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

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Abstract: We examine 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.

Keywords: oil price; OVX; illiquidity premiums; US markets; macroeconomic factors; autoregressive distribution lag (ARDL) model; error correction model (ECM)

JEL Classification: E3; E44; G10; Q40

1. 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 et al. 2007; Miller and Ratti 2009; Chen 2010; Cunado and 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 the illiquidity premium.

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 the 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 cointegration, 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 cointegration 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 cointegration 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 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 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 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 cointegration 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 variables within a current month and in their optimal lagged form, have 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 cointegration 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 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 paper is as follows. Section 2 presents a literature review. Section 3 describes the data and methodology. Section 4 presents the empirical analysis and results. Finally, Section 5 presents conclusions.

2. Literature Review

2.1. 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.

2.2. 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 sceptical 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 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 price and enhancing 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 are 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 et al. (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 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 et al. (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.[1]

2.3. 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 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

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

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 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[2] 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[3]. 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[4].

2.4. 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

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[2] 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.

[3] 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.

[4] 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.

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.

2.5. Macroeconomic Factors

2.5.1. 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. They 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.

2.5.2. 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.

2.5.3. 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. Data and Methodology

3.1. 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;

$$\mathrm{ILLIQ}_{i,t} = (1/\mathrm{N}_{i,t}) \sum\nolimits_{d} \left[(1{,}000{,}000 \times |\mathrm{r}_{i,d,t}|) / \left(\mathrm{p}_{i,d,t} \times \mathrm{v}_{i,d,t} \right) \right]$$

$|r_{i,d,t}|$ 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[5], 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 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.

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

3.2. 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;

$$R_{IML,t} = \alpha_0 + \beta_1 R_{OILt} + \beta_2 R_{OVXt} + \beta_3 R_{S\&Pt} + \beta_4 R_{e,t} + \beta_5 \Delta\pi_t + \beta_6 R_{p,t} + \beta_7 \Delta ffr_t + \beta_8 \Delta r_t + \beta_9 R_{IML,t-1} + \varepsilon_t \quad (1)$$

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 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.

3.3. The VAR Model

We test for cointegration 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;

$$y_t = A_0 + \sum_{i=1}^{p} A_i y_{t-i} + \varepsilon_t \quad (2)$$

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;

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

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

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

$$E(\varepsilon_s \ \varepsilon'_t) = 0 \text{ if } s \neq t$$

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. 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 cointegration and establish a long-run relationship between our variables. Emran et al. (2007) discusses several advantages of the bounds test relative to conventional cointegration 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 cointegration relationship between oil prices, OVX, macroeconomic factors and illiquidity premiums, we set up the bounds test as follows;

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

where R_{IML}, is the illiquidity premium, Δln OIL, Δln OVX, Δln S&P, Δln E, Δln P, Δln ffr and Δln 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). 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 cointegration is rejected. While if the F-statistic is lower than the lower critical bound value, the null hypothesis of no cointegration 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;

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

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

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

where ecm is a vector of residuals from the ARDL long-run model (Equation (4)), 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 illiquidity premium is effective.

The procedure from Equations (3)–(5) 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 establish 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.

3.5. 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 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;

$$R_{OILP} = \max(0, R_{OIL}) \text{ and } R_{OILN} = \min(0, R_{OIL}) \quad (6)$$

$$R_{OVXP} = \max(0, R_{OVX}) \text{ and } R_{OVXN} = \min(0, R_{OVX}) \quad (7)$$

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 (2)). 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)).

