Bulletin of Applied Economics, 2021, 8(1), 149-165
https://doi.org/10.47260/bae/819

Oil Volatility Spillover into Oil Dependent Equity-Sector Stock Returns: Evidence from Major Oil Producing Countries

Rafiqul Bhuyan[1], Mohammad Robbani[1] and Bakhtear Talukder[2]

Abstract

In this paper, we study the effects of oil price volatility on the stock market relevant sectors from several oil producing countries. We investigate the interdependence between oil prices and sector stock indices within OPEC markets and selected major non-OPEC countries such as Russia and United States. By exploring the time-varying dynamics of oil prices and sector-stock indices on the sectoral reaction to oil price shocks we investigate how the shocks in oil prices affect the correlation dynamics of the different sectors. Our study finds that different sectors display heterogeneous dynamic correlation pattern with different oil price shocks origins in different countries. Specifically, the GARCH coefficients in several sectors, such as, industrial, energy and healthcare in some of oil-producing middle-eastern countries are not significant. In addition, the negative coefficients for some sectors in some of the countries indicate the existence of hedging opportunities for portfolio managers.

JEL classification numbers: G11, G12
Keywords: commodity markets, financial markets, time-varying volatility, conditional correlations

1 Introduction

Understanding the volatility dynamics of crude oil price and financial markets has been at the forefront of both energy and finance literature over the past two decades. The energy economics literature has largely focused on addressing the influence of oil price volatilities on stock market returns (Cuando and de Garcia, 2014; Kang et al., 2015; Bouri et al., 2016). The popularity of commodities as alternative assets in portfolio decisions has led to an increased interdependence between financial and commodity markets and has increased the popularity of commodity based securitized financial instruments. Such instruments are increasingly used by hedge funds and other alternative asset managers to offer new hedging and diversification opportunities for investors. As such, research on oil-stock volatility dynamics is very pragmatic and critical for both investment and policy decisions (see, Domanski and Heath, 2007; Tang and Xiong, 2012; Basher and Sadorsky, 2016). Structuring on the evidence and significance of cash flow models on the dependence of stock price on expected discounted cash flow, strands of recent research have accentuated the volatility linkage between oil prices and stock market returns (see, Sadorsky, 1999; Park and Ratti, 2008; Apergis and Miller, 2009; Narayan and Narayan, 2010; Arouri et al., 2011). The general consensus from most studies on the oil-stock nexus is that oil price shocks have negative impact on stock markets.

[1] Department of Accounting and Finance, Alabama A&M University, USA
[2] Department of Finance and Business Law, University of Wisconsin-Whitewater, USA

Article Info: Received: March 25, 2021 Published online: May 2, 2021

Despite a growing literature on the empirical relationship between oil price shocks and stock markets, we are yet to comprehend the dynamic effect of oil price shocks on different equity sector indices in emerging markets (see, Degiannakis et al., 2013; Bouri et al., 2016). In the production process, crude oil serves as an intermediate input and, hence, oil price shocks will likely impact the equity market returns. However, the effects of oil price shocks may not be homogeneous across all equity-sectors because of the differences in extent of oil use and, hence, differences in the dependability on oil for production. In addition, the effects of oil price shocks on equity market returns may also vary across different oil producing countries. Whether or not there is an asymmetric effect across different equity-sectors and across countries will be very useful to different players in the financial market. For instance, financial fund managers can utilize this information for diversification and financial risk management purposes. Further, the availability of such information provided by a study that investigates the differential impact of oil price shocks in an analysis across different equity sectors may also provide the policymakers with important insights that can be used to formulate appropriate regulation framework at the sector level. For instance, if there is a prior knowledge that oil price shocks impact some sectors and don't impact others then policymakers may be able to unmask important effects of oil price shocks that are limited to only certain sectors, which may go undetected in analysis of the aggregate stock return index (Arouri et al., 2012). Hence, it is important to investigate whether the effect of oil price shocks are different or same across different equity-sectors in a sectoral analysis. Yet, the existing literature is limited on the linkages of equity sector and oil price volatility and is surrounded mostly on developed markets particularly in Europe and the US (Malik and Ewing, 2009; Arouri and Nguyen, 2010; Arouri et al., 2012; Fan and Jahan-Parvar, 2012; Broadstock and Filis, 2014).

In this paper, we fill this gap by studying the differential effects of oil price volatility both across different sectors in different countries. We focus on major oil producing countries to investigate the interdependence between oil prices and sector stock indices within OPEC markets and selected major non-OPEC countries such as Russia and United States. More specifically, we examine the dynamic conditional correlation between five equity sectors, (namely, financials, industrials, Oil and Gas, healthcare, real estate, and consumer goods sectors*)* and crude oil prices. We explore the time-varying dynamics of oil prices and sector-stock indices by examining sectoral reaction to oil price shocks. We also investigate how the supply-side or demand-side shocks in oil prices affect the correlation dynamics of the different sectors. Current literature suggests that oil price shocks adversely affect aggregate stock price indices, which may not hold at sectoral levels. Our study explores whether different sectors display heterogeneous dynamic correlation pattern with different oil price shocks origins.

We expect the presence of a heterogeneous rather than herding behavior in the dynamic correlation of sectors during periods of oil price shocks. Hence, a sector level analysis of the correlation behavior between oil prices and equity sectors would provide a more comprehensive understanding of the oil and equity price relationship. Since there may be industry specific responses to oil price shocks and the magnitude of response may vary across various sectors, it is important to study the effects of oil price shocks using a sector-level analysis. Additionally, the aggregate stock indices of different countries may fail to provide important insights of this relationship as each country's industrial base are likely to be different. Unlike previous work on sector level analysis of oil price shocks, not only we cogitate the dynamic nature of the correlation linkage but also justify origins of the oil price shocks and how the various sectors respond (in terms of correlation) to different oil price shocks such as aggregate demand induced shocks, supply-side shocks and/or precautionary demand induced shocks (literature opines different shocks in crude oil market have different effects on stock market, see Kilian and Park, 2009, for example). In order to account for the various shock origins, we split our data sample into sub-samples following the classification by Kilian and Park (2009).

Our research addresses two important issues. First, using full-sample for the entire sample period we examine the behavior of each sector's dynamic correlation following Degiannakis et at., (2013), Hamilton (2009), and Kilian (2009). The full-sample period covers 2000-2015 and a number of oil price shocks origins can be identified within this time period. The origins of oil price shocks and their dates are as follows: (1) 2000-2003 (aggregate and precautionary demand oil price shock); (2) 2004-2007 (aggregate demand oil price shock); (3) 2008-2011 (aggregate demand oil price shocks) and, (4) 2012-2015 (supply-side oil price shock). To examine the dynamic time-varying correlation between different sectors and oil-price indices, we employ the Dynamic Conditional Correlation (DCC)-generalized autoregressive conditional heteroscedasticity (GARCH) framework. Additionally, we also apply Asymmetric Dynamic Conditional Correlation (henceforth, ADCC)-GARCH model to account for asymmetry within the time-varying correlations for negative and positive news.

