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Changes in Demand for Crude Oil and its Correlation with Crude Oil and Stock Market Returns Volatilities: Evidence from Three Asian Oil Importing Countries

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ABSTRACT

While different streams of literature exist investigating the relationship and the conditional correlation between oil import prices, oil returns volatility and stock market returns volatility. The period of the study runs from July 1997 until July 2017 with a monthly data. The objectives of the present paper are the following to investigate the order of the mean equation, the order (*p*,*q*) of the conditional variance and the order (*r*,*s*) of the Diag-BEKK model. Data from the Indian and Indonesian stock market returns series respectively shows the existence of appropriate ARMA(2,2)-EGARCH(2,2) and ARMA(2,2)-IGARCH(2,2) models. The appropriates models of Diag-BEKK(p,q) for China, India and Indonesia are Diag-BEKK(1,2), Diag-BEKK(0,2) and Diag-BEKK(0,2) respectively. In the three Asian Countries, the three variables are correlated. Also, equations show a statistically significant covariation in oil import price, which depends more on its lags than on past errors. Consequently, oil demand are influenced by past information which is common to the crude oil market and the stock market and to its volatilities. They suggest that the comovements of the three series display an extremely volatile trend for the study period.

Keywords: Oil Volatility, Oil Import Price, Stock Market Volatility, Conditional Mean, Conditional variances, Simultaneous Equations Model, OLS
JEL Classifications: B26, C3, C58, D58, G15, Q41

1. INTRODUCTION

Oil is an important global resource in the modern economy and industrial sectors. In the period since the oil price shocks of the 1970s. The same model also suggests that a negative shock to foreign oil demand would increase Asian imports. Intuitively, a reduction in foreign oil demand reduces oil prices, which in turn increases domestic consumption and reduces domestic production, resulting in higher imports. A positive shock to foreign supply would have analogous effects (reducing global prices, increasing domestic consumption and reducing domestic production, implying higher imports). The plausible explanation is that during our sample period global oil demand, rather than oil production, is the main determinant of oil price changes (Wang et al., 2013). Increase in global economic activity stimulates both oil and stock prices, leading to the phenomenon of positive correlations (Filis et al., 2011 and Wang and Liu, 2016). It has been well documented in the literature that crude oil price shocks have essential impacts on the real economy (Hamilton, 1983; Kilian, 2009). As the most popular financial asset, the stock price is certainly affected by the economic fundamentals. Therefore, it is not surprising that quite a large number of studies aim to detect the effects of oil import prices on oil price shocks on stock market activities.

Indeed, according to the IEA (Southeast Asia Energy Outlook, 2015), primary energy demand in ASEAN countries grew by nearly 50% between 2000 and 2013 and would increase by nearly 80% between 2013 and 2040. Indonesia, a heavyweight in the region, is expected to experience annual economic growth of about 4.9% by 2040 (IMF, 2015), population growth of about 0.8% per year (UN, 2013) bringing its population to 311 million in 2040, and an increase in GDP per capita of about 4% (compared to 3.7% for ASIAN countries and 1.6% for OECD countries). With an urbanization rate of 67% in 2040, compared to 53% in 2013, Indonesia would thus undergo a major economic upheaval that would affect all economic sectors, particularly its energy sector. Primary energy consumption, which will increase by 43% between 2003 and 2013, will rise by about 2.5% per year until 2035, with an annual increase in oil consumption of more than 1.1% to more than 2.1 mbpd in 2035.

For example, the demand for crude oil in the whole world has increased by 1.7 million barrels per day (b/d) with 1.8% from January 2017 to February 2017, while the demand for this period has decreased by 0.2 million b/d with 0.2%. According to the annual report of the Organization of Petroleum Exporting Countries (OPEC), the United States is at a leading position in crude oil imports with 7351 b/d followed by China with 6730.9 b/d. On the other hand, Saudi Arabia is at the lead in oil exports with 7163.3 b/d followed by Russia with 4897.5 b/d (OPEC, 2017).

The rapid growth of the Chinese, Indian and Indonesian economies since the beginning of the decade continues unabated. The public authorities have significantly redirected their action towards opening up the economy to market forces. Thus, the orientation towards industry and production increases energy consumption and more particularly oil consumption. Provisions relating to pricing, foreign trade, exchange rates, foreign investment, barriers to entry, domestic markets, the functioning of state-owned enterprises and the financial system have all been modified and therefore the stock markets of these countries are subsequently regulated.

Global purchases of imported crude oil totaled US $873.4 billion in 2017. Overall, the dollar value of crude oil imports for all importing countries was down by an average −47.1% since 2013 when crude oil purchases were valued at $ 1.652 trillion. Year over year, imported crude oil increased in value by 28% from $ 682.5 billion for 2016. Among continents, Asian countries accounted for the highest dollar worth of imported crude oil during 2017 with purchases valued at $429.8 billion or 49.2% of the global total. Over the period 2010-2015, crude oil consumption increased by more than 26%, and crude oil imports increased by more than 40%. Despite the slowdown in the Chinese economy, according to the Energy Statistics Administration (EIA), imports are playing an increasingly important role in meeting Chinese demand.

Imports cover 60% of domestic consumption. Oil imports from China are estimated at 9.7 million barrels per day. Conversely, until the end of 2016, China's oil imports have reached 7.9 million b/d, while Saudi Arabia is the biggest supplier of oil to China with 15% followed by Russia with 14%. Chinese crude oil imports grew strongly in 2017. The State Bureau of Statistics (BES) stated in a press release that crude oil imports jumped 10.1% year-on-year, a record rate, to 460 million tons. Last December alone, crude oil imports rose by about 30% to 43.78 million tons. Oil import prices reached US $162.2 billion, which represents 18.6% of world demand (Figure 1 and Table 1).

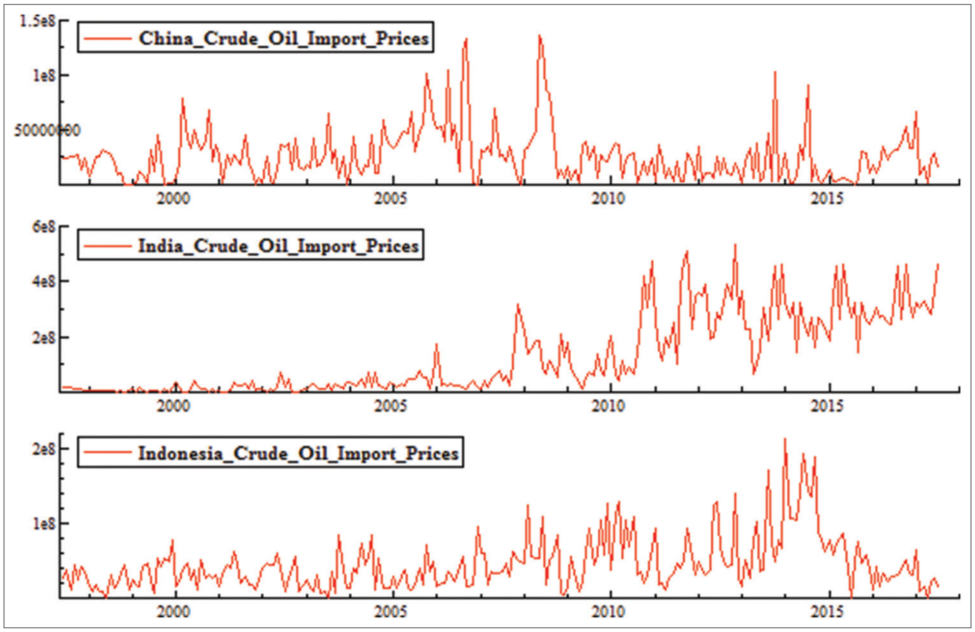
India's very rapid economic development in recent years has led to a change in the national energy problem. The country's desire for energy independence is increasingly coming up against rising demand for both electricity and fuel. The latter is forcing India to insert itself more and more into the circuits of the globalized market by internationalizing its oil companies and by using more and more Western or Chinese technologies. In this context, the challenges that India must face are numerous, since New Delhi must manage an increasing dependence on external supplies and a new development model in a context of energy transition. India is the third largest energy consumer in the world behind China and the United States. India is poorly endowed with energy resources. Second most populous country in the world after China and its 1.379 billion inhabitants, India represents around 17% of the world population but has only 0.65%of the world gas reserves, 0.3% of the reserves of petroleum and 8.3% of coal reserves, according to data from the BP Statistical Review. In India, oil import prices reached US $60.2 billion, which represents 6.9% of world crude oil demand (Figure 1 and Table 1).

In 2014, Indonesia became the 24th largest oil producer in the world, with 1% of world production. Since peaking in 1991 at around 1.65 mbpd, production has halved, mainly due to the maturity of the main oil fields and a lack of investment in exploration and production. For their part, consumption of crude oil and petroleum products has accelerated sharply since the turn of the 2000s (+40% since 2000 for crude oil in particular), leading the country to become a net oil importer from the end of 2003. Imports of petroleum products have increased by nearly 6% per year since 2009, also contributing to the country's oil bill. India recorded a doubling of its energy consumption between 2000 and 2016. However, its consumption per capita (0.67 tons of oil equivalent/toe) is still relatively low and India currently represents only around 6.5% of world energy consumption, far behind China (22%) and the United States (16%). India is now the world's third-largest consumer and third-largest importer in the oil markets. However, almost 15% of imported oil is re-exported as petroleum products to the region. Indian oil production has stagnated for almost 10 years around 0.85 million barrels/day (mb/d). On the coal market, India is the 4th world producer with nearly 8% of the world production and its consumption represents approximately 11% of the world total in 2016. On the gas markets, India is weakly present as producer (0.8% of the international total) and as a consumer (1.4% of the world total). As the largest energy consumer in Southeast Asia (accounting for nearly 36% in 2013 of the region's primary energy consumption), Indonesia could also

Table 1: Crude Oil Importers in 2017

Importer	2017 Crude oil importers	% World total
China	US $162.2 billion	18.6
India	US $60.2 billion	6.9
Indonesia	US $8.2 billion	0.9

Figure 1: Evolution of crude oil import price and oil price and stock market



Source: Made by the author

be a real bridgehead for new markets in OPEC member countries. A member of OPEC since 1962, Indonesia left the Organization in 2009, five years after becoming a net importer on the market. In 2014, Indonesia produced about 0.85 million barrels of oil per day (mbpd) for a consumption of about 1.6 mbpd (BP Statistical Review, 2015). For Indonesia, in 2017, oil import prices reached US $8.2 billion, which represents 0.9% of a total world oil demand (Table 1 and Figure 1).

