International Journal of Energy Economics and Policy

ISSN: 2146-4553

available at http: www.econjournals.com

International Journal of Energy Economics and Policy, 2022, 12(2), 53-71.

Effects of Conditional Oil Volatility on Exchange Rate and Stock Markets Returns

Tarek Bouazizi[1]*, Fatma Mrad[2], Arafet Hamida[3], Sawsen Nafti[2]

[1]University of Tunis El Manar, Tunis, Tunisia, [2]Faculty of Economics and Management of Sousse, Sousse, Tunisia, [3]Higher Institute of Management, Gabès, Tunisia. *Email: tarek.bouazizi@fsegso.u-sousse.tn

Received: 13 November 2021 **Accepted:** 22 February 2022 **DOI:** https://doi.org/10.32479/ijeep.12826

ABSTRACT

The underlying volatility at a given time is called conditional volatility at this particular time and is modeled by various ARMA-GARCH conditional variance equations (GARCH, EGARCH, GJR, APARCH, IGARCH). How important are oil price fluctuations and oil price volatility in foreign exchange markets and stock markets? What is the nature of the relationship between these three markets? What are the political implications if volatility, using appropriate models to determine, turns out to be important? We evaluate these questions empirically, using the specification of Narayan and Narayan (2010). This specification, in our paper, deals with the determination of volatility appropriate models, based on information criteria, of the ARMA-ARCH family conditional volatility of oil returns using daily data for each country independently (i), and revolve around an analysis of the effect of the volatility of black gold price on the returns of the other two markets in Oil Importing Developed Countries category (ii). The selection of appropriate models of oil returns according to the period of the chosen data gives the ARMA(2,2)- GJR(1,2) model for the Germany and the ARMA(2,2)-GJR(2,2) model for the Japan and the USA. The results that the conditional variances of oil returns, foreign exchange market returns and stock market returns are contested and they have a long-term relationship in different countries. In addition, the results of the granger causality tests and the study of impulse response functions have shown that it has a sending effect of the volatility of oil prices on most foreign exchange markets and stock markets, highlighting the strong explanatory power of market volatility, but bidirectional causality is not always present. Our empirical results involved in the prevention of shocks are important for policymakers, for portfolio managers seeking optimal portfolio allocation, for monetary authorities who are studying changes in the exchange rate of the national currency against currencies, for oil-importing countries seeking to minimize their spending on crude oil, and for oil-exporting countries seeking the sound management of oil reserves. They also show that the volatility of crude oil prices on the world market is generally more significant for foreign exchange and stock markets than the volatility of oil price in the local market. This main conclusion gives political implications to policymakers.

Keywords: ARMA-GARCH, Conditional Volatility, Oil Price, Exchange Rate, Stock Market
JEL Classifications: C22, E31, F14

1. INTRODUCTION

Energy markets have been recently marked by considerable price movements. In particular, from 2001 to 2019, energy prices in international exchange platforms have been rising strongly, and record high prices for oil have been accompanied by important volatility and sudden decrease. This high volatility makes oil one of the major macroeconomic factors potentially causing unstable economic conditions for stock markets around the world.

Oil price can impact stock markets trough several channels. First, the price of a share being equal to its discounted future cash flow, rising oil prices can increase the interest rate to limit inflationary pressure, tighten the cost of doing business, put pressure on output prices thus decreasing profits (Jones et al., 2004). High interest rates also make bond investments more attractive than ones stock prices (Chittedi, 2012). Financialization of oil markets and intensive oil trading can also be factored in (Creti et al., 2013). All these effects generally trigger a negative relationship between oil and stock markets, which parallels the one between high oil prices and macroeconomic indicators.

Given that the roots of the link between oil and stock markets are of different nature, it is interesting to explore whether the co-movements between oil and stock price emerge in a given time frame, either short or long-term.

Moreover, while there is a size able empirical literature on oil and stock markets, less is known about this relationship in the context of oil-importing countries.

Most of the studies focus on oil-importing countries, mainly the U.S. However, specific effects on different set of countries are worth investigating. On one hand, an increase of oil prices negatively influences the economy of importing countries. When oil price rises, importing countries can experience strong negative consequences and economic recession (Federer, 1996). Instead, an increase in the oil prices influences positively oil-exporting countries macroeconomic balance. On the other hand, a decrease in the oil prices exhibits a negative relationship with economic growth of oil producers and can generate political and social instability (Yang et al., 2002).

We measure the interaction between oil price and stock markets indices according to the evolutionary co-spectral analysis as defined by Priestley and Tong (Priestley and Tong, 1973). While existing studies applies either VAR or volatility analysis, we choose this technique as it presents several advantages. First, this kind of analysis does not impose any restrictions or pretreatment of the data (as it is the case of volatility analysis, for instance, which requires the series to be stationary, or cointegration techniques applied to time series data integrated of order one). Second, it does not have an end-point problem: no future information is used, implied or required as in band-pass or trend projection methods. In addition, the evolutionary co-spectral analysis gives a robust frequency representation of non-stationary processes.

For the objective and research questions, this thesis contributes to the literature, addressing the following questions on the choices for measuring asymmetric return volatility with appropriate models between the crude oil market, the Brent, stock markets and international currency markets. More specifically, we try to explore and answer the following questions:

i. What is the nature of the long-term relationship between oil returns volatility, exchange rates and stock prices for major oil importing countries?

The purpose of this research question is to deduce, from the cointegration results of the Johansen test, and to determine which model we will identify and quantify the influence of oil returns volatility on the current state of stock and foreign exchange markets in developed oil importing countries and also to study the influence of other major international markets on oil returns volatility.

ii. Are the two markets (foreign exchange and stock market) in this sample of countries isolated from the effect of a shocks of volatility in crude oil market returns?

These questions examine changes in the volatility of oil returns due to unexpected shocks from the crude oil market, as well as from other markets. In other words, this aspect of the current study will determine whether shocks specific to different groups of countries increase the volatility of the Brent market more than shocks from the other two markets. Consequently, this will make it possible to identify which foreign exchange and/or stock markets influence the conditional volatility of oil returns and which of these markets has less influence.

iii. Since the sample of developed countries are the observed relationships between of the crude oil returns volatility, stock market returns and exchange rate returns as they should be in theory?

This feature of current research still evaluates fluctuations in the volatility of oil returns due to the asymmetric effect of volatility on the crude oil market, as well as on other markets. More precisely, it will identify whether a price decreases or bad news from one oil market leads to higher prices or good news in other markets.

iv. What are the dynamic relationships between these three variables and the direction of causality?

The purpose of this research question is to identify the meaning of the possible influence between oil market volatility, stock markets and foreign exchange markets of the different countries of three developed oil importing countries. In addition, this aspect compares and contrasts the direction of causality between the three variables during the period chosen for each country (Germany, Japan and USA). This question, using the Granger causality test, also reveals what oil Brent price volatility can be explained to cause movements in stock prices and exchange rates in the long and/or short term.

2. RELATED LITERATURE

2.1. Some Theories on the Relationship between Returns and Volatility

The relationship between expected returns on assets and conditional volatility has received much attention in the economic and financial literature.

Although a positive relationship between expected returns and expected volatility is consistent with the capital asset pricing model (CAPM) and intuitively attractive, rational conservative investors demand higher expected returns during the most volatile periods, empirical studies have been unable to establish a convincing positive relationship between the risk premium and conditional volatility, using GARCH-M models. Instead, there appears to be stronger evidence of a negative relationship between unexpected returns and innovations to the volatility process, including the work of French et al. (1987) who interpret as indirect evidence of a positive correlation between the risk premium and ex ante volatility. They say that large chunks of good or bad news induce higher expected volatility for future periods than volatility is persistent. If expected volatility and expected returns are positively correlated and future cash flows are not affected, the current price of the stock market should fall. Conversely, the arrival of small pieces of news leads to an expected decrease in future volatility and thus to an increase in the contemporary prices of the stock market index. This theory, known as the volatility reaction theory, therefore depends on two assumptions. Firstly, the persistence of volatility and secondly, the existence of a positive relationship between the expected components of the return and the volatility process.

Another explanation for asymmetric volatility where causality goes in the opposite direction is the leverage effect put forward by Black (1976), which states that if bad (good) news induces a negative (positive) return shock which is then measured by the d parameter preceding the $\sigma_t^2 = \sigma_{t/t-1}^2$ term which should be more negative than large (small) shocks to the increase in the (lower) return process of contemporaneous volatility through ¾΄.΄t, Presumably regardless of the sign of ΄t, which induces a fall (increase) in the current price of the stock market index in the case of large negative initial (small) positive return shocks that are amplified, while large negative initial positive and small negative shocks are attenuated. Since deterministic GARCH models do not contain an unexpected volatility component, which is $\sigma_t^2 = \sigma_{t/t-1}^2$, the question does not arise for this class of volatility models, and parameter d measures only the relationship between expected returns and expected volatility.

We often reason about logarithmic returns when analyzing financial series to allow comparison with other financial series. Moreover, as we will see in the stylized facts, the financial asset price series is not stationary, so we switch to first-order logarithmic differentiation to make the series stationary, which allows us to estimate the parameters of the chosen model. For variations in the vicinity of 0, we will confuse the stock market returns with the logarithmic returns (For $X_t \approx 0$ we have: ln $(1+X_t) \approx X_t$, based on a development limited to order 1).

Indeed:

$$\ln(1+x) = \sum_{k=1} n + (-1)^{(k-1)} \frac{x^k}{k} = x - \frac{x^2}{2} + \ldots + 0(x^{(n+1)}).$$

Since $x \prec\prec 1$, then we can neglect the terms with $k \geq 2$ in front of the first term x. That way, we'll have, ln $(1+x) \approx x$.

Otherwise, ARIMA(r,q,s) models (in our case, we will set q to zero) were used to forecast different types of time series and were compared to a reference model for its validity. Therefore, to capture the long-run trend, many authors have used the ARIMA model, proposed by Box-Jenkins (Box and Jenkins, 1970), to forecast the exchange rate. Pagan and Schwert (1990) found evidence that ARIMA models performed well compared with nonparametric and Markov switching models.

Chen (1997) introduced a new pre-difference transformation for the AR1MA model for forecasting the volatility of the S&P500 index. The forecasting performance of the ARIMA model samples using the new pre-difference transformation was compared to the forecasting performance of the mean reversion and GARCH model samples. The ARIMA model using the new pre-difference transformation introduced in this study was found to be superior to the mean reversion model and the GARCH model in predicting the monthly volatility of the S&P500 index for the forecast comparison periods used in this study.

Volatility comes in many forms and shapes. To be precise when discussing volatility, it is important to be clear about what is meant when the term volatility was used.

Volatility is traditionally defined by standard deviation. Volatility is often preferred to variance because it is measured in the same units as the original data. For example, when using returns, volatility is also in returns, and a volatility of 5% indicates that Â±5% is a significant amount. But realized volatility is defined as the actual volatility used historically to denote a measure of volatility over an arbitrary period of time. Then, the implied volatility is the volatility that will correctly value an option.