To the best of our knowledge, our research is the first to apply the DCC and ADCC-GARCH models to sectoral stock market returns and crude oil prices studies. Our study provides evidence on the dynamic nature of the volatility correlation between crude oil and sectoral returns, which provides important information to financial market investors and policymakers in decisions regarding portfolio selection and diversification, optimal hedging strategy, energy risk management, and market regulations. Moreover, our research accounts for oil price shock origins and provides further evidence on sectoral response to the various oil price shock regimes. Finally, this research adds to the growing literature on the crude oil-stock nexus from the perspective of sectoral indices which makes it possible to counter biases inherent to the use of country-level aggregate indices.

The rest of paper is organized as follows. Section 2 discusses the relevant literature on the relationship between crude oil price and equity-sector markets. We present the econometric method and estimation techniques in section 3. Section 4 presents a summary of the dataset and its preliminary stochastic properties. We discuss our results in section 5 and conclude in Section 6.

2 Literature Review

There is growing literature investigating the volatility linkages between equity and various commodities including crude oil (e.g. Park and Ratti, 2008; Apergies and Miller 2009; Filis et al, 2011; Arouri et al, 2012; Mollick and Assefa, 2013; Chang et al, 2013; Lin et al, 2014; Guesmi and Fattoum, 2014). Here, we only review literature focusing on equity sector and oil price movements. In one of the first major works that investigate whether oil price movements impact equity prices, Nandha and Faff (2008), using data from 35 global industry indices from 1993 to 2005, find that positive oil price shocks have negative effects on all sectors except Mining and Oil & Gas industries. Malik and Ewing (2009) examine volatility spillover between oil prices and oil-dependent equity sector indices from US financial markets. Using weekly data from 1992 to 2008, they find the evidence of significant shocks and volatility transmission between oil prices and selected equity sectors. They further find that the magnitude of transmission varies across different sectors. Their findings thus suggest that investors should consider variant response across sectors in financial risk management and portfolio adjustments, and adopt the idea of cross-sectoral hedging when managing risk in portfolio decisions. This conclusion is further supported by the findings of Kilian and Park (2009), who examine the effects of oil price shocks on four US industrial sectors dependent on oil – Petroleum and Natural Gas, Automobile and Trucks, Retails, and Precious Metals – drawing similar results.

Studies utilizing European data have similar results. For instance, Arouri and Nguyen (2010) analyze the short-term linkage between oil and stock prices using European data and find that there exists a link between fluctuations in sectoral stock returns and oil prices and the sensitivity of this relationship varies from sector to sector. They find that the Food and Beverages, Health Care and Technology sectors respond negatively to oil price increases, whereas the response is positive for the Financial, Oil & Gas, Industrials, Basic Materials and Personal and Household Goods sectors. In financial risk management perspective they also that it is beneficial to adding oil assets to a diversified portfolio of stocks. Malik and Ewing (2009) find that oil price volatility has a number of interdependencies with other market sectors, concluding that this kind of relationship can be used as a hedging mean. They point out that since many financial instruments are index-based, this kind of volatility transmission might be useful for optimal portfolio allocation. Arouri et al. (2011) examine volatility spillovers between oil and stock market sectors in the US and Europe together using data from 1998-2009. They find the evidence of a unidirectional spillover effect from oil to stock markets in Europe and a bidirectional spillover effect between oil and the US stock market sectors.

The relationship between oil prices and stock performance has also been studied at the firm-level. In a sample of 560 US firms, Narayan and Sharma (2011) explore the relationship between oil prices and firm returns. Their findings show that the effects of oil prices depend on the firm size – small firm's stock prices tend to rise in response to increases in oil prices, whereas the reverse is true for the larger firms. Similar results are observed in Europe by Scholtens and Yurtsever (2012) who investigate 38 industries in fifteen European countries using data from 1983 to 2007. They show that most industries/sectors benefit from downward oil price movement except for Oil, Mining and Gas industries who benefit from increased oil prices.

Arouri et al. (2012) explore the volatility linkages between crude oil and equity markets using weekly data from 1998 to 2009 from Europe and report the existence of volatility spillovers between oil prices and sector stock returns. Fan and Jahan-Parvar (2012) on the other hand, looking at the US industry-level returns and oil price predictability connection, find that oil price predictability exists in a relatively small number of industry-level returns, and changes in oil futures prices have virtually no predictive power for industry-level returns. Degiannakis et al. (2013) investigate the relationship between oil prices and industrial sector indices returns from 10 European sectors. They find the existence of contemporaneous correlations between oil prices and sector returns suggesting that the relationship between sector indices and oil prices is contemporaneous and industry/sector specific. Bouri et al. (2016) investigate the relationship between world oil prices and sectoral equity returns in Jordan using data around the Arab uprising and observe variations in the impact of oil price across different equity sectors. More specifically, oil return shocks is significantly associated with Financials and Service sectors, while its association with Industrials sector is insignificant. Recently, Dogah and Premaratne (2018) use VAR model and the Random Forest technique for analyzing the relationship between sectoral equity returns and variation in oil risk factors in BRICS markets during the period between 2007 and 2016. Their results confirm that the oil price volatility has a significant negative effect on basic materials, financials and industrials sectors.

It is clear from the review of the literature that while a significant volume of research on the volatility linkage between oil price and equity sectors exists in the context of developed countries, particularly the US and Europe; literature is very limited on the same issue based on major oil producing countries. The literature does not provide much evidence on the comparative analysis between country-level aggregate stock indices and sector-level indices to explore the possibility of heterogeneous responses during oil price shocks at different time regimes. In this paper, we intend to fill this gap by examining the linkage between sector-stock indices and oil prices for five equity sectors from major oil producing countries using various time regimes of oil price shocks to bring more insights to the literature.

3 Empirical methodology

In the literature on financial volatility modeling, the most widely used specification is the generalized autoregressive conditional heteroscedasticity (GARCH) model. Most of the empirical studies on volatility interdependence, correlations, and hedge ratios between oil markets and other assets apply multivariate GARCH (MGARCH) frameworks such as the Constant Conditional Correlation (CCC)-MGARCH model of Bollerslev (1990), Vector Autoregressive Moving-Average (VARMA)-MGARCH of Ling and McAleer (2003), the BEKK of Baba, Engle, Kraft and Kroner (1990) or the DCC-MGARCH of Engle (2002). While these models are more relevant in the multivariate analysis compared to the univariate models, the multivariate GARCH frameworks does pose serious challenges when dealing with large data sets. In fact, one of the biggest challenges in multivariate GARCH modeling is the issue of identifying the tradeoff between generality and feasibility which is often referred to as the "curse of dimensionality". For example, when the BEKK model is used for more than two variables, the likelihood function tends to behave poorly which causes estimation difficulty (Basher and Sadorsky, 2016). The basic problem is that when the number of estimated parameters are increased, the likelihood function flattens thereby making optimization difficult, if not entirely impossible. Given the objective of our study is to explore the linear dependence in terms of correlation dynamics between oil prices and sector-stock market indices and to investigate the volatility persistent among the series, the above models provide naturally suitable options. However, some of these frameworks, as earlier stated, are excessive in parameters and many lack empirical explanation. In view of this, we consider two multivariate models, the DCC-GARCH (Engle, 2002) and the ADCC-GARCH model (Cappiello et al., 2006), to model the volatility dependence and conditional correlational dynamics between oil prices index and sector-stock market indices. Even though the CCC-GARCH model has generally well-behaved likelihood function and can handle bigger data sets than the fully parameterized models, its assumption of constant conditional correlation seems too restrictive in the sense that correlation coefficient is likely to vary over time due to changes in economic and market conditions. Hence, we do not use the CCC-GARCH model. To allow for the dynamic (time-varying) responses in the conditional correlation, the DCC model proposed by Engle (2002) provides the best alternative and, therefore, this is one of our model choices.

