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The Impact of Terrorism on Crude Oil Returns and Volatility:
A Case Study in the Middle East and Africa

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The Impact of Terrorism on Crude Oil Returns and Volatility:
A Case Study in the Middle East and Africa

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DECLARATION

I hereby declare that this thesis is entirely my own work and that it has not been submitted as an exercise for a degree at any other University.

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ABSTRACT

Purpose: This study explores the impact of terrorism on daily Brent crude oil returns and volatility. From mid 1987 till end of 2013, we examine how successful terrorist attacks with high and low intensity and carried out in the most oil-dependent Middle Eastern and African countries affect Brent dynamics. We also investigate the degree to which attacks against oil businesses and facilities play a role in altering Brent returns and affecting their fluctuations.

Design/ methodology/ approach: We gathered from the Global Terrorism Database (GTD) all the daily terrorist attacks performed against Saudi Arabia, Iran, Iraq, Libya, Algeria, Nigeria and Angola during the sample period. We modeled Brent crude oil returns and volatility using GARCH(1,1) framework.

Findings: Our results show that the return of Brent oil does not depend on the target of the attack (oil facilities) but instead on the number of successful attacks leading thereby to supply shocks in the selected countries. The volatility of crude oil returns exhibits a high persistence, yet it is not statistically significant. Our analysis suggests that such terrorist shocks do not yield to sentiments of fear and chaos in the behavior of traders and investors.

Research limitations: Our findings imply that the persistence of volatility in oil returns may be overestimated due to the absence of structural breaks. Also, asymmetric models could have been applied to better gauge the effect of negative shocks on volatility, and dummies rather than continuous variables to determine the marginal impact of each attack on oil returns and volatility.

Practical implications: Important implications can be drawn for policymakers who must take action in order to prevent terrorism or at least minimize its effect to protect their economies. Moreover, such study would help investors in decision making; especially those concerned with the exposure of their portfolios to oil and terrorism-related risks.

Originality/ value: Prior research has not documented the influence of terrorism on oil returns and volatility against oil-reliant countries. This study is the first to address such a topic especially through disaggregating terrorist incidents among targets and intensity.

Keywords: Brent crude oil, volatility, returns, terrorist attacks, persistence, GARCH, OPEC.

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Contents

Chapter 1: Introduction

1.1 General Background and Importance of the Study

The conventional definition of terrorism used by the U.S. code and the Federal Bureau of Investigation distinguishes between terrorist acts and other forms of crimes. To be considered as a terrorist act, violence must emanate from a social or a political drive, threaten the life of passive victims, and violate by force or intimidation state or federal law. Hoffman (2006) examined the incentive and mindset behind terrorist attacks and the evolution of this trend, in particular, how al Qaeda has evolved since 9/11 using tactics and internet tools to enlarge its popularity. In his 2007 study, Hoffman defined terrorism as a powerful weapon to change a current political situation, and a strategic power to revolutionize international affairs and politics. Abadie and Gardeazabal (2008) demonstrated in their empirical study that with greater terror and uncertainty, terrorism reduces the expected return of investment and more particularly, may induce international investors to diversify sizeable movements of capital across open countries. From this perspective, Enders and Olson (2012) highlighted the effects of attacks on direct costs (human casualties, dislocated commerce, destroyed factories and infrastructure) and on indirect costs by turning away tourism, international trade and foreign direct investment. They also evaluated both macroeconomic and microeconomic economic consequences of terrorist attacks across different economies.

Consequently, the study of terror remains crucial especially in today's world where country risks deteriorate technology, industry, corporations, labor and capital. For this reason, several studies attempted to specify the effects of terrorism on stock markets performance (Karoly & Martell, 2010); its magnitude on bilateral trade (Blomberg and Hess, 2006), its impact on consumer confidence in the real estate and housing market (De Lisle, 2001), and its environmental consequences (Al-Damkhi &Al- Fares, 2010). It became apparent that bombing and violent actions are also a dangerous factor to the energy sector affecting thereby the price of oil (Blomberg *et al*, 2009; Chesney *et al*, 2011).

As major terrorist events rock oil-dependent countries, analysts worry about changes in oil prices. In this context, and as claimed by Blustein, (2004), oil prices jumped from $34.89 in February 2004 to $42.33 in the first of June following a sequence of consecutive terrorist attacks. These incidents comprise "the breakdown of an Iraqi pipeline in mid-March, the Madrid train bombing the same month, attacks on Iraqi oil terminals and pipelines and the killing of foreign workers in a Saudi Red Sea port on May 1" (Blustein, p. A10, 2004). The peak of the oil spike was stirred by the murder of 22 foreign workers in oil industry offices in Saudi Arabia. Moreover, Luft and Korin (2003) ascertained that the impact of striking at least one of the biggest crude oil hubs in the Kingdom of Saudi Arabia such as Abqaid, Ras tanura or Ghawar, would rocket oil prices and spoil economies that depend on the petroleum industry. In fact, conducting acts of sabotage to oil fields, refineries and tankers in the Persian Gulf in the mid of 2004 was exactly the target of al Qaeda led by Bin Laden in order to demolish American and Western economies reliant on oil and make their regimes totally disappear from the Middle East. Considering the heavy petroleum infrastructure of Saudi Arabia, a major supplier of the West, al Qaeda launched several direct attacks to its oil fields. Not only did al Qaeda restrict its actions to the Saudi Kingdom, but also enlarged its strikes across Iraq, Yemen, and Nigeria to even threaten U.S. important suppliers, Venezuela, Mexico and Canada.

Because terrorism and chaos in these countries would lead to uncertainty about the future flow of oil, as well as future supply or demand; this might cause higher volatility in prices. Certainly, volatility is a principal parameter in financial pricing. It gauges the level of sensitivity of prices to news and shocks. It is agreed that crude oil prices are characterized by stochastic, time-varying properties and high level of volatility. During periods of turmoil and uncertainty, oil prices are subjected to volatility clustering. Mean reversion or shock- persistence is often associated to oil volatility characteristics. Understanding crude oil characteristics and dynamics is thus of great importance for price discovery and of interest to economic agents, especially because variations in crude oil returns can bring about considerable effects on the global economic efficiency and productivity. Lardic and Mignon (2008), for instance, found that the economic activity[1] measured by GDP reacts irregularly to oil price shocks. Similarly, Wang (2013) showed that the effect of rising oil prices due to oil shocks is asymmetric on personal consumption expenditures in

[1] Of the United States, the G7, Europe and the Euro area

industrialized economies. In his study about the Japanese economy, Hanabusa (2009) showed that the 2004 spike in oil prices led to major negative repercussions on the country's growth.

1.2 Purpose of the Study

The contribution of this paper mainly comprises three aspects. Firstly, we are interested in detecting the consequences of rising terrorism on the crude oil markets in countries member of the Organization of Petroleum Exporting Countries (OPEC); knowing that, to our knowledge, none of the previous studies analyzed the impact of recurrent terrorist activities in the region on crude oil returns dynamics. To do so we disaggregate terrorist attacks into different groups according to the status of the attack (whether successful or unsuccessful), target and the intensity of the attack. Secondly, we believe that this is an exciting topic that will keep on in the future and be an incentive for governments to induce countermeasures against growing terrorism and fluctuating oil prices. Finally, our interest in this subject resides in the possibility and ease of conducting a reliable empirical study based on a readily available and precise data on terrorism.

From this perspective and in the light of recent terrorism-related events in the Middle East and Africa, the current study aims at investigating the influence of terrorist attacks in the region on the crude oil returns and fluctuations. To this end, we study the countries that are mostly threatened by terrorism due to political conflicts, and above all due to their wealth in oil resources. Successful terrorist attacks especially those hitting frequently oil and gas businesses, oil utilities, pipelines, tankers and wells in order to devastate the economies of oil-dependent countries, might have implications on financial markets and on several economic activities such as decision making about portfolio investment, forecasting, speculation, and so forth. Moreover, the impact of these attacks may be higher than unsuccessful attacks or attacks not targeting the oil industry.