Over the last two decades a greater interest has been born to understand the impact of oil import prices on the oil return volatility stock market return volatility. More specifically, the objectives of the present paper are the following: (i) to investigate the order (*m*,*n*) of the mean equation (ARMA) and the order (*p*,*q*) of the conditional variance and to determinate the appropriate models of the conditional volatility, (ii) to testing the change in volatility of oil returns and stock market returns and (iii) to examine changes in the relation between the import, the oil market return volatility and the stock market return volatility.

The remainder of this paper is organized as follows. Section 2 provides the review of the literature, whereas section 3 describes the relevant variables and dataset used in the empirical analysis and section 4 details the methods used. Section 5 analyses the findings. Finally, the conclusion and policy recommendations are introduced in section 6.

2. LITERATURE REVIEW

The relationship between oil demand, oil price and stock markets has been investigated in extensive studies. In this section, we review the studies which are closely related to the main goal of this paper.

Beyond this input-cost effect, there is still an income effect derived from oil prices decline, since the smaller cost of imported oil tends to increase the disposable income of US households and to decrease inflation and interest rates, leading to greater demand for companies' goods and to higher investment expenditures from firms (Sadorsky, 1999 and Kilian, 2009). Aggregate demand shocks occur due to global business cycle's fluctuation (Kilian, 2009). The increase in crude oil prices in 2006-2007, for example, can be partially explained by aggregate demand shocks motivated by the strong growth in China and in developing countries over the period (Kilian, 2009 and Kilian and Murphy, 2014). These same shocks can explain the uptrend in the US stock market index during these years. Higher Chinese growth, in this sense, may have driven the economy of other regions, that started to demand more US services and products; or may have caused a strong external capital inflow into the US financial markets, increasing its enterprises equities value. In line with Kilian (2009), world non-US oil supply contraction tends to trigger US oil production for US income/economic security and thus have a positive effect on the US oil producers.1 In contrast, US oil supply disruption may raise the US oil import and thus increase the world non-US oil production. The US is an oil importing country whose oil production averaged 11.5% of the global oil production from January 1973 to December 2014. To have a structural interpretation of oil supply shocks. Flow oil-demand shocks have a statistically significant impact on stock returns in Canada, Norway, Russia, Kuwait, Saudi Arabia, and the UAE.

This result is reiterated in Baumeister and Kilian (2016a), which discusses various historical episodes of significant oil price fluctuations, considering the relative forces of supply, demand, inventories, and speculation of crude oil. Importantly, Kilian (2016) also provides informal evidence and back-of-the-envelope calculations to support this finding, in addition to analyzing many other impacts of the shale oil revolution, including oil quality (gravity and sulfur content), Brent-WTI spreads, the oil export ban, oil transportation infrastructure, and more. In the work most closely related to the current paper, Kilian (2017) uses a structural VAR model to simulate a counter-factual scenario without the U.S. oil boom, again finding that the shale revolution had little impact on oil prices. He estimated that the boom reduced Brent oil prices by only about \$10 and \$5 in 2014 and 2015 respectively.

Demand-side explanations for the decline in oil prices are more consistent with the data. As the past work such as Kilian (2008) has shown, demand shocks have historically been important drivers of oil prices. Kilian (2008) in particular introduced a global real activity index for commodity markets for use in a dynamic model of oil prices. More recently, as Baumeister and Kilian (2016c) point out, the second half of 2014 featured many events that raised concern about the strength of the global economy. Baumeister and Kilian (2016b) further note the decline in U.S. non-oil exports, which is suggestive of a slowing global economy. More generally, global economic conditions looked shaky in 2014.

Following Unalmis et al. (2012) analyze the macroeconomic effects of oil supply, oil aggregate demand, and oil specific demand shocks on the basis of a DSGE model. They find that supply and demand shocks produce negative effects on the macro economy.

Aastveit et al. (2015) employ a FAVAR model to identify the supply and demand shocks from different regions, and investigate the effects of supply and demand shocks on the GDP of geographical regions (Asia, Europe, North America and South America). Their results show a greater negative effect of oil market shocks, which increases oil prices in Europe and North America than those in Asia and South America.

Cunado et al. (2015) analyze the macroeconomic effects of oil supply shock, oil aggregate demand shock and oil specific demand shock in Japan, India, Korea, and Indonesia. They find that the effects of these three shocks are different in the four countries. Specifically, oil supply shock has a limited effect, while aggregate demand shock has a significant positive influence on their economy.

Unlike the price and income elasticity of oil demand, the response of oil supply to changes in the oil price has not received much attention recently. Motivated by the oil price shocks of the 1970s, most of the prior literature engages in testing alternative hypotheses about the role of OPEC in the world oil market, without being able to reject any but rather implausible special cases, such as a *constant market sharing* cartel or a strict version of TRT (Jones, 1990).

A strand of papers investigates the spillover between crude oil and stock markets.

As a major input for certain firms, oil can affect stock prices from different channels. For example, higher oil prices can increase the cost of production and reduce future cash flow earnings, dividends or demand and, hence, stock prices. Higher oil prices can also lead to an overestimation of expected inflation and higher nominal interest rates and, hence, depress the earnings and dividends of a firm. Based on diverse level considerations, the earlier literature contributes to exploring oil-stock interactions by using country-level, sector-level or firm-level data (Gupta, 2016). Conversely, the stock market correlations will weaken with increasing oil prices. Therefore, we deduce that stock market correlations can be influenced by oil price fluctuations, and the above inferences lead us to study the oil effect on stock market correlations.

Bhar and Malliaris (2011) also noted the positive influence of the S&P 500 index on oil prices.

These analyses imply that the S&P 500 index could be considered as a predictor in our regression models: growth in the U.S. economy and/or the S&P 500 index could help the world economy to grow, which may increase the global demand for oil, driving up global oil prices. Meanwhile, China ranked first (USD 116.2 billion, 17.3% of total crude oil imports) among crude oil importing countries in 2016 for the first time. Meanwhile, India ranked third (USD 60.9 billion, 9.1%). These facts imply that two emerging Asian countries' economic conditions may influence the global oil prices as well. If they suffer recessions, their demand for oil may fall, possibly resulting in falling oil prices. To reflect the increasing economic impact of China and India on the real global demand for oil, we use their representative stock market indices.

Lastly, the OECD production industry index was employed to represent global oil demand. The OECD is a group of leading economies (31 countries as of 2016). If their economic conditions turn downward, their global oil demand might decrease, perhaps resulting in a global oil price decline. As a speculative demand factor, U.S.'s crude oil backup in the strategic petroleum reserve is employed in our model. Oil inventories or reserves have been recognized as contributing to speculative demand shocks in the literature.

Kilian (2009), Hamilton (2009), Alquist and Kilian (2010), and Kilian and Murphy (2014), focusing on the role of oil inventories as an asset, observed that increased expectations of the future demand for crude oil increased demand for crude oil inventories, leading to a rise in oil prices.

Since shifts in the demand for oil inventories are caused by forward looking behavior in this case, these demand shocks are referred to as *speculative demand shocks* (Kilian and Murphy, 2014). On the one hand, demand shocks emanating from exogenous events such as revolutions, invasions, or wars in the Middle East can increase demand for oil inventories, resulting in increased oil prices as well.

On the other hand, Pirog (2005) pointed out that the U.S. holds strategic oil inventory stocks as a buffer against any potential disruption in oil imports. The release of inventories may increase the market supply of oil, placing downward pressure on U.S. oil prices. Jiao et al. (2014) investigated the effect of China's strategic petroleum reserve on stabilizing domestic oil prices.

Perhaps many nations maintain their own oil inventories, but U.S. oil inventory was larger than anyone else's during our research period. Thus, we used U.S. oil inventories as the speculative demand factor in our models.

Similarly, the impact of oil prices on stock prices have become a prominent issue in recent times. Examining the oil-stock market relationship is important for asset allocation and portfolio risk management since investors' decisions are based not only on the available fundamental information in the stock markets but also on the information prevailing in the oil markets (Mensi et al., 2017).

The transmission between stock and oil markets has not being analyzed separately in terms of oil and financial shocks, and the transmission within stock markets due to oil shocks has not so far been analyzed. The notion that increase in oil prices leads to decrease in stock prices has been widely accepted and seems to be virtually axiomatic (Aloui and Aissa, 2016).

Some papers have investigated the nexus between the oil price and stock market in oil importing and oil exporting economies.

Among them, Mohammadi and Su (2010) analyzed the dynamics of oil price mean and volatility by employing four classes of conditional volatility models with symmetric and asymmetric specifications, namely, GARCH, EGARCH, APARCH and FIGARCH. The authors' study covered the period from January 1997 to October 2009 using weekly data on eleven crude oil spot prices in both oil-exporting and oil-importing countries as well as OPEC and non-OPEC members. The main findings revealed that the conditional volatility of oil returns exhibited time varying behavior, and the conditional variance asymmetric effects were mixed.

Guesmi (2014) studied the dynamics of volatility transmission for oil (Brent) stock market pairs in oil exporting economies (the United Arab Emirates, Kuwait, Saudi Arabia and Venezuela) and oil-importing economies (the United States, Italy, Germany, Netherlands and France). The authors focused on the asymmetry effect and volatility spillover of the oil market on the stock markets by incorporating multivariate GJR-DCC-GARCH specifications. The main findings of the study of Guesmi (2014) unveiled that oil price shocks have a significant impact on oil stock market nexus for both the oil-importing and oil-exporting economies, more specifically in periods of global turmoil.

Bouri (2015) focused on modeling the conditional mean and conditional variance employing an ARMAX-GARCH specification. He examined the shock effects of the 2008 global financial crisis on the volatility spillovers between the oil markets and the stock markets of small oil importing countries, namely, Lebanon and Jordan. His main findings indicated that volatility spillover was stronger from the oil market to the Jordanian stock market than other oil-stock market pairs. Boldanov et al. (2016) studied the time-varying conditional correlation between oil prices (Brent crude oil price) and stock market volatility for oil-importing and oil-exporting countries over the period from January 2000 to December 2014. In their empirical study, the authors treated six major oil-importing/oil-exporting economies, namely, Canada, Russia and Norway (the three oil-exporting countries) and United States, China and Japan (the three oil importing countries). A BEKK-family model was employed in order to study the time-varying oil-stock market nexus for oil-importing and oil-exporting economies. The empirical findings exhibited a time-varying dynamics for oil-importing and oil exporting countries.