The major advantage of DCC-MGARCH model is that it allows for the estimation of conditional covariance matrices for large number of assets in a two-step procedure with smaller number of parameters than most of the MGARCH specifications such as VECH and BEKK. It also captures well persistence in volatility and correlation and time-varying correlations. The DCC-GARCH model, however, does not allow for asset-specific news or any possibility of asymmetric responses in the time-varying conditional correlations between two assets. In fact, while leverage effect and volatility feedback are cited in most volatility studies as the main reasons for asymmetries in return volatility, little theoretical framework is available to justify recent evidence of asymmetric response to joint bad news (negative returns) in correlation (Cappiello et al. 2006). One possible explanation may be the time-varying risk-premium. Given a Capital Asset Pricing Model (CAPM)-type world, a negative systematic shock will induce downward pressure on the return of any pair of assets and will consequently increase the variance of these securities. With betas unchanged, covariance will increase and without proportional changes in idiosyncratic variance, correlation will also increase (see, Cappiello et al. 2006). Therefore, correlation may be higher following negative shock ("bad news") than after positive shock ("good news") of the same magnitude. Following the spectacular fluctuation episodes in the crude oil market, it is very important to investigate the possibility of asymmetric effects in the dynamic correlation between oil prices and sector-stock indices. To address this issue, we employ the ADCC (asymmetric dynamic conditional correlation) framework that can account for asymmetric responses in the dynamic conditional correlation between oil-sector stock indices. The advantage of the ADCC model is that it offers us an appropriate alternative to identify the heterogeneity in the correlation response of sector-stock indices to joint negative or positive innovations from the two market.

The DCC-GARCH model proposed by Engle (2002) is estimated in two stages. In the first stage, univariate volatility GARCH model is fit for each of the assets under the study and estimates of volatility are obtained. In the second stage, the standardized residuals (asset returns transformed by their standard deviations) are used to estimate the conditional correlation. Similar to previous studies, the optimal lag length selected for the univariate GARCH process is the one suggested by the Akaike Information Criterion (AIC). Each asset's returns exhibit autocorrelation, volatility clustering, and fat tails. This suggests an AR (1) mean equation for each GARCH model with multivariate Student t distribution for DCC and ADCC models. Consequently, we use lag one for both the conditional mean and variance equations for the markets we study. With an AR (1) process, the mean equation is expressed as

$$r_t = \mu + \alpha_1 r_{t-1} + \varepsilon_t \quad (1)$$

$$\varepsilon_t \mid \Omega_{t-1} \sim N(0, H_t)$$

where r_t is the $n \times 1$ vector of the asset returns; μ is the intercept (constant) term; α_1 is autoregressive (AR) parameter to account for serial correlation in the market returns and ε_t is a vector of the residual terms. The residual vector ε_t is bivariate and conditionally normally distributed. H_t represents the conditional covariance matrix measurable with respect to the information set at time t from previous period, (Ω_{t-1}) and Ω_{t-1} is the matrix of conditional previous information set.

All DCC class models (including the CCC-GARCH of Bollerslev (1990)) use the fact that H_t can be decomposed as:

$$H_t = D_t R_t D_t^{-1} \tag{2}$$

H_t is an $n \times n$ conditional covariance matrix, R_t is the time-varying correlation matrix and D_t is the diagonal matrix of time-varying standard deviations from the univariate GARCH models on the diagonal. Thus,

$$D_t = diag\left(h_{1,t}^{1/2}, \ldots h_{n,t}^{1/2}\right) \tag{3}$$

$$R_t = diag\left(q_{1,\mathrm{t}}^{1/2}, \ldots q_{\mathrm{n,t}}^{1/2}\right) Q_t \; diag\left(q_{1,\mathrm{t}}^{1/2}, \ldots q_{\mathrm{n,t}}^{1/2}\right) \tag{4}$$

The time-varying conditional variances, h_t (elements of D_t in the equation (2)) are computed from univariate GARCH models. For the GARCH (1, 1) the parameters of H_t can be expressed as:

$$h_{i,t} = \omega_i + \alpha_i \varepsilon_{i,t-1}^2 + \beta_i h_{i,t-1} \tag{5}$$

$$h_{i,t} = \omega_i + \alpha_i \varepsilon_{i,t-1}^2 + \beta_i h_{i,t-1} + \lambda_i X_{i,t} \tag{5a}$$

where $h_{i,t}$ is the conditional variances of assets i at time t, ω_i is the constant term, α_i refers to the ARCH term which transmits news about volatility from previous period and β_i is the first order GARCH term that captures the effect of previous volatility on current volatility. λ_i is the coefficient measuring the volatility of oil price change on the volatility of sectoral stock index return. Q_t from equation (4) is a symmetric definite matrix and the DCC parameter is modeled as:

$$Q_t = \left(1 - \theta_1 - \theta_2\right)\overline{Q} + \theta_1 \eta_{t-1} \, \eta_{t-1}' + \theta_2 Q_{t-1} \tag{6}$$

where θ_1 and θ_2 are non-negative scalar parameters that capture the effect of previous standardized shocks and dynamic conditional correlations on current correlations respectively. Q_t is the $n \times n$ matrix of unconditional correlations of standardized errors η_t. The DCC model is mean reverting as long as $\theta_1 + \theta_2 < 1$.

Next, we estimate the ADCC-GARCH model. Capiello et al. (2006) expand the DCC model and the Glosten-Jagannathan-Runkle (GJR) model of Glosten et al. (1993) by adding an asymmetric term to create the ADCC model. The univariate GJR-GARCH model is given as:

$$h_{i,t} = \omega_i + \alpha_i \varepsilon_{i,t-1}^2 + \beta_i h_{i,t-1} + d_i \varepsilon_{i,t-1}^2 \; I\left(\varepsilon_{i,t-1}\right) \tag{7}$$

Where $I = \begin{cases} 1 \text{ if } \varepsilon_{i,t-1} < 0 \\ 0 \text{ if otherwise} \end{cases}$

For the above specification, d is the parameter which captures asymmetric effects from previous news and a positive value for d means that negative residuals (news/innovations) tend to increase variance more than the positive ones of the same magnitude.