We run two further OLS regressions, first checking the asymmetric impact of oil price returns by inputting R_{OILP} and R_{OILN} into Equation (1) 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;

$$R_{IML} = \alpha_0 + \beta_1 R_{OILP} + \beta_2 R_{OILN} + \beta_3 R_{OVX} + \beta_4 R_{S\&P} + \beta_5 R_e + \beta_6 \Delta\pi + \beta_7 R_p + \beta_8 \Delta ffr + \beta_9 \Delta r + \beta_{10} R_{IML,t-1} + \varepsilon_t \quad (8)$$

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 (1) 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;

$$R_{IML} = \alpha_0 + \beta_1 R_{OIL} + \beta_2 R_{OVXP} + \beta_3 R_{OVXN} + \beta_4 R_{S\&P} + \beta_5 R_e + \beta_6 \Delta\pi + \beta_7 R_p + \beta_8 \Delta ffr + \beta_9 \Delta r + \beta_{10} R_{IML,t-1} + \varepsilon_t \quad (9)$$

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;

$$\Delta \ln OILP = \max(0, \Delta \ln OIL) \text{ and } \Delta \ln OILN = \min(0, \Delta \ln OIL) \quad (10)$$

$$\Delta \ln OVXP = \max(0, \Delta \ln OVX) \text{ and } \Delta \ln OVXN = \min(0, \Delta \ln OVX) \quad (11)$$

We first check the potential asymmetric impact of oil price on illiquidity premiums by inputting variables from Equation (10) into Equation (5);

$$\begin{array}{c} R_{IML,t} = \alpha_0 + \sum_{i=1}^{p} \beta_{1,i}\, R_{IML,t-I} + \sum_{i=0}^{p} \beta_{2,i}\, \Delta \ln\, OILP_{t-i} \\ + \sum_{i=0}^{p} \beta_{3,i}\, \Delta \ln\, OILN_{t-i} + \sum_{i=0}^{p} \beta_{4,i}\, \Delta \ln\, OVX_{t-i} \\ + \sum_{i=0}^{p} \beta_{5,i}\, \Delta \ln\, S\&P_{t-i} + \sum_{i=0}^{p} \beta_{6,i}\, \Delta \ln\, E_{t-i} + \sum_{i=0}^{p} \beta_{7,i}\, \Delta\, \pi_{t-i} \\ + \sum_{i=0}^{p} \beta_{8,i}\, \Delta \ln\, P_{t-i} + \sum_{i=0}^{p} \beta_{9,i}\, \Delta \ln\, ffr_{t-i} + \sum_{i=0}^{p} \beta_{10,i}\, \Delta \ln\, r_{t-I} + \beta_{11}\, ecm_{t-1} + \varepsilon_t \end{array} \quad (12)$$

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 Δln oil price are equal.

Similarly, to check the potential asymmetric impact of oil implied volatility on illiquidity premiums, we input variables from Equation (11) into Equation (5);

$$\begin{array}{c} R_{IML,t} = \alpha_0 + \sum_{i=1}^{p} \beta_{1,i}\, R_{IML,t-I} + \sum_{i=0}^{p} \beta_{2,i}\, \Delta \ln\, OIL_{t-i} + \sum_{i=0}^{p} \beta_{3,i}\, \Delta \ln\, OVXP_{t-i} \\ + \sum_{i=0}^{p} \beta_{4,i}\, \Delta \ln\, OVXN_{t-i} + \sum_{i=0}^{p} \beta_{5,i}\, \Delta \ln\, S\&P_{t-i} + \sum_{i=0}^{p} \beta_{6,i}\, \Delta \ln\, E_{t-i} \\ + \sum_{i=0}^{p} \beta_{7,i}\, \Delta\, \pi_{t-i} + \sum_{i=0}^{p} \beta_{8,i}\, \Delta \ln\, P_{t-i} + \sum_{i=0}^{p} \beta_{9,i}\, \Delta \ln\, ffr_{t-i} \\ + \sum_{i=0}^{p} \beta_{10,i}\, \Delta \ln\, r_{t-I} + \beta_{11}\, ecm_{t-1} + \varepsilon_t \end{array} \quad (13)$$

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 Δln OVX are equal.

4. Empirical Results

4.1. Illiquidity Premiums

Table 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 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.

Table 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.

