD), citing the fact that CSAD is relatively less sensitive to return outliers. Using the methodology set out by Chang et. al (2000), the research finds herding behaviour to be significant within

US REITs on a sub-sector level, along with confirming the hypothesis that herding effects are more pronounced on days with negative market returns relative to days with a positive market return.

We then look to test if investor sentiments impact herding behaviour in the REIT market. Baker and Wurgler (2006) and Kurov (2010) use the CBOE VIX index as an indicator of investor sentiments. This metric employed to gauge investor sentiments implies that, as investors' fear and uncertainty regarding the future health of the economy grows, investors' follow the portfolio insurance approach, hiking up prices for out-of-the-money put options, driving up their implied volatilities. Various past studies such as Tseng and Li (2012), and Philippas, Economou, Babalos and Kostakis (2013) have used the VIX index as an indicator for investor sentiments. Our results confirm that as investor sentiments deteriorate, as indicated by a rise in VIX, herding behaviour becomes more intense within All REITs, and all sub-sectors barring residential.

Motivated by the evidence that herding effects are more pronounced during days of market stress (or days of negative market returns) and high VIX (fear) values, the research utilises a CUSUM Test to identify a structural break within the data set, and using a Quandt-Andrews statistical breakpoint test, the research finds evidence of a breakpoint corresponding to the outbreak of the Covid-19 pandemic. Driven by the presence of a structural break, the research then uses a two-state Markov Switching approach to confirm that herding effects are relatively more prominent during the crash regime. This would indicate that investors discard their own information, and are more inclined to follow the herd, during periods of high market stress.

REITs by regulation have to distribute 90% of their taxable income as dividends in order to maintain their REIT status (Boudry 2011). This provides our biggest motivation to explore the impact of shifts in liquidity on REIT herding, since this regulation would imply that retained earnings would only contribute a small of new investment within the industry, along with confirming the significance of traditional sources of funding (such as credit lines) in terms of their contribution to REIT growth (Huerta, Egly and Escobari, 2016). For this reason, past literature has also shed a light on the importance of short-term flexible funding and credit lines, as a backup liquidity to fund shortages, within the REIT sector (Ott, Riddiough and Yi, 2005). Cetorelli, Goldberg and Ravazzolo (2020) discuss the short-term funding stress during Covid-19, which could significantly disrupt REIT performance, and hence provides an interesting setting for our research, in terms of assessing the impact of liquidity changes on sub-sector REIT herding, during and prior to, the Covid-19 pandemic.

Another key distinguishing feature between various REIT sub-sectors, as reported within literature, has been the debt ratios, which got further highlighted during the Covid-19 pandemic (U.S. Securities and Exchange Commission, 2020). Certain REIT sectors such as industrial REITs saw a marginal change in their leverage positions during this period, but other REIT sectors such as hotels, saw an exponential rise in their debt ratios (U.S. Securities and Exchange Commission, 2020). This provides further justification to not only look at the impact of changes in REIT market-wide liquidity on sub-sector herding, but to also incorporate for sector-wide liquidity shocks.

Blau, Nguyen and Whitby (2020) argue that the concern about liquidity in asset markets is not just the average level of market liquidity, but also the uncertainty of liquidity. Driven by this rationale, the study uses the Amihud (2002) illiquidity measure, and uses it to segment between expected and unexpected illiquidity shocks. Amihud (2002) state that the effects of expected illiquidity are felt straight away, and the impact of unexpected illiquidity is felt via investor sentiments regarding future illiquidity. This research therefore, looks to assess the impact of expected and unexpected sector/market-wide illiquidity shocks on sub-sector herding within US REITs, under varying market regimes.

As a preview of results, the research finds that during the crash regime, a rise in unexpected sector illiquidity enhances herding in all REIT sub-sectors apart from health, while in the non-recessionary phase, expected sector illiquidity enhances herding within residential, retail and warehouse sectors. The lack of significance of unexpected illiquidity shocks during the non-recessionary state also implies that the channel of influence between a rise in unexpected illiquidity and investor sentiments towards heightened future illiquidity, might be weak during these expansionary phases. When the research incorporates for market-wide illiquidity shocks, we find that during the non-recessionary states, herding is positively impacted only by expected market-wide illiquidity shocks, while during the recessionary state, only unexpected market-wide illiquidity shocks enhance herding.

Certain studies such as Baker and Stein (2004) have pointed out that liquidity can be an indicator of market sentiments. They claim that in a market with short-sale constraints and the presence of irrational investors, high market liquidity is an indication of a high market sentiment. Baker and Wurgler (2006) use liquidity as one of the factors in the construction of a sentiment index, and show that investor sentiments play a significant part in impacting stock prices. This adds further robustness to our results concerning the impact of investor sentiments on herding, as both results for the VIX index and illiquidity indicate that a fall in investor sentiments, or a rise in market fear and uncertainty, results in enhanced herding behaviour.

To summarise, this thesis aims to: (i) investigate the existence and magnitude of illiquidity premiums in US stocks, along with assessing the impact of oil price and oil price volatility on these premiums, under recessionary and non-recessionary states; (ii) explore the presence of factor based premiums in the US REIT market, assess if these premiums are associated with a higher risk exposure, along with analysing the impact of financial distress and liquidity crisis on these premiums, under varying market conditions; (iii) investigate the presence and significance of herding within US REITs on a sub-sector level, along with assessing the impact of expected and unexpected sector/market-wide illiquidity shocks on sub-sector herding, under a two-state Markov Regime.

The thesis contributes to the theoretical and empirical literature in several ways:

Contributions in the first empirical chapter:

Consistent with the theoretical claim of Amihud and Mendelson (1986) i.e. that expected returns rise as investors move from liquid to more illiquid stocks, the study confirms the presence and significance of a positive illiquidity premium within US stocks. The study then empirically extends on this theoretical claim, and finds illiquidity premiums to be positive and significant during both recessionary and non-recessionary states, although the relative magnitude of these premiums was found to be more inflated during times of financial crisis. This provides further justification to the argument that investors care more about illiquidity and illiquidity risk during times of financial downturns, since these periods are generally associated with a fall in liquidity.

Driven by the importance of oil as a global resource, several studies have explored the impact of oil price on stock returns. Certain studies have also incorporated for the volatility in oil prices, but have done so by using measures based on historical price movements. We extend on and contribute to the literature by looking at the impact of oil price and oil price volatility on illiquidity premiums within US stocks. Furthermore, our research incorporates for a forward looking oil price volatility measure i.e. OVX index. Using OLS and VAR methodologies, along with using ARDL and ECM modelling as robustness measures, we contribute to the empirical knowledge by finding that oil price has a positive impact on realised illiquidity premiums during the non-recessionary state, and a negative impact during the recessionary state. Oil price volatility has a negative impact of realised illiquidity premiums in the non-recessionary state, while its impact is insignificant during the recessionary state.

The thesis further contributes to the empirical knowledge by establishing an asymmetric impact that oil price volatility has on illiquidity premiums, but finds no such evidence of asymmetry when assessing the impact of oil price.

Contributions in the second empirical chapter:

Theoretically, Fama and French (2015) use the dividend discount model to establish a positive relationship between, book value, profitability and investment, and expected returns within stocks. Along with a size factor (Fama and French, 1992) and a momentum factor (Carhart, 1997), the value, profitability, investment factors, have gained prominence as investment styles. since they can then be used to generate premiums for investors. This thesis uses daily data from 2001 to 2020 and confirms the existence of all 5 premiums as positive and significant within the US REIT market. In doing so, theoretically, the research consolidates on the dividend discount model, and creates an overlap between the general equity market and the REIT market, since the dividend discount model has generally been utilised as a pricing mechanism for general stocks. Furthermore, most empirical research on these premiums circulates around the equity market, and the thesis contributes to empirical literature by confirming their existence within the REIT market.

The Efficient Market Hypothesis put forward by Fama (1970) claims that prices fully reflect all available information, at the present point of time. This implies that the expected return on an any risky asset within the economy, completely captures the risk associated with that asset, and hence is a perfect compensation to investors for exposing themselves to the risk associated with that asset. Efficient markets therefore also rule out the possibility of investors earning a higher expected return without a corresponding rise in risk. Although Ooi et al. (2007) look to assess if value premiums in the US REIT market are associated with a higher risk, this thesis extends on that empirical study by testing the theoretical claim of Fama (1970) for size, profitability, investment and momentum premiums, along with the value premium.
As our risk indicators the thesis utilises standard deviation, beta from the CAPM model, and factor loadings from the Fama–French three factor model, and as an extension to past literature, it also utilises factor loadings on the Fama-French five factor model, and the Carhart four factor model as a robustness measure. Consistent with the Efficient Market Hypothesis, the thesis finds the size, profitability and investment premiums to be associated with a higher risk, and therefore solidifies their role as proxies for systematic risk. In contradiction to the Efficient Market Hypothesis, the thesis finds no significant rise in risk associated with value and momentum strategies, contradicting the belief that these factors might be proxies for systematic risk.

The thesis then contributes to empirical literature by assessing if mispricing has a part to play in the existence of value and momentum premiums without a corresponding rise in risk within US REITs. We do so by utilising the idiosyncratic return volatility as a proxy for arbitrage risk. The results suggest significant evidence of mispricing within value REITs relative to growth REITs, but finds no significant evidence of mispricing within winner REITs relative to loser REITs.

Motivated by the presence of significant and positive factor based premiums in the US REIT market, without a corresponding rise in risk, and without any significant evidence of mispricing, the thesis contributes to literature by assessing a case for omitted factors from these asset pricing models. For this purpose, the research looks to explore the idea that financial distress and liquidity risk might be factors that are part of the information set, and are therefore reflected within asset prices, but have been omitted from conventional asset pricing models. The thesis utilises Auto-Regressive Distributed Lag (ARDL) modelling and Error Correction Modelling (ECM), to develop short- and long-run equilibriums, under three recessionary and non-recessionary states. Our results for the momentum and profitability premiums contradict the risk based explanation, as we find significant evidence of a fall in these premiums (especially in the recessionary states) corresponding to an uptick in default risk and liquidity risk. From a theoretical perspective, the thesis contributes variables that might be part of the information set to price an asset within an efficient market, but these variables may have been excluded from conventional asset pricing models.

Contributions in the third empirical chapter:

Extending on the idea that certain factor premiums in the REIT market can provide superior returns without a corresponding rise in risk, the thesis looks to explore the presence of herding within US REITs, that might drive asset prices away from their fundamental value and thus result in mispricing of these assets. Banerjee (1992) set up a theoretical model to show that individuals looking to maximise their payoffs via investments within asset markets, could optimise their positions by exhibiting "herd behaviour". The thesis utilises the Chang et. Al (2000)'s methodology of cross-sectional absolute deviation (CSAD), and consistent with Banerjee (2000)'s theoretical model, we find herding behaviour to be prevalent in US REITs on a sub-sector level.

The thesis then contributes to the empirical literature by confirming that sub-sector herding within US REITs is more intense during down markets relative to up markets, via a dummy approach. Furthermore, the research identifies a structural break within the data set, and via a Markov Switching Model, establishes that herding is more prevalent during the crash regime relative to the non-recessionary regime.

The research then contributes to empirical literature by assessing the impact of sector-wide illiquidity shocks on sub-sector herding within US REITs. We disentangle the Amihud (2002) illiquidity measure into expected and unexpected components, and assess the impact of expected and unexpected sector on sub-sector premiums in the US REIT market, during recessionary and non-recessionary phases. Our results suggest that, during the crash regime, a rise in unexpected sector illiquidity enhances herding in all REIT sub-sectors apart from health, while during the non-recessionary phase, expected illiquidity shocks have a significant part to play in enhancing herding within residential, retail and warehouse sectors.

The thesis further contributes to the empirical literature by also incorporating market-wide illiquidity shocks. Our findings suggest that during the non-recessionary states, herding is positively impacted only by expected market-wide illiquidity shocks, while during the recessionary state, only unexpected market-wide illiquidity shocks enhance herding.

The research further contributes to the empirical knowledge by assessing the impact of investor sentiments on herding. Based on the work of Baker and Wurgler (2006), Philippas, Economou, Babalos and Kostakis (2013), and using the VIX as an indicator of investor sentiments, along with incorporating the work of Baker and Stein (2004) and Deuskar (2007) who consider liquidity to be an indicator of investor sentiments, our results based on both indicators show that as investors' fear and uncertainty rises, or when investor sentiments are low, herding behaviour becomes more intense.

On the whole, the research adds to existing literature on asset pricing and behavioural finance by consolidating on theoretical frameworks and adding to the empirical knowledge.

This thesis in unique in several ways:

- Although substantial research has been conducted on oil price and stock returns, and a limited amount of research exists on oil price volatility and stock returns, and to the best of our knowledge, no research has been conducted on studying the influence of both factors on illiquidity premiums. For this purpose, the research incorporates a forward-looking OVX implied volatility index. Furthermore, the research includes factors such as industrial production index and exchange rate, whose impact on illiquidity premiums has not been explored within literature, but has implications for portfolio construction, strategy and diversification.
- To the best of our knowledge, no previous study has utilised ARDL and ECM modelling in order to study the impact of oil price, oil price volatility and macroeconomic factors on illiquidity premiums. This provides us with a deeper understanding of short- and long-run elasticities, along with incorporating a mechanism to gauge effective reversion to the long-run equilibrium
- Although the asymmetric impact of oil price and oil price volatility has been studied on stock returns, to the best of our knowledge, no previous study explores their potential asymmetric impact on illiquidity premiums
- To the best of our knowledge, this is the first study to extensively explore the risk associations of profitability and investment based strategies in US REITs, using contemporary risk measures as introduced by Fama and French (2015), along with exploring the potential for mispricing, as a contributor to these premiums
- To the best of our knowledge, no previous study has explored the impact of illiquidity shocks and financial distress on factor based premiums within US REITs, over three recessionary and two non-recessionary phases, along with utilising a methodology that assists in constructing long- and short-run equilibriums. The methodology used further assists in confirming if the reverting mechanism to long-run equilibrium is significant, within each period, for each factor based strategy, along with exploring certain inefficiencies that exist within the market, which could provide lucrative opportunities for investors without a corresponding rise in risk. The research also incorporates significant observations (104) during the most recent COVID-19 phase,

and hence provides academics and investors with an extremely up-to-date outlook on factor based investment strategies within the REIT market.

- Extending on the work of Philippas, Economou, Babalos and Kostakis (2013), this is the first study to incorporate Markov switching and separate components for expected and unexpected sector/market-wide liquidity, to assess their impact on sub-sector herding within US REITS, under varying market regimes, including the most recent Covid-19 outbreak.

The structure of this thesis is as follows. Chapter two, provides established theoretical and empirical literature concerning market-wide and individual asset liquidity, impact of commodity prices and macroeconomic variables on illiquidity and investor sentiments, Real Estate Investment Trusts, their uniqueness from the point of view of an asset class, along with their unique nature on a sub-sector level, their role in portfolio diversification, traditional and contemporary asset pricing models, unique nature of recessions within the US, along with market wide herding. The idea being to first provide a theoretical and empirical background for the research, along with a comparison of how the results in this research stand in-line with past literature. Due to the extensive nature of the literature that has been explored, the thesis provides a common literature within chapter two, and additionally, provides specific literature reviews at the beginning of each empirical chapter.

Chapter Three is first empirical chapter that looks to establish the existence of illiquidity premiums in US stocks, along with assessing the impact of oil price, oil price volatility and other macroeconomic factors on illiquidity premiums, during recessionary and expansionary phases. The chapter also explores potential asymmetric impact of oil price and oil price volatility on illiquidity premiums. Chapter four is relevant to asset pricing within US REITs, and firstly looks to establish the existence and risk associations for size, value, profitability, investment and momentum premiums within US REITs. The study then explores the impact of financial distress and liquidity crisis on these premiums, under recessionary and non-recessionary states. Chapter Five looks to explore the presence and significance of herding within US REITs on a sub-sector level, along with assessing if herding is more prevalent during down markets/recessionary states relative to up markets/expansionary states. The chapter then disentangles expected and unexpected illiquidity shocks, and assesses the impact of expected and unexpected market/sector-wide illiquidity shocks on sub-sector herding within US REITs. Finally, Chapter Six summarises the main results of the thesis and provides concluding remarks.

CHAPTER 2: LITERATURE REVIEW

2.1 Introduction

Chapter One introduced the rationale behind this research, highlighting the theoretical and empirical developments to existing literature that this research provides. This chapter extends and elaborates on that literature.

The chapter is organised as follows: Section 2.2 examines, various methods used to gauge illiquidity, the empirical relationship between illiquidity and stock returns, illiquidity premiums, and the disentanglement between expected and unexpected illiquidity. Section 2.3 explores the literature on relationship between oil price, oil price volatility, interest rate, exchange rate, inflation and the industrial production index, on stock market returns. The section dives deep into exploring these relationships, and establishes links between them to changes in market liquidity and investor sentiment. This then provides the framework to hypothesise about the relationship between these factors and illiquidity premiums, which is explored in great detail within chapter three. Section 2.4 explores Real Estate Investment Trusts (REITs), their traits, their usefulness in an investor portfolio as a substitute for conventional real estate, their ability to generate diversification benefits in a multi-asset portfolio, their relationship with conventional stocks, regulation and funding within the industry, along with focusing on differences within various REIT sub-sectors. Section 2.5 discusses the evolution within asset pricing models, starting from the univariate CAPM model, followed by the Fama-French three factor, Carhart four factor and Fama-French five factor model, along with assessing literature regarding the existence of premiums, based on established risk factors as suggested by these models. Section 2.6 explores the relationship in literature between factor premiums as introduced by the asset pricing models, and, default risk, liquidity crisis and stock market returns. This section also introduces proxies used in literature for default risk and liquidity crisis. Section 2.7 discusses the concept of herding, its significance, various measures for herding, along with exploring literature on herding within REITs, and liquidity as a channel of influence on herding. Finally, section 2.8 discusses the usage in literature of VIX and liquidity as indicators of investor sentiments.

2.2. Illiquidity measures and theoretical framework

2.2.1 Market Liquidity and individual asset liquidity measures

Amihud (2002) claims that liquidity cannot be observed directly, it has multiple facets to it which cannot be captured in a single measure. Brunnermeier and Pedersen (2009) state that liquidity comprises of two facets; market liquidity which translates to the ease of trading an asset, and funding liquidity which implies the ease of obtaining funding. Glosten and Milgrom (1985) argue that illiquidity signifies the impact of order flow on price via the bid-ask spread, which is reflected in either the discount that a seller bears or the premium that a buyer pays, when executing a market transaction (Amihud and Mendelson, 1986). Kyle (1985) proposed a proxy for market liquidity, as the coefficient in a regression of intraday transaction-by-transaction price changes on the dollar volume of trades, where trades are distinguished between "buy" and sell". Higher values of "Kyles Lambda" or the slope coefficient within the regression signify lower liquidity and market depth. Chalmers and Kadlec (1998) use the amortized effective spread as a measure of liquidity. They calculate the effective spread as the difference between the mid-point of the bid-ask spread and the transaction price that follows for a buy or sell transaction. This spread is then divided by the stock's holding period to amortize it. Easley et al. (1992) design a measure that uses intra-day transaction data, and reflects the adverse selection cost resulting from asymmetric information amongst traders which could drive asset prices away from the "full information" price.

Amihud (2002) claim that these measures of illiquidity require microstructure data on transactions and bid-ask quotes which might not be available for most markets, for an extended period of time. They propose a measure that incorporates daily data on returns and volume, which can easily be accessed for a range of economies and for an extended period of time. To measure total market illiquidity, Amihud (2002) firstly derive a measure for each individual stock, which is then aggregated to a market level. Stock level illiquidity on any particular day is defined as the ratio of the absolute daily returns to trading volume in dollar terms, for that particular stock;

$$ILLIQ_{i,d} = [(1{,}000{,}000 \times |r_{i,d}|)/(p_{i,d} \times v_{i,d})] \qquad (2.1)$$

where $|r_{i,d}|$ is the absolute value of return on stock i on day d, $v_{i,d}$ is the trading volume of stock i on day d, $p_{i,d}$ is the closing price of stock i on day d.

To calculate a market measure, Amihud (2002) aggregate the daily ILLIQ values for each stock and divide it by the total number of stocks included within the stock universe on that particular day:

$$AILLIQ_d = (1/N_d) \sum_{i=1}^{n} ILLIQ_{i,d} \qquad (2.2)$$

where N_d is the number of REITs in our universe on day d of our sample.

Based on the rationale that using certain finer measures of gauging market illiquidity might significantly reduce the asset universe under study along with impacting the longevity of the research, hence this research utilises the market measure as designed by Amihud (2002).

Roll (1984) designed a measure to gauge illiquidity for each stock i. Aptly titled the roll estimator, it is calculated as follows:

$$RE_{i,t} = -2\sqrt{-Cov(\Delta P_t, \Delta P_{t-1})} \qquad (2.3)$$

Where t is a trading day within the year for which the measure is calculated, while ΔP_t is the change in price at time t relative to its preceding price.

Corwin and Schultz (2012) design a measure titled the high-low spread to gauge the illiquidity of individual stocks. The estimator is based on the assumption that stock prices follow a constant diffusion process, and the daily observed high price (H^0) is buyer initiated while the daily observed low price (L^0) is seller initiated. The high-low spread for each stock i, at time t, is calculated as follows:

$$HLA_{i,t} = [2(e^a - 1)/(1 + e^a)] \qquad (2.4)$$

where a is calculated as follows:

$$a = [(\sqrt{2\beta} - \sqrt{\beta})/(3 - 2\sqrt{2})] - [\lambda/(3 - 2\sqrt{2})] \qquad (2.5)$$

$$\beta = \sum_{j=0}^{1} [\ln (H^{0}_{t+j}/L^{0}_{t+j})]^{2} \qquad (2.6)$$

$$\lambda = [\ln (H^{0}_{t,\, t+1}/L^{0}_{t,\, t+1})]^{2} \qquad (2.7)$$

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

Said and Giouvris (2017a) showed that the ILLIQ (Amihud, 2002) measure is highly correlated with other measures such as the high-low spread (Corwin and Schultz 2012) and the roll estimator (Roll 1984) signifying that they capture similar aspects of stock illiquidity. Hasbrouck (2003) concluded that the ILLIQ measure is thought to be the most common approach and has the highest correlation with trade-based measures. Based on this rationale, this research utilizes the ILLIQ measure of illiquidity for individual assets.

2.2.2. Theoretical Model for Illiquidity as a pricing factor and Illiquidity Premiums

The CAPM theory states that expected returns on an asset are an increasing function of an asset's systematic risk, since this cannot be diversified away. The CAPM model also proposes that idiosyncratic risk is not priced since it can be diversified away. Empirical works such as Ang, Hodrick, Xing and Zhang (2006) contradict this theory, and find that expected returns on an asset are a decreasing function of the asset's idiosyncratic risk and of its exposure to market risk.

Backed by contradictory empirical evidence regarding the workings of the CAPM model, Amihud and Mendelson (1986) propose a theory that expected returns are an increasing function of the assets' illiquidity (and hence trading costs), citing the fact that investors price these assets to be compensated for these costs. This is the first theoretical model that incorporates for illiquidity within asset pricing. Based on the theory put forward by Amihud and Mendelson (1986), there are two types of illiquidity risks that are priced:

- Sensitivity of asset prices to changes in market illiquidity.
- Exposure to market illiquidity return premium.

The theory further states that illiquidity as a pricing mechanism becomes more significant during times of, higher market illiquidity, higher funding illiquidity and economic stress. Amihud and Mendelson (2015) use this theory to try and tackle the "equity premium puzzle", concluding that in the absence of an unreasonably high level of risk aversion on the part of investors, the significant returns differential between stocks (equity returns) and Treasury bills is a compensation for illiquidity[1], along with it being a compensation of risk. They further add that risk aversion alone cannot explain the difference in returns between equities and treasury bills (unless risk aversion is extraordinarily high). The difference in returns is partly a compensation for illiquidity, and this is backed by high transaction costs involved with equity trades relative to bond trades.

Amihud and Mendelson (1986) further add that if the level of liquidity is priced, then liquidity shocks should also impact asset prices. Market liquidity is a systematic factor, and hence shocks within this impact the prices of individual assets, therefore market-wide liquidity shocks are priced. Additionally, if market return has an impact on asset's liquidity, which in-turn impact its expected return, then the extent of this impact of market return on asset liquidity is another component that is crucial in defining a specific assets' price. Another component within their pricing mechanism stems from the fact that individual stock returns (including individual stock risk premiums and liquidity premiums) vary with market-wide risk premiums and liquidity premiums. In this case the systematic factor that is priced is not shifts in market-wide liquidity, but shifts in market-wide liquidity return premiums.
Amihud and Mendelson (1986) lay down certain propositions for their model:

- Investors wish to maximise the present value of all future cash flows linked to the assets within their portfolio.
- It is assumed that each security has a riskless dividend associated to it, along with some liquidation cost.

[1] Amihud and Mendelson (1991) find illiquidity on the most liquid stocks to be 60 times greater than Treasury bills and 17 times greater than bonds

- In terms of investor behaviour and preferences; all investors are risk neutral, investors can have a need to liquidate their assets and this need can have a random arrival associated to it, investors can differ in terms of the time horizon to liquidation.
- In the equilibrium, the higher the asset's illiquidity costs, the higher the required return on the asset, since investors' require a compensation for heightened risk.
- Less liquid assets are held for a longer time horizon by investors, who amortize the higher liquidity costs associated with these assets, over a longer time period.

Formally, Amihud and Mendelson (1986) propose that the return on any asset j, for investor k, is the gross return on that asset minus the expected liquidation cost:

$r_{j,k} = R_{j,k} - \beta_k S_{j,}$ (2.8)

Where $R_{j,k}$ is the gross return on asset j, while β_k is the probability of liquidation during a certain timeframe, and S_j is the proportional liquidation cost. The theory therefore says that asset illiquidity (proxied by S_j) is a priced characteristic, adding that expected returns are an increasing function of illiquidity:

$R_{j,k} = r_{j,k} + \beta_k S_{j,}$ (2.9)

Amihud and Mendelson (1986) also claim that less liquid assets are held by investors over a longer time horizon (investors with a low β_k), and hence these investors depreciate the high liquidity costs over a longer time, ensuring liquidity costs per period is lower. From the model, one can conclude that $R_{j,k}$ or gross returns on an asset is an increasing function of S_j or the assets liquidation cost (an indication of an assets' illiquidity).

They also claim that the rise in expected returns as investors move from liquid to more illiquid stocks, as a function of illiquidity cost depreciated over time by investors, consistently goes beyond being just a compensation for these costs. They claim illiquidity premiums to be significant and positive, i.e. the excess expected return on illiquid stocks exceeds the compensation for the expected cost of illiquidity.

In terms of finding empirical support for their theory, Amihud and Mendelson (1986) use the the bid-ask spread as a measure of illiquidity, and find that for NYSE stocks traded between

1960 and 1980, average stock return was an increasing function of illiquidity cost, after controlling for systematic and unsystematic risk. Studies such as Brennan and Subrahmanyam (1996), Datar, Naik and Radcliff (1998) and Amihud (2002)[2], all use different measures of illiquidity, and confirm the robustness of the Amihud-Mendelson (1986) asset pricing theory. To add more robustness to their empirical findings, Amihud-Mendelson (1986) also find results consistent with the clientele effect, i.e. frequent traders (associated with a higher β_k) prefer to invest in more liquid assets (assets associated with a lower S_j), while low frequency traders (associated with a lower β_k) prefer to invest in more illiquid assets (assets associated with a higher S_j) since they can depreciate the relatively higher transaction costs over a longer time horizon.

Utilising data for US stocks between 2007 and 2018, and using the Amihud illiquidity measure (Amihud, 2002), in chapter 3, we look to empirically test the theoretical claim of Amihud and Mendelson (1986) of a positive and significant illiquidity premium, during recessionary and non-recessionary states. Amihud and Mendelson (1986) also state that it is not just market-wide liquidity shocks that impact asset pricing, but also market-wide liquidity premiums. Backed by this theoretical claim that market-wide illiquidity premium is a systematic risk factor which is significant in asset pricing, and owing to the significance of oil as a global commodity, we look to assess the impact of, oil price, oil price volatility (using the OVX index), and various other macroeconomic factors, on illiquidity premiums within US stocks, during recessionary and non-recessionary states.

2.2.3 Expected and Unexpected illiquidity

Blau, Nguyen and Whitby (2020) argue that the concern about liquidity in asset markets is not just the average level of market liquidity, but also the uncertainty of liquidity. Amihud (2002) distinguish between expected and unexpected illiquidity shocks. They argue that the effects of expected illiquidity are felt straight away, but the impact of unexpected illiquidity is felt via investor sentiments regarding future illiquidity.

[2] Brennan and Subrahmanyam (1996) use Kyle's (1985) measure of illiquidity, Datar, Naik and Radcliff (1998) measure sotck liquidity using stock turnover (share trading volume relative to the number of shares outstanding), while Amihud (2002) use the Amihud ILLIQ measure of illiquidity.

Amihud (2002) and Paul, Walther and Kuster-Simic (2021), assume that market illiquidity follows an autoregressive model:

$$\ln ALLIQ_d = c_0 + c_1 \ln ALLIQ_{d-1} + v_m \qquad (2.10)$$

At the beginning of day d, investors determine the expected illiquidity on day d, based on the information in period d-I[3]. Therefore:

$$\ln ALLIQ^E_d = c_0 + c_1 \ln ALLIQ_{d-1} \qquad (2.11)$$

The optimal lag length is then determined using the Akaike information criterion (AIC). The residual from equation 2.8 gives us the unexpected illiquidity on day d, $\ln ALLIQ^u_d = v_d$

Amihud (2002) breakdown illiquidity into its expected and unexpected component, and conclude that future stock returns across NYSE from 1964-1997 are an increasing function of expected illiquidity. This they believe is a compensation to investors for a higher liquidity risk. On the other hand, they argue that unexpected illiquidity shocks have a negative impact on current returns. A rise in unexpected illiquidity raises future expected illiquidity, raising future expected returns, and thus resulting in a fall in current prices, and current returns

2.3 Oil price, oil price volatility, macroeconomic factors, stock returns and illiquidity premiums

2.3.1 Oil price, stock returns and illiquidity premiums

Oil is a significant resource for the world economy, and shifts in the price of oil have a significant impact on economic and financial activity. Studies such as Miller and Ratti 2009, Chen 2010, Cunado and Perez de Gracia 2014, claim that a rise in the price of oil could reduce

[3] This is based on Paul, Walther and Kuster-Simic (2021), who say that the expected liquidity at time "d" is based on information in the previous period "d – I", where the optimal lag length for I is determined using the AIC criteria

the local and international competitiveness of firms via a rise in the cost of production, it could negatively impact consumer spending, and hence could have a negative impact on stock markets. On the other hand, studies such Mohanty et al. 2011, Güntner 2014; Tsai 2015, Foroni et al. 2017, propose that a rise in oil prices could enhance earnings for energy firms, the impact of which then seeps down to the rest of the economy, enhancing consumer spending, investments, and eventually having a positive impact on stock prices. This mixed evidence merits further studies on the impact of oil price on stock markets, including facets such as illiquidity premiums.

Studies such as Tsai (2015), Killian and Park (2009), Güntner (2014), Foroni et al. (2017), and Dupoyet and Shank (2018), all find a positive relationship between oil price and the stock market. Investor sentiments is a key driver for this relationship, as a rise in oil price might be seen as bullish sentiments towards global growth. This could potentially have a two-fold impact on illiquidity premiums. On one hand, bullish investor sentiments might reduce investors' risk perception towards illiquid stocks, inducing investments within these stocks (Gai and Vause 2006; González-Hermosillo 2008), resulting in a rise in their price, and hence a rise in realised illiquidity premiums. On the other hand, with extended bullish sentiments present in the market, central banks might look towards monetary tightening in order to avoid an overheating of the economy, and thus constraining market liquidity (Chevapatrakul 2014; Said and Giouvris 2017a). With a fall in overall market liquidity, investor capital is expected to flow towards more liquid stocks, reducing demand for illiquid stocks, thus having a negative impact on their price and therefore on realised illiquidity premiums (Jensen and Moorman 2010; Said and Giouvris 2017a). Furthermore, periods of interest rate hikes are associated with a rise in bond returns (Chevapatrakul 2014), potentially moving capital away from the stock market towards the bond market, reducing demand for illiquid stocks, driving down their price and have a downward impact on realised illiquidity premiums.

On the flipside, there are studies that report a negative relationship between oil price and the stock market. Driesprong, Jacobsen and Maat (2007) find that current and lagged oil price have a negative relationship with stock market returns in both developed and emerging economies. Hondroyiannis and Papapetrou (2001) find a negative correlation between oil price changes and stock market movements in Greece. Driesprong, Jacobsen and Maat (2007) also find a negative relationship between oil prices and stock market returns for both developed and emerging markets. They believe that the relationship becomes even stronger when they introduce lagged monthly oil price, indicating a potential delayed reaction by investors to changes in the price of oil. Miller and Ratti (2009) assess the long-term relationship between oil price and international stock markets between 1971 and 2008. They find that stock markets respond negatively to increases in oil prices in the long run. Chen (2010) finds that an increase in oil prices leads to a higher probability of a bear market within the Standard & Poor's S&P 500 price index. Cunado and Perez de Gracia (2014) disentangle oil price changes as oil demand shocks and oil supply shocks, identified via the sign of the correlation between price changes and global oil production. For 12 oil importing European economies, they find a negative relationship between oil price changes and stock returns. Furthermore, they also find that stock market returns are mostly driven by oil supply shocks.

The relationship between oil price and stock returns can also be sector specific. Narayan and Sharma (2011) find that oil price negatively impacts stock returns for all sectors apart from the energy and transportation sector, within the NYSE. Consistent with this finding, Scholtens and Yurtsever (2012) find a negative relationship between oil price and all stock market industries barring oil and gas, in the euro zone. This varying impact of oil price on stock market returns, merits research exploring the impact of oil price on illiquidity premiums, over various industries within the stock market (since the impact can vary based on the industry under focus).

2.3.2 Oil Price Volatility Measures and stock returns

Most oil price volatility measures introduced within literature have been historical realised measures. Hamilton (1996) constructed a measure to compare the current price of oil with the price over the previous four quarters. A positive (negative) oil price shock is then defined as an increase (decrease) in the current price of oil above (below) the maximum (minimum) price of oil over the past four quarters. The benefit of using this method to construct volatility is that it provides a clear distinction between negative and positive oil price shocks. Hamilton (2003) amends on the initial idea and recommends using a three-year horizon. This then poses a serious question in terms of assessing the optimal number of lags to use in determining oil price shocks.

Park and Ratti (2008) use the sum of square first log differences in daily spot or future prices, to gauge oil price volatility. Between 1986 and 2005, for stock markets in the US and 13 European countries, they find that an increase in oil price volatility has a negative impact on stock returns in 9 out of 14 countries. Elyasiani, Mansur and Odusami (2011) model oil price volatility using a GARCH (1,1) model and measure the impact on stock returns of 13 US industries. They find that an increase in oil price volatility has a negative effect on returns in 9 out of 13 industries.

Diaz, Molero and Perez de Gracia (2016) use a univariate GARCH (1,1) error process to compute the unexpected component and conditional variance of real oil price and they estimate the GARCH model using Maximum Likelihood Estimation (MLE). They estimate the mean function separately from the variance function, using an AR representation for the mean equation lagged to 4 quarters. Generally, while modelling say stock returns, the mean equation in the GARCH process tends to be an MA process. This might be down to the fact that stock prices relative to oil prices might be more significantly determined by demand and supply of traders. Within oil, multiple factors such as for example market collusion might impact its price, and an AR representation is a testament to the impact of passed lagged prices on the current price of oil. Their study is conducted on a monthly frequency for all G7 countries between January 1970 and December 2014. Since the data set includes time periods of varying economic cycles, the data will tend to have blocks or clusters of high and low volatility which they try to capture. Apart from the volatility clustering, the rationale for using a GARCH model includes the fact that volatility is not constant and is seen to be evolving overtime, along with the asymmetry in the way volatility reacts to big price increases or a big price drop. They find that an increase in oil price volatility has an adverse effect on stock markets in G7 countries. Both Park and Ratti (2008) and Diaz, Molero and Perez de Gracia (2016) find that a rise in oil price volatility has a negative impact on stock returns.

Typically, research that have incorporated for oil price volatility use a historical volatility measure. Luo and Qin (2017) use both a realized volatility measure along with the CBOE crude oil volatility index (OVX), which is a forward looking oil price volatility measure, and study the impact on the Chinese stock market. They show that OVX shocks have a negative impact on the stock market, while the impact of realised volatility is insignificant. Similarly, Xiao et al. (2018) also find a negative relationship between OVX and stock market returns in China. Studying the Middle East/African markets, Dutta et al. (2017) find a negative relationship between OVX and stock market returns, while Vu (2019) also confirm this negative relationship for Southeast Asian markets. Dupoyet and Shank (2017) study US stocks, and show that OVX has a negative and significant impact on nine out of ten industries. Therefore, we incorporate for a forward looking measure rather than a realized volatility measure in our research to analyse the impact on illiquidity premiums in the NYSE.

The OVX is a forward looking measure for oil price volatility introduced by the Chicago board of Exchange (CBOE) in May 2007. This volatility figure is reported daily and is calculated using the CBOE volatility index (VIX) methodology. The index takes as inputs strike prices of the call and put options on the US Oil Fund options for near-term options with more than 23 days until expiration, next-term options with less than 37 days until expiration, and risk-free U.S. treasury bill interest rates. The idea being to estimate the implied volatility of US Oil Fund options at an average expiration of 30 days. Given that the OVX index captures market's aggregate future expectation of oil volatility, Peng and Ng (2012), and Dupoyet and Shank (2018) conclude that the OVX provides information about future oil prices quicker than current oil prices themselves.

2.3.3 The impact of Interest rates, exchange rate, inflation, industrial production index and stock market index, on stock prices, market liquidity and illiquidity premiums

Jensen and Moorman (2010) study the link between monetary conditions, market liquidity and illiquidity premiums in the US. They find evidence that expansive monetary shifts (associated with falling interest rates) increase market-wide liquidity causing large price increases in illiquid stocks and raising the return spread between illiquid and liquid stocks substantially.

Using Amihud (2002) measure of illiquidity, Said and Giouvris (2017) split stocks listed on the FTSE All-Share index into 5 equally weighted quintiles. They then define a zero-cost portfolio as one that takes a long position in the illiquid portfolio and a short position in the liquid portfolio [illiquid minus illiquid stocks (IML)]. They conclude that returns on the IML portfolios are the highest during expansive monetary conditions and they tend to be statistically insignificant when monetary conditions are restrictive. Furthermore, they conclude that illiquidity premium falls a few months prior to an expansionary announcement due to a potential "flight-to-liquidity" but after the announcement there is enhanced liquidity in the market, investors are less concerned about illiquidity risks and price of illiquid stocks starts to rise. For this reason, we control for changes in the federal funds rate and the Fed discount rate.

Economic literature also suggests that there is a strong relationship between stock returns and exchange rates. Phylaktis and Ravazzolo (2005) analyse a group of Pacific Basin countries over the period 1980-1998 and find that stock and foreign exchange markets are positively related. Bashir et al. (2016) study the relationship between exchange rate and stock prices within Latin American countries and find evidence of a positive relationship between the two, especially in a longer time frame. Zheng and Su (2017) study the relationship between oil price, exchange rates and market liquidity in China. They conclude that an uptick in the exchange rate tends to decrease market liquidity in China. Therefore, we control not only for exchange rate because it impacts stock returns in general, which includes both illiquid and liquid stocks, but also because it significantly impacts market liquidity.

Consistent with previous studies on the impact of oil price shocks on stock returns including Herrera, Lagalo and Wada (2011), Cunado and Perez de Gracia (2014), and Diaz, Molero and Perez de Gracia (2016), we use monthly seasonally adjusted Industrial Production Index to measure economic activity and study its potential relationship with illiquidity premiums. In line with Fama (1990), Boudoukh and Richardson (1993) and, Kim and In (2005) we also control for change in inflation. Fernández-Amador et al. (2013) study the impact of inflation, industrial production index and stock market index, on stock market liquidity. They conclude that all three of these factors have a significant impact on stock market liquidity.

2.4 Real Estate Investment Trusts

2.4.1 REIT traits and similarities to conventional real estate

Real estate investment Trusts (REITs) are income generating instruments, that are seen as a liquid way of incorporating the real estate sector within an investors' portfolio (Hoesli et al. 2004; Nazlioglu et al. 2016). REITs are required by law to distribute 90% of their taxable income as dividends in order to maintain their REIT status. (Boudry 2011). This ensures that REITs are not only instruments that enable gains to be made via possible capital appreciation, but enable investors to reap benefits of consistent dividend pay outs. According to the National Association of Real Estate Trusts (NAREIT), the 2021 REIT market cap was $1.74 trillion, which translates to 3.3% of the $53 trillion US stock market cap. This growth in market capitalization would provide more assurance to investors in terms of the depth of this market, price stability within the instruments, and finding potential buyers for REITs if current investors are looking to off load their investments.

Zhang and Hansz (2022) claim that via REITs, investors can incorporate the real estate sector within their portfolio at relatively lower costs. Both Clayton and Mackinnon (2003) and Glascock et al. (2000) find a significant long-term relationship between REITs and the private real estate sector. Furthermore, Stephen and Simon (2005) also report on the uniqueness of REITs as an asset class, concluding that their returns cannot be replicated by other asset classes. REITs therefore have a significant role in a multi-asset setting in terms of their uniqueness, along with their use as an efficient and liquid way to substitute for conventional real estate investments, with the added benefit of significantly lower buy in cost.

2.4.2 REITs, general stocks and diversification in a multi-asset portfolio

To assess the benefits that REITs bring along from a portfolio diversification perspective, we need to analyse their similarities or differences with other financial market instruments overtime. Earlier studies such as Karolyi and Sanders (1998) discuss the similarities that REITs share with bonds in terms of stable income generation. Shen et al. (2020) report that REIT returns were strongly correlated with bond returns up until the 1990s. Glascock et al. (2000) conclude that after the structural changes within REITs in the 1990s, and the significant hike in institutional ownership of REITs (Chen and Zhang, 1998), REITs became similar to stocks, and their returns became sensitive to factors which impact small cap stocks and real estate specific drivers (Clayton and Mackinnon 2003).

Although REITs have behaved more like stocks relative to bonds, since the structural changes in the REIT market, Zhang and Hansz (2019) report on some key differences still within these asset classes, claiming that these key differences have resulted in REITs generally excluded from most asset pricing studies, along with signifying the uniqueness of REITs as an asset class. Firstly, unlike stocks, REITs are governed by regulation to distribute 90% of their taxable income as dividends (Boudry 2011). This has serious funding ramifications for REITs, in terms of the fact that general stocks could potentially be highly dependent on retained earnings for efficient performance and future growth, but due to the nature of this regulation, REITs have to be dependent on external sources of funding. A change in market liquidity could then have quite varying impacts on general stocks and REITs. We will revisit this in greater detail later within this section. Second, common stocks are subject to corporate tax, while REITs are exempt, and the only tax levied is on dividends and is based on the investors' personal tax rate. Third, general stocks are usually not treated as an inflation hedge, but investors tend to consider REITs as an inflation hedge (Liu et al. 1997). Fourth, REIT prices tend to fluctuate more with interest rate changes relative to general stocks (Titman and Warga 1986). Once again, this can be seen as a consequence of the regulation that REITs have to distribute 90% of their taxable income as dividends, hence they might be more exposed to external market sources for funding relative to stocks which can utilise retained earnings, and hence any monetary shifts within the market (from an interest rate and liquidity perspective), would have a more significant impact on REIT prices relative to general stocks.

These differences between REITs and general stocks are further highlighted by Chaudhry et al. (1999) who find an inverse relationship between stocks and real estate, and Stephen and Simon (2005) report a low correlation between US REITs and the stock market in the late 1990s.

This would imply that REITs offer potential diversification benefits in a multi-asset portfolio, with Hoesli et al. (2004) reporting that the optimal allocation towards real estate in a multi-asset portfolio is 15 to 25%.

2.4.3 Funding REITs

Given the regulation that REITs have to distribute 90% of their taxable income as dividends, retained earnings would only contribute a marginal proportion of new investment within REITs. Ott, Riddiough and Yi (2005) state that retained earnings only constitute 7% of the overall new REIT investments. Therefore, any shift in interest rates, monetary stance or liquidity from traditional sources could potentially put a significant pressure on REITs growth and future earnings potential (Huerta, Egly and Escobari, 2016).

REITs are generally highly leveraged, typically 5 to 10 times their equity (U.S. Securities and Exchange Commission, 2020). NAREIT (2022) reports that the US REIT industry holds $3 trillion in real assets and around $2 to 2.5 trillion in liabilities, and more than two-thirds of these liabilities is short-term funding. Given REITs dividend pay-out policy, credit lines offer a significant source of back up liquidity to fund cash shortages (Ott, Riddiough and Yi, 2005). Credit lines offer the REIT industry a flexible way of borrowing without committing to long-term finance, and their importance is reflected by the fact that within the REIT industry, unused credit line balance as a percentage of credit lines plus cash represents close to 74% of total liquidity, compared to 45% for firms in other industries (Ooi, Wong and Ong, 2012). Cetorelli, Goldberg and Ravazzolo (2020) discuss the short-term funding stress during Covid-19, primarily existing due to an elevated demand for liquidity. The resulting exposure to interest rate risk, along with a lack of liquidity, could significantly disrupt REIT performance and growth, especially given the sectors dependence on injections of short-term funding.

2.4.4 REIT sub-sectors

REITs invest within a diverse range of real estate sectors such as health, hotel, mortgage, residential, retail and warehouse, allowing investors to lower the relative risk that might come along with conventional real estate investments (Nazlioglu, Gormus and Soytas, 2016). After

1990, the institutional ownership has increased significantly within REITs (Chen and Zhang, 1998). This influx of interest in REITs has resulted in an increased interest in the microstructure of this asset class, including the intrinsic nature of sub-sector REITs. Looking at the asset class as one body can turn out to be misleading. Nazlioglu, Gormus and Soytas (2016) argue that all REITs are not constructed equally, and that various market factors impact these various REITs differently.

Capozza and Korean (1995) empirically show that warehouse REITs generally trade at a discount, while retail REITs trade at a significant premium on average. Peterson and Hsieh (1997) conclude that Mortgage REITs are significantly impacted by both stock and bond market risk factors, while equity REITs are strongly related to stock market risk factors. Cho (2017) use a data set that runs from 2010 to 2015, and conclude that hotel and industrial REITs outperformed all REIT sub-sectors in terms of risk-adjusted returns. Furthermore, they also state that these two sectors have relatively low correlations with stocks and bonds. Although debt ratios within REIT sub-sectors varied considerably, these differences were further highlighted during the Covid-19 economic shock (U.S. Securities and Exchange Commission, 2020). Industrial REITs, which account for 20% of the total REIT market cap equating to $131 billion in quarter 2 of 2020 (NAREIT, 2020), saw a marginal change within their debt ratios, falling from 17% in quarter 4 of 2019 to 16% in quarter 2 of 2020 (U.S. Securities and Exchange Commission, 2020). Relative to this, debt ratio for hotel REITs rose from 30% in quarter 4 of 2019 to 46% in quarter 2 of 2020 (U.S. Securities and Exchange Commission, 2020). According to CBRE (2015), sub-sectors such as health and hotel have enhanced their market position, while traditional REIT sectors such as retail have been losing their market share.

2.5 Theoretical framework, Asset pricing models, risk premiums and style based investment strategies

2.5.1 Efficient Market Hypothesis

Fama (1970) claim that in an efficient market prices fully reflect all available information, at the present point of time. This implies that the expected return on an any risky asset within the economy, completely captures the risk associated with that asset, and hence is a perfect compensation to investors for exposing themselves to the risk associated with that asset. Efficient markets therefore also rule out the possibility of investors earning a higher expected return without a corresponding rise in risk.

The equilibrium expected return on a security is a function of its "risk", but different asset pricing theories might differ in how "risk" is defined. However, Fama (1970) state that all these models that define expected returns show consistency with the following notational representation:

$E(\tilde{p}_{j,t+1} \mathrm{I} \Omega_t) = [1 + E(\tilde{r}_{j,t+1} \mathrm{I} \Omega_t] p_{j,t}$ (2.12)

Where E is the expected value operator, $p_{j,t}$ is the price of security j at time t, $p_{j,t+1}$ is the price of the security at time t + 1, $r_{j,t+1}$ is the one-period percentage return and is defined as $(p_{j,t+1} - p_{j,t}) / p_{j,t}$, Ω_t is the information set and it is assumed that this is fully reflected in the price at t, the tildes represent the fact that $p_{j,t+1}$ and $r_{j,t+1}$ are random variables at t.

Based on the idea that market equilibriums can be stated in terms of expected returns, and these expected returns "fully reflect" the information contained in Ωt, Fama (1970) introduce the idea of a "fair game".

Let $x_{j,t+1}$ be the excess market value of security j, at time t + 1, calculated as the difference between the observed price for security j at time t + 1, and the expected price of security j (at time t +1) that was calculated at time t and based on the information set Ω_t. In a "fair game" this divergence in price would be equal to zero. So;

$x_{j,t+1} = p_{j,t+1} - E(p_{j,t+1} \mathrm{I} \Omega_t)$ (2.13)

Then for a fair game;

$E(\tilde{x}_{j,t+1} \mathrm{I} \Omega_t) = 0$

Similarly, let $z_{j,t+1}$ be the difference between the observed return on security j at time t + 1, and the equilibrium expected return for security j (at time t + 1) that was calculated at time t and based on the information set Ω_t. Fama (1970) then state that in a "fair game", this returns divergence will be equal to zero. So;

$z_{j,\,t+1} = r_{j,\,t+1} - E(\tilde{r}_{j,\,t+1}\ I\ \Omega_t)$ (2.14)

Then for a fair game;

$E(\tilde{z}_{j,\,t+1}\ I\ \Omega_t) = 0$

Furthermore, let $a_j\,(\Omega_t)$ be the funds to be placed by an investor in security j at time t. The total excess market value at t + 1 would then be given by;

$V_{t+1} = \sum_{j=1}^{n} a_j\,(\Omega_t)\,[r_{j,\,t+1} - E(\tilde{r}_{j,\,t+1}\ I\ \Omega_t)]$ (2.15)

For this then to be a fair game or an efficient market;

$E\,(\tilde{V}_{t+1}\ I\ \Omega_t) = \sum_{j=1}^{n} a_j\,(\Omega_t)\ E\,(\tilde{z}_{j,\,t+1}\ I\ \Omega_t) = 0$ (2.16)

In addition to this Fama (1970) state three conditions that are sufficient for market efficiency, but not a necessity;

- Zero transaction costs in trading securities. Although markets can still be efficient as long as transaction costs incorporate all available information. Even large transaction costs that might hinder the flow of transactions, do not guarantee inefficient markets as long as prices "full reflect" these high transaction costs.
- All available information is available to all market participants, although markets can still be efficient if a significant number of investors have access to available information
- All investors agree on the impact of information on current price and distributions of future price for each security. Having said that, markets can still be efficient as long as there isn't a set of investors who can create better evaluations of the available information relative to what might be represented in market prices

Based on the conditions set in terms of equilibrium and functioning of an efficient market by Fama (1970), all asset prices represent all available information implying that the expected return on an any risky asset within the economy, is a compensation to investors for exposing themselves to the risk associated with that asset. From this, it would follow that any factor-based premiums that do exist within the market, would just be a compensation paid to investors for exposing them to a higher risk. If premiums do exist without a corresponding rise in risk, then this would contradict the efficient market hypothesis.

In chapter 4, we look to test out the Efficient Market hypothesis by assessing if excess returns related to size, value, profitability, investment, and momentum premiums within the US REIT market are associated with a higher risk. As our risk indicators, we use standard deviation, beta from the CAPM model, factor loadings from the Fama-French three factor and five factor models, along with using risk adjusted performance measures such as the Sharpe and Treynor ratios. As a robustness measure, the research also analyses the factor loadings from the Carhart four factor model. If our results contradict the Efficient Market Hypothesis, then this could also potentially suggest exclusion of relevant risk factors, that might be priced into these premiums, but are excluded from traditional asset pricing models. For this purpose, chapter four then looks to test out the impact of liquidity risk, and default risk (or financial distress) within the economy, on these factor-based premiums in the US REIT market. In this case, a fall in factor-based premiums, corresponding with a rise in liquidity risk and default risk, would provide evidence against the Efficient Market Hypothesis of information being fully reflected in asset prices, along with contradicting the risk-based explanation of Fama (1970).

2.5.2 The CAPM Model

The Capital Asset Pricing Model (CAPM) was developed by William Sharpe, Jack Treynor, John Lintner and Jan Mossin in the early 1960s, as one of the first framework mechanisms designed to gauge expected returns on an investment, as a function of the risk association of that investment. The CAPM model distinguishes between diversifiable and undiversifiable risk, stating that risk that can be diversified away when held with other investments in a portfolio is not relevant in defining expected returns. Therefore, based on the CAPM, systematic risk is the only relevant factor in asset pricing (Ooi, Webb and Zhou, 2007). Systematic risk which is also referred to as undiversifiable risk or market risk, impacts the whole market, and therefore cannot be diversified against. The CAPM is therefore a univariate model which says that expected returns on an asset or a portfolio is only depend on the market risk associated with that portfolio or asset.

$$R_i - R_f = a_i + b_i(R_m - R_f) + e_i \qquad (2.17)$$

Where R_i is the expected return on an investment i, R_f is the risk free rate usually proxied using the treasury bill rate, R_m is the return on the market portfolio and is usually proxied using a stock market index, when using the CAPM to gauge the expected return on a stock or a portfolio of stocks. Beta represents the systematic risk or market risk associated with an investment. A beta of less than 1 means the investment 'moves slower' than the market, while a beta greater than 1 would imply that the investment moves faster than the market. The market portfolio has a beta of 1 while the beta of the risk free asset is 0. Expected returns on an investment are therefore a positive function of the market risk associated with that investment, and therefore a higher expected return can be seen as a compensation for exposing investors to a higher risk.

The left hand side in 2.9 is referred to as the risk premium on investment i. This is the excess return on i, over and above the risk free rate, that investors should expect to reap from investment i, as a compensation for exposing them to a higher risk relative to the risk free asset. From this we can gauge that "financial premiums" are excess returns for an investor, over and above a benchmark, which the investor should expect to receive, for exposing themselves to a higher risk relative to the benchmark investment.

2.5.3 The Fame-French Three-Factor Model

Fama and French (1992) contest the significance of beta as the sole risk factor in explaining the cross-sectional variation in the return on common stocks over time, and add that a multi-factor model works better in explaining expected asset returns. They argue that small stocks are riskier than big stocks, while value stocks are fundamentally riskier than growth stocks. Empirically they find that, value stocks, in terms of average returns, seem to outperform growth stocks, while small stocks tend to have a higher average return relative to big stocks. Fama and French label the excess returns on value stocks relative to growth stocks as HML (high minus low), while they label the excess returns on small stocks relative to big stocks as

SMB (small minus big). Fama and French conclude that the superior returns on small/value stocks relative to big/growth stocks is a compensation for exposing investors to a higher risk.

Fama and French (1992) add size and book-to-market factors to the existing market factor within the Sharpe-Linter's CAPM model, and show that these capture much of the average stock returns, concluding that these two additional factors must proxy for common risk factors in returns:

$$R_i - R_f = a_i + b_i(R_m - R_f) + s_iSMB + h_iHML + e_i \quad (2.18)$$

Where R_i is the expected return on an investment i, R_f is the risk free rate usually proxied using the treasury bill rate, Rm is the return on the market portfolio and is usually proxied using a stock market index, a_i is the average excess return on the portfolio after adjusting for the known risk factors, SMB (small minus big), HML (high minus low)

Expected returns on an investment then is not only a function of that investment's sensitivity to the market risk premium, but also its sensitivity to the size premium and the value premium. For the construction of the size factor, at the end of June, stocks are divided into five equal quintiles based on their market capitalisation. The difference in returns between the small size and big size portfolios gives us the SMB factor. For our second factor, book-to-market ratio (B/M) is used as a sorting criterion to construct five different portfolios at the end of June each year. Book equity at the end of the fiscal year ending in year t − 1, and market cap at the end of December of year t − 1, is used to rank stocks for portfolio construction from July of year t to June of year t + 1. The stocks with negative book value are omitted from the portfolio construction. The difference in returns between the high B/M (value) and low B/M (growth) portfolios gives us the HML factor.

2.5.4 Fama and French Five-Factor Model

The dividend discount model defines the share price at time t (m_t), as a function of the expected dividend per share [$E(d_{t+\tau})$] and the internal rate of return on expected dividends (r)

$m_t = \sum_{\tau=1}^{\infty} E(d_{t+\tau})/(1+r)^{\tau}$ (2.19)

Miller and Modigliani (1961) extract the implications in equation 2.11 to construct a relationship between expected return, and expected profitability, expected investment and book-to-market (B/M):

$M_t = \sum_{\tau=1}^{\infty} E(Y_{t+\tau} - dB_{t+\tau})/(1+r)^{\tau}$ (2.20)

Where $Y_{t+\tau}$ is the total earnings for period t+τ and $dB_{t+\tau} = B_{t+\tau} - B_{t+\tau-1}$ is the change in total book equity. Dividing by book equity gives:

$M_t/B_t = [\sum_{\tau=1}^{\infty} E(Y_{t+\tau} - dB_{t+\tau})/(1+r)^{\tau}]/ B_t$ (2.21)

From equation 2.13, we can gauge three things about expected returns. Firstly, fixing everything in 2.13 apart from the current stock value M_t and the expected stock return, r. Then a lower value for M_t, equivalently a higher value for B/M, implies higher expected return. Secondly, fixing everything in 2.13 apart from expected future earnings and expected future returns. Then, higher expected earnings imply a higher expected return. Lastly, for fixed values of B_t, M_t and expected earnings, higher expected growth in book equity (investment) implies a lower expected return. Using the final two derivations, Fama and French (2015) add two further factors to their three-factor model of defining expected returns, namely, profitability and investment. RMW (robust minus weak) is the difference between average returns on stocks with robust profitability and weak profitability. While the CMA (conservative minus aggressive) factor is the difference between average returns on stocks with low and high investment:

$R_i - R_f = a_i + b_i(R_m - R_f) + s_iSMB + h_iHML + r_iRMW + c_iCMA + e_i$ (2.22)

Where R_i is the expected return on an investment i, R_f is the risk free rate usually proxied using the treasury bill rate, R_m is the return on the market portfolio and is usually proxied using a stock market index, a_i is the average excess return on the portfolio after adjusting for the known risk factors, SMB (small minus big), HML (high minus low), RMW (robust minus weak), CMA (conservative minus aggressive).

This transition from the three-factor to the five-factor model is also justified empirically by studies such as Titman et al. (2004), and Novy-Marx (2013), who conclude that the Fama–French three factor model is an incomplete model in explaining expected stock returns. Although both new factors, RMW and CMA, derive nicely from the dividend discount model, their economic interpretation is not very clear. The risk based interpretation for RMW would imply that firms that have been profitable historically, carry a higher risk, and therefore offer premiums to investors as compensation for exposing them to a higher risk. But why should a more profitable firm be risker and therefore provide extra compensation to investors?

Ali and Ülkü (2019) claim that the RMW factor seems to combine value with earnings momentum, thus capturing a 'neglected value' effect. Ülkü (2017) look to test whether the RMW factor captures a rationally-priced risk or behavioral mispricing. If the RMW factor does represent mispricing, then it should have a strong, consistent and significant weekend effect, where returns on the RMW portfolio are stronger during the beginning of the week. This could potentially be driven by an under-reaction on the part of investors, to earnings information due to the Uncertain Information Hypothesis (Brown et al. 1988). This private information accumulation will result in abnormal returns on the RMW portfolio, and this accumulation is generally larger during the weekend (Foster and Viswanathan 1990). These abnormal returns could also be down to the behavior of institutional investors who tend to trade on the wrong side during the creation of value-type anomalies, and contribute to mispricing away from value via noise trading through the week (Edelen et al. 2016). It would then take a weekend of 'sound mind' to recognize value. Ülkü (2017) conclude that this Monday effect on RMW premiums is significant and strengthens overtime, confirming the role of behavioural mispricing within RMW portfolios, and provides further support for the 'sound mind' effect explanation.

Empirically, there are very few studies that have explored the effectiveness of RMW and CMA factors on expected returns, and these have been conducted on general stocks rather than REITs. However, Glascock and Lu-Andrews (2014) show that a profitability factor based on gross profit or net operating income has significant predictive power on REIT returns. Bond and Xue (2016) construct investment and profitability factors, and show that both display significant predictive power for REIT returns.

2.5.5 Carhart's Momentum Factor

Carhart (1997) extends on the Fama–French three factor model by adding a fourth factor called momentum, to explain cross-section of stock returns. The WML (winners minus losers) factor is computed using historical returns.

$$R_i - R_f = a_i + b_i(R_m - R_f) + s_i SMB + h_i HML + w_I WML + e_i \qquad (2.23)$$

Where R_i is the expected return on an investment i, R_f is the risk free rate usually proxied using the treasury bill rate, R_m is the return on the market portfolio and is usually proxied using a stock market index, a_i is the average excess return on the portfolio after adjusting for the known risk factors, SMB (small minus big), HML (high minus low), and WML (winners minus losers).

Although significant amount of research has been conducted on assessing the predictive power of the WML factor on expected returns within general stocks, with regards to REITs, the amount of research is still quite limited. Hung and Glascock (2008), and Goebel et al. (2012) show that the momentum factor is significant in explaining the cross-section of REIT returns. They also conclude that the momentum factor is more prevalent in the real estate market rather than in the equity market. Chui et al. (2003) test the predictive power of momentum, size, value and turnover on REIT returns, over two sub-samples, pre- and post-1990. They find evidence that momentum, size and value effects are significant pre-1990, while only the momentum factor is significant in defining expected REIT returns post-1990.