4 Data

We have randomly selected and collected sectoral stock index return data for six OPEC (Organization of Petroleum Exporting Countries) financial markets along with USA and Russia from June 2003 through January 2018 from Bloomberg database. During this timeline, oil prices have jumped above \$130 a barrel and below \$40. World stock markets have also experienced over 58% drop and over 50% rise during a single year. The countries that we have randomly selected are: Indonesia, Kuwait, Nigeria, Qatar, Saudi Arabia and United Arab Emirates (UAE). The sectors that we have selected for this research are those that have available data for all selected countries during the time period in Bloomberg database such as consumer discretionary, consumer staples, energy, financials, healthcare, industrials, and real estate. Although we want to study all sectors, returns data for all sectors are not available for the same time period for all countries. As a result, our study is limited to few available sectors that match for all countries[3]. We utilize the oil price data for both West Texas Intermediate (WTI) and Brent crude oil for the same time period (from June 2003 through January 2018).

5 Results and Discussions

In order to estimate the time-varying effect of oil price changes on the sectoral stock index returns of major oil producing countries, we initially estimate equation 5(a) and estimate the ARCH and GARCH parameters for all countries across all sectors in our sample. We estimate this equation both for WTI and Brent oil prices. Table 1a presents the basic descriptive statistics of sectoral stock index returns for the sample period. The average daily return in all seven sectors ranges from 0.0009% to 0.0017% and the standard deviation ranges from 0.0137% to 0.0310% with financial sector showing the highest volatility and Kurtosis for Indonesia during the sample period. The average daily return and volatility for four Gulf countries display similar results. Consumer Discretionary sector of Russia displays highest daily return, volatility, and Kurtosis compared to other sectors. Although daily average return and volatility seem to be similar across all sectors, energy and health care sectors in the USA show very high Kurtosis. These results are similar for all sectors in case of Nigeria. Table 1b presents the basic descriptive statistics for WTI and Brent crude oil daily price changes. Although daily price changes for both categories seem to range the same way as index returns, they display very high daily volatility compared to index volatilities of equity sectors. We can safely comment that oil price changes experience very high volatility compared to index volatility during our sample period. Overall, it seems that the data are very close to normal distribution even though there is an evidence that the data are leptokurtic. This is true for both sectoral index return and oil price changes.

Table 2 presents the correlations of return among oil producing countries for each sector in our sample. It can be observed that while the correlation coefficients among various countries are small for all the sectors, returns in the Consumer Staples and Financials sectors in the US are negatively correlated with those in Kuwait, Qatar, Saudi Arabia, and UAE. Further, the Energy sector returns in the US are also negative correlated with those in Nigeria, Kuwait, and Saudi Arabia. This negative correlation can be useful for diversification purposes for investors that hold international assets in their portfolios. An interesting observation is that the correlation between returns from Kuwait and Saudi Arabia is 1 for all sectors implying no diversification benefit from including both countries in portfolio.

Tables 3 and 4 present the return volatility of various financial sectors in each selected country incorporating WTI and Brent crude oil price changes respectively. From table 3, we observe that in the US financial market, WTI oil price changes affect the return volatility of all sectors except the industrial sector. It indicates that US consumers react to oil prices changes in all these sectors except the Industrial sector. In Russia, all sectors are affected by WTI price changes except the financial sector. In Indonesia and Nigeria, consumer staples sector is unaffected due to WTI price changes. Few other countries for which GARCH coefficients are not significant are: Kuwait, Nigeria, Saudi Arabia and UAE for the energy sector; Kuwait, Qatar and Saudi Arabia for healthcare sector, and Kuwait, Qatar, Saudi Arabia and UAE for the industrial sector. All Middle Eastern countries are so called oil economy and the effect of WTI oil price changes is the weakest in these countries both qualitatively and quantitatively. More than half the sectors selected in the study remain unaffected by the WTI oil price changes for Kuwait, Qatar, Saudi Arabia, and the UAE.

---

[3] One limitation of using stock return data across different countries (and even different continents) is that dates often do not match for one country with another country due to different holiday schedules of each country. So, in order to match the dates and make those consistent, we exclude the data points for those days of a country that do not match with other countries.

Table 4 presents the results with Brent crude oil price changes and results are very similar with minor changes. For example, in the US financial market, in addition to industrial sector, health care sector is also shown to be not affected by oil price changes. In case of Russia, consumer staple sector is not affected by Brent oil price changes and, for Nigeria, energy and real estate sectors are not affected by Brent crude oil price changes. The results for Middle Eastern countries also show similar pattern of no effect in most sectors. The results show that all parameters for all sectors and all countries both for ARCH and GARCH are highly significant (except ARCH coefficients for the financial sector in Qatar in both tables 3 and 4). The significant ARCH parameters indicate that the volatility from the previous day, as measured by the square of lag residuals, significantly affects the current volatility of the stock index return. Further, all the GARCH (1,1) coefficients are also highly significant indicating that the last period's forecast return volatility significantly affects the current volatility of the stock index return.

Similar to the results for WTI oil price changes, some of the GARCH coefficients for brent crude oil price changes for some countries and sectors are not statistically significant. Those are: Kuwait, Nigeria, Saudi Arabia and UAE for the energy sector; Kuwait, Qatar and Saudi Arabia for healthcare sector, and Kuwait, Qatar, Saudi Arabia and UAE for the industrial sector. The GARCH coefficients for consumer staples for Indonesia and Russia are not also significant. The insignificance of the GARCH coefficients of these countries within these sectors indicate that financial markets basically ignore the impact of oil price changes. The coefficients for the rest of the countries and sectors are highly significant. The results of volatility forecast and the current volatility estimation from previous residuals and previous period's forecast volatility are not surprising given the large number of past studies have similar conclusion. These significant ARCH and GARCH coefficients indicate that inter-temporal volatility of sectoral stock returns of major oil producing countries are very visible and should be evaluated if other factors are contributing to these high volatility level. To examine the effect of oil price volatility, we incorporate the price changes for both WTI and Brent crude oil into the GARCH analysis.

The results for the impact of oil price volatility on the stock return volatility are somewhat mixed. As indicated above, the coefficients for most of the sectors in all Middle Eastern countries (such as, Kuwait, Qatar, Saudi Arabia and UAE) are not significant. In case of WTI oil price, out of possible 28 coefficients (λ) for seven sectors of these four countries, only nine coefficients are significant and the remaining 21 coefficients are statistically insignificant at conventional levels. The common sectors for which oil price volatility does not have a significant impact on stock returns in the Middle Eastern countries are consumer staples, energy, financials, and industrials. The results are similar when Brent oil price is used. On the other hand, for remaining four countries (Indonesia, Nigeria, Russia, and USA), most of the coefficients are significant except five coefficients both for WTI and Brent oil price volatility. Those countries that use oil heavily such as Russia and USA, results imply that oil price volatility affects consumers' behavior affecting return volatilities of various sectors. Negative coefficients for some countries within a sector indicate that there is hedging opportunities among various countries within a specific sector and/or within various countries and various sectors.