Therefore, it would be beneficial for investors trading in such markets to be regularly attentive to political news to enhance their economic projections that are essential for their trading decisions. Accordingly, in order to improve decisions-making practices in chaotic socio-political upheavals, there is a need to know how oil returns dynamics react vis à vis terrorist attacks in general, attacks hitting the oil industry in particular, and how does the intensity of those attacks influence oil returns and its volatility. This way investors and decision makers would measure risks and manage insecurity in a more balanced way.

This thesis will attempt to answer the following research questions:

- RQ 1: Do successful terrorist attacks in countries such as Saudi Arabia, Iran, Iraq, Libya, Algeria, Nigeria and Angola have a higher effect on the return and volatility of crude oil (measured by Brent crude oil) than unsuccessful attacks?

- RQ 2: Do successful terrorist attacks targeting especially the oil industry in the selected countries have a higher impact on the return and volatility of crude oil than unsuccessful attacks targeting the oil industry?

- RQ3: Does the intensity of successful terrorist attacks in the selected countries have a higher impact on the return and volatility of crude oil than unsuccessful attacks?

- RQ4: Does the intensity of successful terrorist attacks targeting the oil industry in the selected countries have a higher effect on the return and volatility of crude oil than unsuccessful attacks targeting the oil industry?

This will be done in the context of a GARCH(1,1) analysis.

1.3 Layout of the thesis

The rest of the paper is organized as follows.

Chapter 2 reviews the relevant literature where we describe the properties of crude oil especially when exposed to shocks. We also point out the determinants that play a role in modifying oil returns.

Chapter 3 introduces the procedures and methodology while presenting the data and variables. Using GARCH(1,1) model, we explore the dynamics of crude-oil returns volatility subject to terrorist attacks while emphasizing on specific terror-components; being the target of the attack, the intensity and whether the attacks are successful or not.

Summary statistics and empirical findings are found in chapter 4 where we discuss the results obtained.

Finally, we conclude in chapter 5 by drawing out the substantive implications of our analysis.

Chapter 2: Review of Literature

2.1 Introduction

Oil prices have experienced several swings and volatility changes during the past decades. Stimulated by this fact, numerous studies in the literature have examined the underlying pattern of oil price volatility as well as the reasons behind crude oil price movements and fluctuations. In this specific literature, we focus on the crude oil price volatility dynamics where high volatility periods alternate with other relatively tranquil periods. Various approaches described the time-varying characteristics of oil fluctuations. These include the stochastic and random walk properties of oil prices volatility, long-term volatility persistence versus mean reversion, volatility clustering around periods with high uncertainty (Abosedra and Laopodis, 1997, Morana, 2001, Bina and Vo, 2007, Matar et. al, 2013), and structural breaks marked by asymmetric reactions of oil movements against infrequent and unusual shocks (Belkhouja and Boutahary, 2011, Ewing and Malik, 2013, Mensi et al., 2014).

In this chapter, we discuss the most prominent drivers responsible for altering global oil prices. Several empirical studies attributed the variations of crude oil prices to the law of supply and demand (Cooper, 2003, Hamilton, 2009, Peersman and Baumeister, 2012). Macroeconomic fundamentals such as precautionary demand or oil-specific demand is also an influential determinant of oil price modification especially in times of fear arising from wars or terrorism, and in periods of uncertainty toward the availability of future oil supplies (Kilian 2009, Alquist and Kilian 2010, Kilian and Murphy 2012). Other empirical investigations provided evidence that financial speculation and economic news might play a role in varying oil prices (Tang and Xiong, 2010, Elder, Miao and Ramchander, 2012, Guo and Kliesen, 2005).

We also discuss the findings of several papers regarding the impact of terrorism on financial markets and most importantly on the crude oil price and its volatility. Findings suggest that the impact of terrorism on financial and commodity markets is only short-lived (Chen and Siems, 2004, Nikkinen et al., 2008, Kollias et al, 2010). Concerning the oil market, the effect of the terror location (centre or periphery) appears to matter, and the effect of terrorism on the oil and stock correlation is not permanent like the impact of wars (Kollias, 2013).

2.2 Literature review

2.2.1 Volatility dynamics

Several studies have examined the volatility path of the crude oil prices. These studies identified volatility persistence versus mean reversion, clustering, jumps in prices, asymmetry and structural breaks. Here below we discuss all these features.

Mean reversion and volatility persistence

Generally, studies reported a stochastic trend and mean-reverting volatility for oil prices (Schwartz, 1997, Sadorsky, 1999, Schwartz and Smith, 2000). Thus, these studies concluded that the volatility of oil prices is not persistent. Low volatility persistence refers to the low memory property of the time series. It is related to how long the effect of volatility lasts. Morard and Balu (2014) modeled the volatility of oil (WTI, Brent and Dubai crude) between January 2012 and February 2014 using three models of GARCH family: GARCH, PARCH and EGARCH. EGARCH best modeled crude oil volatility where the oil market witnessed only a small volatility in prices during this period. Other studies also found low oil-price volatility persistence. According to Pindyck (1999), the price of oil has a stochastic rather than a deterministic trend and is statistically mean reverting, yet its long run movements (over 127 years; from 1869 to 1996) were mostly not extremely volatile. Using Kalman filter model, he proved that volatility has changed over this long period but only slowly.

Ewing et al. (2002) found evidence of the mean-reversion characteristic when examining the volatility of the daily returns for oil and natural gas from 1996 to 2009. Using a GARCH model, they studied the movements of oil and natural gas index[2] returns, and found the so-called volatility clustering in both indexes. This phenomenon showed that periods of high volatility were followed by high volatility and low periods of volatility were also followed by low volatility periods, suggesting time-varying property of oil and gas markets. Thus, both markets experienced low volatility persistence. The two markets reported values of volatility persistence below than 1; with 0.34 for oil index returns and 0.63 for natural gas index returns. In other words, the mean reversion is much faster for oil index returns than for natural gas. Furthermore, Ewing et al. (2002) calculated

[2] Each index comprises 15 major oil companies and 15 major gas companies respectively.

the half-life period to measure the impact of sudden news or information on the performance of the two indexes. The half-life period measures the time it takes for a certain shock to lose half of its initial value. Their results indicate that the impact of news on volatility is not persistent but transitory and that the unconditional variance is mean-reverting. The half-life for a shock on oil series is 0.64 (i.e. less than a day to decay for half of its initial state on the variance of oil returns) and 1.49 on gas series (i.e. around a day and a half to decay for half of its initial state on the variance of gas returns).
Moreover, Narayan and Narayan, (2007) found a low volatility trend while investigating the stochastic character of oil prices volatility. They employed EGARCH model and divided the sample period 1991-2006 into various subsamples using daily data. Their findings provided evidence of low volatility persistence across subsamples but lasting effects for shocks over the whole sample period; implying that oil price movements tend to vary over short periods of time.

On the other hand, many other findings in the literature reported periods of high volatility persistence in oil markets. Ye et al. (2002), for instance, found significant volatility in oil prices between 1992 and 2001. They used a forecasting model to measure the relationship between monthly WTI spot prices volatility and OECD inventory levels, based on the assumption that petroleum inventories are a reliable indicator of market pressures on oil price variations. They attributed the large volatility in prices to OPEC's inaction to influence oil prices through production adjustments, especially after the 9/11 demand shock. Moreover, Askari and Krichene (2008) found a persistent volatility in daily futures prices during the period 2002 till mid-2006, using three models: GARCH, Jump-diffusion model and a Variance-Gamma model. Each time futures prices seemed to stabilize, a drift associated to unexpected pressures was found to drive up prices to higher levels, implying that oil fluctuations were driven by high intensity and frequent shocks. During the sample period, oil prices reflected high levels of market uncertainties with a volatility of around 30%, where prices went up from $21.13 per barrel in 2002 to reach 73.76 in mid-2006. The authors associated the aggressive variations in oil prices to the global and fast economic growth, which led to a stimulus for the world oil demand. Kang and Yoon (2013) also found increased volatility in the weekly oil price during the years 2008-2009 where oil prices rose tremendously till July 2008, mainly due to the Asian economic growth and then dropped from August 2008 to 2009 because of the financial crisis and declined world demand.