Similar to the RMW factor, the economic interpretation for the momentum factor is still unclear: why should a firm which has had consistently higher returns in the past be riskier and offer extra compensation for risk? Carhart (1997) state that they leave the risk interpretation of their momentum factor to the reader. Johnson (2002), and Liu and Zhang (2008) conclude that the expected growth risk increases with expected growth, supporting the argument that the momentum factor within asset pricing does represent an element of systematic risk that investors might be exposed to. On the other hand, Jegadeesh and Titman (1993) do not find any evidence that excess returns on a momentum based strategy is associated to their systematic risk. They interpret the momentum premium as excess returns generated due to investor behavior and an under-reaction from the market to information.

2.5.6 Style based investment strategies

Investors have consistently used style based investment strategies in the stock market to potentially earn higher returns or reap the rewards of risk premia (Said and Giouvris 2017). Each risk factor such as size, value, profitability, investment and momentum, drives a specific risk premium. By going long on assets with positive factor exposure, and shorting assets with negative factor exposure, investors capture the premium associated to these factors (Idzorek and Kowara 2013). The merits of factor-based investment strategies, specifically from a size, value and momentum perspective, comes from empirical evidence mainly within the stock market. The results of these have been varying, not only in terms of the existence of these premiums, but also the risk associated to them (Eun et al. 2010). Furthermore, profitability and investment factors have not yet been extensively researched in terms of their usefulness as investment styles and their ability to generate excess returns, along with their interpretation from a risk compensation perspective. Owing to these gaps in literature, this thesis looks to examine the presence, magnitude and significance of SMB, HML, RMW, CMA and WML premiums within the US REIT market, using daily returns data from July 2001 to June 2020, and constructing long and short portfolios based on these factors.

2.6 Herding

2.6.1 Herding and its significance

Market imperfections such as limits to arbitrage and investors' behavioural biases can lead to irrational market conditions and mispricing within assets. One such feature of market imperfection is herding, which Zhou and Anderson (2011) define as behavioural tendency of investors to follow the action of others rather than their own beliefs and private information. Nofsinger and Sias (1999) define herding as trading in the same direction by a group of investors, over a certain period of time.

Herding could drive asset prices away from fundamental value, potentially creating beneficial trading opportunities for investors. Furthermore, herding could potentially result in co-movement within asset prices via synchronized trades in the same direction, and hence could impact investors' ability to curb risk via diversification (Chiang and Zheng, 2010; Morelli, 2010). Therefore, herd behaviour is of importance to practitioners. For academics, movement of asset prices away from fundamental value contradicts traditional asset pricing models and has theoretical implications (Christie and Huang, 1995). Herding behavior also carries significant importance for policymakers, as during economic downturns, herding behavior could result in exaggerated negative shocks, with investors' trading in the same direction, and this could in-turn pose significant risks to financial stability (Shin, 2010).

2.6.2 Theoretical Model for Herd Behaviour

Keynes (1936) suggested that investors in asset markets are highly influenced by decisions made by previous decision makers, in taking their own decisions. This is backed by the rationale that previous decision makers might have information that current decision makers might not possess but might be important in optimised decision making. Following this, Banerjee (1992) set up a theoretical model to show that individuals looking to maximise their payoffs via investments within asset markets, could optimise their positions by exhibiting "herd behaviour".

Banerjee (1992) define herd behaviour as individuals or entities doing what other individuals and entities are doing, even when their private information may suggest otherwise. Through their theoretical model, they look to study the rationale and implications of such actions. Furthermore, they stress on the significance of the actions of the first mover, since the actions of the first mover could potentially drive herding as a domino effect for other decision makers that follow. They also stress on the significance of the second decision maker, as someone who might ignore their private information and join the herd, inflicting a negative externality on the rest of the population. If the second decision maker had followed their own private information, this would act as a signal to the rest of the population to also follow their own information. Ignoring their own private information from the second mover would result in the entire population following the herd. From an empirical perspective, such herd behaviour could potentially result in significant, deep-rooted and sustained downturns within markets, along with heightened levels of volatility, and hence society might be better off from a welfare perspective if some of the early decision makers were constraint in using only their private information.

Based on the model, any nth investor has a choice of either investing in any one asset or no asset at all. The physical return on the ith asset is given by z(i). There is a unique asset i* such that z(i) = 0 for all i ≠ i* and z(i*) = z, where z > 0. This implies that excess returns on one asset is strictly greater than returns on all other assets. Given this returns structure, all investors would want to invest in i*, but no one knows which asset is i*. There is a probability α that each investor receives a signal telling them that the true i* is i'. But there is no guarantee that the signal is true.

Decision making in this model is sequential, implying that one person is chosen at random to make their decision first. Then the second person (also chosen at random) makes their decision, but they can observe the decision made by the first person and the information contained within their decision. What the second person is not allowed to find out is if the person before them actually got a signal. The game then carries on with the same rules. The idea of the game is to develop a Nash Equilibrium and in-turn the optimal strategy for the players. The game lays down a few assumptions, and to ensure this theoretical model is prudent, there are a set of assumptions laid out which minimise the possibility of herding:

Assumption 1: If the current decision maker has no signal, and all the prior players have chosen $i = 0$, then the current player will always choose $i = 0$ as well.

Assumption 2: If a decision maker receives a signal, and if they are indifferent between choosing their signal or someone else's choice made prior to them, they will always follow their signal.

Assumption 3: When a decision maker is indifferent towards following the different decisions made prior to them, they choose the decision that has the highest value of i.

Assumption 4: The probability that two people should both get the same signal and still be wrong is zero

At the start of the game, the first decision maker either receives a signal or they don't. If they receive a signal, they follow it, while if they do not receive a signal, based on assumption 1, they choose $i = 0$. Now the second decision maker makes their choice. If they receive no signal, they invest in the same asset as the first player. If the second player does receive a signal, and the first player chose $i = 0$, then the second player will follow their signal. If, however the second player does receive a signal and the first player has not chosen $i = 0$, then the second player knows that the first player received a signal as well, and this signal is as likely to be correct as their own signal. In this scenario, assumption 2 comes into play, and therefore the second player follows their own signal.

For the third player, there are two possibilities in terms of receiving or not receiving a signal. If they do not receive a signal;

- If both their predecessors have chosen $i = 0$, then the third player will also choose $i = 0$.
- If only one of their predecessors have not have chosen $i = 0$, then the third player should follow the preceding player who did not choose $i = 0$.
- If both the preceding players have chosen $i \neq 0$, and have agreed with each other in terms of the choice of asset, then the third player should follow them both

- If both the preceding players have chosen i ≠ 0, and have not agreed with each other in terms of the choice of asset, then based on assumption 3, the third player should follow the decision of the player with the highest i.

If the third player did receive a signal i';

- When both preceding players have chosen i = o, the third player will follow their own signal.
- When only one of the preceding players has chosen something different from i = o or i = i', and the other player has chosen i = 0, then the third player will follow their own signal.
- When the third player's signal matches the choices made by one or both of the preceding players, then the third player will always follow their signal, since based on assumption 4, this has to be the correct signal.
- If both players prior to the third player have chosen the same option, and this option is neither i = 0 or i = i', then the third player will ignore their signal and choose the option chosen by the prior players. Although this player has no guarantee that the second player would have received a signal, but the fact that both the first and second player chose the same option, would result in the third player no longer being indifferent between choosing their own signal and the choice made by the players prior to them. This is because there is now less of a likelihood that their signal is correct relative to the ones received by preceding players.

Elaborating on this last point provides us with how it might be a rationale choice of optimising individuals to follow the herd. The third player knows that if the first player picked any option other than i =0, then they must have received a signal. If the third player receives a signal as well (which might be different to the first player), then this is only as good as the first person's signal. If the second player mirrors the first player's choice, then this adds more credibility to the first player's signal being right rather than wrong. In this case, the rationale choice for optimising expected payoffs for the third player would always be to follow the first player, and therefore follow the herd.

This strategy can then be generalised to further decision makers lower down in the chronological order of decision making. For example, if several players have chosen options other than $i = 0$, but only one of them has been chosen by two people. If the next player has a signal that does not match any of the options already chosen, then they should always choose the option that has been chosen by two people. From this one can also deduce that, once an option has been chosen by two people, a player should always follow that option, unless their signal matches one of the options that has already been chosen, in which case, they should follow their own signal.

The theory therefore rationalises when signal receiving individuals would find herding behaviour as optimal, i.e. ignoring their own private signal and following the herd. This can be summarised as; If a player's signal does not match any of the choices that have been made prior, and at least two people have invested in the same asset i, they should ignore their signal and follow the herd, in order to optimise their expected payoffs.

Based on the theoretical implications that it might be the rationale choice in terms of optimising payoffs for individuals to herd, within chapter 5, we use daily data to establish if herding is significant within US REITs on a sub-sector. We then add to this, and look to assess if herding effects are more pronounced on days with negative market returns relative to days with positive market returns. From a more macro perspective, Banerjee (1992) add that herding can result in sustained downturns within markets, along with heightened levels of volatility, which provides further motivation for us to study this phenomenon within up and down markets, and within recessionary and non-recessionary phases. Furthermore, using the VIX index as a gauge of investor sentiments, we look to test if investor sentiments have an impact on herding behaviour.

Driven by the theoretical model of Amihud and Mendelson (1986) which signifies the importance of liquidity within asset pricing, and following the theoretical claim made by Banerjee (1992) that herding as a phenomenon might not only be a rationale choice to optimise payoffs for individuals, but could also sway asset prices, we look to empirically assess the impact of expected and unexpected market/sector-wide illiquidity shocks on herding within

US REITs, on a sub-sector level. Since both herding and illiquidity shocks tend to impact asset prices, we see merit in empirically testing out the impact of these illiquidity shocks on herding.

2.6.3 Herding in Financial Markets

2.6.3.1 Institutional Herding

Results of empirical studies on institutional herding within financial markets have been mixed, with some studies finding evidence against institutional herding. Lakonishok et al. (1992) use data on 769 funds in the US, and they find no significant evidence of herding within pension fund managers, although they do find evidence of herding within smaller stocks. These results are complimented by Wermers (1999) who find little evidence of herding by US mutual funds, but once again they do find evidence of herding within small stocks. Wylie (2005) only find significant evidence of UK fund manager herding for individual stocks with extreme market capitalisation, finding no significant evidence of herding within other stocks. Grinbatt, Titman and Wermers (1995) study momentum based trading strategies and herding behaviour within mutual funds in the US. They find significant evidence of momentum strategies being used by these funds i.e. buying past winners, but they find very little evidence of these funds exhibiting herding behaviour, concluding that there was no significant evidence of these funds buying and selling the same stocks at the same time.

Other studies find evidence in support of institutional herding within financial markets. Choi and Sias (2009) find significant evidence of institutional herding within US industries, concluding that the cross-correlation of institutional investors buying holdings in a particular industry one quarter, and the fraction buying the same industry holdings in the previous quarter, was on average, 39 percent. Kim and Nofsinger (2005) find lower levels of institutional in Japan relative to the US, concluding that herding is dependent on economic conditions and the regulatory environment. Gutierrez and Kelley (2009) find evidence of institutional herding within US stocks, and identify that buy-side institutional herding may have more of a permanent effect than sell-side institutional herding. They rationalise this by concluding that buying decisions are usually backed by information about fundamental stock values, while selling decisions may only be driven by liquidity needs. Using a data set that runs from 1980 to 2005, they conclude that buy herds contribute to the destabilisation of prices, while sell herds results in price stabilisation. Walter and Weber (2006) find evidence of herding by German mutual funds managers, mostly as a consequence of change within the composition of a benchmark index.

Voronkova and Bohl (2005) examine the behaviour of Polish pension fund managers, and conclude that fund managers in evolving markets portray a relatively stronger herding behaviour relative to fund managers in more mature markets. Chang (2010) study the behaviour of foreign institutional investors in emerging markets, and find that when they increase or decrease their holdings within particular industries, mutual funds follow the same investment decisions, in current and subsequent periods. They also claim that this herd behaviour is significant in destabilising asset prices in the short run. Bowe and Domuta (2004) find significant evidence of herding by foreign and domestic investors in the Jakarta Stock Exchange during and after the 1997 Asian crisis. They do find asymmetry in the behaviour of these two classes of investors, finding significant evidence of herding being more intense for foreign investors relative to local investors, after the crisis. Consistent with these results, Choea et al. (1999) find significant evidence of herding by foreign investors in Korea between 1996 and 1997.

2.6.3.2 Aggregate market-wide herding

Literature on market-wide herding has also provided mixed results, with the presence and intensity of herding behaviour being dependent on the time-frame under investigation i.e. recessionary/non-recessionary phases and up/down markets, and industries under question. Chang et. al (2000) find evidence of market-wide herding in Japan, South Korea and Taiwan, and conclude that this is related to news about macroeconomic fundamentals rather than firm specific information. They do not find any evidence of herding in the US and Hong Kong. Gleason et al. (2004) conduct research on structured Exchange Traded Funds (ETFs) in the US. They find no significant evidence of herding during extreme up or down movement within this market. Using daily data from 1998 to 2008, and the CSAD approach, Economou et al. (2011) find significant evidence of herding in the Portuguese, Spanish, Italian and Greek markets, concluding that this herding becomes more intense during the 2007-2008 financial crisis. Johansen and Sornette (1999) study the impact of herding on the creation of asset bubbles. By using data on the Nikkei stock index, they conclude that herding is not only significant in the creation of asset bubbles, but also in the bursting of these bubbles. Consistent with these findings, Shiller (2007) investigated the housing market boom, and claim that the creation of a bubble is down to an optimistic view that prices will increase eternally. These biased believes spread through society, to a point where agents are prepared to ignore their private signals and information, and follow the actions of others.

Although Litimi et al. (2016) find a lack of evidence for herding overall in US stocks, they do find significant evidence of herding on an industry level, especially during the global financial crisis. Chiang and Zheng (2010) investigate herding in 18 different global stocks markets. They find significant evidence of herding in both up and down markets in advanced stocks markets (apart from the US) and in the Asian markets. In the Latin American markets and US, they only find significant evidence of herding during crisis period. Mobarek, Mollah and Keasey (2014) study herding within various European stock markets from 2001 to 2012. Although they find herding effects to be insignificant for the entire sample, they do find significant evidence of herding during the crisis periods. Specifically, they conclude that herding is more intense in most continental countries during the global financial crisis, and in Nordic countries during the Eurozone crisis. Furthermore, they explore the idea of herding spill overs and conclude that Germany has the greatest impact on regional cross-country herding. Using a data set that runs from 2003 to 2011, Messis and Zapranis (2014) find evidence of herding in five developed markets, namely, France, Germany, UK, USA and China. Moreover, they find evidence that unexpected shifts in macroeconomic variables results in the emergence of herding. Their results also confirm the fact that herding becomes more intense during crises periods and during bearish economic conditions.

Zhou and Lai (2009) study stock's in Hong Kong, and claim that the size factor plays a role in herding activity. They conclude that herding is more prevalent in small stocks, along with identifying an asymmetry that investors are more likely to herd when selling rather than buying stocks. Past literature has also provided mixed results for market-wide herding in

Chinese stock markets. Demirer and Kutan (2008) investigate the idea of investors either following their own private information or the market consensus when making investment decisions during periods of market stress, and find no significant evidence of herding. On the other hand, Tan et al. (2008) use a data set that runs from 1994 to 2003, and find significant evidence of herding in Chinese stocks during both up and down markets.

Chapter 3: Oil Price, Oil Price Implied Volatility (OVX) and Illiquidity Premiums in the US: (A)symmetry and the Impact of Macroeconomic Factors

3.1 Abstract

This chapter examines the impact of oil price and oil price volatility on US illiquidity premiums (return on illiquid-minus-liquid stocks), using the US Oil Fund options implied volatility OVX index. We use daily data from 2007 to 2018, taking into account the structural break in June 2009 and controlling for macroeconomic factors. Both OLS and VAR models indicate that oil price has a significantly positive impact and OVX has a significantly negative impact on premiums, for the full sample and post-crisis period. These relationships are potentially driven by investor sentiments and market liquidity. Oil price has a negative impact on premiums during the crisis period. Using an autoregressive distribution lag model and an error correction model, we analyse long- and short-run elasticities. We find that oil price has a significantly positive impact on premiums both in the long- and short-run, for the full sample and post-crisis period. OVX only has a significantly negative impact in the short-run for the full sample. The reverting mechanism to establish long-run equilibrium is effective for the full sample and post-crisis period. Illiquidity premiums do not show any asymmetric responses to oil price changes but we do find evidence of asymmetric response to OVX changes.

3.2 Introduction

Oil as a resource has a significant role in the world economy, hence there has been large amounts of research done to capture the impact of oil price on economic and financial activity. Even in the presence of such extensive research, the relationship between oil price movements and the stock market is still unclear. On the one hand, higher oil prices can hike up the cost of production for firms, impact their local and overseas market sales via lower domestic consumption budgets and a fall in competitiveness, and hence have a negative impact on stock markets (Hondroyiannis and Papapetrou 2001; Driesprong, Jacobsen and Maat 2007; Miller and Ratti 2009; Chen 2010; Cunado and Perez de Gracia 2014). On the other hand, higher oil prices can boost earnings of energy firms which can then spiral down to the overall economy and increase wages, consumer budgets, demand, investment and positively affect the stock market (Mohanty et al. 2011; Güntner 2014; Tsai 2015; Foroni et al. 2017).

This paper looks to extend on the study of the relationship between oil prices and financial markets by looking at potential influences on illiquidity premiums within the NYSE. This relationship is yet to be explored within academic research and therefore makes this paper unique. An ever-expanding asset universe available to investors, greater funding access (Rajan 2006) and the general uptick within availability of information, have all resulted in a rise in the prominence of illiquidity within research and also of illiquidity as an investment style. In addition to these factors, more focus has also been put on illiquidity and liquidity risk as it was a major source for the financial crisis (Brunnermeier 2009; Crotty 2009). The turmoil impacted investor sentiments resulting in a 'flight-to-safety' with regards to their investments, along with skewing central bank policies towards easing monetary conditions with the idea of injecting liquidity within markets. Therefore, an improved liquidity condition can contribute to financial development and economic growth (Bekaert et al. 2007). Furthermore, Acharya and Pedersen (2005) discussed the idea that liquidity is not only risky but also has commonality. This would imply that liquidity has far reaching consequences in terms of its impact on the whole financial system.

Owing to the significance of liquidity as a contributor towards financial and economic progress, and its importance as an investment style, extensive research has been conducted on the hypothesis that returns rise with illiquidity. Although some research such as Amihud and Mendelson (1986), Brennan and Subrahmanyam (1996), Pástor and Stambaugh (2003), Acharya and Pedersen (2005), Li et al. (2011), Amihud et al. (2015), Said and Giouvris (2017a) concluded that returns do rise with illiquidity, others such as Huang (2003), Lo et al. (2004), Novy-Marx (2004), Ben-Rephael et al. (2015), Ang et al. (2013) argued that there is no evidence that the return differential between illiquid and liquid stocks is significantly positive. These are discussed in greater detail within our next section.

We believe that because of this contradictory evidence regarding the existence of illiquidity premiums, it is a subject worth looking into further. Therefore, this paper looks to test the presence and significance of illiquidity premiums for stocks relating to a diverse range of industries within the NYSE. We use the Amihud illiquidity measure (Amihud, 2002) to divide stocks into five equally weighted monthly portfolios. The return differential between the most illiquid and least illiquid portfolios is then defined as the illiquidity premium.

Since oil is such a significant component of domestic goods and services, we believe it is essential to study the impact its price and volatility has on illiquidity premiums, which, according to Said and Giouvris (2017b) as an investment style meet the four criteria of Sharpe (1992) benchmark portfolio requirements namely (1) 'identifiable before fact', (2) 'not easily beaten', (3) 'a viable alternative', and (4) 'low in cost'. This is a relationship which so far has not been explored within academic research. Studying this relationship is even more relevant during a crisis/post-crisis scenario where central banks are opting for expansive monetary policies to inject more liquidity into the market. Theoretically, this uptick in liquidity should make investors more inclined towards illiquid stocks (Jensen and Moorman 2010; Said and Giouvris 2017a), hiking up the prices for these stocks and thus enhancing realised illiquidity premiums.

Owing to the fact that there are no studies currently that link illiquidity premiums to oil price and oil price volatility, we decipher past literature and consider it relevant for our study using the following rationale. First, we explore the literature on the existence of illiquidity premiums and the idea that returns rise with illiquidity. Second, we include a study if it incorporates the impact of oil price and oil price volatility on stock market movements. Since the stock market includes both liquid and illiquid stocks, studying the general impact of oil price and oil price volatility on all stocks is crucial. This study will then extend on this idea and analyse the impact on illiquidity premiums. Third, we include a study within our literature if it analyses the effect of oil price and oil price volatility on cost of financing and perceived risk of holding securities. Fernández-Amador et al. (2013) proposed that stocks are expected to be more liquid if investors can cheaply finance their holdings and perceive low risk of holding securities. If oil price and oil price volatility impact both the cost of financing and risk of holding an asset, then it will follow that oil price and oil price volatility should impact stock market liquidity, which in turn should affect illiquidity premiums (Jensen and Moorman 2010; Said and Giouvris 2017a).

We construct illiquidity portfolios for the full sample and find evidence that illiquidity premiums are both positive and significant. We then set up an OLS model to establish the significance and direction of the impact of oil price, oil price volatility, S&P500 index, exchange rate, inflation, industrial production index, federal funds rate and discount rate within a month, on illiquidity premiums. We find that illiquidity premiums are negatively influenced by oil price volatility and are positively influenced by oil prices in the United States. We then test for co-integration, and once we establish a long run relationship between all our variables, we include them as endogenous variables within a VAR model. Earlier studies, such as Diaz et al. (2016) studied the impact of oil price volatility and macroeconomic factors on stock returns using a VAR model and include oil price volatility as an exogenous variable. Reverse causality between our macroeconomic factors (specifically exchange rate) and oil price/oil volatility further justifies including all of these variables as endogenous. The results of the VAR model are then used to estimate impulse response functions that allow us to identify the impact of oil price and oil price volatility on illiquidity premiums. Consistent with our OLS results, we find that oil price generally has a positive impact while oil price volatility has a negative impact, on illiquidity premiums. Given the results of our OLS and VAR models, we look to formalise the significance and the direction of the influence of current and lagged values of oil price, oil volatility and macroeconomic variables on illiquidity premiums. We adopt the autoregressive distributed lag (ARDL) bounds test developed by Pesaran et al. (2001) to establish co-integration and long-run relationships between our variables. This approach can be used even when the variable series are a mix of I(0) and I(1), overcoming the problems that may result from uncertainties of unit root test results. Furthermore, the bounds test can readily be adjusted to address the potential problem of endogeneity in explanatory variables. The approach also assists us in simultaneously estimating the long-run and short-run impact of oil price, oil volatility, macroeconomic factors on illiquidity premiums, using an ARDL long-run model and an error correction model (ECM). The ECM also indicates if a reverting mechanism to establish the long-run equilibrium relationship between our variables is effective. Our long-run results suggest that oil price has a positive impact on illiquidity premiums but the direction of this influence changes for lagged oil price. In the short-run, illiquidity premiums are positively influenced by oil price and negatively influenced by oil price volatility. Furthermore, the reverting mechanism for sustaining the co-integration relationship between our explanatory variables and illiquidity premiums is extremely relevant.

The results indicate that a rise in oil price volatility enhances the perceived risk of holding illiquid assets, decreasing investors' demand for illiquid securities and negatively impacting stock market liquidity (Goyenko and Ukhov 2009; Qadan and Nama 2018), therefore reducing realised illiquidity premiums. On the other hand, a rise in oil price could be seen by investors as a sign of future bullish economic times (Güntner 2014; Foroni et al. 2017), reducing their perceived aversion towards riskier illiquid instruments and therefore enhancing realised illiquidity premiums. The results signify the importance of both oil price and oil volatility when analysing illiquidity premiums. Furthermore, we use our OLS model to investigate the possible asymmetric impact of oil prices and oil volatility changes within a current month, on illiquidity premiums by using a methodology similar to Mork (1989), Park and Ratti (2008) and, Dupoyet and Shank (2018). Our results show that both oil prices and oil volatility fluctuations do not have any type of asymmetric effect on illiquidity premiums within the United States. To consolidate these findings and to explore any potential impact of current and lagged variables in the short-run, we explore asymmetry using our error correction model. Lagged values of oil price and oil volatility do not show an asymmetric impact on illiquidity premiums. We do find asymmetry within current values of oil volatility indicating that within the short-run, illiquidity premiums do not react to an increase in oil price volatility in the same way that they react to a decrease in it.

Between December 2007 and June 2009, which is a period that has been defined as a crisis by NBER in the United States, volatility within oil prices spiked substantially. Oil prices rose from $96 in December 2007 and peaked at $147.30 in July 2008. This was followed by a steep decline, reaching a low of $32 in December 2008. To capture this structural shift and its impact on illiquidity premiums, we split our sample into two sub-samples; December 2007 to June

2009 which is classified as the financial crisis period, and July 2009 to December 2018 which is classified as the post-crisis period. The ARDL bounds test can be applied to studies with a small sample size (Fang et al. 2016), whereas, the Johansen (1988) approach is not suitable for small sample sizes (Mah 2000). Therefore, using the bounds test approach fits our study perfectly in terms of assessing a co-integration relationship, especially within the recession period.

We construct illiquidity portfolios within both our sub-samples in order to identify and test the existence and significance of illiquidity premiums in a recessionary and post-recessionary phase. We then use the OLS model to identify the direction and magnitude of the relationships between oil price, oil price volatility and our examined macroeconomic variables within a current month, on illiquidity premiums in the current month, for both the recession and post-recession period. After this, we set up a VAR model, identifying all the variables as endogenous. We look to gauge the impact on illiquidity premiums of optimal lagged values of oil price, oil implied volatility, S&P 500 index, exchange rate, inflation, industrial production index, federal funds rate, discount rate and lagged values of illiquidity premiums, during and after the financial crisis. Next, we look to formalize the impact these variables have within a current month and in their optimal lagged form, on illiquidity premiums. For this reason, we set up an ARDL model to identify and test the long-run direction and significance of the relationship between illiquidity premiums and, the current and optimal lagged values of oil price, oil implied volatility, S&P 500 index, exchange rate, inflation, industrial production index, federal funds rate, discount rate, along with lagged values of illiquidity premiums. We conduct this for both our recession and post-recession sub-samples. Lastly, we set up an error correction model (ECM) to identify and test the short-run direction and significance of these relationships within both the recession and post-recession sub-samples. The ECM also provides us with the strength and significance of the reverting mechanism to establish long-run equilibrium, within both the recession and post-recession phase.

We find that illiquidity premiums are positive and significant during both the recession and post-recession sub-samples. The OLS results suggest that illiquidity premiums have a significantly positive relationship with oil price and a significantly negative relationship with

OVX, in the post-crisis period. During the crisis phase, illiquidity premiums are negatively impacted by oil price and the influence of OVX is insignificant. The impulse response functions from our VAR model provide results consistent with the OLS findings within the post-crisis period, as illiquidity premiums have a positive relationship with oil prices and a negative relationship with OVX. During the crisis period, the sensitivity of illiquidity premiums towards oil price and OVX dampens down significantly, but we do find a negative relationship between illiquidity premiums and both of these variables. For the post-crisis period, both the ARDL long-run model and the ECM short-run model show a positive relationship between illiquidity premiums and current oil price. The influence of OVX is only significant in a lagged setting within the short run. The reverting mechanism to establish long-run equilibrium is also significant and effective within this phase. Within the crisis period, both the long-run ARDL model and the short-run ECM model suggest that illiquidity premiums are not significantly influenced by either oil price or OVX.

This paper is unique relative to previous studies in several ways. First, in recognition of oil being a significant component of any economy in terms of production of goods and services, it is essential to consider the impact its price volatility has on financial markets not just in a realized historical way but in a forward-looking manner. Our research incorporates for that by using the forward-looking OVX implied volatility index instead of a realized historical measure of oil price volatility. Second, we are the first to examine the impact of oil price and oil price volatility on illiquidity premiums in the equity market, using a methodology for stock inclusion and creation of zero-cost (illiquid–liquid) portfolios. Although substantial research has been conducted on studying the relationship between oil price and stock returns along with a limited amount of research on stock returns and oil price volatility, to the best of our knowledge, no research has been conducted on the influence of these two variables on illiquidity premiums. Third, although some research exists on the impact of monetary policy on illiquidity premiums, our research includes macroeconomic factors such as exchange rates and industrial production index (to gauge economic activity) which are factors whose relationship has not yet been studied with illiquidity premiums. Fourth, we adopt the ARDL bounds test to examine the co-integration between oil price, oil implied volatility, macroeconomic factors, and illiquidity premium, in a manner that overcomes problems that may arise because of uncertainty of unit root results, endogeneity and small sample size. Fifth, using the long-run ARDL model and the ECM allows us to simultaneously analyse the long-run and short-run elasticities of oil prices, OVX and macroeconomic factors on illiquidity premiums, by establishing significance and direction for current and optimal lagged values of these variables. Furthermore, we incorporate for a mechanism to gauge effective reversion to the long-run equilibrium. Sixth, we assess the transition of these relationships between a recessionary period and a post-recession period. Lastly, testing for a potential asymmetric impact on illiquidity premiums of shifts in oil price and oil volatility provides accurate insights on the impact of positive and negative movements within these variables. Although various studies have explored the asymmetric impact of oil price and oil volatility on stock markets (Park and Ratti 2008; Scholtens and Yurtsever 2012; Cunado and Perez de Gracia 2014; Wang et al. 2013; Herrera et al. 2015; Dupoyet and Shank 2018), to the best of our knowledge, the asymmetric impact of oil price and oil price volatility on illiquidity premiums has not yet been examined.

The structure of this chapter is as follows. Section 3.3 presents a literature review. Section 3.4 describes the data and methodology. Section 3.5 presents the empirical analysis and results. Finally, Section 3.6 concludes.

3.3 Literature Review

3.3.1 Existence of Illiquidity Premiums: Conflicting Results

Various past studies including those that consider the levels of assets' liquidities such as Amihud and Mendelson (1986), Brennan and Subrahmanyam (1996) and Acharya and Pedersen (2005), and those that consider assets' exposures to changes in market liquidity such as Pástor and Stambaugh (2003), conclude that returns increase with illiquidity. Li et al. (2011) used data from Japan over the period 1975 to 2006 and find evidence that stock returns rise with illiquidity. Amihud et al. (2015) examined the illiquidity premium in stock markets across 45 countries and find that the average illiquidity premium across countries is significant and positive. Said and Giouvris (2017a) used three distinct measures of illiquidity over equity data from the UK and conclude that illiquid portfolios generate a higher return relative to liquid portfolios, and this return differential becomes even greater during periods when monetary conditions are expansive.

Although there is a presence of substantial amounts of literature that finds evidence that stock returns' rise in illiquidity, there are still some contradictory results. Lo et al. (2004) argued that illiquidity premiums on assets are insignificant in the presence of zero or very low transaction costs. As transactions costs rise, they find moderate price discounts in illiquid assets but the resulting return premium is quite small. Ben-Rephael et al. (2008) used data from the NYSE and conclude that illiquidity premiums have declined significantly over the past four decades to levels that are not statistically different from zero. They argue that this transition is primarily due to improved liquidity within publicly traded equity. They extend this notion to investment styles, rendering strategies based on illiquidity as unprofitable. Ang et al. (2013) studied US stocks between the periods 1977 to 2008 and found that the illiquidity premium within listed stocks is not significantly different from zero.

3.3.2 Impact of Oil Price on Stock Returns and Market Sentiments

Tsai (2015) used a data set spanning from January 1990 to December 2012 to assess if oil prices impact stock returns in the United States differently prior to, during and after a financial crisis. They conclude that oil price positively impacts US stock returns during and after such a crisis. Kilian and Park (2009), Güntner (2014), and Foroni et al. (2017) all found a positive relationship between oil price and stock returns.

A fall in oil prices could be seen as bearish sentiments towards global growth which could potentially cause stock markets to fall (Güntner 2014; Foroni et al. 2017; Dupoyet and Shank 2018). The effect of such a move on illiquidity premiums can potentially be two-fold. From the perspective of market sentiments, investors might be more skeptical towards illiquid stocks which are generally deemed riskier, as they expect growth to decelerate and therefore might want to move investments towards safer options (Gai and Vause 2006; González-Hermosillo 2008). Such a move would reduce the price of illiquid stocks, shrinking realised illiquidity premiums. The flip side is that bearish sentiments towards global growth might result in central banks following a more expansive monetary policy with the aim of enhancing market liquidity (Chevapatrakul 2014; Said and Giouvris 2017a). With the rise in supply of market liquidity, we would expect capital to flow towards illiquid stocks, raising their demand, and their price, and thus enhancing realised illiquidity premiums (Jensen and Moorman 2010; Said and Giouvris 2017a). Furthermore, in times of interest rate cuts, yields on perceived safe haven investment instruments such as short-term sovereign debt is bound to fall, making relatively illiquid instruments more lucrative from a returns perspective (Chevapatrakul 2014). Such injection in demand could potentially boost up illiquidity premiums.

Other studies found the relationship between oil prices and markets to be negative. Driesprong, Jacobsen and Maat (2007) found a negative relationship between oil prices and stock market returns for both developed and emerging markets. They believed that the relationship becomes even stronger when they introduce lagged monthly oil price, indicating a potential delayed reaction by investors to changes in the price of oil. Cunado and Perez de Gracia (2014) disentangled the oil price changes as oil demand shocks and oil supply shocks, identified via the sign of the correlation between price changes and global oil production. For 12 oil importing European economies, they found a negative relationship between oil price changes and stock returns.

Some studies also found that the impact of oil price changes substantially differing along different industries. Narayan and Sharma (2011) studied the relationship between oil price and stock returns for 560 US firms listed on the NYSE. They found that oil price negatively impacts stock returns for all sectors apart from the energy and transportation sector. Similar to Driesprong, Jacobsen and Maat (2007), they also found a strong lagged effect of oil price on firm returns. Scholtens and Yurtsever (2012) found a negative correlation between oil prices and stock returns for all industries expect the oil and gas sector in the Euro area between 1983 and 2007. Owing to the varied impact of changes in oil price on various industries, we include a diverse range of sectors within our data set[4].

[4] The full list of sectors include; Aerospace and Defence, Automobiles and Parts, Chemicals, Construction and Materials, Electricity, Electronic and Electrical Equipment, Fixed Line Telecommunications, Food and Drug Retailers, Food Producers, Gas, Water and Multiutilities, General Industries, General Retailers, Healthcare Equipment and Services, Household Goods and Home Construction, Industrial Engineering, Industrial Metals and Mining, Industrial Transportation, Leisure Goods, Mining, Oil and Gas Producers, Oil Equipment and

3.3.3 Impact of Oil Price and Oil Price Volatility on Cost of Funding, Risk of Holding Assets and Market Liquidity

Balke et al. (2002) conclude that a rise in oil price volatility raises the perceived risks associated with less creditworthy firms or illiquid stocks. Agents within the economy are more averse to risk which is reflected by a fall in short-term bond yields due to a rise in demand of short-term liquid investment instruments, signifying a fall in stock market liquidity and a rise in bond market liquidity (Goyenko and Ukhov 2009). Therefore, the rise in oil price volatility results in agents within the economy moving towards better quality or more liquid investment instruments i.e., a 'flight to quality' or a 'flight to liquidity', reducing the demand for illiquid instruments, and therefore reducing realised illiquidity premiums. Furthermore, following the rationale put forward by Jensen and Moorman (2010) and Said and Giouvris (2017a) that investors within the equity market care more about liquidity as stock market illiquidity rises, the rise in oil price volatility should result in a fall in stock market liquidity, reducing the demand for all illiquid assets, lowering prices of illiquid assets, affecting the difference in returns between illiquid and liquid stocks and therefore negatively impacting illiquidity premiums.

Qadan and Nama (2018) conducted a study on the United States using five different sentiment indices and concluded that oil returns Granger-cause changes in consumer confidence and investor sentiments. They argue that oil price changes are perceived differently by investors relative to price fluctuations in other goods and have a significant impact on investors' perception of the economy. These results are consistent with Nandha and Faff (2008) and Zhang and Chen (2014) who also concluded that movements in oil price significantly impact consumer confidence. Based on this rationale, changes in oil price would impact investor sentiments and their attitude towards investing in risky securities, namely illiquid stocks (since these are considered to be riskier relative to liquid stocks), which in turn would impact the price of these stocks via an injection or leakage in demand, and therefore impact illiquidity

Services, Personal Goods, Pharmaceuticals and Biotechnology, Software and Computer Services, Technology Hardware and Equipment.

premiums. Qadan and Nama (2018) also found evidence that oil price volatility Granger-causes changes in investor sentiments. They argue that the impact of oil price volatility is significant and persistent on all their five sentiment proxies. Furthermore, they find a significant and negative correlation between the implied oil price volatility measure (OVX) and investor sentiments. This implies that as oil price volatility rises, investors' pessimism towards risky assets including illiquid stocks rises. This reduction in investor demand towards illiquid stocks would have a negative impact on their price causing the price differential between illiquid and liquid stocks to shrink decreasing illiquidity premiums. From this set of literature, it becomes apparent that a rise in oil price volatility impacts the cost of financing and perceived risk of assets which in turn negatively affects stock market liquidity and investors demand for illiquid securities, therefore reducing illiquidity premiums.

Zheng and Su (2017) studied the relationship between market liquidity and oil prices, focusing on the sources that lead to changes in oil price. They argued that stock market liquidity only increases when the positive oil price shocks[5] come from oil-specific demand side. If oil price shocks are generated from oil supply side or the aggregate demand side, stock market liquidity has a negative relationship with oil prices[6]. Connecting this idea to the conclusion made by Jensen and Moorman (2010) and Said and Giouvris (2017a), that illiquidity premiums rise with stock market illiquidity, means that positive oil price shocks brought about by oil-specific demand side factors increase illiquidity premiums while positive oil price shocks brought about by oil supply side factors or aggregate demand factors reduce illiquidity premiums[7].

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5 A positive oil price shock is defined as a drastic increase in the price of oil over a short span of time. Here we assess its impact on stock market liquidity based on three main drivers namely, a rise in the demand for oil, a fall in the supply of oil and a rise in aggregate demand.

6 Zheng and Su (2017) used definitions consistent with Kilian and Murphy (2012) where oil supply side includes a shock to the world production of crude oil; aggregate demand side includes a shock to the demand for crude oil and other industrial commodities associated with the global business cycle; and oil-specific demand side includes a shock to the demand for oil that is specific to the oil market. The latter is designed to capture factors that are independent to aggregate demand shocks such as speculative oil demand shocks.

7 Therefore, a rise in oil price due to a fall in the world production of oil or a global business cycle boom would result in a fall in stock market liquidity, reducing illiquidity premiums. On the other hand, a rise in oil price due to positive speculation within the oil market (a response to anticipated changes in oil market fundamentals), would increase stock market liquidity along with enhancing illiquidity premiums.

3.3.4 Oil Price Volatility Measures

Hamilton (1996) constructed a measure to gauge oil price volatility by comparing the current price of oil with the price over the previous four quarters. Hamilton (2003) amends on the initial idea and recommends using a three-year horizon. This then poses a serious question in terms of assessing the optimal number of lags to use in determining oil price shocks. Park and Ratti (2008) defined oil price volatility as the sum of square first log differences in daily spot or future prices. Their data include stock markets of the United States and 13 European countries spanning from 1986 to 2005. They found that an increase in oil price volatility has a negative impact on stock returns in 9 out of 14 countries. Diaz et al. (2016) used a univariate GARCH (1,1) error process to compute conditional variance of real oil price and found that an increase in oil price volatility has an adverse effect on stock markets in G7 countries.

Typically, research that has incorporated for oil price volatility uses a historical volatility measure. Luo and Qin (2017) used both a realized volatility measure along with the CBOE crude oil volatility index (OVX), which is a forward-looking oil price volatility measure. The results suggest that the OVX shocks have a significant negative impact on the Chinese stock market while the impact of realized volatility is negligible. Xiao et al. (2018) found evidence that the OVX negatively affects Chinese stock returns in bearish periods, and these effects are asymmetric. Dutta et al. (2017) concluded that the OVX impacts both the mean and volatility of stock returns in markets in the Middle East and Africa. Vu (2019) found evidence of a negative relationship between stock returns and the OVX within Southeast Asian markets. Kinateder and Wagner (2017) found evidence that OVX negatively impacts stocks in the United States, and this effect is significantly asymmetric. Bašta and Molnár (2018) found co-movement between implied oil volatility and volatility in stock returns. However, no such relationship is observed for realised volatilities within their research. Dupoyet and Shank (2018) used an implied oil price volatility measure (OVX) along with oil price and several macroeconomic indicators to assess their impact on stock returns in various industries in the United States. They found that implied volatility of oil prices has a negative and significant impact on nine out of ten industries. On the other hand, oil prices have a significant and positive impact on three industries and a negative and significant impact on two industries.

Therefore, we incorporate for a forward-looking measure rather than a realized volatility measure in our research to analyse the impact on illiquidity premiums in the NYSE.

The OVX index was only introduced in May 2007, therefore this paper studies the impact of oil price and oil price uncertainty on illiquidity premiums between 2007 and 2018. The OVX is a daily volatility figure reported by the Chicago Board of Exchange (CBOE) and is calculated using the CBOE volatility index (VIX) methodology. The index takes as inputs strike prices of the call and put options on the US Oil Fund options for near-term options with more than 23 days until expiration, next-term options with less than 37 days until expiration, and risk-free U.S. treasury bill interest rates. The idea is to estimate the implied volatility of US Oil Fund options at an average expiration of 30 days. The advantage of using this measure in our research is that it provides an extension to the existing literature by incorporating a forward-looking volatility measure to assess its impact on financial markets in the US. Furthermore, consistent with the rationale introduced by Peng and Ng (2012) and Dupoyet and Shank (2018), we feel that that the OVX index provides information about future oil prices quicker than current oil prices themselves as the OVX captures market's aggregate expectation of future oil volatility. Although Luo and Qin (2017) and Dupoyet and Shank (2018) used a forward-looking oil price implied volatility measure to analyse the impact on stock returns, this is the first research paper to incorporate that forward-looking measure and study the impact on illiquidity premiums.

3.3.5 Macroeconomic Factors

3.3.5.1 The Effect of Interest Rates

The impact of oil price and oil price volatility on illiquidity premiums cannot be studied in isolation, therefore we incorporate for various other macroeconomic factors that might impact these premiums. Jensen and Moorman (2010) studied the link between monetary conditions, market liquidity and illiquidity premiums in the United States. They used two alternative measures to identify shifts in Federal Reserve monetary policy, namely the federal funds rate and the Fed discount rate. The federal funds rate is used to identify changes in Fed stringency in the short term and changes in this rate are a more common occurrence. On the other hand, the Fed discount rate is seen to identify a fundamental shift in the Fed monetary policy stance and these directional shifts occur less frequently relative to changes in the federal funds rate. Jensen and Moorman (2010) found evidence that expansive monetary shifts increase market-wide liquidity causing large price increases in illiquid stocks and raising the return spread between illiquid and liquid stocks substantially. For this reason, we control for changes in the federal funds rate and the Fed discount rate.

3.3.5.2 The Effect of Exchange Rates

Economic literature also suggests that there is a strong relationship between stock returns and exchange rates. Mollick and Assefa (2013) found evidence that the US stock returns are positively affected by higher oil prices and a fall in the USD/Euro rate, after the 2007–2008 financial crisis. Zheng and Su (2017) studied the relationship between oil price shocks and stock market liquidity within China, controlling for macroeconomic factors such as exchange rate. They found evidence that a positive shock within exchange rate tends to decrease market liquidity. Although the direction of this relationship might be due to the importance China's exports have on the overall economy, the significance of it cannot be ignored. Therefore, we control not only for exchange rate because it impacts stock returns in general, which includes both illiquid and liquid stocks, but also because it significantly impacts market liquidity.

3.3.5.3 The Effect of Industrial Production Index and Inflation

Fernández-Amador et al. (2013) studied the impact of monetary policy on stock market liquidity and control for macroeconomic variables such as inflation, industrial production index and stock market index. They concluded that all three of these factors have a significant impact on stock market liquidity. Owing to the argument put forward by Jensen and Moorman (2010) and Said and Giouvris (2017a), that stock market liquidity should impact illiquidity premiums, it is crucial that we include inflation, industrial production index and stock market index within our model. Finally, consistent with Brunnermeier and Pedersen (2008), Hameed et al. (2010) and Fernández-Amador et al. (2013), who have shown that the return of the previous month influences stock market liquidity, we include a measure for lagged monthly illiquidity premiums within our model.

3.4 Data and Methodology

3.4.1. Measuring Illiquidity and Construction of Illiquidity Portfolios

We collect daily data from January 2006 to December 2018 for 1175 stocks listed on the New York Stock Exchange (NYSE). Data for stock prices, trading volume, trading days and returns are obtained from Datastream using a procedure similar to Amihud et al. (2015). We download only securities that are identified as equity, are listed as 'primary quote' in the NYSE and are traded in the US Dollar. The sample also includes stocks that ceased to exist during the sample period. We apply filters to not include stocks that are listed as American Depository Receipts (ADRs), closed-end funds, exchange-traded funds (ETFs), preference shares and warrants.

To reduce the influence of Datastream errors we apply a combination of filters following the methods of Ince and Porter (2006), Lee (2011), Amihud et al. (2015) and Amihud (2018). Monthly returns are set as missing if they are greater than 500%, greater than 300% and reversed in the following month or less than −100%.

To measure illiquidity, we use the Amihud (2002) illiquidity measure ILLIQ, which, for any given stock is defined as the average ratio of the daily absolute return to the daily trading volume in dollar terms for that stock;

$$ILLIQ_{i,t} = (1/N_{i,t}) \sum_{d} [(1{,}000{,}000 \times |r_{i,d,t}|)/(p_{i,d,t} \times v_{i,d,t})] \qquad (3.1)$$

$|r_{i,d,t}|$ is the absolute value of return on stock i on day d in period t, $v_{i,d,t}$ is the trading volume of stock i on day d, $p_{i,d,t}$ is the closing price of stock i on day d and $N_{i,t}$ is the number of non-zero volume trading days for stock i in period t.

Amihud (2002) and Amihud (2018) argued that there are finer measures of illiquidity but these require microstructure data on transactions and quotes which are unavailable for many stocks and for longer spans of time, therefore would significantly reduce our stock universe. Furthermore, Said and Giouvris (2017a) showed that the ILLIQ measure is highly correlated with other measures such as the high-low spread (Corwin and Schultz 2012) and the roll estimator (Roll 1984) signifying that they capture similar aspects of stock illiquidity. Hasbrouck (2003) concluded that the ILLIQ measure is thought to be the most common approach and has the highest correlation with trade-based measures. Furthermore, compared with liquidity measures computed from high-frequency data, Hasbrouck (2007) reported that 'the Amihud illiquidity measure is more strongly correlated with the TAO-based price impact coefficient'. Based on this rationale, we decide to use the ILLIQ measure of illiquidity.

We calculate ILLIQ for each stock based on daily data in a given year $t - 1$. The average of the daily illiquidity measure in year $t - 1$ is used to rank stocks based on their illiquidity, which are then divided into five equally weighted quintiles. These are then used to construct returns for five equally weighted monthly portfolios in year t, based on their returns each month in year t. Therefore, the average of the daily values of the illiquidity measure for the year 2006 is used to rank stocks into five equal quintiles, and then calculate the monthly quintile returns for the year 2007. This methodology is similar to the moving window approach used by Amihud et al. (2015), Said and Giouvris (2017a) and Amihud (2018). Therefore, our stock ranking period runs from January 2006 to December 2017 while the portfolio construction period runs from May 2007 to December 2018 which is our full sample period, since the OVX values are only available from May 2007. Once the stocks are ranked based on illiquidity, the return differential between the top 20% and bottom 20% is classified as the illiquidity premium every month. The quintiles are rebalanced annually. We also construct illiquidity portfolios within the following sub-samples: December 2007 to June 2009[8], and July 2009 to December 2018. We do this to establish the existence and significance of illiquidity premiums during and after the financial crises.

We select a 12-months window for portfolio rebalancing to keep the portfolio selection process more realistic. First, portfolio rebalancing might involve transaction costs which might be expensive and therefore rebalancing of a higher frequency could erode the investors' returns (Carhart 1997; Kaplan and Schoar 2005). Second, borrowing constraints that the investors may face would imply that adjusting portfolios may not always be possible. Third, Novy-Marx (2004) argue that only long horizon investors hold fewer liquid assets, a phenomenon that

[8] This is categorised as a financial crisis period by NBER in the United States.

Amihud and Mendelson (1986) term 'clientete effects', and our 12-month moving window approach is a representation of such long term investors. Finally, off-loading illiquid securities might require a rigorous search for a buyer relative to liquid securities which would generally have a more vibrant secondary market, therefore increasing the possibility of not being able to trade illiquid assets optimally (Ibbotson et al. 2013). The methodology of using the prior year ($t - 1$) measure for illiquidity to construct quintiles which are then used to calculate portfolio returns in a given year (t) also helps us meet one of the criteria for Sharpe's (Sharpe 1992) specification of a portfolio benchmark, that is 'identifiable before fact'.

To be included in a portfolio in the period that follows, stocks should satisfy the following requirements. A stock should have at least forty valid observations (return and volume) and a trading volume of at least four thousand shares, over the twelve-month window. We remove extreme values of ILLIQ by excluding stocks with ILLIQ in the top and bottom 1% in each twelve-month window. We also remove stocks whose price is in the top or bottom 1%, in each twelve-month window.

3.4.2 Explanatory Variables and OLS Regression Model

Data for the explanatory variables in our model to examine the impact of oil price and oil volatility on illiquidity premiums is collected from a variety of sources. The measure of implied oil price volatility (OVX) is from the Chicago Board of Exchange (CBOE); the federal funds rate and discount rate are from the Federal Reserve website; the USD/EUR closing spot rates and S&P 500 index values are from Datastream; WTI (West Texas Intermediate) crude oil closing prices, Industrial Production Index and CPI YoY% figures are from Bloomberg.

In order to completely capture intra month movements, we use daily data to calculate a monthly average for all the variables apart from CPI and industrial production index, since these are only issued on a monthly frequency.

We employ an OLS model to analyse the impact of oil price and oil price volatility within a month, on illiquidity premiums;

$$R_{IML,t} = a_0 + \beta_1 R_{OIL,t} + \beta_2 R_{OVX,t} + \beta_3 R_{S\&P,t} + \beta_4 R_{e,t} + \beta_5 \Delta\pi_t + \beta_6 R_{p,t} + \beta_7 \Delta ffr_t + \beta_8 \Delta r_t + \beta_9 R_{IML,t-1} + \varepsilon_t \quad (3.2)$$

where R_{IML} represents the illiquidity premium. The first predictor R_{OIL} denotes the monthly return of WTI crude oil prices designed to gauge how movements in the oil market impact illiquidity premiums. The second predictor R_{OVX} is the monthly return on the oil price volatility index (OVX) designed to assess the impact of oil price uncertainty on illiquidity premiums. The third predictor $R_{S\&P}$ represents the total return on the S&P 500 index to control for changes in the macroeconomy and business cycles. The fourth predictor R_e is the monthly return of the US Dollar against Euro based on daily closing spot rates, averaged over the month. This factor is included to control for the impact of exchange rate on illiquidity premiums. The fifth predictor $\Delta\pi$ represents the monthly change in the consumer price index (CPI). The sixth predictor R_p denotes the return on the seasonally adjusted industrial production index which measures the output of industrial establishments in mining, manufacturing and electric and gas utilities. This measure is used to control for changes in economic activity, following Herrera et al. (2011), Cunado and Perez de Gracia (2014), and Diaz et al. (2016). The seventh predictor Δffr represents monthly changes in the daily Federal Funds rate, averaged over the month and is used to control for changes in Fed stringency in the short term. The eighth predictor Δr is the monthly change in Fed discount rate and is used to control for a fundamental shift in the Fed monetary policy stance. Both Δffr and Δr are chosen to control for monetary policy, following Jensen and Moorman (2010) and Said and Giouvris (2017a). Finally, $R_{IML,t-1}$ is a lagged measure of illiquidity premiums while ε_t is the error term.

Our explanatory variables exhibit non-stationarity therefore we transform our independent variables into either returns or first difference. We then use an Augmented Dickey-Fuller unit root test to confirm that the transformed variables are stationary. To unify the interpretation of our results we ensure that each independent variable can be directly interpretable as percentage changes. Since the federal funds rate, fed discount rate and inflation are already quoted in percentage form, we take their first difference. Oil price, OVX, S&P 500 index returns, seasonally adjusted industrial production index and exchange rate are all quoted in US Dollar or index terms, therefore we calculate their returns.

Apart from running the OLS model in Equation (1) for our entire sample, we also run the OLS model for our sub-samples, December 2007 to June 2009, and July 2009 to December 2018, to gauge the relationship between oil price returns, OVX returns and macroeconomic factors in month t, on illiquidity premiums in month t, during and after the financial crisis.

3.4.3 The VAR Model

We test for co-integration between all our variables using the Johansen and Juselius test (Johansen and Juselius 1990). After establishing that there is a long-run relationship between all the variables analysed in our study (illiquidity premiums, oil price, OVX, exchange rate, S&P 500 index, inflation, industrial production index, federal funds rate and discount rate), we set up a VAR model of order p;

$$y_t = A_0 + \sum_{i=1}^{p} A_i y_{t-i} + \varepsilon_t \qquad (3.3)$$

where p is the number of lags (chosen using the Akaike information criterion), y_t is a column vector of all the variables in the model (illiquidity premium, oil price return, OVX return, S&P500 return, exchange rate return, change in inflation, return on the industrial production index, change in federal funds rate and change in discount rate), A_0 is a vector of all the constant terms, A_i is a 9 × 9 matrix of unknown coefficients for each i and ε_t is a column vector with the following properties;

$E(\varepsilon_t) = 0$, for all values of t

$E(\varepsilon_s\, \varepsilon'_t) = \Omega$, if s = t,

where Ω is the variance-covariance matrix with non-zero off diagonal elements

$E(\varepsilon_s\, \varepsilon'_t) = 0$ if $s \neq t$

After estimating the VAR model, we analyse the impact of oil price and oil price volatility through impulse response functions. This is done with the full sample period of May 2007 to December 2018 and the following sub-samples: December 2007 to June 2009, and July 2009 to December 2018. This will help us identify any changes in the reaction of illiquidity premiums to oil price and oil price volatility, during and after the financial crisis.

3.4.4 Robustness - Bounds Test for Cointegration/Long-Run and Short-Run Elasticity: The Long-Run ARDL Model and the Short-Run Error Correction Model

We use an ARDL bounds test as proposed by Pesaran et al. (2001) to test for co-integration and establish a long-run relationship between our variables. Emran et al. (2007) discuss several advantages of the bounds test relative to conventional co-integration tests. First, the bounds test can be used regardless of whether the time series are I(0) or I(1). This helps remove uncertainties that might be created by unit root tests. Second, the bounds test can be adjusted to address possible issues of endogeneity within the explanatory variables. Third, the bounds test can be applied to small sample sizes and therefore works well especially for our analysis within the financial crisis period. The approach also allows us to simultaneously estimate both short-run and long-run relationships. Furthermore, following our OLS and VAR analysis, the approach allows us to identify the significance and direction of the influence of each variable, within the month and within their lags. We choose the optimal lag length using the Akaike information criterion (AIC).

To test the co-integration relationship between oil prices, OVX, macroeconomic factors and illiquidity premiums, we set up the bounds test as follows;

$$R_{IML,t} = \alpha_0 + \sum_{i=1}^{p}\beta_{1,i} R_{IML,t-i} + \sum_{i=0}^{p}\beta_{2,i}\Delta \ln OIL_{t-i} + \sum_{i=0}^{p}\beta_{3,i}\Delta \ln OVX_{t-i} + \sum_{i=0}^{p}\beta_{4,i}\Delta \ln S\&P_{t-i} + \sum_{i=0}^{p}\beta_{5,i}\Delta \ln E_{t-i} + \sum_{i=0}^{p}\beta_{6,i}\Delta \pi_{t-i} + \sum_{i=0}^{p}\beta_{7,i}\Delta \ln P_{t-i} + \sum_{i=0}^{p}\beta_{8,i}\Delta \ln ffr_{t-i} + \sum_{i=0}^{p}\beta_{9,i}\Delta \ln r_{t-i} + \beta_{10}R_{IML,t-1} + \beta_{11}\ln OIL_{t-1} + \beta_{12}\ln OVX_{t-1} + \beta_{13}\ln S\&P_{t-1} + \beta_{14}\ln E_{t-1} + \beta_{15}\pi_{t-1} + \beta_{16}\ln P_{t-1} + \beta_{17}\ln ffr_{t-1} + \beta_{18}\ln r_{t-1} + \varepsilon_t \tag{3.4}$$

where R_{IML}, is the illiquidity premium, Δ ln OIL, Δ ln OVX, Δ ln S&P, Δ ln E, Δ ln P, Δ ln ffr and Δ ln r, are the first differences of natural logs for oil price, OVX index, S&P500 index, US Dollar against Euro exchange rate, industrial production index, federal funds rate and the discount rate, $\Delta\pi$ is the first difference of the inflation rate, ln OIL, ln OVX, ln S&P, ln E, ln P, ln ffr and ln r, are the natural logs for oil price, OVX index, S&P500 index, US Dollar against Euro exchange rate, industrial production index, federal funds rate and the discount rate, π is the inflation rate, e is the error term, and t is the time.

We follow the procedure specified by Pesaran et al. (2001) to examine the existence of a long-run relationship among the variables in Equation (3.4). We do this by performing an F-test for the joint significance of the coefficients as set up in the following hypothesis;

H_0: $\beta 10 = \beta 11 = \beta 12 = \beta 13 = \beta 14 = \beta 15 = \beta 16 = \beta 17 = \beta 18 = 0$

H_1: $\beta 10 \neq \beta 11 \neq \beta 12 \neq \beta 13 \neq \beta 14 \neq \beta 15 \neq \beta 16 \neq \beta 17 \neq \beta 18 \neq 0$

For a given level of significance, if the F-statistic is higher than the upper critical bound level, then the null hypothesis of no co-integration is rejected. While if the F-statistic is lower than the lower critical bound value, the null hypothesis of no co-integration cannot be rejected.

Once the long-run relationship has been established, we set up an ARDL model to analyse the long-run elasticity of oil price, OVX and the macroeconomic factors on illiquidity premiums;

$$R_{IML,t} = \alpha_0 + \sum_{i=1}^{p}\beta_{1,i} R_{IML,t-i} + \sum_{i=0}^{p}\beta_{2,i} \ln OIL_{t-i} + \sum_{i=0}^{p}\beta_{3,i} \ln OVX_{t-i} + \sum_{i=0}^{p}\beta_{4,i} \ln S\&P_{t-i} + \sum_{i=0}^{p}\beta_{5,i} \ln E_{t-i} + \sum_{i=0}^{p}\beta_{6,i}\, \pi_{t-i} + \sum_{i=0}^{p}\beta_{7,i} \ln P_{t-i} + \sum_{i=0}^{p}\beta_{8,i} \ln ffr_{t-i} + \sum_{i=0}^{p}\beta_{9,i} \ln r_{t-I} + \varepsilon_t \quad (3.5)$$

We then proceed to analyse the short-run elasticity between the explanatory variables and illiquidity premiums using the error correction model;

$$R_{IML,t} = \alpha_0 + \sum_{i=1}^{p}\beta_{1,i} R_{IML,t-I} + \sum_{i=0}^{p}\beta_{2,i}\, \Delta \ln OIL_{t-i} + \sum_{i=0}^{p}\beta_{3,i}\, \Delta \ln OVX_{t-i} + \sum_{i=0}^{p}\beta_{4,i}\, \Delta \ln S\&P_{t-i} + \sum_{i=0}^{p}\beta_{5,i}\, \Delta \ln E_{t-i} + \sum_{i=0}^{p}\beta_{6,i}\, \Delta\, \pi_{t-i} + \sum_{i=0}^{p}\beta_{7,i}\, \Delta \ln P_{t-i} + \sum_{i=0}^{p}\beta_{8,i}\, \Delta \ln ffr_{t-i} + \sum_{i=0}^{p}\beta_{9,i}\, \Delta \ln r_{t-I} + \beta_{10}\, ecm_{t-1} + + \varepsilon_t \quad (3.6)$$

where ecm is a vector of residuals from the ARDL long-run model (Equation (3.5)), and the coefficient for ecm_{t-1} indicates whether the mechanism of reverting to the long-run equilibrium is effective. A significant and negative coefficient implies that the reverting mechanism to sustain the long-run equilibrium between the explanatory variables and illiquidity premium is effective.

The procedure from Equations (3.4) to (3.6) is done with the full sample period of May 2007 to December 2018 and the following sub-samples: December 2007 to June 2009, and July 2009 to December 2018. Through this we aim to a) establish robustness for our OLS and VAR results, and b) confirm the influence in terms of significance and direction of each explanatory variable, within the current month and within lags, on illiquidity premiums, during and after the financial crisis.

3.4.5 Asymmetric Effect of Oil Price and Oil Price Volatility on Illiquidity Premiums

In this section we explore the possible asymmetric impact of oil price and oil price implied volatility on illiquidity premiums. The asymmetric impact of oil price and oil volatility on stock markets has been studied previously in literature (Park and Ratti 2008; Scholtens and Yurtsever 2012; Cunado and Perez de Gracia 2014; Wang et al. 2013; Herrera et al. 2015; Dupoyet and Shank 2018, but to the best of our knowledge, the asymmetric impact of oil price and oil price volatility on illiquidity premiums has not yet been examined. If an asymmetric effect is confirmed, then that would indicate that illiquidity premiums do not react the same way to an increase in oil price (or oil volatility) as they would to a decrease in oil price (or oil volatility).