6 Concluding Remarks

In this study, we examine the inter-temporal volatility of sectoral returns of various oil producing countries. We also examine the impact of oil price changes on various financial sectors' return volatilities for a sample of OPEC countries along with Russia and the US. Using GARCH framework, we find that all parameters for all sectors and all countries both for ARCH and GARCH are highly significant (except ARCH coefficients for the financial sector in Qatar). Further, all the GARCH (1,1) coefficients are also found to be highly significant. This finding indicates that the last period's forecast return volatility significantly affects the current volatility of the stock index return. These significant ARCH and GARCH coefficients imply that inter-temporal volatility of sectoral stock returns of major oil producing countries are very visible and should be evaluated by considering other factors that may contribute to these high volatility level.

To examine the effect of oil price volatility, we incorporate the price changes for both WTI and Brent crude oil into the GARCH analysis. The results for the impact of oil price volatility on the stock return volatility are somewhat mixed. As discussed in the earlier section, the coefficients for most of the sectors in all Middle Eastern countries (Kuwait, Qatar, Saudi Arabia, and the UAE) are not significant. In case of WTI oil price, out of total 28 coefficients (λ) for seven sectors of these four countries, only nine coefficients are statistically significant at conventional levels and the remaining 21 coefficients are not significant. These results are intuitive because the Middle Eastern countries are known as oil economy with no other significant source of revenue for the country as well as citizens. Since oil prices have consistently remained above $60 a barrel on average, these countries possess a pile of cash reserve from past sales. As a result, these countries' economy are less affected by daily oil price movements as the latter do not affect consumers' earnings and gas has been significantly cheaper in these countries. The volatility in oil prices has no impact whatsoever on the consumption behavior and day to day life of the citizens of these countries. That may, however, change in the future as oil prices have been showing signs of permanently staying below $50 a barrel and these countries are beginning to change the compensation patterns to employees, charging taxes, increasing health care cost, etc., especially for the expatriates that accounts for the two-thirds of the total population in these countries. It would be interesting to reinvestigate this research question, perhaps, in five years from now, since consistent low oil prices in the last two years have started to have some negative effects on their economy.

The findings of the paper may be important for the fund managers and portfolio investors. Keeping an eye on the price movements of oil prices both in WTI and brent markets, fund managers and investors may be able to identify the sectors and countries where they will be able to get the best diversification of their funds and maximum rate of return on their investment. Individual investors may also be able to use the results of the paper if they try to invest in some sectoral indices that are affected by the oil price movements.

References

Apergis, N., & Miller, S.M. (2009). Do structural oil-market shocks affect stock prices? Energy Economics, 31, 569–575.

Arouri, M. E. H., Jouini, J., & Nguyen, D. K. (2011). Volatility spillovers between oil prices and stock sector returns: Implications for portfolio management. Journal of International money and finance, 30(7), 1387-1405.

Arouri, M. E. H., Jouini, J., & Nguyen, D. K. (2012). On the impacts of oil price fluctuations on European equity markets: Volatility spillover and hedging effectiveness. Energy Economics, 34(2), 611-617.

Arouri, M., & Nguyen, D.K. (2010). Oil prices, stock markets and portfolio investment: evidence from sector analysis in Europe over the last decade. Energy Policy, 38 (8), 4528–4539.

Baba, Y., Engle, R. F., Kraft, D. F., & Kroner, K. F. (1990). Multivariate simultaneous generalized ARCH. Mimeo: Department of Economics, University of California, San Diego.

Basher, S. A., & Sadorsky, P. (2016). Hedging emerging market stock prices with oil, gold, VIX, and bonds: A comparison between DCC, ADCC and GO-GARCH. Energy Economics, 54, 235-247.

Bollerslev, T., (1990), Modelling the Coherence in Short-run Nominal Exchange Rates: A Multivariate Generalized ARCH Model. The Review of Economics and Statistics, 72 (3), 498-505.

Bouri, E., Awartani, B., & Maghyereh, A. (2016). Crude oil prices and sectoral stock returns in Jordan around the Arab uprisings of 2010. Energy Economics, 56, 205-214.

Broadstock, D. C., & Filis, G. (2014). Oil price shocks and stock market returns: New evidence from the United States and China. Journal of International Financial Markets, Institutions and Money, 33, 417-433.

Cappiello, L., Engle, R. F., & Sheppard, K. (2006). Asymmetric dynamics in the correlations of global equity and bond returns. Journal of Financial econometrics, 4(4), 537-572.

Chang, C. L., McAleer, M., & Tansuchat, R. (2013). Conditional correlations and volatility spillovers between crude oil and stock index returns. The North American Journal of Economics and Finance, 25, 116-138.

Cunado, J., & de Gracia, F. P. (2014). Oil price shocks and stock market returns: Evidence for some European countries. Energy Economics, 42, 365-377.

Degiannakis, S., Filis, G., & Floros, C. (2013). Oil and stock returns: Evidence from European industrial sector indices in a time-varying environment. Journal of International Financial Markets, Institutions and Money, 26, 175-191.

Dogha, K.E. and G. Premarante, (2018). Sectoral exposure of financial markets to oil risk factors in BRICS countries. Energy Economics, 76, 228-256.

Domanski, D., & Heath, A. (2007). Financial investors and commodity markets. BIS Quarterly Review, March.

Engle, R. (2002). Dynamic conditional correlation: A simple class of multivariate generalized autoregressive conditional heteroskedasticity models. Journal of Business & Economic Statistics, 20(3), 339-350.

Fan, Q., & Jahan-Parvar, M. R. (2012). US industry-level returns and oil prices. International Review of Economics & Finance, 22(1), 112-128.

Filis, G., Degiannakis, S., & Floros, C. (2011). Dynamic correlation between stock market and oil prices: The case of oil-importing and oil-exporting countries. International Review of Financial Analysis, 20(3), 152-164.

Glosten, L. R., Jagannathan, R., & Runkle, D. (1993). On the relation between the expected value and the volatility of the normal excess return on stocks. Journal of Finance, 48, 1779−1801.

Guesmi, K., & Fattoum, S. (2014). Return and volatility transmission between oil prices and oil-exporting and oil-importing countries. Economic Modelling, 38, 305-310.

Kang, W., Ratti, R. A., & Yoon, K. H. (2015). The impact of oil price shocks on the stock market return and volatility relationship. Journal of International Financial Markets, Institutions and Money, 34, 41-54.

Kilian, L., & Park, C. (2009). The impact of oil price shocks on the US stock market. International Economic Review, 50(4), 1267-1287.

Lin, B., Wesseh, P. K., & Appiah, M. O. (2014). Oil price fluctuation, volatility spillover and the Ghanaian equity market: Implication for portfolio management and hedging effectiveness. Energy Economics, 42, 172-182.

Ling, S., & McAleer, M. (2003). Asymptotic theory for a vector ARMA-GARCH model. Econometric Theory, 19(02), 280-310.