Furthermore, Salisu and Fasanya (2012) compared and estimated different models of the GARCH(1,1) family to determine whether volatility in oil prices is persistent over the period 2000 till 2012. Their findings suggested a stochastic volatility of oil prices across three subsamples (before, after and during financial crises) where the peak occurred during the global financial crises.

Presence of Jumps and irregular volatility in crude oil prices

Another feature of crude oil price volatility is the existence of sudden and substantial movements in returns that arise subject to surprising news. These movements are known as jumps in oil prices (Chan and Maheu, 2002 Maheu and McCurdy, 2004). They lead to structural breaks not only in prices but also in volatility.

Using ICSS methodology over a period study of 9 years, Wilson et al. (1996) found 15 abrupt changes in the variance of oil futures series due to several exogenous events ranging from wars, OPEC policy changes and weather shocks. Gronwald (2012) performed GARCH model to examine the presence of jumps (defined as large returns in the oil market) in daily, weekly and monthly spot prices covering the period 1983 to 2008. In contrast to continuous time series regressions, he found that the fluctuations of crude prices were stimulated by strong and abrupt shocks. Similarly, Lee et al. (2010) studied the jump behavior of both WTI spot prices and WTI futures prices. They used daily data from January 1990 to end of 2007, and employed an auto-regressive jump-intensity model (ARJI) which identified two elements[3] of the conditional variance: a transitory component and a permanent component. The authors confirmed the presence of both components in oil jumps and pointed out that those permanent and transitory components increased after unexpected big events, such as the Iraqi invasion of Kuwait, and the 2003 Iraq war. During the same period of oil volatility, the transitory element increased at a higher pace than the permanent one, being the principal leading factor for oil price jumps.

Sévi (2014) developed the works of Lee et al (2010) and Gronwald (2012) by using intraday data and nonparametric methods. His findings revealed large volatilities in the year 2008, where prices recorded bigger fluctuations in the time of price decline. Volatility clustering was

[3] Based on Engle and Lee (1993) who decomposed the time- varying volatility into transitory and permanent components

evident around the period 2001-2010; this shed light on the heteroskedastic characteristic of oil variations.

Wilmot and Mason (2013) investigated the existence of jumps and irregular volatility in oil spot and futures prices along 1983 throughout 2010: a period exposed to several turbulent events; such as wars, the 9/11 terrorist attacks, global economic recessions and natural disasters (2005 hurricane). The authors applied likelihood ratio tests to evaluate four time-varying processes: jump-diffusion, continuous stochastic diffusion, continuous diffusion with GARCH, and the dual jump-diffusion and GARCH. The model of GARCH and jump diffusion together appeared above all to reflect the best measure of volatility (for all studied frequencies: daily, weekly, monthly data). Along with irregular volatility, jumps associated to sudden information occurred most obviously in 1990 during the first Gulf War, in 2001 after the 9/11 attacks and in late 2008 at the beginning of financial crisis. In contrast to continuous models described by normal distributions, the leptokurtosis mean obtained in the study explained well the discontinuous process of price movements where small fluctuations occur less and large changes happen within the fat tails.

Presence of structural breaks and regime-switching in the volatility of oil price

As reflected in the property of persistence, oil price movements are often influenced by jumps or shocks that can create instability in the structure of returns. Many researchers examined the existence and the impact of multiple structural breaks on the volatility of the price of oil. Much of the results showed regime-switching phenomena and described crude oil markets as unpredictable.

Liao and Suen (2006), for instance, studied oil volatility from 1986 to 2004 and employed Bai and Perron (2013) structural break test to detect the presence of breakpoints in WTI spot prices. They reported a high increase in WTI spot price from $19.02 /barrel to $30.90/barrel following a major structural break in November 1999. Moreover, using the Autoregressive Moving Average (ARMA) model, Ozdemir et al (2013) found that the volatility of the Brent crude oil spot and futures (with a maturity of one, two and three months) is persistent unless the presence of structural breaks is taken into consideration. They studied a sample period covering around 20 years from the 1990s till 2011. Their findings suggest that the volatility of Brent crude oil is unpredictable in the long run, when based on previous information. This is consistent with the random walk model which presumes that price variations are distributed randomly, as well as with the weak-form efficiency conjecture of crude oil markets which assumes unpredictability of pricing to new instantaneous shocks. In theory, the level of market efficiency is determined by the extent to which prices respond directly and immediately to all available information (Fama et al., 1969). The more the markets reflect all available information (even the hidden ones), the more those markets are considered as strong-form efficient (Fama, 1970). In the same way, Ozdemir et al's finding supports the fact that the impact of structural instability is generally asymmetric, implying that spot and future oil prices as well as their volatilities cannot be calculated in a significant way based on precedent changes. When applying empirical investigations on crude oil time-series, the majority of the findings report the presence of structural breaks (Gulen, 1997 and 1999).

Interestingly, switches between low and high volatility regimes arise subject to excessive movements in oil price. Vo (2009) modeled the volatility of the weekly WTI crude oil contracts between 1986 and 2008 using Markov-Switching models. This model incorporates the Markov-Switching (MS) method into the Stochastic Volatility (SV) model in order to avoid any overestimation of long memory. His conclusion was in line with the weak-form efficiency to crude oil markets, denying thereby the predictability characteristic of a highly persistent volatility. Indeed, the persistency level using the MSSV reported a lower value 0.521 instead of 0.957 using the SV framework, implying the existence of shocks that make volatility rebound more quickly due to sudden jumps. His model provided evidence of regime-switching volatility associated to important political and economic events. These include the first Gulf War, the atypical 1996 cold winter, the 1997 Asian financial crisis, the post 9/11 terrorist attacks, the 2003 U.S. invasion of Iraq, etc. Similarly, according to Matar et al. (2013), accounting for structural breaks and regime switches will decrease the persistence of volatility.

In another attempt to identify the existence of structural breaks in the volatility of crude oil spot prices and S&P 500, Belkhouja and Boutahary (2011) use a time-varying FIGARCH. They found two major breaks in the volatility of crude oil; the Gulf War (1990-1991) where prices spiked then returned to their initial levels, and the mid-1990s where prices increased with the economic growth of the U.S. and Asia then rebounded following Asia's recession. However, a decline in oil volatility was recorded between these two regimes. This confirms the findings of previous studies about long memory in the volatility interrupted by switching-regimes. They also found that the WTI returns are more volatile than the returns of the S&P 500 between 1990 and 1999.

In a different way, while examining the impact of oil volatility on the Malysian aggregate investment, Ibrahim and Ahmed (2013) found two important periods of oil fluctuations from 1991 till 2012. They captured permanent (stem from changes in fundamentals) and transitory (arise from sudden disorders) components of the oil conditional volatility using CGARCH model with the inclusion of crisis-dummy variables to better gauge the impact of tensions on Brent oil variations. The first phase suggests a rise in the permanent volatility and several recurrent transitory shocks since the 1998 Asian financial crisis. The second phase is characterized by the overlapping of both rising permanent and temporary volatilities at the occurrence of sudden events; specifically during the Dot Com bubble in early 2000, September 11 terrorist attacks, Enron bankruptcy in 2001, and the most recent sub-prime crisis from 2007 to 2009. Using VAR model to analyze the impact of the two volatility components on Malaysia's economy, the authors employed quarterly real oil prices, a volatility measure, real GDP, real investment, and real lending rate as variables. Interestingly, after two quarters, permanent volatility emerged to have a stronger negative influence on output than transitory volatility. Their results are not consistent with Byrne and Davis (2005b) who found a stronger impact of transitory shocks on developed economies such as the U.S. and other OECD countries.