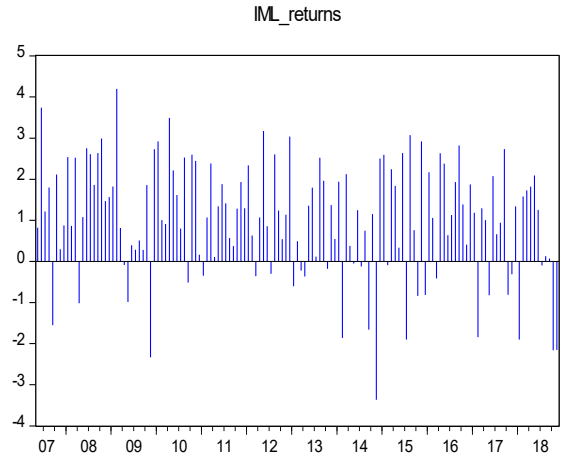


Figure 1. Time series variation in illiquidity premiums.

Table 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 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 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 and 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. 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 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.

4.2. Statistical Analysis

We report the main summary statistics in Table 5[6]. 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 5. Descriptive statistics for explanatory variables.

Variables	Mean	Median	SD	Min	Max	Skewness	Kurtosis
$\mathbf{R_{OIL}}$	0.282989	1.026349	9.357824	−32.62122	29.7144	−0.287811	4.057545
$\mathbf{R_{OVX}}$	1.752078	−0.592552	16.71465	−32.46463	86.05578	1.251708	6.943423
$\mathbf{R_{S\&P}}$	0.518481	1.016153	4.223668	−16.94245	10.77230	−0.754159	4.753738
$\mathbf{R_e}$	0.171299	−0.044200	3.063321	−8.715514	10.77245	0.511372	4.298387
$\mathbf{R_p}$	0.002632	−0.007282	0.870610	−2.795238	5.295741	1.328169	12.42154
$\mathbf{\Delta\pi}$	−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%.

Figure 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.

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

[6] 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).

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 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 started hiking up the rates, ending up at around 2% by the end of 2018.