In addition, the conditional volatility, sought in our case, is the expected future volatility $t+h$ based on all available information up to the moment t.

In financial econometrics, an ARCH is not an architectural feature of a building; it is a fundamental tool for analyzing the temporal variation of the conditional variance. The success of the ARCH (auto-regressive conditional heteroskedasticity) family of models can be attributed to three characteristics:

ARCH processes are essentially ARMA models and many of the tools of linear time series analysis can be directly applied, the ARCH family of models are easy to estimate and many parsimonious models are able to provide a good description of the dynamics of asset volatility.

For the estimation, we use daily returns from Brent prices, exchange rates and stock market prices to estimate

ARMA(r, s)-GARCH(p,q), ARMA(r, s)-EGARCH(p,q), ARMA(r, s)-GJR(p,q), ARMA(r, s)-APARCH(p,q) and ARMA(r, s)-IGARCH(p,q). Hence the persistence of volatility and asymmetric properties are analysed.

2.2. Relationship between Oil Price and its Volatility, Exchange Rate Returns and Stock Market Returns

More generally, for risk aversion, it has been shown that an increase in financial market risk, which has been found to be closely related to uncertainty and risk aversion (2013), leads to an appreciation of the US dollar. In addition, US financial assets are perceived as safe and liquid, which has triggered what we have called a phenomenon of security flight (see for example Fratzscher, 2009). In contrast, the currencies of emerging markets in particular depreciate during periods of increased risk and investors withdraw capital from these countries. On the other hand, increased risk and uncertainty could cause black gold prices to fall as economic activity slows and investors turn to relatively safer financial assets during these periods.

Moreover, it has been shown that oil price volatility increases during periods of heightened uncertainty. Furthermore, the oil market has been and will continue to be a constantly evolving arena. Indeed, oil is so vital to the global economy, it is still present in everyone's daily life and also its market is truly global. While few studies have so far analysed the effects of fluctuations in oil price volatility on the economic and financial variables of oil exporting and importing countries. Thus, this section seeks to examine the effect of oil price volatility on foreign exchange market returns and stock market returns. Similarly, in this section, the incremental power of oil price shocks and oil price volatility in forecasting the state of foreign exchange market returns, stock market returns and volatility are examined in both developed and emerging economies.

There have already been some problems, but none of the existing literature has addressed the question of the effect of movements in oil returns volatility, represented by an appropriate model, on macroeconomic variables. The review of the literature indicates that research on the conditional volatility, as measured by conditional variances, of crude oil is very limited. Thus, this recent literature on the transmission and measurement of the volatility of oil returns has been developed by studying their trends in the markets under consideration. Based on the existing literature, the focus is on three macroeconomic variables: crude oil price volatility, the exchange rate and stock market prices.

In addition, some studies have already examined the implications of the relationship between the volatility of oil returns and foreign exchange market returns on the one hand, and between the volatility of black gold returns and stock market returns on the other. Since the Hamilton seminar (1983), there has been growing interest in the effects of oil prices on stock market returns and on the economy. The purpose of this article is to examine the relationship between oil prices and the stock market from a different perspective. In particular, we define a specification of the regime-switching model and investigate whether oil-price shocks and oil-price volatility can predict the states of the exchange market and the stock market.

In a study of the world's largest oil exporting countries, such as Russia, Norway and Saudi Arabia, Habib and Kalamova (2007) find that oil prices influence the movements of the Russian rouble, but that the currencies of the major oil producers, Norway and Saudi Arabia, are not affected by the volatility of black gold prices. Since oil price volatility directly affects the inflow of foreign currency into the country, it is necessary to study whether it has a direct impact on the volatility of the exchange rate of the Naira. Englama et al. (2010) examine the relationship between oil price and exchange rate volatility in oil exporting Nigeria. They find that exchange rate volatility is positively influenced by oil price volatility.

Malik and Ewing (2009), Oberndorfer (2009) and Sadorsky (1999) further argue that, in addition to oil prices, oil price volatility also has an impact on returns. They provide evidence that increased oil price volatility tends to have a negative effect on stock market returns. Chiou and Lee (2009) also show that oil price volatility has a negative impact on the S&P500 stock market. Furthermore, Sadorsky (1999) on the US economy shows that oil price volatility shocks have asymmetric effects on the economy. By analyzing impulse response functions, he shows that oil price movements are important in explaining movements in stock market returns; after 1986, oil price movements explain more of the variance of the errors than interest rates. Thus, the results finally suggest that positive oil-price shocks reduce real stock market returns, while shocks to real stock market returns have positive effects on interest rates and industrial production.

Nevertheless, the above-mentioned effects of oil stock market performance are far from being defined. The country's status as a crude oil importer or crude oil exporter provides additional information on these effects. Many authors subscribe to the belief that the stock markets of oil-exporting countries tend to benefit from higher oil prices, while the reverse is true for oil-importing countries (see, among others, Lescaroux and Mignon, 2008; Bjornland, 2009; Arouri and Rault, 2010 and Korhonen and Ledyaeva, 2010).

In addition, political and legal institutions affect the extent to which the real exchange rates of oil-exporting countries coincide with oil market volatility. In a simple theoretical model, strong institutions isolate real exchange rates from oil price volatility by generating a regular pattern of fiscal spending over the price cycle. Few empirical studies have examined the impact of oil price volatility on exchange rates. Rickne (2014) finds that adjustments between oil prices and real exchange rates in the sample of 33 oil-exporting countries are conditioned by political and legal institutions.

Specifically, currencies in countries with a high level of bureaucracy are less affected by oil price changes.

Ghosh (2011) also finds the same result, showing that positive and negative shocks have similar effects on exchange rate volatility.

We present in Table 1 three empirical studies that focus on the price of oil and the exchange rate. The three studies found different results.

Ding and Vo (201) conduct their study of exchange rates on a group of 9 currencies, of which eight currencies are valued against the US dollar and trade in the weighted US dollar index (USDX). The other eight currencies are the Canadian dollar (CAD), the Norwegian krone (NOK), the euro (EUR), the Indian rupee (INR), the Japanese yen (JPY), the Singapore dollar (SGD), the real Brazilian (BZR), Mexican peso (MXP).

Table 1: Summary of the three studies on the transmission of volatility between oil prices and exchange rates

Author	Data/country	Transmission of volatility
Ding and Vo (2012)	Daily data (July 2004 to October 2009) - Group of 9 different currencies	No transmission (Before the 2008 financial crisis) and two-way transmission (during the crisis)
Selmi et al. (2012)	Daily data (1972 to 2010) in Morocco and Tunisia	One-way transmission (ranging from oil prices to exchange rates)
Salisu and Mobolaji (2013)	Daily data (January 2002 to March 2012) in Nigeria	Bidirectional transmission between the two variables

With daily data from 2004 to 2009 and using a multivariate model, Ding and Vo (2012) found results that vary over time. Thus, these results show that when the markets are relatively calm (before the 2008 crisis), both oil and foreign exchange markets react simultaneously to shocks and without any detected interaction. But, in times of turbulence, there is a bidirectional interaction of volatility between the two variables.

According to the authors, this bidirectional transmission of volatility is consistent with what is observed in the literature, which shows that there is a bidirectional causality between the two level variables, which explains the bidirectional transmission of their volatilities.

The authors attribute the interaction insignificant before the financial crisis, the results show that, when the markets are relatively stable, the oil and foreign exchange markets react to information of shocks simultaneously, thus failing to exhibit lag behavior driven in both ways.

Selmi et al. (2012) focus on a small oil-importing economy (Morocco) and a small oil-exporting country (Tunisia). The peculiarity of their study is that they consider a direction of transmission. In fact, the purpose of their study is not to determine the direction of the transmission of volatility, but rather to determine the effect of oil price volatility on the real exchange rate, and to compare this impact in depending on the nature of the country (importer or exporter of oil and the exchange rate regime). Their results reveal that whether for a country importing or exporting crude oil, the real price of oil is negatively and significantly related to the volatility of real exchange rates. They also find that the effect of bad news is more intense than that of good news, that is, the relationship between oil prices and the exchange rate reacts more to good news than to bad news for the country. Morocco, while for Tunisia this effect is the opposite.

Salisu and Mobolaji (2013) carried out their study using daily data from Nigeria from 2002 to 2012 and a VAR-GARCH model, they verified the existence of a bidirectional transmission of volatility between the two variables.

So, we see that each of these three studies leads to different results. Here too, there is no specific direction determined by the characteristics of the country or by a category of country. Taking into account these and other studies, the transmission channels between oil prices and exchange rates vary.

Most of the existing literature points to a negative relationship between crude oil prices and the US dollar exchange rate. However, a number of possible explanations for this negative relationship can be summarized as follows:

First, oil-exporting countries want to stabilize the purchasing power of their export earnings (in US dollars) in terms of their imports (Non-US dollar), in order to avoid losses they may have due to currencies pegged to the US dollar.

Second, the depreciation of the US dollar makes oil cheaper in dollars for consumers in non-US regions, thereby changing their demand for crude oil, which eventually causes oil price adjustments, as it is denominated in US dollars.

Third, a fall in the US dollar reduces returns on financial assets denominated in USD, making oil and other commodities more attractive to foreign investors. Commodities are also considered to be inflation-hedged assets, since the depreciation of the US dollar increases the risk of inflationary pressures in the United States.

No doubt, the analysis of financial market movements and comovements is important for effective diversification in portfolio management.

The development of a theoretical framework for modeling the relationship between oil prices and the exchange rate was initiated by Golub (1983) and Krugman (1983). The argument for the transmission of oil price volatility to exchange rates is generally based on the fact that oil is quoted in United States dollars (USD) and, therefore, price fluctuations. Oil price can affect exchange rates through US dollars, taking into account the behaviors of trading countries.

This relationship should not be generalized for both groups of countries, whether they are crude oil exporters or crude oil importers that are running floating exchange rates. For example, when the dollar depreciates, oil-exporting countries should increase oil prices, in order to stabilize purchasing power through export earnings (Salisu and Mobolaji, 2013). Conversely, oil importing countries may have to deplete their reserves against US dollars to pay their expected high oil import bills. Thus, the increase in oil prices may increase the appreciation of the currencies of crude oil exporting countries (due to the increase in US dollar reserves) and may subsequently lead to depreciation of the currencies of oil importing countries due to the highest import bill and production costs (Ding and Vo, 2012).

The energy markets have recently been marked by considerable price movements. In particular, from 2001 to 2016, energy prices in international trading platforms rose sharply, and record oil prices were accompanied by significant volatility and sudden decline. This high volatility makes oil one of the main macroeconomic factors potentially causing unstable economic conditions for stock markets around the world.

Aloui et al. (2008) show that changes in crude oil prices significantly lead to volatility in the stock returns of six developed countries, using univariate and multivariate approaches. As shown earlier, researchers have extensively examined the relationship between oil price shocks and a country's macroeconomics. But there is relatively little research on the relationship between oil price shocks and financial markets, except those that focused on developed countries. Empirical studies have obtained very heterogeneous results, depending on the countries or groups of countries studied.