Another important contribution to the literature is Ewing and Malik's study (2013). The latter used a univariate and multivariate GARCH models to model the volatility of daily gold and oil futures from July 1993 till mid-2010. Their results were in line with previous findings about the considerable persistence of market volatility. In fact, oil and gold series were both found to have a persistent volatility. However, when structural breaks were included in the variance equation of the univariate GARCH, volatility persistence decreased sharply for oil futures and gold. The breaks were endogenously detected using the iterated cumulative sums of squares (ICSS) algorithm. Interestingly, their findings imply that the impact of shocks in the oil market drop from 34 days to 3 days and from 69 days to 5 days in the gold market when the presence of structural breaks is not neglected. This leads to the conclusion that when breaks occur, markets respond quickly at first, and then absorb those shocks until they lose half of their initial impact.

More recently, Mensi et al (2014) analyzed the dynamic form and time-varying efficiency of the crude oil market over the period 1990 to 2012 using the Hurst[4] exponent and Shannon entropy[5] methods. They also employed Bai and Perron's test (2003) to capture the presence of structural breaks in daily WTI and Brent spot series. The authors showed that the oil market efficiency is time-varying. They found evidence of three sudden breaks associated with volatile WTI and Brent due to variations in international geopolitical and economic conditions. Based on Hurst and Shannon methods, both price benchmarks appear to be weak-form efficient. The volatility of prices does not follow a predictable pattern but is rather influenced by macroeconomic concerns such as inflation, economic growth, interest rates and by other geopolitical aspects.

Although the majority of papers in the literature provide evidence of a high probability of occurrence for sudden changes in oil markets, Arouri et al (2010) on the other hand, found no evidence for structural breaks (except for one cut-off point, for the UAE and Qatar). Using GARCH and Bai and Perron's test (2003) to study the weekly spot crude oil FOB price changes (measured in dollars per barrel) in four OPEC countries (Qatar, Kuwait, Saudi Arabia and United Arab Emirates), the authors showed high predictability (time-varying autocorrelation) in short-term changes over the whole sample (from 1997 through 2008) apart from few short periods. This implies that during most of the time-path, oil market volatility was persistent and far from being weak-form efficient.

Similarly, Zhang et al. (2014) used time-varying TGARCH model in order to test the weak-form efficiency hypothesis on daily and weekly oil spot prices. They conducted their study from 2001 through August 2013 on four major oil markets, namely WTI, Brent, Dubai and Daqing. When applied on weekly data, TGARCH attested good efficiency in the four markets excluding some inefficient phases. However, with daily data, findings revealed asymmetries in volatility reactions to new shocks and irregular efficiency.

Along with the dynamics of oil price volatility, understanding the determinants of oil prices is crucial for all market players because oil plays a vital role in the performance of the economy worldwide. Factors including demand and supply, precautionary demand, financial speculation, economic news and geopolitical events along with terrorism, have been brought forth to clarify oil prices movements.

[4] Classical test to detect persistence in time series

[5] Tool for modeling the nonlinear dynamic system

2.2.2 Demand and supply

Much of the literature emphasized on the law of demand and supply as the most influential determinants of oil prices. The demand side implies that change in economic growth, energy consumption substitutes or other technological diversification techniques, and price inelasticity of demand affect the oil price's volatility. Economic growth, for instance, associated with a 40% increase in global oil demand between 1980 and 2008, caused oil prices to reach their highest level, as reported by the US Energy Information Administration (EIA, 2009). Despite the few oil substitutes, many researchers observed the inelastic demand character of crude oil with respect to price changes (Kalymon (1975), Cooper (2003) and Hamilton (2009). For example, as oil price rises, consumers are unlikely to reduce their oil consumption because this commodity is a necessity. Affording a fuel efficient car can be a solution to price spikes, yet not a solution to people with low incomes. Similarly, the impact of small excess in demand would lead to a great upsurge in oil prices to reach market equilibrium. Furthermore, Hamilton (2009) showed that the impact of income variations on the demand for oil appears to be lower in developed economies than in the developing ones which are considered to have unit income elasticity. The same point has been made by Gately and Huntington (2002) who studied the income elasticity of 25 OECD countries, 11 emerging countries and 11 other oil-exporting countries over 1971 till 1997. They found lower income elasticity for the rich countries (0.5) and an average of 1.17 and 1.11 respectively for the other countries.

On the other hand, the behavior of oil supply is closely related to its inelastic nature. This is practically shown in the costly process of oil production. Thus, oil supply requires an extended term to be produced and to be affected by oil price variations. Peersman and Baumeister (2012) supported empirically Hamilton's (2009) conclusion. They used a time-varying vector autoregressive model to show that supply has become over the years more inelastic. In addition to the nature of global supply, the coordination between price and production strategies led by OPEC's supply decisions play a key role in determining the global oil price. This is because OPEC possesses the largest level of oil exports and reserves. According to the (EIA, 2014), reductions in OPEC production targets often trigger price increases. Moreover, geopolitical interests and events can also threaten oil supplies and cause disruptions. Whereas the intensity and duration of the geopolitical shock could lead to potential supply interruptions; the existence of spare reserves and large producers to compensate supply disruptions play an important role in stabilizing prices. Likewise, if crude stocks are not plenty enough to offset the related supply disturbances, crude prices might soar to an unexpected level. Last but not least, exogenous factors such as weather changes can affect oil supply. Hurricane Katrina, for instance, wiped out around one hundred off-shore oil facilities and more than 70 percent of crude production in mid-2006, which led to sharp and sustained increases in crude prices (Bamberger, 2008). Nevertheless, the impact of natural disasters on oil prices is not persistent. As oil flow rebounds, prices recover as well.

2.2.3 Precautionary Demand

Beside oil demand and supply determinants, a large number of empirical studies attempted to investigate the impact of macroeconomic fundamentals on oil price volatility. To quantify the nature of shocks that cause oil price fluctuations, Kilian (2009) decomposed oil price variations into three measurable components: supply shocks due to changes in oil production, aggregate demand shocks driven by variations in the business cycle, and oil-specific or precautionary demand shocks for price fluctuations that cannot be clarified by neither supply nor demand shocks. Precautionary demand shocks often occur when there is uncertainty about upcoming oil supplies arising from wars, revolutions or weather disruptions. For example, past events in 1979 such as the onset of Khomeini in Iran, the Iranian hostage crisis, the Soviet invasion of Afghanistan and the possibility of Iranian oil wells destruction, all led to sharp rise in oil price due to raised fears of supply shortfalls (Barsky and Kilian, 2002; Kilian, 2009). Kilian (2009) estimated a VAR model to analyze the response of the real price of oil to oil supply shocks (measured by volatile innovations to global oil production), global demand shocks (measured by the demand for all industrial commodities) and precautionary demand shocks (gauged in the residuals) between 1975 and 2007. His model assessed the movement of the real oil price and found that each type of shock affected oil prices differently. For example, supply shocks triggered short term and temporary increases in the real price of oil. Global demand shocks brought about sustained but postponed increases in prices. Most importantly, increases in demand for industrial commodities including crude oil led to large, immediate and persistent increases in crude oil prices. In fact, there seems to be a general agreement that oil price volatility driven by exogenous events such as wars, terrorism, strikes, etc is the result of oil-specific demand shocks or precautionary demand shocks (Kilian 2009, Alquist and Kilian 2010, Kilian and

Murphy 2012). Large and immediate oil variations are therefore the consequence of more fear and uncertainty toward the accessibility of future oil supplies.

Indeed, precautionary demand shocks determined by speculative behaviors of market players appear to be crucial factors that influence the volatility of real price of crude oil. If for example, investors expect future oil prices to rise due to anticipated supply losses vis-à-vis future global demand; investors' likely behavior would be to buy and save crude oil until prices increase (Alquist and Kilian, 2010). As a result, this excess in demand increases oil prices. To further highlight this theory, Kilian and Murphy (2011) augmented Klian's (2009) model and estimated a structural VAR model where speculative demand was captured explicitly by a proxy for crude oil inventories driven by expectations unrelated to flow in demand and supply shocks. The authors found that speculative demand shifts were responsible for oil price fluctuations in years 1979, 1986, 1999 and 2000. Yet, their results suggested that dramatic changes in oil prices during high volatility episodes and particularly during 2003 and mid-2008 were mostly caused by macroeconomic fundamentals.