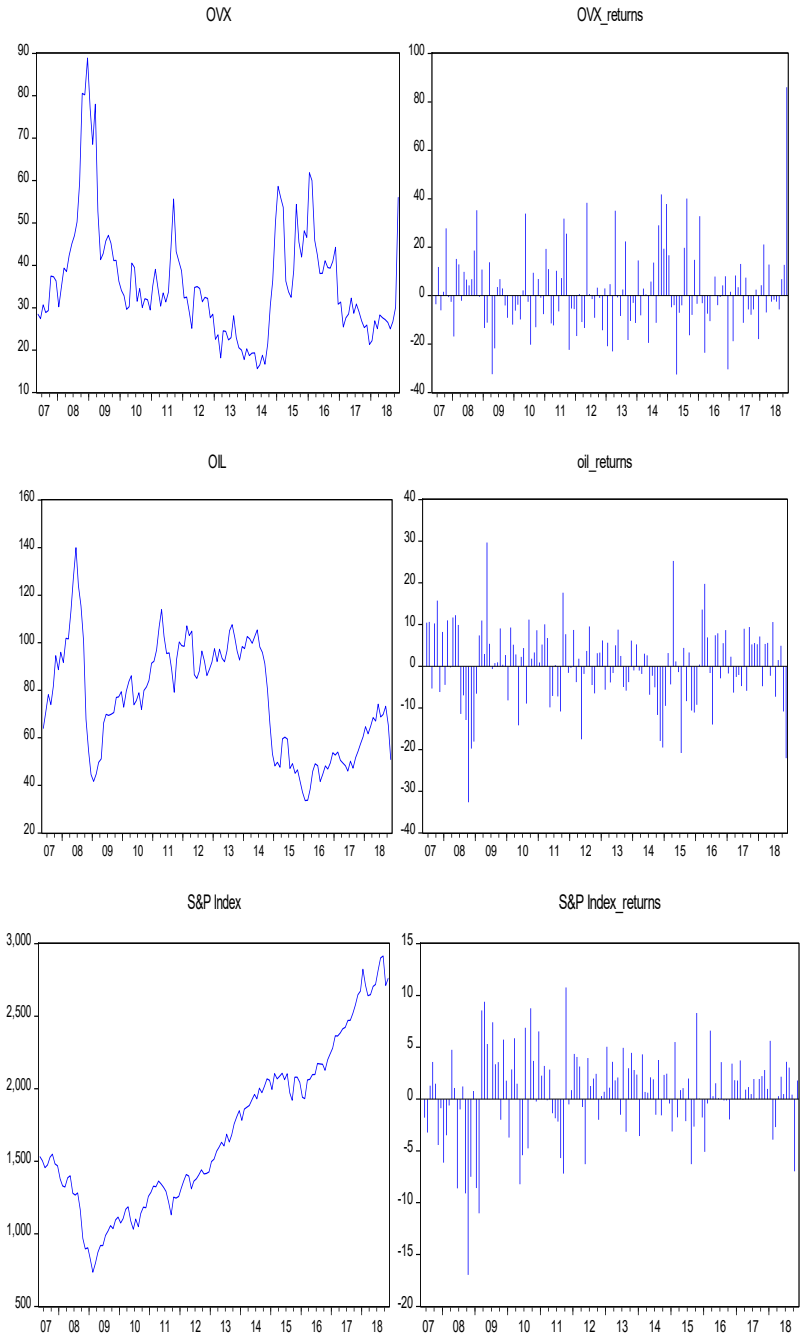


Figure 2. *Cont.*

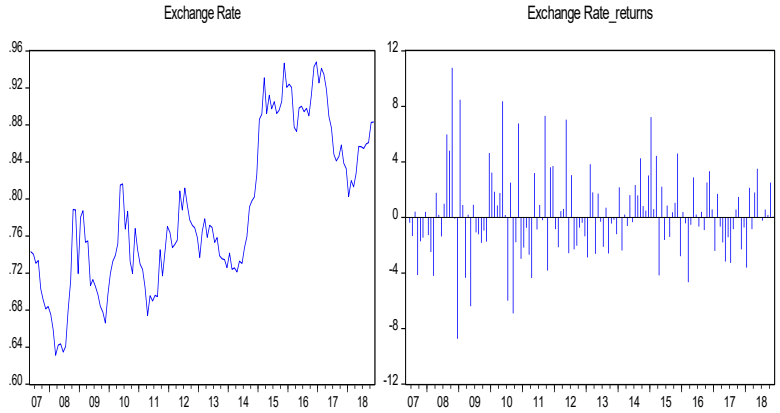


Figure 2. Time series volatility for OVX, WTI oil prices, S&P 500 index and exchange rate in levels (**left**) and returns (**right**) for the full sample between May 2007 and December 2018.

Table 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.