Bjornland (2009) pointed out that Norway, a net oil exporter, has benefited from oil price increases, showing temporary increases in economic growth, whereas Canada, also a net-oil exporter, has shown instead declines in economic growth, more in line with the effects of oil price hikes in oil-importing countries.

In sum, this paper contributes to the growing literature concerning the effect of Asian oil import prices on oil price and stock markets volatilities in the following ways. Above all, different from the existing literature, which mostly investigates oil import prices, oil price and stock market relationships, this paper innovatively proposes to investigate the effect of oil import prices fluctuations of the three Asian countries on oil and stock markets volatilities correlations.

3. DATA DESCRIPTION

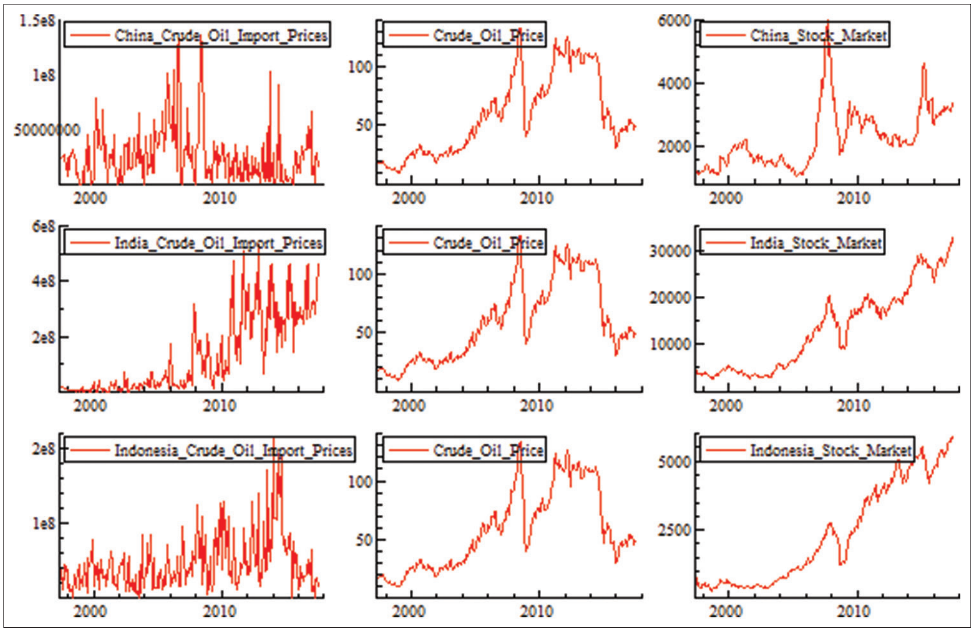
We use monthly prices for the Brent crude oil price, three stock market indices and three crude oil import prices over the period from June 1997 through to July 2017, in order to construct their monthly volatilities. The three market indices represent three oil-importing countries are SSE Composite Index (000001.SS) for China, Indian S&P bse sensex (ˆbsesn) for India and Jakarta Composite Index (ˆJKSE) for Indonesia. The Brent crude oil price is used for analysis as the prices generated in the Brent basket compose the main price benchmarks on the basis of which 70%of international trade in oil is directly or indirectly priced. the demand for oil of the month "j" is obtained in volume of U.S. Energy Information Administration multiplied by the price of a barrel of oil of the month "j". All variables are expressed in US dollar terms. In Our study, the choice of countries in our sample is motivated by the fact that they are all among the largest oil importers in World (Table 1).

Figure 2 presents the movements of returns and conditional volatility during the period of the study. The monthly Brent crude oil price and stock Market returns were generated as the first log-difference multiplicated by 100, *yt* Æ 100 ¤ *log* (P*t*/P*t*¡1), where P*t* reflects the daily closing price at the given time *t*.

To do so we focus on crude oil import prices, the crude oil price (The Brent) and the stock markets of three Asian oil-importing countries (China, India and Indonesia), employing a Diag-BEKK model. The period of investigation runs from June 1997 until July 2017. Figure 2 presents the crude oil import price, the Brent crude oil prices and the stock market, in dollars, from June 1997 to July 2007. The three economic variables movements show some important peaks and troughs during the period of the study. We observe from Figure 2 strong movements in prices of crude oil imports that are not stable and also that they are characterized by several peaks in the three Asian Countries (China, India and Indonesia).

In china, many peaks are observed in among which in May 2007, in May 2008, in October 2013 and in January 2017, etc. In India,

Figure 2: evolution of crude oil import price and oil price and stock market



Source: Made by the author

according to china, we observe many peaks that see for example June 2006, in July 2005, in October 2007, in January 2009, in September 2013 and in March 2017, etc.

In Indonesia, among the peak we mention those in December 1999, in May 2002, in October 2005, in February 2008, in March 2010, in June 2012, in September 2014 and in January 2017. And the figure shows more rapid others fluctuations of oil import price. Thus the Table 1 shows the price evolution of crude oil imports in the three Asian countries and their percentage at the world level.

The main peaks which are observed from Figure 2 are in December 1998, where prices have almost halved in one year. Another peak is observed in September 2000, which was a result of a continuing increase in oil prices since 1999. From 1992 until late 2008 we observe a continuing increase in oil prices, with same disruptions (e.g. during 2007), as well. The prices reached a peak in late 2008. Another peak is observed in June 2009, where prices increased by more than 60% since the January 2009 price levels. In addition, from 2012 until late 2016 we observe a continuing decrease in oil prices, with same disruptions (e.g. during 2012-2014), as well. A final peak is observed February 2017 where prices increased slowly.

Brent crude oil prices fell below 50 US $ per barrel in January 2015 (Figure 2) due to higher than expected international supply, a strong dollar and weak global demand, particularly from China, India and Indonesia. The Brent price of crude oil declined from $112 in June 2014 to a low of $31 in January 2016 (both nominal prices), a cumulative decrease of more than 70%. Some attribute the decline to increased oil production due to the U.S. shale revolution. Beginning in June 2014, the nominal Brent price of crude oil began a rapid decline, falling from $112 in June to $62 in December, a 6-month decline of 44%. The price continued to fall in 2015 and 2016, reaching a low of $31 in January 2016, a cumulative decrease of more than 70%.

Brent crude oil prices fell below US $50 per barrel in January 2015 due to higher than expected international supply, a strong dollar and particularly weak global demand from China. In June 2015, India has replaced Japan to become the third largest oil importer after the United States and China. The oil import bill had reached USD 71.2 billion in 2016-2017, accounting for almost 37%of the total import bill and almost 80% of the total crude oil requirement. As per the recent estimate by the Indian central bank, the Reserve Bank of India (RBI), a drop of 10 dollar per barrel in crude oil prices would increase the India's current account balance by USD9 billion or 0.5% of GDP (Singhal and Ghosh, 2016). In fact, a report by International Energy Agency (IEA) suggests that India would need to import 7.2 million barrels of crude oil per day by 2040 to become the world's second largest importer, just behind China.

4. MODEL FRAMEWORK

We investigate the relationship between the crude oil import prices and the volatility of oil price and stock market returns. Nonetheless, it is first required to estimate the respective volatilities.

4.1. Estimation of Volatility

- The ARCH and GARCH models, certainly the most common ones.
- The IGARCH and FIGARCH models, which allow the integrated and the fractional integrated extensions of the GARCH model.
- Three asymmetric models: GJR, EGARCH and APARCH.
- The available models are ARCH , GARCH , EGARCH , GJR, APARCH , IGARCH , FIGARCH, FIEGARCH (Bollerslev

and Mikkelsen, 1996) and FIAPARCH (Tse, 1998). Finally, explanatory variables can enter both the mean and the variance equations.

These models:

- The ARCH (Engle, 1982) and GARCH (Bollerslev, 1986) models, certainly the most common ones.
- The IGARCH (Engle and Bollerslev, 1986) and FIGARCH (Baillie et al., 1996 and Chung, 1999) models, which allow the integrated and the fractional integrated extensions of the GARCH model.
- Three asymmetric models: GJR (Glosten et al., 1996), EGARCH (Nelson, 1991) and APARCH (Ding et al., 1993).

All these models can be estimated by Approximate (Quasi-) Maximum Likelihood under three assumptions: Normal, Student-t or GED errors. Moreover, explanatory variables can be added both in the mean and in the variance equations.

4.1.1. Analysis of box-Jenkins models: Conditional mean equation ARMA models

Let us consider a univariate time series y_t. If $\Psi_{t-1}1$ is the information set at time t-1, so its functional form of the conditional mean of any financial time series y_t is defined in the equation 1 as follows:

$$y_t = E(y_t \mid \Psi_{t-1}) + \varepsilon_t \tag{1}$$

On the other hand, $E(y_t \mid \Psi_{t-1})$determines the conditional mean of y_t given by Ψ_{t-1} and ε_t is the disturbance term (or unpredictable part), with $E(\varepsilon_t) = 0$ and $E(\varepsilon_t \varepsilon_s) = 0$, $t \neq s$. Where $E(.|.)$denotes the conditional expectation operator. But in some other cases, in order to model the serial dependence and to obtain the equation which represents the function of the conditional mean, the principal models of a temporal series ARMA(r, s), a tool specified to correctly interpret and predict future values of the series to be studied is used to adjust the data to eliminate this linear dependence and obtain the residue ε_t which is decorrelated (but not independent). With:

$$y_t = \mu + \sum_{i=1}^{r} \Phi_i y_{t-i} + \sum_{j=1}^{s} \varphi_j \varepsilon_{t-j} + \varepsilon_t$$

The conditional mean ARMA(r, s) is stationary when all the roots of the function $\Phi(z) = 1 - \Phi_1 z - \Phi_2 z - \ldots - \Phi_p z = 0$ are outside the unit circle.