Kilian and Murphy (2011) followed by Baumeister and Peersman, (2012) conducted their empirical studies based on Kilian's model (2009) but considered respectively, a structural VAR model and a Bayesian time-varying parameter vector autoregression model (TVP-VAR) with sign restrictions on the impulse response functions in order to capture immediate oil dynamic practices. A negative supply shock due to wars, for example, was linked to a positive short term response of the real price of oil and a negative impact of oil production. On the other hand, demand responses in the form of aggregate demand and oil-specific shocks are differentiated through sign restrictions: Increases in global unexpected demand shocks are associated with positive signs on both world industrial production and oil prices, while increases in oil-specific shocks driven by fear of supply shortages, lead to negative signs on production activity as a result of the oil price increase. Rather than imposing sign restrictions on all shocks responses such as the case in Baumeister and Peersman, Kilian and Murphy (2012) casted doubt on the validity of the latter study, and pursued their analysis by inducing boundary restrictions on the magnitude of oil shocks responses. Because supply and demand elasticities of oil are close to zero (Hamilton, 2009b; Killian, 2009a; Kilian and Murphy, 2010), they considered sign restrictions alone insufficient to explain the sensitivity of crude prices with respect to different types of shocks. Thus the need for an upper bound (0.025) on the impact price elasticity of oil supply which will take into consideration the steepness of supply curve and in turn make supply shocks magnitude more valid. Lower bounds on the impact price of price elasticity of demand were also imposed based on the assumption that the impact price elasticity of oil demand is inferior to the related long-run price elasticity of oil demand (Sweeney, 1984). Accordingly, not only boundaries serve as a complementary to assumptions on sign restrictions, but also help diminish all models with high elasticities. Interestingly, both studies found that the volatility in the real oil prices was primarily due to oil-specific demand shocks and rarely to supply disruptions. Although Kilian and Murphy (2012) attributed the rise of oil prices between 1979 and 1980 to both precautionary and global demand shocks and that of the first Gulf War mostly to oil-market specific demand shocks; models based solely on sign restrictions emphasized much on the role of supply shocks while minimizing the role of precautionary demand.

Subsequently, more studies analyzed the role of speculative demand on the variations of oil prices. Kilian and Lee (2013) modified some aspects of Kilian and Murphy's (2012) study by considering the percentage change in the real price of oil instead of the log deviations of the price. They examined the extent to which oil prices are affected by speculative shifts based on above-ground crude oil inventories proxies collected from Energy Intelligence Group[6] rather than the U.S. Energy Information Administration. Similarly, they found that between 2003 and mid- 2008 speculative demands had no impact on oil fluctuations. They also confirmed that the increase in oil prices was due to speculation in periods such as in 1979 after the Iranian revolution, in 1990 near the time of the invasion of Kuwait, in 2002 in the months leading up to the 2003 Iraq War. Furthermore, it is worth noting that Kilian and Lee's (2013) study is essentially innovative in terms of highlighting the impact of speculation during political tensions across the Arab region. They studied the variation in oil prices over time by employing counterfactuals[7], an alternative approach to studying each actual price subject to a driver shock at a specific point in time. The evolution of counterfactual and actual prices over time was plotted from 1984 till mid-2012, and examined in function of the three structural shocks: supply shocks, aggregate demand shocks and speculative demand shocks. The impact of each shock on real prices was determined by the vertical difference between the counterfactual and the actual price. For example, if the counterfactual price is lower than the actual, this implies that the underlying shock moved up the price of oil. Their findings showed accordingly, that the increase in oil prices in 2011 and 2012 was due to speculative demand

[6] The EIG provides a larger data coverage than EIA (crude oil inventory data by region, in maritime transport and oil transit)

[7] The difference between the real price of oil and the fitted value correlated with the shock

driven by political tensions in Libya (increase between 3 and 13 dollars due to change in expectations) rather than oil supply shortages in the country. The Libyan turmoil pressure on prices was only temporary. Indeed, they found no speculative demand pressures arising after the Arab Spring in 2011. When it comes to the slight increase of crude prices (from 0 to 9 dollars) as a result of Iranian disturbances (oil import ban set by EU in 2012 against nuclear danger), they found no evidence for speculative demand shocks. The combination of lower oil supply expectations and lower demand due to the European crisis was found responsible of the variation. Besides, they showed that not only speculative pressures may increase real oil prices, but also their reduction can lower real prices. They found evidence that after the 2008-2009 financial crises, when oil supply expectations were assumed to be at low levels because of the recession, crude prices declined given that counterfactuals exceeded the actual price subject to the speculative shock.

More recently, Baumeister and Kilian (2014) upgraded Kilian and Murphy's (2012) work in an attempt to analyze oil structural shocks following explicit events in oil markets as well as their sequences if any. In their study, they measure risks caused by oil price forecasts, and use real-time forecast scenarios about future oil supply and demand based on previous or hypothetical occurrences. Their VAR model based on additional identifying restrictions showed for instance, that additional precautionary demand triggered by turmoil in the Middle East (similar to the 1979 unrest) would raise the price of crude oil by 20 percent in the long run. Whereas an unanticipated global recovery, similar to 2007 and mid 2008 economic growth, would lead to a 50 percent increase, also in the long run.

When it comes to studying the sharp increase of the 2007-08 oil prices, Hamilton (2009) emphasized on the elevated demand for oil driven by rapid global growth, as the key contributor to the shock. Hamilton (2009) observed that before 2003 price shocks where caused primarily by supply disruptions, whereas after 2005 crude oil production was stagnant and the demand side was stronger. Kilian (2009) and Kilian and Murphy's (2010) results were also in line with the fact that oil-specific demand caused soaring oil prices between 2007 and mid 2008, however they did not approve that supply shocks played an important role in the years before. According to Kilian (2008), all price variations that cannot be identified empirically as supply or aggregate demand shocks will fall under the precautionary demand category. In contrast to Hamilton's observation, Kilian's regression underscored that only a minimal portion of the crude price increases during oil crisis (episodes such as 1973-1974, 1990-1991, and 2002-2003) can be linked to oil production shifts. This evidence was also shown respectively in Kilian (2009) and Kilian and Murphy's (2010) structural models where the 1971-1973 and 1978-81 oil price shocks were chiefly due to oil demand shifts.

Another strand of the literature has explained the unprecedented heights of 2003-08 oil price shock, where crude oil went up from $32 per barrel at the end of 2003 to $147 in July 2008. As demonstrated by Kilian and Hicks (2012), the unexpected growth in emerging countries (Brazil, Russia, India, China (BRIC) and other countries) and the repeated growth surprises were responsible for the surge. The Chinese consumption for oil, for example, has been rising at an approximately 7 percent compound annual rate since 1990 as a consequence of unexpected rapid growth. This interpretation is consistent with a standard demand shock; as the demand curve shifts to the right (driven by sudden economic growth) along with the upward sloping supply curve (stable aggregate oil supply) the real crude oil price will rise (Barsky and Kilian 2002). Similarly, the sharp drop in oil to less than $40 a barrel in mid-2008, was the outcome of negative growth shocks hitting the economy at the onset of the global financial crisis. The key insight on which Kilian and Hicks (2012) have built their regressions was through modeling the impact of unexpected economic growth on the volatility of oil price for the period 2000 till end of 2008. The model relied on one-year forecasts of real GDP growth, available on a monthly basis, as a measure to capture global demand shocks. Actually, in previous studies, the quantification of aggregate demand shocks was captured through a proxy of economic activity variations that were based on dry cargo shipping freight rates[8] in OECD industrial markets (Barsky and Kilian, 2002, Kilian, 2009a and Alquist and Kilian, 2010). Kilian and Hicks (2012) examined the extent to which volatility was explained by real unexpected GDP growth of both China and India as emerging countries, and the US, Japan and Germany as OECD economies. It is significant that the authors captured the exogenous surprises to real activity based on the Economist Intelligence Unit's forecasts, and relied on immediate and lagged news shocks to calculate the percent variation in the real crude price. The unexpected growth surprises for China and India were almost twice as all growth surprises in OECD countries and triple of those of Germany and Japan together; yet all

[8] They consist of cargoes made up of grain, fertilizer, oilseeds, coal, iron ore, and scrap metal. Researchers have identified a positive correlation between economic activity and ocean cargo rates (Martin Stopford 1997; Jan T. Klovland 2004)

regressions showed at the beginning a relatively slow increase in prices to reach their maximum in one year in the case of China and almost one year and four months in the case of OECD economies. The authors' results implied that the real oil price was much affected by global growth surprises from 2003 until mid 2008. All in all, their findings added more evidence to the literature that large oil spikes during this period were neither caused by OPEC's influence nor speculation by oil traders but rather by shifts in aggregate demand for oil driven by unexpected economic growth.