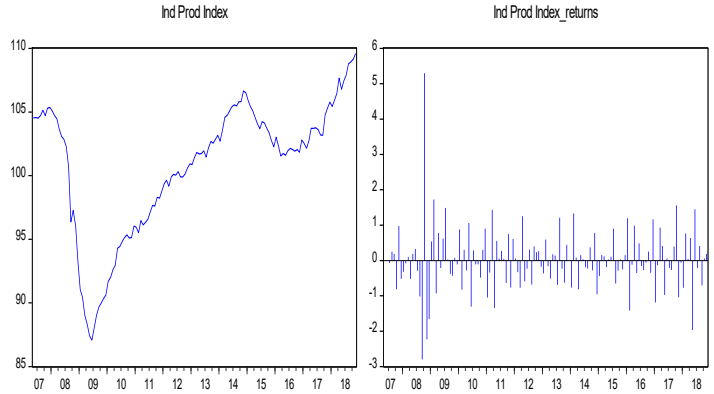


Figure 3. *Cont.*

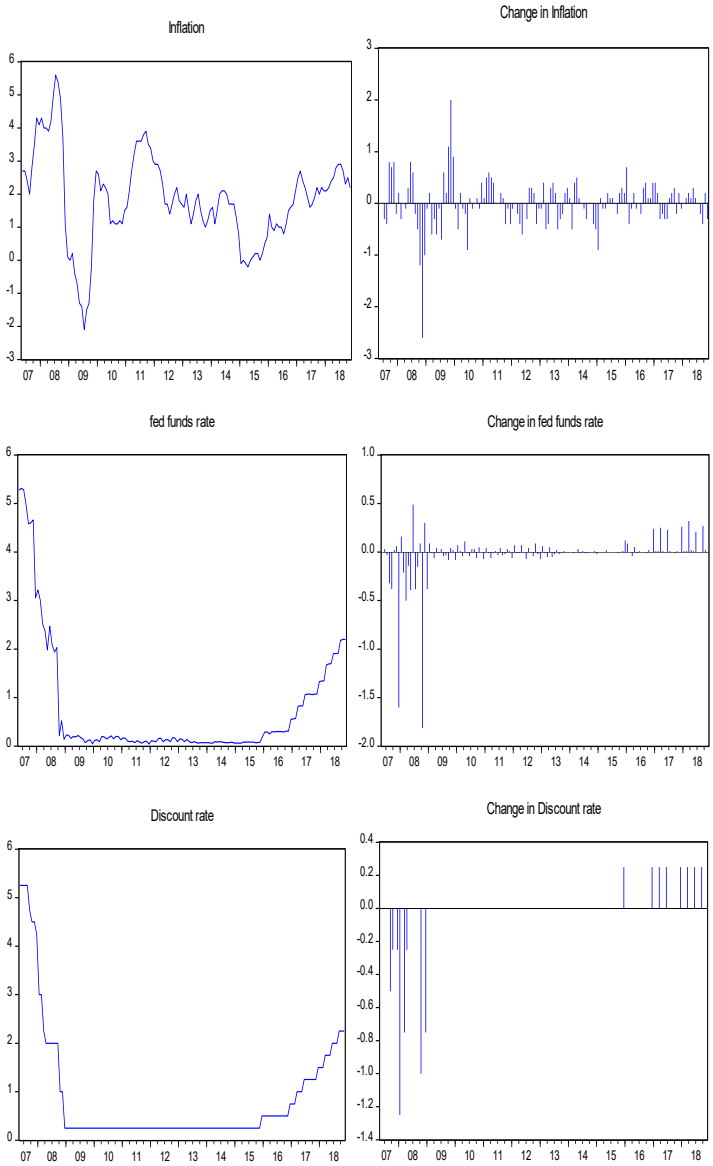


Figure 3. Time series volatility for industrial production index, inflation, federal funds rate and discount rate in levels (**left**) and returns (**right**) for the full sample between May 2007 and December 2018.

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 6 reveals some high correlation levels between independent variables, the variance

inflation factor as shown in Table 7, has values around 1, confirming that there is no multicollinearity issues with the model.

Table 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.

Table 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 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 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.

4.3. OLS Results

Table 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 9. OLS regression results (full sample).

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	1.288339 ***	0.139588	9.229604	0.0000
R_{OIL}	0.030870 **	0.014641	2.108434	0.0370
R_{OVX}	−0.015871 **	0.007768	−2.043225	0.0431
R_e	0.062820	0.042591	1.474947	0.1427
Δr	−0.533502	0.712226	−0.749063	0.4552
$R_{S\&P}$	−0.180027 ***	0.031003	−5.806708	0.0000
$R_{IML,t-1}$	−0.176447 **	0.079659	−2.215031	0.0285
Δffr	−0.000364	0.553206	−0.000657	0.9995
R_p	−0.137945	0.128176	−1.076211	0.2839
Δπ	−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. Δπ 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 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 illiquidity premiums.