We use a similar methodology as Mork (1989), Park and Ratti (2008) and, Dupoyet and Shank (2018) and separate oil price returns and oil implied volatility returns into positive and negative time series;

$$R_{OILP} = \max(0, R_{OIL}) \text{ and } R_{OILN} = \min(0, R_{OIL}) \tag{3.7}$$

$$R_{OVXP} = \max(0, R_{OVX}) \text{ and } R_{OVXN} = \min(0, R_{OVX}) \tag{3.8}$$

Positive oil price returns every month are defined as the maximum value between the return on oil price in a particular month and zero, while negative oil price returns every month are defined as the minimum value between return on oil price in a particular month and zero (Equation (3.7)). Similarly, positive returns on oil price volatility every month are defined as the maximum value between the return on oil price volatility in a particular month and zero, while negative oil price volatility returns every month are defined as the minimum value between return on oil price volatility in a particular month and zero (Equation (3.8)).

We run two further OLS regressions, first checking the asymmetric impact of oil price returns by inputting R_{OILP} and R_{OILN} into Equation (3.2) and using R_{OILP}, R_{OILN}, R_{OVX}, $R_{S\&P}$, R_e, $\Delta\pi$, R_p, Δffr and Δr as predictors for illiquidity premium;

$$R_{IML} = \alpha_0 + \beta_1 R_{OILP} + \beta_2 R_{OILN} + \beta_3 R_{OVX} + \beta_4 R_{S\&P} + \beta_5 R_e + \beta_6 \Delta\pi + \beta_7 R_p + \beta_8 \Delta ffr + \beta_9 \Delta r + \beta_{10} R_{IML,t-1} + \varepsilon_t \quad (3.9)$$

We use a Chi-square test to test for asymmetry with the null hypothesis being that the coefficients on the positive and negative oil price returns are equal.

Next, we check for the asymmetric impact of oil implied volatility by inputting R_{OVXP} and R_{OVXN} into Equation (3.2) and using R_{OIL}, R_{OVXP}, $R_{OVXN,}$ $R_{S\&P}$, R_e, $\Delta\pi$, R_p, Δffr and Δr as predictors for illiquidity premium;

$$R_{IML} = \alpha_0 + \beta_1 R_{OIL} + \beta_2 R_{OVXP} + \beta_3 R_{OVXN} + \beta_4 R_{S\&P} + \beta_5 R_e + \beta_6 \Delta\pi + \beta_7 R_p + \beta_8 \Delta ffr + \beta_9 \Delta r + \beta_{10} R_{IML,t-1} + \varepsilon_t \quad (3.10)$$

Once again we use a Chi-square test to test for asymmetry with the null hypothesis being that the coefficients on the positive and negative oil volatility returns are equal.

To establish robustness within these findings and to check for potential asymmetric impact of current and lagged values of oil price and oil price implied volatility on illiquidity premiums in the short-run, we run two further ECM regressions. We separate oil price and oil volatility into positive and negative time series;

$$\Delta \ln OVXP = \max(0, \Delta \ln OIL) \text{ and } \Delta \ln OILN = \min(0, \Delta \ln OIL) \quad (3.11)$$

$$\Delta \ln OVXP = \max(0, \Delta \ln OIL) \text{ and } \Delta \ln OILN = \min(0, \Delta \ln OIL) \quad (3.12)$$

We first check the potential asymmetric impact of oil price on illiquidity premiums by inputting variables from Equation (3.11) into Equation (3.6);

$R_{IML,t} = \alpha_0 + \sum_{i=1}^{p} \beta_{1,i} R_{IML,t-I} + \sum_{i=0}^{p} \beta_{2,i} \Delta \ln OILP_{t-i} + \sum_{i=0}^{p} \beta_{3,i} \Delta \ln OILN_{t-i} + \sum_{i=0}^{p} \beta_{4,i} \Delta \ln OVX_{t-i} + \sum_{i=0}^{p} \beta_{5,i} \Delta \ln S\&P_{t-i} + \sum_{i=0}^{p} \beta_{6,i} \Delta \ln E_{t-i} + \sum_{i=0}^{p} \beta_{7,i} \Delta \pi_{t-i} + \sum_{i=0}^{p} \beta_{8,i} \Delta \ln P_{t-i} + \sum_{i=0}^{p} \beta_{9,i} \Delta \ln ffr_{t-i} + \sum_{i=0}^{p} \beta_{10,i} \Delta \ln r_{t-I} + \beta_{11}\, ecm_{t-1} + \varepsilon_t$ (3.13)

We use p different Chi-square tests (separately for current terms and lagged terms) to test for asymmetry with the null hypothesis being that the coefficients for positive and negative Δ ln oil price are equal.

Similarly, to check the potential asymmetric impact of oil implied volatility on illiquidity premiums, we input variables from Equation (3.12) into Equation (3.6);

$R_{IML,t} = \alpha_0 + \sum_{i=1}^{p} \beta_{1,i} R_{IML,t-I} + \sum_{i=0}^{p} \beta_{2,i} \Delta \ln OIL_{t-i} + \sum_{i=0}^{p} \beta_{3,i} \Delta \ln OVXP_{t-i} + \sum_{i=0}^{p} \beta_{4,i} \Delta \ln OVXN_{t-i} + \sum_{i=0}^{p} \beta_{5,i} \Delta \ln S\&P_{t-i} + \sum_{i=0}^{p} \beta_{6,i} \Delta \ln E_{t-i} + \sum_{i=0}^{p} \beta_{7,i} \Delta \pi_{t-i} + \sum_{i=0}^{p} \beta_{8,i} \Delta \ln P_{t-i} + \sum_{i=0}^{p} \beta_{9,i} \Delta \ln ffr_{t-i} + \sum_{i=0}^{p} \beta_{10,i} \Delta \ln r_{t-I} + \beta_{11}\, ecm_{t-1} + + \varepsilon_t$ (3.14)

Once again we use p different Chi-square tests (separately for current terms and lagged terms) to test for asymmetry with the null hypothesis being that the coefficients for positive and negative Δ ln OVX are equal.

3.5 Empirical Results

3.5.1 Illiquidity Premiums

Table 3.1 shows the summary statistics for our dependent variable which is illiquidity premium. We provide monthly statistics in percentage form along with the skewness and kurtosis levels. The divergence between the mean and the median does not seem too big and the argument for symmetric distribution is supported by a small skewness level and kurtosis close to 3. We use a Jarque-Bera test to check for normality of the distribution and fail to reject the null hypothesis of normal distribution at 1% significance. Figure 3.1 shows the time series variation in illiquidity premiums. Even during the recession period, there seem to be more months with positive illiquidity premiums relative to negative months.

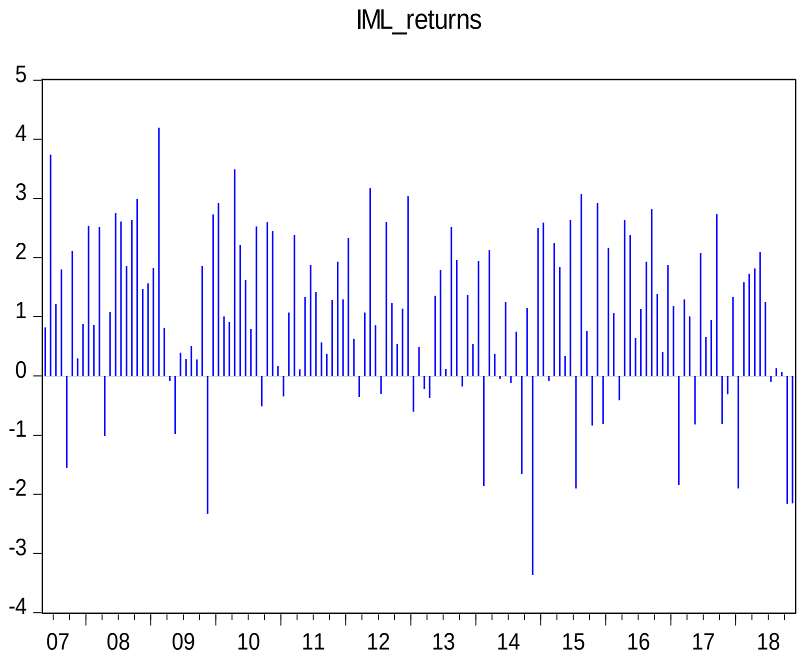


Figure 3.1 Time series variation in illiquidity premiums.

Table 3.1. Descriptive statistics for dependent variable.

Variables	Mean	Median	SD	Min	Max	Skewness	Kurtosis	Jarque-Bera (p-Value)
Illiquidity Premiums	1.025632	1.136595	1.403141	−3.359947	4.193543	−0.508377	3.078249	0.049222 ***

This table provides descriptive statistics for the illiquidity premium for the full sample from May 2007 to December 2018. Mean, median, standard deviation (SD), minimum value (Min), maximum value (Max) have all been multiplied by 100 to make them easier to read and therefore they are in percentage form. Significance is shown at 10% (*), 5% (**) and 1% (***) levels.

Table 3.2 shows equally weighted, average monthly returns for quintile portfolios formed using the Amihud (2002) illiquidity measure. As mentioned in the last section, quintile portfolio ranks are determined using the value of the Illiquidity measure in the year prior to the year in which returns are measured. The final column in Table 3.2 shows the illiquidity premium which is the return on the illiquid–liquid portfolio, i.e., taking a long position on the most illiquid quintile while taking a short position on the most liquid quintile. The illiquidity premium is both positive and statistically significant for our data sample. Furthermore, the quintile returns seem to increase monotonically with stock illiquidity, which means that returns are strictly increasing as we move from the high liquidity quintile to low liquidity quintile. This is consistent with other studies such as Jensen and Moorman (2010) and Said and Giouvris (2017a), who also find evidence for returns increasing monotonically with a rise in illiquidity.

Table 3.2 Average monthly returns for quintile portfolios.

Mean Monthly Portfolio Return (%)					
Liquidity Portfolio					
Liquid	**2**	**3**	**4**	**Illiquid**	**Illiquid-Liquid**
2.0576%	2.5704%	2.7622%	2.9513%	3.0832%	1.0256% *** (0.0000)

This table shows equally weighted, average monthly returns for quintile portfolios formed using the Amihud (2002) illiquidity measure. Quintile portfolio ranks are determined using the value of the Illiquidity measure in the year prior to the year in which returns are measured. Therefore the ranking period lasts from 2006 to 2017 while the portfolio construction period lasts from 2007 to 2018. Portfolios are rebalanced annually. Illiquidity premium is defined as the return on the illiquid–liquid portfolio, i.e., taking a long position on the most illiquid quintile while taking a short position on the most liquid quintile. p-values for the t test are shown in brackets and significance is shown at 10% (*), 5% (**) and 1% (***) levels.

Tables 3.3 and 3.4 show equally weighted, average monthly returns for quintile portfolios formed using the Amihud (2002) illiquidity measure during the financial crisis and for the post-crisis period. The illiquidity premiums are both positive and statistically significant within both the sub-samples. Once again the quintile returns seem to increase monotonically with stock illiquidity, which means that returns are strictly increasing as we move from the high liquidity quintile to low liquidity quintile. The illiquidity premiums seem to be larger in magnitude during the financial crisis relative a post-crisis setting. This is explained by higher returns within the most liquid quintiles and lower returns within the most illiquid quintiles during the post-crisis period compared to the financial crisis period.

Table 3.3 Average monthly returns for quintile portfolios (financial crisis).

Mean Monthly Portfolio Return (%)					
Liquidity Portfolio					
Liquid	**2**	**3**	**4**	**Illiquid**	**Illiquid-Liquid**
1.9662%	2.5382%	3.2676%	3.3763%	3.4877%	1.5214% *** (0.0000)

This table shows equally weighted, average monthly returns for quintile portfolios formed using the Amihud (2002) illiquidity measure. For the financial crisis sub-sample between December 2007 to June 2009. Quintile portfolio ranks are determined using the value of the Illiquidity measure in the year prior to the year in which returns are measured. Portfolios are rebalanced annually. Illiquidity premium is defined as the return on the illiquid–liquid portfolio, i.e., taking a long position on the most illiquid quintile while taking a short position on the most liquid quintile. *p*-values for the t test are shown in brackets and significance is shown at 10% (*), 5% (**) and 1% (***) levels.

Table 3.4 Average monthly returns for quintile portfolios (post financial crisis).

Mean Monthly Portfolio Return (%)					
Liquidity Portfolio					
Liquid	**2**	**3**	**4**	**Illiquid**	**Illiquid–Liquid**
2.1160%	2.6476%	2.7354%	2.9187%	3.0471%	0.9312% *** (0.0000)

This table shows equally weighted, average monthly returns for quintile portfolios formed using the Amihud (2002) illiquidity measure. For the post financial crisis sub-sample between July 2009 to December 2018. Quintile portfolio ranks are determined using the value of the illiquidity measure in the year prior to the year in which returns are measured. Portfolios are rebalanced annually. Illiquidity premium is defined as the return on the illiquid–liquid portfolio, i.e., taking a long position on the most illiquid quintile while taking a short position on the most liquid quintile. *p*-values for the t test are shown in brackets and significance is shown at 10% (*), 5% (**) and 1% (***) levels.

3.5.2 Statistical Analysis

We report the main summary statistics in Table 3.5[9]. Monthly statistics are provided in percentage form along with their respective skewness and kurtosis levels. Overall, the skewness and kurtosis levels within the variables signifies non-normality. The divergence between the mean and median values is a testament to the non-symmetric nature of the distribution. This seems to be more extreme for OVX, exchange rate and the production index where even the signs change between the mean and median values.

Table 3.5. Descriptive statistics for explanatory variables.

Variables	Mean	Median	SD	Min	Max	Skewness	Kurtosis
R_{OIL}	0.282989	1.026349	9.357824	−32.62122	29.7144	−0.287811	4.057545
R_{OVX}	1.752078	−0.592552	16.71465	−32.46463	86.05578	1.251708	6.943423
$R_{S\&P}$	0.518481	1.016153	4.223668	−16.94245	10.77230	−0.754159	4.753738
R_e	0.171299	−0.044200	3.063321	−8.715514	10.77245	0.511372	4.298387
R_p	0.002632	−0.007282	0.870610	−2.795238	5.295741	1.328169	12.42154
$\Delta\pi$	−0.003623	0.000000	0.471588	−2.600000	2.000000	−0.691787	10.70069
Δffr	−0.022319	0.000000	0.238230	−1.810000	0.490000	−5.215882	38.04126
Δr	−0.021739	0.000000	0.182437	−1.250000	0.250000	−4.276949	25.60979

This table provides descriptive statistics for all variables for the full sample from May 2007 to December 2018. Mean, median, standard deviation (SD), minimum value (Min), maximum value (Max) have all been multiplied by 100 to make them easier to read and therefore they are in percentage form. R_{OIL} denotes the monthly return of WTI crude oil prices. R_{OVX} is the monthly return on the oil price volatility index (OVX). $R_{S\&P}$ represents the total return on the S&P 500 index. R_e is the monthly return of the USD against Euro $\Delta\pi$ represents the monthly change in the consumer price index (CPI). R_P denotes the return on the seasonally adjusted industrial production index Δffr represents monthly changes in the daily Federal Funds rate Δr is the monthly change in Fed discount rate.

The majority of our data set includes the 2008 financial crisis and a post crisis period, which becomes apparent by observing the large standard deviation levels associated to some of the variables, specifically oil, OVX, S&P returns and exchange rate. The negative mean values for federal funds rate and the discount rate can also be seen as the Federal Reserve looking to add impetus within the economy by loosening their monetary policy stance, usually associated with a slow down within an economy. Furthermore, the biggest divergence in the maximum and minimum returns is seen within the OVX where the highest returns are around 86% while the lowest returns are close to −32%.

[9] We use an augmented Dickey–Fuller unit root test to confirm that all variables are stationary in returns (Illiquidity Premiums, Lagged Illiquidity Premiums, Oil, OVX, S&P Index, Exchange Rate, Industrial Production Index) and in first difference (Inflation, Federal Funds Rate and Discount Rate)

Figure 3.2 shows time series volatility for OVX, WTI oil prices, S&P 500 index and exchange rate in levels (left) and returns (right) for the full sample between May 2007 and December 2018. During the financial crisis of 2008, oil prices and the S&P 500 index seem to dip together. Oil prices also appear to rise along with the S&P 500 index as the market recovers, while the OVX tends to move in the opposite fashion. During the financial crisis of 2008, the OVX index spiked up as the S&P index plummeted. In general, spikes in the OVX index do correspond with downward movements within the S&P index.

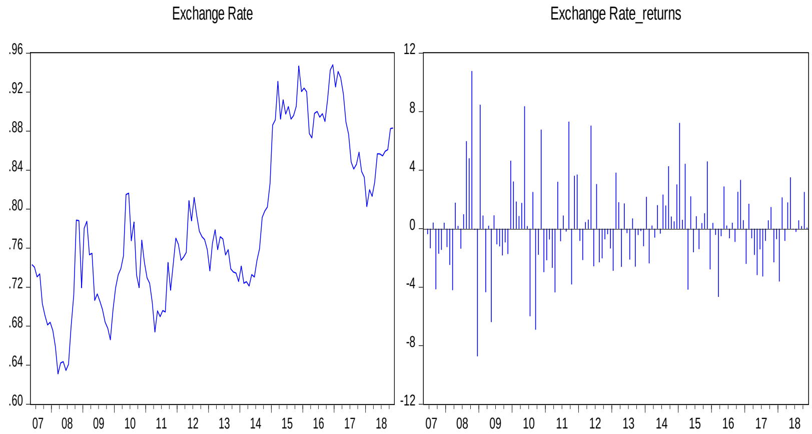
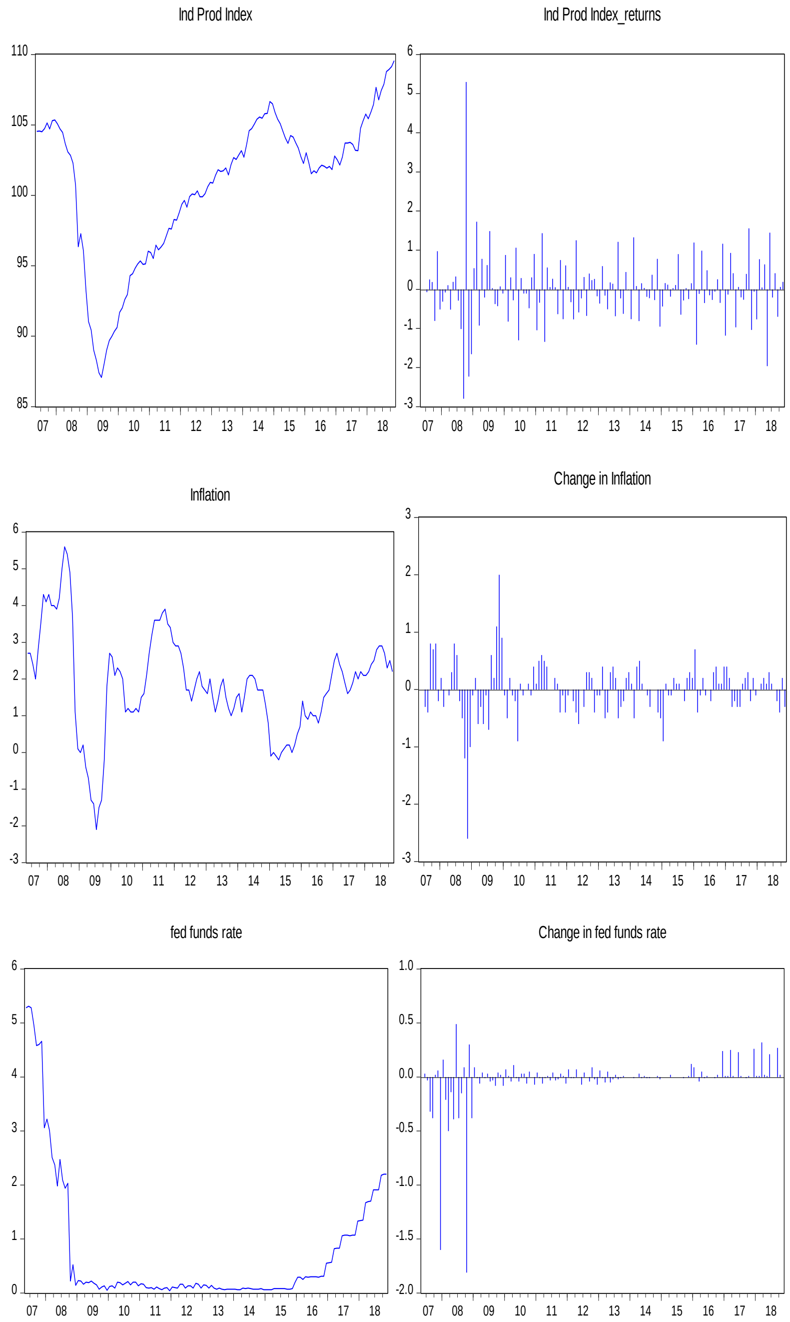


Figure 3.2. Time series volatility for OVX, WTI oil prices, S&P 500 index and exchange rate in levels (**left**) and returns (**right**) for the full sample between May 2007 and December 2018.

Furthermore, exchange rate looks to move in the opposite direction to oil price moves. This could probably be down to the fact that within the time frame of our data set, the US was a net importer of oil (Eia.gov 2018). Therefore, a rise in oil prices potentially increases the import bill for the United States, creating a downward pressure on the US Dollar. On the other hand, the exchange rate looks to move in unison with the OVX index. This could potentially be down to the status of the US dollar as a safe haven. Hence, as volatility rises, there is a movement of funds towards the US dollar, creating an upward demand push on the currency and having a positive impact on its price.

The return plots show that the OVX returns tend to be more volatile than the S&P 500, with returns spiking to a maximum of 86%. Furthermore, while the OVX and exchange rate returns move in the same direction, the magnitude of returns seems to be quite different. Similarly, returns on oil and the S&P index seem to move in unison but the magnitude of the absolute returns seem to be far greater for oil relative to the S&P index.

Figure 3.3 plots the time series volatility for industrial production index, inflation, federal funds rate and discount rate in levels (left) and returns (right) for the full sample between May 2007 and December 2018. The industrial production index saw a significant dip during the financial crisis but begins to appreciate after 2009. Inflation also fell sharply during the financial crisis but has since returned to pre-crisis levels. Prior to the crisis, the federal funds rate and the discount rate were both close to 5%. During the crisis, the Federal Reserve brought the rate down to near zero. Finally, at the end of 2015 the Federal Reserve starting hiking up the rates, ending up at around 2% by the end of 2018.



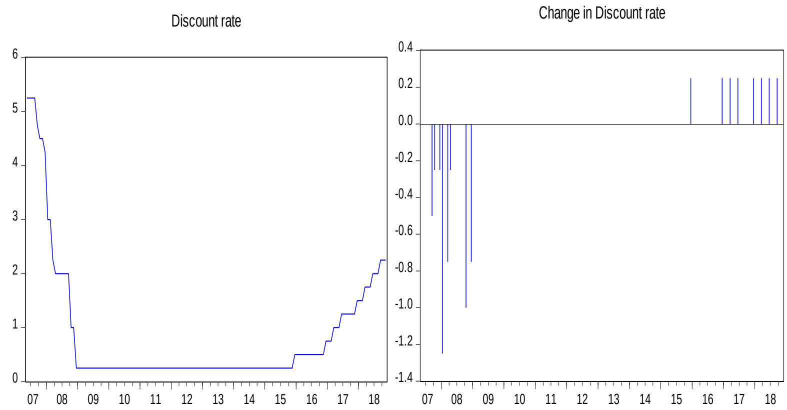


Figure 3.3. Time series volatility for industrial production index, inflation, federal funds rate and discount rate in levels (**left**) and returns (**right**) for the full sample between May 2007 and December 2018.

Table 3.6 reports the cross-correlation levels. Oil price returns show a correlation of 44% with S&P 500 returns while returns on the oil price volatility (OVX) display a −37% correlation with S&P 500 returns. Additionally, return on exchange rate shows a −45% correlation with return on oil price and a 27% correlation with return on the OVX index. Oil price shows a positive correlation while oil price volatility shows a negative correlation with inflation and our monetary policy measures of federal funds rate and discount rate. Generally, a rise in the stock market index would be associated with easing of monetary policy, but our correlation matrix suggests otherwise. This might be down to the fact that within the time frame considered, the Fed cut interest rates to near zero levels during the time of recession, which is a period where one would expect the stock index to plummet. The Fed only started hiking up the interest rate close to the end of 2015, which is when it would have assumed that the economy was well on the path of recovery and hence the need for monetary contraction. A recovery and post recovery period would generally be associated with a hike in the stock market index and thus it coincides with the hike in interest rates. Lastly, we find a very high correlation between the federal funds rate and discount rate which can be expected as they are both a representation of the Federal Reserve's monetary policy stance.

Table 3.6. Correlation.

	R_{OIL}	R_{OVX}	$R_{S\&P}$	R_e	R_p	$\Delta\pi$	Δffr	Δr
R_{OIL}	1.000000							

R_{OVX}	−0.515526	1.000000						
	0.0000	-----						
$R_{S\&P}$	0.436175	−0.372988	1.000000					
	0.0000	0.0000	-----					
R_e	−0.450407	0.268942	−0.503466	1.000000				
	0.0000	0.0015	0.0000	-----				
R_p	−0.068782	−0.005011	−0.167158	0.210115	1.000000			
	0.4245	0.9537	0.0509	0.0137	-----			
$\Delta\pi$	0.268988	−0.095837	0.143181	−0.123850	0.075038	1.000000		
	0.0015	0.2653	0.0951	0.1493	0.3835	-----		
Δffr	0.153786	−0.150212	0.150438	−0.140117	−0.282147	0.136181	1.000000	
	0.0728	0.0798	0.0793	0.1025	0.0008	0.1126	-----	
Δr	0.178791	−0.113110	0.216698	0.020163	−0.120173	0.096643	0.553829	1.000000
	0.0366	0.1882	0.0110	0.8151	0.1619	0.2612	0.0000	-----

The table provides correlation of the variables for the full sample from May 2007 to December 2018. R_{OIL} denotes the monthly return of WTI crude oil prices. R_{OVX} is the monthly return on the oil price volatility index (OVX). $R_{S\&P}$ represents the total return on the S&P 500 index. R_e is the monthly return of the USD against Euro $\Delta\pi$ represents the monthly change in the consumer price index (CPI). R_p denotes the return on the seasonally adjusted industrial production index Δffr represents monthly changes in the daily Federal Funds rate Δr is the monthly change in Fed discount rate. *p*-values are shown underneath the correlation values.

Theoretically, one could argue that the macroeconomy drives oil prices, which should therefore follow the S&P 500 index. Schalck and Chenavaz (2015) found that macroeconomic factors play a significant part in defining oil prices. They argue that exchange rates have a negative effect while global demand and the S&P index have a positive impact on oil commodity returns. One could also argue that a causation may exist the other way, i.e., oil prices causing movements within macroeconomic factors. A rise in oil price could be construed as a potential rise in demand within the economy, positively impacting the sentiments and potentially filtering through to raising S&P index levels. Since the US is a significant net oil importer within our selected data set, a rise in oil prices could potentially hike up the import bill, increasing global supply of the US dollar and potentially have a negative influence on the US dollar exchange rate. Furthermore, a hike in oil prices could also potentially raise cost of input for firms, negatively impacting production levels and therefore having a downward effect on economic activity and the industrial production index. Similarly, changes in macroeconomic variables may cause a change in oil price volatility, but we could also potentially have a two-way relationship. We therefore look to test the direction of the causality, if present, between oil prices, OVX and macroeconomic factors. Although Table 3.6 reveals some high correlation levels between independent variables, the variance inflation factor as shown in Table 3.7, has values around 1, confirming that there is no multi-collinearity issues with the model.

Table 3.7. Variance inflation factors.

Variable	VIF
R_{OIL}	1.762357
R_{OVX}	1.595214
$R_{S\&P}$	1.620351
R_e	1.611710
R_P	1.170689
$\Delta\pi$	1.141725
Δffr	1.644278
Δr	1.598733

The table provides correlation of the variables for the full sample from May 2007 to December 2018. R_{OIL} denotes the monthly return of WTI crude oil prices. R_{OVX} is the monthly return on the oil price volatility index (OVX). $R_{S\&P}$ represents the total return on the S&P 500 index. R_e is the monthly return of the USD against Euro $\Delta\pi$ represents the monthly change in the consumer price index (CPI). R_P denotes the return on the seasonally adjusted industrial production index Δffr represents monthly changes in the daily Federal Funds rate Δr is the monthly change in Fed discount rate.

Table 3.8 reports Granger causality test results for oil price/OVX and other macroeconomic variables that are at least statistically significant in one direction. Our results suggest that oil price causes movements in the S&P 500 index, industrial production index and inflation, while exchange rate causes movements in oil price. On the other hand, we find that exchange rate causes movements in the OVX, and the OVX causes movements in inflation.

Table 3.8. Granger causality.

Null Hypothesis:	F-Statistic	Prob.
RETURNS_INDEX does not Granger Cause ROIL	0.71831	0.4895
ROIL does not Granger Cause RETURNS_INDEX	3.89303	0.0228 **
R_EX does not Granger Cause ROIL	3.37319	0.0373 **
ROIL does not Granger Cause R_EX	0.42901	0.6521
PROD_INDEX_RETURNS does not Granger Cause ROIL	0.22039	0.8025
ROIL does not Granger Cause PROD_INDEX_RETURNS	2.86024	0.0609 *
INF does not Granger Cause ROIL	0.51422	0.5992
ROIL does not Granger Cause INF	8.55440	0.0003 ***
R_EX does not Granger Cause ROVX	2.77747	0.0659 *
ROVX does not Granger Cause R_EX	1.60471	0.2049
INF does not Granger Cause ROVX	0.12542	0.8822
ROVX does not Granger Cause INF	2.95734	0.0554 *

The table reports only the Granger causality test results between oil price/OVX and other macroeconomic variables that are at least significant in one direction, for the full sample between May 2007 and December 2018. Significance is shown at 10% (*), 5% (**) and 1% (***) levels.

3.5.3 OLS Results

Table 3.9 reports the OLS estimates for the full sample period. The results show that illiquidity premiums have a positive and statistically significant relationship with oil prices while they have a negative and statistically significant relationship with implied oil volatility. The opposite effects of oil price and its implied volatility on illiquidity premiums can be explained by the fact that oil prices and OVX tend to be negatively correlated. The results also show the importance of incorporating oil volatility in any model designed to study the impact of oil on financial markets.

Table 3.9. OLS regression results (full sample).

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	1.288339 ***	0.139588	9.229604	0.0000
$\mathbf{R_{OIL}}$	0.030870 **	0.014641	2.108434	0.0370
$\mathbf{R_{OVX}}$	−0.015871 **	0.007768	−2.043225	0.0431
$\mathbf{R_e}$	0.062820	0.042591	1.474947	0.1427
$\mathbf{\Delta r}$	−0.533502	0.712226	−0.749063	0.4552
$\mathbf{R_{S\&P}}$	−0.180027 ***	0.031003	−5.806708	0.0000
$\mathbf{R_{IML,t-1}}$	−0.176447 **	0.079659	−2.215031	0.0285
$\mathbf{\Delta ffr}$	−0.000364	0.553206	−0.000657	0.9995
$\mathbf{R_P}$	−0.137945	0.128176	−1.076211	0.2839
$\mathbf{\Delta\pi}$	−0.093619	0.232829	−0.402093	0.6883

This table presents the results for the full sample period between May 2007 and December 2018, where the dependent variable is R_{IML} which is the illiquidity premium. R_{OIL} denotes the monthly return of WTI crude oil prices. R_{OVX} is the monthly return on the oil price volatility index (OVX). R_e is the monthly return of the USD against Euro. Δr is the monthly change in Fed discount rate. $R_{S\&P}$ represents the total return on the S&P 500 index. $R_{IML,t-1}$ represents lagged illiquidity premiums. Δffr represents monthly changes in the daily Federal Funds rate. R_P denotes the return on the seasonally adjusted industrial production index. $\Delta\pi$ represents the monthly change in the consumer price index (CPI). Standard errors, t-statistics and the associated *p*-values are listed next to the coefficients. Significance is shown at 10% (*), 5% (**) and 1% (***) levels. Coefficients are multiplied by 100 to make them easier to read.

An explanation for the positive relationship between oil prices and illiquidity premiums could be based on investor sentiments within the market. Amihud (2002) along with Said and Giouvris (2017b) argue that small firms are usually more illiquid compared to larger firms and therefore small stocks are subject to greater illiquidity risk. A rise in oil prices could be perceived by investors as a sign of global economic recovery and an indication of future positive economic times (Güntner 2014; Foroni et al. 2017), making them relatively more prone to taking risks in order to earn a higher return. This injection of demand towards illiquid stocks could potentially hike their prices, enhancing returns on these stocks along with increasing realised illiquidity premiums. On the other hand, a decrease in oil prices can be perceived by investors as a slow-down of the global economy and a bleak future economic outlook, making them more averse towards risk. This could potentially result in a flow of funds towards more liquid and safer stocks, and therefore have a negative impact on realised illiquidity premiums.

Another possible explanation for this positive relationship stems from the argument put forward by Peter Ferderer (1996). They argue that although a rise in oil prices leads to income transfers from countries that are net importers of oil (such as the US) to oil exporting countries, depressing liquidity within the oil importing countries, this impact is offset by a rise in demand for US exports within the oil exporting countries. The result being a rise in market liquidity and illiquidity premiums within the US. All coefficients have been converted in percentage form within our regression and therefore for our model and data set, a 1% increase in the return of WTI crude oil prices results in a 0.031% increase in illiquidity premiums.

A similar argument based on investor sentiment can be used to analyse the negative relationship between implied oil price volatility (OVX), which captures the market's aggregate expectation of future oil volatility, and illiquidity premiums. A rise in the OVX index shows the market's belief of higher oil price volatility in the future, which could result in an increase in uncertainty and hence could potentially make investors more risk averse. This would imply a 'flight to quality' and funds being channeled towards relatively safer liquid stocks carrying less illiquidity risk. This lack of demand associated to illiquid stocks could potentially drive down realised illiquidity premiums. This result is consistent with the argument put forward by Bernanke and Gertler (1989) that a rise in oil price volatility increases the probability of bankruptcy and default on loans, along with raising the cost of external finance, creating barriers for firms to borrow and resulting in investors following a 'flight to quality' or a 'flight to liquidity' strategy away from illiquid stocks. It is also consistent with the results of Qadan and Nama (2018) who find a negative correlation between the implied oil price volatility measure (OVX) and investor sentiments, implying that a rise in OVX makes investors more pessimist towards risky assets including illiquid stocks. Again, this decrease in demand for illiquid stocks would have a negative impact on their price, resulting in a fall in their returns and realised illiquidity premiums. This uptick in perceived risk associated with illiquid stocks and the resulting 'flight to liquidity' strategy followed by investors brings along a leakage of liquidity from the stock market towards the bond market (Goyenko and Ukhov 2009). The reduction in liquidity within the stock market results in an even stronger negative relationship between oil price volatility and illiquidity premiums (Jensen and Moorman 2010; Said and Giouvris 2017b). Therefore, the negative relationship not only exists because of an enhancement in investor pessimism towards illiquid stocks but also because of the eventual fall in stock market liquidity. The relationship is further justified by the significant negative correlation between oil price and the OVX index.

From a firm perspective, Baum et al. (2006) argued that a rise in volatility creates more uncertainty within firms regarding their future cash flows and therefore they might not want to hold illiquid assets. This puts a downward pressure on the demand for illiquid assets, reducing their price and thus reducing realised illiquidity premiums. They argue that although these investment decisions are firm specific, increased volatility does create more cash flow uncertainty and firms respond in a homogeneous manner by parking funds in more liquid assets. A fall in the future expectation of oil volatility can be perceived as more economic stability going forward. This may result in investors being more adventurous, seeking to enhance their returns. A 'flight to illiquidity' can then result in a rise in demand of illiquid stocks, hiking their prices and thus raising realised illiquidity premiums. From our results, a rise in the return on the oil price volatility index (OVX) of 1% results in a 0.016% fall in illiquidity premiums

While the main focus of our paper is the impact of oil price and oil price volatility on illiquidity premiums, controlling for a variety of other variables helps assess their statistical significance. The S&P 500 index that measures the stock performance of 500 large companies on stock exchanges in the US, is statistically significant and has a negative impact on illiquidity premiums. Eleswarapu and Reinganum (1993) and Elfakhani (2000) argued that illiquidity premiums are a result of the size effect i.e., small firms are considered to be less liquid and thus should obtain higher return. Using this rationale, one can see why returns on the S&P 500 index and illiquidity premiums would be negatively related. As returns on the index go up, this signifies higher returns on larger, more liquid stocks. The higher return on these instruments results in a channeling of funds towards these securities relative to smaller illiquid stocks. This potentially reduces demand for illiquid stocks and impacts realised illiquidity premiums via a price effect. Based on our results, a rise in S&P 500 index returns of 1% leads to a 0.18% fall in illiquidity premiums.

One month lagged illiquidity premiums have a significant and negative relationship with premiums in the current month. As the price differential between illiquid and liquid stocks goes up one-month prior, investors may look to sell their illiquid stocks in order to realise profits, this potentially increases the supply of these stocks within the market, creating a downward impact on their prices and hence reducing illiquidity premiums in the current month.

The monetary policy indicators that we use in our model, namely the federal funds rate and the Fed discount rate seem to have no statistically significant impact on illiquidity premiums[10]. This is an indication that regardless of the Federal Reserve's monetary stance, the existence and magnitude of the illiquidity premiums remains unaffected. Jensen and Moorman (2010) and Said and Giouvris (2017a) conclude that illiquidity premiums are significant and positive during phases of monetary expansion, as they are positively impacted by a higher supply of liquidity within the market during these periods. During restrictive monetary scenarios, illiquidity premiums seem to be insignificant. Within our data set, there is a phase of monetary expansion after the recession when interest rates were slashed from around 5% to near 0% levels, over a period of time. Interest rates stayed at that near 0% level up until the end of 2015, when the Fed started raising rates, which eventually went up to 2% by the end of 2018. Illiquidity premiums in our study seem to be positive and significant during times of interest rate cuts and even during times of interest rate hikes. Rather than just conventional business cycle booms which might result in central bank monetary tightening in order to not over-heat the economy, recovery from an economic recession could create far more significant positive shifts in investor sentiments which may supersede the more general impact of interest rate hikes. Therefore, the fact that the data set includes a recession period and recovery from it, the time frame used may play a key role in the insignificance of monetary shifts on illiquidity premiums within this paper.

Tables 3.10 and 3.11 report the OLS estimates for the two sub-samples, that is during the financial crisis and a post-crisis period. The post-crisis results are very similar to the findings within our full sample, with illiquidity premiums having a positive and statistically significant relationship with oil prices and a negative and statistically significant relationship

[10] Discount rate lagged two periods has a significant negative impact on illiquidity premiums, therefore as discount rate goes down two months' prior, the illiquidity premium rises in the current month. This potentially indicates a lagged positive impact on stock market liquidity and investor sentiments of the fed slashing interest rates.

with implied oil volatility. Furthermore, the S&P500 index and one month lagged illiquidity premiums have a significant and negative relationship with premiums in the current month.

During the financial crisis, the direction of the impact of oil prices on illiquidity premiums changes to a significantly negative relationship. Illiquidity and liquidity risk was identified as a major source for the financial crisis (Brunnermeier 2009; Crotty 2009). With the United States being a net oil importer, a rise in oil prices could potentially reduce market liquidity even further, which may result in a reduction in illiquidity premiums within this time frame. The other major changes within the financial crisis period relative to the post-crisis period are the significance of exchange rate and inflation in impacting illiquidity premiums. The US Dollar is considered a safe-haven investment and a rise in the US Dollar–Euro rate may trigger investors to place funds within the currency relative to investing within illiquid stocks. This is even more plausible in a crisis scenario where investors might be more risk averse, potentially depressing investors' demand for illiquid stocks, reducing their price and therefore shrinking realised illiquidity premiums. On the other hand, inflation has a positive impact on illiquidity premiums. A rise in general price levels would impact investors' real income. Investors may look to earn higher returns on their investments to enhance their nominal income in order to match the rise in prices and maintain their standard of living. For this reason, investors may look to park their funds within illiquid stocks, as a means of earning a higher return, enhancing the demand of these stocks and raising illiquidity premiums. The S&P 500 still has a significantly negative relationship with illiquidity premiums within the recession period.

Table 3.10. OLS regression results (financial crisis).

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	1.358777 ***	0.402288	3.377619	0.0082
R_{OIL}	−0.053505 *	0.024567	−2.177926	0.0574
R_{OVX}	−0.005574	0.016295	−0.342058	0.7402
$R_{S\&P}$	−0.147643 ***	0.040964	−3.604238	0.0057
R_e	−0.118983 *	0.064873	−1.834089	0.0998
$\Delta\pi$	1.007808 **	0.326382	3.087820	0.0130
R_p	0.027289	0.163546	0.166860	0.8712
Δffr	−0.085097	0.495356	−0.171789	0.8674
Δr	0.537531	0.708752	0.758419	0.4676
$R_{IML,t-1}$	0.183660	0.169410	1.084113	0.3065

This table presents the results for the financial crisis sub-sample period between December 2007 and June 2009, where the dependent variable is R_{IML} which is the illiquidity premium. R_{OIL} denotes the monthly return of WTI crude oil prices. R_{OVX} is the monthly return on the oil price volatility index (OVX). R_e is the monthly return of the USD against Euro. Δr is the monthly change in Fed discount rate. $R_{S\&P}$ represents the total return on the S&P 500 index. $R_{IML,t-1}$ represents lagged illiquidity premiums. Δffr represents monthly changes in the daily Federal Funds rate. R_P denotes the return on the seasonally adjusted industrial production index. $\Delta\pi$ represents the monthly change in the consumer price index (CPI). Standard errors, t-statistics and the associated *p*-values are listed next to the coefficients. Significance is shown at 10% (*), 5% (**) and 1% (***) levels. Coefficients are multiplied by 100 to make them easier to read.

Table 3.11. OLS regression results (post financial crisis).

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	1.411284 ***	0.169302	8.335879	0.0000
$\mathbf{R_{OIL}}$	0.053631 ***	0.018699	2.868092	0.0050
$\mathbf{R_{OVX}}$	−0.018525 *	0.009374	−1.976241	0.0508
$\mathbf{R_{S\&P}}$	−0.198415 ***	0.041920	−4.733169	0.0000
$\mathbf{R_e}$	0.080658	0.051597	1.563224	0.1211
$\mathbf{\Delta\pi}$	−0.187556	0.300619	−0.623899	0.5341
$\mathbf{R_p}$	−0.087853	0.170698	−0.514667	0.6079
Δffr	0.201471	3.145379	0.064053	0.9491
Δr	−1.447185	3.489305	−0.414749	0.6792
$\mathbf{R_{IML,t-1}}$	−0.250377 ***	0.091011	−2.751069	0.0070

This table presents the results for the post financial crisis sub-sample period between July 2009 and December 2018, where the dependent variable is R_{IML} which is the illiquidity premium. R_{OIL} denotes the monthly return of WTI crude oil prices. R_{OVX} is the monthly return on the oil price volatility index (OVX). R_e is the monthly return of the USD against Euro. Δr is the monthly change in Fed discount rate. $R_{S\&P}$ represents the total return on the S&P 500 index. $R_{IML,t-1}$ represents lagged illiquidity premiums. Δffr represents monthly changes in the daily Federal Funds rate. R_P denotes the return on the seasonally adjusted Industrial Production Index. $\Delta\pi$ represents the monthly change in the consumer price index (CPI). Standard errors, t-statistics and the associated *p*-values are listed next to the coefficients. Significance is shown at 10% (*), 5% (**) and 1% (***) levels. Coefficients are multiplied by 100 to make them easier to read.

3.5.4 Co-integration and VAR Analysis

Next, we check for co-integration between all the variables using the Johansen and Juselius test (Johansen and Juselius 1990). Table 3.12 and 3.13 presents the results using trace and the maximum eigenvalue tests. The trace statistic suggests the existence of four co-integrating vectors while the maximum eigenvalue suggests the existence of two co-integrating vectors. We therefore reject the null hypothesis of no co-integration and conclude that there is a long-run relationship between all the variables analysed in our paper.

Table 3.12. Johansen and Juselius co-integration test (trace statistic)

Hypothesized No. of CE(s)	Eigenvalue	Trace Statistic	0.05 Critical Value	Prob.
None *	0.462833	296.2086	197.3709	0.0000
At most 1 *	0.425503	213.5561	159.5297	0.0000
At most 2 *	0.257112	139.8395	125.6154	0.0051
At most 3 *	0.213710	100.3105	95.75366	0.0234
At most 4	0.163141	68.33333	69.81889	0.0653

This table presents the results of the Johansen and Juselius test using trace statistics for illiquidity premiums, oil price, OVX, exchange rate, S&P 500 index, inflation, industrial production index, federal funds rate and discount rate. The first column represents the number of cointegrating relationships under the null hypothesis with the corresponding *p*-values in the last column. * denotes rejection of the null hypothesis of no cointegration at 5% level.

Table 3.13. Johansen and Juselius co-integration test (maximum eigenvalue)

Hypothesized No. of CE(s)	Eigenvalue	Trace Statistic	0.05 Critical Value	Prob.
None *	0.462833	82.65247	58.43354	0.0001
At most 1 *	0.425503	73.71664	52.36261	0.0001
At most 2	0.257112	39.52896	46.23142	0.2182
At most 3	0.213710	31.97718	40.07757	0.3042
At most 4	0.163141	23.68728	33.87687	0.4786

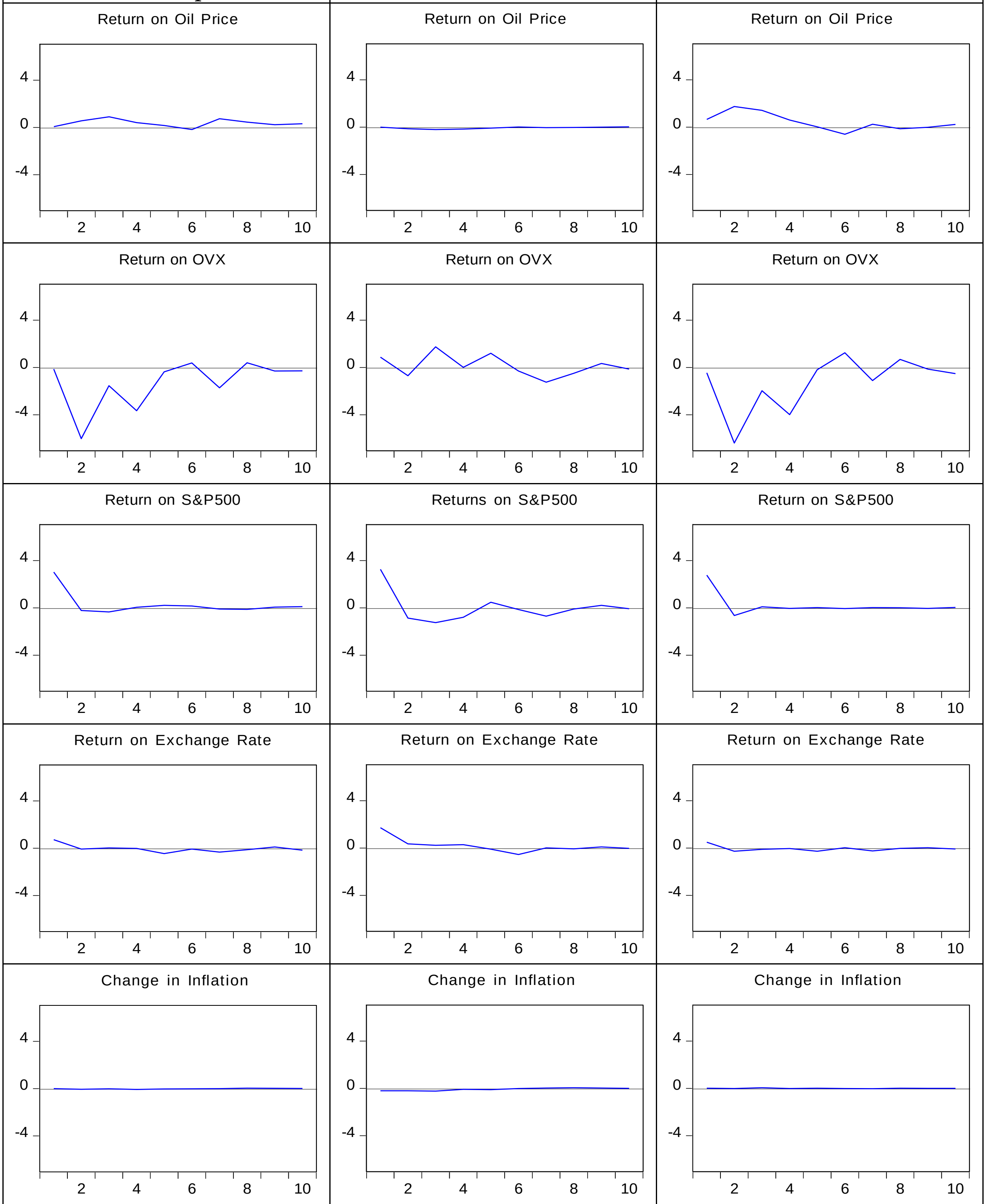
This table presents the results of the Johansen and Juselius test using maximum eigenvalue for illiquidity premiums, oil price, OVX, exchange rate, S&P 500 index, inflation, industrial production index, federal funds rate and discount rate. The first column represents the number of cointegrating relationships under the null hypothesis with the corresponding *p*-values in the last column. * denotes rejection of the null hypothesis of no cointegration at 5% level.

After estimating the VAR model in Equation (3.3), we analyse the impact of oil price, oil implied volatility and the macroeconomic factors on illiquidity premiums through impulse response functions. This is done for the full sample, the financial crisis period and the post-crisis period, and is shown in Figure 3.4.

First, consistent with our OLS estimates, we find a change in how illiquidity premiums react to oil price changes during and after the financial crisis. We find a positive relationship between oil prices and illiquidity premiums in the post-recession period, and although we do find a negative relationship during the financial crisis, illiquidity premiums are relatively less sensitive to changes in oil price during this phase. Overall, we find a positive relationship between the two variables for the full sample.

Oil implied volatility has a relatively larger negative impact on illiquidity premiums after the crisis period. Although illiquidity premiums have a more subdued response to oil implied volatility during the recession phase, we still find diminishing premiums linked to higher oil price volatility.

Full Sample	Financial Crisis	Post-Crisis



Full Sample	Financial Crisis	Post-Crisis

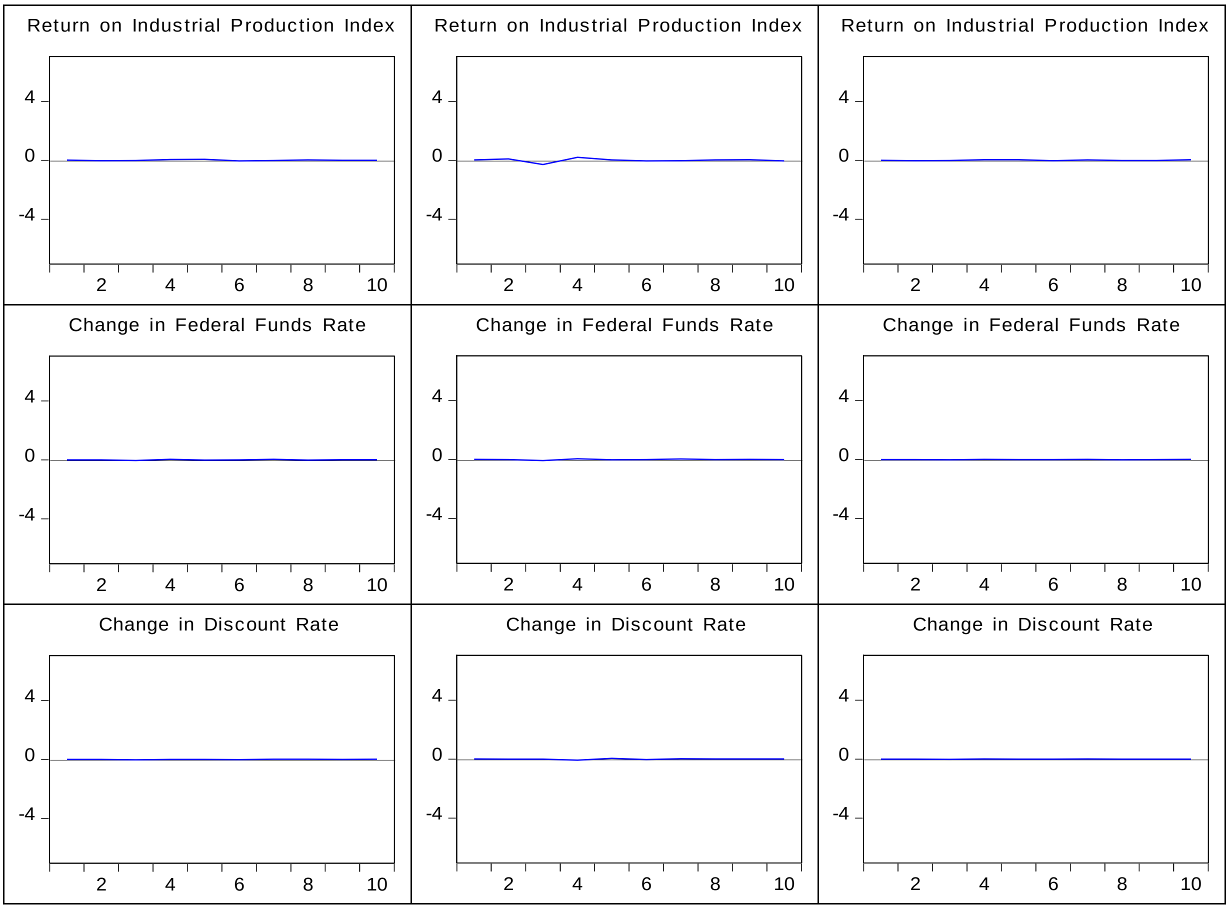


Figure 3.4. Impulse response functions for the response of illiquidity premiums to shocks in oil price returns, OVX returns, S&P 500 returns, returns on exchange rate, change in inflation, returns on industrial production index, change in federal funds rate and change in discount rate. This includes the full sample from May 2007 to December 2018 and sub-samples titled financial crisis (December 2007 to June 2009) and post-crisis (July 2009 to December 2018).

The S&P500 index has a significantly negative relationship with illiquidity premiums both during and after the financial crisis. This is consistent with the rationale put forward by Eleswarapu and Reinganum (1993) and Elfakhani (2000), who argue that illiquidity premiums are a result of the size effect i.e., small firms are considered to be less liquid and thus should obtain higher return. A hike in the index is an indication of higher returns on larger, more liquid stocks. Such a move would make investors more inclined towards these larger stocks, reducing the demand for illiquid stocks and therefore having a downward impact on illiquidity premiums. The response of illiquidity premiums to a rise in the S&P 500 index is stronger during the financial crisis relative to the post-crisis period. A possible explanation for this could be the fact that investors may have a higher risk aversion towards riskier illiquid stocks during a recessionary phase. Furthermore, the negative reaction of illiquidity premiums is smoothly close to zero during two months of the shock, within the post-crisis period. During the crisis phase, this impact lingers on a lot longer and smoothens out to zero around the eighth month mark.

Exchange rate has a negative impact on illiquidity premiums both during and after the financial crisis. Consistent with our OLS results, this impact is a lot stronger during the financial crisis. Given the status of the US Dollar as a safe haven investment, investors might be more inclined towards investing in the Dollar as the US Dollar/Euro rate appreciates. This may especially be true during a crisis phase, as investors may be more skeptical towards riskier illiquid instruments during a recessionary period.

The impact of industrial production index, federal funds rate and the discount rate seems largely insignificant. Illiquidity premiums do show a slight positive response to a rise in inflation during the financial crisis but this is not significant.

3.5.5 Robustness - Bounds Test, the Long-Run ARDL Model and the Short-Run Error Correction Model

Table 3.14 reports the results of the bounds test for co-integration for the full sample. The computed F-statistic is significantly greater than the critical upper bound values at the 5% and 10% levels of significance. This indicates that a co-integration relationship exists between oil price, oil price volatility, the examined macroeconomic variables and illiquidity premiums.

Table 3.14. The results of the bounds test for co-integration (full sample)

Computed F-Statistic	10% Critical I(0)	10% Critical I(1)	5% Critical I(0)	5% Critical I(1).	ARDL Specs	H_0: No Cointegrate-Ion
27.38822	1.95	3.06	2.22	3.39	(1,1,1,0,1,0,0,0,0)	Reject

This table represents results of the bounds test for the full sample (May 2007 to December 2018). The ARDL specs are the optimal lags for illiquidity premium, oil price, OVX, S&P 500 index, exchange rate, inflation, industrial production index, federal funds rate and discount rate, as specified by the Akaike info criterion (AIC). The F-statistic is for a joint test of the following hypothesis as set up in Equation (3): H0: $\beta10 = \beta11 = \beta12 = \beta13 = \beta14 = \beta15 = \beta16 = \beta17 = \beta18 = 0$.

Once a long-run relationship has been established between the examined variables, we use the long-run ARDL model as specified in Equation (3.5) to estimate long-run elasticities for the variables in the model, for the full sample period. The results in Table 3.15 indicate that oil price within the month has a significantly positive impact on illiquidity premiums while one month lagged oil prices have a significantly negative influence on premiums. Both current and lagged values of OVX have an insignificant impact on illiquidity premiums. Consistent with our earlier OLS and VAR estimates, the S&P 500 index and one month lagged illiquidity premiums have a negative impact on illiquidity premiums in the current month. The direction of the relationship changes for one month lagged measure of the index, which has a significantly positive relationship with illiquidity premiums.

Table 3.16 shows short-run elasticities using the error correction model in Equation (3.6). The lagged values of the explanatory variables seem largely insignificant possibly because the effects of these variables occur within the month. Illiquidity premiums have a significantly positive relationship with oil price and a significantly negative relationship with OVX. The S&P 500 index once again has a negative influence on illiquidity premiums. The short-run exchange rate coefficient is significantly positive. More importantly, the coefficient for the error correction term is significantly negative, implying that the reverting mechanism for sustaining the long-run relationship between the explanatory variables and illiquidity premium is extremely relevant.

Table 3.15. Long-run ARDL model (full sample)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.068333	0.218789	0.312323	0.7553
OIL	0.040888 **	0.016412	2.491387	0.0141
OIL(-1)	−0.039628 **	0.015622	−2.536602	0.0125
OVX	−0.008455	0.008811	−0.959510	0.3392
OVX(-1)	0.011875	0.009368	1.267607	0.2074
S&P	−0.169166 ***	0.031589	−5.355201	0.0000
S&P(-1)	0.159571 ***	0.033698	4.735307	0.0000
E	0.069077	0.047749	1.446678	0.1506
E(-1)	−0.038125	0.045075	−0.845824	0.3993
Π	0.001654	0.002669	0.619766	0.5366
π (-1)	0.000229	0.002650	0.086237	0.9314
P	−0.021247	0.175813	−0.120852	0.9040
P(-1)	0.021454	0.161216	0.133078	0.8944
Ffr	0.000242	0.004006	0.060311	0.9520
ffr(-1)	−0.000526	0.004005	−0.131240	0.8958
R	−0.010510	0.009717	−1.081536	0.2816
r(-1)	0.009068	0.009430	0.961590	0.3382
$R_{IML,t-1}$	−0.220512 ***	0.081605	−2.702198	0.0079

This table presents the results for the full sample period between May 2007 and December 2018, where the dependent variable is R_{IML} which is the illiquidity premium. OIL denotes the natural log of oil price, OVX denotes the natural log of OVX, S&P denotes the natural log of the S&P index, E denotes the natural log of exchange rate, π denotes inflation, P denotes the natural log of industrial production index, ffr is the natural log of the federal funds rate while r is the natural log of the discount rate Standard errors, t-statistics and the associated *p*-values are listed next to the coefficients. Significance is shown at 10% (*), 5% (**) and 1% (***) levels.

Table 3.16. Short-run error correction model (full sample).

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.006721 **	0.003293	2.041367	0.0435
DOIL	0.038803 **	0.015856	2.447246	0.0159
DOIL(-1)	−0.008964	0.018891	−0.474529	0.6360
DOVX	−0.014719 *	0.008842	−1.652418	0.0986
DOVX(-1)	0.005638	0.009303	0.606092	0.5456
DS&P	−0.170787 ***	0.032250	−5.295671	0.0000
DS&P(-1)	0.081126	0.057576	1.409023	0.1615
DE	0.104548 **	0.048107	2.173224	0.0318
DE(-1)	0.010501	0.049029	0.214186	0.8308
Dπ	0.000761	0.002976	0.255657	0.7987
Dπ(-1)	−0.000687	0.002979	−0.230772	0.8179
DP	−0.217711	0.159059	−1.368743	0.1737
DP(-1)	0.175077	0.167084	1.047840	0.2969
Dffr	4.54E−05	0.003935	0.011543	0.9908
Dffr(-1)	−0.001607	0.003802	−0.422682	0.6733
Dr	−0.013658	0.009625	−1.419042	0.1585
Dr(-1)	0.015431	0.009748	1.583002	0.1161
$R_{IML,t-1}$	0.379569	0.285463	1.329658	0.1862
ECM(-1)	−0.658301 **	0.300074	−2.193795	0.0302

This table presents the results for the full sample period between May 2007 and December 2018, where the dependent variable is R_{IML} which is the illiquidity premium. DOIL, DOVX, DS&P, DE, DP, Dffr and Dr, are the first differences of natural logs for oil price, OVX index, S&P500 index, US Dollar against Euro exchange rate, industrial production index, federal funds rate and the discount rate, Dπ is the first difference of the inflation rate. ECM denotes the error correction term. Standard errors, t-statistics and the associated p-values are listed next to the coefficients. Significance is shown at 10% (*), 5% (**) and 1% (***) levels.