Equation 1 is the conditional mean equation which has been studied and modelled in many ways. Two of the most famous specifications are the Autoregressive (AR) and Moving Average (MA) models. In addition, to specify the order (r, s) of the process ARMA, we will use the Akaike information criterion (AIC) and the Bayesian Schwarz criterion (BIC) and to determine the conditional mean ARMA, search for the term corresponding to the minimum values of the two criteria. In our study, the choice of ordering ARMA models from the AIC information criterion for the crude oil price and the stock market returns.

As we have known, dependence is very common in time series observations. So, to model this temporal financial series, as a function of time, we start with the models of the conditional ARMA univariate. To motivate this model, basically, we can follow two lines of thought. In the first line, for a time series x_t, we can model that the level of its current observations depends on the level of its shifted observations. In the second line, we can model only in the case where the observations of a random variable at the moment t are not only affected by the shock at the moment t, but also the old shocks that took place before that moment t. For example, if we notice a negative shock to the economy, then we expect this negative impact to affect the economy negatively or positively either now or in the near future.

4.1.2. Variance equation: Further univariate GARCH models

We use just five conditional variance models: GARCH, EGARCH, GJR, APARCH and IGARCH models. The Generalized ARCH (GARCH) model of Bollerslev (1981) is based on an infinite ARCH specification and it allows to reduce the number of estimated parameters by imposing nonlinear restrictions on them. The GARCH (p,q) model can be expressed as:

$$\sigma_t^2 = \omega + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-1}^2 + \sum_{j=1}^{p} \beta_j \sigma_{t-1}^2 \tag{2}$$

4.1.2.1. EGARCH Model

The Exponential GARCH (EGARCH) model, originally introduced by Nelson (1991), is re-expressed in Bollerslev and Mikkelsen (1996) as follows:

$$\log \sigma_t^2 = \omega + \left[1 - \beta(L)\right]^{-1} \left[1 - \alpha(L)\right] g(z_{t-1}) \tag{3}$$

The value of $g(z_{t-1})$ depends on several elements. Nelson (1991) notes that, to accommodate the asymmetric relation between stock returns and volatility changes (…) the value of g(z_t) must be a function of both the magnitude and the sign of z_t.

4.1.2.2. Glosten, Jagannathan, and Runkle Model (GJR)

This popular model is proposed by Gloste and al. (1993). Its generalized version is given by:

$$\sigma_t^2 = \omega + \sum_{i=1}^{q} (\alpha_i \varepsilon_{t-i}^2 + \gamma_i S_{t-i}^- \varepsilon_{t-i}^2) + \sum_{j=1}^{p} \beta_j \sigma_{t-j}^2 \tag{4}$$

Where $S_t^-$is a dummy variable that take the value 1 when γ_i is negative and 0 when it is positive.

4.1.2.3 APARCH Model

This model has been introduced by Ding and al. (1993). The APARCH(p,q) model can be expressed as:

$$\sigma_t^\delta = \omega + \sum_{i=1}^{q} \alpha_i \left(\mid \varepsilon_{t-i} \mid - \gamma_i \varepsilon_{t-i} \right)^\delta + \sum_{j=1}^{p} \beta_j \sigma_{t-j}^\delta \tag{5}$$

Where $\delta \succ 0$ and $-1 \prec \gamma_i \prec 1$ ($i = 1,\ldots,q$).

The parameter δ plays the role of a Box-Cox transformation of σ_t while γ_i reflects the so-called leverage effect. Properties of the APARCH model are studied in He and Terasvirta (1999a, 1999b).

4.1.2.4. IGARCH Model

The GARCH(p,q) model can be expressed as an ARMA process. Using the lag operator L, we can rearrange Equation 2 as:

$$\left[1-\alpha(L)-\beta(L)\right]\varepsilon_t^2=\omega+\left[1-\beta(L)\right](\varepsilon_t^2-\sigma_t^2) \tag{6}$$

When the $\left[1-\alpha(L)-\beta(L)\right]$ polynomial contains a unit root, i.e. the sum of all the α_i and the β_j is one, we have the IGARCH(p,q) model of Engle and Bollerslev (1986).

It can then be written as:

$$\Phi(L)(1-L)\varepsilon_t^2=\omega+\left[1-\beta(L)\right](\varepsilon_t^2-\sigma_t^2) \tag{7}$$

Where $\left[1-\alpha(L)-\beta(L)\right](1-L)^{-1}$ is of order $\max\left\{p,q\right\}-1$.

We can rearrange Equation 7 to express the conditional variance as a function of the squared residual.

4.2. Diag-Bekk(p,q) Model

A less general version known as the Diag-Bekk(p,q)model is commonly applied:

$$H_t=A_0A_0^{'}+\sum_{i=1}^{p}(A_i\varepsilon_{t-i}\varepsilon_{t-i}^{'}A_i^{'})+\sum_{j=1}^{q}B_JH_{t-j}B_J^{'} \tag{8}$$

Where the matrices A*i* and B*j* are again restricted to being diagonal. The Diag-BEKK(p,q) model requires the estimation of (n(n+2)/2) + n(p+q) parameters. The advantage is that the Diag-Bekk(p,q) model guaranteed to be positive definite and is regarded as a parsimonious version of the Diag-VECH model, as it requires the estimation of fewer parameters than the Diag-VECH model.

4.3. Simultaneous Equation Model

The model in which there is a single dependent variable and one or more explanatory variables then the model is called a single equation model. On the other hand, a system of equations representing a set of relationships among variables or describing the joint dependence of variables is called simultaneous equation. In such models there are more than one equation one of the mutually or jointly dependent or endogenous variables.

In our paper, let us consider the following Crude Oil Import Prices (COIP), Conditional Volatility Crude Oil Returns (*CondV_COR*) and Conditional Volatility Stock Market Returns (CondV_SMR) models at time *t* in equations 9, 10 and 11:

$$COIP=\alpha_0+\alpha_1\,CondV\_COR+\alpha_2\,CondV\_SMR+\mu_{1t} \tag{9}$$

$$CondV\_COR=\beta_0+\beta_1\,COIP+\beta_2\,CondV\_SMR+\mu_{2t} \tag{10}$$

$$CondV\_SMR=\gamma_0+\gamma_1\,COIP+\gamma_2\,CondV\_COR+\mu_{3t} \tag{11}$$

5. FINDINGS AND ANALYSIS

5.1. Selection of Order ARMA Models

5.1.1. Conditional mean models

First, we estimate the conditional average by selecting the orders $r = 0, 1, 2$ et $s = 0, 1,2$ of the crude oil returns and the stock market returns. Based on the information criteria, detailed results are listed in the Tables 2-8. In all, we choose the three ARMA models, corresponding to the minimum AIC values, of the four series in the Table 2 for each Asian country.

An ARMA model, or Autoregressive Moving Average model, is used to describe weakly stationary stochastic time series in terms of two polynomials. The first of these polynomials is for autoregression, the second for the moving average.

Often this model is referred to as the ARMA(*p*,*q* model; where:
p is the order of the autoregressive polynomial,
q is the order of the moving average polynomial.

The equation is given by:

$$X_t=c+\varepsilon_t+\sum_{i=1}^{p}\varphi_iX_{t-i}+\sum_{j=1}^{q}\theta_j\varepsilon_{t-j}$$

Where: φ is the autoregressive model's parameters, θ represent the moving average model's parameters. ***c*** is a constant and "indicated error terms (white noise).

The ARMA model for crude oil returns is ARMA(1,0). The mean equation models (ARMA models) of stock market returns in China, India and Indonesia are ARMA(2,0), ARMA(2,2) and ARMA(2,2) respectively.

Volatility tends to change quite slowly over time, and, as shown in Ding et al. (1993) among others, the effects of a shock can take a considerable time to decay. Therefore the distinction between stationary and unit root processes seems to be far too restrictive. Indeed, the propagation of shocks in a stationary process occurs at an exponential rate of decay (so that it only captures the short-memory), while for a unit root process the persistence of shocks is infinite.

In the conditional mean, the ARFIMA specification has been proposed to fill the gap between short and complete persistence, so that the short-run behavior of the time-series is captured by the ARMA parameters, while the fractional differencing parameter allows for modelling the long run dependence (Laurent 2005; 2018).

5.1.2. Conditional mean - Conditional variance appropriate models

After fixing the (r, s) order of the ARMA process, we will, in a first step, perform tests to choose the order of the variance equation among GARCH, EGARCH, GJR, APARCH and IGARCH based on the statistics Akaike, Shibata, Schwarz and Hannan-Quinn, to determine the best models for conditional volatility of the brent returns. However, the appropriate model for each

Table 2: ARMA (r, s): Determination of appropriate autoregressive moving average model

	Crude oil Returns	Stock Market Returns of the Countries		
		China	India	Indonesia
The appropriates models	ARMA (1,0)	ARMA (2,0)	ARMA (2,2)	ARMA (2,2)

For more details, please see Appendix A for the full model information criteria

Table 3: The results of choice order (p, q) of conditional volatility models

Series	The appropriate model	Information Criteria (to be minimized)			
		Akaike	Shibata	Schwarz	H.-Quinn
Crude Oil Returns Volatility	ARMA (1,0)-APARCH (2,1)	7.149673	7.147037	7.279427	7.201943
China Stock Market Returns Volatility	ARMA (2,0)- GJR (2,2)	6.789140	6.785242	6.947728	6.853025
India Stock Market Returns Volatility	ARMA (2,2)-EGARCH (2,2)	6.618280	6.612891	6.805702	6.693780
Indonesia Stock Market Returns Volatility	ARMA (2,2)-IGARCH (2,2)	6.591902	6.588664	6.736073	6.649979

Table 4: Estimated parameters vector for crude oil and china stock market returns volatilities

(Box 1) Crude Oil Returns Volatility ARMA (1,0)-APARCH (2,1)		(Box 2) China Stock Market Returns Volatility ARMA (2,0)-GJR (2,2)	
Parameters names	Estimated parameters vector	Parameters names	Estimated parameters vector
Cst (M)	0.097410	Cst (M)	0.249211
AR (1)	0.184638	AR (1)	0.083919
Cst (V)	0.254944	AR (2)	0.084616
ARCH (Alpha1)	0.224104	Cst (V)	0.433908
GARCH (Beta1)	−0.059718	ARCH (Alpha1)	0.599023
GARCH (Beta2)	0.728201	ARCH (Alpha2)	−0.441836
APARCH (Gamma1)	0.555592	GARCH (Beta1)	0.652484
APARCH (Delta)	0.270856	GARCH (Beta2)	0.249440
ARCH-in-mean (var)	0.002982	GJR (Gamma1)	−0.677365
		GJR (Gamma2)	0.558939
		ARCH-in-mean (var)	0.010796