Malik, F., & Ewing, B. T. (2009). Volatility transmission between oil prices and equity sector returns. International Review of Financial Analysis, 18(3), 95-100.

Mollick, A. V., & Assefa, T. A. (2013). US stock returns and oil prices: The tale from daily data and the 2008–2009 financial crisis. Energy Economics, 36, 1-18.

Nandha, M., & Faff, R. (2008). Does oil move equity prices? A global view. Energy Economics, 30(3), 986-997.

Narayan, P. K., & Narayan, S. (2010). Modelling the impact of oil prices on Vietnam's stock prices. Applied Energy, 87, 356–361.

Narayan, P. K., & Sharma, S. S. (2011). New evidence on oil price and firm returns. Journal of Banking & Finance, 35(12), 3253-3262.

Park, J., & Ratti, R.A. (2008). Oil price shocks and stock markets in the US and 13 European countries. Energy Economics, 30, 2587–2608.

Sadorsky, P. (1999). Oil price shocks and stock market activity. Energy Economics, 21(5), 449-469.

Scholtens, B., & Yurtsever, C. (2012). Oil price shocks and European industries. Energy Economics, 34(4), 1187-1195.

Tang, K., & Xiong, W. (2012). Index investment and the financialization of commodities. Financial Analysts Journal, 68(5), 54-74.

Table 1a: Descriptive Statistics of daily percentage of change of sectoral stock returns of eight countries.

		Indonesia	Kuwait	Nigeria	Qatar	Russia	Sarabia	UAE	USA
Consumer Discretionary	Mean	0.0012	0.0004	0.0003	0.0006	0.0032	0.0004	0.0012	0.0010
	Median	0.0006	-0.0003	0.0000	0.0000	0.0008	-0.0003	0.0000	0.0008
	Std. Dev.	0.0192	0.0175	0.0181	0.0326	0.0975	0.0175	0.0335	0.0144
	Skewness	-0.0906	0.0368	-0.1169	0.0847	39.758	0.0371	0.4761	0.7885
	Kurtosis	9.1120	6.8084	8.7041	6.8095	83.676	6.8063	7.1661	14.0111
Consumer Staples	Mean	0.0011	-0.0002	0.0007	0.0009	0.0022	-0.0002	0.0011	0.0005
	Median	0.0011	-0.0007	0.0001	0.0000	0.0003	-0.0007	0.0000	0.0005
	Std. Dev.	0.0137	0.0203	0.0125	0.0220	0.0820	0.0203	0.0236	0.0087
	Skewness	-0.0529	1.1158	0.3172	0.1824	35.2095	1.1158	0.3928	0.2871
	Kurtosis	9.8605	16.9903	5.3759	8.3955	15.6040	16.9903	7.7025	15.8421
Energy	Mean	0.0009	0.0001	-0.0004	0.0000	0.0001	0.0001	-0.0008	0.0010
	Median	0.0007	-0.0001	-0.0004	0.0000	0.0002	-0.0001	-0.0013	0.0007
	Std. Dev.	0.0213	0.0196	0.0156	0.0158	0.0219	0.0196	0.0224	0.0194
	Skewness	-0.6713	0.0660	0.4114	0.3332	-0.2145	0.0660	0.4662	5.1041
	Kurtosis	12.5312	4.4976	5.7761	11.5163	21.272	4.4974	7.0442	110.1139
Financials	Mean	0.0017	0.0005	0.0004	0.0046	0.0007	0.0005	0.0006	0.0007
	Median	0.0012	0.0005	-0.0003	0.0003	0.0000	0.0005	0.0006	0.0006
	Std. Dev.	0.0310	0.0106	0.0161	0.1946	0.0245	0.0106	0.0141	0.0195
	Skewness	12.0624	-0.0848	0.7205	48.6847	-0.4519	-0.0847	1.5382	0.8958
	Kurtosis	481.4172	9.6349	10.415	26.0300	15.880	9.6362	28.043	18.3480
Health Care	Mean	0.0010	0.0014	0.0004	0.0026	0.0004	0.0014	0.0026	0.0011
	Median	0.0008	0.0000	0.0000	0.0000	0.0000	0.0000	0.0001	0.0009
	Std. Dev.	0.0165	0.0424	0.0162	0.0217	0.0266	0.0424	0.0240	0.0114
	Skewness	-0.0341	-1.1509	0.0623	1.1415	3.5780	-1.1509	0.7589	4.8305
	Kurtosis	9.6190	12.8319	8.7161	7.1799	70.3766	12.8319	7.3138	80.8946
Industrials	Mean	0.0012	0.0003	0.0003	0.0002	0.0002	0.0003	0.0008	0.0006
	Median	0.0011	0.0005	0.0000	0.0003	0.0001	0.0005	0.0009	0.0007
	Std. Dev.	0.0185	0.0152	0.0185	0.0170	0.0181	0.0152	0.0193	0.0144
	Skewness	-0.3190	-0.3562	0.1180	-0.2291	-0.4530	-0.3561	-0.3193	-1.7557
	Kurtosis	16.3846	6.3651	6.3716	9.2297	21.0902	6.3655	15.4357	29.8366
Real Estate	Mean	0.0013	0.0002	-0.0002	0.0003	0.0010	0.0002	0.0002	0.0005
	Median	0.0015	0.0005	0.0000	-0.0002	-0.0002	0.0005	0.0001	0.0006
	Std. Dev.	0.0184	0.0122	0.0223	0.0214	0.0279	0.0122	0.0223	0.0193
	Skewness	0.1234	-0.7067	0.1589	0.2842	1.4586	-0.7067	0.3402	0.7213
	Kurtosis	8.4705	7.9145	7.8325	6.9526	25.8215	7.9141	9.4614	21.8473

Table 1b: Descriptive Statistics of percentage change in daily price of Brent and WTI crude oil.

	WTI	Brent
Mean	0.011359	0.002493
Median	0.020000	0.010000
Std. Dev.	1.616688	1.515768
Skewness	-0.010493	-0.263190
Kurtosis	11.86369	5.742210
Correlation	.9863	

Table 2: Correlations of index returns among oil producing countries for each sector