Table 3.17 reports the results of the bounds test for co-integration for the financial crisis period. The computed F-statistic is significantly greater than the critical upper bound values at the 5% and 10% levels of significance. This indicates that a co-integration relationship exists between oil price, oil price volatility, the examined macroeconomic variables and illiquidity premiums, during the financial crisis.

Table 3.17. The results of the bounds test for co-integration (financial crisis)

Computed F-Statistic	10% Critical I(0)	10% Critical I(1)	5% Critical I(0)	5% Critical I(1).	ARDL Specs	H_0: No Cointegrate-Ion
12.46757	1.95	3.06	2.22	3.39	(1,0,0,1,0,0,0,0,0)	Reject

This table represents results of the bounds test for the crisis sub-sample (December 2007 to June 2009). The ARDL specs are the optimal lags for illiquidity premium, oil price, OVX, S&P 500 index, exchange rate, inflation, industrial production index, federal funds rate and discount rate, as specified by the Akaike info criterion (AIC). The F-statistic is for a joint test of the following hypothesis as set up in Equation (3): H0: β10 = β11 = β12 = β13 = β14 = β15 = β16 = β17 = β18 = 0.

Table 3.18 shows the results of the long-run ARDL model during the crisis period. Illiquidity premiums are no longer sensitive to changes in oil price and oil implied volatility during this period. Consistent with the results of the full sample, we find that the S&P 500 index and one month lagged illiquidity premiums have a negative impact on illiquidity premiums in the current month. One month lagged measure of the S&P index has a significantly positive relationship with illiquidity premiums.

Table 3.19 shows short-run elasticities using the error correction model. Once again, oil price and oil implied volatility have no significant impact on illiquidity premium. The S&P index has a significant negative impact on illiquidity premium but the lag term in this instance is insignificant, possibly because the effect of the S&P index on illiquidity premium occurs within the month. Although the error correction term is negative, it is insignificant. This would imply that the reverting mechanism to sustain the long-run relationship between the examined variables and illiquidity premium is ineffective.

Table 3.18. Long-run ARDL model (financial crisis)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.340159	0.423604	0.803013	0.4272
OIL	0.012840	0.029692	0.432431	0.6680
OIL(-1)	−0.003696	0.024839	−0.148817	0.8825
OVX	−0.017197	0.015784	−1.089524	0.2832
OVX(-1)	0.007858	0.015679	0.501181	0.6193
S&P	−0.131034 ***	0.047184	−2.777085	0.0087
S&P(-1)	0.095321 *	0.049323	1.932573	0.0612
E	0.073530	0.072390	1.015755	0.3165
E(-1)	−0.028086	0.066771	−0.420625	0.6765
π	0.000923	0.003788	0.243600	0.8089
π (-1)	0.002482	0.004000	0.620493	0.5388
P	0.101280	0.228464	0.443306	0.6602
P(-1)	−0.116143	0.248906	−0.466613	0.6436
ffr	0.007128	0.005607	1.271255	0.2118
ffr(-1)	−0.001566	0.005863	−0.267173	0.7909
r	−0.019223	0.012976	−1.481471	0.1472
r(-1)	0.013005	0.014162	0.918264	0.3646
$R_{IML,t-1}$	−0.272942 *	0.141408	−1.930178	0.0615

This table presents the results for the financial crisis period between December 2007 and June 2009, where the dependent variable is R_{IML} which is the illiquidity premium. OIL denotes the natural log of oil price, OVX denotes the natural log of OVX, S&P denotes the natural log of the S&P index, E denotes the natural log of exchange rate, π denotes inflation, P denotes the natural log of industrial production index, ffr is the natural log of the federal funds rate while r is the natural log of the discount rate Standard errors, t-statistics and the associated p-values are listed next to the coefficients. Significance is shown at 10% (*), 5% (**) and 1% (***) levels.

Table 3.19. Short-run error correction model (financial crisis).

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.009386	0.005529	1.697589	0.0987
DOIL	0.005792	0.026907	0.215263	0.8308
DOIL(-1)	0.013893	0.026676	0.520787	0.6059
DOVX	−0.020331	0.014652	−1.387589	0.1743
DOVX(-1)	0.005240	0.014409	0.363646	0.7184
DS&P	−0.114489 **	0.044005	−2.601744	0.0136
DS&P(-1)	0.025393	0.060738	0.418074	0.6785
DE	0.096478	0.073419	1.314066	0.1976
DE(-1)	0.004250	0.073081	0.058154	0.9540
Dπ	−0.002926	0.004192	−0.698014	0.4899
Dπ(-1)	0.004552	0.003965	1.148065	0.2590
DP	−0.073862	0.194115	−0.380505	0.7059
DP(-1)	−0.061939	0.224250	−0.276205	0.7841
Dffr	0.007686	0.005040	1.524998	0.1365
Dffr(-1)	−0.000188	0.005697	−0.033009	0.9739
Dr	−0.021979	0.014022	−1.567454	0.1263
Dr(-1)	0.014763	0.014677	1.005878	0.3216
$R_{IML,t-1}$	0.247399	0.402831	0.614151	0.5432
ECM(-1)	−0.552298	0.445126	−1.240767	0.2232

This table presents the results for the financial crisis period between December 2007 and June 2009, where the dependent variable is R_{IML} which is the illiquidity premium. DOIL, DOVX, DS&P, DE, DP, Dffr and Dr, are the first differences of natural logs for oil price, OVX index, S&P500 index, US Dollar against Euro exchange rate, industrial production index, federal funds rate and the discount rate, Dπ is the first difference of the inflation rate. ECM denotes the error correction term. Standard errors, t-statistics and the associated p-values are listed next to the coefficients. Significance is shown at 10% (*), 5% (**) and 1% (***) levels.

Table 3.20 reports the results of the bounds test for co-integration for the post-crisis period. The computed F-statistic is significantly greater than the critical upper bound values at the 5% and 10% levels of significance. This indicates that a long-run relationship exists between oil price, oil price volatility, the examined macroeconomic variables, and illiquidity premiums, during the post-crisis period.

Table 3.20. The results of the bounds test for co-integration (post-crisis).

Computed F-Statistic	10% Critical I(0)	10% Critical I(1)	5% Critical I(0)	5% Critical I(1).	ARDL Specs	H_0: No Cointegrate-Ion
24.48194	1.95	3.06	2.22	3.39	(1,1,0,1,0,0,0,0,0)	Reject

This table represents results of the bounds test for the post-crisis sub-sample (July 2009 to December 2018). The ARDL specs are the optimal lags for illiquidity premium, oil price, OVX, S&P 500 index, exchange rate, inflation, industrial production index, federal funds rate and discount rate, as specified by the Akaike info criterion (AIC). The F-statistic is for a joint test of the following hypothesis as set up in Equation (3): H0: $\beta 10 = \beta 11 = \beta 12 = \beta 13 = \beta 14 = \beta 15 = \beta 16 = \beta 17 = \beta 18 = 0$.

Table 3.21 shows results of the long-run ARDL model during the post-crisis period. Oil price has a positive impact on illiquidity premiums within this period, while the OVX coefficient is insignificant. We also find that S&P index and one month lagged values of illiquidity premium have a negative impact on illiquidity premium.

Oil price has a positive influence on illiquidity premium in the short-run, as shown in Table 3.22. The lagged values of oil price are all insignificant. OVX has an insignificant impact on illiquidity premium, but the coefficient for third lag is significantly positive. This indicates a potential delayed response within illiquidity premiums of a rise in OVX. The current value of the S&P 500 index has a negative influence while the one month lagged value has a positive impact, on illiquidity premium. Two contrasting results relative to the short-run ECM for the full sample are that two month lagged values of exchange rate and discount rate have a significantly negative impact on illiquidity premium. As the US Dollar/Euro rate goes up, investors might be more inclined towards moving a greater chunk of their portfolio into foreign exchange, specifically the US Dollar. This might involve selling off their investments within illiquid stocks. Off-loading illiquid securities might require a rigorous search for a buyer relative to liquid securities which would generally have a more vibrant secondary market. This could potentially increase the time taken to realise the sale of these instruments

(Ibbotson et al. 2013), explaining the delayed fall in price within these stocks, and therefore a delayed fall in illiquidity premium. This stickiness within the secondary market for illiquid stocks might also be a potential explanation for the delayed negative response to a rise in discount rate. As the discount rate is hiked, bond market instruments become more lucrative as their yields go up. Investors might look to move funds from illiquid stocks to the bond market, but due to a potential lack of buyers, the actual realization of this sale might get delayed. This delay in sale may cause a delay in terms of the downward movement in price of illiquid stocks and thus a delay in the fall in illiquidity premium. The coefficient for the error correction term is significantly negative, indicating that the reverting mechanism for sustaining the co-integration relationship between the examined variables and illiquidity premium is extremely relevant.

Table 3.21. Long-run ARDL model (post-crisis)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.466964	0.451033	1.035321	0.3038
OIL	0.041190 *	0.023644	1.742096	0.0855
OIL(-1)	−0.032239	0.031005	−1.039786	0.3017
OIL(-2)	−0.021040	0.029749	−0.707251	0.4815
OIL(-3)	0.008949	0.022632	0.395401	0.6936
OVX	−0.013467	0.012965	−1.038728	0.3022
OVX(-1)	0.017964	0.016080	1.117216	0.2674
OVX(-2)	−0.001539	0.016399	−0.093847	0.9255
OVX(-3)	−0.001768	0.013491	−0.131063	0.8961
S&P	−0.175635 ***	0.050389	−3.485577	0.0008
S&P(-1)	0.229509 ***	0.072552	3.163370	0.0022
S&P(-2)	−0.086908	0.081848	−1.061822	0.2916
S&P(-3)	0.040272	0.057874	0.695855	0.4886
E	0.079207	0.067371	1.175684	0.2433
E(-1)	−0.009185	0.099100	−0.092685	0.9264
E(-2)	−0.155365	0.097139	−1.599405	0.1138
E(-3)	0.096508	0.069899	1.380683	0.1714
π	−0.001217	0.004222	−0.288334	0.7739
π(-1)	−0.000825	0.006402	−0.128881	0.8978
π(-2)	0.002371	0.006232	0.380398	0.7047
π(-3)	0.001481	0.003914	0.378457	0.7061
P	−0.372692	0.341082	−1.092674	0.2779
P(-1)	0.466448	0.372189	1.253257	0.2139
P(-2)	−0.584704	0.372488	−1.569728	0.1206
P(-3)	0.382184	0.287689	1.328463	0.1879
ffr	0.000302	0.006860	0.044043	0.9650
ffr(-1)	−0.001066	0.005888	−0.181028	0.8568
ffr(-2)	0.000235	0.005740	0.040909	0.9675
ffr(-3)	0.000431	0.006230	0.069143	0.9451
Dr	−0.010216	0.019663	−0.519542	0.6049
Dr(-1)	0.023079	0.023065	1.000611	0.3201
Dr(-2)	−0.034801	0.023910	−1.455476	0.1496
Dr(-3)	0.018590	0.019948	0.931930	0.3543
$\mathbf{R_{IML,t-1}}$	−0.248926 **	0.115774	−2.150093	0.0347
$\mathbf{R_{IML,t-2}}$	−0.021788	0.121211	−0.179757	0.8578
$\mathbf{R_{IML,t-3}}$	0.147398	0.109816	1.342225	0.1835

This table presents the results for the post-crisis period between July 2009 and December 2018, where the dependent variable is R_{IML} which is the illiquidity premium. OIL denotes the natural log of oil price, OVX denotes the natural log of OVX, S&P denotes the natural log of the S&P index, E denotes the natural log of exchange rate, π denotes inflation, P denotes the natural log of industrial production index, ffr is the natural log of the federal funds rate while r is the natural log of the discount rate Standard errors, t-statistics and the associated p-values are listed next to the coefficients. Significance is shown at 10% (*), 5% (**) and 1% (***) levels.

Table 3.22. Short-run error correction model (post-crisis)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.000677	0.005309	0.127618	0.8988
DOIL	0.038671 *	0.021259	1.819028	0.0729
DOIL(-1)	−0.024388	0.024224	−1.006766	0.3173
DOIL(-2)	−0.012653	0.022039	−0.574125	0.5676
DOIL(-3)	0.030766	0.022085	1.393051	0.1677
DOVX	−0.013120	0.011771	−1.114672	0.2686
DOVX(-1)	0.021735	0.013696	1.586931	0.1167
DOVX(-2)	0.004859	0.013042	0.372529	0.7105
DOVX(-3)	0.021192 *	0.012490	1.696749	0.0939
DS&P	−0.177465 ***	0.049437	−3.589748	0.0006
DS&P(-1)	0.210425 ***	0.075769	2.777177	0.0069
DS&P(-2)	−0.070150	0.061639	−1.138075	0.2587
DS&P(-3)	0.058706	0.059339	0.989330	0.3257
DE	0.071916	0.062934	1.142719	0.2568
DE(-1)	0.011273	0.068364	0.164897	0.8695
DE(-2)	−0.170500 **	0.072915	−2.338333	0.0220
DE(-3)	0.067019	0.070157	0.955279	0.3425
π	−0.000233	0.004061	−0.057440	0.9543
π(-1)	−0.000618	0.004032	−0.153170	0.8787
π(-2)	−0.000171	0.004065	−0.042133	0.9665
π(-3)	0.004643	0.003631	1.278818	0.2049
DP	−0.394991	0.306940	−1.286866	0.2021
DP(-1)	0.350906	0.274584	1.277954	0.2052
DP(-2)	−0.554900 **	0.270399	−2.052153	0.0436
DP(-3)	0.222211	0.274246	0.810261	0.4204
Dffr	0.002040	0.006742	0.302623	0.7630
Dffr(-1)	0.001920	0.007348	0.261311	0.7946
Dffr(-2)	0.005104	0.007456	0.684586	0.4957
Dffr(-3)	0.003874	0.006463	0.599393	0.5507
Dr	−0.011566	0.019251	−0.600803	0.5498
Dr(-1)	0.014563	0.021086	0.690635	0.4919
Dr(-2)	−0.041569 *	0.021141	−1.966292	0.0530
Dr(-3)	0.013603	0.020565	0.661497	0.5103
$R_{IML,t-1}$	0.576073 *	0.293655	1.961733	0.0535
$R_{IML,t-2}$	0.214100	0.129947	1.647598	0.1036
$R_{IML,t-3}$	0.203167 *	0.118340	1.716811	0.0901
ECM(-1)	−0.846074 ***	0.310598	−2.724019	0.0080

This table presents the results for the post-crisis period between July 2009 and December 2018, where the dependent variable is R_{IML} which is the illiquidity premium. DOIL, DOVX, DS&P, DE, DP, Dffr and Dr, are the first differences of natural logs for oil price, OVX index, S&P500 index, US Dollar against Euro exchange rate, industrial production index, federal funds rate and the discount rate, Dπ is the first difference of the inflation rate. ECM denotes the error correction term. Standard errors, t-statistics and the associated p-values are listed next to the coefficients. Significance is shown at 10% (*), 5% (**) and 1% (***) levels.

3.5.6 Asymmetric Effect of Oil Price and Oil Volatility on Illiquidity Premium

Table 3.23 shows the estimated coefficients for R_{OILP} and R_{OILN} along with the Chi-square statistics for the said coefficients. We fail to reject the null hypothesis of equal coefficients and therefore conclude that illiquidity premiums do not exhibit any asymmetric response to oil price changes.

Table 3.23. Regression results for positive and negative oil price changes.

Variable	Coefficient	Std. Error	t-Statistic	Prob.
R_{OILP}	0.015365	0.023466	0.654796	0.5138
R_{OILN}	0.049191 *	0.026148	1.881224	0.0622
Test Statistic	**Value**	**Probability**		
Chi-square	0.715872	0.3975		

H_0: R_{OILP} = R_{OILN}. This table reports the results of the Chi-square test of the null hypothesis of no asymmetry under the OLS model with R_{OILP} and R_{OILN} being he positive and negative values of oil price changes for the full sample period between May 2007 and December 2018. The variables R_{OVX}, R_e, Δr, $R_{S\&P}$, R_{ILIQ}, Δffr, R_p and $\Delta\pi$ are still included in the model. Standard errors, t-statistics and the associated p-values are listed next to the coefficients. Significance is shown at 10% (*), 5% (**) and 1% (***) levels. Coefficients are multiplied by 100 to make them easier to read.

Table 3.24 displays the estimated coefficients for R_{OVXP} and R_{OVXN} along with the Chi-square statistics for the said coefficients. We fail to reject the null hypothesis of equal coefficients and therefore conclude that oil price implied volatility does not have any asymmetric impact on illiquidity premiums.

Table 3.24. Regression results for positive and negative oil price volatility.

Variable	Coefficient	Std. Error	t-Statistic	Prob.
R_{OVXP}	−0.023187 **	0.010657	−2.175751	0.0314
R_{OVXN}	−0.001435	0.016359	−0.087694	0.9303
Test Statistic	**Value**	**Probability**		
Chi-square	0.715872	0.3975		

H_0: $R_{OVXP} = R_{OVXN}$. This table reports the results of the Chi-square test of the null hypothesis of no asymmetry under the OLS model with R_{OVXP} and R_{OVXN} being the positive and negative values of oil price volatility for the full sample period between May 2007 and December 2018. The variables R_{OIL}, R_e, Δr, $R_{S\&P}$, R_{ILIQ}, Δffr, R_P and $\Delta\pi$ are still included in the model. Standard errors, t-statistics and the associated p-values are listed next to the coefficients. Significance is shown at 10% (*), 5% (**) and 1% (***) levels. Coefficients are multiplied by 100 to make them easier to read.

Table 3.25 displays the estimated coefficients for $\Delta \ln OILP_t$, $\Delta \ln OILN_t$, $\Delta \ln OILP_{t-1}$ and $\Delta \ln OILN_{t-1}$ along with the Chi-square statistics for the said coefficients. We fail to reject the null hypothesis of equal coefficients and therefore conclude that current and lagged oil price do not have any asymmetric impact on illiquidity premiums in the short-run.

Table 3.26 displays the estimated coefficients for $\Delta \ln OVXP_t$, $\Delta \ln OVXN_t$, $\Delta \ln OVXP_{t-1}$ and $\Delta \ln OVXN_{t-1}$ along with the Chi-square statistics for the said coefficients. Although we do not find asymmetry in response to lagged values of OVX, we do find evidence of asymmetry for current values of OVX. This would imply that illiquidity premiums do not react to an increase in oil price volatility in the same way that they react to a decrease in it, in the short-run.

Table 3.25. Regression results for positive and negative oil price changes.

Variable	Coefficient	Std. Error	t-Statistic	Prob.
Δ ln $OILP_t$	0.006171	0.027464	0.224681	0.8226
Δ ln $OILN_t$	0.066180 ***	0.024954	2.652039	0.0091
Δ ln $OILP_{t-1}$	0.000766	0.028756	0.026621	0.9788
Δ ln $OILN_{t-1}$	−0.026704	0.027304	−0.978009	0.3301
Test Statistic	**Value**	**Probability**		
Chi-square (current)	2.067795	0.1504		
Chi-square (lagged)	0.449969	0.5023		

H_0: Δ ln $OILP_t$ = Δ ln $OILN_t$. H_0: Δ ln $OILP_{t-1}$ = Δ ln $OILN_{t-1}$. This table reports the results of two Chi-square tests of the null hypothesis of no asymmetry under the ECM model with Δ ln $OILP_t$ and Δ ln $OILN_t$ being the current positive and negative values of oil price changes, and Δ ln $OILP_{t-1}$ and Δ ln $OILN_t$-1 being the lagged positive and negative values of oil price changes, for the full sample period between May 2007 and December 2018. We still run the ECM model as in Equation (12): $R_{IML,t} = \alpha_0 + \sum_{i=1}^{p}\beta_{1,i} R_{IML,t-I} + \sum_{i=0}^{p}\beta_{2,i} \Delta \ln OILP_{t-i} + \sum_{i=0}^{p}\beta_{3,i} \Delta \ln OILN_{t-i} + \sum_{i=0}^{p}\beta_{4,i} \Delta \ln OVX_{t-i} + \sum_{i=0}^{p}\beta_{5,i} \Delta \ln S\&P_{t-i} + \sum_{i=0}^{p}\beta_{6,i} \Delta \ln E_{t-i} + \sum_{i=0}^{p}\beta_{7,i} \Delta \pi_{t-i} + \sum_{i=0}^{p}\beta_{8,i} \Delta \ln P_{t-i} + \sum_{i=0}^{p}\beta_{9,i} \Delta \ln ffr_{t-i} + \sum_{i=0}^{p}\beta_{10,i} \Delta \ln r_{t-I} + \beta_{11}\, ecm_{t-1} + \varepsilon_t$, but only report coefficients for oil price standard errors, t-statistics and the associated p-values are listed next to the coefficients. Significance is shown at 10% (*), 5% (**) and 1% (***) levels.

Table 3.26. Regression results for positive and negative oil price volatility changes.

Variable	Coefficient	Std. Error	t-Statistic	Prob.
Δ ln $OVXP_t$	−0.03352 **	0.013539	−2.475424	0.0148
Δ ln $OVXN_t$	0.011461	0.015197	0.754133	0.4523
Δ ln $OVXP_{t-1}$	−0.009341	0.014485	−0.644914	0.5203
Δ ln $OVXN_{t-1}$	0.029244 *	0.016193	1.806023	0.0735
Test Statistic	**Value**	**Probability**		
Chi-square (current)	3.921903 **	0.0477		
Chi-square (lagged)	2.501447	0.1137		

H_0: Δ ln $OVXP_t$ = Δ ln $OVXN_t$. H_0: Δ ln $OVXP_{t-1}$= Δ ln $OVXN_{t-1}$. This table reports the results of two Chi-square tests of the null hypothesis of no asymmetry under the ECM model with Δ ln $OILP_t$ and Δ ln $OILN_t$ being the current positive and negative values of oil price changes, and Δ ln $OILP_{t-1}$ and Δ ln $OILN_t$-1 being the lagged positive and negative values of oil price changes, for the full sample period between May 2007 and December 2018. We still run the ECM model as in equation 13: $R_{IML,t}= \alpha_0 + \sum_{i=1}^{p}\beta_{1,i} R_{IML,t-I} + \sum_{i=0}^{p}\beta_{2,i} \Delta \ln OIL_{t-i} + \sum_{i=0}^{p}\beta_{3,i} \Delta \ln OVXP_{t-i} + \sum_{i=0}^{p}\beta_{4,i} \Delta \ln OVXN_{t-i} + \sum_{i=0}^{p}\beta_{5,i} \Delta \ln S\&P_{t-i} + \sum_{i=0}^{p}\beta_{6,i} \Delta \ln E_{t-i} + \sum_{i=0}^{p}\beta_{7,i} \Delta \pi_{t-i} + \sum_{i=0}^{p}\beta_{8,i} \Delta \ln P_{t-i} + \sum_{i=0}^{p}\beta_{9,i} \Delta \ln ffr_{t-i} + \sum_{i=0}^{p}\beta_{10,i} \Delta \ln r_{t-I} + \beta_{11}\, ecm_{t-1} + \varepsilon_t$, but only report coefficients for oil price standard errors, t-statistics and the associated p-values are listed next to the coefficients. Significance is shown at 10% (*), 5% (**) and 1% (***) levels.

3.6 Conclusion

The paper examines the impact of oil price and implied oil price volatility on illiquidity premiums in the United States between 2007 and 2018. Between December 2007 and June 2009, which is a period that has been defined as a crisis by NBER in the United States, there was a significant increase in oil price volatility. To capture this structural shift and its impact on illiquidity premiums, we split our sample into two sub-samples; December 2007 to June 2009 which is classified as the financial crisis period, and July 2009 to December 2018 which is classified as the post-crisis period. Because of the conflicting evidence in past literature about the existence of positive and statistically significant illiquidity premiums, along with the rising prominence of illiquidity as an investment style especially since the financial crisis, we felt that conducting research on liquid and illiquid stocks still has its merits. For this purpose, we used an established methodology for stock inclusion, the Amihud (2002) ILLIQ measure to rank stocks based on their illiquidity and constructed illiquid–liquid (IML) portfolios. We found evidence that illiquidity premium is positive and statistically significant in the United States for the full sample, and during both the recession and post-recession sub-samples.

Owing to the significance of oil as a global resource, we then look to test the impact of oil price and oil implied volatility on illiquidity premiums. We estimated oil price volatility using the OVX index, a forward-looking measure of implied oil price volatility published by the Chicago Board of Exchange since 2007, and controlled for a wide array of variables including stock index returns, exchange rate, economic activity, inflation and monetary policy. We set up an OLS model to establish the significance and direction of the examined variables within a month, on illiquidity premiums. We find that illiquidity premiums are negatively influenced by oil price volatility and are positively influenced by oil prices, for the full sample and during the post-crisis period. During the crisis phase, illiquidity premiums are negatively impacted by oil price and the influence of OVX is insignificant. We then constructed a VAR model, treating all the variables in our model as endogenous, to determine the lagged impact on illiquidity premium. The impulse response functions from our VAR model provide results consistent with the OLS findings for the full sample and within the post-crisis period, as illiquidity premiums have a positive relationship with oil prices and a negative relationship with OVX. During the crisis period, the sensitivity of illiquidity premiums towards oil price and OVX dampens down significantly, but we do find a negative relationship between illiquidity premiums and both of these variables.

We then estimated the long-run and short elasticity of oil price, oil volatility and the examined macroeconomic factors on illiquidity premiums, using an ARDL long-run model and an error correction model (ECM). Using the autoregressive distributed lag (ARDL) bounds test developed by Pesaran et al. (2001) we established co-integration and long run relationships between all our variables, in the full sample and in the two sub-samples. For the full sample, our long-run results suggested that oil price has a positive impact on illiquidity premiums but the direction of this influence changes for lagged oil price. In the short-run, illiquidity premiums are positively influenced by oil price and negatively influenced by oil price volatility. Furthermore, the reverting mechanism for sustaining the co-integration relationship between our explanatory variables and illiquidity premiums is extremely relevant. For the post-crisis period, both the ARDL long-run model and the ECM short-run model show a positive relationship between illiquidity premiums and current oil price. The influence of OVX is only significant in a lagged setting within the short run. The reverting mechanism to establish long-run equilibrium is also significant and effective within this phase. Within the crisis period, both the long-run ARDL model and the short-run ECM model suggest that illiquidity premiums are not significantly influenced by either oil price or OVX.

Additionally, we also tested for any potential asymmetric impact on illiquidity premiums of an increase or decrease in oil price, and an increase or decrease in oil implied volatility, within current and lagged terms. We did not find any evidence of asymmetric impact that current or lagged oil price might have on illiquidity premiums. Although we did not find any asymmetric impact of lagged OVX values, our ECM model does suggest asymmetry within current values of oil volatility, indicating that within the short-run, illiquidity premiums do not react to an increase in oil price volatility in the same way that they react to a decrease in it.

Prior literature such as Park and Ratti (2008), Elder and Serletis (2010), Jo (2014) and Diaz et al. (2016) used a variety of realised oil price volatility measures. The fact that these measures are backward-looking and sensitive to the length of the look-back window, pose a serious question in terms of assessing the optimal number of lags to use in determining oil price shocks. Our first contribution to the literature is examining the impact of oil volatility on illiquidity premiums using a forward-looking measure which is capable of adjusting quickly to new information, relative to realised measures. Second, although some research exists on the impact of monetary policy on illiquidity premiums, our research includes macroeconomic factors such as exchange rates and industrial production index (to gauge economic activity) which are factors whose relationship has not yet been studied with illiquidity premiums. Third, we adopt the ARDL bounds test to examine the co-integration between oil price, oil implied volatility, macroeconomic factors and illiquidity premium, in a manner that overcomes problems that may arise because of the uncertainty of unit root results, endogeneity and small sample size. Fourth, using the long-run ARDL model and the ECM allows us to simultaneously analyse the long-run and short-run elasticities of oil prices, OVX and macroeconomic factors on illiquidity premiums, by establishing significance and direction for current and optimal lagged values of these variables. Furthermore, we incorporate for a mechanism to gauge effective reversion to the long-run equilibrium. Fifth, we assess the transition of these relationships between a recessionary period and a post-recession period. Lastly, to the best of our knowledge, the asymmetric impact of oil price and oil price volatility on illiquidity premiums has not yet been examined.

The research is useful for academics looking to analyse the impact of oil price and oil volatility on illiquidity premiums in the short- and long-run, within a recession and post-recession phase. This can be extended on over various other geographies along with possibly assessing the impact of other macroeconomic factors on illiquidity premiums. With an ever-expanding asset universe and an increase in availability of information to investors, this research will also be useful for practitioners looking to gauge the usefulness of illiquidity as an investment style for portfolio optimisation, investment strategies during and after a recessionary phase, and investors looking to hedge against oil price movements and oil price volatility within the long- and short-run.

Chapter 4: Fama–French–Carhart Factor-Based Premiums in the US REIT Market: A Risk Based Explanation, and the Impact of Financial Distress and Liquidity Crisis from 2001 to 2020

4.1 Abstract

The study investigates the impact of financial distress (credit spread) and liquidity crises (TED spread) on size, value, profitability, investment and momentum premiums within the US Real Estate Investment Trust market. Using daily data from 2001 to 2020, we examine the presence, magnitude and significance of these premiums, along with assessing if these premiums are associated with higher risk. The study then employs Auto-regressive distributed lag and Error Correction Modeling to establish the long/short-run impact of financial distress and liquidity crisis on these premiums during recessionary and non-recessionary phases, including COVID-19. Premiums associated with all five factors are positive and significant. Secondly, in contradiction to the Efficient Market Hypothesis, we find that value and momentum portfolios provide superior returns without exposing investors to higher risk while portfolios based on size, profitability and investment, do tend to expose investors to a higher risk. Thirdly, in contradiction to the risk based explanation of Fama–French/Carhart (2015/1997), we find significant evidence of a fall in profitability and momentum premiums with an uptick in financial distress and liquidity crisis. On the other hand, size, value and investment premiums rise with financial distress/liquidity crisis, only during the recessionary phases. This impact is insignificant during non-recessionary phases.

4.2 Introduction

Real estate investment trusts (REITs) are income generating instruments, that are diversified, liquid, and provide investors with the ease of incorporating the real estate sector within their portfolios at relatively lower costs compared to conventional real estate investments (Hoesli et al. 2004; Nazlioglu et al. 2016; Zhang and Hansz 2019)[11].

Early studies on REITs considered these instruments similar to bonds in terms of their ability to generate stable streams of income (Karolyi and Sanders 1998). REIT returns were strongly correlated with bond returns up until the 1990s (Shen et al. 2020). After the structural changes within the REIT market in the early 1990s, REITs became similar to stocks (Glascock et al. 2000), and their returns became more sensitive to factors, which impact small cap stocks and real estate specific drivers (Clayton and Mackinnon 2003). Following the structural changes within the REIT market, the ownership structures have drastically changed as well. Post 1990, institutional ownership within REITs has increased significantly (Chen and Zhang 1998). As participation within REITs increases, and as their returns behavior, relative to other financial assets, transitions overtime, it is expected that investors would put more focus on finding out if factor based investment strategies that generate positive premiums within the stock market, can also be used to generate excess returns within REITs.

Although REITs and certain segments of stocks have behaved in a similar manner after the structural changes within the REIT market, there are still essential differences between REITs and other equities (Zhang and Hansz 2019), which has resulted in REITs typically being excluded from most asset pricing studies, and still makes REITs a unique asset class. Firstly, certain stocks might not pay any dividends, but REITs are required by law to distribute 90% of their taxable income as dividends in order to maintain their REIT status[12] (Boudry 2011).

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11 According to the National Association of Real Estate Trusts (NAREIT), the 2021 REIT market cap was $1.74 trillion, which translates to 3.3% of the $53 trillion US stock market cap (NAREIT 2022b). The market cap of listed REITs globally has risen from $10 billion in 1990 to approximately $2.5 trillion today, operating within 41 countries and regions (NAREIT 2022a). This allows global investors to incorporate the real estate sector within multi-asset portfolios, as an investment vehicle and diversification tool. Based on market cap, the US accounts for approximately 70% of the global REIT market.

12 For this reason, we collect daily data for REIT returns inclusive of dividends.

Second, although common stocks are subject to corporate or trust taxation, REITs are exempt, and the only tax that is levied is on dividends and is according to the investors' personal tax rate (Gyourko and Keim 1992). Third, REITs pass their profits directly through to the individual tax returns of their shareholders, eliminating potential benefits of debt financing. Given the fact that REITs hold relatively large illiquid assets, accumulation of debt provides no tax benefit and magnifies potential bankruptcy costs (Harrison et al. 2011). Therefore, REITs, relative to corporations, are associated with lower debt levels (Zhang and Hansz 2019). Fourth, REIT prices tend to fluctuate more with interest rate changes, relative to dividend stocks (Titman and Warga 1986). Fifth, general stocks are usually not treated as an inflation hedge, but investors tend to consider REITs as an inflation hedge (Liu et al. 1997). Given the unique nature of REITs relative to general stocks, it is important to test asset pricing models, and factor based investment strategies within the REIT market, when historically most empirical testing of these models and strategies has focused on general stocks.

Fama and French (1992) identify a value and size premium in US stocks. Value stocks, in terms of average returns, seem to outperform growth stocks, while small stocks tend to have a higher average return relative to big stocks. Fama and French label the excess returns on value stocks relative to growth stocks as HML (high minus low), while they label the excess returns on small stocks relative to big stocks as SMB (small minus big)[13].

Carhart (1997) extends on the Fama–French three factor model by adding a fourth factor called momentum, to explain cross-section of stock returns. The WML (winners minus losers) factor is computed using historical returns.

Following the work of Titman et al. (2004), and Novy-Marx (2013), who conclude that the Fama–French three factor model is an incomplete model in explaining expected stock returns, Fama and French (2015) add two further factors to the model, namely, profitability and investment. RMW (robust minus weak) is the difference between average returns on stocks

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[13] These excess returns have given rise to style based investment strategies, where the size premium strategy involves buying small stocks and selling big stocks, while the value premium strategy involves buying value stocks and selling growth stocks.

with robust profitability and weak profitability. While the CMA (conservative minus aggressive) factor is the difference between average returns on stocks with low and high investment.

Style based investment strategies have been used consistently by investors in the stock market to potentially earn higher returns or reap the rewards of risk premia (Said and Giouvris 2017). Each risk factor such as size, value, profitability, investment and momentum, drives a specific risk premium. Investors capture the premium associated to these factors by going long on assets with positive factor exposure, and shorting assets with negative factor exposure (Idzorek and Kowara 2013). The merits of factor-based investment strategies, specifically from a size, value and momentum perspective, comes from empirical evidence mainly within the stock market. The results of these have been varying, not only in terms of the existence of these premiums, but also the risk associated to them (Eun et al. 2010). Furthermore, profitability and investment factors have not yet been extensively researched in terms of their usefulness as investment styles and their ability to generate excess returns, along with their interpretation from a risk compensation perspective. Owing to these gaps in literature, this chapter looks to examine the presence, magnitude and significance of SMB, HML, RMW, CMA and WML premiums within the US REIT market, using daily returns data from July 2001 to June 2020, and constructing long and short portfolios based on these factors. We find all these premiums to be significant and positive within the REIT market.

We then look to examine if these strategies that yield superior returns, expose investors to a higher risk. Efficient market hypothesis would suggest that the higher returns associated with these strategies is a compensation for exposing investors to higher risk. Previous studies, such as Ooi et al. (2007), find that HML investment strategy provides significant positive returns without exposing investors to higher risk. Consistent with the results of Ooi et al. (2007), we also find that the HML strategy provides excess returns, and we fail to detect any significant relative rise in systematic risk within portfolios containing value REITs versus those of growth REITs. Additionally, we find similar results for the WML strategy, that is, it provides significantly positive returns without any significant increase in investors' risk. This potentially suggests systematic mispricing of value and high momentum REITs, which is in contradiction to the market efficiency hypothesis. For the SMB, RMW and CMA strategies, we find that excess returns are associated with a significant rise in systematic risk, indicating that these premiums might serve as compensation for exposing investors' to higher risk.

We further analyze the relationship between risk and return associated to these factor based investment strategies by assessing two risk-adjusted performance measures, namely, the Sharpe ratio[14] and Treynor ratio[15]. Apart from the RMW strategy, we fail to find significantly weaker risk adjusted performance for SMB, HML, CMA and WML strategies.

Lastly, we look to test the impact of default risk, liquidity crises and stock market index, on the SMB, HML, RMW, CMA and WML premiums within the US REIT market. This study goes through three phases of financial crises, which correspond to an increase in the risk of corporate default. Although Fama and French (1996) and modern finance theory suggest that investors require a higher return on small/value stocks relative to big/growth as a compensation for their enhanced vulnerability as a consequence of an uptick in financial distress, the fact that there is mixed evidence in literature regarding the impact of default risk on value and size premiums, adds more relevance to this study. Certain studies, such as Griffin and Lemmon (2002), Vassalou and Xing (2004) and, Penman et al. (2007), conclude that investors require a higher return on value stocks relative to growth stocks during periods of high financial distress, while other studies, such as Mohanram (2005) and Huang et al. (2013), either argue that default risk only impacts the return of stocks within a certain book-to-market threshold or that factor premiums do not appear to be driven by financial distress. Furthermore, REITs are regulated by the fact that they have to distribute 90% of their taxable earnings as dividends. This could make REITs more prone to default risk relative to similar firms in other sectors (Chung et al. 2016). This mixed evidence on the impact of financial distress on factor premiums within general stocks, and the unique nature of REITs, provides more rationale for exploration of the impact of default risk on factor premiums within the US REIT market.

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[14] Excess return earned by the portfolio (over the risk free rate) relative to its total risk.

[15] Excess return earned by the portfolio (over the risk free rate) relative to its systematic risk.

Most of these previous studies omit liquidity crises when assessing the impact of financial distress. Caballero and Krishnamurthy (2009) use the 2007 crisis to link changes in interest rates, credit market conditions, leverage and risk premiums, with the liquidity crisis. They conclude that the liquidity crisis resulted in a fall in interest rates, a rise in leverage and risk premiums, and an increase in the vulnerability of the financial sector to shocks. Hahn and Lee (2006) conclude that factor premiums are compensations for higher risk due to changes in interest rate and credit market conditions. In connection with our previously stated links between financial distress and factor premiums, this adds further support for us to study the relationship between liquidity crisis, default risk and factor premiums.

The idea of controlling for the stock market stems from the fact that REITs exhibited low correlation with the US stock market in the late 1990s, and hence would offer diversification benefits to investors holding a multi-asset portfolio, which includes exposure to the stock market (Stephen and Simon 2005). This benefit is further supported by Chaudhry et al. (1999) who find an inverse long-term relationship between stocks and real estate. For this purpose, previous studies, such as Hoesli et al. (2004), conclude that the optimal allocation to real estate in a multi-asset portfolio is 15 to 25%. This makes our research extremely useful for investors with style based exposures within REITs, along with stock market investments, as part of their portfolio. The results will help us to assess how factor based REIT investments perform under varying market conditions, along with identifying if the directional relationship of the factor based REIT investments and stock market returns are positive or negative, assisting in the understanding of optimal portfolio diversification in a multi-asset setting.

Glascock et al. (2000) find a significant long-term relationship between REITs and the private real estate market. Clayton and Mackinnon (2003) show a stronger co-integration relationship between the two since the 1990s. This indicates a higher relative integration between REITs and the real estate market than with financial assets, further consolidating the diversification perks of REITs in a multi-asset portfolio. Furthermore, Stephen and Simon (2005) stress that REITs are a unique asset class, and their returns cannot be replicated by other asset classes.

By way of preview, we find that during the recessionary phases, credit spread, which is a proxy for financial distress, and TED spread, which acts as a proxy for the probability of a liquidity crisis, have a positive and significant impact on size, value and investment premiums, while this impact is mostly insignificant during non-recessionary phases. Small, value, and conservative investment REITs are more vulnerable to default and liquidity risks, and with a rise in general risk levels within the economy during recessionary phases, investors demand a higher compensatory return on these REITs. This result is consistent with the risk based explanation of Fama and French (1996) who imply that factor premiums are a compensation for a non-diversifiable risk factor.

For momentum and profitability premiums, we do find significant evidence of a fall in these premiums corresponding to a rise in the probability of financial default and liquidity crisis. With a rise in default risk and in probability of a liquidity crisis, investors might be more inclined to channel their funds towards REITs with robust profitability and a healthy historical performance (REITs that have seen higher returns in the short- and medium-term). This injection in demand towards robust profitability and winner REITs implies a fall in compensatory premiums required to incentivise investors to channel their funds towards these instruments. Based on Fama and French (2015) and Carhart (1997), RMW and WML are common risk factors. A fall in these premiums following a rise in financial distress and probability of liquidity crisis, contradicts Fama and French (1996) and the Efficient Market Hypothesis. These results also fail to support the systematic risk explanation for RMW and WML factors.

We also find that the S&P 500 index has a significant and negative impact on all premiums in the non-recessionary states. A rise in the index might make investors more optimistic about the future state of the economy (Essa and Giouvris 2020), hence resulting in a fall in premiums needed to incentivise investors to park their funds within these riskier REITs. Within a multi-asset portfolio setting, investors can then associate a bullish stock market to a fall in factor premiums within REITs. This impact is reversed for all premiums apart from WML during the recessionary states. A rise in returns of the largest 500 stocks could result in a channeling of funds towards these large stocks, and hence requiring a larger compensatory premium in order to incentivise investors to route their funds within riskier REITs. These results could have a significant bearing on optimal diversification within recessionary and non-recessionary states, for investors constructing a multi-asset portfolio.

Ooi et al. (2007) test the risk based explanation suggested by Fama and French (1992) that superior returns associated with value strategy would be accompanied by higher risk. For their risk indicators they use standard deviation, beta from the CAPM model, and factor loadings from the Fama–French three factor model. We extend on this study by testing this risk based explanation for not just the value premium but also for SMB, RMW, CMA, and WML strategies. We not only use the risk measures as suggested by Ooi et al. (2007), but also use the factor loadings on the Fama–French five factor, and the Carhart four factor model as a robustness measure, and in doing so, we test the risk based explanation of Fama and French (1996) and the Efficient Market Hypothesis. If these strategies that produce superior returns, are accompanied by a higher systematic risk, then we can conclude that the premiums are a compensation for exposing investors to a higher risk. For any strategy, if we fail to find a significant rise in systematic risk, we then look to explore the role of mispricing in the existence of these premiums. But why would mispricing persist in the presence of professional arbitrageurs? Ali et al. (2003) argue that idiosyncratic volatility is of relatively more concern to specialised arbitrageurs, adding that their motivation to keep the ratio of reward-to-risk low in the short term, deters arbitrage activity in high volatility stocks. Following the work of Ooi et al. (2007), for factor strategies where we do not find a significant rise in systematic risk, we use the square root of the residual variance form the CAPM model, as a measure of idiosyncratic return volatility, and a proxy for arbitrage risk, in order to assess the impact of mispricing on the existence of these premiums.

Furthermore, the research looks to gauge the risk-adjusted performances of these factor based strategies within the REIT market using Sharpe and Treynor ratios. Lastly, this paper is unique as it looks at the impact of default risk, liquidity crises, and the stock market index, on these premiums, establishing long- and short-run relationships using Auto-Regressive Distributed Lag (ARDL) modeling and Error Correction Modeling (ECM), for three recessionary phases, and two non-recessionary phases, namely the dot-com crash, the expansionary phase following the dot-com crash, the 2007/08 financial crisis, the expansionary period following the financial crisis, and the COVID-19 phase. Furthermore, the uniqueness of these three recessionary phases, allows us to establish a deep understanding of the impact of the surrounding macroeconomic environment on these premiums. The research also incorporates significant observations (104) during the most recent COVID-19 phase, and hence provides academics and investors with an extremely up-to-date outlook on factor based investment strategies within the REIT market.

The structure of this chapter is as follows. Section 4.3 presents a literature review. Section 4.4 describes the data and methodology. Section 4.5 presents the empirical analysis and results. Section 4.6 presents practical implications for REIT investors. Finally, Section 4.7 concludes.

4.3. Literature Review

4.3.1 SMB and HML Premiums; Empirical Evidence from Stock/REIT Market and Extrapolation Theory

Fama and French (1992) add size and book-to-market factors to the existing market factor within the Sharpe-Linter's CAPM model, and show that these capture much of the average stock returns. Fama and French conclude that these two additional factors must proxy for common risk factors in returns. They contend that small stocks are riskier than big stocks, and value stocks are riskier than growth stocks. Consequently, the superior returns associated with small and value stocks is merely a compensation for exposing investors to higher risk. Chen and Zhang (1998) highlight that value stocks i) are riskier than growth stocks because they are usually firms in financial distress, ii) are highly leveraged, and iii) are associated with higher uncertainty regarding future earnings

In contrast, Lakonishok et al. (1994), and Skinner and Sloan (2002) find no evidence of value stocks being exposed to a higher risk relative to growth stocks. They associate superior returns to systematic mispricing of value and growth stocks by investors. Investors tend to be overly optimistic about future prospects of growth stocks, while they tend to be overly pessimistic about prospects of value stocks, and when these expectations are not realized, it results in a higher return on value stocks and a lower return on growth stocks (Ooi et al. 2007). This is referred to as extrapolation theory.

The persistence of these premiums might then be due to transaction costs and arbitrage risk. Shleifer and Vishny (1997), and Ali et al. (2003) conclude that value premiums cannot be easily arbitraged away due to idiosyncratic risk. Although most previous studies on asset pricing have focused on the general stock market and have excluded REITs due to their unique nature, Ooi et al. (2007) find value premiums to be prevalent within the REIT market, along with finding mixed results for risk adjusted performance of value REITs relative to growth REITs. They do find higher arbitrage risk associated with value REITs relative to growth REITs, leaving value REITs relatively more prone to mispricing. Furthermore, they do not find significant evidence of investors being exposed to a higher risk while parking funds within value REITs relative to growth REITs.

4.3.2 RMW and CMA Premiums: Empirical Evidence from Stock/REIT Market and Sound Mind Effect

Fama and French (2015) add two further factors to their three factor model, namely, robust-minus-weak profitability (RMW) and conservative-minus-aggressive (CMA) investment factors. They conclude that this five factor model works better in defining expected returns relative to the three factor model. Although these are few in number, most studies that look to test the effectiveness of RMW and CMA factors on expected returns have been conducted on general stocks rather than REITs. However, Glascock and Lu-Andrews (2014) show that a profitability factor based on gross profit or net operating income has significant predictive power on REIT returns. Bond and Xue (2016) construct investment and profitability factors, and show that both display significant predictive power for REIT returns.

Factors included in the Fama and French model depict risk attributes for which investors are compensated in the form of expected returns. The initial factors, market risk, SMB and HML fit this risk based description quite well from an interpretation perspective. Although both new factors, RMW and CMA, derive nicely from the dividend discount model, their economic interpretation is not very clear. The risk based interpretation for RMW would be that historically profitable firms carry a higher risk and therefore provide compensation to their investors. But why should a more profitable firm be risker and therefore provide extra compensation to investors?

Ali and Ülkü (2019) conclude that the RMW factor seems to combine value with earnings momentum, thus capturing a 'neglected value' effect. Ülkü (2017) look to test whether the RMW factor captures behavioral mispricing or a rationally-priced risk. They believe that if the RMW factor does represent mispricing, then it should have a strong, consistent and significant weekend effect, where returns on the RMW portfolio are stronger during the beginning of the week. This could potentially be a result of under-reaction by investors to earnings information due to the Uncertain Information Hypothesis (Brown et al. 1988). This private information accumulation will result in abnormal returns on the RMW portfolio, and this accumulation is generally larger during the weekend (Foster and Viswanathan 1990). These abnormal returns could also be down to the behavior of institutional investors who tend to trade on the wrong side during the creation of value-type anomalies, and contribute to mispricing away from value via noise trading through the week (Edelen et al. 2016). It would then take a weekend of 'sound mind' to recognize value. Ülkü (2017) find that this Monday effect on RMW premiums is significant and strengthens overtime, confirming the role of mispricing within RMW portfolios, and provides further support for the 'sound mind' effect explanation.

4.3.3 WML Premium: Empirical Evidence from Stock/REIT Market and Their Interpretation

Carhart (1997) show that a momentum factor is significant in explaining expected asset returns, when included as a factor along with market beta, SMB and HML, within the Fama and French three-factor model. Although significant amount of research has been conducted on assessing the predictive power of the WML factor on expected returns within general stocks, with regards to REITs, the amount of research is still quite limited. Chui et al. (2003) test the predictive power of Momentum, size, value and turnover on REIT returns, over two sub-samples, pre- and post-1990. They find evidence that momentum, size and value effects are significant pre-1990, while only the momentum factor is significant in defining expected REIT returns post-1990. Hung and Glascock (2008), and Goebel et al. (2012) show that the momentum factor is significant in explaining the cross-section of REIT returns. They also conclude that the momentum factor is more prevalent in the real estate market rather than in the equity market.

Similar to the RMW factor, the economic interpretation for the momentum factor is still unclear: why should a firm which has had consistently higher returns in the past be riskier and offer extra compensation for risk? Carhart (1997) state that they leave the risk interpretation of their momentum factor to the reader. Johnson (2002), and Liu and Zhang (2008) conclude that the expected growth risk increases with expected growth, supporting the argument that the momentum factor within asset pricing does represent an element of systematic risk that investors might be exposed to. On the other hand, Jegadeesh and Titman (1993) do not find any evidence that excess returns on a momentum based strategy is due to their systematic risk. They interpret the momentum premium as excess returns generated due to investor behavior and an under-reaction from the market to information.

4.3.4 Impact of Financial Distress and Liquidity Crisis on Factor Premiums

Fama and French (1996) and Chan and Chen (1991) relate common risk factors, i.e., size and value, to financial distress in a firm, indicating that financial distress is a systematic risk and should be compensated with a positive premium. Past studies have shown mixed results for the impact of default risk on value and size premiums. Ivaschenko (2003), Garlappi and Yan (2011), and Elgammal and Mcmillan (2014) find significant evidence that value premiums in the stock market increase with default risk and financial distress, while Elgammal et al. (2016) find that both size and value premiums within the US stock market, rise with default risk. This is consistent with the argument put forward by Fama and French (1996) and modern finance theory that investors require a higher return on small/value stocks relative to big/growth as a compensation for their enhanced vulnerability as a consequence of financial distress. Moreover, various studies, such as Vassalou and Xing (2004), Campbell et al. (2008), find a negative relationship between default risk and stock returns, which contradicts the belief that investors require higher returns for bearing higher risk. Other researchers, such as Piotroski (2000), find that only high book-to-market stocks with a lower financial health, earn relatively lower returns, while Huang et al. (2013) conclude that financial distress does not have any significant influence on size and value premiums within the Chinese stock market. Due to this mixed evidence of the impact of default risk on factor premiums, the unique nature of REITs and their specific regulatory requirements, along with the fact that financial distress risks are heightened during recessionary phases (this paper covers three unique phases within the data set), provides a clear justification for assessing its impact on factor based premiums within the REIT market.

Acharya and Pendersen (2005), Galariotis and Giouvris (2007, 2009) and Lim and Giouvris (2017) discuss the idea that liquidity is not only risky but also has commonality. There has been an increased focus on liquidity and liquidity risk as this was considered as a major source of the 2007/08 financial crisis (Brunnermeier 2009; Crotty 2009). This resulted in investors practicing a "flight-to-safety" strategy with regards to their investments, and in central banks practicing an expansionary monetary policy in order to inject and enhance liquidity within the market. Therefore, liquidity impacts credit conditions and interest rates within the economy. Hahn and Lee (2006) conclude that size and value premiums are compensations for exposing investor to higher risks related to changing market conditions and interest rates. Based on this argument, we feel that there are merits to including liquidity crisis, along with financial distress, when studying the impact on factor based premiums within the REIT market.

Campbell et al. (2008), and Elgammal et al. (2016), use credit spread as a proxy for financial distress and default risk. They define credit spread as the difference between yields on BAA corporate bonds and AAA corporate bonds. Tang and Yan (2010) discuss the counter-cyclical nature of credit spreads, increasing during recessions and contracting during expansionary phases. Longstaff and Schwartz (1995) conclude that this cyclical nature results in a negative correlation between credit spreads and interest rates. Tang and Yan (2010) state that, across firms, credit spread falls with growth in firm's cash flow. The growth rate in firm's cash flow is generally positively related to economic growth, and hence Tang and Yan (2010) conclude that credit spread tends to widen during economic downturns, as these periods are also generally associated with cash flow shortages and an uptick in the probability of default. Furthermore, Tang and Yan (2010) link economic downturns with a rise in investor risk aversion. This would mean that investors would require a higher risk premium for holding riskier assets, impacting risk premiums and credit spreads. Given the fact that risk aversion and credit spread tend to inflate during recessionary times, and since factor premiums are based on empirically established risk factors, efficient market hypothesis would suggest that these factor premiums would be significantly impacted by credit spread. Hence, we see merit in including this factor within our research of the impact of financial distress and liquidity crisis on factor premiums within the REIT market.

Akdi et al. (2020) define the TED spread as the difference between the 3-month LIBOR rate on Eurodollars (LIBOR) and the 3-month US Treasury Bill Rate. They argue that the TED spread is an accurate proxy for fluctuations in global liquidity levels and perceived risk. This is consistent with the findings of Tse and Booth (1996) and Cesa-Bianchi et al. (2015). Miranda-Agrippino and Rey (2015) argue that the TED spread is a powerful index for explaining Global Financial Cycles, which include aspects, such as global risk appetite, global liquidity and global systematic risk. Elgammal et al. (2016) conclude that during recessionary times, as default risk rises, TED spread tends to widen and is accompanied by a fall in investors' confidence. On the other hand, they conclude that during expansionary times, the TED spread narrows and investor confidence is enhanced. Breen et al. (1989) provide evidence of TED spread's ability to forecast performance of the stock market. Similarly, Tse and Booth (1996) show that changes in TED spread have a significant influence on stock price volatility. Since historical research has shown that the TED spread significantly impacts equity prices and factor premiums via investor sentiments, we feel that it is essential to test the impact of TED spread on REIT factor premiums, during recessionary and non-recessionary phases.

4.3.5 The Effect of Stock Market Returns

The impact of financial distress and liquidity crisis on REIT factor premiums cannot be studied in isolation, therefore we incorporate for stock market changes that might impact these premiums. Karolyi and Sanders (1998) conclude that variations in both stock and bond returns have significant predictive power in explaining REIT returns. Bouri et al. (2020) test the relationship between the equity market and REITs in 19 countries during the dot-com crisis, the 2007/08 financial crisis, European sovereign debt crisis and the Brexit period in the UK.

They find a significant impact of equity markets over REITs, in not only the developed markets, but also in the emerging REIT markets. These relationships are particularly strong during the global financial crisis and the sovereign debt crisis. Allen et al. (2000) use a sample of publicly traded REITs and show that their returns are sensitive to changes in the stock market. They conclude that this sensitivity factor becomes stronger for REITs with a high financial leverage. Clayton and Mackinnon (2003) show the transition within REITs from being primarily influenced by economic factors that drive large cap stocks through the 1970s and 1980s, to being more strongly impacted by small cap stocks and real estate specific factor in the 1990s. Given the transitioning nature of this relationship, we feel including the stock market index as an explanatory variable, adds usefulness for investors looking to create mixed-asset portfolios, specifically investors that have factor-based REIT investments. These investors would then see value in assessing the impact of stock market movements on factor premiums within the REIT market, during recessionary and non-recessionary phases.

4.4 Data and Methodology

4.4.1 Measuring Factor Premiums and Construction of Factor-Based Portfolios

We collect daily data for REIT returns, inclusive of dividends, since REITs are required by law to distribute 90% of their annual taxable income in the form of dividends to shareholders, from July 2000 to June 2020, using the Bloomberg database. This includes a universe of 246 REITs and 4753 observations. We download only securities that are identified as United States REITs, including both equity and mortgage REITs. The sample also includes REITs that ceased to exist during the sample period.

To reduce the influence of Bloomberg errors, we apply a combination of filters following the methods of Ince and Porter (2006), Lee (2011) and, Amihud et al. (2015). Daily returns are set as missing if they are greater than 200% or less than −100%.

We construct portfolios based on size, value, profitability, investment and momentum. We follow the methodology introduced by Fama and French (1992, 2015) to rank and divide the REITs in our sample into five quintiles, for each of the above-mentioned factors. This means we match returns from July of year t to June of year t + 1, against annual accounting data of a REIT for the fiscal year ending in the calendar year t − 1. This ensures that accounting information is available prior to information on returns. For reasons of brevity, the methodology for constructing factor portfolios has been included within the Appendix A at the end of this chapter.

Apart from momentum portfolios, which are rebalanced monthly, all other factor portfolios are rebalanced annually. This has been done to make the portfolio selection process more realistic. Firstly, Lakonishok et al. (1994), and Ooi et al. (2007) point out that investors need a long time-horizon for certain style-based strategies to pay off, such as "a value strategy", and they conclude that in the short-term these strategies may underperform the market. Secondly, portfolio rebalancing might involve high transaction costs, which may deter investors from rebalancing at a high frequency (Carhart 1997; Kaplan and Schoar 2005). Thirdly, investors may face high borrowing costs or a lack of leverage to fund these portfolio rebalancing activities. Finally, since higher compensation on these strategies might be due to higher risk, the possibility of not being able to trade these REITs optimally due to their risk association is a realistic prospect (Ibbotson et al. 2013). The methodology of using the prior year (t − 1) measure for factors to construct quintiles, which are then used to calculate portfolio returns in a given year (t) also helps us to meet one of the criteria for Sharpe's (Sharpe 1992) specification of a portfolio benchmark, that is "identifiable before fact".

To reduce the impact of extreme values, we remove REITs with market cap, B/M, profitability and investment values in the top and bottom 1% in each twelve-month window. Furthermore, we remove extreme values of momentum by excluding REITs with momentum in the top and bottom 1% in each one-month window. The average number of REITs per portfolio was 30, the maximum number was 44 (220 REITs over 5 portfolios) in 2019/20, while the minimum per portfolio was 20 (100 REITs over 5 portfolios) in 2001/02, ensuring that all quintile portfolios were diversified.

4.4.2 Gauging Risk and Risk Adjusted Performance of Factor-Based Strategies

According to Fama and French (1992), superior returns derived from factor strategies are a compensation for exposing investors to a higher risk. To test this hypothesis, we use several conventional risk measures including the standard deviation, beta derived from the Sharpe-Linter's CAPM model (Equation (4.1)), factor loadings from the Fama and French three factor model (Equation (4.2)), and factor loadings from the Fama and French five factor model (Equation (4.3)). As a robustness measure, we also assess the factor loadings from the Carhart (1997) four factor model (Equation (4.4)).

$$R_i - R_f = a_i + b_i(R_m - R_f) + e_i \quad (4.1)$$

$$R_i - R_f = a_i + b_i(R_m - R_f) + s_iSMB + h_iHML + e_i \quad (4.2)$$

$$R_i - R_f = a_i + b_i(R_m - R_f) + s_iSMB + h_iHML + r_iRMW + c_iCMA + e_i \quad (4.3)$$

$$R_i - R_f = a_i + b_i(R_m - R_f) + s_iSMB + h_iHML + w_IWML + e_i \quad (4.4)$$

where R_i is the daily portfolio return for each quintile within each factor, R_f is the daily one-month Treasury bill rate, R_m is the value-weighted daily return on all NYSE and NASDAQ stocks, a_i is the average excess return on the portfolio after adjusting for the known risk factors, SMB (small minus big), HML (high minus low), RMW (robust minus weak), CMA (conservative minus aggressive), and WML (winners minus losers) are obtained from French's website. Risk associated with each portfolio is then assessed using the coefficients corresponding to excess returns on the market, SMB, HML, RMW, CMA and WML. If the risk-based explanation is correct then small, value, robust profitability, conservative investment and winner REITs should exhibit significantly higher risk relative to big, growth, weak profitability, aggressive investment and loser REITs.

Next, we use the Treynor ratio and the Sharpe ratio, to gauge the risk-adjusted performance of each portfolio. Furthermore, following Shleifer and Vishny (1997), Ali et al. (2003), and Ooi et al. (2007), we calculate the arbitrage risk associated with each portfolio, and this is represented by the idiosyncratic return volatility (captured by the square root of the residual variance derived from the CAPM model). This potentially will provide us with evidence on the role of arbitrage risk in deterring arbitrageurs from exploiting potential mispricing related to these factor-based premiums.

4.4.3 Explanatory Variables

Following Elgammal et al. (2016), we define credit spread as the difference between the Moody's BAA index and AAA index as reported by Bloomberg. Credit spread acts as a proxy for financial distress, and the change in credit spread can be interpreted as the excess return on a portfolio of corporate bonds (Hull et al. 2004; Huang and Huang 2012).

The TED spread is derived as the difference between the yields on 3-month LIBOR and 3-month T-Bills, and is calculated on a daily frequency using data from Bloomberg. The TED spread acts as a proxy for the probability of a liquidity crisis and represents the perceived risk in the global financial system (Elgammal et al. 2016). As the TED spread widens, investors perceive credit risk and default risk to rise, leading them to withdraw liquidity. Daily S&P 500 index values are from Datastream.

Due to the presence of significant correlation between our explanatory variables, we orthogonalize the variables to avoid any issues of multicollinearity. To conduct this, we set up the following regressions and extraction procedure for our explanatory variables[16]:

$$\text{Credit Spread}_t = \alpha_0 + \text{TED Spread}_t + \Delta\ \text{S\&P}_t + \varepsilon_{CS} \quad (4.5)$$

$$\text{TEDSpread}_t = \alpha_0 + \Delta \text{S\&P}_t + \varepsilon_{TED} \quad (4.6)$$

The residual term from Equation (4.5) is then used in place of credit spread, while the residual term from Equation (4.6) is used in place of TED Spread, within our model to test the impact of default risk, liquidity crisis and the stock market, on REIT factor premiums.