Table 5: Estimated parameters vector for India and Indonesia stock market returns volatilities

(Box 3) India Stock Market Returns Volatility ARMA (2,2)-EGARCH (2,2)		(Box 4) Indonesia Stock Market Returns Volatility ARMA (2,2)-IGARCH (2,2)	
Parameters names	Estimated parameters vector	Parameters names	Estimated parameters vector
Cst (M)	0.339948	Cst (M)	0.912117
AR (1)	0.195386	AR (1)	−0.429914
AR (2)	0.407430	AR (2)	−0.307416
MA (1)	−0.185353	MA (1)	0.552500
MA (2)	−0.350810	MA (2)	0.285657
Cst (V)	−3.539080	Cst (V)	0.118379
ARCH (Alpha1)	0.271343	ARCH (Alpha1)	−0.034955
ARCH (Alpha2)	−1.376006	ARCH (Alpha2)	−0.122439
GARCH (Beta1)	1.936002	GARCH (Beta2)	−0.779037
GARCH (Beta2)	−0.936099	ARCH-in-mean (var)	0.002297
EGARCH (Theta1)	−0.048959		
EGARCH (Theta2)	0.058474		
ARCH-in-mean (var)	0.014130		

variable will be one of five models: ARMA(r, s) -GARCH(p,q), ARMA(r, s)-EGARCH(p,q), ARMA(r, s)-GJR(p,q), ARMA(r,s)-APARCH(p,q) et ARMA(r, s)-IGARCH(p,q). These models are the extension of the ARCH process with various features to explain the obvious features of financial time series, such as the leverage effect and the asymmetry.

The Table 2 shows the selection of the ARMA model with the minimum of the AICT and AIC criterion. In the same context, the Table 3 shows the selected appropriate of the *mean equation - conditional variance equation* models and represent the corresponding results of the four statistics (Akaike, Shibata, Schwarz and Hannan-Quinn) the lowest for each model chosen.

The Table 3 shows the results of the information criteria tests and the corresponding appropriate conditional volatility models, containing the moving average and conditional variance equations.

The results of determining the appropriate conditional volatility models from the information criteria (Akaike, Shibata, Scchwarz and Hannan-Quinn) are shown in the Table 3. Movements in oil market returns show an AR(1)-APARCH(2,1) type model, but

Table 6: Volatilities and normality test

Series	Oil returns volatility			China stock market returns volatility		
	Statistic	t-test	p-value	Statistic	t-test	p-value
Skewness	−0.44231	2.8264	0.0047080	−0.072169	0.46116	0.64468
Excess Kurtosis	−0.18063	0.57942	0.56230	0.39861	1.2787	0.20101
Jarque-Bera	8.2198	.NaN	0.016410	1.8122	.NaN	0.40409
ARCH 1-2 test:	F (2,234) = 0.86898[0.4207]			F (2,233) = 0.97820 [0.3775]		
ARCH 1-5 test:	F (5,228) = 0.78567 [0.5609]			F (5,227) = 0.61016 [0.6922]		
ARCH 1-10 test:	F (10,218) = 1.1412 [0.3327]			F (10,217)= 0.34167 [0.9687]		
Series	**India Stock Market Returns Volatility**			**Indonesia Stock Market Returns Volatility**		
	Statistic	**t-test**	**p-value**	**Statistic**	**t-test**	**p-value**
Skewness	−0.30196	1.9295	0.053666	−0.79297	5.0671	4.0392e-007
Excess Kurtosis	0.048346	0.15508	0.87676	1.1938	3.8294	0.00012844
Jarque-Bera	3.7012	.NaN	0.15715	39.732	.NaN	2.3566e-009
ARCH 1-2 test:	F (2,234) = 0.86898[0.4207]			F (2,233) = 0.14214 [0.8676]		
ARCH 1-5 test:	F (5,228) = 0.97955[0.4310]			F (5,227) = 0.37207 [0.8675]		
ARCH 1-10 test:	F (10,218) = 1.1028[0.3612]			F (10,217)= 0.34167 [0.9687]		

Table 7: The ARMA (0,0)-Diag-BEKK (p, q) Selection and Akaike Information Criteria: Case of the Three Asian Countries

ARMA (0,0)- Diag-BEKK (p, q)	Information Criteria (to be minimized)			
	Akaike	Shibata	Schwarz	H.-Quinn
China				
ARMA (0,0)-Diag-BEKK (1,2)	57.666679	57.656602	57.926186	57.771218
India				
ARMA (0,0)-Diag-BEKK (0,2)	58.803524	58.796421	59.019780	58.890640
Indonesia				
ARMA (0,0)-Diag-BEKK (0,2)	56.984398	56.977296	57.200655	57.071514

returns in the Chinese stock market show an AR(2)-GJR(2,2) type model. In addition, data from the Indian and Indonesian stock market returns series respectively show the existence of appropriate ARMA(2,2)-EGARCH(2,2) and ARMA(2,2)-IGARCH(2,2) models.

5.1.3. Filtering and parameter estimation for appropriate volatility models

Tables 4 and 5 summarizes the parameters for crude oil returns volatility and the stock market returns volatility of the three Asian Countries.

Once again, the APARCH model suggest the presence of a leverage effect on the crude oil (Box 1, Table 4). Importantly, is significantly different from 2 ($\hat{\gamma}_2$= 0.270856) but not significantly different from 1. However, if $\gamma \neq 0$ and/or $\gamma \neq 2$, this condition depends on the assumption made on the innovation process. This suggests that, instead of modelling the conditional variance (GARCH), it is more relevant in this case to model the conditional standard deviation. This result is in line with those of Taylor (1986), Schwert (1990) and Ding, Granger, and Engle (1993) who indicate that there is substantially more correlation between absolute returns than squared returns, a stylized fact of high frequency financial returns (often called "long memory").

The output reported below (Box 2, Table 4) suggests the presence of such an effect on the China stock market returns volatility since $\hat{\gamma}_2$= 0.558939 with a robust t-value of 2.826. The output reported in Box 3 (Table 5) corresponds to the ARMA(2,2)-EGARCH(2,2) with a GED distribution. Interestingly, both θ_1 and θ_2 are significant. Note that the degree of freedom of the GED distribution is significantly lower than 2, confirming that the standardized residuals are fat-tailed.

For Indonesia stock market returns volatility, the output reported in Box 4 (Table 5) corresponds to the ARMA(2,2)-IGARCH(2,2) with a GED distribution. Interestingly, the GARCH (β_2) now equals −0.779037 against −0.034955 for the corresponding ARCH (α_1) model. Any likelihood ratio test (LRT), asymptotically 2(1), would reject the ARCH (1) model in favor of the GARCH (2,2). The results means that the memory of a large deviation persists for only one period.

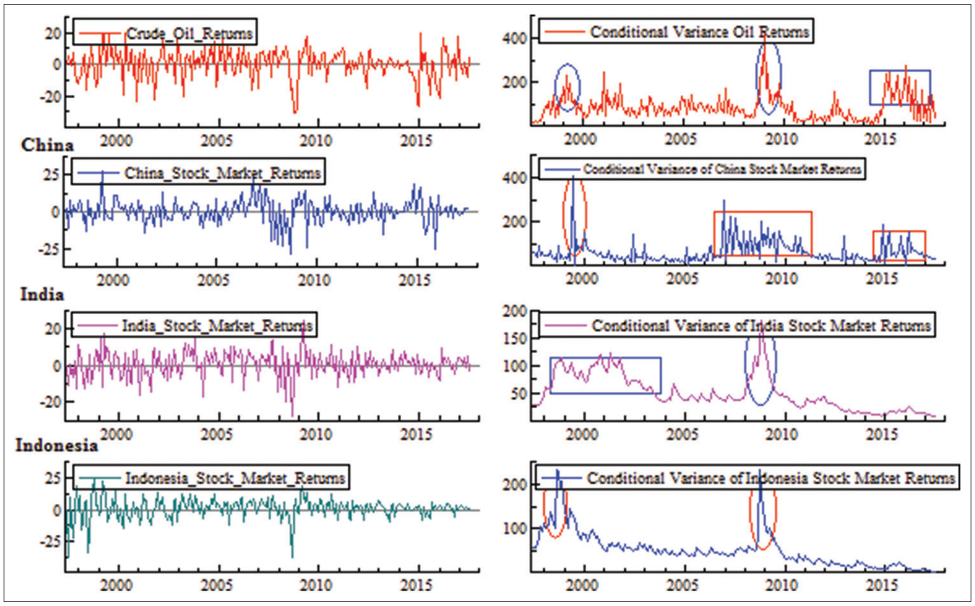
Figure 3 shows peaks and troughs. The volatility of crude oil returns are lengthened the volatility of the stock market returns of China, India and Indonesia. That indicate strong transmission between returns and conditional volatility for the monthly series after Asian Economic Crisis (July, 1997) and during Financial Crisis (2008-2009).

Our research findings via a novel and rigorous approach suggested in this article may contribute to the work of professionals in both spheres (see the related literature in the next section). This study investigates the world's top Asian oil-importing countries so as to examine the role of oil demand to hedge the oil and stock market returns volatilities.

5.1.4. Normality test

Table 6 summarizes the descriptive statistics and stochastic properties for crude oil returns volatility and the stock market returns volatility of the three Asian Countries.

Figure 3: Returns and conditional volatilities



Source: Made by the author

All skewness coefficients of the volatility of the returns series are negative those indicating that all distributions are skewed to the right of the median, and therefore all distributions are skewed to the left. Thus confirming that analysts tend to revise their forecasts downwards. In line with the literature on the characteristics of oil returns volatility and the three Asian stock market returns volatility, are found to be leptokurtic in our sample period as they exhibit strong negative skewness and excess kurtosis.

Kurtosis measures the pointed or flat character of the distribution of the series. The Kurtosis of the normal distribution is 3. If the Kurtosis is greater than 3 (thick tails), the distribution is rather sharp (leptokurtic distribution); if the Kurtosis is <3, the distribution is rather flat (distribution is called platikurtic). The Kurtosis of our distribution oil import price, oil returns volatility and stock market returns volatilities of China, India and Indonesia is less than 3which means that our distribution is flat.