As shown in Table 2, for the seven empirical studies we chose, the results are distributed as follows:

- Three empirical studies have shown unidirectional transmission (but not always in the same direction)
- Two studies found one-way and two-way transmissions
- A study verified the existence of bidirectional transmission
- And in the last study, there is no transmission of volatility.

2.2.1. Unidirectional transmission

Among the results which show a unidirectional transmission of volatility, we cite the one found by Aloui et al. (2008). A study that takes into account two indicators of crude (WTI and Brent) and six major stock markets of the world (France, USA, Germany, Japan, United Kingdom and Canada). The authors verified a positive transmission of the volatility of the stock market index to the WTI, only for the United States, the direction of transmission is in the reverse direction.

The second empirical study is that of Malik and Ewing (2009) who also examined the transmission of volatility between oil prices and stock market indices. A peculiarity of their study is that they considered five different sector indexes of the United States and, also, using weekly data from the period 1992 to 2008. Their results show a transmission of the volatility of the financial industrial and industrial sectors and consumption at oil prices. The direction of transmission is in the opposite direction for the volatilities of the other two sectors (Health sector and Technology sector).

The third empirical study is that of Shaharudin et al. (2009), their analysis is based on oil prices and the stock prices of oil and gas companies in the United States, India and the United Kingdom. They showed, using daily data from 2003 to 2008 and a GJR-GARCH model, the existence of a volatility transmission relationship in each of these countries, ranging from the price of oil to the stock prices of these companies.

2.2.2. Unidirectional and bidirectional transmissions

Other empirical work has found in addition to unidirectional transmission, bidirectional transmission, such as those of Arouri et al. (2011a) and Chaibi and Gomes (2013).

First, Arouri et al. (2011a) studied the transmission between crude oil prices and European and American stock indexes of different sectors (automotive, financial, industrial, technology, basic materials, telecommunications and utilities) using weekly data during the period 1998-2009 in a VAR-GARCH model. The authors showed a unidirectional transmission of volatility, ranging from the price of oil to industrial sector indices in Europe, while in the United States the transmission is bidirectional, checking that the intensity of this transmission varies by sector. They explain that this is due to factors specific to each sector, such as the level of oil consumption, competition and concentration in the sector.

Second, Chaibi and Gomes (2013) examined the transmission of volatility between the two variables over two samples larger than those of previous studies, such as developed countries (the MSCI World Adjusted Market Cap Index) and emerging countries (the MSCI Frontier Markets Index). The authors show that there is a significant transmission of volatility between oil prices and financial markets.

As for the direction of transmission, it is more often from the price of oil to the financial markets than the reverse. In addition, two-way transmission has been detected in some emerging economies (Jordan, Oman, Kazakhstan, Kuwait and United Arab Emirates). It should be noted that this study used data ranging from 2008 to 2013, which corresponds to a period of turbulence in financial markets (including the 2008 financial crisis). The authors believe that certain cyclical factors may have biased the results of certain transmissions of volatility, because in times of crisis, the contagion or the transmission of effects are accentuated.

2.2.3. Bidirectional transmissions

In a study by Awartani and Maghyereh (2013) through which the authors examined the effects of the dynamics and volatility of returns between oil and equities during the period 2004-2012 for a sample of the countries of the Cooperation Council of the Gulf States. Their results show that there are two-way and asymmetric transmissions and that the oil market sends more than it receives to other markets. The authors explain this asymmetry by the fact that any rise in oil prices leads to more income and wealth in oil-exporting countries, which stimulates economic activity and financial markets. So, taking into account these variables in the levels, the causality goes from oil prices to financial markets.

2.2.4. No transmission

Oskooe (2011) carried out his study for Iran and concluded that there was no phenomenon of transmission of volatility between these two variables. According to the author, there is no effect between the volatility of Iran's stock returns and the international oil market, which implies a long-term lasting effect on stock market performance. This can be a good sign for foreign investors and for portfolio managers to invest.

We can see that the results of studies on the transmission of volatility between oil prices and financial markets are very heterogeneous, as there is no specific direction related to the characteristics of the country or a category of countries. Taking into account the above results in Table 4.3, authors, among others Aloui et al. (2008) and Chaibi and Gomes (2013) did not find the same meaning for the transmission of volatility, in particular with regard to the export of oil from countries (Canada, Iran and Kuwait). So we see that for countries with a common characteristic in terms of exporting crude oil, the results are quite different. However, we note that in the case of unidirectional transmission, the direction is more often oil prices than stock prices.

In this section 1.2 we performed the same tests and interpreting the results with those of the above authors. In short, we show that oil price returns and oil price volatility have the power to predict the state of exchange rate returns and stock market returns. Nevertheless, we emphasize that the full effects of the volatility of oil-price returns can only be revealed if we distinguish between oil-price shocks. Thus, we suggest that oil-price volatility shocks have increased power in predicting the state of the exchange market and the stock market. Finally, a clear distinction is made between oil-price shocks that affect movements in the returns on foreign exchange and stock markets in most developed oil importing countries.

2. CHOICE OF DATA AND MODEL SPECIFICATION

2.1. Data Description

Following a large body of research on the significant effect of oil returns on exchange rate returns and stock market prices. Following Narayan and Narayan (2010), the oil prices shocks are defined as unpredictable innovations to exchange rate and stock market.

Basher et al. (2012) the model supports stylized facts. In particular, positive shocks to oil prices tend to depress emerging market stock prices and US dollar exchange rates in the short run. The model also captures stylized facts regarding movements in oil prices. A positive oil production shock lowers oil prices while a positive shock to real economic activity increases oil prices. There is also evidence that increases in market stock prices increases oil prices.

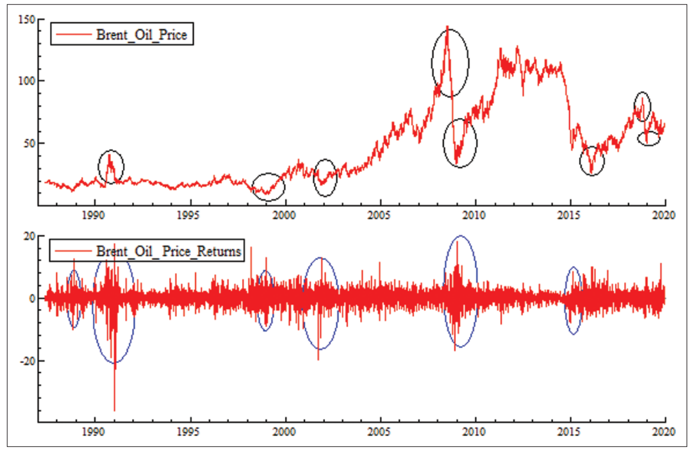
Data on oil prices over the 1987:12-2008:4 period were taken from Hamilton (2009), while the remaining data were updated from the US Energy Information Agency (EIA) database. In the EIA data, oil prices is defined as crude oil including lease condensate.

Recent research has documented that the oil price reacts differently to exchange rate shocks than stock market shocks. In particular, Hammoudeh et al. (2004) investigated spillover effects and dynamic relationships of five daily S&P oil sector stock indices and five daily oil prices for the US oil markets using cointegration techniques as well as ARCH-type models. They show evidence of some volatility spillover from the oil futures market and the stock returns of some oil sectors.

In this study, we use daily data for oil prices, exchange rate and stock market indices. The sample consists of oil-importing developed countries (Germany, Japan and USA). The following criteria had to be satisfied for inclusion in the sample: (i) The countries studied need to have a well-established stock market and (ii) the selected countries have to be in the top 20 oil-importing countries. The Brent crude oil index was used as it accounts for 65% of the global daily oil production (IMF, 2010). The data range from 20th/5/1987 to 9th/12/2019 and were extracted from the energy information administration (EIA). Figure 1 presents the Brent crude oil prices in dollars and its returns. For this study, daily data is collected on oil prices, exchange rates and developed market stock prices. Our daily data cover 5956 observations for the Germany and 10203 observations for the Japan and the USA in the sample period.

The study period is selected on the basis of data availability and intends to cover the major economic and political events over recent years such as the last global financial crisis, the September 11 terrorist attack in the US, the second Gulf War, the Russian economic crisis, and the different monetary and financial crises in the Asian, Latin American, and Middle East regions (Arouri et al., 2014). The choice of this study period thus enables us to come to shocks conclusions on the link between the oil market returns volatility, the foreign market returns and the stock market returns.

Figure 1: Evolution of crude oil price and its returns: Brent



Source: Done by the author

Oil price movements show some significant peaks and troughs during the study period. The main peaks are observed between 2007 and 2008. Another peak is observed in June 2009, when prices increased by more than 60% from their January 2009 price levels. All these changes are linked to aggregate demand-related oil price shocks. Such demand related oil price shock occurred during the Asian economic crisis, the second took place in 2000, when interest rates decreased significantly creating a bust in the housing market and construction industries. The third took place in the period 2006–2007, a result of the rising demand for oil in China, while the fourth demand-related oil price shock occurred during the global financial crisis of 2008.

In recent years, the price of oil has experienced very strong variations. It started in 2008 with a real oil shock which led to a significant rise in prices that began in 2003 but which accelerated with greater demand from emerging countries with strong economic growth such as China and India. The 2008 global economic crisis was the spark that allowed oil prices to soar.

Thus, in just a few months, between January and July 2008, the price of oil rose from $ 96 per barrel for Brent to $ 144. But just after this surge in prices, the price of oil fell sharply from $ 130 to $ 40 between July and December of the same year. In response to the decline, OPEC has called on oil-producing countries to reduce their production in an effort to maintain their incomes. As a result, the price of a barrel has stabilized at around $ 80.

Around 2010, a resumption of economic growth and greater demand for oil from importing countries helped push prices up again. In addition, the geopolitical problems that affected the Arab world in 2011 led to fears about the production capacities of some countries, which caused a further significant increase with a barrel of Brent which reached a high of 128 dollars in March. Around 2013, the price of a barrel again stabilized at around $ 100. Thus, oil is traded in dollars. The drop in crude oil prices observed since July 2014 was concomitant with the end of the quantitative easing policy of the Fed, the US central bank, while the European Central Bank on the contrary stepped up its support for activity. Suddenly, the dollar strengthens against the euro, limiting the fall in the price of a barrel for European countries.

In 2014, we witnessed a further significant drop in oil prices which fell below the threshold of 50 dollars due in particular to too much production due to the increasing production of shale gas in the United States and despite continued demand rising. At the same time, OPEC, which generally reacts to this type of situation by limiting production, decides, under the influence of Saudi Arabia, to maintain production levels in order to force American shale gas producers to reduce theirs. Against the backdrop of these tensions, the price of a barrel of Brent oil collapsed again and reached 28 dollars at the start of 2016, its lowest level since 2003. During the outbreak of the Covid-19 pandemic, the price of a barrel of oil had, in fact, experienced a drastic decline: while it was 67.8 dollars at the end of 2019.