By far macroeconomic fundamentals do extremely well at explaining oil price variations. Demand and supply remain among the most leading factors of oil-market behavior, even during the latest oil price shock. By mid- 2014, after 5 years of price stability at nearly $110 per barrel, oil prices more than halved, to reach the sharpest yearly decline since the 2008 financial crisis.

2.2.4 Financial Speculation

In addition to the law of supply and demand, financial speculation is considered by many analysts a critical determinant of oil prices. Because oil is storable, financial investors are able to speculate in this commodity by taking short or long positions in the expectation of making high returns, regardless of the market's economic fundamentals. This is what drove Greenspan (2004) and Masters (2008, 2010) to claim that after 2003, the surge in oil future prices followed by increases in spot oil prices were utmost driven by increased financial firms' speculations. Masters estimated that the "commodity index trading strategies had risen from $13 billion at the end of 2003 to $260 billion as of March 2008" (Masters, 2008, p2) with approximately 70% of the future contracts representing energy prices. Meanwhile, the price of oil increased from $32 per barrel at the end of 2003 to the highest level ever reached, amounting to $147 in July 2008.

Singleton (2011) found empirical evidence that the growth in speculative activities around 2008 had a positive impact on returns of crude oil future prices. Using weekly time-series of positions related to index investors and managed-money spread, and after controlling for variables such as U.S. and emerging countries' stock returns, open interests and lagged futures returns, he showed that the increase in trading activities for both indices had the most important impacts on oil futures prices. From a different perspective, Tang and Xiong (2011) concluded that the risk appetite of investors captured by financial speculation determines greatly the price of commodities. They showed that after 2004, agricultural commodities being part of the GSCI and DJ-AIG indices have been affected primarily by changes in oil prices, U.S. exchange rate and global equity index. According to them, this co-movement is caused by spillover effects mainly driven by rising flows of index speculators and investors to commodities.

On the contrary, Alquist and Gervais (2013) found that the surge in oil prices during 2003 till 2008 was not triggered by financial speculations. The authors employed Working's T-index (1960) as a measurement of speculative shocks arising from financial (or non-commercial) positions between 2000 and 2010. As long as the values of the T-index are high and the number of speculators' short positions exceeds the increased hedging positions (or commercial participants such as dealers, merchants, manufacturers), the market is considered unstable and driven by speculative pressures. After computation, the T-index has shown a rise at the time of the price surge in mid-2008, yet the same values were recorded when oil prices were lower during 2003 and 2005. In addition, the T-index implied a low speculative influence in 2010 as commercial positions were much higher than non-commercial ones. This validated the modest role of speculations over that period of time. To further gauge the relationship between changes in net[9] positions and changes in WTI future prices, the authors estimated bivariate Granger causality tests for the periods 1993-2010, 2003-2008 and 2003-2010. They gathered all data about financial and commercial positions from Commodity Futures Trading Commission's (CFTC) weekly Commitments of Traders reports. They showed a positive but weak correlation between net long speculative positions and simultaneous variations in oil prices. Their general results demonstrated that changes in positions did not predict oil-price changes, but changes in oil prices did predict changes in positions. The authors' conclusion is consistent with those of other studies including the International Monetary Fund (2006, 2008), and Büyük§ahin and Harris (2011) who also employed the Granger causality test from mid- 2000 till March 2009 but used daily data on position changes (futures and options) from the U.S. CFTC's Large Trader Reporting system (LTRS). Their study did not detect any statistical evidence that position variations by commercial or non- commercial firms thoroughly led to price volatility.

Moreover, several arguments appear to cast doubt on whether speculations affect the supply of oil. In their study, Alquist and Gervais (2013) claimed that oil prices do not respond instantly to

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[9] Long minus short positions

supply shocks driven by financial speculations such as storing oil in the ground in expectation of higher prices. Although suppliers can speculate by extracting or delaying its withdrawal from grounds, oil supply remains influenced by long run tendencies. According to Hamilton (2009), the connection between initial oil wells' discoveries and increase in oil prices is based on a lagged period of around ten years.

2.2.5 Economic News

Aside from financial speculation, researchers often encountered detection difficulties while studying the impact of economic news on oil price movements. Guo and Kliesen (2005) detected through a narrative approach the relation between economic news (retrieved from the Wall Street Journal) and the top ten oil futures price fluctuations during the period 1983 and 2004. Their results implied that major oil futures volatilities were linked to news related to OPEC developments and political chaos across the Middle East. They reached the same conclusion with the largest forty oil volatilities that were associated with exogenous non-economic news. To further justify their findings, they conducted a forecasting regression during the same sampling period to assess whether macroeconomic variables anticipated oil variations. Among all tested predictive economic variables (past realized oil variance, stock market variance, default premium[10], term premium[11], growth rate of real GDP), the growth rate of real GDP was the only significant variable (negative correlation). In contrast with several studies (Kilian 2008; Hamilton 2009, Kilian 2009a; Alquist and Kilian 2010; Kilian and Murphy 2011; Kilian and Hicks 2012; Baumeister and Peersman 2009) which assumed that economic fundamentals are responsible for oil price volatility, Guo and Kliesen (2005) ascertained that the sources of oil price volatility are exogenous shifts and not endogenous outcomes of such shifts. On the other hand, Kilian and Vega (2011) investigated the impact of daily and monthly standard macroeconomic news on the instability of crude oil price. Surprisingly, they found a weak impact on crude variations. Their study revealed that oil prices are more sensible to long term shocks than to immediate ones caused by news concerning U.S macroeconomic announcements between 1983 and 2008. Their work makes a noteworthy contribution to the literature on the relation between news shocks and oil volatility. It claims that oil prices are

[10] The difference between the yield on Baa- and Aaa-rated corporate bonds

[11] The difference between the yield on 10-year Treasury notes and 3-month Treasury bills

predetermined to macroeconomic aggregates rather than to instantaneous news shocks; in contrast to the widely held presumption that oil prices reactions are similar to those of other financial asset prices (Kilian, 2009; Alquist & Kilian, 2010). Similarly, Chatrath, Miao and Ramchander (2011) reached an analogous conclusion by using intraday data and by differentiating between stock and flow in commodities.

In contrast to the above studies, Elder, Miao and Ramchander (2012) used a remarkable methodology with intraday records on economic news[12] and WTI crude oil in order to further analyze the news arrival impact on oil price jumps. Evidence is found that over the sample 2005 till 2010, a significant and positive correlation existed between positive surprises in employment news and increases in WTI prices. Large and inconsistent fluctuations were registered, especially following the onset of news that are directly related to economic theory, and more particularly after the intraday scheduled announcements and at market opening. While 30% of the news on changes in nonfarm payrolls were followed by oil price movements (Elder et al., 2012), findings of Kilian and Vega (2011) differed in their results. The latter revealed evidence using conventional asymptotic *p*-values, that nonfarm payroll news has no impact on crude oil prices. This consistently relates to their key finding that oil is a commodity not to be treated as any other financial asset.