16 We use an Augmented Dickey–Fuller unit root test to confirm that both credit spread and TED spread are stationary in levels while the S&P 500 index is stationary in first difference.

4.4.4 Bounds Test for Co-integration/Long-Run and Short-Run Elasticity: The Long-Run ARDL Model and the Short-Run Error Correction Model

The factor premiums and our explanatory variables are a mix of I(0) and I(1), therefore we use an Autoregressive distributed lag (ARDL) bounds test as proposed by Pesaran et al. (2001), to test for co-integration and establish a long-run relationship between our variables. The ARDL bounds test can be used regardless of whether the time series are I(0) or I(1), and thus removes uncertainties that might be created by unit root tests. Another advantage of using the bounds test is that it can be adjusted to address potential issues of endogeneity within the explanatory variables (Shahe Emran et al. 2007).

To test the co-integration relationship between credit spread, TED spread and the S&P 500 index on our factor premiums (SMB, HML, RMW, CMA, WML), we set up the bounds test as follows:

$$R_{Premium,t} = \alpha_0 + \sum_{i=1}^{p}\beta_{1,i}\, R_{Premium,t-i} + \sum_{i=0}^{p}\beta_{2,i}\, \Delta CS_{t-i} + \sum_{i=0}^{p}\beta_{3,i}\, \Delta TED_{t-i} + \sum_{i=0}^{p}\beta_{4,i}\, \Delta \ln S\&P_{t-i} + \beta_5 R_{Premium,t-1} + \beta_6 CS_{t-1} + \beta_7 TED_{t-1} + \beta_8 \ln S\&P_{t-1} + \varepsilon_t \quad (4.7)$$

where $R_{Premium}$, denotes each of the five premiums defined in Section 4.4.1, Δ CS and Δ TED are the first-differences of the residual terms extracted from Equation (4.5) and (4.6), respectively, and Δ ln S&P is the first differences of natural logs for the S&P500 index. CS and TED are the residual terms from Equation (4.5) and (4.6), respectively, while ln S&P is the natural log for the S&P500 index, e is the error term, and t is the time.

We follow the procedure specified by Pesaran et al. (2001) to examine the existence of a long-run relationship among the variables in Equation (4.7). We do this by performing an F-test for the joint significance of the coefficients as set up in the following hypothesis;

H0. $\beta_5 = \beta_6 = \beta_7 = \beta_8 = 0.$

H1. $\beta_5 \neq \beta_6 \neq \beta_7 \neq \beta_8 \neq 0.$

For a given level of significance, if the F-statistic is higher than the upper critical bound level, then the null hypothesis of no co-integration is rejected, while if the F-statistic is lower than the lower critical bound value, the null hypothesis of no co-integration cannot be rejected.

Once the long-run relationship has been established, we set up an ARDL model to analyze the long-run elasticity of financial distress, liquidity crises and the stock market on our five factor premiums[17]:

$$R_{Premium,t} = \alpha_0 + \sum_{i=1}^{p}\beta_{1,i}\, R_{Premium,\, t-i} + \sum_{i=0}^{p}\beta_{2,i}CS_{t-i} + \sum_{i=0}^{p}\beta_{3,i}TED_{t-i} + \sum_{i=0}^{p}\beta_{4,i}lnS\&P_{t-i} + \varepsilon_t \qquad (4.8)$$

We then proceed to analyze the short-run elasticity between the explanatory variables and illiquidity premiums using the error correction model:

$$R_{Premium,t} = \alpha_0 + \sum_{i=1}^{p}\beta_{1,i}\, R_{Premium,t-i} + \sum_{i=0}^{p}\beta_{2,i}\, \Delta CS_{t-i} + \sum_{i=0}^{p}\beta_{3,i}\, \Delta TED_{t-i} + \sum_{i=0}^{p}\beta_{4,I}\, \Delta lnS\&P_{t-i} + \beta_5\, ecm_{t-1} + \varepsilon_t \qquad (4.9)$$

where ecm is a vector of residuals from the ARDL long-run model (Equation (4.8)), and the coefficient for ecm_{t-1} indicates whether the mechanism of reverting to the long-run equilibrium is effective. A significantly negative coefficient implies that the reverting mechanism to sustain the long-run equilibrium between the explanatory variables and each of our factor premiums is effective.

4.4.5 Sub-periods

To test the impact of financial distress, liquidity crises and the stock market, on each of our factor premiums, during recessionary and non-recessionary phases, we use recession dates as provided by the NBER to create sub-samples within our full sample, which runs from July 2001 to June 2020. The dot-com crash period runs from July 2001 to November 2001 and is referred to as period 1. The non-recessionary phase that follows the dot-com crash runs from December 2001 to November 2007 and is referred to as period 2. The third sub-sample is the 2007/08 financial crisis, which runs from December 2007 to June 2009, is referred to as period

[17] We use an Augmented Dickey–Fuller unit root test to confirm that all variables are stationary in returns (factor premiums associated with size, value, profitability, investment and momentum).

3. The fourth sub-sample is the non-recessionary phase that follows the 2007/08 crisis, runs from July 2009 to January 2020, and is referred to as period 4. Finally, the period from February 2020 to June 2020 corresponds with the COVID-19 phase, and is referred to as period 5. The unique nature of all of these recessionary periods, in terms of their causes and ramifications, justifies merit in studying these phases in isolation.

Although we have significant number of observations within each of our recessionary phase, 100, 394 and 103, the bounds test provides an advantage as it can be applied to small sample sizes. Therefore, it works well especially for our analysis within the financial crises periods. Furthermore, the approach allows us to identify the significance and direction of the influence of each variable, within the month and within their lags. We choose the optimal lag length using the Akaike information criterion (AIC).

4.5 Empirical Results

4.5.1 Significance, Direction and Magnitude of Factor Premiums

Table 4.1 shows daily summary statistics for our five factor premiums namely, SMB, HML, RMW, CMA and WML. All five factor premiums are positive and significantly different from zero. The mean daily-after-formation return for REIT portfolios formed based on size and value are 0.8221% and 0.4811%, respectively. Both SMB and HML portfolios have positive skewness[18] and a kurtosis level significantly higher than 3[19]. The positive skewness would imply an increase in the probability of small loses accompanied by a few large gains but would reduce the occurrence of large loses. The high kurtosis levels translate to an increase in the probability of extreme outcomes.

[18] Most values are clustered on the left tail of the distribution, right tail is longer. The outliers of the distribution are further out towards the right.

[19] Excess kurtosis means fat tails. This means that there are lots of outliers on both sides. This indicates instances of extremely small and extremely large values.

Table 4.1. Descriptive Statistics for Factor Premiums.

Variables	Mean	SD	Min	Max	Skewness	Kurtosis	Jarque–Bera (*p*-Value)
SMB	0.0082 ***	0.0429	−0.1957	0.3837	3.0162	20.2315	0.0000 ***
HML	0.0048 ***	0.0285	−0.1292	0.3377	5.1486	51.5316	0.0000 ***
RMW	0.0005 *	0.0193	−0.0908	0.1033	−0.1349	6.2990	0.0000 ***
CMA	0.0008 ***	0.0142	−0.0844	0.0918	0.9882	8.5094	0.0000 ***
WML	0.0010 ***	0.0150	−0.1346	0.1008	−0.1195	9.9946	0.0000 ***

This table provides descriptive statistics for the SMB, HML, RMW, CMA and WML premiums for the full sample from July 2001 to June 2020. Significance is shown at 10% (*), 5% (**) and 1% (***) levels.

The mean daily-after-formation return for REIT portfolios formed based on profitability and momentum are 0.0464% and 0.1038%, respectively. Both RMW and WML portfolios have a negative skewness. This implies an uptick in the probability of frequent small gains, but these are accompanied by few large loses. Although kurtosis levels for these two portfolios is still relatively lower compared to the SMB and HML portfolios, it is still significantly greater than 3, implying a high probability for extreme outcomes.

The mean daily-after-formation return for the REIT portfolio formed based on investment is 0.0819%. Similar to the SMB and HML portfolios, the CMA portfolio has a positive skewness, translating to frequent small losses accompanied by a few large gains. The kurtosis level for the CMA portfolio is similar to the levels observed within the RMW and WML portfolios, and this is significantly lower than those of the SMB and HML portfolios. Therefore, relative to the SMB and HML portfolios, the CMA portfolio is less prone to extreme outcomes. We use a Jarque–Bera test to check for normality of the distribution and reject the null hypothesis of normal distribution at 1% significance for all five factor-based portfolios.

Figure 4.1–4.5[20] show the time series variation in all 5 factor premiums, with percentage returns for each factor based portfolio on the vertical axis (Recessionary phases have been shaded in grey). The CMA and WML portfolios seem to be relatively less volatile, while the SMB portfolio seems to have the most returns volatility. This is signified by the standard deviations associated to each of these portfolios. For all factor-based portfolios, returns seem to spike during the recessionary phases, and these seem most pronounced during the 2007/08 crisis and the COVID-19 phase.

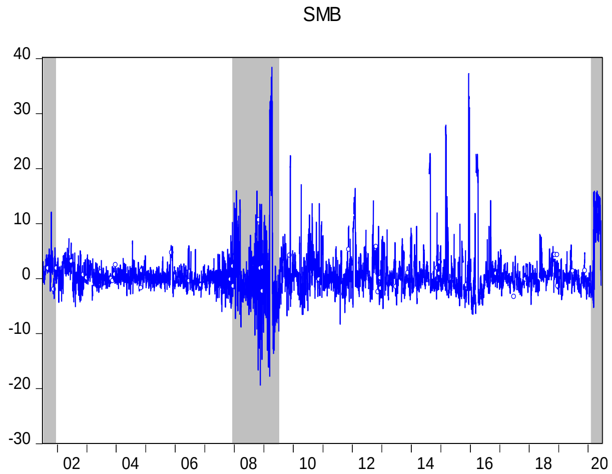

Figure 4.1. Time series variation in SMB premiums.

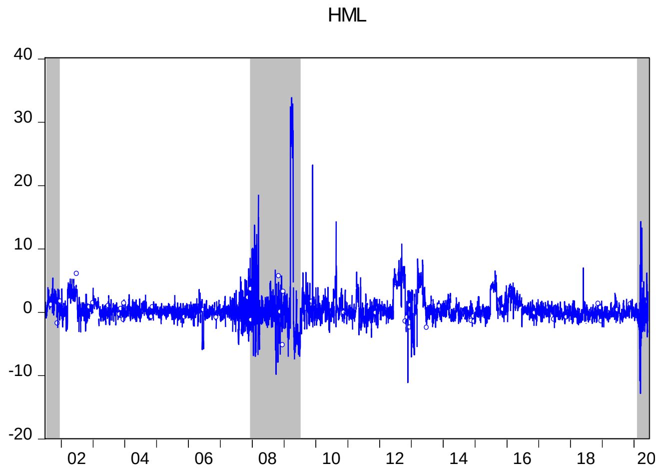

Figure 4.2. Time series variation in HML premiums.

20 The x-axis shows years while the y-axis shows the premiums in percentage terms. Note that the scaling on the y-axis in these graphs varies based on the dispersion of these individual premiums.

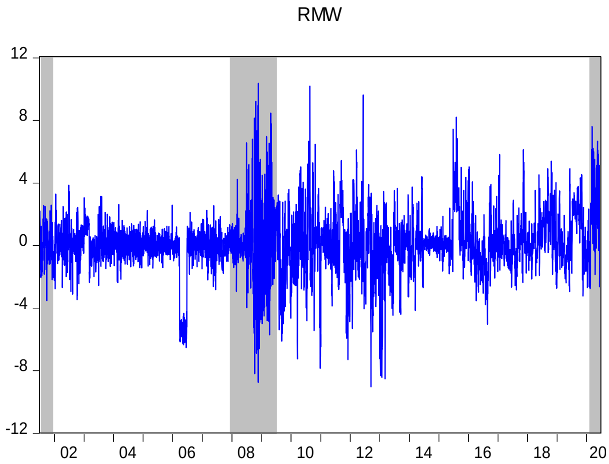

Figure 4.3. Time series variation in RMW premiums.

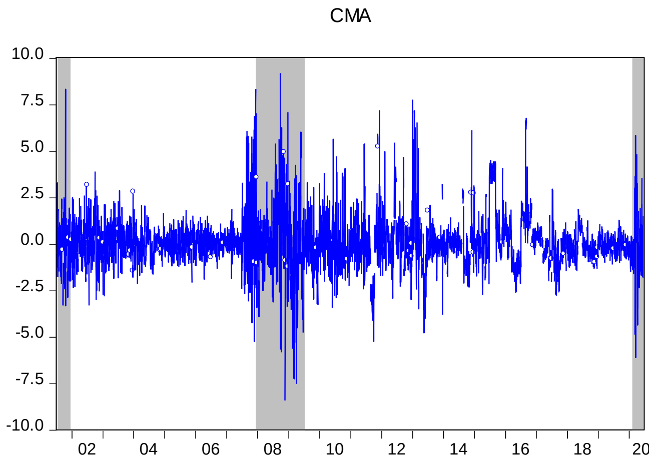

Figure 4.4. Time series variation in CMA premiums.

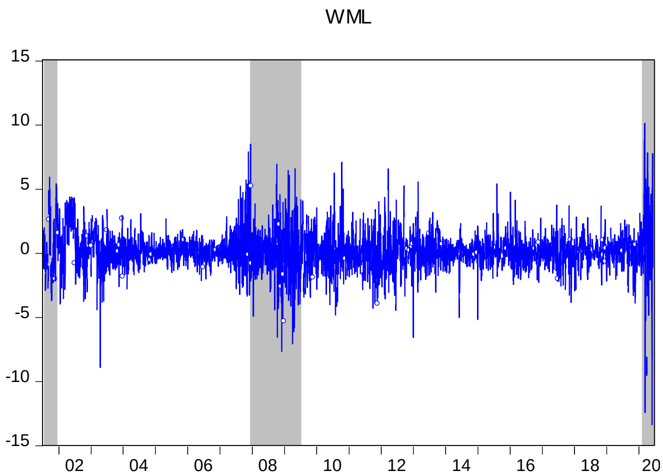

Figure 4.5. Time series variation in WML premiums.

4.5.2. Risk Associated with Factor-Based Strategies

4.5.2.1 SMB

In Tables 4.2–4.6, no additional information is gained from the factor loadings from the Fama–French three factor model, relative to the factor loadings on the five factor model, hence only the latter is shown.

Table 4.2 presents the results for risks associated with portfolios constructed using small REITs (Q1) relative to portfolios of big REITs (Q5), along with their ability to generate abnormal returns. The mean excess daily-after-formation return for small REITs is higher than big REITs (0.8320% vs. 0.0099%), equating to an average SMB premium of 0.8221% (=0.8320% − 0.099%). The standard deviation for small REITs (4.1054%) is significantly higher than that of big REITs (1.8732%), indicating a higher relative volatility for returns on the small portfolio. The risk-adjusted performance indicators, i.e., the Sharpe and Treynor ratios show a better risk adjusted performance for small REITs.

The average systematic risk of the small portfolio (0.17) is higher than that of the big portfolio (0.16). After adjusting for the five known risk factors in panel B, excess returns for the small portfolio (Q1) averaged 0.78%, as compared to 0.04% for the big portfolio (Q5). Consistent with the Efficient Market Hypothesis and the risk-based argument of Fama and French, a higher alpha observed for the small portfolio (Q1) is accompanied by a higher systematic risk. Therefore, although the SMB portfolio achieves positive excess returns, it does expose investors to a higher risk as well.

Table 4.2 Risk measures for Small and Big REIT portfolios (2001–2020).

Panel A: Summary Statistics	**Q1 (Small)**	**Q2**	**Q3**	**Q4**	**Q5 (Big)**
Excess Means	0.8320	0.0251	0.0028	0.0137	0.0099
Standard Deviation	4.1054	1.7094	1.8459	1.9179	1.8732
CAPM Beta (Univariate)	0.1702 ***	0.1211 ***	0.1491 ***	0.1587 ***	0.1605 ***
Sharpe Ratio	0.2027	0.0147	0.0015	0.0071	0.0053
Treynor Ratio	0.0489	0.0021	0.00002	0.0009	0.0006
√Var(e) (Involatility)[21]	4.0877	1.6826	1.8067	1.8752	1.8283
Panel B: Fama and French Five Factor Model: $R_i - R_f = a_i + b_i(R_m - R_f) + s_iSMB + h_iHML + r_iRMW + c_iCMA + e_i$	**Q1 (Small)**	**Q2**	**Q3**	**Q4**	**Q5 (Big)**
a_i	0.7752 ***	−0.0163	−0.0476 *	−0.0400	0.0440 *
Beta	0.1698 ***	0.1209 ***	0.1486 ***	0.1582 ***	0.1599 ***
SMB	0.0321	0.1051 **	0.0966 ***	0.0954 **	0.0783 *
HML	0.0878	0.1233 ***	0.1369 ***	0.1381 ***	0.1189 ***
RMW	−0.0702	0.0262	0.0048	0.0036	−0.0211
CMA	−0.0477	−0.1412 ***	−0.1799 ***	−0.1636 ***	−0.1724 ***

This table provides summary statistics, and results from the univariate CAPM model and multivariate Fama–French five factor models, for small (Q1) and big (Q5) REIT portfolios. Involtility has been calculated using the square root of the residual variance derived from the CAPM model. Significance is shown at 10% (*), 5% (**) and 1% (***) levels.

4.5.2.2 HML

Table 4.3 shows that the mean excess daily-after-formation return for value REITs is higher than growth REITs (0.4379% vs. −0.0432%), equating to a daily average value premium of 0.4811% [=0.4379% − (−0.0432)]. The standard deviation for the value portfolio is 3.011% compared to 1.7315% for the growth portfolio, indicating that returns on the value portfolio are significantly more volatile relative to the growth portfolio. Both the Sharpe ratio and Treynor ratio indicate a relatively better risk-adjusted performance for value REITs.

The CAPM beta in Table 4.3 for the value portfolio is 0.09 versus 0.14 for the growth portfolio, indicating a lower market risk on the value portfolio. After adjusting for the five known risk factors in panel B of Table 3, excess returns of the value portfolio over the growth portfolio is

21 The square root of the residual variance derived from the univariate CAPM model is used to represent idiosyncratic return volatility, and this is an indicator for arbitrage risk.

0.4982% (=0.4088 − (−0.0894)). Overall, the lower systematic risk and higher alphas associated to Q1 relative to Q5 may indicate that a value strategy within the REIT market is able to produce abnormal returns without exposing investors to more risk. This is inconsistent with the risk based argument of Fama and French.

The HML factor loading for value REITs is higher and significant than growth REITs (0.24 vs. 0.09), indicating that value REITs returns might be more sensitive to changes in the value premium within the market, relative to growth REITs. The SMB factor loading for value REITs is relatively lower (0.03 vs. 0.07), indicating that value REITs might be relatively less sensitive to changes in the size premium within the market.

Authors such as Shleifer and Vishny (1997), and Ali et al. (2003) have argued that the value premium of stocks with high idiosyncratic risk cannot easily be arbitraged away and as a result, these stocks are exposed to more systematic mispricing. Idiosyncratic return volatility (measured by square root of variance derived from the CAPM model) is a representation of arbitrage risk (Ooi et al. 2007). Panel A demonstrates that the idiosyncratic risk (Involatility) decreases from the value REIT portfolio (3.0064%) to the growth REIT portfolio (1.6956%), but the idiosyncratic risk of REITs does not decrease monotonically with B/M ratio. This potentially provides an explanation for the role of arbitrage risk in preventing arbitrageurs from exploiting mispricing related to value REITs. Consistent with their lower idiosyncratic risk, growth REITs are less prone to mispricing relative to value REITs.

Table 4.3. Risk measures for Value and Growth REIT portfolios (2001–2020).

Panel A: Summary Statistics	Q1 (Value)	Q2	Q3	Q4	Q5 (Growth)
Excess Means	0.4379	0.0301	0.0052	0.0870	−0.0432
Standard Deviation	3.0111	1.7988	1.7861	1.8996	1.7315
CAPM Beta (Univariate)	0.0888 ***	0.1326 ***	0.1287 ***	0.1442 ***	0.1370 ***
Sharpe Ratio	0.1454	0.0167	0.0029	0.0458	−0.0250
Treynor Ratio	0.0493	0.0023	0.0004	0.0060	−0.0032
√Var(e) (Involatility)	3.0064	1.7680	1.7554	1.8653	1.6939
Panel B: Fama and French Five Factor Model: $R_i - R_f = a_i + b_i(R_m - R_f) + s_iSMB + h_iHML + r_iRMW + c_iCMA + e_i$	**Q1 (Value)**	**Q2**	**Q3**	**Q4**	**Q5 (Growth)**
a_i	0.4088 ***	−0.0153 ***	−0.0382	0.0388	−0.0894 ***
Beta	0.0885 ***	0.1324 ***	0.1283 ***	0.1436 ***	0.1366 ***
SMB	0.0346 ***	0.0869 **	0.0891 ***	0.0932 **	0.0744 *
HML	0.2412 ***	0.1543 ***	0.1273 ***	0.1128 ***	0.0886 ***
RMW	0.0032	0.0357	−0.0038	−0.0321	−0.0160
CMA	−0.1340	−0.1537 ***	−0.1433 ***	−0.1576 ***	−0.1380 ***

This table provides summary statistics, and results from the univariate CAPM model and multivariate Fama–French three factor and five factor models, for value (Q1) and growth (Q5) REIT portfolios. Involatility has been calculated using the square root of the residual variance derived from the CAPM model. Significance is shown at 10% (*), 5% (**) and 1% (***) levels.

4.5.2.3 RMW

Table 4.4 shows the mean excess daily-after-formation return for REITs with robust profitability is higher than returns for REITs with weak profitability (0.1513% vs. 0.1049%), equating to an average RMW premium of 0.0464% (=0.1513% − 0.1049%). The standard deviation for REITs with robust profitability (1.9689%) is significantly higher than that of REITs with weak profitability (1.8390%). The Sharpe ratio shows a better volatility adjusted performance for the robust profitability portfolio, but the Treynor ratio shows a relatively superior systematic risk adjusted performance for the weak profitability portfolio.

The average systematic risk for the robust profitability portfolio (0.17) is higher than that of the weak profitability portfolio (0.09), indicating a higher market risk associated with the robust profitability portfolio. After adjusting for the five known risk factors in panel B, excess return for the robust portfolio (Q1) averaged 0.0925%, as compared to 0.0740% for the weak portfolio (Q5). Overall, a higher alpha observed for Q1, accompanied by a higher systematic risk indicates that a robust profitability strategy is able to produce abnormal returns, but it does expose investors to a higher risk. This is consistent with the risk-based explanation of Fama and French.

Table 4.4 Risk measures for Robust and Weak Profitability REIT portfolios (2001–2020).

Panel A: Summary Statistics	**Q1 (Robust)**	**Q2**	**Q3**	**Q4**	**Q5 (Weak)**
Excess Means	0.1513	0.0083	0.2534	0.0863	0.1049
Standard Deviation	1.9689	1.8534	1.9755	1.7389	1.8390
CAPM Beta (Univariate)	0.1712 ***	0.1451 ***	0.1158 ***	0.1206 ***	0.0902 ***
Sharpe Ratio	0.0768	0.0045	0.1283	0.0496	0.0570
Treynor Ratio	0.0088	0.0006	0.0219	0.0072	0.0116
√Var(e) (Involatility)	1.9207	1.8158	1.9387	1.7119	1.8218
Panel B: Fama and French Five Factor Model: $R_i - R_f = a_i + b_i(R_m - R_f) + s_iSMB + h_iHML + r_iRMW + c_iCMA + e_i$	**Q1 (Robust)**	**Q2**	**Q3**	**Q4**	**Q5 (Weak)**
a_i	0.0925 ***	−0.0404	0.2142 ***	0.0445 *	0.0740 ***
Beta	0.1710 ***	0.1445 ***	0.1155 ***	0.1207 ***	0.0901 ***
SMB	0.0742 *	0.1060 ***	0.0779 *	0.1082 ***	0.0326
HML	0.1170 ***	0.1431 ***	0.1190 ***	0.1378 ***	0.1050 ***
RMW	0.0278	−0.0113	0.0081	0.0462	0.0210
CMA	−0.1275**	−0.1915 ***	−0.1462 ***	−0.1075 **	−0.0758

This table provides summary statistics, and results from the univariate CAPM model and multivariate Fama–French three factor and five factor models, for robust profitability (Q1) and weak profitability (Q5) REIT portfolios. Involatility has been calculated using the square root of the residual variance derived from the CAPM model. Significance is shown at 10% (*), 5% (**) and 1% (***) levels.

4.5.2.4 CMA

Table 4.5 shows that the mean excess daily-after-formation return for conservative investment REITs is higher than for aggressive investment REITs (0.0369% vs. −0.0450%), equating to a daily average CMA premium of 0.0819% [=0.0369% − (−0.0450%)]. The standard deviation for the conservative investment portfolio (1.8521%) is higher than that of the aggressive investment portfolio (1.6339%) indicating a higher relative volatility on the conservative investment portfolio. Both risk adjusted measures show a better performance for the conservative investment portfolio.

Table 4.5A shows the beta associated with conservative investment REITs is significantly lower than that of aggressive investment REITs (0.10 versus 0.13), translating to a relatively lower market risk for the conservative investment portfolio.

After adjusting for the five known risk factors in panel B, the intercept for the conservative investment portfolio (Q1) is not statistically significant, indicating that there are no abnormal returns to be gained from holding this portfolio. The insignificant alpha for the conservative portfolio (Q1) implies that excess returns on this portfolio are completely explained by the Fama and French (2015) risk factors. Panel B also shows significantly higher loadings for SMB (0.09 vs. 0.06), HML (0.14 vs. 0.11) and CMA (−0.09 vs. −0.16) factors on the conservative investment portfolio, relative to the aggressive investment portfolio. The higher factor loadings provide justification that the existence of a positive CMA premium is accompanied by a higher systematic risk, and therefore, investors looking to avail CMA premiums within US REITs would be exposed to a higher risk.

Table 4.5. Risk measures for Conservative and Aggressive Investment REIT portfolios (2001–2020).

Panel A: Summary Statistics	**Q1 (Conservative)**	**Q2**	**Q3**	**Q4**	**Q5 (Aggressive)**
Excess Means	0.0369	0.0104	0.0436	0.1854	−0.0450
Standard Deviation	1.8521	1.7424	1.7496	1.8793	1.6339
CAPM Beta (Univariate)	0.1014 ***	0.1398 ***	0.1308 ***	0.1235 ***	0.1264 ***
Sharpe Ratio	0.0199	0.0059	0.0249	0.0987	−0.0275
Treynor Ratio	0.0036	0.0007	0.0033	0.0150	−0.0036
√Var(e) (Involatility)	1.8346	1.7062	1.7202	1.8473	1.6010
Panel B: Fama and French Five Factor Model: $R_i - R_f = a_i + b_i(R_m - R_f) + s_iSMB + h_iHML + r_iRMW + c_iCMA + e_i$	**Q1 (Conservative)**	**Q2**	**Q3**	**Q4**	**Q5 (Aggressive)**
a_i	0.0023	−0.0370	−0.0010	0.1427 ***	−0.0875 ***
Beta	0.1014 ***	0.1393 ***	0.1305 ***	0.1235 ***	0.1259 ***
SMB	0.0887 **	0.0952 **	0.0989 **	0.1066 **	0.0622 *
HML	0.1429 ***	0.1319 ***	0.1186 ***	0.1352 ***	0.1100 ***
RMW	0.0189	0.0076	0.0215	0.0451	−0.0020
CMA	−0.0949 *	−0.1667 ***	−0.1582 ***	−0.1132 **	−0.1614 ***

This table provides summary statistics, and results from the univariate CAPM model and multivariate Fama–French three factor and five factor models, for conservative investment (Q1) and aggressive investment (Q5) REIT portfolios. Involatility has been calculated using the square root of the residual variance derived from the CAPM model. Significance is shown at 10% (*), 5% (**) and 1% (***) levels.

4.5.2.5 WML

Table 4.6 shows the mean excess daily-after-formation return for winner REITs is higher than loser REITs (0.1599% vs. 0.0560%), equating to a daily average WML premium of 0.1038% (=0.1599% − 0.0560%). The standard deviation for the winner REITs portfolio is 1.6832% versus 1.8184% for the loser REITs portfolio, indicating that returns on the winner portfolio are associated with significantly less volatility relative to the loser portfolio. Both the Sharpe ratio and Treynor ratio show that the risk-adjusted performance for winner REITs is superior to that of loser REITs.

The average systematic risk for the winner portfolio (0.11) is lower than that for the loser portfolio (0.12). Panel B reveals that the alpha for the winner portfolio is positive and statistically significant. The intercept for the other quintile portfolios (Q2, Q3, Q4 and Q5) are not statistically significant, indicating that there are no abnormal returns to be gained from holding these portfolios. After adjusting for the five known risk factors, the excess return on the winner portfolio (Q1) averaged 0.1215%. Although the five factor model (panel B in Table 4.6) indicates a relatively higher CMA factor loading associated to winner stocks (−0.11 vs. −0.17), the model does indicate a lower and significant SMB (0.07 vs. 0.09) and HML (0.10 vs. 0.12) factor loadings for winner REITs. The lower systematic risk and higher alpha for Q1 indicates that a winner strategy is able to produce higher abnormal returns, without exposing investors to a higher risk. This is in contradiction with the risk based argument which implies that WML is a common risk factor, and the associated premium is a compensation for exposure to a non-diversifiable risk.

Owing to the fact that the existence of a higher return on winner REITs is not associated with a higher systematic risk, we look to assess if mispricing has a role to play in the existence of WML premiums. A higher idiosyncratic (arbitrage) risk would imply that arbitrageurs are deterred from exploiting mispricing related to winner REITs. Our results indicate that the idiosyncratic risk of winner REITs (1.6581%) is lower than the corresponding idiosyncratic risk on loser REITs (1.7935%), implying that winner REITs are relatively less prone to mispricing. One potential explanation for our results then might be the argument put forward by Jegadeesh and Titman (1993) that the momentum premium might be interpreted as excess returns generated due to investor behavior and an under-reaction from the market to information, potentially due to transaction costs, but resulting in a consistently positive and significant return on momentum strategy.

Table 4.6. Risk measures for Winner and Loser REIT portfolios (2001–2020).

Panel A: Summary Statistics	**Q1 (Winner)**	**Q2**	**Q3**	**Q4**	**Q5 (Loser)**
Excess Means	0.1599	0.0068	0.0147	0.0073	0.0560
Standard Deviation	1.6832	1.6312	1.6552	1.6301	1.8184
CAPM Beta (Univariate)	0.1132 ***	0.1285 ***	0.1309 ***	0.1315 ***	0.1217 ***
Sharpe Ratio	0.0950	0.0041	0.0089	0.0045	0.0308
Treynor Ratio	0.0141	0.0005	0.0011	0.0006	0.0046
√Var(e) (Involatility)	1.6581	1.5984	1.6218	1.5959	1.7935
Panel B: Fama and French Five Factor Model: $R_i - R_f = a_i + b_i(R_m - R_f) + s_iSMB + h_iHML + r_iRMW + c_iCMA + e_i$	**Q1 (Winner)**	**Q2**	**Q3**	**Q4**	**Q5 (Loser)**
a_i	0.1215 ***	−0.0369	−0.0297	−0.0376	0.0153
Beta	0.1129 ***	0.1281 ***	0.1305 ***	0.1312 ***	0.1211 ***
SMB	0.0665 *	0.0894 **	0.0831 **	0.0879 **	0.0905 **
HML	0.0976 ***	0.0973 ***	0.1332 ***	0.1181 ***	0.1247 ***
RMW	0.0015	0.0076	0.0158	0.0211	−0.0099
CMA	−0.1113 **	−0.1458 ***	−0.1582 ***	−0.1379 ***	−0.1701 ***

This table provides summary statistics, and results from the univariate CAPM model and multivariate Fama–French three factor and five factor models, for winner (Q1) and loser (Q5) REIT portfolios. Involatility has been calculated using the square root of the residual variance derived from the CAPM model. Significance is shown at 10% (*), 5% (**) and 1% (***) levels.

4.5.3. Robustness Check for Excess Returns and Risk

In addition to the CAPM and Fama–French models, we use the Carhart four factor model as a robustness measure to gauge the ability of our factor based strategies to extract abnormal returns, along with assessing the relative risks associated with these strategies. These results are displayed in Tables 4.7–4.11. From a risk perspective, we find results that are in-line with our previous findings in terms of relative betas and factor loadings, for each strategy.

The WML factor is unique to the Carhart four factor model, relative to the univariate CAPM model and multivariate Fama–French models. We find a lower WML factor loading for our HML and WML strategies, while we observe a higher WML factor loading for our RMW and CMA strategies. This result provides further credence to the fact that value and momentum strategies might help to generate abnormal excess returns without exposing investors to a higher relative risk, while the RMW and CMA strategies might be associated with a rise in relative risk for investors.

Table 4.7. Robustness check for Small and Big REIT portfolios (2001–2020).

Carhart four factor model: $R_i - R_f = a_i + b_i(R_m - R_f) + s_iSMB + h_iHML + w_iWML + e_i$	Q1 (Small)	Q2	Q3	Q4	Q5 (Big)
a_i	0.7775 ***	−0.0143	−0.0460 *	−0.0383	−0.0431
Beta	0.1659 ***	0.1188 ***	0.1464 ***	0.1560 ***	0.1582 ***
SMB	0.0897	0.1194 ***	0.1193 ***	0.1187 ***	0.1049 ***
HML	−0.0174	0.0222	0.0284	0.0322	0.0311
WML	−0.2376	−0.1370 ***	−0.1544 ***	−0.1549 ***	−0.1338 ***

This table provides results from the Carhart four factor model for small (Q1) and big (Q5) REIT portfolios. Significance is shown at 10% (*), 5% (**) and 1% (***) levels.

Table 4.8. Robustness check for Value and Growth REIT portfolios (2001–2020).

Carhart Four Factor Model: $R_i - R_f = a_i + b_i(R_m - R_f) + s_iSMB + h_iHML + w_iWML + e_i$	Q1 (Value)	Q2	Q3	Q4	Q5 (Growth)
a_i	0.4118 ***	−0.0131	−0.0366	0.0398	−0.0887 ***
Beta	0.0847 ***	0.1303 ***	0.1261 ***	0.1416 ***	0.1352 ***
SMB	0.0698	0.0988 ***	0.1133 ***	0.1257 ***	0.0955 ***
HML	0.1027 *	0.0469	0.0306	0.0224	0.0179
WML	−0.2272 ***	−0.1392 ***	−0.1480 ***	−0.1508 ***	−0.1075 ***

This table provides results from the Carhart four factor model for value (Q1) and growth (Q5) REIT portfolios. Significance is shown at 10% (*), 5% (**) and 1% (***) levels.

Table 4.9. Robustness check for Robust and Weak Profitability REIT portfolios (2001–2020).

Carhart Four Factor Model: $R_i - R_f = a_i + b_i(R_m - R_f) + s_iSMB + h_iHML + w_iWML + e_i$	Q1 (Robust)	Q2	Q3	Q4	Q5 (Weak)
a_i	0.0938 ***	−0.0392	0.2155 ***	0.0467 *	0.0761 ***
Beta	0.1697 ***	0.1426 ***	0.1139 ***	0.1187 ***	0.0880 ***
SMB	0.0801 *	0.1320 ***	0.0937 **	0.1140 ***	0.0456
HML	0.0428	0.0422	0.0342	0.0448	0.0223
WML	−0.0877 ***	−0.1470 ***	−0.1161 ***	−0.1177 ***	−0.1241 ***

This table provides results from the Carhart four factor model for robust profitability (Q1) and weak profitability (Q5) REIT portfolios. Significance is shown at 10% (*), 5% (**) and 1% (***) levels.

Table 4.10. Robustness check for Conservative and Aggressive Investment REIT portfolios (2001–2020).

Carhart Four Factor Model: $R_i - R_f = a_i + b_i(R_m - R_f) + s_iSMB + h_iHML + w_iWML + e_i$	Q1 (Conservative)	Q2	Q3	Q4	Q5 (Aggressive)
a_i	0.0039	−0.0351	0.0007	0.1446 ***	−0.0864 ***
Beta	0.0997 ***	0.1370 ***	0.1286 ***	0.1218 ***	0.1242 ***
SMB	0.1003 **	0.1181 ***	0.1132 ***	0.1101 ***	0.0825 **
HML	0.0670 *	0.0220	0.0204	0.0500	0.0205
WML	−0.1067 ***	−0.1593 ***	−0.1295 ***	−0.1018 ***	−0.1276 ***

This table provides results from the Carhart four factor model for conservative investment (Q1) and aggressive investment (Q5) REIT portfolios. Significance is shown at 10% (*), 5% (**) and 1% (***) levels.

Table 4.11. Robustness check for Winner and Loser REIT portfolios (2001–2020).

Carhart Four Factor Model: $R_i - R_f = a_i + b_i(R_m - R_f) + s_iSMB + h_iHML + w_iWML + e_i$	Q1 (Winner)	Q2	Q3	Q4	Q5 (Loser)
a_i	0.1223 ***	−0.0358	−0.0281	−0.0359	0.0173 *
Beta	0.1119 ***	0.1267 ***	0.1287 ***	0.1294 ***	0.1184 ***
SMB	0.0785 **	0.1042 ***	0.0993 ***	0.1013 ***	0.1227 ***
HML	0.0388	0.0165	0.0358	0.0268	0.0057
WML	−0.0804 ***	−0.1088 ***	−0.1318 ***	−0.1226 ***	−0.1877 ***

This table provides results from the Carhart four factor model for winner (Q1) and loser (Q5) REIT portfolios. Significance is shown at 10% (*), 5% (**) and 1% (***) levels.

4.5.4 Statistical Analysis for Explanatory Variables

We report the main summary statistics in Table 4.12. Daily statistics are provided for mean values along with their respective skewness and kurtosis levels. Overall, the skewness and kurtosis levels of the variables signifies non-normality. Our data set runs through the dot-com crash, the non-recessionary phase following the dot-com crash, the 2007/08 crisis, the non-recessionary phase following the 2007/08 crisis, and the COVID-19 phase. These variations in phases become apparent by observing the large standard deviation levels associated with all our explanatory variables.

Table 4.12. Descriptive Statistics for Explanatory Variables.

Variables	Mean	SD	Min	Max	Skewness	Kurtosis
DCS	0.0000905	0.024616	−0.300000	0.470000	3.096665	70.96143
DTED	0.0000261	0.049873.	−0.800000	0.996250	0.758200	88.69920
DSNP	0.394754	20.42972	−324.8900	230.3800	−1.331192	39.33516

This table provides descriptive statistics for all variables for the full sample from July 2001 to June 2020. DCS denotes the daily change in credit spread, DTED denotes the daily change in the TED spread, DSNP represents the daily change in the S&P 500 index.

Figure 4.6 shows time series volatility for Credit Spread, TED Spread and S&P 500 index (left) and first difference (right) for the full sample between July 2001 and June 2020. Both credit spread and TED spread rise together during the 2007/08 crisis, peaking in 2008. Furthermore, they both rise in unison during the COVID-19 phase. This is an expected result as financial distress and the possibility of a liquidity crisis are both anticipated to rise during a financial crisis. The first difference plots suggest that changes in TED spread tend to be more volatile relative to changes in credit spread during the 2007/08 crisis, but during the COVID-19 phase, credit spread seems to be relatively more volatile. This is further backed by the argument that illiquidity and liquidity risk was a major source for the 2007/08 financial crisis (Brunnermeier 2009; Crotty 2009). Both TED spread and Credit spread seem to move in the opposite direction to the S&P 500 index, during the financial crisis of 2008, and the COVID-19 phase. A rise in the probability of liquidity crisis and default risk during these recessionary phases might negatively impact investor sentiments within the economy, which might result in channeling of funds from the stock market to safe haven investments, such as the US Dollar.

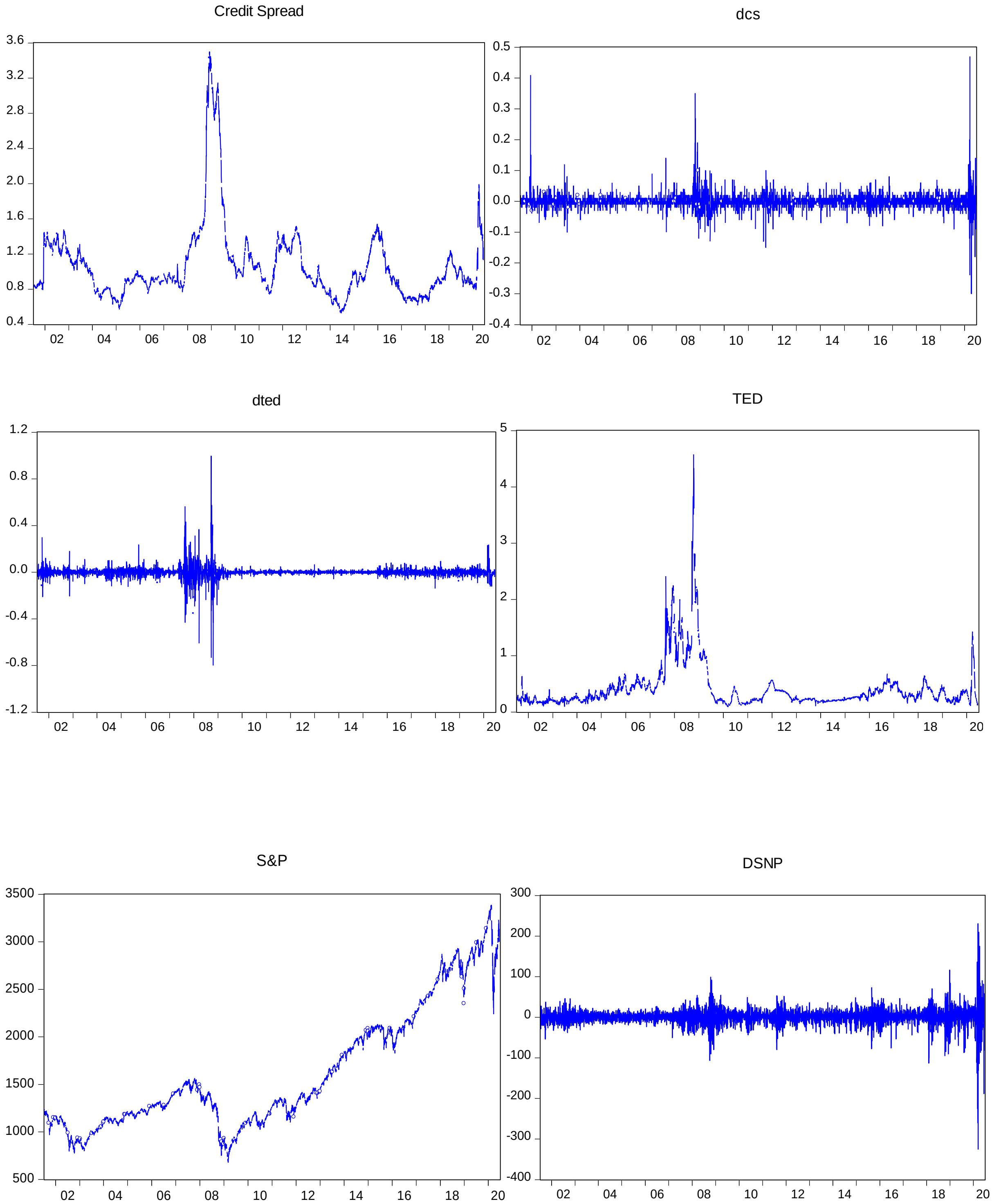

Figure 4.6. Time series volatility for Credit Spread, TED Spread, S&P 500 index levels (**left**) and returns (**right**) for the full sample between July 2001 to June 2020.

Due to the significant correlation levels, we orthogonalise our variables using the system set out in Equations (4.5) and (4.6). Table 4.13 then confirms no significant correlations between our explanatory variables.

Table 4.13. Correlation after Orthogonalization.

Correlation Probability	CS	TED	DSNP
CS	1.000000 -----		
TED	-8.71×10^{-16} 1.0000	1.000000 -----	
DSNP	-2.10×10^{-15} 1.0000	8.32×10^{-16} 1.0000	1.000000 -----

The table provides correlation of the variables for the full sample from July 2001 to June 2020. CS and TED are the residual terms from Equation (4.5) and (4.6), respectively, while DSNP represents the daily change in the S&P 500 index.

Theoretically, one could argue that the macroeconomy drives credit spread and TED spread, via sovereign and corporate bond yields and the perceived risk on corporate debt. One could also argue that a causation may exist the other way, i.e., credit spread and TED spread causing movements within macroeconomic factors, via changes in the probability of financial distress, liquidity crisis and default risk. We therefore look to test the direction of the causality, if present, between credit spread, TED spread and the S&P 500 index.

Table 4.14 reports results for Granger causality. Our results suggest that a significant two-way causality exists between credit spread and TED spread, and between TED spread and the S&P 500 index. Furthermore, the S&P 500 index causes movements within credit spread.

Table 4.14. Granger Causality.

Null Hypothesis:	F-Statistic	Prob.
DTED does not Granger Cause DCS	7.2165	0.0007 ***
DCS does not Granger Cause DTED	2.9158	0.0543 *
DSNP does not Granger Cause DCS	25.0571	0.0000 ***
DCS does not Granger Cause DSNP	1.5750	0.2071
DSNP does not Granger Cause DTED	5.3350	0.0048 ***
DTED does not Granger Cause DSNP	3.0718	0.0464 **

The table reports only the Granger Causality test results between credit spread, TED spread, S&P 500 index, for the full sample between July 2001 and June 2020. Significance is shown at 10% (*), 5% (**) and 1% (***) levels.

4.5.5. Bounds Test for Co-integration

Tables A1–A5[22] report the results of the bounds test for co-integration between SMB, HML, RMW, CMA and WML premiums, and our explanatory variables, for the three recessionary periods and the two non-recessionary periods. The computed F-statistic is significantly greater than the critical upper bound values at the 5% and 10% levels of significance. This indicates that a co-integration relationship exists between each of our factor premiums, and credit spread, TED spread, S&P 500 index, during all five periods.

Once a long-run relationship has been established between our factor premiums and the examined variables, we use the long-run ARDL model and short-run ECM model as specified in Equations (4.8) and (4.9), to estimate long-run and short-run elasticities for the variables in the model, during recessionary and non-recessionary phases.

[22] For reasons of clarity within the main body of this chapter, these results are presented in the Appendix A section.

4.5.6 The Long-Run ARDL Model and the Short-Run Error Correction Model

4.5.6.1 SMB, HML and CMA

Recession

Tables 4.15–4.17 show that credit spread, and TED spread have a significant and positive impact on both SMB, HML and CMA premiums, both in the short- and long-run, during recessionary states. These results are consistent with the risk-based explanation of Fama and French (1996, 2015), that SMB, HML and CMA premiums are proxies for systematic risk. Therefore, with a rise in general risk levels within the economy, investors demand a higher compensatory return on these REITs.

Table 4.15. Long-run ARDL model and short-run error correction model for SMB (Recession).

Variable	Long Run			Short-Run		
	Dot-com	**2007/08**	**COVID-19**	**Dot-com**	**2007/08**	**COVID-19**
	Coefficient (*p*-Value)	**Coefficient (*p*-Value)**	**Coefficient (*p*-Value)**	**Coefficient (*p*-Value)**	**Coefficient (*p*-Value)**	**Coefficient (*p*-Value)**
Con	**72.06 (0.01)**	−23.45 (0.29)	29.44 (0.65)	−0.14 (0.75)	−0.02 (0.94)	0.39 (0.57)
SMB (−1)	**0.21 (0.03)**	**0.35 (0.00)**	**0.39 (0.00)**	**1.07(0.00)**	**1.31 (0.01)**	**0.95 (0.00)**
CR	23.72 (0.11)	2.13 (0.75)	8.24 (0.11)	16.61 (0.24)	4.99 (0.44)	2.69 (0.57)
CR (−1)		**20.79 (0.02)**			**24.32 (0.00)**	
TED	6.10 (0.44)	−1.43 (0.71)	1.60 (0.86)	4.94 (0.50)	−0.61 (0.87)	−1.92 (0.80)
TED (−1)		**17.27 (0.00)**			**19.42 (0.00)**	
S&P	**−57.93 (0.00)**	**−152.86 (0.00)**	**−42.25 (0.00)**	**−56.36 (0.00)**	**−156.95 (0.00)**	**−24.67 (0.08)**
S&P (−1)	**48.17 (0.00)**	**237.68 (0.00)**	**38.38 (0.01)**	**39.22 (0.03)**	**235.16 (0.00)**	**45.06 (0.00)**
ECM (−1)				**−0.87 (0.00)**	**−0.99 (0.05)**	**−0.55 (0.00)**

This table represents results for the three recession periods, the dot-com crash (July 2001 to November 2001), the 2007/08 crisis (December 2007 to June 2009), and COVID-19 (February 2020 to June 2020). CR, TED, S&P denote credit spread, TED spread, S&P 500 index *p*-values are listed next to the coefficients. Bold figures mean significant.

Table 4.16. Long-run ARDL model and short-run error correction model for HML (Recession).

	Long-Run			Short-Run		
	Dot-com	**2007/08**	**COVID-19**	**Dot-com**	**2007/08**	**COVID-19**
Variable	**Coefficient (*p*-Value)**	**Coefficient (*p*-Value)**	**Coefficient (*p*-Value)**	**Coefficient (*p*-Value)**	**Coefficient (*p*-Value)**	**Coefficient (*p*-Value)**
Constant	**29.47 (0.09)**	−33.14 (0.10)	−161.02 (0.12)	**0.51 (0.09)**	0.01 (0.97)	−0.06 (0.84)
HML (−1)	**0.43 (0.00)**	**0.76 (0.00)**	**0.18 (0.09)**	**0.66 (0.00)**	**0.99 (0.00)**	**0.59 (0.03)**
CR	**17.19 (0.08)**	6.16 (0.32)	**19.37 (0.00)**	13.09 (0.16)	5.26 (0.28)	**16.82 (0.01)**
CR (−1)					**10.93 (0.03)**	
TED	4.35 (0.40)	1.04 (0.77)	−3.42 (0.68)	4.04 (0.41)	0.76 (0.79)	−10.73 (0.18)
TED (−1)			**23.21 (0.02)**		**11.92 (0.00)**	**15.47 (0.07)**
S&P	−10.66 (0.29)	**−42.36 (0.00)**	0.35 (0.98)	−5.99 (0.52)	**−40.01 (0.00)**	8.68 (0.53)
S&P (−1)		**46.98 (0.00)**	**51.16 (0.00)**		**70.93 (0.00)**	**47.76 (0.00)**
ECM (−1)				**−0.20 (0.09)**	**−0.51 (0.00)**	**−0.49 (0.09)**

This table represents results for the three recession periods, the dot-com crash (July 2001 to November 2001), the 2007/08 crisis (December 2007 to June 2009), and COVID-19 (February 2020 to June 2020). CR, TED, S&P denote credit spread, TED spread, S&P 500 index *p*-values are listed next to the coefficients. Bold figures mean significant.

Table 4.17. Long-run ARDL model and short-run error correction model for CMA (Recession).

	Long-Run			Short-Run		
	Dot-com	**2007/08**	**COVID-19**	**Dot-com**	**2007/08**	**COVID-19**
Variable	**Coefficient (*p*-Value)**	**Coefficient (*p*-Value)**	**Coefficient (*p*-Value)**	**Coefficient (*p*-Value)**	**Coefficient (*p*-Value)**	**Coefficient (*p*-Value)**
Constant	14.85 (0.58)	−20.56 (0.10)	−8.48 (0.76)	0.03 (0.85)	0.01 (0.90)	−0.09 (0.60)
CMA (−1)	0.15 (0.15)	**0.15 (0.00)**	**0.19 (0.06)**	0.45 (0.38)	**0.91 (0.00)**	**0.52 (0.09)**
CR	12.90 (0.23)	**−13.42 (0.03)**	**1.68 (0.07)**	11.43 (0.26)	**−10.34 (0.08)**	**6.28 (0.02)**
CR (−1)		**18.20 (0.03)**			**18.57 (0.00)**	
TED	−0.86 (0.31)	−0.95 (0.53)	0.02 (0.96)	−0.36 (0.66)	−1.26 (0.40)	0.44 (0.70)
TED (−1)		−0.87 (0.71)		**1.36 (0.09)**	−0.50 (0.75)	
TED (−2)		**4.58 (0.05)**			**3.95 (0.01)**	
S&P	7.49 (0.55)	**−37.16 (0.00)**	0.99 (0.78)	10.60 (0.39)	**−38.85 (0.00)**	**14.71 (0.01)**
S&P (−1)		**47.51 (0.00)**			**38.17 (0.00)**	
ECM (−1)				**−0.31 (0.08)**	**−0.77 (0.00)**	**−0.25 (0.00)**

This table represents results for the three recession periods, the dot-com crash (July 2001 to November 2001), the 2007/08 crisis (December 2007 to June 2009), and COVID-19 (February 2020 to June 2020). CR, TED, S&P denote credit spread, TED spread, S&P 500 index *p*-values are listed next to the coefficients. Bold figures mean significant.

Fama and French (1996), Chan and Chen (1991), conclude that small stocks generally have poorer earnings and profitability relative to big stocks, and link size premiums to greater financial risk. They also conclude that value stocks carry a higher financial risk relative to growth stocks. Based on these factors, small and value REITs are more vulnerable to the risk of default, leading investors to demand a higher compensatory return on small and value REITs as leverage, default risk and credits spreads rise.

Elgammal et al. (2016) identify that value stocks are more vulnerable to default risk relative to growth stocks, since they have higher levels of leverage associated to them. They also find a positive relationship between credit spreads and HML premiums in the stock market. A rise in leverage, proxied by credit spread (Ivaschenko 2003; Molina 2005), increases the risk associated with value stocks, as these tend to be more levered than other firms. Therefore, investors require a higher return on value REITs when credit spreads rise. Furthermore, Vassalou and Xing (2004) suggest that book-to-market effects are concentrated within firms with a high risk of default, which is consistent with our findings of a positive relationship between credit spread and value premiums.

An up-tick in the probability of a liquidity crisis may reduce the availability of funds for leverage, therefore enhancing the risk of default and financial distress. This relationship is again consistent with the risk-based argument that investors would demand a higher return for being exposed to a higher risk. Bernanke (1983) and, Giesecke et al. (2014) conclude that small stocks are more vulnerable to liquidity risk relative to big stocks. In a scenario where there is sharp fall in liquidity during a financial crisis, larger firms might have access to credit alternatives, something small firms might not have access to, raising the risk associated with small REITs relative to big REITs, and thus investors demand a higher compensatory return, eventually enhancing the SMB premium.

Our result in Table 4.16 is also consistent with the argument that value premiums are proxies for systematic risk (Fama and French 1992, 2006), hence it is expected that a rise in the probability of a liquidity crisis will enhance value premiums, since it limits the availability of funds, and value stocks tend to be more leveraged than other firms (Elgammal et al. 2016), resulting in a higher compensatory return for investors if they choose to take an exposure on riskier value REITs.

Both credit spread and TED spread seem to have only a short-run impact on HML premiums during the 2007/08 crisis, as shown in Table 4.16. This is in contrast to the other two recession periods. One possible reason for this might be the depth of this recession, along with its significance in terms of impact on markets and investor sentiments. Given the extent of this recession, the uncertainty of the long-run would be something that would play a part in investors' decision making. Therefore, the stronger short-run influence might be a testament to the fact that during this phase, investors are primarily concerned with returns in the short-run.

Fama and French (2015) show that investment is a significant factor in defining average returns, identifying it as a risk factor, derived from the dividend discount model. Similar to our results within the REIT market, Fama and French (2015) find a positive CMA premium within general stocks. Based on their risk-based argument, this would mean that firms with conservative investment strategies have a higher risk associated to them, potentially due to lower prospects relative to firms with aggressive investment strategies, and therefore the CMA premium is a compensation for investors, for exposing them to higher risk. A rise in the probability of default and liquidity crisis implies a rise in general risk levels with the economy, resulting in a higher compensatory return for investors if they choose to take an exposure on conservative investment (weak prospects) REITs, hence raising CMA premiums.

Based on these results, it is clear that establishing and understanding the relationship between financial distress/liquidity crisis and size/value/investment premiums is crucial for investors and fund managers to derive an investment strategy during a crisis period.

The S&P 500 index has a significant and negative impact on SMB premiums in all three recessionary phases. A possible explanation for this stems from investor sentiments. A rise in the index might make investors more optimistic about the future state of the economy (Essa and Giouvris 2020), reducing the perceived risk associated with small stocks, and hence resulting in a fall in SMB premiums.

For lagged values of the S&P 500 index, the sign of the relationship between the stock market index and SMB premiums is reversed. We also find that the S&P 500 index overall has a positive and significant influence on HML and CMA premiums during recessionary phases. As returns on the index go up, this signifies higher returns on larger stocks, inducing investors' to channel funds towards these securities. This potentially reduces demand for riskier small/value/conservative (weaker prospects) REITs, which in-turn need to provide higher returns in order to incentivise investors, thus resulting in a rise in SMB/HML/CMA premiums.

So, for current values of S&P 500 index, investor sentiment tends to dominate the impact on SMB premiums, while the channeling of funds tends to dominate for lagged measures of the S&P 500 index.

We also find that lagged values of SMB, HML and CMA premiums have a positive and significant impact on current size, value and investment premiums respectively, implying that these might have some forecasting power. In summary, credit spread and TED spread have a significant and positive impact on SMB, HML and CMA premiums during recessionary phases. The S&P 500 has a mixed impact on SMB premiums, while it has a positive impact on HML and CMA premiums.

Non-Recession

Tables 4.18–4.20 show that credit spread has no significant impact on SMB, HML and CMA premiums during the non-recessionary phases. This is consistent with Huang et al. (2013) who argue that SMB premiums are not driven by financial distress risk. This would also suggest that during economic up-turns, investors are less concerned with financial distress, probability of default.

Table 4.18. Long-run ARDL model and short-run error correction model for SMB (Non-Recession).

Variable	Long-Run		Short-Run	
	Post Dot-com	Post 2007/08	Post Dot-com	Post 2007/08
	Coefficient (*p*-Value)	Coefficient (*p*-Value)	Coefficient (*p*-Value)	Coefficient (*p*-Value)
Constant	2.13 (0.38)	2.47 (0.14)	0.02 (0.71)	**0.13 (0.03)**
SMB (−1)	**0.27 (0.00)**	**0.67 (0.00)**	**1.01 (0.00)**	**0.81 (0.00)**
CR	−0.48 (0.81)	2.31 (0.48)	−0.65 (0.75)	2.68 (0.40)
TED	0.51 (0.69)	**7.14 (0.06)**	0.43 (0.74)	5.91 (0.11)
S&P	**−58.87 (0.00)**	**−62.70 (0.00)**	**−58.45 (0.00)**	**−60.07 (0.00)**
ECM (−1)			**−0.75 (0.00)**	**−0.22 (0.00)**

This table represents results for the two non-recession periods, post dot-com crisis (December 2001 to November 2007) and post 2007/08 crisis (July 2009 to January 2020). CR, TED, S&P denote credit spread, TED spread, S&P 500 index *p*-values are listed next to the coefficients. Bold figures mean significant.

Table 4.19. Long-run ARDL model and short-run error correction model for HML (Non-Recession).

Variable	Long-Run		Short-Run	
	Post Dot-com	Post 2007/08	Post Dot-com	Post 2007/08
	Coefficient (*p*-Value)	Coefficient (*p*-Value)	Coefficient (*p*-Value)	Coefficient (*p*-Value)
Constant	1.08 (0.59)	**1.62 (0.05)**	−0.01 (0.65)	**0.07 (0.02)**
HML (−1)	**0.37 (0.00)**	**0.67 (0.00)**	**1.09 (0.00)**	**0.85 (0.00)**
CR	1.26 (0.45)	0.69 (0.66)	0.43 (0.78)	0.40 (0.80)
TED	0.83 (0.43)	−0.61 (0.74)	0.29 (0.76)	−0.50 (0.77)
S&P	**−24.29 (0.00)**	**−12.58 (0.00)**	**−23.71 (0.00)**	**−10.67 (0.00)**
ECM (−1)			**−0.84 (0.00)**	**−0.32 (0.00)**

This table represents results for the two non-recession periods, post dot-com crisis (December 2001 to November 2007) and post 2007/08 crisis (July 2009 to January 2020). CR, TED, S&P denote credit spread, TED spread, S&P 500 index *p*-values are listed next to the coefficients. Bold figures mean significant.

Table 4.20. Long-run ARDL model and short-run error correction model for CMA (Non-Recession).

Variable	Long-Run		Short-Run	
	Post Dot-com	Post 2007/08	Post Dot-com	Post 2007/08
	Coefficient (p-Value)	Coefficient (p-Value)	Coefficient (p-Value)	Coefficient (p-Value)
Constant	1.75 (0.28)	0.68 (0.24)	0.03 (0.31)	−0.00 (0.99)
CMA (−1)	**−0.09 (0.00)**	**0.46 (0.00)**	**0.30 (0.06)**	**1.27 (0.00)**
CR	0.77 (0.56)	1.04 (0.35)	0.62 (0.64)	1.20 (0.28)
TED	−0.03 (0.97)	0.12 (0.93)	−0.30 (0.72)	0.11 (0.93)
S&P	**−4.96 (0.05)**	3.56 (0.10)	**−5.04 (0.05)**	**3.69 (0.09)**
S&P (−2)				**−4.57 (0.04)**
ECM (−1)			**−0.39 (0.01)**	**−0.88 (0.00)**

This table represents results for the two non-recession periods, post dot-com crisis (December 2001 to November 2007) and post 2007/08 crisis (July 2009 to January 2020). CR, TED, S&P denote credit spread, TED spread, S&P 500 index *p*-values are listed next to the coefficients Bold figures mean significant.