Also, volatility is defined as the strength of the current trend. The higher the volatility, the more likely the trend is to continue over time.

2.2. Box-Jenkins Model Analysis

Let us consider a univariate time series y_t. If Ψ_{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:

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

On the other hand, $E(y_t|\Psi_{t-1})$ 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 (Bouazizi et al., 2021).

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.

2.2. Variance Equation: Further Univariate GARCH Models

We use just five conditional variance models: GARCH, EGARCH, GJR, APARCH and IGARCH models (Bouazizi et al., 2021). 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:

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

2.2.1. 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.

2.2.2. Glosten, Jagannathan, and Runkle model (GJR model)

This popular model is proposed by Glosten et 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.

2.2.3. APARCH model

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

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

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).

2.2.4. 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:

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

When the [1–$\alpha(L)$–$\beta(L)$] 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:

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

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

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

2.3. The VAR and VECM Models

The simplest measure corresponds to Granger causality, which analyzes whether past oil prices or exchange rates help explain the current value of the other variable. In the context of vector autoregressive models (VAR), another frequently adopted technique is the consideration of impulse response functions. They measure the reaction of one variable to a shock of another variable. The general advantage of VAR models is that oil and exchange rate dynamics can be assessed without any assumptions related to causalities. Such a proceeding allows for providing a distinction between supply and demand shocks in the context of oil prices, and allows for an important bridge between theory and empirics.

The idea of cointegration is also related to Granger causality. When conducting cointegration analysis, the long-run coefficient reflects the direction and intensity of the long-run relationship between the nominal oil price and exchange rates. The adjustment coefficients measure the speed of adjustment to long-run deviations for each variable. If, as an example, only the oil price (but not the exchange rate) adjusts to long-run equilibrium, the causality essentially runs from oil prices to exchange rates. Two different frameworks are considered in the context of cointegration:

The Engle and Granger methodology (1987) adopts single equation estimates where one variable is assumed to be the dependent variable. The multivariate Johansen methodology (1996) essentially resembles a VAR model which incorporates long-run dynamics and allows for the simultaneous estimation of several long-run relationships, if detected.

Thus, in this study, taking into consideration the model used in the Narayan and Narayan papers (2007, 2010), stock market prices (St-Market), exchange rates (Ex-Rate) and oil prices (Brent) are jointly determined either by a VAR model or by the VECM model and this after the Johansen cointegration tests. However, the cointegration test is usually done to examine whether two or more time series share a common stochastic drift or not. For example, if two or more variables are co-integrated, they must obey a long-term equilibrium relationship, although they may diverge significantly from this short-term equilibrium. The exogenous variables are constant. Anyway, assuming that the VAR and VECM models contain four lagged values of the endogenous variables, the following equation 8:

$$Y_t=\alpha+\sum_{j=1}^{p}A_jY_{t-j}+\mu_t \quad (8)$$

Where Y_t represents the column vector k*1 of the variables in level in this case but α represents the column vector k*1 of the constants. Moreover, A_j indicates the matrix of coefficients k*k, p shows the length of the delay and $\propto_t$ represents the column vector k*1 of the residuals.

The VAR and VEC models are an operational econometric methods, it is considered a widespread method of time series modeling, it is characterized by simplicity and it is very dynamic. Its simplicity is explained by the fact that no distinction can be made between endogenous and exogenous variables; all the variables being considered as endogenous (See Sims, 1980).

The equation (9) summarizes the relationship between the stock returns *(R_St-Market*), the foreign exchange market returns (*R_Ex-Rate)* and the Brent returns conditional volatility (*CondV Brent)*

Table 2: Summary of studies that have focused on the transmission of volatility between oil prices and stock prices

Authors	Data and country sample	Transmission of volatility
Aloui et al. (2008)	Daily data (period between January 1989 and October 2007)/for France, United States, Japan, Germany, Canada and United Kingdom	Unidirectional transmission (But the transmission directions are not the same for all countries)
Malik and Ewing (2009)	Weekly (January 1992 to April 2008) for Five Sectors of US Stock Indices	Unidirectional transmission (the directions of the transmission are not the same for all sectors)
Shaharudin et al. (2009)	Daily data (August 2003 to August 2008) stock prices of oil and gas companies for the United States, India and the United Kingdom)	Unidirectional transmission (from oil prices to stock indexes)
Arouri et al. (2011a)	Weekly data (from January 1998 to December 2009) on European and American stock market indices	Unidirectional transmission in Europe (ranging from oil prices to stock market indices) and two-way (in the United States)
Oskooe (2011)	Weekly data (January 1999 to December 2010) for Iran	No transmission
Awartani and Maghyereh (2013)	Weekly data (January 2004 to March 2012) for Gulf Cooperation Council countries	Bidirectional transmission
Chaibi and Gomes (2013)	Weekly data (January 1998 to December 2009) Group of 54 countries around the world	Unidirectional transmissions (from oil prices to stock indexes) in some countries and Bidirectional in others

(Narayan and Narayan, 2010). The estimation equation model can be expressed as:

$$R_{-\{St-Market\}} = \beta_0 + \beta_1 * R_{-\{Ex-Rate\}} + \beta_2 * CondV\_Brent + \varepsilon_t \quad (9)$$

3. EMPIRICAL RESULTS

3.1. Volatility of Oil Returns and Appropriate Models: Selection of the ARMA and ARMA-Asymmetric Model Order

3.1.1. ARMA models selection

The determination of appropriate models is as follows:

First, we estimate the conditional average, by selecting the orders $p = 0,1,2$ and $q = 0,1,2$ in the Table 3 of Brent prices. Next, we choose the three appropriate ARMA models, corresponding to the minimum AIC values, of the three series in the Table 4 for each developed country importing crude oil.

The results are as follows:

3.1.2. ARMA models- asymmetric models selection

After setting the (r, s) order of the ARMA process, we will, in a first step, test the order of the variance equation among GARCH, EGARCH, GJR, APARCH and IGARCH using Akaike, Shibata, Schwarz and Hannan-Quinn statistics to determine the best models rated CondV-Brent for the conditional volatility of Brent returns. However, the appropriate model for each variable will be one of the following 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) and ARMA(r, s)-IGARCH(p,q). These models are an extension of the ARCH process with various features to explain the obvious features of financial time series, such as Skewness and leverage.

Table 5, represent the results of the four lowest statistics (Akaike, Shibata, Schwarz, and Hannan-Quinn) for each selected model.

Table 3: ARMA (r, s) model order selection with crude oil price returns data

ARMA	AIC		
(p, q)	Germany	Japan	USA
ARMA (0,0)	4.09799116	4.11363482	4.11363482
ARMA (0,1)	4.09831008	4.11364013	4.11364013
ARMA (0,2)	4.0979599	4.11328148	4.11328148
ARMA (1,0)	4.09831182	4.11365796	4.11365796
ARMA (1,1)	4.09840842	4.11339376	4.11339376
ARMA (1,2)	4.09829351	4.11345099	4.11345099
ARMA (2,0)	4.09791922	4.11327214	4.11327214
ARMA (2,1)	4.09825739	4.11328293	4.11328293
ARMA (2,2)	4.09771663	4.11223067	4.11223067

Table 4: Appropriate ARMA (r, s) models

	List of countries		
	Germany	Japan	USA
The appropriate model of the ARMA Mobile Average	ARMA (2,2)	ARMA (2,2)	ARMA (2,2)

The Table 5 represents the results of the information criteria tests and the appropriate models of the conditional volatility of black gold market returns.

3.2. Preliminary Results

3.2.1. Descriptive and graphical analysis

Series returns are found to be stationary based on both Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) tests. The motivation for using the PP test is to take into account the possible presence of ARCH or GARCH errors. Although, the ADF test accommodates serial correlation, by explicitly specifying the structure of the error correlation series, the PP test does not assume that the specific type of serial correlation or heteroskedasticity in the disorders may be more powerful than the ADF test under a wide range of circumstances (for more details, see Phillips and Perron). Detailed test results are available from the authors upon request.

Returns are calculated on an aggravated continuous basis and expressed as percentages:

$$r_t=100*\ln(P/P_{t-1})=100*[\ln(P_t)-\ln(P_{t-1})]=100*\ln(1+R_t)$$

Where $R_t=(P_t-P_{t-1})/P_{t-1}$ is the relative price change and P_t is the stock market price of a variable at time t.

The results in Table 6 show that all average daily returns are low and close to zero. While for our sample (developed oil-importing countries) the average daily returns for stock prices, exchange rates and Brent show an increase, with the exception of the average daily returns which show the opposite for the stock price and the exchange rate of Japan and the exchange rate of the United States. Given that, the average daily returns are between –0.0016 and 0.2788. The volatility (represented by the standard deviation) of all three returns is between 0.1738 and 1.8920, implying that the risk is variable.

Similarly, the Skewness coefficients are less than 1 and negative and significant, in accordance with the results found by Jones and Kaul, for most of the variables, which highlights the existence of an asymmetric phenomenon in the volatility of the different series and hence the empirical distribution is spread to the right. This asymmetry can be explained by the fact that the deviations are larger in one direction than in the other.

Kurtosis values are well above 3, which shows the leptokurtic nature of the empirical distributions and therefore the tails of these

Table 5: Choice of the order (p, q) of the variance equation and ARMA model – asymmetric model

	Akaike	Shibata	Schwarz	Hannan-Quinn
Germany				
ARMA (2,2)-GJR (1,2)	3.880318	3.880310	3.893803	3.885003
Japan				
ARMA (2,2)-GJR (2,2)	3.839563	3.839560	3.848776	3.842678
USA				
ARMA (2,2)-GJR (2,2)	3.839563	3.839560	3.848776	3.842678

distributions, based on data for oil-importing developed countries, are thick. In other words, the Jarque-Bera normality statistics confirmed that none of the series is normal and while the null hypothesis of normality is significantly rejected for all three variables.

According to the ARCH-LM heteroskedasticity test (1-5), on data for this group of countries, the results show the existence of a strong conditional heteroskedasticity with a significance level of 1% ($p-value \prec 0.01$) and therefore the daily returns are strongly explained by these past values.

r_t=100*ln(P_t/P_{t-1}).