Skewness is a measure of the asymmetry of the series distribution around its mean. The Skewness of a symmetry distribution, such as the normal distribution is zero. Positive Skewness means the distribution has an elongated tail to the right and Negative Skewness means that the distribution has an elongated tail to the left. The Skewness of the four variables distribution are negative. This means that our distribution is biased to the left and as a result oil import price, oil returns volatility and stock market returns volatilities of China, India and Indonesia react more to a negative shock than to a positive shock.

However, all the series of returns volatility depart from normality as indicated by the Jarque-Bera test. The Residue normality test of oil price volatility and Indonesia stock market returns volatility (with respectively JB = 8.2198 and JB = 39.732) indicates that the residues are abnormal, therefore the residues are normal (Indeed, JB < 5.99). The Residue normality test of China stock market returns conditional volatility volatility and India stock market returns volatility (with respectively JB = 1.8122 and JB = 3.7012) shows that the residues are normal, therefore the residues are normal (Indeed, JB < 5.99). The JB test for normality shows it departs from the normal distributions.

The Ljung-Box Q statistics show that the returns of oil price and stock market and its volatilities series have serial correlation, which indicates the existence of volatility clustering, and the Autoregressive Conditional Heteroscedasticity (ARCH) Lagrange Multiplier (LM) test results confirm this. The null hypothesis of no ARCH effects is rejected if the probability values (pvalues) of these tests are greater Than any of the conventional level of statistical significance (10%, 5%, and 1%). The acceptation of H0 implies presence of ARCH effect in the series. Thus, ARCH effects are present, the estimated parameters should be significantly different from zero (the series are volatile). The presence of ARCH effects in all series suggests that the volatility associated with the oil import price.

5.2. Appropriate Model of the Diag-BEKK

The assumption of constant conditional correlation as a synthetic measure of cross correlation has been widely used for its simplicity. This overly restrictive hypothesis is rejected here because the correlation of markets is variable over time (Tse and Tsui, 2002, Longin and Solnik, 2001). This variability is mainly related to the development of financial activities, financial engineering, capital movements and the progress of international portfolio management. The analysis then sheds light on these increases.

Empirically, it has been observed that the cross correlations of index returns are dynamic and present bullish trends linked to crisis events (Boyer, 1999). Other authors have reported persistence and memory in correlations (Christodoulakis, 2007). Another characteristic of correlations is asymmetry. Martens and Poon (2001) find that correlation responds more to negative than positive shocks: correlation is high in period of high volatility and decreased in calm periods. The use of a model with a change of regime reduces this asymmetry (Ang and Bekaert, 2002).

The select order of ARMA(0,0)-Diag-BEKK(p,q) by detail is in Tables 7-9. The parameters (p,q) chosen for the data from the three Asian countries are in the Table 7.

The information criteria (Akaike, Shibata, Schwarz and Hannan-Quinn) is a measure of the quality of a statistical model. The appropriates models of ARMA(0,0)-Diag-BEKK(p,q) for China, India and Indonesia are Diag-BEKK(1,2), Diag-BEKK(0,2) and Diag-BEKK(0,2) respectively.

Conditional variance-covariance equations effectively capture the volatility and cross volatility among the oil import price, the oil returns volatility and the stock markets returns volatility in the three Asian countries because most coefficients are statistically significant (Tables 9-12 for China, India and Indonesia respectively in Appendix B and C). Specifically, Robust Standard Errors (Sandwich formula) implied by the Diagonal BEKK Specification are presented below.

Tables 10-12 shows Diagonal parameters C11, C22 and C33, are statistically significant, suggesting that the oil import price of China, India and Indonesia are dependent on their first lags.

Results of Diag-BEKK model for China are reported in Table 10. For China, a negative correlation (−5.601376) between crude oil imports and oil price volatility and a positive correlation (1.644708) between crude oil imports and stock price volatility. Results of Diag-BEKK model for India are reported in Table 11. For India, the correlation between crude oil import prices (−14.395124) and the volatility of black gold returns and the volatility of stock market returns (−5.474734) is negative. Results of Diag-BEKK model for Indonesia are reported in Table 12 For Indonesia, the correlation between crude oil import prices (−7.453878) and the volatility of black gold returns and stock market returns (−1.866951) is negative.

The other coefficients ($a_{1.11}$, $a_{1.22}$, $a_{1.33}$, $a_{2.11}$, $a_{2.22}$ and $a_{2.33}$) of the Diag-BEKK results are positive in the case of the three Asian countries. Under the assumption of conditional normality, the parameters of the Diagonal-BEKK model of any of the above specifications can be estimated by maximizing the log-likelihood. Ici, the log-likelihood for China (−6959.668), India (−7100.226) and Indonesia (−6880.112), are negatively.

From these empirical results in Tables 10-12, we conclude a strong evidence of correlation effect and the presence of a stronger negative effect. Also, equations show a statistically significant covariation in oil import price, which depends more on its lags than on past errors. Consequently, oil demand are influenced by past information which is common to the crude oil market and the stock market and to its volatilities. They suggest that the comovements of the three series display an extremely volatile trend for the study period.

5.3. Simultaneous Equation Models

This study assessed the market models (crude oil demand, crude oil price and stock market) of three countries in the Asian region for the period July 1997-July 2017, and the results are presented in Tables 13-15 (Appendix in D).

For China, in Table 13, we find that oil market returns volatility have a negative (−28002.1) and statistically significant effect (at the 5% level) on oil import price but and stock market returns volatility have a positive (16363.3) and statistically significant effect (at the 5% level) on oil import price (Equation 1, Table 13). Oil import price have a negative and statistically significant impact (−7.19916e-008) on oil returns volatility. Oil demand price has a negative impact (−1.06572e-007) on stock market returns volatility (Equation (2) and (3) in Table 13).

For India, the results in Table 14 shows that oil market returns volatility have a positive (18373.2) and statistically significant effect(at the 5% level) on oil import price but and stock market returns volatility have a negative (−623211) and statistically significant effect(at the 5% level) on oil import price (Equation (1), Table 14). Oil demand has a positive effect (3.06777e-008) on crude oil returns volatility, whereas it has a negative effect (−3.83159e-009) on stock market returns volatility (Equation (2) and (3) in Table 14).

In Table 15, we find that oil market returns and stock market returns volatilities have a negative (have the coefficients −56588.4 and −144942 respectively) and statistically significant effect (at the 5% level) on Indonesia oil import price (Equation 1, Table 15). There are also negative and statistically significant impacts of oil import on oil returns volatility (−1.17452e-007) and stock market returns volatility (−2.41713e-008) (Equation (2) and (3) in Table 15).

We find also that oil import price have in significant impacts on the crude oil price and on the three Asian stock market (China, India and Indonesia). Results in Tables 13-15 shows that oil import of China and Indonesia have a negative impact on oil returns volatility but oil import of India have a positive impact on crude oil returns volatility. The findings reveal also that crude oil imports of the three Asian countries have a negative impact on stock market.

6. CONCLUDING REMARKS

Given that oil still serves as an important source of energy to propel the engine of economic activity, oil price changes must be able to predict economic activity through the demand for this energy and in turn stock market returns. However, the ability of oil demand to predict oil price changes and stock market returns is not conclusive.

One important implication of this study is that adding volatilities only from these three Asian countries will not diversify away oil demand. Investors must diversify their portfolios employing not only emerging, but also developed market stocks. Correlations and volatility effects between oil market and stock market must be studied and taken into account. The last but not the least, the high level of oil prices and its volatility may weaken Asian countries against external shocks and crisis. Decision makers in the Asian world must now design policies not only looking at domestic estimates, but also by considering the fact that Asian markets are now highly linked both among each other and with the global markets. Hence, global financial landscape has changed, and the Asian world is no exception. Any country is currently seeking to substitute petroleum demand imports for its *renewable energy* to reduce its energy dependence.

The ARMA model for crude oil returns is ARMA(1,0). The mean equation models (ARMA models) of stock market returns in China, India and Indonesia are ARMA(2,0), ARMA(2,2) and ARMA(2,2) respectively. In addition, data from the Indian and Indonesian stock market returns series respectively show the existence of appropriate ARMA(2,2)¡EGARCH(2,2) and ARMA(2,2)¡IGARCH(2,2) models. The appropriates models of ARMA(0,0)-D*iag*-BEKK(p,q) for China, India and Indonesia are D*iag*-BEKK(1,2), D*iag*-BEKK(0,2) and D*iag*-BEKK(0,2) respectively. The results of the conditional volatilities means that the memory of a large deviation persists for only one period.

In the the three Asian Countries, the three variables are correlated. Also, equations show a statistically significant covariation in oil import price, which depends more on its lags than on past errors. Consequently, oil demand are influenced by past information which is common to the crude oil market and the stock market and to its volatilities. They suggest that the comovements of the three series display an extremely volatile trend for the study period.

This paper has some limitations that could be addressed in future research. First, the planned volume of crude oil import and it can be replaced in part by renewable energy for example. Other ways for demand taking into account reserves and transport costs calculations would be an interesting subject in the future study. Second, the Oil Asian national production and it role to reduce oil demand that are not affected by extreme events are assumed unbounded. Determining appropriate long memory models for them would and others data be a possible future extension.

REFERENCES

Aastveit, K.A., Bjornland, H.C., Thorsrud, L.A. (2015), What drives oil prices? Emerging versus developed economies. Journal of Applied Economics, 30(7), 1013-1028.

Aloui, R., Aissa, M.S.B. (2016), Relationship between oil, stock prices and exchange rates: A vine copula based GARCH method. The North American Journal of Economics and Finance, 37, 458-471.

Aloui, R., Hammoudeh, S., Nguyen, D.K. (2013), A time-varying copula approach to oil and stock market dependence: The case of transition economies. Energy Economics, 39, 208-221.

Alquist, R., Kilian, L. (2010), What do we learn from the price of crude oil futures? Journal of Applied Econometrics, 25, 539-573.

Ang, A., Bekaert, G. (2002), International asset allocation with regime shifts. Review of Financial Studies, 15(4), 1137-1187.