Another analysis assessed the volatility of WTI crude oil prices using both symmetric and asymmetric GARCH models from 2000 till 2012 (Salisu and Fasanya, 2012). The results of the regression suggested that oil prices exhibit sensitivity to news but in an asymmetric way. Bad news, more than the good ones, tend to raise the volatility in the oil price and investors in the oil market respond more likely to bad news than to good news[13]. This is the leverage effect discussed by Matar et al. (2013) as one of the important characteristics of the oil market volatility for daily data. Besides, Salisu and Fasanya's (2012) study is mostly notable for being the first to cover and compare oil variations in subsamples before, during and after the financial crises. There exists a stochastic volatility of oil prices across the subsamples where the peak occurred during the global financial crises.

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[12] To recognize better the intensity of each economic release, " the realized announcement surprise is standardized by dividing the difference between the realized value and the consensus forecast by its sample time-series standard deviation" (Elder et al., 2012, p.9).

[13] "Good news' for the U.S. economy is an announcement surprise that should lead to an increase in the price of cyclically-sensitive assets, for example higher-than-expected GDP growth, industrial production, non-farm payrolls, consumer confidence, or inflation" (Roache and Rossi, 2009, p.12).

2.2.6 Terrorism

While crude price fluctuations show mostly stochastic variances, this means that several factors, other than supply and demand for crude oil interplay to influence such volatility. The presence of socio-political events such as wars, military conflicts and terrorist attacks seems to have a great influence on fluctuations in the oil market. One reason behind the altered behavior of financial markets is that political conflicts bring about demand and supply fears, not for actual disruptions, but for future oil supply availability. Consequently new market risk premiums will arise, and in turn will raise the volatility of prices and will affect investment allocation (Bialkowski et al., 2008).

According to Hamilton (1985), political events such as the Iranian revolution or the Suez Canal crisis, labor strikes and wars were principally the cause of unstable oil prices during that time. In a subsequent study, he looked further into the consequences of those incidents. Iran failed to produce "5.4 million barrels per day in the immediate aftermath of the 1978 revolution, and an additional 3.1 mb/d drop from Iraq when the two nations subsequently went to war in 1980" (Hamilton,2009b, p.18-19). As a result of those supply disturbances produced mostly from political turmoil, he asserted that the real price of crude oil augmented tremendously by approximately 80% between the years 1979 and 1980.

Obviously, because exogenous political instabilities, such as wars, armed conflicts and terrorism, generate higher risk and uncertainty, they can increase volatility in oil returns (Bialkowski et al., 2008). Ample evidence in favor of the impact of sociopolitical actions on financial markets' behavior was reported by several papers. (Amihud and Wohl, 2004; Eldor and Melnick, 2004; Schneider and Troeger, 2006; Drakos, 2010; Guidolin and La Ferrara, 2010; Enders et al., 2011; Kollias et al., 2010, 2011, 2013). The impact is a function of the magnitude, depth and duration of each action. Bialkowski et al. (2008) stated that political events can shake financial and commodity markets directly by destabilizing investors' sentiments and thus modifying asset valuation and investment decisions. As wars and military conflicts arise, market participants adjust their behaviors according to the expected preparatory phases and ending results of those conflicts. For instance, Choudhry (2010), showed such behavior in the event of the World War II. Similarly, Amihud and Wohl (2004) found evidence that throughout the second Gulf War, investors modified their investment decisions to the risk of Saddam Hussein's collapse and to the war's final effect.

Unlike wars, terrorist attacks are sudden and unexpected. Wars and military operations might extend through time and territories, whereas violent terrorist attacks are one-day events with considerable and immediate consequences due to rising insecurity and fear. Sandler et al. (1983) shed light on the exogenous character of terrorism by describing it as "premeditated, threatened or actual use of force or violence to attain a political goal through fear, coercion, or intimidation". Markets can be unsettled by the brutality and harshness of the attacks more than by the number of successful terrorist incidents (Enders and Sandler, 2000).

Several studies have examined the impact of terrorism on markets. Abadie and Gardeazabal (2008) showed in cross-country regressions based on stochastic AK endogenous growth model[14] that with greater terror and uncertainty, violent actions reduce the expected return of investment, and more particularly may induce international investors to diversify sizeable movements of capital across open countries. Drakos (2004) also highlighted the adverse impact of the 9/11 on airline shares where uncertainty raised insurance premiums and consumer fear lowered airline tickets leading thereby to lower stock returns. On the other hand, Drakos (2010) found that the lowest daily stock market returns for a sample of 22 countries were only clustered around the day of terror, where investors' sentiments were the most deteriorated. In addition, he showed using ARCH models over the period 1994-2004 that the adverse impact of terrorism on returns is eight times higher when psychological impacts are major rather than minor.

Chen and Siems (2004) using event study methodology found that the effects of the 9/11 terrorist attacks were less persistent on the U.S capital markets compared to global markets. They attribute this result to the possible growing resilience of the U.S to violent incidents. Broadly similar findings were reported by Kollias et al (2010), claiming that the effects of two major terrorist incidents in Europe (the bomb attacks of 11th March 2004 in Madrid and 7th July 2005 in London) on the returns and volatility of the equity markets were only short-lived. Although both markets were negatively affected by terrorism, London equity markets recovered in a quicker way than Madrid markets. The authors attribute this disparity to the nature of attacks. This could be interpreted as suggesting that suicide attacks in London were completely ceased, associated to

[14] Terrorism was integrated as a stochastic Poisson process, with events that destroy some fraction of the capital stock of a country.

lesser feelings of insecurity among citizens compared to the sudden threat of bombings in the case of Madrid.

When it comes to the oil markets, few empirical studies focused on the direct influence of terrorism in shaping oil prices fluctuations. Blomberg, Hess, and Jackson (2009) found that terrorism has a positive impact on oil stock prices. Based on break points tests the Zivot-Andrews test and the Lumsdaine- Papell test, they found that this relationship exists when two conditions are held: oil firms acting as monopolies and violent attacks are not very frequent. They concluded that the frequency of conflicts affects oil profitability differently. As terrorist acts amplify, oil stock prices do not raise as a response to clashes. This, however, is not the case when periods are described as capacity constraints. To further examine the role of terrorism on commodity markets, Chesney, Reshetar, and Karaman (2011) conducted an event-study approach, a non-parametric methodology, and a filtered GARCH-EVT approach. According to them the non-parametric methodology was the most fitting study by which they showed that short-term terrorist actions have both positive and negative impacts on the oil/gas returns. Yet, negative returns are more frequent than positive ones. The decline in oil prices are the results of diminished consumer confidence, weak trust in the economic and political situation and lower demand of oil. The renowned case in point would be the 9/11 terrorist attacks which led to downward pressure on oil prices by around 35% in mid-November (BBC News, 2008); essentially due to an undermined US economy, high uncertainty and increases in Russian production. On the other hand, short term increases in oil prices following terrorist events are mostly attributed to the amplified level of damage caused to the transportation sector and petroleum production as well as to the global state of the oil market demand. The higher the global oil demand at the time of the terrorist strike, the more positive will be the impact of events on oil prices. Thus, investors' anxiety and sentiments of fear convert into rising prices.

Moreover, Kollias et al. (2013) examined the impact of terrorism and war on the volatility of stock and oil price returns as well as on oil price–stock index covariance. Daily Brent spot price and WTI spot price indices were examined along with daily prices of major stock indices (DAX, CAC-40, FTSE-100, and S&P500). Terrorism data was taken from the Global Terrorism Data base (GTD) and from Enders and Sandler (2011) who divided events between *centre* and *periphery* attacks. The authors incorporated in a BEKK-GARCH model dummy variables to account for terrorist attacks. They constructed the dummies based on the short or long durations (such as Iraq wars) of the attacks. Their findings show that oil and stock co-movements are mostly affected during the early stages of both Iraqi wars. This implies that the long-lasting nature of wars prompts enduring effects on market participants' behaviors. Nevertheless, terrorist shocks do not produce similar permanent results on the oil and stock correlation. Although the covariance between CAC, DAX and oil returns was sensitive to terrorist incidents, the correlation between the S&P500, FTSE1000 and oil returns was unresponsive[15] to terrorism. In addition, they found that *centre* terrorist attacks exert more considerable and significant impact on the correlation and volatility of markets compared to *periphery* ones.