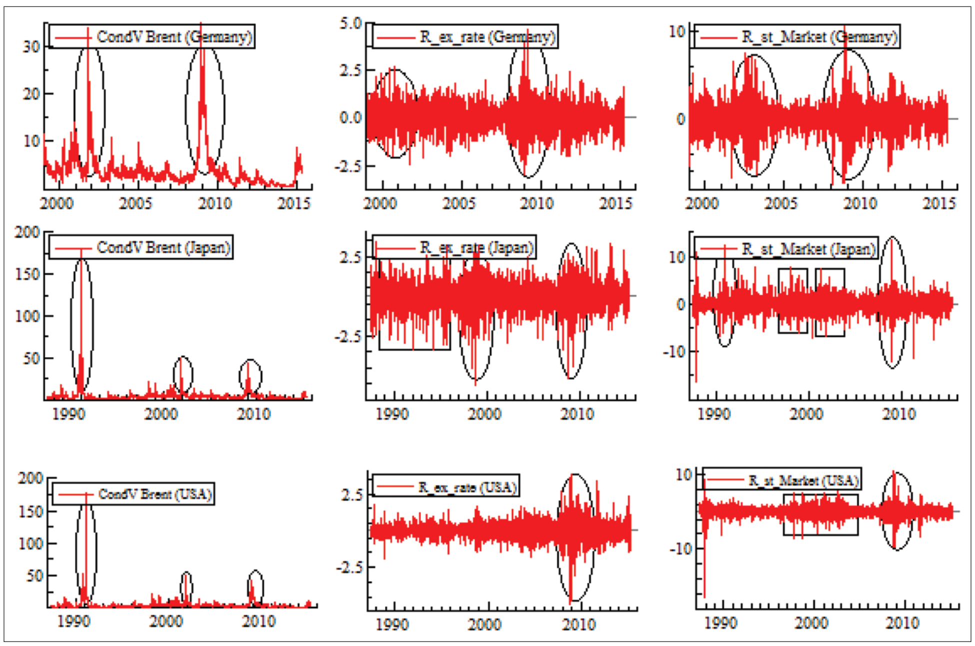
Second, consider the observed time-series graphs of the volatility of oil returns and daily returns in the foreign exchange and stock markets of oil-importing developed countries, as shown in the Figure 2.

In Figure 2, the evident movement in the volatility of oil returns shows that in most oil-importing developed countries, low volatility is followed by low volatility and high volatility is followed by high volatility. It is evident that the time series have seen a sharp increase in crude oil price volatility around the years 2002-2003 and 2008-2009, for the European country (Germany), and 1992-1993, for Japan and the United States.

Arriving at the series of returns for foreign exchange markets and stock markets for most of this category of countries, none of the 6 time series graphs of daily returns show a discernible time trend and the series fluctuates around an average level of returns between –2.5 and 2.5 for the former (foreign exchange returns) and is between –5 and 5 for the latter (stock market returns) but both remain close to zero, which justifies the high volatility of daily returns.

Second, let's look at the observed time series graphs of the volatility of oil returns and daily returns of the foreign exchange markets and the stock markets of oil-importing developed countries, as shown in the Figure 2.

Figure 2: Oil price volatility versus exchange rate and stock market returns source: Done by the author



Source: Done by the author

Table 6: Descriptive statistics and interpreting statistics

	Mean	Standard deviation	Skeweness	Kurtosis	Jarque-Bera	ARCH-LM		Number of rt
						F(.)	[.]	
Germany								
R_St-Market	0.013608	1.279122	0.015024	10.27579	13135.24***	78.309	0.0000	5955
R_Ex-rate	0.001386	0.523985	0.125200	7.514039	5071.488***	12.773	0.0000	5955
R_Brent	0.029388	1.877082	–0.281417	12.08255	20547.09***	21.144	0.0000	5955
Japan								
R_St-Market	–0.001538	1.237599	–0.325308	15.65265	68231.36***	164.36	0.0000	10202
R_Ex-rate	–0.001579	0.568050	–0.482975	10.59642	24926.34***	51.481	0.0000	10202
R_Brent	0.011936	1.892010	–0.771632	26.04634	226788.5***	51.383	0.0000	10202
USA								
R_St-Market	0.019895	0.978077	–1.537493	45.27895	763859.8***	73.263	0.0000	10202
R_Ex-rate	–0.000989	0.393754	–0.073347	16.86624	81741.02***	93.918	0.0000	10202
R_Brent	0.011936	1.892010	–0.771632	26.04634	226788.5******	51.383	0.0000	10202

***Significant to 1%

In Figure 2, the clear pattern of volatility of oil returns shows that in most oil-importing developed countries, low volatility is followed by low volatility and high volatility is followed by high volatility. It is evident that the time series have seen a sharp increase in crude oil price volatility around the years 2002-2003 and 2008-2009, for the one

European country (Germany), and 1992-1993, for Japan and the United States.

3.2.2. Unit root and cointegration

3.2.2.1. The study of stationarity

The three unit root tests (ADF, PP and KPSS) are performed with interception for all variables in their levels and the tests are performed with their first differences and so on. We used the ADF, PP and KPSS tests to examine the stationarity of the time series of daily returns on stock prices, exchange rates and oil prices. In all the tests, the null hypothesis of the presence of a unit root in the data generation process of the given time series of returns is tested against the alternative hypothesis of stationarity or the absence in an equivalent manner of the unit root. Rejection of the null hypothesis implies that the corresponding time series of the original variable is non-stationary and contains a stochastic trend component.

The Table 7 present the results of the unit root tests, Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) and Kwiatkowski -Phillips-Schmidt-Shin (KPSS), such as stock prices, exchange rates and oil prices in first difference.

However, applying the same test to the first differences of the three variables shows that the null hypothesis of a unit root is rejected in all cases, even at a significance level of 1%. While the series are stationary.

Overall, applying the unit root tests on daily returns for developed oil importing countries, the result is that the series returns are stationary.

The results of the stationarity study for the four groups of countries indicate that all three returns series are stationary. Therefore, we can conclude that the observed time series (log) of stock prices, exchange rates, and crude oil prices contain a time trend.

This finding implies that the existence of a (long-run) relationship between the variables of interest can be examined using the technique of cointegration analysis (Trace and Eingen tests). We tried to study the stationarity of the variables at the levels before studying the stationarity of the returns series. The results (available on request) from the unit root tests do not reject the null hypothesis of a unit root for the stock market, exchange rate and oil price levels.

3.2.2.2. Cointegration analysis between conditional variances of oil returns and foreign exchange

The results of the Johansen test cointegration for the the three developed oil importing countries are in Tables 9-11 (Appendices A). Returns and Stock Market Returns Johansen's test result in the Table 9 shows that a cointegration equation exists at 5%. Therefore, a long-run equilibrium relationship exists between stock prices, exchange rates and the conditional volatility of oil prices. The t-trace statistical value is 3,095,049, which is above the critical (trace) value of 2,979,707 at the five percent significance level. This trace statistic shows that the variables have a long term relationship at a significance level of 5%. For the Max-Eigen statistic, the result shows that the long-term relationship between the variables is at the five percent significance level. The Max-Eigen statistic at 25.11164 is above the critical value (Eigen) at 21.13162 at a level of 5%.

In Germany, stock prices (DAX), exchange rates (EUR/USD) and the conditional volatility of oil prices (ARMA(2.2)-GJR(1.2)) are co-integrated and have a long-term relationship. The result of Johansen's test in Table 10 shows that a cointegrating equation exists at 5%. Therefore, there is a long-run equilibrium relationship between stock prices, exchange rates and the conditional volatility

Table 7: Unit root test of returns series

Variables	ADF		PP		KPSS	
	t-stat	Crit.(1%)	t-stat	Crit.(1%)	LM-Stat	Crit.(1%)
Germany						
EUR/USD	–76.43139	–3.431269	–76.43629	–3.431269	0.207184	0.739000
DAX	–78.08272	–3.431269	–78.18389	–3.431269	0.177710	0.739000
Brent	–76.58256	–3.431269	–76.62685	–3.431269	0.264914	0.739000
Japan						
JPY/USD	–99.83644	–3.431269	–99.82968	–3.431269	0.119888	0.739000
NIKKEI	–74.76974	–3.431269	–104.5379	–3.431269	0.169143	0.739000
Brent	–99.88696	–3.431269	–99.88164	–3.431269	0.058041	0.739000
USA						
CAD/USD	–101.2998	–3.431269	–101.3572	–3.431269	0.119615	0.739000
S&P 500	–76.12548	–3.431269	–109.2748	–3.431269	0.113281	0.739000
Brent	–99.88696	–3.431269	–99.88164	–3.431269	0.058041	0.739000

Table 8: Hansen's test of instability

Countries	Lc Statistics	Stochastic Trends (m)	Deterministic Trends (k)	Excluded Trends (p2)	Prob.
Germany	4.28E-05	2	0	0	>0.2
Japan	2.24E-05	2	0	0	>0.2
USA	2.49E-05	2	0	0	>0.2

of oil prices. The t-trace statistical value is 48.22609, which is above the critical (trace) value of 29.79707 at the five percent significance level. This trace statistic shows that the variables have a long term relationship at a significance level of 5%. For the Max-Eigen statistic, the result shows that the long-term relationship between the variables is at the five percent significance level. The Max-Eigen statistic at 36.14001 is above the critical value (Eigen) at 21.13162 at a level of 5%.

In Japan, stock prices (NIKKEI225), exchange rates (JPY/USD) and conditional oil price volatility (ARMA(2.2)-GJR(2.2)) are co-integrated and have a long-term relationship.

The United States: Johansen's test result in Table 11 shows that a cointegrating equation exists at 5%. Therefore, there is a long-run equilibrium relationship between stock prices, exchange rates and the conditional volatility of oil prices. The t-trace statistical value is 3,764,385, which is above the critical (trace) value of 2,979,707 at the five percent significance level. This trace statistic shows that the variables have a long term relationship at the five percent significance level. For the Max-Eigen statistic, the result shows that the long-term relationship between the variables is at the five percent significance level. The Max-Eigen statistic at 34.19431 is above the critical value (Eigen) at 21.13162 at a level of 5%. In the United States, stock prices (S&P500), exchange rates (CAD/USD) and conditional oil price volatility (ARMA(2.2)-GJR(2.2)) are co-integrated and have a long-term relationship.

3.2.2.3. Parameter instability test: Hansen's test on conditional volatility of oil returns and foreign exchange and stock market returns

Although we have performed Johansen tests of cointegration between stock returns $R_{\_St\text{-}Market}$, foreign exchange returns $R_{\_Ex\text{-}Rate}$ and the conditional volatility of oil returns CondV-Brent, our continuing interest is to examine the stability of the long-run relationship between these three variables, using the equation specified by Narayan and Narayan (2010) defined as follows:

$$R_{\_\{St-Market\}} = \beta_0 + \beta_1 * R_{\_\{Ex-Rate\}} + \beta_2 * CondV\_Brent + \varepsilon_t$$

Given the evidence of residual stationarity in the equation 8 and that for developed crude oil exporting countries, we estimate the stability relationship of Hansen's parameters (Hansen, 1992) in the long run.

Table 8 represent the results of Hansen's test applied to the volatility of oil returns, foreign exchange returns and stock market returns for developed oil-importing countries.

These results suggest that the null hypothesis of parameter stability cannot be rejected.

In the same context of our study of the stability of the model's parameters with the three variables under consideration, this could be interpreted as an indication that fluctuations in the volatility multiplier relationship of oil returns are caused by sudden changes in the conduct of foreign exchange and stock markets in different countries.

4.3. The Main VAR and VEM Models

4.3.1. Modeling of the oil returns volatility on foreign exchange and stock market returns

Table 12, using the AIC test to model VEC, represents the results of this test to select the number of p delays for all oil-importing developed countries.