Another possible explanation for this positive relationship stems from the argument put forward by 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 channelled towards relatively safer liquid stocks carrying less illiquidity risk. This lack of demand associated to illiquid stocks could potentially drive down 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 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 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 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 channelling of funds towards these securities relative to smaller illiquid stocks. This potentially reduces demand for illiquid stocks and impacts 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[7]. 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 10 and 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 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 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

[7] 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.

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 10. OLS regression results (financial crisis).

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	1.358777 ***	0.402288	3.377619	0.0082
$\mathbf{R_{OIL}}$	−0.053505 *	0.024567	−2.177926	0.0574
$\mathbf{R_{OVX}}$	−0.005574	0.016295	−0.342058	0.7402
$\mathbf{R_{S\&P}}$	−0.147643 ***	0.040964	−3.604238	0.0057
$\mathbf{R_e}$	−0.118983 *	0.064873	−1.834089	0.0998
$\mathbf{\Delta\pi}$	1.007808 **	0.326382	3.087820	0.0130
$\mathbf{R_p}$	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
$\mathbf{R_{IML,t-1}}$	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. Δπ 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 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. Δπ 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.

4.4. Cointegration and VAR Analysis

Next, we check for cointegration between all the variables using the Johansen and Juselius test (Johansen and Juselius 1990). Tables 12 and 13 presents the results using trace and the maximum eigenvalue tests. The trace statistic suggests the existence of four cointegrating vectors while the maximum eigenvalue suggests the existence of two cointegrating vectors. We therefore reject the null hypothesis of no cointegration and conclude that there is a long-run relationship between all the variables analysed in our paper.

Table 12. Johansen and Juselius cointegration 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 13. Johansen and Juselius cointegration 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 (2), 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 4.