Baillie, R.T., Bollerslev, T., Mikkelsen, H.O. (1996), Fractionally integrated generalized autoregressive conditional heteroskedasticity. Journal of Econometrics, 73, 3-20.

Baumeister, C., Kilian, L. (2016a), Forty years of oil price fluctuations: Why the price of oil may still surprise us. Journal of Economic Perspectives, 30(1), 139-160.

Baumeister, C., Kilian, L. (2016b), Lower oil prices and the US economy: Is this time different? Brookings Papers on Economic Activity, 2016(2), 287-357.

Baumeister, C., Kilian, L. (2016c), Understanding the decline in the price of oil since June 2014. Journal of the Association of Environmental and Resource Economists, 3(1), 131-158.

Bhar, R., Malliaris, A.G. (2011), Oil prices and the impact of the financial crisis of 2007-2009. Energy Economics, 33, 1049-1054.

Bjornland, H.C. (2009), Oil price shocks and stock market booms in an oil exporting country. Journal of Political Economy, 56, 232-254.

Boldanov, R., Degiannakis, S. and Filis, G. (2016), Time-varying correlation between oil and stock market volatilities: Evidence from oil-importing and oil-exporting countries. International Review of Financial Analysis, 48, 209-220.

Bollerslev, T., Mikkelsen, H.O. (1996), Modeling and pricing long memory in stock market volatility. Journal of Econometrics, 73, 151-184.

Bollerslev, T. (1986), Generalized autoregressive conditional heteroskedasticity. Journal of Econometrics, 31, 307-327.

Bouri, E. (2015), Oil volatility shocks and the stock markets of oil-importing MENA economies: A tale from the financial crisis. Energy Economics, 51, 590-598.

Boyer, B.H., Gibson, M.S. and Loretan, M. (1999), Pitfalls in Test for Changes in Correlations. Vol. 3. International Finance Discussion Paper. p597-617.

Christodoulakis, G. (2007), Common volatility and correlation clustering in asset returns. European Journal of Operational Research, 182(3), 1263-1284.

Chung, C. (1999), Estimating a generalized long memory process. Journal of Econometrics, 73(1), 237-259.

Cuddington, J.T., Dagher, L. (2015), Estimating short and long-run demand elasticities: A primer with energy-sector applications. Energy Journal, 36(1), 185-208.

Cunado, J., Jo, S., de Gracia, F.P. (2015), Macroeconomic impacts of oil price shocks in Asian Economies. Energy Policy, 86, 867-879.

Ding, Z., Granger, C.W.J. and Engle, R.F. (1993), A long memory property of stock markets returns and a new model. Journal of Empirical Finance, 1, 83-106.

Engle, R.F. and Bollerslev, T. (1986), Modeling the persistence of conditional variances. Econometric Review, 5, 1-50.

Engle, R.F. (1982), Autoregressive conditional heteroskedasticity with estimates of the variance of United Kingdom inflation. Econometrica, 50(4), 987-1007.

Filis, G., Degiannakis, S. and 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, 152-164.

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

Guesmi, K. (2014), Comovements and Volatility Spillovers between Oil Prices and Stock Markets: Further Evidence for oil Exporting and Oil Importing Countries, Emerging Market and Global Economy: A Handbook. Oxford, UK: Elsevier. p371-382.

Gupta, K. (2016), Oil price shocks, competition, and oil and gas stock returns-global evidence. Energy Economics, 57, 140-153.

Hamilton, J.D. (2009), Understanding crude oil price. Energy Journal, 30, 179-206.

Hamilton, J.D. (1983), Oil and the macroeconomy since World War II. Journal of Political Economy, 91, 228-248.

Hamilton, J.D. (1985), Historical causes of postwar oil shocks and recessions. Energy Journal, 6(1), 97-116.

Hamilton, J.D. (2013), Historical oil shocks. In: Parker, R.E., Whaples, R.M., editors. The Rutledge Handbook of Major Events in Economic History. New York: Routledge, Taylor and Francis Group. p239-265.

He, C., Terasvirta, T. (1999a), Fourth moment structure of the GARCH (p, q) process. Econometric Theory, 15, 824-846.

He, C., Terasvirta, T. (1999b), Properties of moments of a family of GARCH processes. Journal of Econometrics, 92, 173-192.

Huang, B.N., Hwang, M.J., Peng, H.P. (2005), The asymmetry of the impact of oil price shocks on economic activities: An application of the multivariate threshold model. Energy Economics, 27, 455-476.

Jiao, J., Han, K., Wu, G., Li, L., Wei, Y. (2014), The effect of an SPR on the oil price in China: A system dynamics approach. Applied Energy, 133, 363-373.

Jones, C.T. (1990), OPEC behavior under falling prices: Implications for cartel stability. Energy Journal, 11, 117-129.

Kilian, L. (2009), Not all oil price shocks are alike: Disentangling demand and supply shocks in the crude oil market. American Economic Review, 99(3), 1053-1069.

Kilian, L., Murphy, D. (2014), The Role of Inventories and Speculative Trading in the Global Market for Crude Oil. Michigan: University of Michigan.

Kilian, L. (2008), The economic effects of energy price shocks. Journal of Economic Literature, 46(4), 871-909.

Kilian, L. (2016), The impact of the shale oil revolution on U.S. oil and gasoline prices. Review of Environmental Economics and Policy, 10(2), 185-205.

Kilian, L. (2017), The impact of the fracking boom on Arab oil producers. Energy Journal, 38(6), 137-160.

Kilian, L., Murphy, D. (2014), The Role of Inventories and Speculative Trading in the Global Market for Crude Oil Shocks, Working Paper, University of Michigan.

Laurent, S. (2005-2018), Estimating and Forecasting ARCH Models Using GARCH 8. England: Timberlake Consultants Ltd. p1-450.

Longin, F., Solnik, B. (2001), Extreme correlation of international equity markets. Journal of Finance, 56, 651-678.

Martens, M., Poon, S.H. (2001), Returns synchronization and daily correlation dynamics between international stock markets. Journal of Banking and Finance, 25, 1805-1827.

Mensi, W., Hammoudeh, S., Shahzad, S.J.H., Shahbaz, M. (2017), Modeling systemic risk and dependence structure between oil and stock markets using a variation al mode decomposition based copula method, Journal of Banking and Finance, 75, 258-279.

Mohammadia, H., Su, L. (2010), International evidence on crude oil price dynamics: Applications of ARIMA-GARCH models author links open overlay panel. Energy Economics, 32(5), 1001-1008.

Nelson, D.B. (1991), Conditional heteroskedasticity in asset returns: A new approach. Econometrica, 59, 347-370.

Nusair, S.A. (2016), The Effects of oil price shocks on the economies of the Gulf Co-operation: Council countries: Nonlinear analysis. Energy Policy, 91, 256-267.

Nusair, S.A. (2016), The macroeconomic effects of oil price shocks: Evidence from a statistical identification approach. Journal of International Money and Finance, 61, 30-44.

Pirog, R. (2005), World Oil Demand and its Effect on Oil Prices. CRS Report, NO. RL32530.

Ross, S. (1989), Information and volatility: The no-arbitrage martingale approach to timing and resolution irrelevancy. Review of Financial Studies, 44(1), 1-17.

Sadorsky, P. (1999), Oil price shocks and stock market activity. Energy Economics, 21(2), 449-469.

Singhal, S., Ghosh, S. (2016), Returns and volatility linkages between international crude oil price, metal and other stock indices in India: Evidence from VAR-DCC-GARCH models. Resources Policy, 50, 276-288.

Tse, Y.K., Tsui, A.K.C. (2002), A multivariate GARCH model with time-varying correlations. Journal of Business and Economic Statistics, 20, 351-362.

Tse, Y.K. (1998), The conditional heteroskedasticity of the yen-dollar exchange rates. Journal of Applied Econometrics, 13, 49-56.

Unalmis, D., Unalmis, I., Unsal, D.F. (2012), On oil price shocks: The role of storage. IMF Economic Review, 60(4), 505-532.

Wang, Y., Liu, L. (2016), Crude oil and world stock markets: Volatility spillovers, dynamic correlations, and hedging. Empirical Economics, 50, 1481-1509.

Wang, Y., Wu, C., Yang, L. (2013), Oil price shocks and stock market activities: Evidence from oil-importing and oil-exporting countries.

APPENDICES

Appendix A: The Result of Selection Order ARMA (m,n)

Table 8: Selection Order (m, n) ARMA Model

Order of ARMA Model	Crude Oil Returns		China Stock Market Returns	
	AIC.T	AIC	AIC.T	AIC
(0,0)	1756.25304	7.25724395	1680.79764	6.94544481
(0,1)	1755.5132	7.25418679	1682.42078	6.95215197
(0,2)	1757.24597	7.26134697	1683.59168	6.95699042
(1,0)	1754.91807	7.25172755	1682.29234	6.95162122
(1,1)	1756.37658	7.25775445	1682.94105	6.95430187
(1,2)	1758.25698	7.26552471	1683.85312	6.95807074
(2,0)	1756.54448	7.25844825	1679.45593	6.93990053
(2,1)	1758.31341	7.26575789	1684.27057	6.95979576
(2,2)	1759.40535	7.27027005	1682.51613	6.95254599
Order of ARMA Model	**India Stock Market Returns**		**Indonesia Stock Market Returns**	
	AIC.T	**AIC**	**AIC.T**	**AIC**
(0,0)	1619.8047	6.69340784	1692.45401	6.99361162
(0,1)	1621.69738	6.70122883	1687.56562	6.97341164
(0,2)	1623.53934	6.70884025	1688.79503	6.97849188
(1,0)	1621.68323	6.70117036	1690.04014	6.98363695
(1,1)	1623.59801	6.70908269	1689.03512	6.97948396
(1,2)	1623.99373	6.71071791	1690.7904	6.98673717
(2,0)	1623.50812	6.70871125	1688.88779	6.97887517
(2,1)	1623.99751	6.71073352	1690.47522	6.98543478
(2,2)	1626.01256	6.71906015	1682.14208	6.95100034

Appendix B: Selection of the ARMA(0,0)-Diag-BEKK(p,q)Order: Case of the Three Asian Countries

Table 9: Selection of the ARMA (0,0)-Diag-BEKK (p, q) Order: Case of the Three Asian Countries