The results of the VECM model presented in Tables 13-15 (Appendices B) for Germany, Japan and the United States, respectively, show that the coefficients on stock market returns and exchange rate returns are statistically significant when volatility (conditional variances) of crude oil prices is used as the independent variable.

The estimates show, based on the results in the same tables, that the coefficients of the stock market returns of the majority of oil-importing developed countries, with the exception of Japan, are positive. In addition, the coefficients of exchange rate returns of the same sample, with the exception of Germany, are positive. Therefore, the conditional volatility of oil returns affects positively, in line with the results shown by Sadorsky (1999), Malik and Ewing (2009), Oberndorfer (2009) and Chiou and Lee (2009) and contrary to those verified by Arouri and Rault (2010), Korhonen and Ledyaeva (2010) and Lescaroux and Mignon (2008) for the oil-importing countries, the stock markets of this sample, except Germany, and it affects the foreign exchange markets of the same subgroup, except Germany, positively, in accordance with the results verified by Glosh (2011) and Englama et al. (2010). In particular, movements in this volatility affect the German stock market positively and the German foreign exchange market negatively.

For Germany, movements in stock market returns affect the conditional variances of oil returns positively (the coefficients of the conditional variance are positive) but movements in exchange rate returns in both countries affect the conditional variability of black gold returns negatively (the coefficients of the conditional variance are negative).

But, for Japan and the United States, these changes in oil return volatility affect both markets positively.

3.3.2. Response impulses from the effect of conditional volatility shocks on foreign exchange and stock market returns

In this study, we would like to examine the effect of oil-price volatility shocks on exchange rate and stock market returns. Each figure contains a response impulse function that will show the impact of oil-price volatility shocks on the other two returns on our variables (exchange rate returns and stock market returns), but we will examine the sign of the effect, if it is as expected. We have changed the number of periods based on the number of observations for each country independently.

Let us now look at impulse responses for the cases of the three oil-importing developed countries:

For Germany (5955 observations, Figure 3), in the first 7 periods, the effect of oil price volatility shocks on stock market returns is once positive and once negative. Then, for the last three periods, this effect is stable. Moreover, the responses of exchange rate returns to these shocks fluctuated between stable and positive, but remained low for the first 9 periods. Then, at the end of the period, these responses become positive, moving the series away from its trend.

We can find, from the Figure 4 (10202 observations), an insignificant and stable effect with very small fluctuations, positive or negative, in the volatility of crude oil price returns CondV-Brent on stock market returns $R_{\_Nikkei}$ and foreign exchange returns $R_{\_JPY/USD}$.

We can see some graphical results, based on the Figure 5 (10202 observations), consistent with those of Japan, which show a non-significant and stable effect with very small fluctuations, positive negative, in the volatility of crude oil price returns CondV_Brent on stock market returns $R_{\_S\&P500}$ and foreign exchange returns $R_{\_CAD/USD}$.

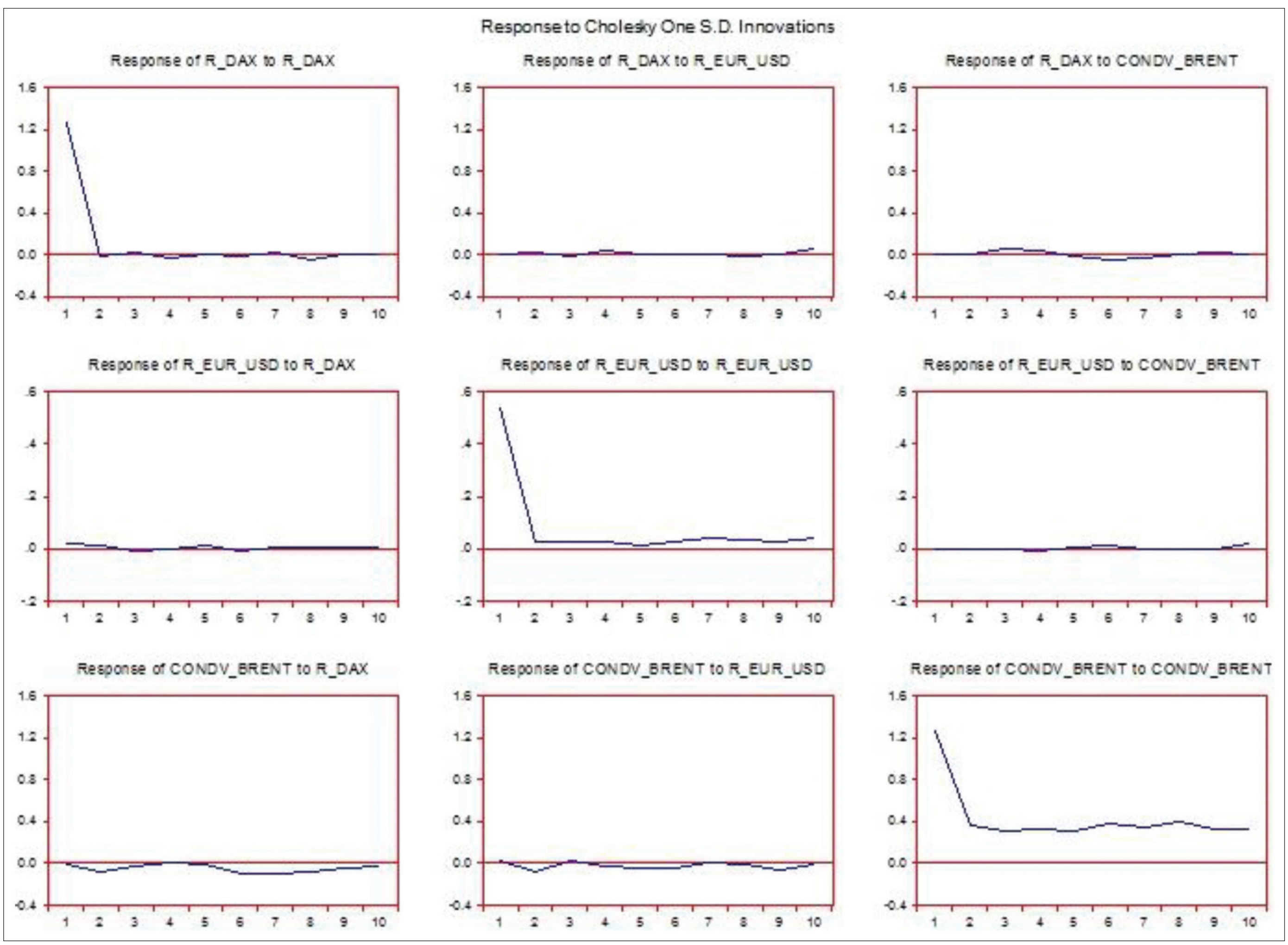
3.3.3. Granger causality and block exogeneity tests between conditional variances of oil returns and other market returns

In this section, the Granger causality and block exogeneity tests analyzes the individual role of macroeconomic variables, in particular changes in foreign exchange market returns and fluctuations in stock market returns, in explaining the volatility of Brent crude oil prices by making the lags of the other variables zero.

Here, we adopted the VAR (VEC) Granger Causality/Block Exogeneity Wald tests to examine the causal relationship between crude oil price volatility and the returns of the other two macroeconomic variables, such as foreign exchange returns and stock returns, for a sample of developed countries that import oil. The results are in Tables 16-18.

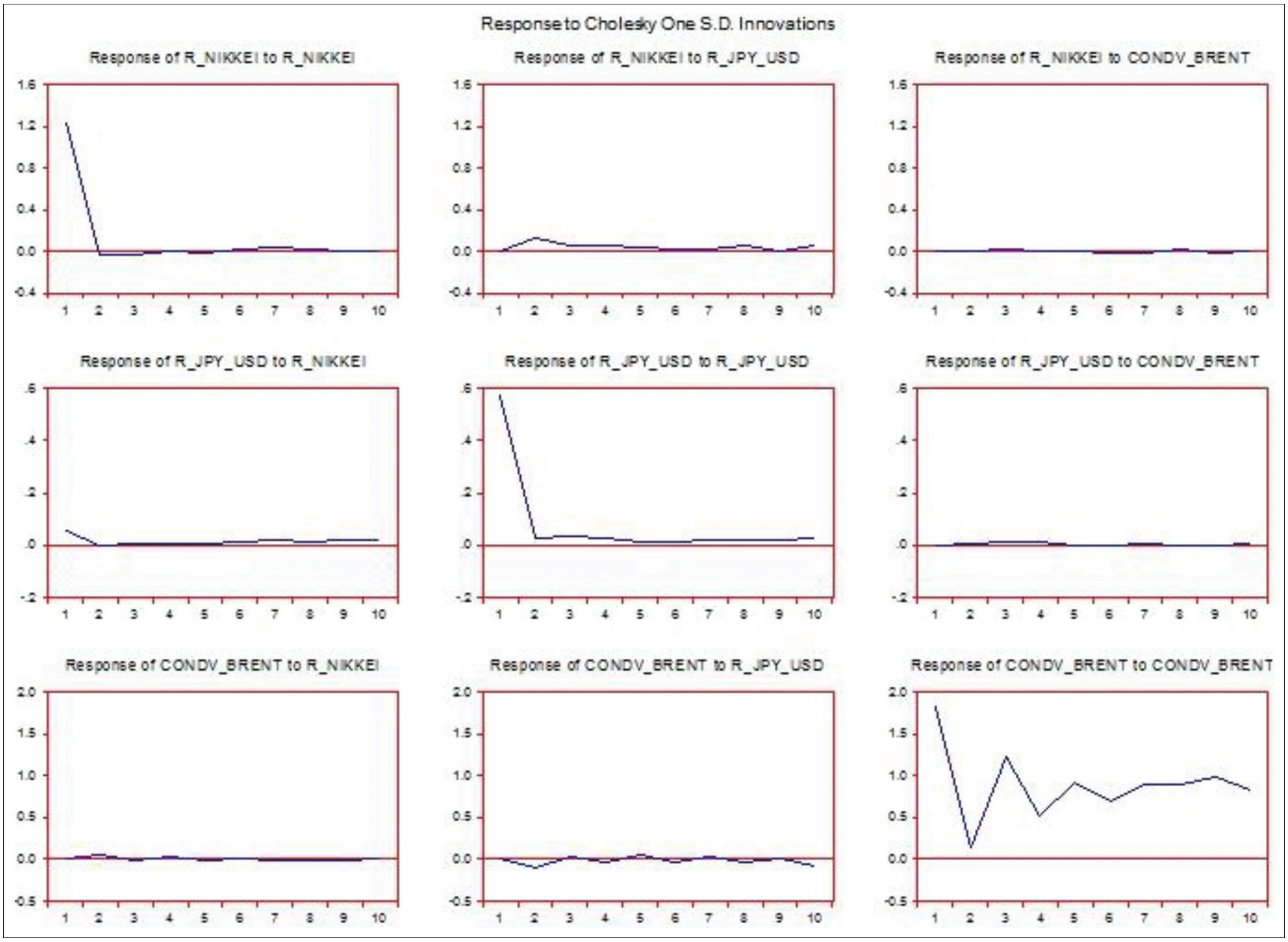
The results of this analysis show a unidirectional causal relationship ranging from the volatility of oil returns to stock market returns in this sample, except for Japan and the USA (Tables 17 and 18), and similarly to exchange rate returns but for all oil-importing developed countries. In addition, stock market returns have a causal effect on exchange rate returns in Japan (Table 17). But in the United States, the direction of the causal relationship is bi-directional between the latter two variables (Table 18).