On the other hand, TED spread only has a significant positive impact on SMB premiums during the non-recessionary phase following the 2007/08 crisis, in the long-run (Table 4.18). A rise in the probability of a liquidity crisis might enhance investors' perceived risk on small REITs relative to big REITs, leading investors to demand a higher compensatory premium, in-turn increasing SMB premiums. This result supports the systematic risk explanation for size premiums. The impact of TED spread is insignificant on HML and CMA premiums.

Investor sentiments tend to dominate the impact of the S&P 500 index on SMB, HML and CMA premiums, during the non-recessionary phases. A rise in the index might make investors more optimistic about the future state of the economy (Essa and Giouvris 2020), reducing the perceived risk associated with small/value/conservative investment REITs, and hence resulting in a fall in SMB/HML/CMA premiums.

Overall, our results suggest that TED spread has a significant positive influence on SMB premiums, while the S&P 500 index has a significant negative influence on SMB, HML and CMA premiums in non-recessionary phases. Furthermore, we find evidence of lag premiums having forecasting power during both non-recessionary periods, both in the long- and short-run. Furthermore, we once again find that the coefficient for the error correction term is significantly negative.

4.5.6.2 RMW and WML

Recession

Although the RMW factor derives nicely as a risk factor from the dividend discount model, its economic interpretation is still unclear. The risk based argument would deem firms with robust profitability are relatively riskier and thus would offer a premium or compensation for that risk. Ülkü (2017) shows that RMW might be a proxy for capturing mispricing away from 'value'. Ali and Ülkü (2019) believe that investors may underreact to earnings because of uncertainty of information (Brown et al. 1988) and due to transaction costs (Ülkü 2017), and hence contribute to mispricing. Thus, when earnings information is persistent, accumulation of private information would translate into abnormal returns for the RMW portfolio.

Carhart (1997) show that a momentum factor is significant in explaining expected asset returns, when included as a factor along with market beta, SMB and HML, within the Fama and French three-factor model. The latter three factors represent risk attributes, which provide investors compensation for bearing them, however, the economic interpretation for the momentum factor is still unclear. One interpretation is that the expected growth risk increases with expected growth, supporting the argument that the momentum factor within asset pricing does represent an element of systematic risk that investors might be exposed to (Johnson 2002; Liu and Zhang 2008). On the other hand, momentum premium might be interpreted as excess returns generated due to investor behavior and an under-reaction from the market to information (Jegadeesh and Titman 1993). We find no significant evidence of winner REITs exposing investors to a higher risk relative to loser REITs, along with no significant presence of mispricing. Our results support the argument of an under-reaction from the market in connection to historical returns of winner REITs, potentially due to transaction costs, but resulting in a consistently positive and significant return on momentum strategy.

Tables 4.21 and 4.22 show that credit spread has a significant and negative relationship with RMW and WML premiums. Additionally, TED spread also has a significant and negative impact on RMW premiums. Sentiment based investor behavior tends to dominate the impact of mispricing for both of these relationships. With a rise in default risk and in the probability of a liquidity crisis, investors might be more inclined to channel their funds towards REITs with robust profitability or REITs that have seen higher returns in the short- and medium-term, enhancing the price of these instruments, and having a downward impact on compensatory premiums required to incentivise investors. This result contradicts the argument that RMW and WML premiums are proxies for systematic risk.

Table 4.21. Long-run ARDL model and short-run error correction model for RMW (Recession).

Variable	Long-Run			Short-Run		
	Dot-com	**2007/08**	**COVID-19**	**Dot-com**	**2007/08**	**COVID-19**
	Coefficient (*p*-Value)	**Coefficient (*p*-Value)**	**Coefficient (*p*-Value)**	**Coefficient (*p*-Value)**	**Coefficient (*p*-Value)**	**Coefficient (*p*-Value)**
Constant	−9.83 (0.53)	7.10 (0.44)	**102.38 (0.00)**	−0.02 (0.86)	−0.01 (0.91)	0.28 (0.36)
RMW (−1)	**0.34 (0.00)**	−0.08 (0.14)	**0.39 (0.00)**	**0.70 (0.01)**	**0.93 (0.01)**	**0.87 (0.00)**
CR	**−17.78 (0.06)**	**5.13 (0.07)**	−2.59 (0.39)	**−20.26 (0.02)**	4.36 (0.11)	−3.10 (0.22)
CR (−1)		**−14.51 (0.00)**			**−15.54 (0.00)**	
TED	−4.42 (0.36)	**4.57 (0.01)**	−0.54 (0.91)	−5.43 (0.23)	**4.36 (0.01)**	0.09 (0.98)
TED (−1)		**−10.72 (0.00)**			**−11.16 (0.00)**	
S&P	1.35 (0.89)	**59.57 (0.00)**	−2.77 (0.68)	2.26 (0.80)	**59.29 (0.00)**	3.58 (0.61)
ECM (−1)				**−0.33 (0.08)**	**−1.09 (0.01)**	**−0.52 (0.00)**

This table represents results for the three recession periods, the dot-com crash (July 2001 to November 2001), the 2007/08 crisis (December 2007 to June 2009), and COVID-19 (February 2020 to June 2020). CR, TED, S&P denote credit spread, TED spread, S&P 500 index *p*-values are listed next to the coefficients. Bold figures mean significant.

Table 4.22. Long-run ARDL model and short-run error correction model for WML (Recession).

Variable	Long-Run			Short-Run		
	Dot-com	2007/08	COVID-19	Dot-com	2007/08	COVID-19
	Coefficient (*p*-Value)	**Coefficient (*p*-Value)**	**Coefficient (*p*-Value)**	**Coefficient (*p*-Value)**	**Coefficient (*p*-Value)**	**Coefficient (*p*-Value)**
Constant	13.77 (0.50)	**21.22 (0.02)**	**91.65 (0.09)**	0.02 (0.92)	−0.01 (0.92)	0.18 (0.63)
WML (−1)	**0.56 (0.00)**	−0.07 (0.16)	**0.19 (0.06)**	**0.79 (0.00)**	0.41 (0.13)	**0.53 (0.07)**
CR	2.68 (0.74)	**−1.13 (0.00)**	**−3.59 (0.02)**	5.20 (0.65)	−0.97 (0.71)	**−10.31 (0.03)**
TED	4.48 (0.34)	−0.05 (0.80)	−2.64 (0.10)	1.31 (0.83)	1.36 (0.39)	1.52 (0.84)
S&P	−1.74 (0.55)	**−2.96 (0.01)**	**−11.20 (0.09)**	**−28.33 (0.02)**	**−9.04 (0.05)**	**−28.04 (0.02)**
ECM (−1)				**−0.28 (0.07)**	**−0.47 (0.09)**	**−0.27 (0.02)**

This table represents results for the three recession periods, the dot-com crash (July 2001 to November 2001), the 2007/08 crisis (December 2007 to June 2009), and COVID-19 (February 2020 to June 2020). CR, TED, S&P denote credit spread, TED spread, S&P 500 index *p*-values are listed next to the coefficients. Bold figures mean significant.

The S&P 500 has a significant and positive relationship with RMW premiums during the 2007/08 crisis, both in the long- and short-run. This relationship tends to be dominated by mispricing rather than investor sentiments. We have already established in the last section that REITs with robust profitability tend to be associated with higher arbitrage risk (as shown in panel A of Table 4.4 where the idiosyncratic risk for the robust profitability portfolio is higher than that of the weak profitability portfolio). Therefore, taking advantage of this anomaly might not be a 'free for all' for investors. Given this scenario, as the S&P 500 index goes up, the arbitrage risk associated with robust profitability REITs might make investors underreact to earnings (Ali and Ülkü, 2019), resulting in an accumulation of private information regarding the persistence of these returns, and resulting in an inflationary RMW premium.

The S&P 500 index has a significant and negative relationship with WML premiums during the recessionary phases. Jegadeesh and Titman (1993) associate the existence of the WML premium to an under-reaction from the market to information. A rise in the S&P 500 index might induce investors to channel their funds according to market information and historical returns of winner REITs, potentially enhancing demand for winner REITs and thus reducing WML premiums.

Overall, our results indicate that during recessionary phases credit spread has a negative influence on RMW and WML premiums, while TED spread only has a negative impact on RMW premiums. The S&P 500 index has a positive influence on RMW premiums while it has a negative influence on WML premiums.

Non-Recession

Tables 4.23 shows that both Credit spread and TED spread have a positive and significant relationship with RMW premiums during the non-recessionary phase that follows the dot-com crisis, both in the long- and short-run. Additionally, credit spread also has a positive impact on premiums during the non-recessionary phase that follows the 2007/08 crisis. This result suggests that investors underreact to earnings (Ülkü 2017; Ali and Ülkü 2019) in non-recessionary phases, as default risk and the probability of liquidity crisis goes up. This results in an accumulation of information regarding future earnings, hiking up RMW premiums. This finding supports the risk based explanation for the profitability premium put forward by Fama and French (2015), that the profitability premium acts as a compensation for a non-diversifiable risk factor.

Table 4.23. Long-run ARDL model and short-run error correction model for RMW (Non-Recession).

Variable	Long-Run		Short-Run	
	Post Dot-com	**Post 2007/08**	**Post Dot-com**	**Post 2007/08**
	Coefficient (*p*-Value)	**Coefficient (*p*-Value)**	**Coefficient (*p*-Value)**	**Coefficient (*p*-Value)**
Constant	1.05 (0.48)	**−2.10 (0.01)**	−0.01 (0.70)	0.02 (0.58)
RMW (−1)	**0.33 (0.00)**	**0.54 (0.00)**	**0.88 (0.01)**	**1.02 (0.00)**
CR	**2.46 (0.04)**	**3.31 (0.04)**	**2.41 (0.05)**	**3.39 (0.03)**
TED	**1.80 (0.02)**	1.65 (0.38)	**1.68 (0.03)**	2.09 (0.27)
S&P	**−10.21 (0.00)**	**−5.27 (0.09)**	**−9.92 (0.00)**	**−5.42 (0.09)**
S&P (−1)				**−8.50 (0.01)**
ECM (−1)			**−0.56 (0.08)**	**−0.48 (0.05)**

This table represents results for the two non-recession periods, post dot-com crisis (December 2001 to November 2007) and post 2007/08 crisis (July 2009 to January 2020). CR, TED, S&P denote credit spread, TED spread, S&P 500 index *p*-values are listed next to the coefficients. Bold figures mean significant.

The varying impact of credit spread on WML premiums during the two non-recessionary phases, as shown in Table 4.24, is a testament to the unique nature of these sub-periods. Similar to the recessionary phase, investor sentiments tend to dominate this relationship during the non-recessionary phase that follows the 2007/08 financial crisis. A rise in the probability of financial distress within the economy results in investors routing funds towards historically winner REITs, having a downward impact on compensatory premiums required to incentivize investors. Once again, this result contradicts the belief that WML premiums are proxies for systematic risk. On the other hand, results from the non-recessionary phase that follows the dot-com crash show evidence of investors underreacting to earnings (Jegadeesh and Titman 1993) in non-recessionary phases, as default risk goes up. This results in an accumulation of information regarding future earnings, resulting in an uptick in WML premiums. This finding supports the risk based explanation that the momentum premium acts as a compensation for a non-diversifiable risk factor. In this period, we also find that the WML premium rises with the probability of a liquidity crisis, adding further credibility to the risk based explanation (Johnson 2002; Liu and Zhang 2008).

Table 4.24. Long-run ARDL model and short-run error correction model for WML (Non-Recession).

Variable	Long-Run		Short-Run	
	Post Dot-com	Post 2007/08	Post Dot-com	Post 2007/08
	Coefficient (*p*-Value)	Coefficient (*p*-Value)	Coefficient (*p*-Value)	Coefficient (*p*-Value)
Constant	0.42 (0.82)	**−1.76 (0.01)**	0.04 (0.33)	0.00 (0.84)
WML (−1)	**0.19 (0.00)**	**0.26 (0.00)**	**0.80 (0.00)**	**0.44 (0.00)**
CR	**3.56 (0.02)**	**−2.43 (0.06)**	**3.07 (0.05)**	**−2.58 (0.05)**
TED	**1.83 (0.06)**	0.40 (0.79)	1.57 (0.11)	0.29 (0.85)
S&P	**−10.54 (0.00)**	−2.18 (0.39)	**−9.90 (0.00)**	−2.41 (0.35)
ECM (−1)			**−0.62 (0.00)**	**−0.19 (0.01)**

This table represents results for the non-recession period (December 2001 to November 2007) and the second non-recession period (July 2009 to January 2020). CR, TED S&P denote credit spread, TED spread, S&P 500 index. *p*-values are listed next to the coefficients.

The S&P 500 has a significant and negative impact on RMW and WML premiums during the non-recessionary phase, both in the long- and short-run. This relationship is driven by investor sentiments rather than mispricing, which was the case during the recessionary phases. A rise in the index might make investors more optimistic about the future state of the economy (Essa and Giouvris 2020), therefore investors are willing to act on earnings information (even though robust profitability REITs carry a higher arbitrage risk), enhancing the price of profitable/winner REITs and having a downward impact on RMW and WML premiums.

To summarize, both credit spread and TED spread have a positive impact, on RMW premiums during expansionary phases. On the other hand, the impact of financial distress and liquidity crisis on WML premiums is mixed, and is dependent on the time period that is considered. We find evidence of lag RMW and WML premiums having forecasting power during both non-recessionary periods, both in the long- and short-run. We also find that the coefficient for the error correction term is significantly negative, implying that the reverting mechanism for sustaining the long-run relationship between the explanatory variables and RMW/WML premiums is extremely relevant.

4.6 Practical Implication for REIT Investors

We identify an inefficiency in the REIT market, that astute investors can take advantage of, to earn superior returns. Between 2001 and 2020, we find that the excess daily returns on HML and WML strategies within REITs equates to 0.4811% and 0.1038% respectively. Our risk analysis (from the CAPM and Fama–French five factor models) shows that superior returns on these strategies are not associated to a higher systematic risk. Investors can therefore take advantage of these superior returns without a significant uptick in their risk exposure.

While we find significant evidence of mispricing for value REITs, we find that growth REITs are less exposed to mispricing. This translates to the fact that the superior returns on value REITs are relatively stronger than the inferior returns on growth REITs. Barkham and Ward (1999) associate this asymmetry to the fact that growth REITs attract more institutional investors and therefore are less prone to mispricing. On the other hand, value REITs are mostly held by small investors (Ooi et al. 2007), who underestimate the growth potential of value REITs via naïve extrapolation[23].

From Figure 4.2 (Section 4.5.1) we can see that value REITs seem the most underpriced during the 2007/08 recession, with HML premiums peaking to a maximum value of 33.7674%. Although our results from the CAPM and Fama–French models may indicate most of this uptick in HML premiums is not due to a higher systematic risk but instead due to mispricing and naive extrapolation, we do find significant evidence of the probability of default risk and liquidity crisis being priced within these premiums during recessionary states. However, during non-recessionary states we find these factors to have no significant impact on HML premiums, contradicting the argument that value premiums are proxies for systematic risk. This is crucial for investors and fund managers that are looking to build a HML investment strategy during recessionary and non-recessionary periods.

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23 Investors tend to be overly optimistic about future prospects of growth stocks, while they tend to be overly pessimistic about prospects of value stocks, and when these expectations are not realized, it results in a higher return on value stocks and a lower return on growth stocks (Ooi et al. 2007).

WML premiums peaked to a maximum level of 10.0766% during the COVID-19 recessionary phase. Based on idiosyncratic returns volatility, we find no significant evidence of winner REITs being more prone to mispricing relative loser REITs. Furthermore, from our regression analysis over the five sub-samples, we find that the probability of default risk and liquidity crisis have a significant and positive impact on WML premiums only during the non-recessionary phase that follows the dot-com crash. For investors and fund managers, this provides crucial information on the ability of WML premiums to provide excess returns without a corresponding rise in risk, during recessionary periods.

Our results also provide useful benefits to investors from a portfolio diversification perspective. From our regression analysis, we find a significant and negative relationship between the S&P500 index and WML premiums, both during recessionary and non-recessionary states. Investors with a multi-asset portfolio, with indexed exposure to the stock market, would benefit from diversification perks that a WML strategy within REITs can bring along. This diversification benefit is further supported by negative correlation levels[24]. between WML premiums and the S&P500 index.

On the other hand, we only find a significant and negative relationship between the S&P500 index and HML premiums, during non-recessionary phases. This again is supported by significant and negative correlation levels[25] between the two variables, and is useful information for investors and fund managers looking to diversify their portfolio.

In a nutshell, the WML strategy might assist investors in generating excess returns without a corresponding rise in risk during recessionary phases, while the HML strategy might only be able to achieve this for investors during non-recessionary states. As a diversification measure, within a multi-asset portfolio with indexed stock market exposure, the WML strategy provides diversification perks both during recessionary and non-recessionary phases, while

24 We find a significant and negative correlation between the S&P500 Index and WML premiums (−2.3%) for our full sample.

25 We find significant and negative correlation between the S&P500 Index and HML premiums during the non-recessionary phase that follows the dot-com crash (−13.5%) and the non-recessionary phase that follows the 2007/08 recession (−16%).

the diversification benefits of the HML strategy are only really felt during non-recessionary phases.

4.7 Conclusion

In summary, this chapter has contributed to a better understanding of the existence of factor based premiums within the REIT market, the risk associated with these premiums, and the impact of default risk and liquidity crisis on these premiums during recessionary and expansionary phases.

Currently, there is a lack of clear evidence in literature regarding the existence of positive and statistically significant SMB, HML, RMW, CMA and WML premiums within the US REIT market. This, coupled with the fact that the US REIT sector has a significantly rising market capitalization (an uptick in interest within the asset class), it has witnessed a hike in institutional investment (Chen and Zhang 1998), and the transitioning returns behavior within the sector relative to stocks, potentially providing diversification benefits in a multi-asset portfolio (Glascock et al. 2000), we feel that there are merits to conducting research on the existence of these premiums within the US REIT market.

Between July 2001 and June 2020, we find the presence of significant and positive premiums associated with size, value, profitability, investment and momentum based strategies. Astute investors can take advantage of these premiums to earn superior returns in the REIT market. Risk analysis reveals that the excess returns based on size, profitability and investment are associated with a higher systematic risk. This is consistent with the risk-based explanation of Fama and French (1996, 2015) and the Efficient Market Hypothesis. Our results for the value premium and momentum premiums contradict the risk-based explanation. We do find a higher idiosyncratic risk for value REITs relative to growth REITs, supporting the hypothesis that value REITs are systematically mispriced, potentially due to naive extrapolation by investors, and provides an explanation for why arbitrageurs might be deterred from exploiting this mispricing within value REITs. On the other hand, a relatively lower idiosyncratic risk associated with winner REITs implies that these REITs are less prone to mispricing compared to loser REITs. Our results support the argument of an under-reaction from the market in connection to historical returns of winner REITs (Jegadeesh and Titman 1993), potentially due to transaction costs, but resulting in a consistently positive and significant return on momentum strategy.

Finally, this paper examines the impact of financial distress and liquidity crisis, on factor based premiums within the US REIT market, controlling for stock market returns. Our data set spans from July 2001 to June 2020, which includes periods of significant shifts within financial distress and the probability of liquidity crisis. To capture this structural shift and its impact on factor premiums, we split our sample into five sub-samples, based on recessionary and non-recessionary periods as specified by NBER.

During recessionary phases, we find that both credit spread and TED spread have a significant and positive impact on SMB, HML and CMA premiums. As the probability of financial distress and liquidity crisis rises, the general risk levels within the economy rise, enhancing the relative risk associated with small, value and conservative investment (weak prospects) REITs. Therefore, investors demand a higher compensatory return on these REITs. These results are consistent with the risk-based explanation of Fama and French (1996, 2015). During non-recessionary phases, both credit spread and TED spread seem to have mostly an insignificant influence on these factor premiums.

For both RMW and WML, investor sentiments tend to dominate the impact of credit spread and TED spread on these premiums during recessionary phases. As the probability of financial distress and liquidity crisis goes up, investors' route more funds towards robust profitability and winner REITs, enhancing the price of these REITs, and having a downward or negative impact on compensatory premiums required to incentivize investors. This is in contradiction to the risk-based explanation of Fama and French (2015) and Carhart (1997). During expansionary phases, generally we find the effect of an under-reaction from investors dominate these relationships, resulting in inflated premiums with a rise in credit spread and TED spread.

The impact of the S&P 500 index is negative on all premiums, during the non-recessionary state, implying that investors with portfolio exposures to factor based REIT premiums and stock indexing, would see a fall in their premiums with a corresponding rise in the index or as a consequence of a bullish stock market. This impact is reversed for all premiums in the recessionary state, apart from WML, which still has a negative relationship with the S&P 500 index.

Factor based style investment strategies have been used extensively as a portfolio constructing mechanism within stocks, to beat the market. This chapter looks to assess the ability of these strategies to generate abnormal returns within the US REIT market using daily returns and a data set that spans 19 years (4754 observations). In terms of the risk associated with these strategies, prior literature, such as Ooi et al. (2007), test the risk associated with value strategies within the REIT market using standard deviation, beta from the CAPM model, and factor loadings from the Fama–French three factor model. We extend on this study by testing this risk based explanation for not just the value premium but also for SMB, RMW, CMA, and WML strategies. Additionally, we not only use the risk measures as suggested by Ooi et al. (2007) but also use the factor loadings on the Fama–French five factor, and the Carhart four factor model as a robustness measure. Furthermore, we assess the role of arbitrage risk in deterring arbitrageurs from exploiting potential mispricing related to these factor-based premiums, hence providing us with a deeper understanding on the role of mispricing in the existence of these premiums.

Thirdly, this study is unique in terms of explicitly examining the relationship between default risk, liquidity crises, stock market index, and factor based REIT premiums, establishing long- and short-run relationships using Auto-Regressive Distributed Lag (ARDL) modeling and Error Correction Modeling (ECM), for three recessionary phases, and two non-recessionary phases. This provides us the opportunity to assess common risk factors as established within Fama and French (1992, 2015) and Carhart (1997), within the US REIT market, and test their interpretation as proxies for systematic risk. This study further adds value as it tests out these relationships during the recent COVID-19 phase, incorporating 104 observations during this time frame.

This research is useful for academics and practitioners looking to analyze the impact of default risk, liquidity crisis and the stock market on factor based premiums in the US REIT market, in the short- and long-run, within recessionary and non-recessionary phases. This can be extended on over other geographies, along with assessing the impact of other macroeconomic factors on these factor premiums. Another possible extension could be to assess role of mispricing and arbitrage risk within the existence of these premiums, especially within RMW and CMA premiums, as it is currently an under-researched segment, and would greatly assist in understanding the interpretation of these factor based premiums. This research will also be useful for practitioners looking to strategise efficiently during recessionary and expansionary phases, in terms of diversification in a multi-asset portfolio, balancing risk and return, and utilizing factor based investment strategies within portfolio optimization.

Appendix A

Portfolio Formation

At the end of June, REITs are divided into five equal quintiles based on their market capitalisation[26]. The difference in returns between the small size and big size portfolios gives us the SMB factor. For our second factor, book-to-market ratio (B/M) is used as a sorting criterion to construct five different portfolios at the end of June each year. Book equity at the end of the fiscal year ending in year $t - 1$, and market cap at the end of December of year $t - 1$, is used to rank REITs for portfolio construction from July of year t to June of year $t + 1$. The REITs with negative book value are omitted from the portfolio construction. The difference in returns between the high B/M (value) and low B/M (growth) portfolios gives us the HML factor.

For our third factor, profitability, we rank REITs at the end of June in year t, based on accounting information for the fiscal year ending $t - 1$, and that is revenues minus cost of goods sold, minus selling, general and administrative expenses, minus interest expense all

[26] Stock price multiplied by shares outstanding.

divided by book equity. The difference in returns between the robust and weak profitability portfolios gives us the RMW factor. Our fourth factor, investment, is constructed as the change in total assets from fiscal year ending in year t − 2 to the fiscal year ending t − 1, divided by total assets from the fiscal year ending in year t − 2. This investment factor is then used to rank REITs at the end of June in year t. The difference in returns between the conservative and aggressive investment portfolios gives us the CMA factor. Finally, following the work of Carhart (1997), the momentum factor in month t is calculated as the total return of each REIT from month t − 11 to t − 1. REITs are ranked in month t based on this momentum factor. The difference in returns between the winner and loser portfolios gives us the WML factor.

Table A1. The results of the bounds test for co-integration for SMB.

Computed F-Statistic	10% Critical I(0)	10% Critical I(1)	5% Critical I(0)	5% Critical I(1).	ARDL Specs	H_0: No Cointegration
4.50259	2.12	3.23	2.45	3.61	(1,0,0,1)	Reject
127.15276	2.12	3.23	2.45	3.61	(1,0,0,0)	Reject
22.34528	2.12	3.23	2.45	3.61	(1,1,1,1)	Reject
78.040046	2.12	3.23	2.45	3.61	(1,0,1,0)	Reject
13.34180	2.12	3.23	2.45	3.61	(1,0,0,1)	Reject

This table represents results of the bounds test for the first period (July 2001 to November 2001), the second period (December 2001 to November 2007), the third period (December 2007 to June 2009), the fourth period (July 2009 to January 2020) and the fifth period (February 2020 to June 2020). The ARDL specs are the optimal lags for SMB premium, credit spread, TED spread and the S&P 500 index, as specified by the Akaike info criterion (AIC). The F-statistic is for a joint test of the following hypothesis as set up in Equation (5): H0: $\beta 5 = \beta 6 = \beta 7 = \beta 8 = 0$.

Table A2. The results of the bounds test for co-integration for HML.

Computed F-Statistic	10% Critical I(0)	10% Critical I(1)	5% Critical I(0)	5% Critical I(1).	ARDL Specs	H_0: No Cointegration
7.97392	2.12	3.23	2.45	3.61	(1,0,0,0)	Reject
107.38706	2.12	3.23	2.45	3.61	(1,0,0,0)	Reject
7.74321	2.12	3.23	2.45	3.61	(1,1,1,1)	Reject
79.15930	2.12	3.23	2.45	3.61	(1,0,0,0)	Reject
13.55075	2.12	3.23	2.45	3.61	(1,0,1,1)	Reject

This table represents results of the bounds test for the first period (July 2001 to November 2001), the second period (December 2001 to November 2007), the third period (December 2007 to June 2009), the fourth period (July 2009 to January 2020) and the fifth period (February 2020 to June 2020). The ARDL specs are the optimal lags for HML premium, credit spread, TED spread and the S&P 500 index, as specified by the Akaike info criterion (AIC). The F-statistic is for a joint test of the following hypothesis as set up in Equation (5): H0: $\beta5 = \beta6 = \beta7 = \beta8 = 0$

Table A3. The results of the bounds test for co-integration for RMW.

Computed F-Statistic	10% Critical I(0)	10% Critical I(1)	5% Critical I(0)	5% Critical I(1).	ARDL Specs	H_0: No Cointegration
6.68511	2.12	3.23	2.45	3.61	(1,0,0,0)	Reject
41.47505	2.12	3.23	2.45	3.61	(1,0,0,0)	Reject
123.26916	2.12	3.23	2.45	3.61	(1,1,1,0)	Reject
80.04605	2.12	3.23	2.45	3.61	(1,0,0,1)	Reject
7.224149	2.12	3.23	2.45	3.61	(1,0,0,0)	Reject

This table represents results of the bounds test for the first period (July 2001 to November 2001), the second period (December 2001 to November 2007), the third period (December 2007 to June 2009), the fourth period (July 2009 to January 2020) and the fifth period (February 2020 to June 2020). The ARDL specs are the optimal lags for RMW premium, credit spread, TED spread and the S&P 500 index, as specified by the Akaike info criterion (AIC). The F-statistic is for a joint test of the following hypothesis as set up in Equation (5): H0: $\beta5 = \beta6 = \beta7 = \beta8 = 0$.

Table A4. The results of the bounds test for co-integration for CMA

Computed F-Statistic	10% Critical I(0)	10% Critical I(1)	5% Critical I(0)	5% Critical I(1).	ARDL Specs	H_0: No Cointegration
11.78537	2.12	3.23	2.45	3.61	(1,0,1,0)	Reject
258.17366	2.12	3.23	2.45	3.61	(1,0,0,0)	Reject
51.30978	2.12	3.23	2.45	3.61	(1,1,2,1)	Reject
83.47141	2.12	3.23	2.45	3.61	(1,0,0,2)	Reject
13.05765	2.12	3.23	2.45	3.61	(1,0,0,0)	Reject

This table represents results of the bounds test for the first period (July 2001 to November 2001), the second period (December 2001 to November 2007), the third period (December 2007 to June 2009), the fourth period (July 2009 to January 2020) and the fifth period (February 2020 to June 2020). The ARDL specs are the optimal lags for CMA premium, credit spread, TED spread and the S&P 500 index, as specified by the Akaike info criterion (AIC). The F-statistic is for a joint test of the following hypothesis as set up in Equation (5): H0: $\beta5 = \beta6 = \beta7 = \beta8 = 0$.

Table A5. The results of the bounds test for co-integration for WML

Computed F-Statistic	10% Critical I(0)	10% Critical I(1)	5% Critical I(0)	5% Critical I(1).	ARDL Specs	H_0: No Cointegration
3.67679	2.12	3.23	2.45	3.61	(1,0,0,0)	Reject
123.17816	2.12	3.23	2.45	3.61	(1,0,0,0)	Reject
64.07647	2.12	3.23	2.45	3.61	(1,0,0,0)	Reject
221.19466	2.12	3.23	2.45	3.61	(1,0,0,0)	Reject
9.049073	2.12	3.23	2.45	3.61	(1,0,0,0)	Reject

This table represents results of the bounds test for the first period (July 2001 to November 2001), the second period (December 2001 to November 2007), the third period (December 2007 to June 2009), the fourth period (July 2009 to January 2020) and the fifth period (February 2020 to June 2020). The ARDL specs are the optimal lags for WML premium, credit spread, TED spread and the S&P 500 index, as specified by the Akaike info criterion (AIC). The F-statistic is for a joint test of the following hypothesis as set up in Equation (5): H0: $\beta5 = \beta6 = \beta7 = \beta8 = 0$.

Chapter 5: What is the effect of VIX and (un)expected illiquidity on sectoral herding in US REITs during (non)crises? Evidence from a Markov switching model (2014 – 2022)

5.1 Abstract

The study investigates the impact of sector and market-wide illiquidity shocks (Amihud, 2002) on herding within US Real Estate Investment Trusts (REITs), on a sub-sector level, including health, hotel, mortgage, residential, retail and Warehouse REITs. Using daily data from January 2014 to February 2022, and consistent with noise trader risk theory (De Long, Shleifer, Summers and Waldmann, 1990), the research confirms the existence of herding behaviour within US REITs on a sub-sector level, along with identifying that herding effects are intense on days with negative market returns as compared to days with positive market returns. Assessing the impact of investor sentiments via the VIX index, we find that herding behaviour rises with a hike in investor uncertainty and fear. Motivated by the presence of a structural break within our data set corresponding to the Covid-19 outbreak, we use a Markov Switching approach and find significant evidence of sub-sector herding being more intense during the crash regime/covid-19 phase, relative to the expansionary phase. When assessing illiquidity, our results confirm that i) during the expansionary phase only expected illiquidity (market and sector-wide) enhances sub-sector herding within US REITs while ii) during the crash phase only unexpected illiquidity (market and sector-wide) enhances sub-sector herding within US REITs

5.2 Introduction

The global financial crisis of 2008 depicted that asset prices may not follow traditional asset pricing models, and that they might be extremely sensitive to changes in market sentiments (Philippas, Economou, Babalos and Kostakis, 2013). Market imperfections such as limits to arbitrage and investors' behavioural biases can lead to irrational market conditions and mispricing within assets. One such feature of market imperfection is herding, which Zhou and Anderson (2011) define as behavioural tendency of investors to follow the action of others rather than their own beliefs and private information. Nofsinger and Sias (1999) define herding as trading in the same direction by a group of investors, over a certain period of time.

Herding could potentially drive asset prices away from fundamental value. This provides lucrative trading opportunities, and hence herding behavior is of importance to practitioners. Furthermore, synchronized trades, in the same direction, could also result in co-movement within asset prices, potentially reducing investors' ability to curb risk via diversification (Chiang and Zheng, 2010; Morelli, 2010). For academics, movement of asset prices away from fundamental value contradicts traditional asset pricing models and has theoretical implications (Christie and Huang, 1995). During economic downturns, herding behavior could result in exaggerated negative shocks, as investors' start trading in the same direction, and this could pose significant risks to financial stability (Shin, 2010). Therefore, herding behavior also carries significant importance for policymakers. Our research looks to test out noise trader risk theory within the US REIT market, that is, investment decisions made by unskilled or uninformed investors driven by the notion of herd trading behaviour and resulting in asset prices moving away from their fundamental value (De Long, Shleifer, Summers and Waldmann, 1990).

The 2008 crisis highlighted the idea that liquidity is not only risky but also has commonality (Lim and Giouvris, 2017). This would imply that liquidity has far reaching consequences in terms of its impact on the whole financial system. Crotty (2009) considered illiquidity to be a major source for the 2007/08 financial crisis, concluding that asset prices react significantly to liquidity effects. As one might expect, research on market liquidity has significantly increased over the past decade, but these studies mostly circulate around the US stock market (Paul, Walther and Kuster-Simic, 2021). Gloscock and Lu-Andrews (2014) suggest that a higher market liquidity within the real estate market makes it easier to finance properties and trade. Amihud (2002) suggests that stock market illiquidity is positively related to expected market returns. Given Efficient Market Hypothesis, which suggests that a higher expected return is a compensation for a heightened risk, a rise in illiquidity would imply a higher risk within the market. Given this rise in risk which an illiquidity shock can bring along, we look to assess its impact on herding and asset mispricing within US REITs on a sub-sector level, during recessionary and non-recessionary phases.

Huberman and Halka (2001), along with Galariotis and Giouvris (2007, 2009), and Lim and Giouvris (2017) conclude that commonality in liquidity is an established phenomenon at both industry/sector and market levels for different stock markets around the world, and it is priced. This implies that at a portfolio level, one cannot diversify against liquidity shocks, and supports the idea that aggregate liquidity plays a significant role in asset pricing (Bali et al. 2016). Blau, Nguyen and Whitby (2020) argue that the concern about liquidity in asset markets is not just the average level of market liquidity, but also the uncertainty of liquidity. Amihud (2002) distinguish between expected and unexpected illiquidity shocks. They argue that the effects of expected illiquidity are felt straight away, but the impact of unexpected illiquidity is felt via investor sentiments regarding future illiquidity. For this purpose, we disentangle our illiquidity shocks into expected and unexpected market/sector illiquidity, and assess the impact that both have on herding within REITs, under varying market regimes. Furthermore, to the best of our knowledge, there are no present studies that explore the impact of current average level market/sector illiquidity (expected), and future uncertainty of market/sector illiquidity (unexpected), on sub-sector herding within US REITs, making our study unique.

Another aspect of liquidity as pointed by Baker and Stein (2004), is that liquidity can be an indicator of market sentiments. They claim that in a market with short-sale constraints and the presence of irrational investors, high market liquidity is an indication of a high market sentiment. Consistent with this, Baker and Wurgler (2006) use liquidity as one of the factors in the construction of a sentiment index, and show that investor sentiments play a significant part in impacting stock prices. Deuskar (2007) argue that markets are more liquid when investor sentiments are high. Baker and Wurgler (2006) also suggest that the CBOE VIX index is a good indicator for market sentiments, capturing investors' fear and anxiety regarding economic conditions. As investors' uncertainty regarding the future health of the economy rises, they hike up the demand for portfolio insurance instruments such as out-of-the-money put options, resulting in a rise in the VIX index (Simon, 2003). For this reason, the VIX index has also been termed "investors fear gauge" (Whaley, 2009). Given the fact that liquidity potentially acts as a sentiment indicator, along with the fact that we look to assess its impact on herding, we look to utilise an alternative measure for market sentiment as well, i.e. the VIX index, in order to add robustness to our findings regarding the impact of investor sentiment on sub-sector REIT herding.

REITs are seen as a liquid way of incorporating real estate within an investors' portfolio, at relatively lower costs (Zhang and Hansz, 2022)[27]. REITs by regulation have to distribute 90% of their taxable income as dividends in order to maintain their REIT status (Boudry 2011). Given this regulation, retained earnings would only contribute a small proportion of new investment within the industry[28]. Therefore, a fall in liquidity from traditional sources would put significant pressure on REITs operations, growth and future earnings potential. (Huerta, Egly and Escobari, 2016).

After 1990, the institutional ownership has increased significantly within REITs (Chen and Zhang, 1998). This influx of interest in REITs has resulted in an increased interest in the microstructure of this asset class, including the intrinsic nature of sub-sector REITs. Looking at the asset class as one body can turn out to be misleading. We elaborate further on this within the literature review. For this purpose, we feel it is important to not only look at REITs as one asset class, when assessing the impact of illiquidity on market herding, but also consider REIT sub-sectors in order to see any potential varying behaviour within these. Academics would find it useful, as it provides a deeper understanding into the differences within REITs on a sub-sector level, while for investors, it is useful in terms of assessing which REIT sub-sector

[27] According to the National Association of Real Estate Trusts (NAREIT), the 2021 REIT market cap was $1.74 trillion, which translates to 3.3% of the $53 trillion US stock market cap.
[28] Otti, Riddiough and Yi (2005) state that retained earnings only constitute 7% of the overall new REIT investments

might be more prone to mispricing via herding, as a consequence of illiquidity shocks, within a recessionary and non-recessionary setting.

Our paper contributes to the existing literature in the following way;

i. Most of existing literature circulates around the impact of illiquidity on stock returns within the US (Hibbert et al. 2009). Studies that do look at liquidity within REITs generally focus on the average market liquidity (Clayton and Mackinnon, 2000; Cannon and Cole, 2011). The unique nature of each REIT sub-sector merits assessing the impact of not just market-wide illiquidity on REITs, but also assessing the impact of sub-sector liquidity movements. To the best of our knowledge, no study currently looks at the impact of expected and unexpected illiquidity on sub-sector herding within US REITs, during recessionary and non-recessionary phases.

ii. Certain studies such as Galariotis, Krokida and Spyrou (2016) explore the relationship between herding and liquidity within the equity market. Blau, Nguyen and Whitby (2020) argue that the concern about liquidity in asset markets is not just the average level of market liquidity, but also the uncertainty of liquidity. We add to this literature by going a step further and breaking down illiquidity into its expected and unexpected components. Furthermore, given the regulation that REITs have to distribute 90% of their taxable income as dividends, liquidity from traditional sources of short-term funding such as credit lines would play a key role in REIT operations and performance, and this is our biggest motivator to study this relationship within the US REIT market

iii. The study is also unique as it explores the presence of herding, within the US REIT market on a sub-sector level, and the impact of expected and unexpected illiquidity shocks on herding, during and after the Covid-19 pandemic. Given the deviation of asset prices from levels suggested by traditional asset pricing models during the 2007/08 financial crisis[29], we feel that practitioners and academics would be interested in assessing if asset prices did potentially see a drift away from traditional asset pricing

[29] We would have incorporated for this recessionary phase within our study, but could not do this due to data and sample restrictions, primarily concerning sub-sector REITs

models during the Covid-19 phase, and if herding had a role to play within this mispricing. Furthermore, the changes in market structure during the Covid-19 pandemic, as identified by the presence of a structural break in our data set, serves as the motivation for exploring the impact on illiquidity on herding within REITs

As a preview of results, we find that herding effects are significant within US REITs on a sub-sector level. In terms of gauging asymmetry between up and down markets, we find that herding effects are more pronounced on days with negative market returns relative to days with a positive market return[30]. We also find that a rise in the VIX index enhances herding within all REITs and all REIT sub-sectors barring residential. Based on the existence of a structural break, we proceed to use a Markov Switching approach with two states, in order to assess herding in both regimes. During the crash regime, we find significant evidence of herding within Health, Residential, Warehouse and Mortgage sectors. During the expansionary regime, we find no significant evidence of herding behaviour within any sub-sectors barring Mortgage REITs. These results are consistent with Babalos, Balcilar and Gupta (2015) who use data on US REITs from 2004 and 2013, and provide some rationale for this asymmetry in herding with regards to recessionary and non-recessionary phases. They mention that one potential explanation for this is that "investors discard their own information and choose to mimic institutional investors during high market stress periods".

We then look to assess the impact of expected and unexpected sector-wide illiquidity on sub-sector herding, under each Markov regime. During the crash regime/covid phase, a rise in unexpected sector illiquidity enhances herding in all REIT sub-sectors apart from health. This implies that a sudden and unexpected rise in illiquidity presently during a crash regime, enhances investors' current negative sentiments towards future illiquidity shocks, and through that channel, enhances herding currently. During the non-recessionary phase, we find that expected illiquidity shocks have a significant part to play in enhancing herding within residential, retail and warehouse sectors. The lack of significance of unexpected

[30] Motivated by evidence that herding is relatively more pronounced on negative market days, and owing to the fact that our data set runs through the Covid-19 phase, we use a CUSUM Test to identify a structural break within our data set. We further employ a Quandt-Andrews statistical breakpoint test and find evidence of a breakpoint on 18th March 2020, corresponding to the start of the Covid-19 pandemic.

illiquidity shocks during the non-recessionary state also implies that the channel of influence between a rise in unexpected illiquidity and investor sentiments towards heightened future illiquidity, might be weak during these expansionary phases[31]. Lastly, when we incorporate for market-wide illiquidity shocks, we find that during the non-recessionary states, herding is positively impacted only by a rise in expected illiquidity shocks, while during the recessionary state, only increases in unexpected illiquidity shocks enhance herding.

The structure of this chapter is as follows. Section 5.3 presents a literature review. Section 5.4 describes the data and methodology. Section 5.5 presents the empirical analysis and results. Finally, Section 5.6 concludes.

5.3 Literature Review

5.3.1 Herding: Empirical evidence and its consequences on asset pricing

From the perspective of market-wide herding, Christie and Huang (1995) are the first ones to use cross-sectional dispersion of stock returns as a proxy for herding. The idea being, that as herding rises, the cross-sectional dispersion of stock returns is expected to decline and cluster around the market return. Within their results, Christie and Huang (1995) found evidence against herding within US stocks, concluding that the measure of dispersion rises during market downturns. Chang et. al (2000) extend on Christie and Huang (1995) by introducing non-linearity in the relationship between dispersion and market return, along with introducing cross-sectional absolute dispersion (CSAD) of asset returns, to examine the presence of herding. Consistent with Christie and Huang (1995), Chang et. al (2000) find no significant evidence of herding in US stocks, but do find evidence of herding in South Korea and Taiwan.

Using Chang et. al (2000)'s measure of absolute deviation, between the period 1980-2010, Zhou and Anderson (2011) find significant evidence of herding within US REITs during days of extreme negative returns, but when they segment their data between dates for the 2007/08

[31] Using our breakpoint date to divide the data set into two, and running two separate OLS regressions, from 2nd January 2014 to 18th March 2020, and then 19th March 2020 to 28th February 2022, as a robustness measure, confirms the consistency of our results.

recession and non-recessionary dates, they actually find that the dispersion of asset returns was increasing during the recessionary dates, indicating that a rise in herding behaviour during market downturns might not be true during the 2007/08 financial crisis. Philippas, Economou, Babalos and Kostakis (2013) use a data set that includes the 2008 financial crisis, and they conclude that herding effects within REITs are felt relatively stronger during days of extreme negative market returns, but this cannot be attributed to the financial crisis. Contradictory to these findings, using a data set from 2004 to 2013, Babalos, Balcilar and Gupta (2015) use a regime switching approach and find significant evidence of herding during the crash regime in almost all REIT sub-sectors.

Demirer and Kutan (2006) and Shin (2010) argue that during heightened market volatility, the effects of herding might be most felt, as initial negative shocks may be amplified. This would have significant consequences for investors, not only in terms of sharp fall in prices resulting in amplified realised and unrealised losses, but also from the point of view of driving asset prices away from their fundamental value. Chiang and Zheng (2010) and Morelli (2010) argue that synchronised trades also pose a threat of significant co-movement within asset returns, which reduces the ability of investors to hedge against risk via diversification. Given i) the contradictory results with regards to the hypothesis of a rise in herding during crash regimes, ii) the unique nature of each recessionary period in the US, iii) the risk herding might bring along in terms of mispricing of assets, along with the ability of herding to nullify the impact of diversification, we feel that there are merits in terms of usefulness to investors, in testing the hypothesis of whether herding behaviour is more pronounced during the most recent Covid-19 phase, relative to the preceding non-recessionary phase.

5.3.2 Liquidity and REITs

Pricing models within REITs have generally not incorporated for liquidity, but the 2007/08 global financial crisis has shown that asset prices react significantly to liquidity effects (Paul, Walther and Kuster-Simic, 2021). Illiquidity impacts how easily assets can be sold, posing a threat to financial stability, and making illiquidity a risk. Amihud and Mendelson (1986) use bid-ask spread as a proxy for illiquidity, and test the hypothesis that investors are compensated for holding less liquid assets via a higher return. They find that bid-ask spread has a positive relationship with stock returns, after controlling for market beta, market capitalization and volatility, confirming the hypothesis that liquidity is a risk that is priced in within US stocks. Based on the idea of illiquidity being a risk factor, Essa and Giouvris (2020) confirm the existence of an illiquidity premium within US stocks. Amihud (2002) design a measure for illiquidity that incorporates prices and trading volume, and conclude that illiquidity is positively related to expected market returns. They themselves argue that there are finer measures of illiquidity, but these require microstructure data. This would be hard to obtain for REITs, and would significantly reduce the asset universe and longevity of the research, both being crucial factors for a comprehensive study to look at the impact of illiquidity on herding. Furthermore, Amihud (2002) breakdown illiquidity into its expected and unexpected component. They conclude that future stock returns across NYSE from 1964-1997 are an increasing function of expected illiquidity. This they believe is a compensation to investors for a higher liquidity risk. On the other hand, they argue that unexpected illiquidity shocks have a negative impact on current returns. A rise in unexpected illiquidity raises future expected illiquidity, raising future expected returns, and thus resulting in a fall in current prices, and current returns. For this reason, this paper uses both expected and unexpected illiquidity components, in order to gauge their impact on herding, during recessionary and non-recessionary phases, and assess if the impact of expected and unexpected illiquidity shocks is indeed varying.

Most research concerning illiquidity and asset pricing revolves around stocks and bonds (Hibbert et al., 2009). Although a handful of studies look at the impact of market illiquidity on REIT returns, to the best of our knowledge, no study currently exists that looks at the impact of current and future expectation of sector/market illiquidity on herding within US REITs. Huberman and Halka (2001) and Galariotis and Giouvris (2007) find a market and industry-wide commonality in liquidity, supporting the notion that liquidity shocks cannot be diversified against on a portfolio level. This also affirms the fact that market and industry-wide liquidity plays a significant role in asset pricing (Bali et al., 2016). Essa and Giouvris (2023) use a data set from 2001 to 2020, spanning three recessionary and two non-recessionary phases, and find significant evidence of illiquidity being priced in size, value and investment premiums, but not in profitability and momentum premiums, within US REITs.

The fact that REITs have to distribute 90% of their taxable income as dividends in order to maintain their REIT status (Boudry 2011), becomes the biggest motivation for our study to test the impact of liquidity on herding within REITs. The idea being that a fall in liquidity from traditional sources would put significant pressure on REITs operations, growth and future earnings potential. (Huerta, Egly and Escobari, 2016). REITs are highly leveraged, typically at 5 to 10 times their equity (U.S. Securities and Exchange Commission, 2020). The US REIT industry holds around $3 trillion in real estate assets with $2 to $2.5 trillion in liabilities, and more than two-thirds of these liabilities is short term funding (NAREIT, 2022). Ott, Riddiough and Yi (2005) stress on the importance of credit lines as back up liquidity to fund cash shortages, especially given REITs dividend pay-out policy. Credit lines are crucial for REITs in terms of facilitating borrowing without committing to long-term finance. Ooi, Wong and Ong (2012) state that "bank liquidity represents 73.8% of total liquidity available to REITs, which is much higher than 45% registered by general firms", signifying the relative importance of bank financing and credit lines for REITs, as compared to other sectors. Cetorelli, Goldberg and Ravazzolo (2020) discuss the short-term funding stress during Covid-19, primarily existing due to an elevated demand for liquidity. The resulting exposure to interest rate risk, along with a lack of liquidity, could significantly disrupt REIT performance and growth, especially given the sectors dependence on injections of short-term funding. Based on the uniqueness of the REIT industry with regards to short-term funding and credit lines, and given the stress within the short-term funding market during the Covid-19 pandemic, we feel analysing the impact of liquidity shocks on herding in REITs, prior to and during the Covid-19 pandemic has its merits.

Cetorelli, Goldberg and Ravazzolo (2020) discuss the idea that a heightened demand for liquidity created a short-term funding stress during Covid-19. Given the dividend pay-out regulation on REITs, along with their dependence on flexible short-term funding, puts investors at a significant downside risk with regards to these investments during times of liquidity strain. Lin and Vandell (2007) and Krainer et al. (2010) claim that illiquidity risk is priced in the real estate markets. Benveniste et el. (2001) and Zheng et al. (2015) find a positive correlation between illiquidity and returns, within real estate investments. Subrahmanyam (2007) find significant liquidity spillovers from non-REITs to REITs, which would imply that investment decisions within non-REIT markets could drive investment decisions within the real estate market with a time lag. Hoesli et al. (2017) compliment this result by concluding that there are significant co-movements within US REIT and equity markets, which are generally impacted by the liquidity channel, and are quite significant during down markets.

Philippas, Economou, Babalos and Kostakis (2013) assess the impact of channels through which herding could arise within REITs, and one of these channels is funding conditions proxied using 3-month LIBOR. They find that a rise in the 3-month LIBOR (implying tighter funding conditions), reduces the cross-sectional dispersion within REIT returns and therefore, implies a rise in correlated activity from investors, contributing to enhancement of herd like behaviour in the market. Given this result, and given the dependence of REITs on short-term funding for efficient REIT performance and growth, we feel exploring both expected and unexpected market/sector illiquidity as a potential channel to impact herding is crucial in understanding this phenomenon within the REIT market, during both recessionary and non-recessionary phases.

5.3.3 REITs as a unique asset class (idiosyncrasies) and sub-sector REITs

A key distinction between common stocks and REITs is that common stocks are subject to corporate or trust taxation, while REITs are exempt from this, and the only tax levied is on dividends and is based on the individuals' personal tax rate (Gyourko and Keim, 1992). Titman and Warga (1986) claim that REIT price levels fluctuate more with interest rate changes relative to common stocks. Liu et al. (1997) conclude that common stocks are not usually treated as an inflation hedge, but investors do use REITs as a hedge against inflation. Stephen and Simon (2005) report a low correlation between US REITs and the stock market in the late 1990s, while Chaudhry et al. (1999) find an inverse long-term relationship between stocks and real estate. This would imply that REITs potentially offer diversification benefits to investors holding a multi-asset portfolio. Hoesli et al. (2004) report that the optimal allocation towards real estate in a multi-asset portfolio is 15 to 25%.

Both Clayton and Mackinnon (2003) and Glascock et al. (2000) find a significant long-term relationship between REITs and the private real estate sector. Furthermore, Stephen and

Simon (2005) also report on the uniqueness of REITs as an asset class, concluding that their returns cannot be replicated by other asset classes. Given this significant role that REITs have in a multi-asset setting in terms of their uniqueness, along with REITs being used as a relevant substitute for conventional real estate investments, any market-based action such as herding, which might contribute to mispricing of these assets away from their fundamental value, would be useful research for investors.

Nazlioglu, Gormus and Soytas (2016) argue that all REITs are not constructed equally, and that various market factors impact these various REITs differently. For example, Capozza and Korean (1995) empirically show that retail REITs trade at a significant premium on average, while warehouse REITs generally trade at a discount. Peterson and Hsieh (1997) show that equity REITs are strongly related to stock market risk factors, on the other hand, Mortgage REITs are significantly impacted by stock and bond market risk factors. Cho (2017) show that between 2010-2015, hotel and industrial REITs outperformed all REIT sub-sectors in terms of risk-adjusted returns, and that these sub-sectors have relatively low correlations with stocks and bonds. Although debt ratios within REIT sub-sectors varied considerably, these differences were further highlighted during the Covid-19 economic shock (U.S. Securities and Exchange Commission, 2020). Industrial REITs account for 20% of the total REIT market cap equating to $131 billion in quarter 2 of 2020 (NAREIT, 2020). The change in debt ratios for Industrial REITs was marginal, falling from 17% in quarter 4 of 2019 to 16% in quarter 2 of 2020 (U.S. Securities and Exchange Commission, 2020). On the other hand, debt ratio for hotel REITs rose from 30% in quarter 4 of 2019 to 46% in quarter 2 of 2020 (U.S. Securities and Exchange Commission, 2020). According to CBRE (2015), traditional REIT sectors such as retail have been losing their market share, and sub-sectors such as health and hotel have enhanced their market position. Owing to the uniqueness of REIT sub-sectors, we feel that it is crucial to not treat REITs as one asset class, but to incorporate REIT sub-sectors, and assess the impact of expected/unexpected sector/market illiquidity shocks on herding within each REIT sub-sector.

5.4 Data and Methodology

5.4.1 Measure for Herding

Christie and Huang (1995) were the first to use cross-sectional dispersion of asset returns (measured by cross-sectional standard deviation) as a measure of capturing herding in a market setting. The rationale for using this measure is that, herding implies that investors forego their private information and follow the market's opinion. Under such a situation, asset returns tend to cluster around the market portfolio return, decreasing the dispersion of asset returns, and indicating herding. Although this returns-based measure to capture herding has its foundations in CAPM theory, Christie and Huang (1995) suggest a conclusion which is in contrast to this theory. They believe that during extreme market conditions, investors have more tendency to let go of their individual beliefs and information, and in-turn follow "the herd", resulting in a fall in dispersion during these periods. On the other hand, traditional asset pricing models such as the CAPM model, predict a rise in cross-sectional dispersion during extreme market movements, since individual assets differ in their sensitivity to market returns.

Chang et. al (2000) extend on the work of Christie and Huang (1995) by introducing non-linearity in the relationship between dispersion and market return. Furthermore, instead of using cross-sectional standard deviation (CSSD) to measure dispersion, Chang et. al (2000) use the cross-sectional absolute deviation (CSAD), citing the fact that CSAD is less sensitive to return outliers relative to CSSD (Zhou and Anderson, 2011). The CSAD is calculated as follows:

$$CSAD_t = \sum_{i=1}^{N} [R_{i,t} - R_{m,t}] / N \qquad (5.1)$$

where $R_{i,t}$ is the observed return for firm i at time t. $R_{m,t}$ is the cross-sectional average return of N assets at time t, and N is number of assets in the universe we examine.

Chang et. al (2000)'s benchmark model to test the existence for herding is then set up as follows:

$$CSAD_t = a + \beta_1 \, |R_{m,t}| + \beta_2 \, R^2_{m,t} + e_t \qquad (5.2)$$

where $R_{m,t}$ is the cross-sectional average return of N assets at time t. It is a market index for All REITs, and has been constructed as an equally weighted average of All REIT returns. The total number of REITs in our universe range from 132 to 174.

Chang et. al (2000) introduce non-linearity within their explanatory variables i.e. the squared market return. This would imply that they base this explanatory variable on the overall fluctuation in the market, rather than the direction of this fluctuation. Chang et. al (2000) conclude that under normal market conditions, the relationship between dispersion and market returns is linear, as suggested by traditional asset pricing models. But under extreme market conditions, they hypothesize that herding would cause this relationship to be non-linear; either decreasing or increasing at a decreasing rate. Both of these states would indicate that dispersion would be lower if herding exists. Hence the introduction of a non-linear term.

Hypothesis 1: Herding effects are significant within the entire REIT asset group

Based on the model in equation 5.2, if $\beta_2 < 0$, then that implies that the cross-sectional dispersion of REIT returns decline and cluster around an equally weighted market REIT index, and this implies herding.

Hypothesis 2: Herding effects are significant on a sub-sector level

We then proceeded to construct a similar model for sub-sector REITs. These sectors include Health, Hotel, Mortgage, Residential, Retail and Warehouse.

Herding on a sub-sector level is then gauged by setting up the following model:

$$CSAD_t = a + \beta_1 \, | \, R_{j,t} \, | + \beta_2 \, R^2_{j,t} + e_t \qquad (5.3)$$

where $R_{j,t}$ is the sectoral return, and CSAD measure on a sub-sector level is defined as:

$CSAD_t = \sum_{i=1}^{N} |R_{i,t} - R_{j,t}| / N$, where N is the number of REITs in each sector J. If herding within any sector is prevalent then we expect $\beta_2 < 0$.

Hypothesis 3a: Herding effects become more intense on days with negative market returns as compared to positive market returns

Next, we examine whether herding behaviour becomes more intense on days with negative market returns relative to days with positive market returns, using a dummy approach within equation 5.2:

$$CSAD_t = a + \beta_1 |R_{m,t}| + \beta_2 D^{Down} |R_{m,t}| + \beta_3 R^2_{m,t} + \beta_4 D^{Down} R^2_{m,t} + e_t \qquad (5.4)$$ [32]

where D^{Down} is a dummy variable taking the value 1 on days with negative market returns, and the value 0 on days with positive market returns. If herding effects are prevalent, we expect $\beta_3 < 0$, with $\beta_4 < \beta_3$ if effects are more pronounced on days with negative market returns

Hypothesis 3b: A rise in the VIX index enhances herding

Next, we examine if investor sentiments impact herding behaviour in the REIT market. Following the work of Baker and Wurgler (2006) and Kurov (2010), we use the CBOE VIX index as an indicator of investor sentiments. We incorporate this VIX variable within equation 5.2;

$$CSAD_t = a + \beta_1 |R_{m,t}| + \beta_2 R^2_{m,t} + \beta_3 R_{VIX,t} + e_t \qquad (5.5)$$

where $R_{VIX,t}$ is the return on the VIX index on day t. A significant and negative β_3 would imply that a rise in market stress and fear regarding economic conditions, investors would be more

[32] For our sub-sector study, the equation is set up as $CSAD_t = a + \beta_1 |R_{j,t}| + \beta_2 D^{Down} |R_{j,t}| + \beta_3 R^2_{j,t} + \beta_4 D^{Down} R^2_{j,t} + e_t$

inclined to discard their private information and follow the market consensus, contributing to a hike in herding behaviour.

Driven by the evidence that herding effects are more pronounced during days of market stress (or days of negative market returns) and high VIX (fear) values, we look to examine whether a structural break has occurred during the full sample period. Firstly, we run a CUSUM Test to identify if there is indeed any evidence of a structural break. Once we establish that there is a significant structural break within our data set, we then use a Quandt-Andrews statistical breakpoint test to identify an exact breakpoint in terms of a structural break

Hypothesis 4: Herding effects are stronger during a crisis period, relative to an expansionary period

Based on the identification of a breakpoint and structural break, we employ a Markov regime switching model to investigate herding under different market regimes

We use a Markov switching model with 2 regimes based on 2 reasons; Firstly, the identification of a single breakpoint using Quandt-Andrews statistical breakpoint test, and secondly, comparing log-likelihood values for Markov Switching Models with 2 and 3 regimes. The two-state Markov Switching Model is set up as follows:

$$CSAD_t = a, s_i + \beta_1, s_i \mid R_{m,t} \mid + \beta_2, s_i R^2_{m,t} + e_t \qquad (5.6)$$

where $\varepsilon t \sim$ i.i.d.$(0, \sigma^2_{St})$ and S_t is a discrete regime variable taking values in {1,2} following a two-state Markov process. The state variable S_t is defined as a two-state first order Markov chain, such that the probability of being in state 1 at time t given that state 1 was observed at time t – 1 equals p_{11}. The probability of being in state 2 at time t given that state 2 was observed at time t – 1 equals p_{22}. Therefore,

$p(s_t = 1 \mid s_{t-1} = 1) = p_{11}$

$p(s_t = 2 \mid s_{t-1} = 1) = 1 - p_{11}$

$p(s_t = 1 \mid s_{t-1} = 2) = 1 - p_{22}$

$p(s_t = 2 \mid s_{t-1} = 2) = p_{22}$

These probabilities are accumulated together in the transition matrix:

$$P = \begin{bmatrix} p_{11} & 1 - p_{22} \\ 1 - p_{11} & p_{22} \end{bmatrix}$$

Therefore, to generalise, p_{ij} is the probability of being in regime i at time t + 1 given that the market was in regime j at time t, where i and j take values {1,2}. The transition probabilities satisfy $\sum_{i=0}^{2} pij = 1$

Having explored the existence of herding under varying market regimes, we look to uncover the impact of liquidity as a potential channel that could amplify herding, under varying states of the world. Our conjecture is that, given REITs dependence on short-term flexible funding and their dividend pay-out regulation, a rise in sector/market illiquidity would result in adverse funding conditions, and via that channel, would impact real estate market conditions. We believe that such an adverse illiquidity shock would impact each REIT sub-sector, leading to correlated activity with regards to investors, and contributing to the development of herd like behaviour. We break these illiquidity shocks into their expected and unexpected components based on the work of Amihud (2002) and set up hypothesis 5 as follows:

Hypothesis 5a: During the expansionary phase, expected sector/market illiquidity enhances sub-sector herding,

This would imply that a current rise in illiquidity does not have a significant impact on investors' future expectation of illiquidity i.e. the channel of influence between a rise in unexpected illiquidity and investor sentiments towards heightened future illiquidity might be weak, during expansionary phases

Hypothesis 5b: During the crisis phase, unexpected sector/market illiquidity, enhances sub-sector herding

This would suggest that investors are more concerned with illiquidity shocks during recessionary phases, and a current and sudden rise in illiquidity during recessionary states, does heighten investor sentiments towards a future expectation of a fall in liquidity

We look to test the impact of expected and unexpected sector illiquidity shocks on herding within All REITs and REIT sub-sectors. i.e. Health, Hotel, Mortgage, Retail, Residential and Warehouse. If we assume constant parameters throughout the estimation period, without distinguishing between different market phases, the model would be set up as follows:

$$CSAD_t = a + \beta_1 \mid R_{m,t} \mid + \beta_2 R^2_{m,t} + \beta' X_t + e_t \qquad (5.7)$$

where X is a vector of explanatory variables, and specific to our case, it includes expected and unexpected sector illiquidity.