ARMA (0,0)- Diag-BEKK (p, q)	Information Criteria (to be minimized)			
	Akaike	Shibata	Schwarz	Hannan-Quinn
China				
ARMA (0,0)-Diag-BEKK (0,0)	58.380773	58.378137	58.510527	58.433043
ARMA (0,0)-Diag-BEKK (0,1)	57.999152	57.994537	58.172157	58.068845
ARMA (0,0)-Diag-BEKK (0,2)	57.674890	57.667787	57.891146	57.762006
ARMA (0,0)-Diag-BEKK (1,1)	57.781068	57.773966	57.997325	57.868184
ARMA (0,0)-Diag-BEKK (1,2)	57.666679	57.656602	57.926186	57.771218
India				
ARMA (0,0)-Diag-BEKK (0,0)	60.698497	60.695861	60.828251	60.750767
ARMA (0,0)-Diag-BEKK (0,1)	59.166092	59.161477	59.339097	59.235785
ARMA (0,0)-Diag-BEKK (0,2)	58.803524	58.796421	59.019780	58.890640
ARMA (0,0)-Diag-BEKK (1,1)	59.006539	58.999436	59.093654	59.093654
ARMA (0,0)-Diag-BEKK (1,2)	58.828317	58.818240	59.087825	58.932856
Indonesia				
ARMA (0,0)-Diag-BEKK (0,0)	58.755823	58.753187	58.885577	58.808093
ARMA (0,0)-Diag-BEKK (0,1)	57.265914	57.261299	57.438919	57.335607
ARMA (0,0)-Diag-BEKK (0,2)	56.984398	56.977296	57.200655	57.071514
ARMA (0,0)-Diag-BEKK (1,1)	57.087110	57.080008	57.303367	57.174226
ARMA (0,0)-Diag-BEKK (1,2)	57.009181	56.999104	57.268689	57.113720

Appendix C: Robust Standard Errors (Sandwich formula)

Table 10: Diag-BEKK Estimates: ARMA (0,0)-Diagonal BEKK (1,2)

#1: China_Crude_Oil_Import_Prices - #2: China_CondV_COR - #3: China_CondV_SMR				
	Coefficient	SE	t-value	t-prob.
Cst1	25798437.065928	3.2390e+005	79.65	0.0000
Cst2	73.652716	7.1208	10.34	0.0000
Cst3	43.654826	3.3167	13.16	0.0000
C_11	24290765.604520	1.3561e+005	179.1	0.0000
C_12	−5.601376	3.0621	−1.829	0.0687
C_13	1.644708	2.1414	0.7681	0.4433
C_22	38.435502	4.5486	8.450	0.0000
C_23	0.687867	2.0642	0.3332	0.7393
C_33	18.371716	5.7875	3.174	0.0017
b_1.11	0.000000	0.025102	0.00	1.0000
b_1.22	0.025937	0.11533	0.2249	0.8223
b_1.33	0.396700	0.37730	1.051	0.2942
a_1.11	0.349810	0.073206	4.778	0.0000
a_1.22	0.153471	0.074490	2.060	0.0405
a_1.33	0.823457	0.25069	3.285	0.0012
a_2.11	0.236790	0.096877	2.444	0.0153
a_2.22	0.738989	0.16341	4.522	0.0000
a_2.33	0.405633	0.28065	1.445	0.1498
No. Observations: 242			No. Parameters: 18	
No. Series: 3			Log Likelihood: −6959.668	

Table 11: Diag-BEKK Estimates: ARMA (0,0)-Diagonal BEKK (0, 2)

#1: India_Crude_Oil_Import_Prices - #2: India_CondV_COR - #3: India_CondV_SMR				
	Coefficient	SE	t-value	t-prob.
Cst1	128157129.876033	1.9985e+007	6.413	0.0000
Cst2	58.354759	8.9369	6.530	0.0000
Cst3	35.527066	1.2477	28.47	0.0000
C_11	140884943.231823	1.9160e+007	7.353	0.0000
C_12	−14.395124	4.0329	−3.569	0.0004
C_13	−5.474734	1.5672	−3.493	0.0006
C_22	33.094575	4.5526	7.269	0.0000
C_23	0.301107	0.61542	2.216	0.0277
C_33	4.118022	0.61961	6.646	0.0000
a_1.11	0.539847	0.072710	7.425	0.0000
a_1.22	0.301107	0.10017	3.006	0.0029
a_1.33	0.776531	0.063650	12.20	0.0000
a_2.11	0.512827	0.066736	7.684	0.0000
a_2.22	0.895909	0.20013	4.477	0.0000
a_2.33	0.501609	0.072942	6.877	0.0000
No. Observations: 242			No. Parameters: 15	
No. Series: 3			Log Likelihood: −7100.226	

Table 12: Diag-BEKK Estimates: ARMA (0,0)-Diagonal BEKK (0,2)

#1: Indonesia_Crude_Oil_Import_Prices -#2: Indonesia_CondV_COR–#3:Indonesia_CondV_SMR				
	Coefficient	SE	t-value	t-prob.
Cst1	46254825.082645	5.5851e+005	82.82	0.0000
Cst2	73.619890	7.7281	9.526	0.0000
Cst3	41.118423	2.4689	16.65	0.0000
C_11	35623372.346509	2.0227e+005	176.1	0.0000
C_12	−7.453878	3.6849	−2.023	0.0443
C_13	−1.866951	0.90682	−2.059	0.0407
C_22	37.847640	3.5638	10.62	0.0000
C_23	2.340060	1.8787	1.246	0.2142
C_33	5.962022	1.1221	5.313	0.0000
a_1.11	0.495711	0.15038	3.296	0.0011
a_1.22	0.265161	0.10653	2.489	0.0135
a_1.33	0.860685	0.12681	6.787	0.0000
a_2.11	0.232689	0.10643	2.186	0.0298
a_2.22	0.732492	0.11525	6.356	0.0000
a_2.33	0.509128	0.095163	5.350	0.0000
No. Observations: 242			No. Parameters: 15	
No. Series: 3			Log Likelihood: −6880.112	

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Appendix D: Simultaneous Equation Models

Table 13: Simultaneous Equation Models: China

Equation (1) for: Equation (1) for: China_Crude_Oil_Import_Prices_1				
	Coefficient	**SE**	**t-value**	**t-prob.**
China_Crude_Oil_Import_Prices_1	0.451076	0.05813	7.76	0.0000
China_CondV_COR_1	−28002.1	2.528e+004	−1.11	0.2691
China_CondV_SMR_1	16363.3	2.978e+004	0.549	0.5832
Constant U	1.55623e+007	3.353e+006	4.64	0.0000
Equation (2) for: China_CondV_COR				
	Coefficient	**SE**	**t-value**	**t-prob.**
China_Crude_Oil_Import_Prices_1	−7.19916e-008	1.412e-007	−0.510	0.6106
China_CondV_COR_1	0.405668	0.06139	6.61	0.0000
China_CondV_SMR_1	0.00369456	0.07232	0.0511	0.9593
Constant U	52.8482	8.142	6.49	0.0000
Equation (3) for: China_CondV_SMR				
	Coefficient	**SE**	**t-value**	**t-prob.**
China_Crude_Oil_Import_Prices_1	−1.06572e-007	1.251e-007	−0.852	0.3952
China_CondV_COR_1	0.149679	0.05441	2.75	0.0064
China_CondV_SMR_1	0.171269	0.06410	2.67	0.0081
Constant U	40.4573	7.217	5.61	0.0000

Table 14: Simultaneous Equation Models: India

Equation (1) for: Equation (1) for: India_Crude_Oil_Import_Prices_1				
	Coefficient	**SE**	**t-value**	**t-prob.**
India_Crude_Oil_Import_Prices_1	0.768619	0.04221	18.2	0.0000
India_CondV_COR_1	18373.2	8.871e+004	0.207	0.8361
India_CondV_SMR_1	−623211	1.874e+005	−3.32	0.0010
Constant U	6.10940e+007	1.418e+007	4.31	0.0000
Equation (2) for: India_CondV_COR				
	Coefficient	**SE**	**t-value**	**t-prob.**
India_Crude_Oil_Import_Prices_1	3.06777e-008	2.886e-008	1.06	0.2889
India_CondV_COR_1	0.329591	0.06065	5.43	0.0000
India_CondV_SMR_1	0.487613	0.1281	3.81	0.0002
Constant U	29.2274	9.693	3.02	0.0028
Equation (3) for: India_CondV_SMR				
	Coefficient	**SE**	**t-value**	**t-prob.**
India_Crude_Oil_Import_Prices_1	−3.83159e-009	4.227e-009	−0.906	0.3656
India_CondV_COR_1	−0.0277840	0.008883	−3.13	0.0020
India_CondV_SMR_1	0.981289	0.01877	52.3	0.0000
Constant U	3.74641	1.420	2.64	0.0089

Table 15: Simultaneous Equation Models: Indonesia

Equation (1) for: Equation (1) for: Indonesia_Crude_Oil_Import_Prices_1				
	Coefficient	**SE**	**t-value**	**t-prob.**
Indonesia_Crude_Oil_Import_Prices_1	0.435494	0.05770	7.55	0.0000
Indonesia_CondV_COR_1	−56588.4	3.516e+004	−1.61	0.1088
Indonesia_CondV_SMR_1	−144942	5.031e+004	−2.88	0.0043
Constant U	3.84367e+007	5.451e+006	7.05	0.0000
Equation (2) for: Indonesia_CondV_COR				
	Coefficient	**SE**	**t-value**	**t-prob.**
Indonesia_Crude_Oil_Import_Prices_1	−1.17452e-007	9.759e-008	−1.20	0.2300
Indonesia_CondV_COR_1	0.355253	0.05947	5.97	0.0000
Indonesia_CondV_SMR_1	0.265205	0.08510	3.12	0.0021
Constant U	47.4073	9.221	5.14	0.0000
Equation (3) for: Indonesia_CondV_SMR				
	Coefficient	**SE**	**t-value**	**t-prob.**
Indonesia_Crude_Oil_Import_Prices_1	−2.41713e-008	3.063e-008	−0.789	0.4307
Indonesia_CondV_COR_1	−0.0171018	0.01866	−0.916	0.3604
Indonesia_CondV_SMR_1	0.923650	0.02671	34.6	0.0000
Constant U	6.28404	2.894	2.17	0.0309