Figure 3: The impulse responses of foreign exchange and stock markets to oil return volatility shocks for the case of Germany



Source: Done by the author

Figure 4: The impulse responses of foreign exchange and stock markets to oil return volatility shocks for the case of Japan



Source: Done by the author

4. CONCLUSION

The objective of this research, is to deepen our understanding of the link between crude oil price volatility and its impact on exchange rates and stock market prices in the case of developed oil-importing countries. In this paper, we have estimated, in the section 1.2, the volatility of oil prices and its impact on the returns of the other two markets for each country independently.

We can summarize the empirical results of estimating the impact of oil price volatility on the returns of the other two markets in the section 1.2 in a few main points as follows:

The relationship between the conditional variances of oil returns, stock market returns and foreign exchange market returns is long term in most developed oil-importing countries. Moreover, for the three countries, the impact of oil market volatility on stock market returns in Germany and the United States of America is positive, but for Japan it is negative.

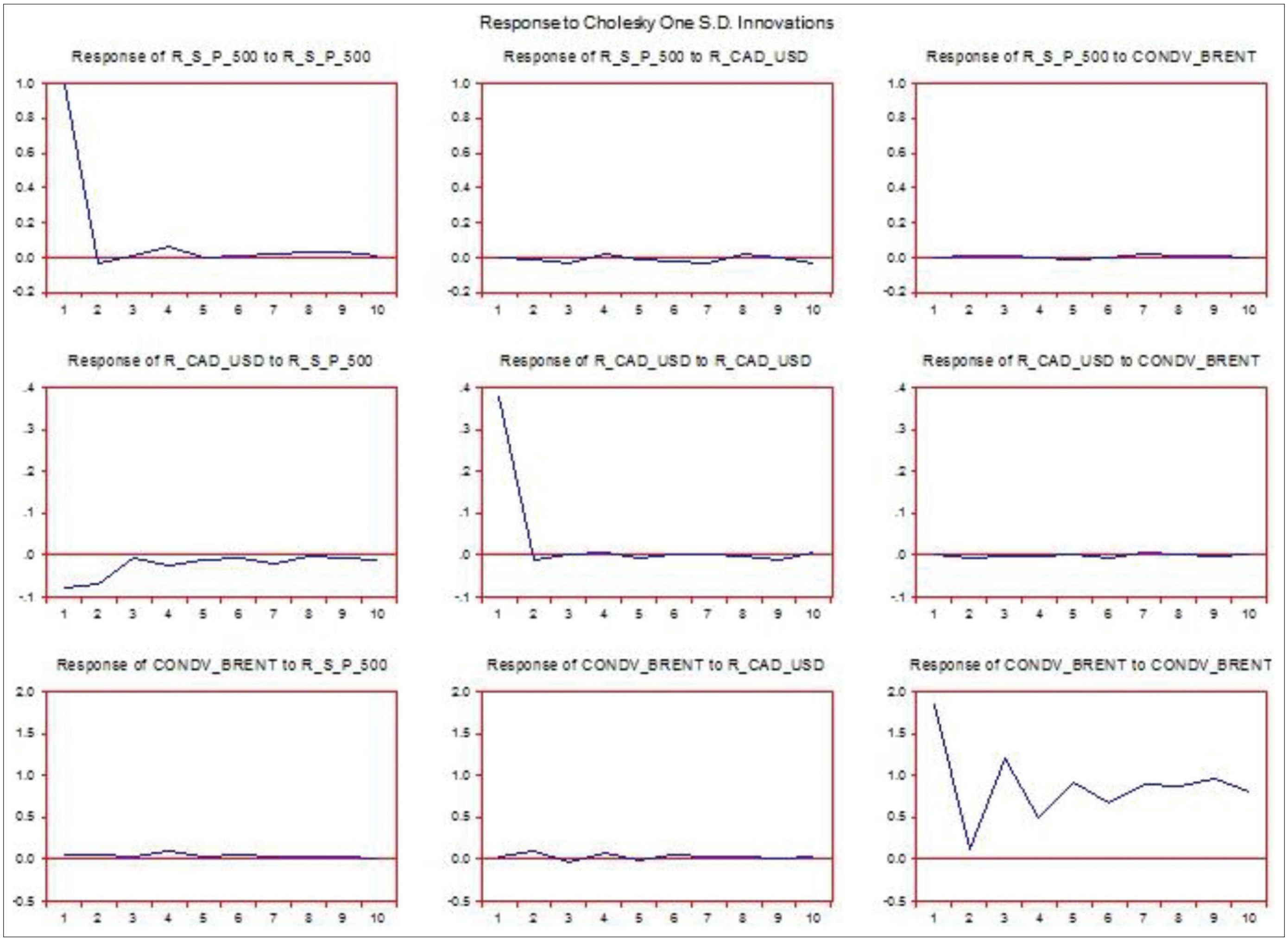
Oil market returns Volatility have a positive impact on the foreign exchange markets of Japan and the United States of America and a negative impact on the euro foreign exchange market. Given that our cointegration results indicate at least one cointegrating relationship between the conditional volatility of oil returns, stock returns and foreign exchange returns for three countries. Therefore, we estimated a VECM model for each country. Next, we analyzed the effects of oil price volatility fluctuations on foreign exchange market returns and stock market returns by determining impulse response functions.

The Figures 3-5 for these functions show that the responses of most stock and foreign exchange markets show reactions at the beginning of negative or positive periods and at the end of stable periods to shocks to oil-price volatility returns.

Similarly, for oil-importing developed countries, any shock in the Brent market generates positive and/or negative reactions to stabilize at the end of periods.

According to the results in the Annex Tables C, the causal relationship for developed crude oil importing countries between crude oil price volatility and stock market returns is only unidirectional in Germany from oil price volatility to stock market returns. Japan and the United States of America have no causal relationship. While for our sample, all the three developed

Figure 5: The impulse responses of foreign exchange and stock markets to oil return volatility shocks for the case of USA



Source: Done by the author

oil importing countries have a unidirectional causal relationship ranging from the volatility of oil returns to the returns of foreign exchange markets.

In conclusion, noted that a good analysis of the evolution of the price of a barrel of oil naturally also involves fundamental analysis which is complementary to technical analysis. This analysis is based primarily on a study of publications and events that are likely to have an impact on the price of black gold. Here are a few concrete examples:

- The value of the dollar on the foreign exchange market: Indeed, oil being quoted in dollars, a weak dollar can encourage purchases by buyers with another currency who will thus gain on the exchange rate and vice versa for a strong dollar
- The decisions of OPEC and OPEC +: As everyone knows, the Organization of Petroleum Producing Countries is in charge of regulating oil production in the world. However, the supply of oil is, along with demand, one of the elements that will influence the price of this raw material on the market
- Global economic health: As industry is the largest consumer of oil, it is obvious that the global economy influences the demand for black gold and therefore the evolution of prices
- New energies and the environment: In the same way, we will closely follow the evolution of the changes operating in environmental matters with the aim of promoting green energies to the detriment of fossil fuels
- Geopolitical conflicts: Finally and as history has shown, wars and other geopolitical conflicts with producing or importing countries can have an impact on the price of the barrel.

REFERENCES

Aloui, C., Jammazy, R., Imen, D. (2008), Crude oil market shocks and stock market returns. Journal of Energy Market, 3, 69-96.

Arouri, M.E.H. and Rault, C. (2010), Oil prices and stock markets in GCC countries: Empirical evidence from panel analysis. International Journal of Finance and Economics, 17(3), 242-253.

Arouri, M.E.H., Boubaker, S., Nguyen, D.K. (2014), Emerging markets and global economy. In: Guesmi K, editor. Comovements and Volatility Spillovers between Oil Prices and Stock Markets: Further Evidence for Oil-Exporting and Oil-Importing Countries. Ch. 16. Cambridge, Massachusetts: Academic Press, Elsevier, USA.

Arouri, M.E.H., Jouini, J., Nguyen, D.K. (2011a), 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., Lahiani, A., Nguyen D.K. (2011b), Return and volatility transmission between world oil prices and stock markets of the GCC countries. Economic Modelling, 28(4), 1815-1825.

Awartani, B., Maghyereh, A.I. (2013), Dynamic spillovers between oil and stock markets in the gulf cooperation council countries. Energy Economics, 36, 28-42.

Basher, S.A., Haug, A.A., Sadorsky, P. (2012), Oil prices, exchange rates and emerging stock markets. Energy Economics, 34, 227-240.

Bekaert, G., Hoerowa, M., Lo Duca, M. (2013), Risk, uncertainty and monetary policy. Journal of Monetary Economics, 60, 771-788.

Black, F. (1976), Studies of stock price volatility changes. In: Proceedings of the 1976, Meetings of the Business and Economics Statistics Section. Alexandria, Virginia: American Statistical Association. p177-181.

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

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

Bouazizi, T., Hadhek, Z., Mrad, F., Lafi, M. (2021), Changes in demand for crude oil and its correlation with crude oil and stock market returns volatilities: Evidence from three asian oil importing countries. International Journal of Energy Economics and Policy, 11(3), 27-43.

Box, G.E.P., Jenkins, G.M. (1970), Time Series Analysis Forecasting and Control. San Francisco: Holden Day.

Chaibi, A., Gomes, M. (2013), Volatility Spillovers between Oil Prices and Stock Returns: A Focus on Frontier Markets. IPAG Business School, Working Paper Series.

Chen, J. (1997), Forecasting the S&P 500 Index volatility. International Review of Economics and Finance, 6(4), 391-404.

Chiou, J., Lee, Y. (2009), Jump dynamics and volatility: Oil and the stock markets. Energy, 34, 788-796.

Chittedi, K.R. (2012), Do oil prices matters for Indian stock markets? An empirical analysis. International Journal of Economics and Business Research, 2, 2-10.

Creti, A., Joets, M., Mignon, V. (2013), On the links between stock and commodity markets volatility. Energy Economics, 37, 16-28.

Ding, L., Vo, M. (2012), Exchange rates and oil prices: A multivariate stochastic volatility analysis. The Quarterly Review of Economics and Finance, 52(1), 15-37.

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

Efimova, O., Serlitis, A. (2009), Oil price shocks and stock market booms in an oil exporting country. Scottish Journal of Political Economy, 2(5), 232-254.

Englama, A., Duke, O.O., Ogunleye, T.S., Ismail, F.U. (2010), Oil prices and exchange rate volatility in Nigeria: An empirical investigation. Economic and Financial Review, 48(3), 31-48.