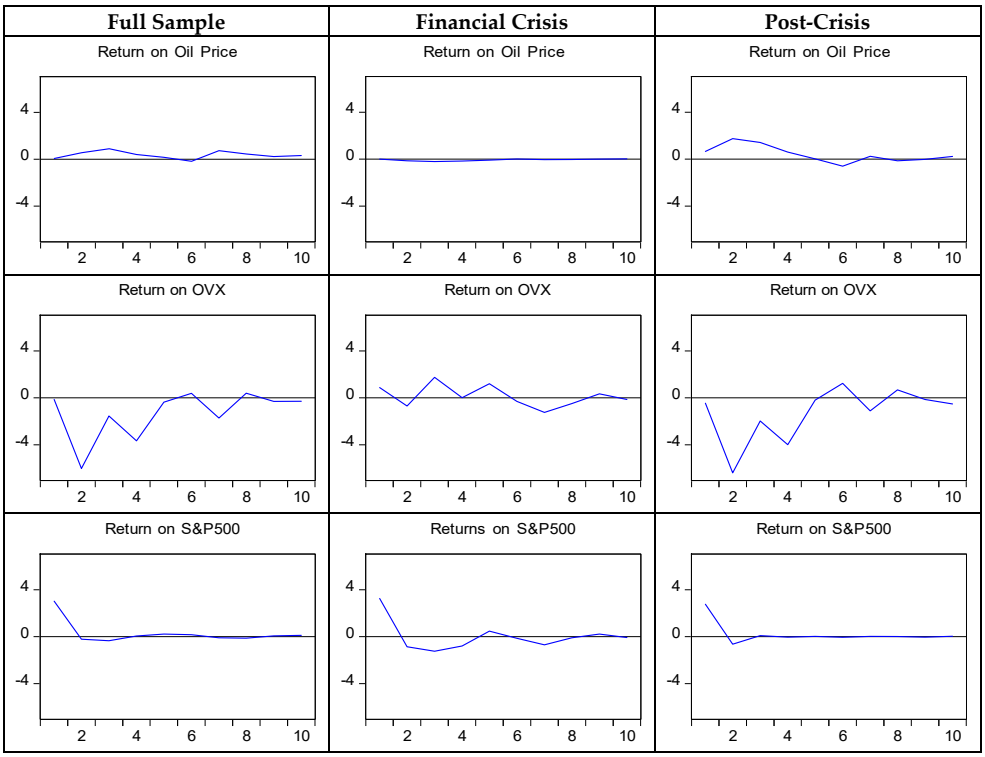


Figure 4. *Cont.*

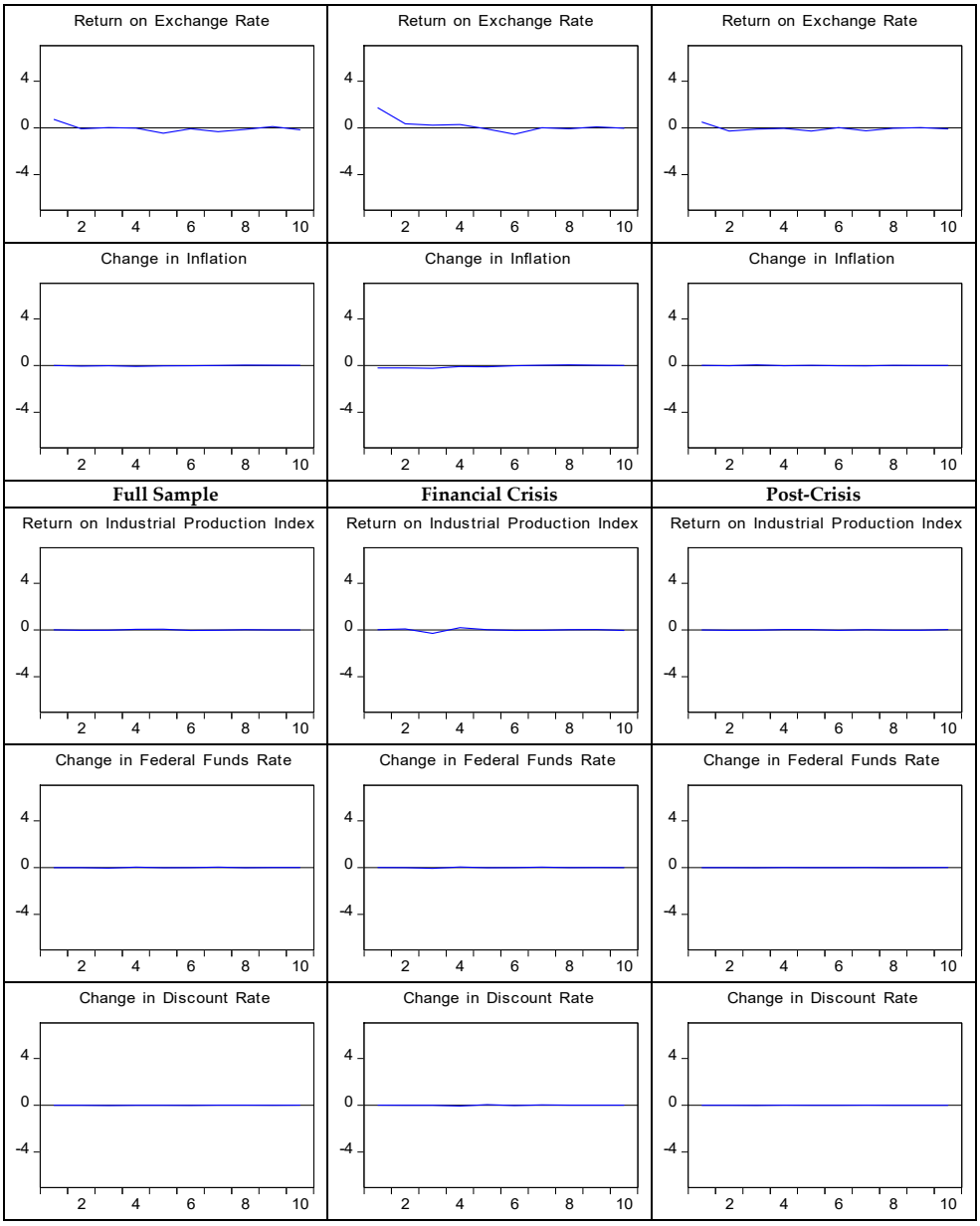


Figure 4. Impulse response functions for the response of illiquidity premiums to shocks in oil price returns, OVX returns, S&P 500 returns, returns on exchange rate, change in inflation, returns on industrial production index, change in federal funds rate and change in discount rate. This includes the 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).