		Indonesia	Kuwait	Nigeria	Qatar	Russia	Sarabia	UAE	USA
Consumer Discretionary	Indonesia	1							
	Kuwait	0.0469	1.0000						
	Nigeria	0.0041	-0.0005	1.0000					
	Qatar	0.0284	0.0279	0.0394	1.0000				
	Russia	0.0378	0.0158	-0.0019	0.0116	1.0000			
	SArabia	0.0469	1.0000	-0.0002	0.0279	0.0158	1.0000		
	UAE	0.0293	0.0803	0.0045	0.0107	-0.0588	0.0806	1.0000	
	USA	0.0747	0.0033	0.0122	0.0033	0.0190	0.0034	0.0049	1.0000
Consumer Staples	Indonesia	1.0000							
	Kuwait	0.0665	1.0000						
	Nigeria	0.0643	0.0421	1.0000					
	Qatar	0.0769	0.0743	-0.0001	1.0000				
	Russia	0.0463	-0.0008	0.0106	-0.0426	1.0000			
	SArabia	0.0665	1.0000	0.0421	0.0743	-0.0008	1.0000		
	UAE	0.0919	0.0276	0.0706	0.0787	-0.0063	0.0276	1.0000	
	USA	0.0641	-0.0028	0.0046	-0.0317	0.0724	-0.0028	0.0002	1.0000
Energy	Indonesia	1.0000							
	Kuwait	0.0569	1.0000						
	Nigeria	0.0310	0.0286	1.0000					
	Qatar	0.1940	0.1182	0.0219	1.0000				
	Russia	0.3637	0.0597	0.0455	0.1226	1.0000			
	SArabia	0.0569	1.0000	0.0286	0.1182	0.0597	1.0000		
	UAE	0.2795	0.1157	-0.0020	0.2795	0.1997	0.1157	1.0000	
	USA	0.1177	-0.0596	-0.0120	0.0320	0.2593	-0.0596	0.1372	1.0000
Financials	Indonesia	1.0000							
	Kuwait	0.0523	1.0000						
	Nigeria	0.0113	-0.0152	1.0000					
	Qatar	-0.0089	0.0132	0.0642	1.0000				
	Russia	0.1453	0.0663	0.0407	0.0046	1.0000			
	SArabia	0.0523	1.0000	-0.0152	0.0132	0.0663	1.0000		
	UAE	0.1041	0.2090	0.0526	0.0311	0.1386	0.2091	1.0000	
	USA	0.0272	-0.0084	-0.0011	-0.0054	0.2639	-0.0083	0.0778	1.0000

Health Care	Indonesia	1.0000							
	Kuwait	0.0164	1.0000						
	Nigeria	0.0303	0.0172	1.0000					
	Qatar	0.0786	-0.0127	-0.0566	1.0000				
	Russia	0.0597	-0.0185	0.0551	0.0473	1.0000			
	SArabia	0.0164	1.0000	0.0172	-0.0127	-0.0185	1.0000		
	UAE	-0.0105	-0.0384	0.0840	-0.0293	-0.0035	-0.0384	1.0000	
	USA	0.0563	0.0602	-0.0068	0.0158	0.0545	0.0602	0.0220	1.0000
Industrials	Indonesia	1.0000							
	Kuwait	0.0970	1.0000						
	Nigeria	0.0007	0.0034	1.0000					
	Qatar	0.1593	0.1869	0.0256	1.0000				
	Russia	0.1871	0.0668	0.0511	0.1170	1.0000			
	SArabia	0.0969	1.0000	0.0034	0.1869	0.0668	1.0000		
	UAE	0.1903	0.1648	0.0034	0.2722	0.1134	0.1648	1.0000	
	USA	0.0999	0.0458	0.0300	0.0717	0.1711	0.0458	0.0940	1.0000
Real Estate	Indonesia	1.0000							
	Kuwait	0.1592	1.0000						
	Nigeria	-0.0247	0.0043	1.0000					
	Qatar	0.1181	0.1919	0.0025	1.0000				
	Russia	0.1270	0.0623	0.0263	0.0522	1.0000			
	SArabia	0.1592	1.0000	0.0043	0.1919	0.0623	1.0000		
	UAE	0.2664	0.2632	0.0388	0.2521	0.1278	0.2632	1.0000	
	USA	0.1390	0.0205	-0.0071	-0.0088	0.0902	0.0205	0.0466	1.0000
Oil Prices	Brent	0.1096	0.0192	0.0028	0.0099	0.0790	0.0192	0.0749	-0.0046
	WTI	0.0967	0.0144	0.0033	0.0074	0.0697	0.0144	0.0622	-0.0027

Table 3: GARCH results of individual countries with WTI oil price change.
Equation 5a: $h_{i,t} = \omega_i + \alpha_i \varepsilon_{i,t-1}^2 + \beta_i h_{i,t-1} + \lambda_i X_{i,t}$

		Consumer Discretionary	Consumer Staples	Energy	Financials	Health Care	Industrials	Real Estate
Indonesia	Constant	4.78E-06	5.26E-06	1.09E-05	0.000753	3.74E-05	3.79E-06	9.23E-06
	α	0.06653	0.107146	0.152283	-0.00185	0.19975	0.111026	0.127024
	β	0.921186	0.86686	0.831044	0.513177	0.679479	0.88284	0.851302
	λ	-2.90E-06	-2.80E-07	-3.74E-06	0.000141	-1.38E-05	-3.40E-06	-6.44E-06
	R^2	0.01055	0.009404	0.016384	0.000721	0.008992	0.004655	0.013074
Kuwait	Constant	4.39E-06	4.13E-05	3.25E-05	4.80E-06	0.000375	6.03E-06	8.57E-06
	α	0.072995	0.143543	0.139768	0.126937	0.35513	0.114934	0.142313
	β	0.915562	0.754737	0.779153	0.8293	0.497409	0.856151	0.790495
	λ	-4.88E-06	**-4.69E-06**	-1.26E-06	4.22E-08	2.96E-05	-1.59E-06	-2.19E-06
	R^2	-0.00054	-0.00136	0.001104	-0.00015	-0.00339	-0.00142	-0.0034
Nigeria	Constant	4.70E-06	1.97E-05	1.20E-05	5.61E-05	6.72E-05	1.90E-05	0.0002
	α	0.142573	0.280293	0.17511	0.381935	0.137866	0.126112	0.163871
	β	0.839541	0.604874	0.788785	0.434235	0.62288	0.815237	0.447113
	λ	1.99E-06	-9.01E-07	6.11E-08	-7.48E-06	-2.63E-05	-3.81E-06	-2.37E-05
	R^2	0.000798	-0.00195	-0.001644	-0.0023	-0.00101	-0.00136	0.000077
Qatar	Constant	8.37E-05	5.77E-06	1.18E-05	0.036448	8.44E-05	1.14E-05	2.60E-05
	α	0.061539	0.104517	0.218201	-0.00094	0.167351	0.163513	0.268597
	β	0.860597	0.885128	0.765529	0.585543	0.632777	0.804297	0.696745
	λ	**-2.70E-06**	-2.11E-08	-3.08E-06	-0.00516	-1.72E-06	1.02E-06	9.26E-07
	R^2	0.002715	-0.00044	0.00192	-0.00038	-0.00886	0.004518	-0.00035
Russia	Constant	0.00191	0.006201	6.62E-06	1.36E-05	4.47E-05	1.39E-05	1.84E-05
	α	0.164247	-0.00139	0.078768	0.087369	0.177135	0.248842	0.135839
	β	0.468418	0.568918	0.901136	0.882782	0.736337	0.747739	0.860322
	λ	-0.00041	-0.00059	4.01E-06	-1.22E-06	1.59E-05	-2.94E-06	-5.09E-06
	R^2	0.00043	-0.00009	0.079834	0.047965	0.012232	0.024992	0.015542
Saudi Arabia	Constant	4.35E-06	4.13E-05	3.25E-05	4.84E-06	0.000375	6.03E-06	8.57E-06
	α	0.072671	0.143543	0.139795	0.127531	0.35513	0.114923	0.142266
	β	0.916036	0.754737	0.779113	0.828302	0.497409	0.856166	0.79055
	λ	-4.85E-06	-4.69E-06	-1.26E-06	3.73E-08	2.96E-05	-1.59E-06	-2.19E-06
	R^2	-0.00056	-0.00136	0.001103	-0.00015	-0.00339	-0.00142	-0.00341
UAE	Constant	5.50E-06	2.38E-05	4.01E-05	4.49E-06	-4.31E-07	1.19E-05	1.28E-05
	α	0.054988	0.120075	0.171939	0.214859	-0.00038	0.268555	0.126122
	β	0.939913	0.841011	0.75491	0.799444	0.993142	0.746373	0.846662
	λ	-4.23E-07	1.76E-06	-4.50E-06	-4.18E-06	-9.00E-06	-2.86E-07	**-2.77E-06**
	R^2	0.000079	-0.00131	0.012625	0.003792	-0.00541	0.000415	0.005723