We then employ a Markov regime switching model to investigate the impact of expected and unexpected sector illiquidity on sector-wide herding, under different market regimes. Similar to equation 5.6, we set up a Markov switching model with 2 regimes, and this time incorporate for sector illiquidity shocks;

$$CSAD_t = a, s_i + \beta_1, s_i \mid R_{m,t} \mid + \beta_2, s_i R^2_{m,t} + \beta', s_i X_t + e_t, \quad (5.8)$$

where X_t is a vector containing expected and unexpected sector-wide illiquidity when assessing sectoral herding within REITs.

Lastly, we incorporate for expected and unexpected market illiquidity shocks within a two-state Markov regime switching model, to assess the impact of changes in overall REIT market illiquidity on sector-wide herding. X_t then is a vector containing expected and unexpected market illiquidity shocks.

5.4.2 Data and Illiquidity Factor

We collect daily data for REIT returns, inclusive of dividends, since REITs are required by law to distribute 90% of their annual taxable income in the form of dividends to shareholders, along with REITs price and volume data, from January 2014 to February 2022, using the Bloomberg database. This includes 2035 observations, and includes REITs that ceased to exist during the sample period.

To reduce the influence of Bloomberg errors, we apply a combination of filters following the methods of Ince and Porter (2006) and Amihud et al. (2015; 2018). Daily returns are set as missing if they are greater than 200% or less than 100%.

To measure illiquidity, we use the Amihud (2002) illiquidity measure ILLIQ, which, for any given REIT, on any particular day, is defined as the ratio of the absolute daily return to trading volume in dollar terms, for that REIT:

$$ILLIQ_{i,d} = [(1{,}000{,}000 \times |r_{i,d}|)/(p_{i,d} \times v_{i,d})] \quad (5.9)$$

where $|r_{i,d}|$ is the absolute value of return on stock i on day d, $v_{i,d}$ is the trading volume of stock i on day d, $p_{i,d}$ is the closing price of stock i on day d

To calculate a market measure, we aggregate the daily ILLIQ values for each REIT and divide it by the total number of REITs included within our universe on that particular day:

$$AILLIQ_d = (1/N_d) \sum_{i=1}^{n} ILLIQ_{i,d} \quad (5.10)$$

where N_d is the number of REITs in our universe on day d of our sample.

A REIT is included if during the 12-month period, it has a price between \$5 and \$1,000. REITs are deleted if they have less than 40 trading days or a trading volume of less than 4,000 shares, in the 12-month window. The sample in each 12-month excludes REITs within the top and bottom 1%, in terms of their Illiquidity. Finally, we remove REITs whose price is in the top 1%

in each 12-month window. After applying our filters, the total number of REITs in our universe range from 132 to 174.

We then proceed to construct a measure of sector level illiquidity within health, hotel, mortgage, residential, retail and warehouse, by segmenting REITs based on their sector, calculating individual REIT illiquidity using equation 5.9, and then using equation 5.10 to calculate the sector illiquidity, where N now signifies the total number of REITs on a particular day, within a particular sector. The number of REITs within each sector ranged between 13 and 16 for health, 13 and 18 for hotel, 34 and 45 for mortgage, 24 and 33 for residential, 40 and 51 for retail, 14 and 19 for warehouse.

Amihud (2002) argues that there are finer measures of illiquidity, but they require microstructure data on transactions, and bid/ask quotes, which cannot be obtained for a large universe, or for extended periods of time, especially in the case of REITs. This would have a significant impact on the number of assets within our universe, and the length of our study. Relative to this, the ILLIQ measure requires a simple construction based on data that is easily available on a daily basis for a long time-series i.e. absolute returns (inclusive of dividends), price and volume, allowing us to conduct a more comprehensive analysis relative to high-frequency data. Furthermore, empirically, the ILLIQ measure is highly correlated with other illiquidity measures such as the Roll estimator (Roll, 1984) and the High-low spread (Corwin and Schultz, 2012), implying that they capture similar aspects of illiquidity. Hasbrouck (2003) conclude that the ILLIQ measure is thought to be the most common approach to capture illiquidity. Based on these reasons, we decide to use the ILLIQ measure of illiquidity.

Based on the work of Paul, Walther and Kuster-Simic (2021), we assume that market illiquidity follows an autoregressive model:

$$\ln ALLIQ_d = c_0 + c_1 \ln ALLIQ_{d-l} + v_m \qquad (5.11)$$

At the beginning of day d, investors determine the expected illiquidity on day d, based on the information in period d-l. Therefore:

$$\ln ALLIQ^{E}_{d} = c_0 + c_1 \ln ALLIQ_{d-1} \qquad (5.12)$$

We choose the optimal lag length using the Akaike information criterion (AIC). The residual from equation 5.11 gives us the unexpected illiquidity on day d, $\ln ALLIQ^{u}_{d} = v_d$.

We incorporate these terms for expected and unexpected market illiquidity within equation 5.8 for All REITs (incorporating expected and unexpected market illiquidity) and for each sub-sector (incorporating expected and unexpected sector-wide illiquidity):

$$CSAD_t = a, s_i + \beta_1, s_i\ I\ R_{m,t}\ I + \beta_2, s_i\ R^2_{m,t} + \beta_3, s_i\ \ln ALLIQ^{E}_{t} + \beta_4, s_i\ \ln ALLIQ^{u}_{t} + e_t, \qquad (5.13)$$

Negative values for β_3 implies a rise in sector-wide herding with a rise in expected sector illiquidity, while negative values of β_4 implies a rise in sector-wide herding with a rise in unexpected sector illiquidity.

As a robustness measure to our Markov Switch model as set up in equation 5.13, we look at the impact of expected/unexpected sector illiquidity on sub-sector herding by utilizing the breakpoint as identified by the Quandt-Andrews statistical breakpoint test, and conducting a sub-period analysis, for All REITs and each sector.

$$CSAD_t = a + \beta_1\ I\ R_{m,t}\ I + \beta_2\ R^2_{m,t} + \beta_3\ \ln ALLIQ^{E}_{t} + \beta_4 \ln ALLIQ^{u}_{t} + e_t, \qquad (5.14)$$

Furthermore, we also test out the impact of market-wide illiquidity, on herding within each sector using the following model:

$$CSAD_t = a, s_i + \beta_1, s_i\ I\ R_{m,t}\ I + \beta_2, s_i\ R^2_{m,t} + \beta_3, s_i\ \ln ALLIQ^{E}_{t,m} + \beta_4, s_i\ \ln ALLIQ^{u}_{t,m} + e_t, \qquad (5.15)$$

where $ALLIQ^{E}_{t,m}$ and $ALLIQ^{u}_{t,m}$ represent the expected and unexpected market-wide illiquidity.

5.5 Results

5.5.1 Benchmark Tests, Dummy Approach and the impact of VIX

Table 5.1 shows the daily summary statistics for the CSAD measure and the market return, for all US REITs. Table 5.2a and 5.2b reports summary statistics for sectoral returns and the sectoral CSAD measure. The standard deviation levels signify that returns within Hotel and Mortgage sectors are relatively more volatile, compared to the other sectors. This is further complimented by relatively more extreme maximum and minimum values within these sectors. Returns within Warehouse REITs seem to have the lowest volatility.

Table 5.1

	ALL REIT Market Return	**ALL REIT CSAD**
Mean	0.0102	1.6877
Median	0.0036	1.4920
Max	11.4425	12.3281
Min	-17.0805	0.7056
Std Dev	1.4754	0.8924
Obs	2058	2058

This table provides summary statistics for the equally weighted US REIT market portfolio and the cross-sectional absolute deviation for all US REITs which is defined as: $CSAD_t = \sum_{i=1}^{N} |R_{i,t} - R_{m,t}| / N$, where $R_{i,t}$ is the observed return for firm i, $R_{m,t}$ is the cross-sectional average return of N assets and N is number of assets in the universe we examine on day t.

Table 5.2a

	Health Sector Return	Hotel Sector Return	Mortgage Sector Return	Residential Return	Warehouse Return	Retail Sector Return
Mean	-0.2946	0.0056	-0.0290	0.1475	0.0951	0.0411
Median	-0.0993	0.0634	-0.0994	0.0519	0.1342	0.0477
Max	17.7895	30.9949	25.6859	10.3516	7.1691	16.3350
Min	-22.1484	-26.2603	-22.2614	-16.7370	-12.7876	-15.4732
Std Dev	1.8989	2.3332	2.0113	1.9190	1.1740	1.5873
Obs	2058	2058	2058	2058	2058	2058

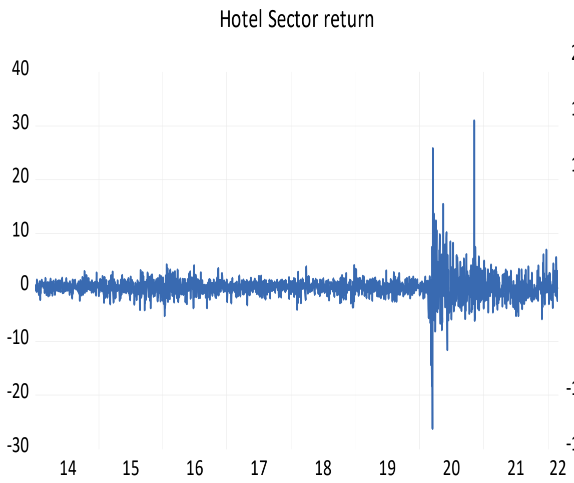
This table provides summary statistics for each equally weighted US REIT sector portfolio (average return of N assets and N is number of assets in the sector we examine on day t)

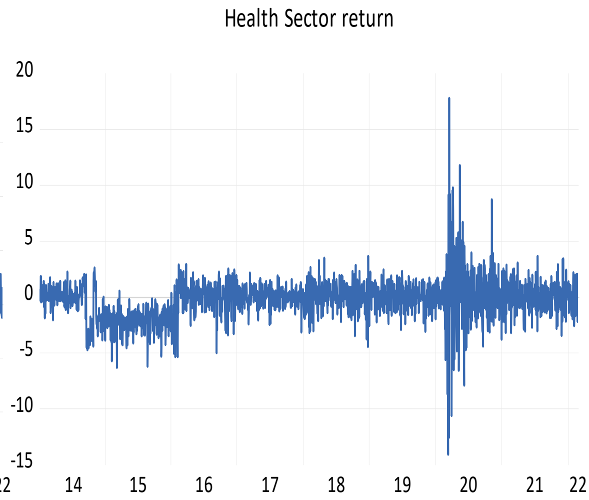
Table 5.2b

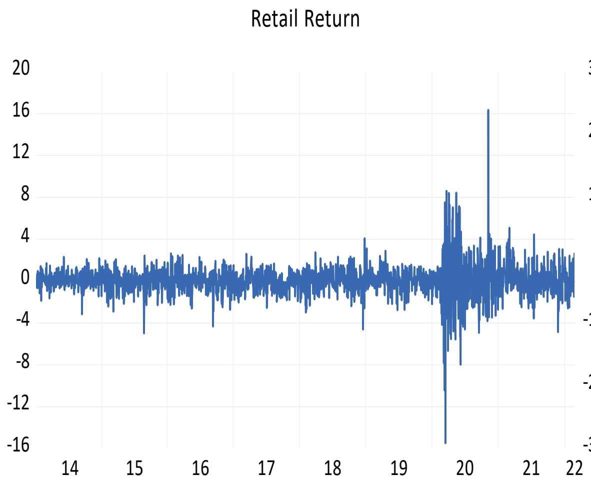
	Health Sector CSAD	Hotel Sector CSAD	Mortgage Sector CSAD	Residential CSAD	Warehouse CSAD	Retail Sector CSAD
Mean	1.3811	1.0786	2.3780	2.3773	0.8728	1.1091
Median	0.7277	0.8072	1.9320	1.7558	0.7916	0.9225
Max	12.6231	19.3135	19.6942	12.6446	5.7371	10.2149
Min	0.2337	0.1966	0.3920	0.3979	0.1960	0.3657
Std Dev	1.4552	0.9816	1.6247	1.8493	0.4165	0.7003
Obs	2058	2058	2058	2058	2058	2058

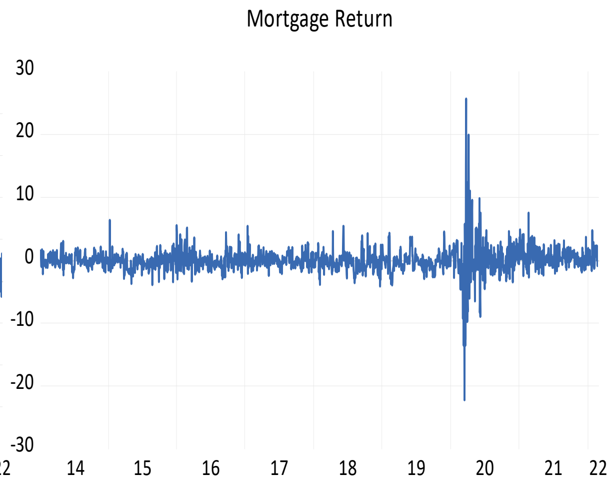
This table provides summary statistics for cross-sectional absolute deviation for each US REIT sector which is defined as: $CSAD_t = \sum_{i=1}^{N} |R_{i,t} - R_{j,t}| / N$, where $R_{i,t}$ is the observed return for REIT i, $R_{j,t}$ is the sectoral return and N is the number of REITs in each sector J.

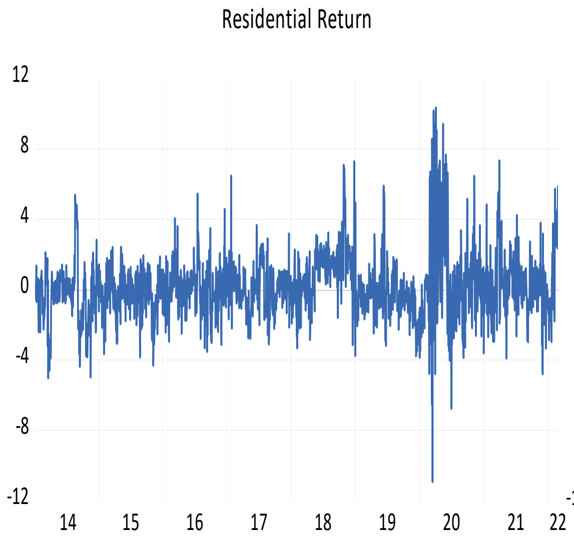
Figure 5.1 plots the time series of returns within all REITs and within each sub-sector. For the market REIT return, and returns within each sub-sector, we observe a significant rise in volatility which coincides with the Covid-19 pandemic.

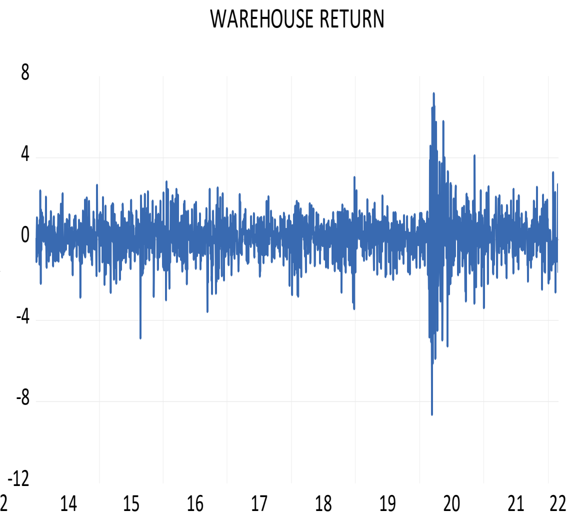

Hotel Sector return
40
30
20
10
0
-10
-20
-30
14
15
16
17
18
19
20
21
22


Health Sector return
20
15
10
5
0
-5
-10
-15
14
15
16
17
18
19
20
21
22


Retail Return
20
16
12
8
4
0
-4
-8
-12
-16
14
15
16
17
18
19
20
21
22


Mortgage Return
30
20
10
0
-10
-20
-30
14
15
16
17
18
19
20
21
22


Residential Return
12
8
4
0
-4
-8
-12
14
15
16
17
18
19
20
21
22


WAREHOUSE RETURN
8
4
0
-4
-8
-12
14
15
16
17
18
19
20
21
22

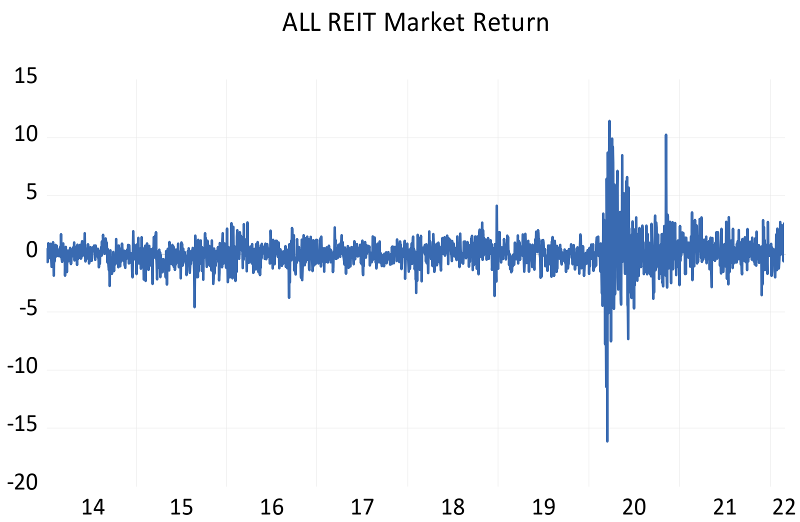


Figure 5.1. Time Series variation in each REIT Sector return and the All REIT Market index return

We then proceed to examining the existence of herding within all REITs and sub-sectors, for our entire sample group (January 2014 to February 2022) using equations 5.2 and 5.3, which are also presented in the legend below table 5.3. Panel A in table 5.3 reports the result for all REITs, while the results of the sectors are displayed in Panel B. For all REITs, CSAD of daily returns is increasing with the absolute magnitude of market returns, as β_1 is statistically significant and greater than zero. A statistically significant and positive coefficient β_2 indicates negative herding or anti-herding behaviour for all REITs within the full sample. For our full-sample sectoral study, we find negative estimated β_2 coefficients for Health, Mortgage and Residential sectors, indicating that herding effects are encountered within these sectors. Although we find β_2 coefficients significantly different from zero within Hotel, Retail and Warehouse sectors, these are all positive, indicating anti-herding behaviour.

Table 5.3

Panel A: All REITs	$\vert R_{m,t} \vert$	$R^2_{m,t}$
All REITs	0.4419 (0.00)	0.1309 (0.00)
Panel B: REIT sectors	$\vert R_{j,t} \vert$	$R^2_{j,t}$
Health	0.7514 (0.00)	-0.0215 (0.00)
Hotel	0.2934 (0.00)	0.0070 (0.00)
Mortgage	0.9372 (0.00)	-0.0152 (0.00)
Residential	1.1459 (0.00)	-0.0314 (0.00)
Retail	0.02681 (0.00)	0.0171 (0.00)
Warehouse	0.01399 (0.00)	0.0269 (0.00)

This table provides results for the benchmark model: which is defined as: $CSAD_t = a + \beta_1 \vert R_{m,t} \vert + \beta_2 R^2_{m,t} + e_t$, where $CSAD_t$ represents the cross-sectional absolute deviation of REIT returns with respect to the market portfolio return $R_{m,t}$. The sample period is January 2014 to February 2022. Panel A contains the estimated coefficients for All REITs. Panel B contains the results for each sector and utilises the model $CSAD_t = a + \beta_1 \vert R_{j,t} \vert + \beta_2 R^2_{j,t} + e_t$, where $R_{j,t}$ is the average sectoral return. P-values are listed next to the coefficients

Next, we examine whether herding behaviour becomes more intense on days with negative market returns relative to days with positive market returns, using a dummy approach as set out in equation 5.4 (which can also be found in the legend below table 5.4). Table 5.4 shows that, for all REITs and within Health, Hotel, Retail and Warehouse sectors, we find that $\beta_4 < \beta_3$, indicating that herding effects are relatively more pronounced on days with negative market returns. Within Mortgage and Residential sectors, we find significant evidence of herding, but no evidence that this is relatively more pronounced on days with negative market returns.

Table 5.4

Panel A: All REITs	**$\vert R_{m,t} \vert$**	**$D^{Down} \vert R_{m,t} \vert$**	**$\beta_3 R^2_{m,t}$**	**$\beta_4 D^{Down} R^2_{m,t}$**
All REITs	0.3115 (0.00)	0.3061 (0.29)	0.04923 (0.00)	-0.0388 (0.00)
Panel B: REIT sectors	**$\vert R_{j,t} \vert$**	**$D^{Down} \vert R_{j,t} \vert$**	**$\beta_3 R^2_{j,t}$**	**$\beta_4 D^{Down} R^2_{j,t}$**
Health	0.1142 (0.01)	0.8188 (0.00)	0.0291 (0.00)	-0.0636 (0.00)
Hotel	0.3148 (0.00)	-0.0172 (0.32)	0.0088 (0.00)	-0.0066 (0.00)
Mortgage	1.0281 (0.00)	-0.1691 (0.00)	-0.0145 (0.00)	-0.0046 (0.12)
Residential	1.2057 (0.00)	-0.1293 (0.02)	-0.0376 (0.00)	0.0089 (0.32)
Retail	0.2871 (0.00)	-0.0574 (0.01)	0.0218 (0.00)	-0.0069 (0.02)
Warehouse	0.0722 (0.00)	0.0717 (0.00)	0.0489 (0.00)	-0.0259 (0.00)

This table provides results for the model $CSAD_t = a + \beta_1 \vert R_{m,t} \vert + \beta_2 D^{Down} \vert R_{m,t} \vert + \beta_3 R^2_{m,t} + \beta_4 D^{Down} R^2_{m,t} + e_t$, where $CSAD_t$ represents the cross-sectional absolute deviation of REIT returns with respect to the market portfolio return $R_{m,t}$ and D^{Down} is a dummy variable that takes the value of 1 during days with negative returns, and 0 otherwise. The sample period is January 2014 to February 2022. Panel A contains the estimated coefficients for All REITs. Panel B contains the results for each sector and utilises the model $CSAD_t = a + \beta_1 \vert R_{j,t} \vert + \beta_2 D^{Down} \vert R_{j,t} \vert + \beta_3 R^2_{j,t} + \beta_4 D^{Down} R^2_{j,t} + e_t$, where $R_{j,t}$ is the average sectoral return. P-values are listed next to the coefficients

Huerta, Egly and Escobari (2016) draw a connection between the volatility in investor sentiments and the volatility within asset prices, including REIT prices. Philippas, Economou, Babalos and Kostakis (2013) find that during periods of heightened fear and uncertainty regarding the future outlook of the economy, investors tend to be more inclined to follow the market herd. Following the work of Baker and Wurgler (2006), Philippas, Economou, Babalos and Kostakis (2013) use the CBOE VIX index as a measure of investor sentiments. As investors' fear and uncertainty regarding the future health of the economy grows, investors' follow the portfolio insurance approach, hiking up prices for out-of-the-money put options, driving up their implied volatilities. Various past studies such as Tseng and Li (2012), and Kurov (2010) have used the VIX index as an indicator for investor sentiments. Figure 5.2 depicts a time series plot for the VIX index, showing a significant spike, and realizing its highest values coinciding with the Covid-19 pandemic. Based on this evidence, and motivated by noise trader risk theory, we look to assess if depleting investor sentiments regarding the future health of the economy, as realized during the crisis period, coincides with heightened herding behavior. Table 5.5 shows the results for the model set up in equation 5.5 (which can also be found in the legend below table 5.5). Our results confirm that as investor sentiments deteriorate, as indicated by a rise in VIX, herding behaviour becomes more intense within All REITs, and all sub-sectors barring residential.

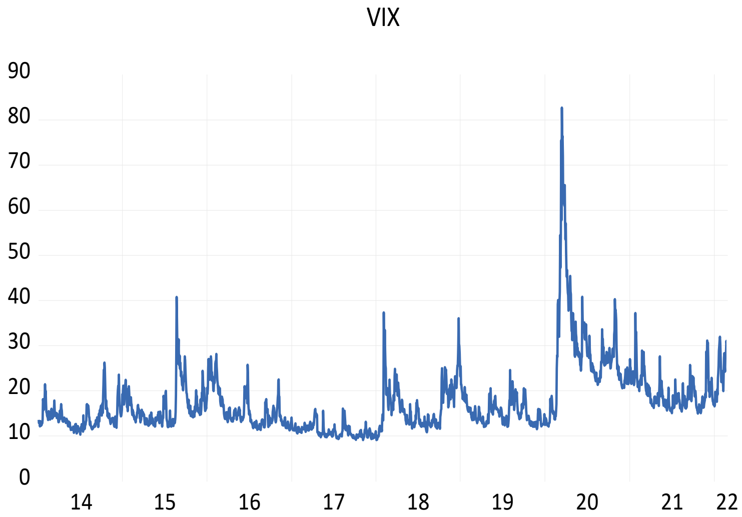


Figure 5.2. Time Series variation in the VIX index

Table 5.5

Panel A: All REITs	$\lvert R_{m,t} \rvert$	$R^2_{m,t}$	$R_{VIX,t}$
All REITs	0.3734 (0.00)	0.0266 (0.00)	-0.4981 (0.00)
Panel B: REIT sectors	$\lvert R_{j,t} \rvert$	$R^2_{j,t}$	$R_{VIX,t}$
Health	0.7649 (0.00)	-0.0203 (0.00)	-0.9617 (0.00)
Hotel	0.2864 (0.00)	0.0078 (0.00)	-0.6066 (0.00)
Mortgage	0.9425 (0.00)	-0.0144 (0.00)	-0.7117 (0.01)
Residential	1.1014 (0.00)	-0.0217 (0.00)	-0.0930 (0.77)
Retail	0.2520 (0.00)	0.0207 (0.00)	-0.3433 (0.00)
Warehouse	0.0792 (0.00)	0.0436 (0.00)	-0.2325 (0.01)

This table provides results for the model: $CSAD_t = a + \beta_1 \lvert R_{m,t} \rvert + \beta_2 R^2_{m,t} + R_{VIX,t} + e_t$, where $CSAD_t$ represents the cross-sectional absolute deviation of REIT returns with respect to the market portfolio return $R_{m,t}$. and $R_{VIX,t}$ is the return on the VIX index on day t. The sample period is January 2014 to February 2022. Panel A contains the estimated coefficients for All REITs. Panel B contains the results for each sector and utilises the model $CSAD_t = a + \beta_1 \lvert R_{j,t} \rvert + \beta_2 R^2_{j,t} + R_{VIX,t} + e_t$, where $R_{j,t}$ is the average sectoral return. P-values are listed next to the coefficients

Driven by the evidence that herding effects are more pronounced during days of market stress (or days of negative market returns) and high VIX (fear) values, we look to examine whether a structural break has occurred during the full sample period. Firstly, we run a CUSUM Test to identify if there is indeed any evidence of a structural break. This is displayed in figure 5.3:

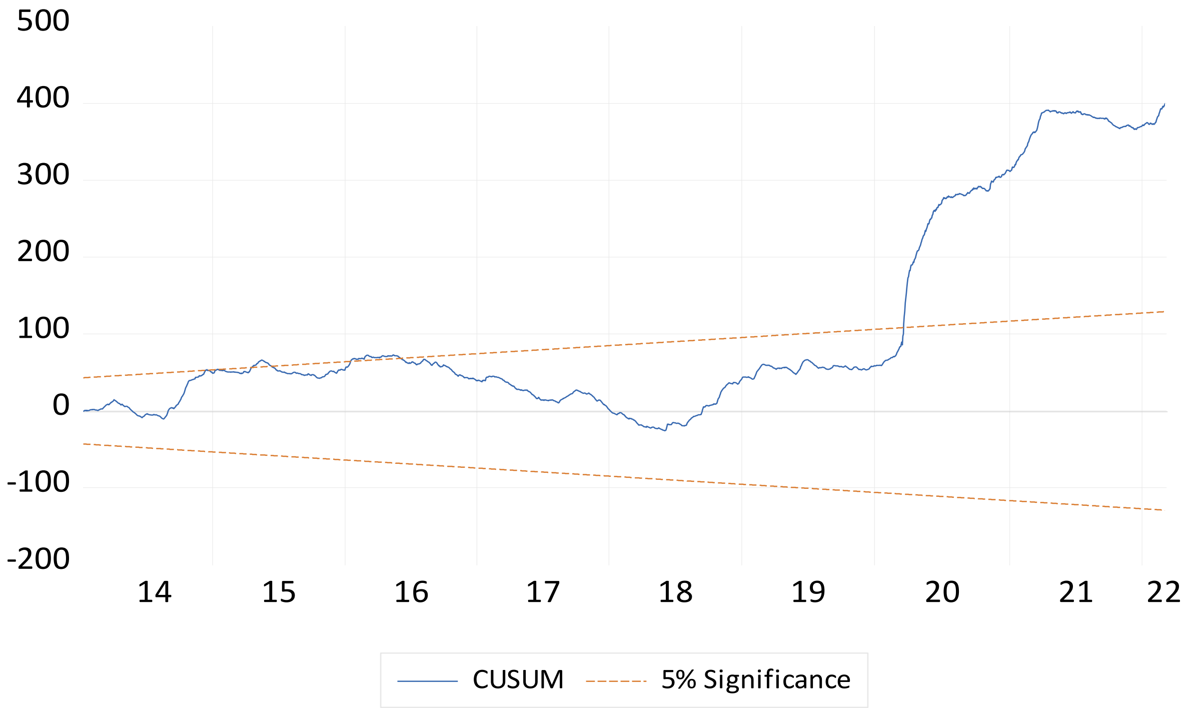


Figure 5.3. Result for the CUSUM Test: January 2014 to February 2022

The CUSUM Test does reveal that there is evidence of a structural break in 2020. Therefore, we then use a Quandt-Andrews statistical breakpoint test and find evidence of a breakpoint on 18th March 2020. Based on this evidence, we feel there is merit to investigating herding behaviour between different market regimes and employing a dynamic model to capture herding.

5.5.2 Exploring Herding under different market regimes

After examining herding behaviour for all US REITs and REIT sub-sectors using constant parameters throughout the estimation period, we now look to distinguish between different market regimes. For this purpose, we use a Markov Switching Model with two regimes as laid down in equation 5.6 (also included in the legend below table 5.6). The rationale of using two regimes is based on the fact that we identify a single breakpoint using the Quandt-Andrews statistical breakpoint test. Furthermore, we compare log-likelihood of values of the two-regime model with constant variance, two-regime model with regime dependent variance, the three-regime model with constant variance, and the three-regime model with regime dependent variance. Our log-likelihood results suggest that the two regime constant variance model provides the better results.

Table 5.6 displays result for all REITs and each sub-sector, within recessionary and non-recessionary regimes. $\beta_{1,1}$ and $\beta_{2,1}$ represent coefficients for $R_{m,t}$ and $R^2_{m,t}$ respectively in state 1, or the non-recessionary state. $\beta_{1,2}$ and $\beta_{2,2}$ represent coefficients for $R_{m,t}$ and $R^2_{m,t}$ respectively in state 2, or the recessionary state. During the crash regime, represented by state 2 in table 5.6, we find significant evidence of herding within Health, Residential, Warehouse and Mortgage sectors. This is indicated by statistically significant and negative coefficients for $R^2_{m,t}$ during the recessionary state, within these sectors. During the expansionary regime, represented by state 1 in table 5.6, we find no significant evidence of herding behaviour within any sub-sectors barring Mortgage REITs. These results are consistent with past literature such as Galariotis, Rong and Spyrou (2015), who also find significant presence of herding within US stocks during the Sub-prime crisis. Furthermore, Galariotis, Rong and Spyrou (2015) distinguish between herding on fundamental information and intentional herding[33], claiming that herding in US stocks during the sub-prime was a result of intentional herding or herding on non-fundamentals, while herding during earlier crises such as the Asian crisis or the Russian crisis was based on fundamental information. They conclude that drivers of herding behavior are period and country specific. In light of our results, and in connection with Babalos, Balcilar and Gupta (2015)[34], who study herding in US REITs between 2004 and 2013, a possible explanation for why herding is relatively more intense during the crash regime could be that, "investors discard their own information and choose to mimic institutional

[33] Bikhchandani and Sharma (2000) make a distinction between herding that corresponds to macroeconomic announcements and events, e.g. changes in the federal funds rate, announcements on unemployment, inflation, gross domestic product, consumer confidence etc. This provides investors with a common information set, and herding towards the consensus, on the back of this information is referred to as "spurious herding" or herding based on fundamentals. On the other hand, herding by investors that intentionally follows the behaviour of others, without any fundamental backing, is referred to as "intentional herding"

[34] Babalos, Balcilar and Gupta (2015) find herding effects to be significantly stronger in US REITs within the recessionary phase relative to the non-recessionary phase. They conclude that "A possible explanation is that investors discard their own information and choose to mimic institutional investors during high market stress periods and thus herding is more prevalent during the crash regime"

investors during high market stress periods" and thus potentially causing herding to be more prevalent during the crash regime than in the expansionary regime.

Table 5.6

		All REITs	Health	Hotel	Mortgage	Residential	Retail	Warehouse
Non-recessionary	**$\beta_{1,1}$** $R_{m,t}$	0.2322 (0.00)	0.0603 (0.00)	0.1708 (0.00)	0.6203 (0.00)	0.5949 (0.00)	0.1254 (0.00)	0.0751 (0.00)
	$\beta_{2,1}$ $R^2_{m,t}$	0.0184 (0.00)	0.0309 (0.00)	0.0085 (0.00)	-0.0049 (0.01)	0.0011 (0.87)	0.0199 (0.00)	0.0242 (0.00)
Recessionary	**$\beta_{1.2}$** $R_{m,t}$	0.0317 (0.54)	0.2242 (0.00)	0.1581 (0.00)	0.9000 (0.00)	0.8279 (0.00)	0.2870 (0.00)	0.4919 (0.00)
	$\beta_{2,2}$ $R^2_{m,t}$	0.07192 (0.00)	-0.0046 (0.00)	0.0215 (0.00)	-0.0096 (0.00)	-0.0236 (0.00)	0.0130 (0.00)	-0.0101 (0.00)
	P_{11}	0.9853	0.9954	0.9848	0.9575	0.9761	0.9845	0.9683
	P_{12}	0.0147	0.0046	0.0152	0.0425	0.0239	0.0155	0.0317
	P_{21}	0.1199	0.0224	0.0945	0.2133	0.0924	0.0838	0.5293
	P_{22}	0.8801	0.9776	0.9054	0.7867	0.9076	0.9162	0.4707
	λ_1	67.94	215.54	65.94	23.51	41.87	64.68	31.54
	λ_2	8.34	44.64	10.57	4.69	10.82	11.93	1.89

This table presents results for the two-state Markov switching model as set out in the following equation: $CSAD_t = a_{,s_i} + \beta_{1,s_i} \mid R_{m,t} \mid + \beta_{2,s_i} R^2_{m,t} + e_t$, where $CSAD_t$ represents the cross-sectional absolute deviation of REIT returns with respect to the market portfolio return $R_{m,t}$. $\beta_{1,1}$ and $\beta_{2,1}$ represent coefficients for $R_{m,t}$ and $R^2_{m,t}$ respectively in state 1, or the non-recessionary state. $\beta_{1.2}$ and $\beta_{2,2}$ represent coefficients for $R_{m,t}$ and $R^2_{m,t}$ respectively in state 2, or the recessionary state. The sample period is January 2014 to February 2022. P represents the transition probabilities of either remaining in the same regime, or switching regimes. λ represents the constant expected duration in each regime, in terms of the number of days. P-values are listed next to the coefficients

5.5.3 Expected and Unexpected Sector Illiquidity

Now that we have established the existence of herding within US REITs, we look to explore potential channels that could impact herding. Illiquidity is a factor that has historically impacted stock returns (Amihud et. al, 2015) and REIT returns (Paul, Walther and Kuster-Simic, 2021). Furthermore, given the fact that REITs have to distribute 90% of their taxable income as dividends in order to maintain their REIT status (Boudry 2011), therefore, retained earnings only contribute a small proportion of REIT funding. This increases REITs reliance on traditional sources of raising funds such as credit lines (Ooi, Wong and Ong, 2012), and any negative shocks to liquidity which may impact these traditional funding channels, could have a significant impact on REIT growth, operations and earnings potential. To the best of our knowledge, there are no studies currently that explore the impact of current average level sector illiquidity, and future uncertainty of sector illiquidity, on sub-sector herding within US REITs, within a two-state Markov switching setting, segmenting between expansionary and crash regimes, making our study unique.

Our hypothesis is that a rise in sector illiquidity would affect the real estate market conditions (Paul, Walther and Kuster-Simic, 2021), and lead to correlated activity on the part of investors, contributing to herd behaviour (Philippas, Economou, Babalos and Kostakis, 2013). Furthermore, our conjecture is also that the impact of illiquidity in enhancing herding behaviour would be more pronounced during a crash regime relative to during an expansionary regime (Babalos, Balcilar and Gupta. 2015).

Running the model in equation 5.13 (which can also be found in the legend under table 5.7), Table 5.7 displays results for all REITs, and the results on a sectoral level. $\beta_{1,1}$, $\beta_{2,1}$, $\beta_{3,1}$, $\beta_{4,1}$ represent coefficients for $R_{m,t}$, $R^2_{m,t}$, ln $ALLIQ^E_t$ and ln $ALLIQ^u_t$, respectively, in state 1, or the non-recessionary state. $\beta_{1,2}$, $\beta_{2,2}$, $\beta_{3,2}$, $\beta_{4,2}$ represent coefficients for $R_{m,t}$, $R^2_{m,t}$, ln $ALLIQ^E_t$ and ln $ALLIQ^u_t$, respectively, in state 2, or the recessionary state. A negative and significant value of β_3 in either state, would indicate that a rise in expected illiquidity enhances herding within that particular state. On the other hand, a negative and significant value of β_4 in either state, would indicate that a rise in unexpected illiquidity enhances herding within that particular state

For All REITs, our results show that increases in unexpected market illiquidity negatively impacts/reduces REIT returns dispersion, during the recessionary phase, confirming our conjecture that as unexpected liquidity deteriorates during recessionary phases, herding behaviour becomes more intense. The impact on herding of both expected and unexpected changes in illiquidity during the non-recessionary phase is insignificant.

The sub-sector results display a similar story for the recessionary phase. For all sectors, apart from health, increases in unexpected sector illiquidity are negatively related to the dispersion of REIT returns, implying a positive relationship between unexpected sector-wide illiquidity shocks and herding during the recessionary phase. This would imply that a rise in unexpected sector illiquidity during a recessionary phase, significantly heightens future expectation of a fall in liquidity, and therefore enhances present herding behaviour.

With regards to the health sector, these results are consistent with past literature that explores the performance of the US health sector during and after Covid-19. Rhyan, Turner and Miller (2020) report that although the US health sector saw drops in March and April of 2020, government spending within the health sector, equating to 18% of Gross Domestic Product by the second half of 2020, ensured that prices within the sector have continued to rise. Since herding is a sentiment driven behaviour, the impetus provided by the government, and the healthy rise in prices within the sector, provide justification for a lack of negative investor sentiments towards this sector, driving down herd behaviour within the sector, even during times of liquidity strain and economic recession.

Our results suggest that investors' who have holdings within Hotel, Mortgage, Residential, Retail and Warehouse REIT sectors, during the Covid-19 phase, could have serious consequences for their investments. Crotty (2009) considered illiquidity to be a major source for the 2007/08 financial crisis, while Cetorelli, Goldberg and Ravazzolo (2020) discuss the short-term funding stress during Covid-19, primarily existing due to an elevated demand for liquidity. REITs dividend pay-out constraint, and their dependence on conventional sources of short–term funding, creates significant downside risks for investors with regards to these investments. Shin (2010) report that negative movements within asset prices could be exponentially over blown due to herding, as investors start trading in the same direction. This has serious implications for investors, not only in terms of a steep fall in price and a potential rise in realised and unrealised losses, but also from the perspective of driving their asset values away from their fundamental value. Lastly, Morelli (2010) argue that synchronised trades also pose a threat of significant co-movement within asset returns, which reduces the ability of investors to hedge against risk via diversification. Five out of our six sub-sectors face significant challenges via herding during the Covid-19 phase, resulting in a co-movement within these sectors, and resulting in a fall in investors' ability to diversify by spreading their funds amongst these REIT sub-sectors.

Furthermore, our results also suggest that expected illiquidity changes have a significant part to play in terms of enhancing herding behaviour during the non-recessionary phase. A rise in expected sector illiquidity during the non-recessionary phase, reduces REIT returns dispersion within residential, retail and warehouse sectors. From the results in table 5.7, it also becomes apparent that during non-recessionary phases, the channel of influence between a rise in unexpected illiquidity and investor sentiments towards heightened future illiquidity, might be weak.

In terms of liquidity as a proxy for market sentiments, both our results for the VIX index and for illiquidity confirm that as investor sentiments deteriorate (due to a high VIX and illiquidity), herding within sub-sector REITs rise, during both recessionary and non-recessionary states. Although not comparable, Galariotis, Krokida and Spyrou (2016) [who concentrate on stocks (not REITs), measure liquidity (not illiquidity) and use a completely different time sample] conclude that a rise in stock market liquidity significantly explains a rise in herding, irrespective of recessionary or non-recessionary states, within G4 economies (Germany is an exception), where a rise in liquidity is seen as a proxy for improved investor sentiments. We believe that this variation in results could potentially be down to the fundamental and regulatory differences between the equity and REIT markets as explained in introduction and the literature review.

Table 5.7

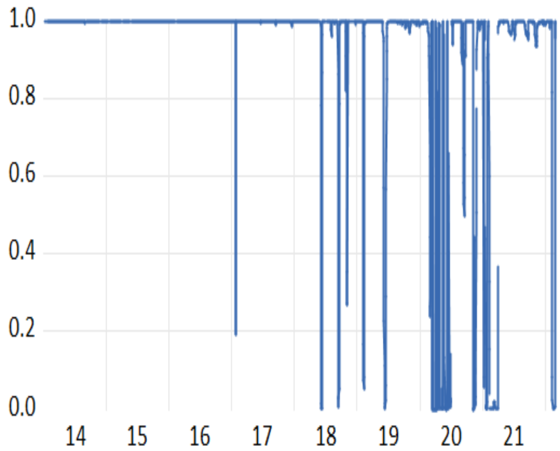
Non-recession	All REITs	Health	Hotel	Mortgage	Residential	Retail	Warehouse
$\beta_{1,1}R_{m,t}$	0.2140 (0.00)	0.0971 (0.00)	0.1741 (0.00)	0.5980 (0.00)	0.5588 (0.00)	0.1005 (0.00)	0.0717 (0.00)
$\beta_{2,1}R^2_{m,t}$	0.0260 (0.00)	0.0247 (0.00)	0.0085 (0.00)	-0.0031 (0.09)	0.0186 (0.00)	0.0297 (0.00)	0.0224 (0.00)
$\beta_{3,1}ALLIQ^E_t$	-0.0208 (0.16)	0.1591 (0.00)	0.0728 (0.00)	-0.0441 (0.33)	-0.0533 (0.09)	-0.0921 (0.00)	-0.0099 (0.09)
$\beta_{4,1}ALLIQ^u_t$	0.0031 (0.88)	-0.1701 (0.00)	-0.0553 (0.01)	0.0165 (0.74)	0.0560 (0.12)	0.0518 (0.00)	0.0162 (0.03)
Recession							
$\beta_{1.2}R_{m,t}$	-0.1049 (0.06)	0.0120 (0.68)	-0.0162 (0.52)	0.8770 (0.00)	0.3122 (0.00)	0.1900 (0.00)	0.2637 (0.00)
$\beta_{2,2}R^2_{m,t}$	0.0697 (0.00)	0.0279 (0.00)	0.0241 (0.00)	-0.0091 (0.00)	0.0980 (0.00)	0.0127 (0.00)	0.0094 (0.38)
$\beta_{3,2}ALLIQ^E_t$	2.1424 (0.00)	-0.7932 (0.00)	1.0982 (0.00)	0.3078 (0.00)	0.2256 (0.01)	0.7819 (0.00)	0.4428 (0.00)
$\beta_{4,2}ALLIQ^u_t$	-1.4584 (0.00)	0.5155 (0.00)	-0.7829 (0.00)	-0.2246 (0.03)	-0.1457 (0.09)	-0.6094 (0.00)	-0.2678 (0.00)
P_{11}	0.9876	0.9953	0.9857	0.9582	0.9657	0.9833	0.9791
P_{12}	0.0124	0.0047	0.0143	0.0418	0.0343	0.0167	0.0209
P_{21}	0.1415	0.0233	0.0955	0.2039	0.1406	0.1041	0.4449
P_{22}	0.8585	0.9767	0.9045	0.7961	0.8594	0.8959	0.5551
λ_1	80.77	210.72	70.11	23.95	29.13	59.80	47.91
λ_2	7.07	42.97	10.48	4.90	7.11	9.61	2.25

This table presents results from the two-state Markov switching model as set out as: $CSAD_t = a,\ s_i + \beta_1,\ s_i \mid R_{m,t} \mid + \beta_2,\ s_i R^2_{m,t} + \beta_3,\ s_i \ \ln ALLIQ^E_t + \beta_4,\ s_i \ \ln ALLIQ^u_t + e_t$, where $CSAD_t$ represents the cross-sectional absolute deviation of REIT returns with respect to the market portfolio return $R_{m,t,}$ ln $ALLIQ^E_t$ and ln $ALLIQ^u_t$ represent the natural logarithm of the expected and unexpected sector-wide illiquidity. $\beta_{1,1}$, $\beta_{2,1}$, $\beta_{3,1}$, $\beta_{4,1}$ represent coefficients for $R_{m,t}$, $R^2_{m,t}$, ln $ALLIQ^E_t$ and ln $ALLIQ^u_t$, respectively in state 1, or the non-recessionary state. $\beta_{1.2}$, $\beta_{2,2}$, $\beta_{3,2}$, $\beta_{4,2}$ represent coefficients for $R_{m,t}$, $R^2_{m,t}$, ln $ALLIQ^E_t$ and ln $ALLIQ^u_t$, respectively in state 2, or the recessionary state. . P represents the transition probabilities of either remaining in the same regime, or switching regimes. λ represents the constant expected duration in each regime, in terms of the number of days. P-values are listed next to the coefficients

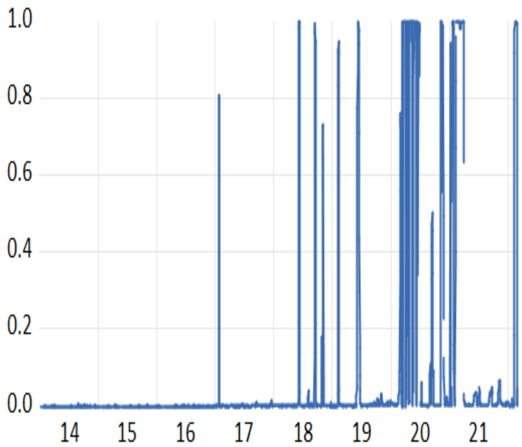
Figure 5.5 displays the smoothed probability graphs within each state, for All REITs and for all REIT sub-sectors

All REITs

P [Non-recessionary regime] smoothed

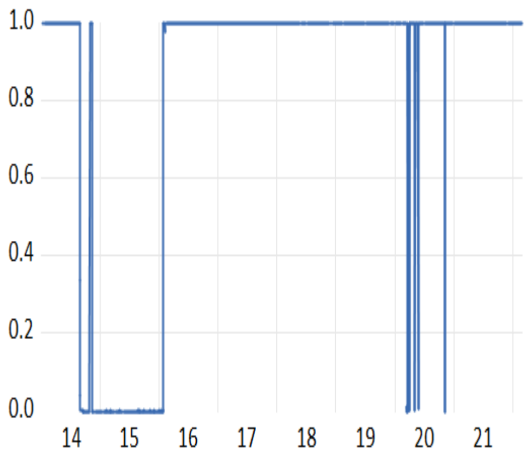


P [Recessionary regime] smoothed

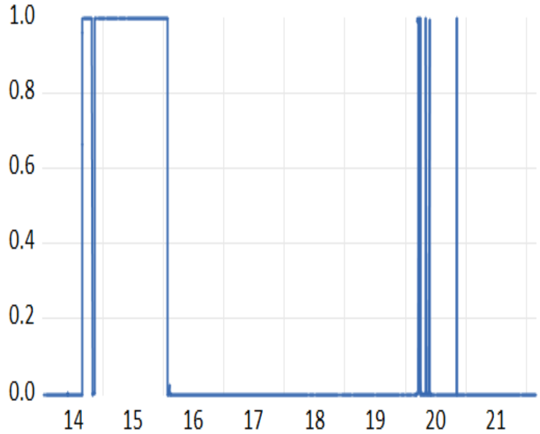


Health

P [Non-recessionary regime] smoothed

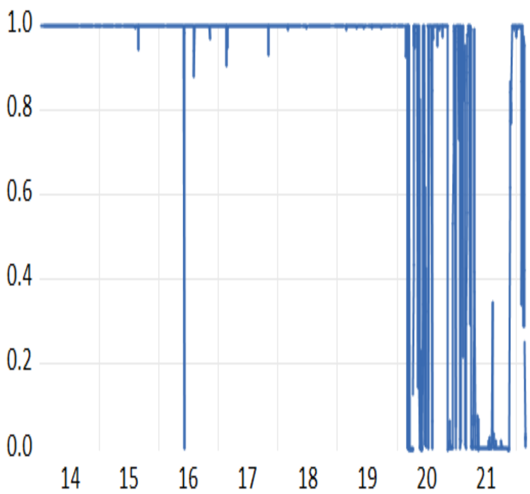


P [Recessionary regime] smoothed

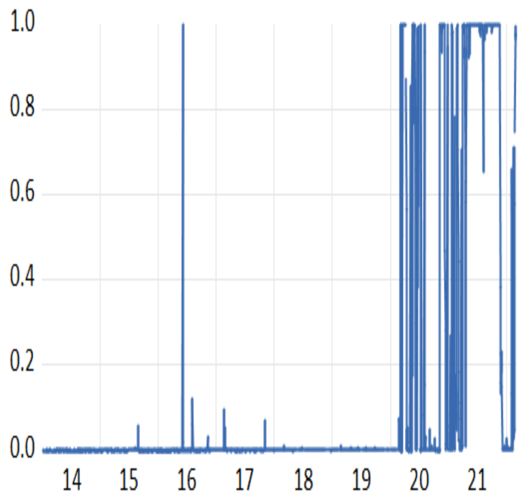


Hotel

P [Non-recessionary regime] smoothed

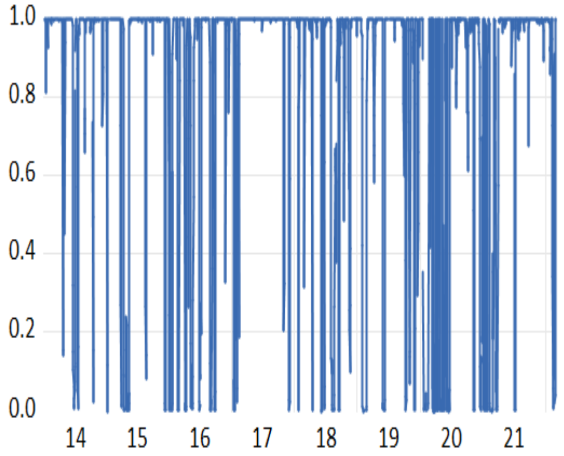


P [Recessionary regime] smoothed

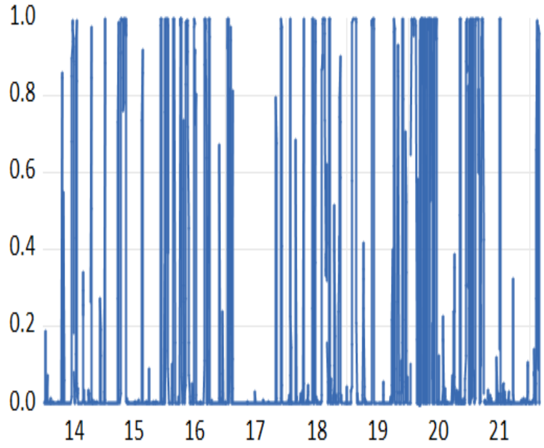


Mortgage

P [Non-recessionary regime] smoothed

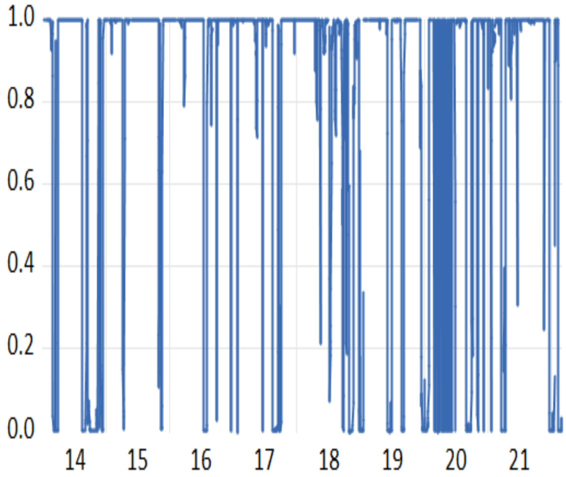


P [Recessionary regime] smoothed

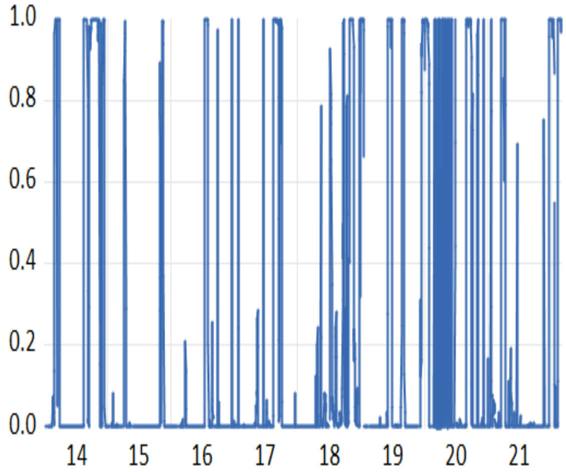


Residential

P [Non-recessionary regime] smoothed



P [Recessionary regime] smoothed



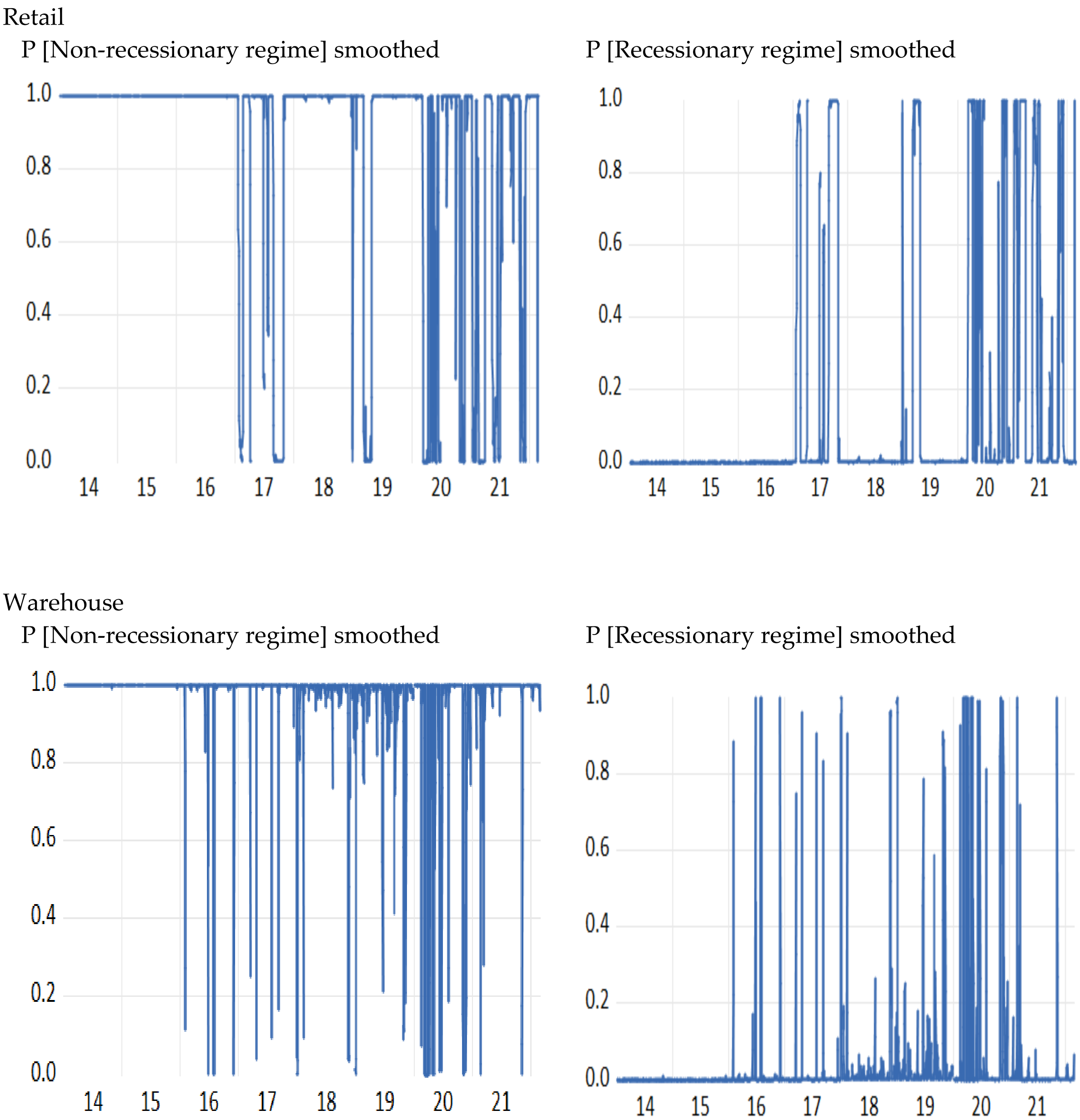


Figure 5.5. Transition probabilities between the two regimes

5.5.4 Robustness

As a robustness measure, we also assess the impact of expected and unexpected illiquidity shocks on herding within All REITs and sub-sectors. Using the Quandt-Andrews statistical breakpoint test, we identified that a structural break occurred on the 18th of March 2020. We therefore incorporate our expected and unexpected sector illiquidity factors within equation 5.7 (also presented in the legend under table 5.8), and run two separate regressions, one from 2nd January 2014 to 18th March 2020 (non-recessionary phase), and the other from 19th March 2020 up until 28th February 2022 (recessionary/Covid and post-covid phase), using equation 5.14. These results are presented in table 5.8. A significant and negative β_3 would indicate that herding rises with expected sector illiquidity, while a significant and negative β_4 would indicate that herding rises with unexpected sector illiquidity. Comparing these results to our two-state Markov Switching model reveals that all our results match, apart from only the recessionary phase within the health sector.

Once again, expected illiquidity shocks play a significant part in enhancing herding during the expansionary phase. During the recessionary phase, unexpected rise in illiquidity significantly impacts investors' expectations of future illiquidity, potentially due to heightened risk levels and negative sentiments regarding the general health of the economy, resulting in an enhanced herding behaviour in the current time. This confirms the robustness within our findings.

Table 5.8

Non-Recession	**All REITs**	**Health**	**Hotel**	**Mortgage**	**Residential**	**Retail**	**Warehouse**
β_1	0.1920 (0.00)	1.0781 (0.00)	0.1762 (0.00)	1.1058 (0.00)	0.9541 (0.00)	0.1087 (0.00)	0.0272 (0.15)
β_2	0.0259 (0.00)	-0.0517 (0.00)	0.0081 (0.00)	-0.0289 (0.00)	0.02713 (0.01)	0.0288 (0.00)	0.0520 (0.00)
β_3	-0.0050 (0.75)	0.9079 (0.00)	0.0741 (0.00)	0.0391 (0.44)	-0.1398 (0.00)	-0.1351 (0.00)	-0.0200 (0.00)
β_4	-0.0043 (0.82)	-0.8921 (0.00)	-0.0403 (0.04)	-0.0510 (0.36)	0.1128 (0.02)	0.0821 (0.00)	0.0203 (0.02)
Recession							
β_1	0.0559 (0.31)	-0.0443 (0.21)	0.0648 (0.06)	0.5523 (0.00)	1.0751 (0.00)	0.2035 (0.00)	0.1506 (0.00)
β_2	0.0595 (0.00)	0.0363 (0.00)	0.0158 (0.00)	0.0038 (0.21)	-0.0477 (0.00)	0.0224 (0.00)	0.0233 (0.01)
β_3	1.1544 (0.00)	0.7414 (0.00)	0.4743 (0.00)	1.5013 (0.00)	0.9853 (0.00)	0.2002 (0.01)	0.1534 (0.00)
β_4	-0.8528 (0.00)	-0.5874 (0.00)	-0.4380 (0.00)	-1.1617 (0.00)	-0.8875 (0.00)	-0.2999 (0.00)	-0.0832 (0.02)

This table presents results for the model $CSAD_t = a, s_i + \beta_1 \mid R_{m,t} \mid + \beta_2 R^2_{m,t} + \beta_3 \ln ALLIQ^E_t + \beta_4 \ln ALLIQ^u_t + e_t$, run firstly for the non-recessionary period 2nd January 2014 to 18th March 2020, and then for the recessionary period 19th March 2020 up until 28th February 2022. $CSAD_t$ represents the cross-sectional absolute deviation of REIT returns with respect to the market portfolio return $R_{m,t}$, $\ln ALLIQ^E_t$ and $\ln ALLIQ^u_t$ represent the natural logarithm of the expected and unexpected sector-wide illiquidity. β_1, β_2, β_3, β_4 represent coefficients for $R_{m,t}$, $R^2_{m,t}$, $\ln ALLIQ^E_t$ and $\ln ALLIQ^u_t$ respectively, firstly for the non-recessionary period and then followed by the recessionary period. P-values are listed next to the coefficients

5.5.5 Expected and Unexpected Market Illiquidity

Next, we look to explore the impact of market-wide illiquidity within US REITs, on herding within each sub-sector, during recessionary and non-recessionary phases, using the model in equation 5.15, which has also been presented in the legend under table 5.9. The results in table 5.9 show that herding is an increasing function of expected market-wide illiquidity shocks during the expansionary phase. Although this confirms the role of illiquidity in enhancing herding, the lack of impact of our unexpected market component reaffirms the fact that current rise in illiquidity does not have a significant impact on investors' future expectation of illiquidity, during the non-recessionary state. The results also show that herding within sub-sector REITs rises with unexpected market-wide illiquidity shocks during the recessionary state. This would also suggest that investors are more concerned with illiquidity shocks during recessionary phases, and a current and sudden rise in illiquidity during recessionary states, does impact investor sentiments regarding future illiquidity shocks.