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.

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 more risky 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 sceptical 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.

4.5. Bounds Test, the Long-Run ARDL Model and the Short-Run Error Correction Model

Table 14 reports the results of the bounds test for cointegration 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 cointegration relationship exists between oil price, oil price volatility, the examined macroeconomic variables and illiquidity premiums.

Table 14. The results of the bounds test for cointegration (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 Cointegration
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: $\beta 10 = \beta 11 = \beta 12 = \beta 13 = \beta 14 = \beta 15 = \beta 16 = \beta 17 = \beta 18 = 0$.

Once a long-run relationship has been established between the examined variables, we use the long-run ARDL model as specified in Equation (4) to estimate long-run elasticities for the variables in the model, for the full sample period. The results in Table 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 16 shows short-run elasticities using the error correction model in Equation (5). 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 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 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 17 reports the results of the bounds test for cointegration 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 cointegration relationships exists between oil price, oil price volatility, the examined macroeconomic variables and illiquidity premiums, during the financial crisis.

Table 17. The results of the bounds test for cointegration (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 Cointegration
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 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 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 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 20 reports the results of the bounds test for cointegration 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 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(−)	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 20. The results of the bounds test for cointegration (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 Cointegration
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: β10 = β11 = β12 = β13 = β14 = β15 = β16 = β17 = β18 = 0.

Table 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 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 cointegration relationship between the examined variables and illiquidity premium is extremely relevant.

Table 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
$R_{IML,t-1}$	−0.248926 **	0.115774	−2.150093	0.0347
$R_{IML,t-2}$	−0.021788	0.121211	−0.179757	0.8578
$R_{IML,t-3}$	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 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.

4.6. Asymmetric Effect of Oil Price and Oil Volatility on Illiquidity Premium

Table 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 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 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 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 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 25. Regression results for positive and negative oil price changes.

Variable	Coefficient	Std. Error	t-Statistic	Prob.
Δln $OILP_t$	0.006171	0.027464	0.224681	0.8226
Δln $OILN_t$	0.066180 ***	0.024954	2.652039	0.0091
Δln $OILP_{t-1}$	0.000766	0.028756	0.026621	0.9788
Δln $OILN_{t-1}$	−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: $\Delta\ln OILP_t = \Delta\ln OILN_t$. H_0: $\Delta\ln OILP_{t-1} = \Delta\ln OILN_{t-1}$. This table reports the results of two Chi-square tests of the null hypothesis of no asymmetry under the ECM model with $\Delta\ln OILP_t$ and $\Delta\ln OILN_t$ being the current positive and negative values of oil price changes, and $\Delta\ln OILP_{t-1}$ and $\Delta\ln OILN_{t-1}$ 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 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 26. Regression results for positive and negative oil price volatility changes.

Variable	Coefficient	Std. Error	t-Statistic	Prob.
Δln OVXP$_t$	−0.03352 **	0.013539	−2.475424	0.0148
Δln OVXN$_t$	0.011461	0.015197	0.754133	0.4523
Δln OVXP$_{t-1}$	−0.009341	0.014485	−0.644914	0.5203
Δln 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: Δln OVXP$_t$ = Δln OVXN$_t$. H_0: Δln OVXP$_{t-1}$ = Δln 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 Δln OILP$_t$ and Δln OILN$_t$ being the current positive and negative values of oil price changes, and Δln OILP$_{t-1}$ and Δln 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.

5. Conclusions

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 cointegration 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 cointegration 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 cointegration 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.

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