USA	Constant	3.30E-06	3.11E-06	3.14E-05	3.84E-06	7.47E-05	2.72E-06	2.30E-06
	α	0.121089	0.117429	0.275107	0.098975	0.151706	0.09031	0.110981
	β	0.867664	0.834517	0.598855	0.883301	0.565031	0.897785	0.879334
	λ	-3.27E-06	-8.05E-07	-8.81E-06	-2.63E-06	1.55E-05	-4.61E-07	**-9.44E-07**
	R^2	0.007095	0.020695	0.183849	0.021014	0.023641	0.046745	0.029946

Coefficients in bold are significant 5% and 10% level. Coefficients in red are not statistically significant at any conventional levels. All other coefficients are significant below 5% level.

Table 4: GARCH results of individual countries with Brent oil price change.
Equation 5a: $h_{i,t} = \omega_i + \alpha_i \varepsilon_{i,t-1}^2 + \beta_i h_{i,t-1} + \lambda_i X_{i,t}$

		Consumer Discretionary	Consumer Staples	Energy	Financials	Health Care	Industrials	Real Estate
Indonesia	Constant	4.41E-06	5.43E-06	1.06E-05	0.000765	3.44E-05	0.0001	9.67E-06
	α	0.066773	0.110154	0.149139	-0.00198	0.19071	0.17308	0.126819
	β	0.921932	8.63E-01	0.834645	0.503002	0.696996	0.569534	0.849949
	λ	-5.18E-06	2.67E-07	**-4.06E-06**	0.000131	-1.42E-05	-4.04E-05	-5.33E-06
	R^2	0.010944	0.009496	0.020581	-0.00012	0.009003	0.011499	0.01584
Kuwait	Constant	4.28E-06	4.30E-05	3.23E-05	4.01E-06	0.000384	6.03E-06	8.52E-06
	α	0.075453	0.146873	0.13969	0.111801	0.348633	0.11507	0.142887
	β	0.913516	0.746846	0.779633	0.851638	0.496248	0.855889	0.789881
	λ	-4.04E-06	**-4.86E-06**	-6.18E-07	1.25E-06	2.25E-05	-9.54E-07	-7.54E-07
	R^2	0.000383	-0.00153	0.000793	-1E-06	-0.00197	0.00024	-0.00262
Nigeria	Constant	4.79E-06	1.94E-05	1.15E-05	4.82E-05	5.96E-05	1.94E-05	1.47E-07
	α	0.145286	0.280171	0.172242	0.347764	0.127298	0.134215	0.040312
	β	0.836958	0.607064	0.793658	0.489515	0.649825	0.807537	0.959602
	λ	1.91E-06	-2.41E-06	-1.37E-06	-6.39E-06	-1.26E-05	-8.68E-06	1.66E-07
	R^2	0.000881	-0.00291	-0.00157	-0.00152	-9.1E-05	-0.00163	0.000367
Qatar	Constant	8.71E-05	5.86E-06	1.12E-05	0.034837	9.00E-05	1.06E-05	2.66E-05
	α	0.061346	0.106288	0.194323	-0.0009	0.17411	0.153412	0.270498
	β	0.857446	0.883387	0.783825	0.568261	0.612434	0.816039	0.693754
	λ	**8.20E-06**	**-4.71E-07**	-6.94E-06	-0.01133	-3.79E-06	-2.32E-07	-2.05E-06
	R^2	0.002156	-0.00013	0.003712	-0.00052	-0.00693	0.006729	-0.00029
Russia	Constant	0.006392	0.00036	7.27E-06	1.36E-05	4.28E-05	1.38E-05	1.72E-05
	α	0.461042	0.124978	0.080764	0.080358	0.157527	0.229751	0.113469
	β	0.43273	0.4786	0.897177	0.888968	0.755794	0.760364	0.877539
	λ	-0.00196	1.29E-06	3.66E-06	-5.30E-06	1.33E-05	-5.44E-06	-1.32E-05
	R^2	-0.00678	-0.00043	0.077459	0.053853	0.017133	0.025336	0.016105
Saudi Arabia	Constant	4.22E-06	4.30E-05	3.23E-05	4.06E-06	0.000384	6.03E-06	8.52E-06
	α	0.074985	0.146873	0.139714	0.112676	0.348633	0.115059	0.142846
	β	0.914173	0.746846	0.779599	0.850231	0.496248	0.855904	0.789929
	λ	-4.02E-06	**-4.86E-06**	-6.18E-07	1.25E-06	2.25E-05	-9.54E-07	-7.52E-07
	R^2	0.000349	-0.00153	0.000793	0.000004	-0.00197	0.000241	-0.00262
UAE	Constant	5.88E-06	2.47E-05	4.11E-05	4.62E-06	-7.07E-07	1.20E-05	1.23E-05
	α	0.054955	0.125545	0.172044	0.216911	-0.0024	0.268792	0.124102
	β	0.939275	0.834426	0.752258	0.796948	0.996102	0.745556	0.849913
	λ	-3.53E-06	7.34E-06	-2.92E-06	-4.75E-06	-3.69E-06	-1.70E-06	-3.33E-06
	R^2	0.000232	-0.00139	0.018492	0.006617	-0.00471	0.000488	0.007681

	Constant	3.26E-06	3.12E-06	3.21E-05	3.71E-06	2.23E-05	2.63E-06	2.09E-06
	α	0.121376	1.12E-01	0.228472	0.098291	0.445133	0.091249	0.109558
USA	β	0.867417	0.838917	0.634369	0.884421	0.434631	0.89745	0.882417
	λ	-3.84E-06	-1.33E-06	-9.91E-06	-1.93E-06	-6.37E-07	-4.60E-07	-1.46E-06
	R^2	0.012497	0.024938	0.176244	0.027895	0.020377	0.053579	0.034676

Coefficients in bold are significant 5% and 10% level. Coefficients in red are not statistically significant at any conventional levels. All other coefficients are significant below 5% level.