During both the non-recessionary and recessionary states, the rise in herding via a market-wide illiquidity shock is felt within the hotel, mortgage, retail and residential sectors. For the non-recessionary phase, the impact is felt from a rise in expected market-wide illiquidity, while for the recessionary state, the impact is felt from a rise unexpected market-wide illiquidity shocks.

Table 5.9

Non-recession	Health	Hotel	Mortgage	Residential	Retail	Warehouse
$\beta_{3,1}ALLIQ^{E}_{t,m}$	0.0253 (0.19)	-0.0239 (0.09)	-0.1223 (0.00)	-0.0897 (0.01)	-0.1003 (0.00)	-0.0070 (0.45)
$\beta_{4,1}ALLIQ^{u}_{t,m}$	-0.0274 (0.26)	0.0175 (0.34)	0.0583 (0.11)	0.0553 (0.20)	0.0419 (0.01)	0.0050 (0.68)
Recession						
$\beta_{3,2}ALLIQ^{E}_{t,m}$	-0.0641 (0.20)	1.3966 (0.00)	-0.0093 (0.92)	0.2018 (0.07)	0.2418 (0.00)	0.4644 (0.00)
$\beta_{4,2}ALLIQ^{u}_{t,m}$	0.0443 (0.33)	-1.0414 (0.00)	-0.1018 (0.07)	-0.2853 (0.02)	-0.2655 (0.00)	-0.1123 (0.25)
P_{11}	0.9951	0.9867	0.9595	0.9648	0.9853	0.9713
P_{12}	0.0049	0.0133	0.0405	0.0352	0.0147	0.0287
P_{21}	0.0239	0.1001	0.7900	0.1415	0.0884	0.4708
P_{22}	0.9761	0.8999	0.2100	0.8585	0.9116	0.5292
λ_1	204.80	74.99	24.68	28.43	68.03	34.80
λ_2	41.77	9.99	4.76	7.07	11.31	2.12

This table presents results for the model $CSAD_t = a, s_i + \beta_1, s_i \mid R_{m,t} \mid + \beta_2, s_i R^2_{m,t} + \beta_3, s_i \ln ALLIQ^{E}_{t,m} + \beta_4, s_i \ln ALLIQ^{u}_{t,m} + e_t$, where $CSAD_t$ represents the cross-sectional absolute deviation of REIT returns with respect to the market portfolio return $R_{m,t}$, $\ln ALLIQ^{E}_{t,m}$ and $\ln ALLIQ^{u}_{t,m}$ represent the natural logarithm of the expected and unexpected market-wide illiquidity. For reasons of brevity, only coefficients corresponding to expected/unexpected market illiquidity are shown. $\beta_{3,1}$, $\beta_{4,1}$ represent coefficients for $\ln ALLIQ^{E}_{t,m}$ and $\ln ALLIQ^{u}_{t,m}$ respectively in state 1, or the non-recessionary state. $\beta_{3,2}$, $\beta_{4,2}$ represent coefficients for $\ln ALLIQ^{E}_{t,m}$ and $\ln ALLIQ^{u}_{t,m}$ respectively in state 2. P represents the transition probabilities of either remaining in the same regime, or switching regimes. λ represents the constant expected duration in each regime, in terms of the number of days. P-values are listed next to the coefficients

5.6 Conclusion

This paper has contributed to a better understanding of the existence of herding behaviour within REITs on a sub-sector level, the asymmetry in herding between up and down markets, the effect of VIX along with the significance of expected and unexpected sector/market illiquidity as a significant channel for the development of herding within sub-sector REITs during recessionary and non-recessionary phases. Given the fact that herding could drive asset prices away from their fundamental value, this could result in a co-movement of asset prices reducing the benefits of diversification. Furthermore, the fact that it could exaggerate negative shocks, makes herding a significant topic of research for academics, practitioners and policy makers.

Although extensive research has been conducted on herding within the stock market, REITs provide an interesting market to study since US REITs are reported to have a low correlation with stocks since the late 1990s (Stephen and Simon, 2005), their uniqueness in terms of their returns not being replicated by other asset classes (Stephen and Simon, 2005), their growing market capitalization (NAREIT, 2022), and their relevance as a substitute for conventional real estate investments (Clayton and Mackinnon, 2003), all factors that have increased the significance of REITs as a diversification tool in a multi-asset portfolio. Crotty (2009) considered illiquidity to be a major source for the 2007/08 financial crisis, concluding that asset prices react significantly to liquidity effects, while Bali et al. (2016) support the idea that aggregate liquidity plays a significant role in asset pricing. The fact that REITs by regulation have to distribute 90% of their taxable income as dividends in order to maintain their REIT status (Boudry 2011), becomes our biggest motivation to assess the impact of illiquidity as a channel that prospectively enhances herding within REITs. The regulation implies that retained earnings only contribute a small proportion of new investment within the industry, and a fall in liquidity from traditional sources such as credit lines, would put significant pressure on REITs operations and earnings potential. (Huerta, Egly and Escobari, 2016).

The research uses daily data from 2nd January 2014 to 28th February 2022, providing significant data points during and after the Covid-19 outbreak, and hence making this data set quite unique. Using Chang et. al (2000) measure of cross-sectional absolute deviation (CSAD), we find significant evidence of herding within REITs on a sub-sector level, along with utilizing a dummy approach to establish that herding is more intense for all REITs and within Health, Hotel, Retail and Warehouse sectors, on days with negative market returns relative to days with positive market returns. After identifying a structural break within our data set that corresponds with the outbreak of the Covid-19 pandemic, we apply a two-state Markov switching model, to establish that herding is prevalent within Health, Residential, Warehouse and Mortgage sectors, during the crash regime, and is only significantly present in the Mortgage sector, during the non-recessionary phase.

Using Amihud (2002), we construct variables for expected and unexpected sector illiquidity, and incorporate them within a two state Markov switching model. Our results show that for All REITs and all sub-sectors apart from health, increases in unexpected illiquidity are negatively related to the dispersion of REIT returns, and thus result in an enhancement in herding behaviour, during the crash regime. An explanation for the exclusion of the health sector has been provided in the previous section, and is primarily driven by significant government spending within the sector during the covid-19 phase, ensuring that prices within the sector continued to rise, resulting in a relative lack of negative investor sentiments towards this sector, and thus driving down herding behaviour even during times of liquidity strain. Our non-recessionary results indicate the significance of expected illiquidity shocks, in enhancing herding behaviour within residential, retail and warehouse sectors. These results not only justify the use of expected and unexpected components when studying the impact of sector-wide illiquidity, especially with a structural break within the data set, but it is also a testament to the unique nature of each REIT sub-sector. These results are also confirmed by running two separate OLS regressions, using the structural break dates as identified by the Quandt-Andrews breakpoint test, and providing robustness to our study. Finally, we incorporate for market-wide expected and unexpected illiquidity shocks within our two-state Markov switching model, in order to assess their impact on sector-wide herding. Our results show that within both recessionary and non-recessionary states, herding within hotel, mortgage, retail and residential sectors is positively influenced by market-wide illiquidity shocks, confirming the role market illiquidity shocks play in influencing sub-sector REIT herding. However, the impact in the non-recessionary state is felt via a rise in expected market-wide illiquidity, while during the crash phase, it is unexpected market-wide illiquidity shocks that significantly influence herding behaviour.

Future extensions to this study could look at other channels apart from liquidity which may influence sub-sector herding within REITs, along with assessing the impact on REIT industries in other geographies. The study of liquidity as an amplification channel for herding can also be extrapolated towards other asset markets.

CHAPTER 6: Conclusion

The thesis has progressed the empirical knowledge on asset pricing and behavioural finance, along with consolidating on theoretical frameworks within the field. Chapter 3 investigates the significance of illiquidity as an investment style within US equities, along with assessing the relationship between illiquidity premiums, oil price, oil price volatility, and several other macroeconomic variables. Chapter 4 explores the significance of factor based premiums in the REIT market, along with exploring their risk based explanation, after which, it looks to study the relationship between factor based premiums, and, financial distress and liquidity crisis. Chapter 5 investigates the presence of herding behaviour in US REITs on a sub-sector, and then explores the relationship between market and sector-wide illiquidity, on sub-sector herding under varying states of the world.

Highlights from Chapter 3

Key findings

Consistent with the theoretical framework of Amihud and Mendelson (1986), we find illiquidity premiums to be positive and significant within US stocks, during both recessionary and non-recessionary states. This conclusion not only helps consolidate on the fact that illiquidity is a risk factor that is priced in within stocks, but also creates profitable avenues for investors by constructing style based investment strategies i.e. going long on illiquid stocks and going short on liquid stocks, to earn a premium, regardless of recessionary or non-recessionary states.

Our results also indicate that realised illiquidity premiums have a significantly positive relationship with oil price in the non-recessionary period, and a significant negative relationship during the recessionary state. In terms of the impact or oil price volatility, we find that the OVX index has a negative relationship with realised illiquidity premiums in the non-recessionary state, while this influence seems largely insignificant during the recessionary state. The relationships are potentially driven by market sentiments and market liquidity. Lastly, in assessing asymmetry in impact, Illiquidity premiums do not show any asymmetric responses to oil price changes but our results do indicate significant evidence of asymmetric response to OVX changes.

Implications for investors and possible extensions for further academic research

The research has significant implications for investors, specifically ones that have a buy-to-sell approach when it comes to designing a stylised stock investment strategy based on liquidity. The research outlines the impact that oil price, oil price volatility, and macroeconomic indicators have on the realisation of illiquidity premiums, for investors who already have a long position in illiquid stocks and a corresponding short position in liquid stocks. The research has further implications for investors who not only hold a style based liquidity strategy within stocks, but also have holdings within oil as a commodity, in a multi-asset setting. Our results suggest that during non-recessionary states, a fall in oil price, also results in a corresponding fall in illiquidity premiums. Given the direction of this relationship during the non-recessionary state, investors can look at various avenues to diversify against this co-movement. Our results show that returns on the dollar against the euro display a negative correlation with oil prices, along with our short-run Error Correction Model displaying a negative impact of the US Dollar/Euro rate on illiquidity premiums. Investors in a multi-asset portfolio setting, within non-recessionary states, could then hedge their existing long positions in illiquid-liquid stocks and oil, by going long in the US Dollar.

The negative impact of oil price on realised illiquidity premiums during the recessionary state implies that, investors with holdings within both as part of a multi-asset portfolio, would already see movements in opposite directions based on their positions. Our results also indicate that inflation has a significant and positive impact on illiquidity premiums. During times of heightened inflation, central banks' monetary stance would generally be towards interest rate hikes and tightening. Investors can diversify their risks by looking at opportunities within bonds, which might have a more lucrative interest bearing return during times of monetary contraction. While during times of falling inflation, central banks might be looking to cut interest rates and in-turn follow a policy of monetary expansion. This could potentially reduce returns on interest bearing bonds, and non-interest bearing safe haven investments such as gold might seem lucrative for investors.

The research within this chapter is useful for academics looking to analyse the impact of oil price and oil volatility on illiquidity premiums in the short- and long-run, within a recession and post-recession phase. This can be extended on over various other geographies along with possibly assessing the impact of other macroeconomic factors on illiquidity premiums. With an ever-expanding asset universe and an increase in availability of information to investors, this research will also be useful for practitioners looking to gauge the usefulness of illiquidity as an investment style for portfolio optimisation, investment strategies during and after a recessionary phase, and investors looking to hedge against oil price movements and oil price volatility within the long- and short-run.

Highlights from Chapter 4

Key findings

Consistent with the findings of Fama and French (1992, 2015) and Carhart (1997), we find significant and positive premiums associated with size, value, profitability, investment and momentum factors in the US REIT market. Consistent with the Efficient Market Hypothesis put forward by Fama (1970), the thesis finds the size, profitability and investment premiums to be associated with a higher risk, and therefore solidifies their role as proxies for systematic risk. In contradiction to the Efficient Market Hypothesis, the thesis finds no significant rise in risk associated with value and momentum strategies, contradicting the belief that these factors might be proxies for systematic risk.

Owing to the lack of significant evidence in terms of a rise in systematic risk with regards to certain factor based premiums in the REIT market, the chapter examines the impact of financial distress and liquidity crisis, on factor based premiums within the US REIT market, controlling for stock market returns, in order to assess whether these risk factors are priced within the factor premiums. Our key findings, which have significant takeaways for investors, suggest that the momentum and value premiums contradict the risk based explanation, as we find significant evidence of a fall in momentum premiums during the recessionary state, and no significant rise within value premiums in the non-recessionary state, corresponding to an uptick in default risk and liquidity risk.

Implications for investors and possible extensions for further academic research

In a nutshell, the WML strategy might assist investors in generating excess returns without a corresponding rise in risk during recessionary phases, while the HML strategy might only be able to achieve this for investors during non-recessionary states.

The research also has implications for investors from a portfolio diversification perspective in a multi-asset setting with exposure to common stocks. Our regression results show a negative relationship between S&P500 index and WML premiums, both during recessionary and non-recessionary states. Furthermore, we also find a significant negative correlation between WML premiums and the S&P500 index. This confirms the fact that investors with a multi-asset portfolio, with indexed exposure to the stock market, would benefit from diversification perks that a WML strategy within REITs can bring along, during both recessionary and non-recessionary states. For HML premiums, we only find a significant negative relationship between the S&P500 index and HML premiums during the non-recessionary phase. This is supported by significant and negative correlation levels between the two variables. Investors can therefore utilise HML strategies within REITs to diversify a portfolio with indexed stock market exposure, during non-recessionary states.

This research is useful for academics and practitioners looking to analyze the impact of default risk, liquidity crisis and the stock market on factor based premiums in the US REIT market, in the short- and long-run, within recessionary and non-recessionary phases. This can be extended on over other geographies, along with assessing the impact of other macroeconomic factors on these factor premiums. Another possible extension could be to assess role of mispricing and arbitrage risk within the existence of these premiums, especially within RMW and CMA premiums, as it is currently an under-researched segment, and would greatly assist in understanding the interpretation of these factor based premiums. This research will also be useful for practitioners looking to strategise efficiently during recessionary and expansionary phases, in terms of diversification in a multi-asset portfolio, balancing risk and return, and utilizing factor based investment strategies within portfolio optimization.

Highlights from Chapter 5

Key findings

Following the lack of evidence, we find in terms of conventional risk factors, illiquidity, and financial distress, being priced within certain premiums in the US REIT market, chapter five looks to see if behavioral traits such as herding plays a part in the pricing of US REITs. Utilising Chang et. Al (2000)'s methodology of cross-sectional absolute deviation (CSAD), and consistent with Banerjee (1992)'s theoretical model, we find herding behaviour to be prevalent in US REITs on a sub-sector level. Our results confirm that sub-sector herding within US REITs is more intense during down markets relative to up markets, and is more prevalent during crash regimes relative to non-recessionary phases. Our results also indicate that as investors' fear and uncertainty rises, or when investor sentiments are low, herding behaviour becomes more intense.

The fact that REITs by regulation have to distribute 90% of their taxable income as dividends in order to maintain their REIT status (Boudry 2011), becomes our biggest motivation to assess the impact of illiquidity as a channel that prospectively enhances herding within REITs. The regulation implies that retained earnings only contribute a small proportion of new investment within the industry, and a fall in liquidity from traditional sources such as credit lines, would put significant pressure on REITs operations and earnings potential (Huerta, Egly and Escobari, 2016). Disentangling the Amihud (2002) illiquidity measure into expected and unexpected components, our results suggest that during the crash regime, a rise in unexpected sector illiquidity enhances herding in all REIT sub-sectors apart from health, while during the non-recessionary phase, expected illiquidity shocks have a significant part to play in enhancing herding within residential, retail and warehouse sectors.

These results not only justify the use of expected and unexpected components when studying the impact of sector-wide illiquidity, especially with a structural break within the data set, but it is also a testament to the unique nature of each REIT sub-sector. The lack of significance of unexpected illiquidity shocks during the non-recessionary state also implies that the channel of influence between a rise in unexpected illiquidity and investor sentiments towards heightened future illiquidity, might be weak during these expansionary phases. Finally, we incorporate for market-wide illiquidity shocks, and find that during the non-recessionary states, herding is positively impacted only by expected market-wide illiquidity shocks, while during the recessionary state, only unexpected market-wide illiquidity shocks enhance herding.

Implications for investors and possible extensions for further academic research

Capozza and Seguin (1998) discuss the benefits of constructing diversified REIT portfolios based on sector distinctions. Based on our results though, these perks of diversification might be eroded by herding effects within the sector. During the recessionary state, a rise in unexpected illiquidity enhances herding within 5 out of 6 REIT sub sectors. This co-movement in prices within REIT sub-sectors is significant in investors' decision making, as it could potentially erode investors' ability to curb risk via diversification (Chiang and Zheng, 2010). Shin (2010) claim that such co-movements in asset prices pose a greater threat during economic downturns, as initial downward movements could spiral into exaggerated negative shocks, which could pose significant risks to the overall stability of the financial system.

Herding within these REIT sectors could also potentially result in asset prices moving away from their fundamental values, along with the risk of the creation of an asset bubble. Given this scenario during the crash regime, investors might be better off making focused REIT investments within a particular sector (focusing their expertise on this one particular sector), and then diversifying their portfolio by constructing exposures to liquid common stocks. The idea of diversifying using liquid common stocks is based on a two-fold rationale; i) As REITs are required to distribute 90% of their taxable income as dividends, a rise in unexpected illiquidity could significantly impact REIT performance. If such a scenario was coupled with holdings of illiquid stocks within an investors' portfolio, then the overall portfolio could run a significantly high liquidity risk. ii) The reported low correlation, and inverse relationship, between US common stocks and US REITs (Chaudhry et al., 1999; Stephen and Simon, 2005).

In the non-recessionary phase, our results suggest that investors' should take a focused approach and invest within either retail, residential or warehouse sectors. The rationale for this is that all three of these sectors show co-movements and a joint rise in herding, with a rise in expected illiquidity. Investors can then utilise the mortgage, hotel and health sectors, as a diversification measure within REITs. Overall, we would expect investors to follow the 15 to 25% proportion that Hoesli et al. (2004) sets out as the optimal allocation towards real estate in a multi-asset portfolio.

Given the fact that herding could drive asset prices away from fundamental value, could result in a co-movement of asset prices reducing the benefits of diversification, and the fact that it could exaggerate negative shocks, makes herding a significant topic of research for academics, practitioners and policy makers. Future extensions to this study could look at other channels apart from liquidity which may influence sub-sector herding within REITs, along with assessing the impact on REIT industries in other geographies. The study of liquidity as an amplification channel for herding can also be extrapolated towards other asset markets.

To conclude , this thesis has: (i) confirmed the existence of illiquidity premiums in US stocks, along with assessing the impact of oil price and oil price volatility on these premiums, controlling for macroeconomic indicators, under recessionary and non-recessionary states; (ii) confirmed the presence of factor based premiums in the US REIT market, along with assessing if these premiums are associated with a higher risk exposure, and analysed the impact of financial distress and liquidity crisis on these premiums, under varying market conditions; (iii) established the presence and significance of herding within US REITs on a sub-sector level, confirming that herding is relatively more intense during down markets/days with negative returns, along with establishing the significance of expected and unexpected sector/market-wide illiquidity shocks on sub-sector herding, under a two-state Markov Regime.

References

Acharya, V.V. and Pedersen, L.H., 2005. Asset pricing with liquidity risk. *Journal of financial Economics*, *77*(2), pp.375-410.

Akdi, Y., Varlik, S. and Berument, M.H., 2020. Duration of global financial cycles. *Physica A: Statistical Mechanics and its Applications,* 549, p.124331.

Ali, A., Hwang, L.S. and Trombley, M.A., 2003. Arbitrage risk and the book-to-market anomaly. *Journal of Financial Economics*, 69(2), pp.355-373.

Ali, F. and Ülkü, N., 2019. Monday effect in the RMW and the short-term reversal factors. *International Review of Finance*, 19(3), pp.681-691.

Allen, M.T., Madura, J. and Springer, T.M., 2000. REIT characteristics and the sensitivity of REIT returns. *Journal of Real Estate Finance and Economics*, 21(2), p.141.

Amihud, Y. and Mendelson, H., 1986. Liquidity and stock returns. *Financial Analysts Journal*, *42*(3), pp.43-48.

Amihud, Y. and Mendelson, H., 1991. Liquidity, maturity, and the yields on US Treasury securities. *The Journal of Finance*, 46(4), pp.1411-1425.

Amihud, Y., 2002. Illiquidity and stock returns: cross-section and time-series effects. *Journal of financial markets*, 5(1), pp.31-56.

Amihud, Y., 2018. Illiquidity and stock returns: A revisit. *Critical Finance Review, Forthcoming*.

Amihud, Y., Hameed, A., Kang, W. and Zhang, H., 2015. The illiquidity premium: International evidence. *Journal of financial economics*, *117*(2), pp.350-368.

Ang, A., Hodrick, R.J., Xing, Y. and Zhang, X., 2006. The cross-section of volatility and expected returns. *The journal of finance*, 61(1), pp.259-299.

Ang, A., Shtauber, A.A. and Tetlock, P.C., 2013. Asset pricing in the dark: The cross-section of OTC stocks. *The Review of Financial Studies*, 26(12), pp.2985-3028.

Babalos, V., Balcilar, M. and Gupta, R., 2015. Herding behavior in real estate markets: novel evidence from a Markov-switching model. *Journal of Behavioral and Experimental Finance*, *8*, pp.40-43.

Baker, M. and Wurgler, J., 2006. Investor sentiment and the cross-section of stock returns. *The journal of Finance*, *61*(4), pp.1645-1680.

Bali, T.G., Engle, R.F. and Murray, S., 2016. *Empirical asset pricing: The cross section of stock returns*. John Wiley & Sons.

Balke, N.S., Brown, S.P. and Yucel, M.K., 2002. Oil price shocks and the US economy: Where does the asymmetry originate?. *The Energy Jou*rnal, 23(3).

Banerjee, A.V., 1992. A simple model of herd behavior. *The quarterly journal of economics*, 107(3), pp.797-817.

Barkham, R. and Ward, C., 1999. Investor sentiment and noise traders: Discount to net asset value in listed property companies in the UK. *Journal of Real Estate Research*, 18(2), pp.291-312.

Bašta, M. and Molnár, P., 2018. Oil market volatility and stock market volatility. *Finance Research Letters*, 26, pp.204-214.

Baum, C.F., Caglayan, M., Ozkan, N. and Talavera, O., 2006. The impact of macroeconomic uncertainty on non-financial firms' demand for liquidity. *Review of financial economics,* 15(4), pp.289-304.

Bekaert, G., Harvey, C.R. and Lundblad, C., 2007. Liquidity and expected returns: Lessons from emerging markets. *The review of financial studies*, *20*(6), pp.1783-1831.

Ben-Rephael, A., Kadan, O. and Wohl, A., 2008. The diminishing liquidity premium. SSRN Electronic Journal. *Center for Financial Studies* (CFS) Working Paper, No. 2008/52.

Ben-Rephael, A., Kadan, O. and Wohl, A., 2015. The diminishing liquidity premium. *Journal of Financial and Quantitative Analysis,* 50(1-2), pp.197-229.

Benveniste, L., Capozza, D.R. and Seguin, P.J., 2001. The value of liquidity. *Real estate economics*, *29*(4), pp.633-660.

Bernanke, B.S., 1983. Irreversibility, uncertainty, and cyclical investment. *The quarterly journal of economics*, 98(1), pp.85-106.

Blau, B.M., Griffith, T. and Whitby, R.J., 2020. Comovement in the cryptocurrency market. *Economics Bulletin*, *40*(1), p.1.

Bond, S. and Xue, C., 2017. The cross section of expected real estate returns: Insights from investment-based asset pricing. *The Journal of Real Estate Finance and Economics*, 54, pp.403-428.

Boudry, W.I., 2011. An examination of REIT dividend payout policy. *Real Estate Economics*, *39*(4), pp.601-634.

Bouri, E., Gupta, R. and Wang, S., 2020. Nonlinear contagion between stock and real estate markets: International evidence from a local Gaussian correlation approach. *International Journal of Finance & Economics*, 27(2), pp.2089-2109.

Bowe, M. and Domuta, D., 2004. Investor herding during financial crisis: A clinical study of the Jakarta Stock Exchange. *Pacific-Basin Finance Journal*, 12(4), pp.387-418.

Breen, W., Glosten, L.R. and Jagannathan, R., 1989. Economic significance of predictable variations in stock index returns. *The Journal of finance*, 44(5), pp.1177-1189.

Brennan, M.J. and Subrahmanyam, A., 1996. Market microstructure and asset pricing: On the compensation for illiquidity in stock returns. *Journal of financial economics*, 41(3), pp.441-464.

Brown, K.C., Harlow, W.V. and Tinic, S.M., 1988. Risk aversion, uncertain information, and market efficiency. *Journal of financial economics*, 22(2), pp.355-385.

Brunnermeier, M.K. and Pedersen, L.H., 2009. Market liquidity and funding liquidity. *The review of financial studies*, 22(6), pp.2201-2238.

Caballero, R.J. and Krishnamurthy, A., 2009. Global imbalances and financial fragility. *American Economic Review*, 99(2), pp.584-588.

Campbell, J.Y., Hilscher, J. and Szilagyi, J., 2008. In search of distress risk. *The Journal of finance*, 63(6), pp.2899-2939.

Cannon, S.E. and Cole, R.A., 2011. Changes in REIT liquidity 1988–2007: evidence from daily data. *The Journal of Real Estate Finance and Economics*, 43, pp.258-280.

Capozza, D. and Korean, S., 1995. Property type, size and REIT value. *Journal of Real Estate Research*, *10*(4), pp.363-379.

Carhart, M.M., 1997. On persistence in mutual fund performance. *The Journal of finance*, 52(1), pp.57-82.

Cesa-Bianchi, A., Cespedes, L.F. and Rebucci, A., 2015. Global liquidity, house prices, and the macroeconomy: Evidence from advanced and emerging economies. *Journal of Money, Credit and Banking*, 47(S1), pp.301-335.

Cetorelli, N., Goldberg, L.S. and Ravazzolo, F., 2020. *Have the Fed swap lines reduced dollar funding strains during the Covid-19 outbreak?* (No. 20200522). Federal Reserve Bank of New York.

Chalmers, J.M. and Kadlec, G.B., 1998. An empirical examination of the amortized spread. *Journal of Financial Economics*, 48(2), pp.159-188.

Chan, K.C. and Chen, N.F., 1991. Structural and return characteristics of small and large firms. *The journal of finance*, 46(4), pp.1467-1484.

Chang, C., 2010. Herding and the role of foreign institutions in emerging equity markets. *Pacific-Basin Finance Journal*, 18(2), pp.175-185.

Chang, E.C., Cheng, J.W. and Khorana, A., 2000. An examination of herd behavior in equity markets: An international perspective. *Journal of Banking & Finance*, *24*(10), pp.1651-1679.

Chaudhry, M.K., Neil Myer, F.C. and Webb, J.R., 1999. Stationarity and cointegration in systems with real estate and financial assets. *The Journal of Real Estate Finance and Economics*, *18*, pp.339-349.

Chen, N.F. and Zhang, F., 1998. Risk and return of value stocks. *The Journal of Business*, *71*(4), pp.501-535.

Chen, S.S., 2010. Do higher oil prices push the stock market into bear territory?. *Energy Economics,* 32(2), pp.490-495.

Chevapatrakul, T., 2014. Monetary environments and stock returns revisited: A quantile regression approach. *Economics Letters*, 123(2), pp.122-126.

Chiang, T.C. and Zheng, D., 2010. An empirical analysis of herd behavior in global stock markets. *Journal of Banking & Finance*, *34*(8), pp.1911-1921.

Cho, H., 2017. The role of sub-sector REITs in mixed-asset portfolios in Japan. *Journal of Real Estate Literature*, *25*(2), pp.389-408.

Choe, H., Kho, B.C. and Stulz, R.M., 1999. Do foreign investors destabilize stock markets? The Korean experience in 1997. *Journal of Financial economics,* 54(2), pp.227-264.

Choi, N. and Sias, R.W., 2009. Institutional industry herding. *Journal of financial economics,* 94(3), pp.469-491.

Christie, W.G. and Huang, R.D., 1995. Following the pied piper: do individual returns herd around the market?. *Financial Analysts Journal*, *51*(4), pp.31-37.

Chui, A.C., Titman, S. and Wei, K.J., 2003. The cross section of expected REIT returns. *Real Estate Economics*, 31(3), pp.451-479.

Chung, R., Fung, S., Shilling, J.D. and Simmons–Mosley, T.X., 2016. REIT stock market volatility and expected returns. *Real Estate Economics*, 44(4), pp.968-995.

Clayton, J. and MacKinnon, G., 2003. The relative importance of stock, bond and real estate factors in explaining REIT returns. *The Journal of Real Estate Finance and Economics*, *27*, pp.39-60.

Corwin, S.A. and Schultz, P., 2012. A simple way to estimate bid-ask spreads from daily high and low prices. *The journal of finance*, *67*(2), pp.719-760.

Crotty, J., 2009. Structural causes of the global financial crisis: a critical assessment of the 'new financial architecture'. *Cambridge journal of economics*, *33*(4), pp.563-580.

Cunado, J. and de Gracia, F.P., 2014. Oil price shocks and stock market returns: Evidence for some European countries. *Energy Economics*, 42, pp.365-377.

Datar, V.T., Naik, N.Y. and Radcliffe, R., 1998. Liquidity and stock returns: An alternative test. *Journal of financial markets*, 1(2), pp.203-219.

De Long, J.B., Shleifer, A., Summers, L.H. and Waldmann, R.J., 1990. Noise trader risk in financial markets. *Journal of political Economy*, *98*(4), pp.703-738

Demirer, R. and Kutan, A.M., 2006. Does herding behavior exist in Chinese stock markets?. *Journal of international Financial markets, institutions and money*, *16*(2), pp.123-142.

Diaz, E.M., Molero, J.C. and de Gracia, F.P., 2016. Oil price volatility and stock returns in the G7 economies. *Energy Economics*, 54, pp.417-430.

Driesprong, G., Jacobsen, B. and Maat, B., 2007. Striking oil: another puzzle?. *Journal of financial economics*, 89(2), pp.307-327.

Dupoyet, B.V. and Shank, C.A., 2018. Oil prices implied volatility or direction: Which matters more to financial markets?. *Financial Markets and Portfolio Management*, 32, pp.275-295.

Dutta, A., Nikkinen, J. and Rothovius, T., 2017. Impact of oil price uncertainty on Middle East and African stock markets. *Energy*, 123, pp.189-197.

Easley, D. and O'Hara, M., 1992. Adverse selection and large trade volume: The implications for market efficiency. *Journal of Financial and Quantitative Analysis*, 27(2), pp.185-208.

Economou, F., Kostakis, A. and Philippas, N., 2011. Cross-country effects in herding behaviour: Evidence from four south European markets. *Journal of International Financial Markets, Institutions and Money*, 21(3), pp.443-460.

Edelen, R.M., Ince, O.S. and Kadlec, G.B., 2016. Institutional investors and stock return anomalies. *Journal of Financial Economics*, 119(3), pp.472-488.

Eia.gov. 2018. U.S. Energy Information Administration (EIA). Available online: https://www.eia.gov/ (accessed on). September 02, 2019

Elder, J. and Serletis, A., 2010. Oil price uncertainty. *Journal of Money, Credit and Banking*, 42(6), pp.1137-1159.

Eleswarapu, V.R. and Reinganum, M.R., 1993. The seasonal behavior of the liquidity premium in asset pricing. *Journal of Financial Economics*, 34(3), pp.373-386.

Elfakhani, S., 2000. Short positions, size effect, and the liquidity hypothesis: implications for stock performance. *Applied Financial Economics*, 10(1), pp.105-116.

Elgammal, M.M. and McMillan, D.G., 2014. Value premium and default risk. *Journal of Asset Management*, 15, pp.48-61.

Elgammal, M.M., Bas, T., Gough, O., Shah, N. and van Dellen, S., 2016. Do financial distress and liquidity crises affect value and size premiums? *Applied Economics*, 48(39), pp.3734-3751.

Essa, M.S. and Giouvris, E., 2020. Oil price, oil price implied volatility (OVX) and illiquidity premiums in the US:(a) symmetry and the impact of macroeconomic factors. *Journal of Risk and Financial Management*, *13*(4), pp.70

Essa, M.S. and Giouvris, E., 2023. Fama–French–Carhart Factor-Based Premiums in the US REIT Market: A Risk Based Explanation, and the Impact of Financial Distress and Liquidity Crisis from 2001 to 2020. *International Journal of Financial Studies*, *11*(1), pp.12

Eun, C.S., Lai, S., Roon, F.A.D. and Zhang, Z., 2010. International diversification with factor funds. *Management Science*, 56(9), pp.1500-1518.

Fama, E.F. and French, K.R., 1992. The cross-section of expected stock returns. *The Journal of Finance,* 47(2), pp.427-465.

Fama, E.F. and French, K.R., 1996. Multifactor explanations of asset pricing anomalies. *The journal of finance*, 51(1), pp.55-84.

Fama, E.F. and French, K.R., 2006. The value premium and the CAPM. *The Journal of Finance*, 61(5), pp.2163-2185.

Fama, E.F. and French, K.R., 2017. International tests of a five-factor asset pricing model. *Journal of financial Economics*, 123(3), pp.441-463.

Fama, E.F., 1970. Efficient capital markets: A review of theory and empirical work. *The journal of Finance,* 25(2), pp.383-417.

Fang, H., Chang, T.Y., Lee, Y.H. and Chen, W.J., 2016. The impact of macroeconomic factors on the real estate investment trust index return on Japan, Singapore and China. *Investment Management and Financial Innovations*, 13(4), pp.242-253.

Ferderer, J.P., 1996. Oil price volatility and the macroeconomy. *Journal of macroeconomics*, 18(1), pp.1-26.

Fernández-Amador, O., Gächter, M., Larch, M. and Peter, G., 2013. Does monetary policy determine stock market liquidity? New evidence from the euro zone. *Journal of Empirical Finance*, 21, pp.54-68.

Foroni, C., Guérin, P. and Marcellino, M., 2017. Explaining the time-varying effects of oil market shocks on US stock returns. *Economics Letters*, 155, pp.84-88.

Foster, F.D. and Viswanathan, S., 1990. A theory of the interday variations in volume, variance, and trading costs in securities markets. *The Review of Financial Studies*, 3(4), pp.593-624.

Gai, P. and Vause, N., 2005. Measuring investors' risk appetite. *International Journal of Central Banking* 2: 167-188.

Galariotis, E & Giouvris, E, 2009 Systematic Liquidity and Excess Returns: Evidence From The London Stock Exchange. *The Review Of Accounting & Finance*:, 8 (3), pp. 279-307, https://doi.org/10.1108/14757700910980868

Galariotis, E and Giouvris, E, 2007 Liquidity Commonality On The London Stock Exchange, *Journal Of Business Finance And Accounting*, 34(1), pp. 374-388

Galariotis, E.C. and Giouvris, E., 2009. Systematic liquidity and excess returns: Evidence from the London stock exchange. *Review of Accounting and Finance*, 8(3), pp.279-307.

Galariotis, E.C., Krokida, S.I. and Spyrou, S.I., 2016. Herd behavior and equity market liquidity: Evidence from major markets. *International Review of Financial Analysis*, 48, pp.140-149

Galariotis, E.C., Rong, W. and Spyrou, S.I., 2015. Herding on fundamental information: A comparative study. *Journal of Banking & Finance*, 50, pp.589-598.

Garlappi, L. and Yan, H., 2011. Financial distress and the cross-section of equity returns. *The journal of finance,* 66(3), pp.789-822.

Gavriilidis, K., Kallinterakis, V. and Ferreira, M.P.L., 2013. Institutional industry herding: intentional or spurious?. Journal of International Financial Markets, *Institutions and Money*, 26, pp.192-214.

Gavriilidis, K., Kallinterakis, V. and Tsalavoutas, I., 2016. Investor mood, herding and the Ramadan effect. *Journal of Economic Behavior & Organization*, 132, pp.23-38.

Gertler, M. and Bernanke, B., 1989. Agency costs, net worth and business fluctuations. In Business cycle theory. Edward Elgar Publishing Ltd.

Giesecke, K., Longstaff, F.A., Schaefer, S. and Strebulaev, I.A., 2014. Macroeconomic effects of corporate default crisis: A long-term perspective. *Journal of Financial Economics*, 111(2), pp.297-310.

Glascock, J.L. and Lu-Andrews, R., 2014. The profitability premium in real estate investment trusts. *Available at SSRN 2375431*.

Glascock, J.L., Lu, C. and So, R.W., 2000. Further evidence on the integration of REIT, bond, and stock returns. *The Journal of Real Estate Finance and Economics*, *20*, pp.177-194.

Gleason, K.C., Mathur, I. and Peterson, M.A., 2004. Analysis of intraday herding behavior among the sector ETFs. *Journal of empirical Finance*, 11(5), pp.681-694.

Glosten, L.R. and Milgrom, P.R., 1985. Bid, ask and transaction prices in a specialist market with heterogeneously informed traders. *Journal of financial economics*, 14(1), pp.71-100.

Goebel, P.R., Harrison, D.M., Mercer, J.M. and Whitby, R.J., 2013. REIT momentum and characteristic-related REIT returns. *The Journal of Real Estate Finance and Economics*, 47, pp.564-581.

González-Hermosillo, B., 2008. Investors risk appetite and global financial market conditions. Washington, DC: International Monetary Fund.

Goyenko, R.Y. and Ukhov, A.D., 2009. Stock and bond market liquidity: A long-run empirical analysis. *Journal of Financial and Quantitative Analysis*, 44(1), pp.189-212.

Griffin, J.M. and Lemmon, M.L., 2002. Book-to-market equity, distress risk, and stock returns. *The Journal of Finance*, 57(5), pp.2317-2336.

Grinblatt, M., Titman, S. and Wermers, R., 1995. Momentum investment strategies, portfolio performance, and herding: A study of mutual fund behavior. *The American economic review,* pp.1088-1105.

Güntner, J.H., 2014. How do oil producers respond to oil demand shocks?. *Energy Economics*, 44, pp.1-13.

Gutierrez, R.C. and Kelley, E.K., 2009. Institutional herding and future stock returns. Available at SSRN 1107523.

Gyourko, J. and Keim, D.B., 1992. What does the stock market tell us about real estate returns?. *Real Estate Economics*, *20*(3), pp.457-485.

Hahn, J. and Lee, H., 2006. Yield spreads as alternative risk factors for size and book-to-market. *Journal of Financial and Quantitative Analysis*, 41(2), pp.245-269.

Hamilton, J.D., 1996. This is what happened to the oil price-macroeconomy relationship. *Journal of monetary economics*, 38(2), pp.215-220.

Hamilton, J.D., 2003. What is an oil shock?. *Journal of econometrics*, 113(2), pp.363-398.

Harrison, D.M., Panasian, C.A. and Seiler, M.J., 2011. Further evidence on the capital structure of REITs. *Real Estate Economics*, 39(1), pp.133-166.

Hasbrouck, J., 2002. Trading costs and returns for US equities: The evidence from daily data. *NYU Stern School Department of Finance Working Paper*.

Hasbrouck, J., 2007. Empirical market microstructure: The institutions, economics, and econometrics of securities trading. Oxford University Press.

Herrera, A.M., Lagalo, L.G. and Wada, T., 2011. Oil price shocks and industrial production: Is the relationship linear?. *Macroeconomic dynamics*, 15(S3), pp.472-497.

Herrera, A.M., Lagalo, L.G. and Wada, T., 2015. Asymmetries in the response of economic activity to oil price increases and decreases?. *Journal of International Money and Finance*, 50, pp.108-133.

Hibbert, J., Kirchner, A., Kretzschmar, G., Li, R. and McNeil, A., 2009. Liquidity premium: Literature review of theoretical and empirical evidence. *Barrie & Hibbert research report*.

Hoesli, M., Kadilli, A. and Reka, K., 2017. Commonality in liquidity and real estate securities. *The Journal of Real Estate Finance and Economics*, *55*, pp.65-105.

Hoesli, M., Lekander, J. and Witkiewicz, W., 2004. International evidence on real estate as a portfolio diversifier. *Journal of Real Estate Research*, *26*(2), pp.161-206.

Hondroyiannis, G. and Papapetrou, E., 2001. Macroeconomic influences on the stock market. *Journal of economics and finance*, 25(1), pp.33-49.

Huang, J.Z. and Huang, M., 2012. How much of the corporate-treasury yield spread is due to credit risk?. *The Review of Asset Pricing Studies*, 2(2), pp.153-202.

Huang, M., 2003. Liquidity shocks and equilibrium liquidity premia. *Journal of Economic Theory*, 109(1), pp.104-129.

Huang, Y., Yang, J. and Zhang, Y., 2013. Value premium in the Chinese stock market: free lunch or paid lunch?. *Applied Financial Economics*, 23(4), pp.315-324.

Huberman, G. and Halka, D., 2001. Systematic liquidity. *Journal of Financial Research*, *24*(2), pp.161-178.

Huerta, D., Egly, P.V. and Escobari, D., 2016. The liquidity crisis, investor sentiment, and REIT returns and volatility. *Journal of Real Estate Portfolio Management*, *22*(1), pp.47-62.

Hull, J., Predescu, M. and White, A., 2004. The relationship between credit default swap spreads, bond yields, and credit rating announcements. *Journal of banking & finance*, 28(11), pp.2789-2811.

Hung, S.Y.K. and Glascock, J.L., 2008. Momentum profitability and market trend: evidence from REITs. *The Journal of Real Estate Finance and Economics*, 37, pp.51-69.

Ibbotson, R.G., Chen, Z., Kim, D.Y.J. and Hu, W.Y., 2013. Liquidity as an investment style. *Financial Analysts Journal*, 69(3), pp.30-44.

Idzorek, T.M. and Kowara, M., 2013. Factor-based asset allocation vs. asset-class-based asset allocation. *Financial Analysts Journal*, 69(3), pp.19-29.

Ince, O.S. and Porter, R.B., 2006. Individual equity return data from Thomson Datastream: Handle with care!. *Journal of Financial Research*, *29*(4), pp.463-479.

Ivaschenko, I.V., 2003. How much leverage is too much, or does corporate risk determine the severity of a recession?. *SSRN Electronic Journal*. Available online: https://ssrn.com/abstract=879078

Jegadeesh, N. and Titman, S., 1993. Returns to buying winners and selling losers: Implications for stock market efficiency. *The Journal of finance*, 48(1), pp.65-91.

Jensen, G.R. and Moorman, T., 2010. Inter-temporal variation in the illiquidity premium. *Journal of Financial Economics*, 98(2), pp.338-358.

Jo, S., 2014. The effects of oil price uncertainty on global real economic activity. *Journal of Money, Credit and Banking,* 46(6), pp.1113-1135.

Johansen, A. and Sornette, D., 1999. Financial" anti-bubbles": Log-periodicity in gold and Nikkei collapses. *International Journal of Modern Physics C*, 10(04), pp.563-575.

Johansen, S. and Juselius, K., 1990. Maximum likelihood estimation and inference on cointegration--with applications to the demand for money. *Oxford Bulletin of Economics and statistics*, 52(2), pp.169-210.

Johanson, S., 1988. Statistical analysis of cointegration vectors. *Journal of economic dynamics and control.* 12: 231-254.

Johnson, T.C., 2002. Rational momentum effects. *The Journal of Finance*, 57(2), pp.585-608. Kaplan,

Kang, W., Hameed, A. and Viswanathan, S., 2010. Stock market declines and liquidity. *Journal of Finance*, 65: 257–93.

Kaplan, S.N. and Schoar, A., 2005. Private equity performance: Returns, persistence, and capital flows. *The journal of finance*, 60(4), pp.1791-1823.

Kaplan, S.N. and Schoar, A., 2005. Private equity performance: Returns, persistence, and capital flows. *The journal of finance*, 60(4), pp.1791-1823.

Karolyi, G.A. and Sanders, A.B., 1998. The variation of economic risk premiums in real estate returns. *The Journal of Real Estate Finance and Economics*, 17, pp.245-262.

Keynes, J.M., 1937. The general theory of employment. *The quarterly journal of economics,* 51(2), pp.209-223.

Kilian, L. and Murphy, D.P., 2012. Why agnostic sign restrictions are not enough: understanding the dynamics of oil market VAR models. *Journal of the European Economic Association,* 10(5), pp.1166-1188.

Kilian, L. and Park, C., 2009. The impact of oil price shocks on the US stock market. *International economic review*, 50(4), pp.1267-1287.

Kim, K.A. and Nofsinger, J.R., 2005. Institutional herding, business groups, and economic regimes: Evidence from Japan. *The Journal of Business*, 78(1), pp.213-242.

Kinateder, H. and Wagner, N., 2017. Oil and Stock Market Returns: Direction, Volatility or Liquidity?. SSRN Electronic Journal. doi:10.2139/ssrn.3085832(Lee 2011) Lee, Kuan-Hui. 2011. The world price of liquidity risk. *Journal of Financial Economics* 99: 136–61.

Krainer, J., Spiegel, M.M. and Yamori, N., 2010. Asset Price persistence and real estate market illiquidity: evidence from Japanese land values. *Real Estate Economics*, *38*(2), pp.171-196.

Kurov, A., 2010. Investor sentiment and the stock market's reaction to monetary policy. *journal of Banking & Finance*, *34*(1), pp.139-149.

Kyle, A.S., 1985. Continuous auctions and insider trading. Econometrica: *Journal of the Econometric Society*, pp.1315-1335.

Lakonishok, J., Schleifer, A. and Vishny, R.W., 2005. Contrarian investment, extrapolation, and risk. *Advances in Behavioral Finance*, 2, pp.273-316.

Lakonishok, J., Shleifer, A. and Vishny, R.W., 1992. The impact of institutional trading on stock prices. *Journal of financial economics*, 32(1), pp.23-43.

Lee, K.H., 2011. The world price of liquidity risk. *Journal of Financial Economics*, 99(1), pp.136-161.

Lee, S. and Stevenson, S., 2005. The case for REITs in the mixed-asset portfolio in the short and long run. *Journal of Real Estate Portfolio Management*, 11(1), pp.55-80.

Li, B., Sun, Q. and Wang, C., 2014. Liquidity, liquidity risk and stock returns: Evidence from Japan. *European Financial Management*, 20(1), pp.126-151.

Lim, S. and Giouvris, E., 2017. On the Pricing of Commonality Across Various Liquidity Proxies in the London Stock Exchange and the Crisis. In *Handbook of Investors' Behavior During Financial Crises* (pp. 447-470). Academic Press.

Lin, Z. and Vandell, K.D., 2007. Illiquidity and pricing biases in the real estate market. *Real Estate Economics*, *35*(3), pp.291-330.

Litimi, H., BenSaïda, A. and Bouraoui, O., 2016. Herding and excessive risk in the American stock market: A sectoral analysis. *Research in International Business and Finance*, 38, pp.6-21.

Liu, C.H., Hartzell, D.J. and Hoesli, M.E., 1997. International evidence on real estate securities as an inflation hedge. *Real estate economics*, *25*(2), pp.193-221.

Liu, L.X. and Zhang, L., 2008. Momentum profits, factor pricing, and macroeconomic risk. *The Review of Financial Studies*, 21(6), pp.2417-2448.

Lo, A.W., Mamaysky, H. and Wang, J., 2004. Asset prices and trading volume under fixed transactions costs. *Journal of Political Economy*, 112(5), pp.1054-1090.

Longstaff, F.A. and Schwartz, E.S., 1995. A simple approach to valuing risky fixed and floating rate debt. *The Journal of Finance*, 50(3), pp.789-819.

Luo, X. and Qin, S., 2017. Oil price uncertainty and Chinese stock returns: New evidence from the oil volatility index. *Finance Research Letters*, 20, pp.29-34.

Mah, J.S., 2000. An empirical examination of the disaggregated import demand of Korea—the case of information technology products. *Journal of Asian economics*, 11(2), pp.237-244.

Messis, P. and Zapranis, A., 2014. Herding towards higher moment CAPM, contagion of herding and macroeconomic shocks: Evidence from five major developed markets. *Journal of Behavioral and Experimental Finance*, 4, pp.1-13.

Miller, J.I. and Ratti, R.A., 2009. Crude oil and stock markets: Stability, instability, and bubbles. *Energy economics*, 31(4), pp.559-568.

Miranda-Agrippino, S. and Rey, H., 2015. World asset markets and the global financial cycle. Cambridge, MA: National Bureau of Economic Research.

Mobarek, A., Mollah, S. and Keasey, K., 2014. A cross-country analysis of herd behavior in Europe. *Journal of International Financial Markets, Institutions and Money*, 32, pp.107-127.

Mohanram, P.S., 2005. Separating winners from losers among lowbook-to-market stocks using financial statement analysis. *Review of accounting studies*, 10, pp.133-170.

Mohanty, S.K., Nandha, M., Turkistani, A.Q. and Alaitani, M.Y., 2011. Oil price movements and stock market returns: Evidence from Gulf Cooperation Council (GCC) countries. *Global Finance Journal*, 22(1), pp.42-55.

Molina, C.A., 2005. Are firms underleveraged? An examination of the effect of leverage on default probabilities. *The Journal of Finance*, 60(3), pp.1427-1459.

Mollick, A.V. and Assefa, T.A., 2013. US stock returns and oil prices: The tale from daily data and the 2008–2009 financial crisis. *Energy Economics*, 36, pp.1-18.

Morelli, D., 2010. European capital market integration: An empirical study based on a European asset pricing model. *Journal of International Financial Markets, Institutions and Money*, *20*(4), pp.363-375.

Mork, K.A., 1989. Oil and the macroeconomy when prices go up and down: an extension of Hamilton's results. *Journal of political Economy*, 97(3), pp.740-744.

Nandha, M. and Faff, R., 2008. Does oil move equity prices? A global view. *Energy economics*, 30(3), pp.986-997.

Narayan, P.K. and Sharma, S.S., 2011. New evidence on oil price and firm returns. *Journal of Banking & Finance*, 35(12), pp.3253-3262.

NAREIT (2022). REITs Widen Their Global Reach. Available at: https://www.reit.com/news/reit-magazine/march-april-2022/reits-widen-their-global-reach (Accessed 15 February 2023)

NAREIT (2022). REITWatch. Available at: https://www.reit.com/sites/default/files/reitwatch/RW2207.pdf (Accessed 15 February 2023)

NAREIT. 2022a. REITs Widen Their Global Reach. Available online: https://www.reit.com/news/reit-magazine/march-april-2022/reits-widen-their-global-reach (accessed on 15 November 2022).

NAREIT. 2022b. REIT Watch. Available online: https://www.reit.com/sites/default/files/reitwatch/RW2207.pdf (accessed on 15 November 2022).

Nazlioglu, S., Gormus, N. and Soytas, U., 2016. Oil prices and real estate investment trusts (REITs): Gradual-shift causality and volatility transmission analysis. *Energy Economics*, 60, pp. 168-175.

Nofsinger, J.R. and Sias, R.W., 1999. Herding and feedback trading by institutional and individual investors. *The Journal of finance*, *54*(6), pp.2263-2295.

Novy-Marx, R., 2004. On the excess returns to illiquidity. Center for Research in Security Prices, Graduate School of Business, University of Chicago.

Novy-Marx, R., 2013. The other side of value: The gross profitability premium. *Journal of financial economics*, 108(1), pp.1-28.

Ooi, J., Webb, J. and Zhou, D., 2007. Extrapolation theory and the pricing of REIT stocks. *Journal of Real Estate Research*, 29(1), pp.27-56.

Ooi, J.T., Wong, W.C. and Ong, S.E., 2012. Can bank lines of credit protect REITs against a credit crisis?. *Real Estate Economics*, *40*(2), pp.285-316.

Ott, S.H., Riddiough, T.J. and Yi, H.C., 2005. Finance, investment and investment performance: Evidence from the REIT sector. *Real Estate Economics*, *33*(1), pp.203-235.

Park, J. and Ratti, R.A., 2008. Oil price shocks and stock markets in the US and 13 European countries. *Energy economics*, 30(5), pp.2587-2608.

Pástor, Ľ. and Stambaugh, R.F., 2003. Liquidity risk and expected stock returns. *Journal of Political economy*, 111(3), pp.642-685.

Paul, T., Walther, T. and Küster-Simic, A., 2020. Empirical analysis of the illiquidity premia of German real estate securities. *Financial Markets and Portfolio Management*, pp.1-58.

Peng, Y. and Ng, W.L., 2012. Analysing financial contagion and asymmetric market dependence with volatility indices via copulas. *Annals of Finance*, 8, pp.49-74.

Penman, S.H., Richardson, S.A. and Tuna, I., 2007. The book-to-price effect in stock returns: accounting for leverage. *Journal of accounting research*, 45(2), pp.427-467.

Pesaran, M.H., Shin, Y. and Smith, R.J., 2001. Bounds testing approaches to the analysis of level relationships. *Journal of applied econometrics*, 16(3), pp.289-326.

Peterson, J.D. and Hsieh, C.H., 1997. Do common risk factors in the returns on stocks and bonds explain returns on REITs?. *Real Estate Economics*, *25*(2), pp.321-345.

Philippas, N., Economou, F., Babalos, V. and Kostakis, A., 2013. Herding behavior in REITs: Novel tests and the role of financial crisis. *International Review of Financial Analysis*, *29*, pp.166-174.

Piotroski, J.D., 2000. Value investing: The use of historical financial statement information to separate winners from losers. *Journal of Accounting Research*, pp.1-41.

Qadan, M. and Nama, H., 2018. Investor sentiment and the price of oil. *Energy economics*, 69, pp.42-58.

Rajan, R.G., 2006. Has finance made the world riskier?. *European financial management*, 12(4), pp.499-533.

Rhyan, C., Turner, A. and Miller, G., 2020. Tracking the US health sector: The impact of the COVID-19 pandemic. *Business Economics*, *55*, pp.267-278.

Roll, R., 1984. A simple implicit measure of the effective bid-ask spread in an efficient market. *The Journal of finance*, *39*(4), pp.1127-1139.

Said, H. and Giouvris, E., 2017. Illiquidity as an investment style during the financial crisis in the United Kingdom. In Handbook of Investors' Behavior During Financial Crises (pp. 419-445). Academic Press.

Said, H. and Giouvris, E., 2017. Illiquidity, Monetary conditions, and the financial crisis in the United Kingdom. In Handbook of Investors' Behavior During Financial Crises (pp. 277-302). Academic Press.

Schalck, C. and Chenavaz, R., 2015. Oil commodity returns and macroeconomic factors: A time-varying approach. *Research in International Business and Finance*, 33, pp.290-303.

Scholtens, B. and Yurtsever, C., 2012. Oil price shocks and European industries. *Energy Economics*, 34(4), pp.1187-1195.

Shahe Emran, M., Shilpi, F. and Alam, M.I., 2007. Economic liberalization and price response of aggregate private investment: time series evidence from India. *Canadian Journal of Economics/Revue canadienne d'économique*, 40(3), pp.914-934.

Sharpe, W.F., 1978. Major investment styles. *The Journal of Portfolio Management*, 4(2), pp.68-74.

Sharpe, W.F., 1992. Asset allocation: Management style and performance measurement. *Journal of portfolio Management*, 18(2), pp.7-19.

Shen, J., Hui, E.C. and Fan, K., 2021. The beta anomaly in the REIT market. *The Journal of Real Estate Finance and Economics*, 63, pp.414-436.

Shiller, R.J., 2007. Understanding Recent Trends in House Prices and Home Ownership. *Federal Reserve Bank of Kansas City*, Kansas City, pp. 89-123.

Shin, H.S., 2010. *Risk and liquidity*. Oxford University Press.

Shleifer, A. and Vishny, R.W., 1997. The limits of arbitrage. *The Journal of finance*, 52(1), pp.35-55.

Skinner, D.J. and Sloan, R.G., 2002. Earnings surprises, growth expectations, and stock returns or don't let an earnings torpedo sink your portfolio. *Review of accounting studies,* 7(2-3), pp.289-312.

Sklavos, K., Dam, L. and Scholtens, B., 2013. The liquidity of energy stocks. *Energy Economics*, 38, pp.168-175.

Stephen, L. and Simon, S., 2005. The case for REITs in the mixed-asset portfolio in the short and long run. *Journal of Real Estate Portfolio Management*, *11*(1), pp.55-80.

Subrahmanyam, A., 2007. Liquidity, return and order-flow linkages between REITs and the stock market. *Real Estate Economics*, *35*(3), pp.383-408.

Tan, L., Chiang, T.C., Mason, J.R. and Nelling, E., 2008. Herding behavior in Chinese stock markets: An examination of A and B shares. *Pacific-Basin finance journal*, 16(1-2), pp.61-77.

Tang, D.Y. and Yan, H., 2010. Market conditions, default risk and credit spreads. *Journal of Banking & Finance,* 34(4), pp.743-753.

Titman, S. and Warga, A., 1986. Risk and the performance of real estate investment trusts: A multiple index approach. *Real Estate Economics*, *14*(3), pp.414-431.

Titman, S., Wei, K.J. and Xie, F., 2004. Capital investments and stock returns. *Journal of financial and Quantitative Analysis,* 39(4), pp.677-700.

Tsai, C.L., 2015. How do US stock returns respond differently to oil price shocks pre-crisis, within the financial crisis, and post-crisis?. *Energy Economics,* 50, pp.47-62.

Tse, Y. and Booth, G.G., 1996. Common volatility and volatility spillovers between US and Eurodollar interest rates: Evidence from the futures market. *Journal of Economics and Business*, 48(3), pp.299-312.

Tseng, J.J. and Li, S.P., 2012. Quantifying volatility clustering in financial time series. *International Review of Financial Analysis*, *23*, pp.11-19.

U.S. Securities and Exchange Commission (2020). U.S. Credit Markets Interconnectedness and the Effects of the COVID-19 Economic Shock. Available at: https://www.sec.gov/files/US-Credit-Markets_COVID-19_Report.pdf (Accessed 15 February 2023)

Ülkü, N., 2017. Monday effect in Fama–French's rmw factor. *Economics Letters*, 150, pp.44-47.

Vassalou, M. and Xing, Y., 2004. Default risk in equity returns. *The journal of finance*, 59(2), pp.831-868.

Voronkova, S. and Bohl, M.T., 2005. Institutional traders' behavior in an emerging stock market: Empirical evidence on polish pension fund investors*. Journal of Business Finance & Accounting, 32(7-8), pp.1537-1560.*

Vu, T.N., 2019. Impact of crude oil price volatility on southeast Asian stock returns. *Southeast Asian Journal of Economics*, 7(2), pp.107-125.

Walter, A. and Moritz Weber, F., 2006. Herding in the German mutual fund industry. *European Financial Management*, 12(3), pp.375-406.

Wang, Y., Wu, C. and Yang, L., 2013. Oil price shocks and stock market activities: Evidence from oil-importing and oil-exporting countries. *Journal of Comparative economics*, 41(4), pp.1220-1239.

Wermers, R., 1999. Mutual fund herding and the impact on stock prices. *The Journal of Finance*, 54(2), pp.581-622.

Wylie, S., 2005. Fund manager herding: A test of the accuracy of empirical results using UK data. *The Journal of Business*, 78(1), pp.381-403.

Xiao, J., Zhou, M., Wen, F. and Wen, F., 2018. Asymmetric impacts of oil price uncertainty on Chinese stock returns under different market conditions: Evidence from oil volatility index. *Energy Economics*, 74, pp.777-786.

Zhang, C. and Chen, X., 2014. The impact of global oil price shocks on China's bulk commodity markets and fundamental industries. *Energy policy*, 66, pp.32-41.

Zhang, Y. and Hansz, J.A., 2022. Industry concentration and US REIT returns. *Real Estate Economics*, *50*(1), pp.247-267

Zheng, X. and Su, D., 2017. Impacts of oil price shocks on Chinese stock market liquidity. *International Review of Economics & Finance*, 50, pp.136-174.

Zheng, X., Chau, K.W. and Eddie, C.M., 2015. Liquidity risk and cross-sectional return in the housing market. *Habitat international*, *49*, pp.426-434.

Zhou, J. and Anderson, R.I., 2011. An empirical investigation of herding behavior in the US REIT market. *The Journal of Real Estate Finance and Economics*, pp.1-26

Zhou, J. and Anderson, R.I., 2013. An empirical investigation of herding behavior in the US REIT market. *The Journal of Real Estate Finance and Economics*, *47*, pp.83-108.

Zhou, R.T. and Lai, R.N., 2009. Herding and information based trading. *Journal of Empirical Finance*, 16(3), pp.388-393.