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

Engle, R.F., Granger, C.W. (1987), Cointegration and error correction: Representation, estimation and testing. Econometrica, 55, 251-276.

Federer, J.P. (1996), Oil price volatility and the macroeconomy. Journal of Macroeconomics, 18(1), 1-26.

Fratzscher, M. (2009), What explains global exchange rate movements during the financial crisis? Journal of International Money and Finance, 28, 1390-1407.

French, K.R., Schwert, G.W., Stambaugh, R.F. (1987), Expected stock returns and volatility. Journal of Financial, 19, 3-30.

Ghosh, S. (2011), Examining crude oil price exchange rate nexus for India during the period of extreme oil price volatility. Applied Energy, 88(5), 1886-1889.

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.

Golub, S. (1983), Oil prices and exchange rates. Economics Journal, 93, 576-593.

Habib, M.M., Kalamova, M.M. (2007), Are there Oil Currencies? The Real Exchange Rate of Oil Exporting Countries, ECB Working Paper, No. 839.

Hamilton, D.J. (2009), Understanding crude oil prices. Energy Journal, 30(2), 179-206.

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

Hammoudeh, S., Dibooglu, S., Aleisa, E. (2004), Relationships among U.S. oil prices and oil industry equity indices. International Review of Economics and Finance, 13(4), 427-453.

Hansen, B.E. (1992), Tests for parameter instability in regressions with I(1) processes. Journal of Business and Economic Statistics, 10, 321-335.

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.

Johansen, S. (1988), The mathematical structure of error correction models. Contemporary Mathematics Society, 80, 359-386.

Jones, C.M., Kaul, G. (1996), Oil and stock markets. Journal of Financial, 51(2), 463-491.

Jones, D.W., Paul, N.L., Inja, K.P. (2004), Oil price shocks and the macroeconomy: What has been learned since 1996? The Energy Journal, 25(2), 1-32.

Korhonen, I., and Ledyaeva, S. (2010), Trade linkages and macroeconomic effects of the price of oil. Energy Economics, 32(4), 848-856.

Krugman, P. (1983), Oil shocks and exchange rate dynamics. In: Frankel, J.A., editor. Exchange Rates and International macroeconomics. Chicago: University of Chicago Press.

Lescaroux, F., Mignon, V. (2008), On the influence of oil prices on economic activity and other macroeconomic and financial variables. OPEC Energy Review, 32(4), 343-380.

Malik, F., Ewing, B. (2009), Volatility transmission between oil prices and equity sector returns. Energy, 18, 95-100.

Malik, F., Ewing, B. (2009), Volatility transmission between oil prices and equity sector returns. Energy, 18, 95-100.

Narayan, P.K., Narayan S. (2007), Modelling oil price volatility. Energy Policy, 35(12), 6549-6553.

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

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

Oberndorfer, U. (2009), Energy prices, volatility and the stock market: Evidence from the eurozone. Energy Policy, 37(12), 5787-5795.

Oskooe, P.S.A. (2011), Oil Price Shock and Stock Market in an Oil Exporting Country: Evidence from Causality in Mean and Variance Test. International Conference on Applied Economics. p443-451.

Pagan, A., Schwert, G.W. (1990), Alternative models for conditional stock volatility. Journal of Econometrics, 45, 267-290.

Priestley, M.B., Tong, H. (1973), On the analysis of bivariate non-stationary processes. Journal of the Royal Statistical Society, Series B, 35, 135-166.

Rickne, J.K. (2014), Oil Prices and Real Exchange Rate Movements in Oil-Exporting Countries: the Role of Institution, IFN Working Paper No. 810.

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

Salisu, A.A., Mobolaji, H. (2013), Modeling returns and volatility transmission between oil price and USD Nigeria exchange rate. Energy Economics, 39, 169-179.

Selmi, R., Bouoiyour, J., Ayachi, F. (2012), Another look at the interaction between oil price uncertainty and exchange rate volatility: The case of small open economies. Procedia Economics and Finance, 1, 346-355.

Shaharudin, R.S., Fazilah, S., Sonal, B. (2009), Performance and volatility of oil and gas stocks: A comparative study on selected O&G companies. International Business Research, 2(4), 87-99.

Sims, C. (1980), Macroeconomics and reality. Econometrica, 48, 1-48.

Yang, C.W., Hwang, M.J., Huang, B.N. (2002), An analysis of factors affecting price volatility of the US oil market. Energy Economics, 24, 107-119.

APPENDICES

A. Cointegration Test between of the Oil Returns Volatility and the Returns from Other Markets

Table 9: Johansen cointegration test between conditional variances of oil returns and foreign exchange and stock

The Trace test				
H_0	H_1	λ_{tr} Test	λ_{tr} (0.95)	Prob.**
r=0*	r=1	30.95049	29.79707	0.0367
r≤1	r=2	5.838857	15.49471	0.7145
r≤2	r=3	1.918658	3.841466	0.1660
The Max-Eigen-value Test				
H_0	H_1	λ_{max} Test	λ_{max} (0.95)	Prob.**
r=0*	r=1	25.11164	21.13162	0.0130
r≤1	r=2	3.920199	14.26460	0.8677
r≤2	r=3	1.918658	3.841466	0.1660

Table 10: Johansen cointegration test between conditional variances of oil returns and foreign exchange and stock market returns: Japan

The Trace test				
H_0	H_1	λ_{tr} Test	λ_{tr} (0.95)	Prob.**
r=0*	r=1	48.22609	29.79707	0.0001
r≤1	r=2	12.08609	15.49471	0.1528
r≤2	r=3	3.002200	3.841466	0.0831
The Max-Eigen-value Test				
H_0	H_1	λ_{max} Test	λ_{max} (0.95)	Prob.**
r=0*	r=1	36.14001	21.13162	0.0002
r≤1	r=2	9.083885	14.26460	0.2792
r≤2	r=3	3.002200	3.841466	0.0831

Table 11: Johansen cointegration test between the conditional variance of oil returns and foreign exchange and stock market returns: The United States

The Trace test				
H_0	H_1	λ_{tr} Test	λ_{tr} (0.95)	Prob.**
r=0*	r=1	37.64385	29.79707	0.0051
r≤1	r=2	3.449536	15.49471	0.9428
r≤2	r=3	0.945185	3.841466	0.3309
The Max-Eigen-value Test				
H_0	H_1	λ_{max} Test	λ_{max} (0.95)	Prob.**
r=0*	r=1	34.19431	21.13162	0.0004
r≤1	r=2	2.504351	14.26460	0.9741
r≤2	r=3	0.945185	3.841466	0.3309

B. Results of VAR and VEC Modelling of Oil Price Volatility and Exchange Rate Returns and Stock Market Returns

Table 12: Lag order selection in VECM

Countries	AIC			
	1	2	3	4
The Germany	8.784456	8.784456	8.480504	8.402502*
The Japan	9.459072	9.311002	9.257943	9.220811*
The USA	8.218548	8.053766	8.000918	7.961107*

Table 13: The VECM model for Germany: Oil price volatility and returns in the other two markets

Error Correction	D (R_DAX)	D (R_EUR_USD)	D (CONDV_BRENT)
CointEq1	–0.907334 (–32.8481)	–0.148895 (–12.2619)	–0.119122 (–4.33031)
D (R_DAX(–4))	–0.011302 (–0.87397)	0.037149 (6.53447)	0.062869 (4.88156)
D (R_EUR_USD(–4))	0.174095 (5.99123)	–0.183017 (–14.3269)	0.021460 (0.74154)
D (CONDV_BRENT(–4))	0.047102 (3.69086)	–0.002075 (–0.36990)	–0.180789 (–14.2247)
C	–0.000228 (–0.01364)	0.000438 (0.05947)	6.37E–05 (0.00382)

Table 14: The VECM model for the Japan: Oil price volatility and returns in the other two markets

Error Correction:	D (R_NIKKEI)	D (R_JPY_USD)	D (CONDV_BRENT)
CointEq1	–0.896769 (–41.3046)	0.171321 (16.0922)	–0.008650 (–0.26966)
D (R_NIKKEI(–4))	–0.059428 (–6.05938)	–0.048776 (–10.1423)	0.008762 (0.60468)
D (R_JPY_USD(–4))	–0.160115 (–7.75772)	–0.136548 (–13.4919)	0.024264 (0.79570)
D (CONDV_BRENT(–4))	–0.004671 (–0.69767)	0.004907 (1.49472)	0.022036 (–2.22785)
C	–9.17E–05 (–0.00737)	–6.61E-05 (–0.01083)	3.54E-05 (0.00193)

Table 15: The VECM model for the USA: Oil price volatility and returns in the others two markets

Error Correction	D (R_S_P_500)	D (R_CAD_USD)	D (CONDV_BRENT)
CointEq1	–0.950673 (–37.8933)	–0.203569 (–19.5664)	0.056300 (1.21211)
D (R_S_P_500(–4))	0.004646 (0.44075)	0.015746 (3.60186)	0.037112 (1.90154)
D (R_CAD_USD(–4))	0.304533 (12.9239)	–0.166307 (–17.0191)	0.000306 (0.00702)
D (CONDV_BRENT(–4))	0.000280 (0.05244)	0.001291 (0.58198)	–0.024425 (–2.46721)
C	0.000106 (0.01058)	–3.27E-05 (-0.00790)	5.88E-05 (0.00318)

C. Study of the Causality Between Oil Price Volatility and Returns

Table 16: Result of the VEC Granger causality/block exogeneity Wald test: The Germany

Dependent variables	Independent variables	Chi-sq value	Probability value	Implication
St-Market	Ex-Rate	1.736883	0.4196	No Causality
	CondV Brent	2.205901	0.3319	No Causality
Ex-Rate	St-Market	5.503981	0.0638	No Causality
	CondV Brent	2.234877	0.3271	No Causality
CondV Brent	St-Market	58.03861	0.0000	Existence of Causality
	Ex-Rate	68.57524	0.0000	Existence of Causality

Table 17: Result of the VEC Granger causality/block exogeneity Wald test: The Japan

Dependent variables	Independent variables	Chi-sq value	Probability value	Implication
St-Market	Ex-Rate	74.55792	0.0000	Existence of Causality
	CondV Brent	0.232599	0.8902	No Causality
Ex-Rate	St-Market	5.086778	0.0786	No Causality
	CondV Brent	4.264087	0.1186	No Causality
CondV Brent	St-Market	0.274125	0.8719	No Causality
	Ex-Rate	18.35311	0.0001	Existence of Causality

Table 18: Result of the VEC Granger causality/block exogeneity Wald test: The USA

Dependent variables	Independent variables	Chi-sq value	Probability value	Implication
St-Market	Ex-Rate	8.613988	0.0135	Existence of Causality
	CondV Brent	0.520315	0.7709	No Causality
Ex-Rate	St-Market	287.4726	0.0000	Existence of Causality
	CondV Brent	1.321067	0.5166	No Causality
CondV Brent	St-Market	1.020786	0.6003	No Causality
	Ex-Rate	71.72137	0.0000	Existence of Causality