2.3 Conclusion

Obviously oil price movements and volatility are shaped by a number of different endogenous and exogenous factors, which surely makes projections on forward-looking oil prices quite vague. Not only do macroeconomic fundamentals associated with speculation, abrupt economic news and geopolitical greed distress oil price stability, but also and most importantly nowadays terrorist attacks are causing potential implications on crude price volatility. The influence of successful terrorist acts that hit oil fields and facilities is considered damaging to the global economy, especially in recent years where oil markets are tighter than during the past years (Johnston, 2008). However, the literature has not far examined how the terrorist activity in oil-rich countries would exert any effect on oil price movement and volatility.

Therefore, in the midst recent terrorism emerging in the Arab Spring countries and Africa, it is of great importance to know how assaults in these countries would change the price of crude oil and to which extent would prices be volatile vis-à-vis violent actions aiming to destroy the oil industry. The focus of the study will be on major Middle Eastern oil producers that are mostly vulnerable to terror, in particular, Saudi Arabia, Iraq, Iran in addition to Libya, Angola and Algeria in the African continent and Nigeria which is "home to the largest part of Africa's oil reserves, and is the fifth largest oil supplier to the U.S" (Luft & Korin, 2003,1). In fact, in all these countries, terrorist organizations recognize the destruction of oil resources as a useful mean to jeopardize opponent governments. According to EIA (2014), if only terrorists block or attack one of the most

[15] S&P500 and FTSE100 are considered to be more able of absorbing the impact of terrorism

important petroleum chokepoints[16] such as the Strait of Malacca or the Strait of Hormuz, this would raise global energy costs (rerouting tend to inhibit total sea transport capacity), hence global oil prices. The sensitivity of energy prices to terrorism highlights the crucial role that oil plays in the world's economy. Indeed, it would be beneficial for consumers and investors who trade in such markets to be regularly attentive to news about terrorist strikes in order to enhance respectively their consumption behavior and projections that are essential for their trading decisions.

[16] EIA states that nearly 63% of the global oil production is transported via maritime routes. the Strait of Malacca and the Strait of Hormuz carry the world's biggest volume of oil transit.

Chapter 3: Procedures and Methodology

3.1 Introduction

According to the British Petroleum Statistical Review of World Energy (2014), the Middle East embraces the largest reserves for oil and natural gas, accounting for 47.9% of the total worldwide reserves at end of 2013, followed by South and Central America which hold merely 19.5% of total reserves. More specifically, OPEC[17] member countries carry most of the reserves, nearly 72% of the global total oil reserves. Unfortunately, the recurrent phenomenon of terrorism has become a global threat to such oil-rich countries which hampers both their political and economic stability.

This study attempts to investigate the impact of terrorism in countries wealthy in oil and generally exposed to terrorist incidents on crude oil returns and its volatility. The studied countries are a combination of OPEC member countries, more particularly Saudi Arabia, Iraq, Iran, Nigeria, Angola, Algeria, and Libya. This thesis disaggregates terrorism into different categories according to the target of the attack, the intensity of the attack, and whether the attack was successful or unsuccessful.

Accordingly, the following research questions will be addressed:

- RQ 1: Do successful terrorist attacks in Saudi Arabia, Iran, Iraq, Libya, Algeria, Nigeria and Angola have a higher impact on the return and volatility of crude oil (measured by Brent crude oil) than unsuccessful attacks?

- RQ 2: Do successful terrorist attacks targeting especially the oil industry (gas/oil businesses, oil utilities, and maritime oil tankers) in Saudi Arabia, Iran, Iraq, Libya, Algeria, Nigeria and Angola have a higher impact on the return and volatility of crude oil than unsuccessful attacks targeting the oil industry?

[17] OPEC countries are twelve; including Angola, Ecuador, Iran, Iraq, Kuwait, Libya, Nigeria, Qatar, Saudi Arabia, United Arab Emirates and Venezuela.

- RQ3: Does the intensity of successful terrorist attacks in Saudi Arabia, Iran, Iraq, Libya, Algeria, Nigeria and Angola have a higher impact on the return and volatility of crude oil than other attacks?

- RQ4: Does the intensity of successful terrorist attacks targeting the oil industry in Saudi Arabia, Iran, Iraq, Libya, Algeria, Nigeria and Angola have a higher effect on the return and volatility of crude oil than unsuccessful attacks targeting the oil industry?

By successful attacks we mean any attack type that took place; whether there was assassination, hijacking, kidnapping, bombings, assaults etc. except for assassination where the target must inevitably be killed.

3.2 Sample of studies

Since we are interested in tracking the influence of terrorist activities on oil returns and oil volatility in terms of persistence, sensibility and responsiveness in general, and attacks aiming oil targets in specific; we only study the countries that are both rich in oil and very vulnerable to terror. According to the OPEC Statistical Annual Bulletin (2013), around 80% of the world's crude oil reserves are found in countries member of OPEC, which absorb nearly 1,200.83 billion barrels of reserves (see figure 1 in the appendix). These countries rely heavily on crude oil exports to finance their budgets, with Saudi Arabia having the highest revenues from net oil exports, around 274 billion dollars according to the EIA (2014). It is followed by Kuwait (92 billion dollars), Iraq (86 billion dollars), Nigeria (84 billion dollars), Venezuela (62 billion dollars), Algeria (57 billion dollars), UAE (53 billion dollars), Qatar (42 billion dollars), Libya (33 billion dollars), Angola (27 billion dollars) and Ecuador (11 billion dollars) (see figure 2 in the appendix). Oil export revenues in Iran are currently ambiguous because of the latest sanctions applied.

In this thesis, we selected seven OPEC member countries that have a high susceptibility to violence with terrorist attacks leading to several wounded and killed people. They are categorized in two regions: Middle East and North of Africa (MENA) with Saudi Arabia, Iraq, Iran, Algeria, and Libya; and the Sub-Saharan Africa comprising Nigeria and Angola. Our choice of countries is not random. Although Kuwait outperforms all other OPEC members (excluding Saudi Arabia) in reserves exports, it is considered almost stranger to terrorism with only 39 successful attacks throughout 1987-2013. Likewise, despite its high oil production in 2013 (see figure 3 in the appendix); we excluded UAE from the sample because it is subject to lesser terrorist attacks over the years, with only 4 successful attacks out of 7. As for Qatar and Ecuador, they have less important crude oil production and violence. They witnessed 4 successful attacks out of 5 and 118 successful attacks out of 127 respectively. Besides, Venezuela is one of the highly ranked countries in oil production (2.2 million bbl/ day); however, terrorism attacks solely constituted 156 successful assaults.

Nevertheless, the selection of each of the oil-wealthy countries being Saudi Arabia, Iraq, Iran, Nigeria, Angola, Algeria, and Libya is based on a fundamental criterion: they all belong to the world's most volatile regions vulnerable to terror. Concerning Saudi Arabia, it has the world's largest crude oil production capacity and is one of the richest reserve countries; carrying 16% of the world's total reserves. Knowing that its terrorist attacks are not that numerous compared to other countries (63 successful out of 69), this does not mean that its vulnerability to terror might not have an impact on the global oil price. According to Johnston (2008) the 2006 terrorist attempt to destroy the world's biggest oil refinery[18], Abqaiq would have been a disaster to the oil international market if it succeeded. After all, despite its failure, that action led to a $2.5 increase per oil barrel. Moreover, analysts Luft and Korin (2003) ascertained that the impact of striking at least one of the biggest crude oil hubs in the kingdom of Saudi Arabia such as Abqaiq, Ras tanura or Ghawar, would rocket oil prices and spoil economies that depend on the petroleum industry.

When it comes to Iraq, the *Oil & Gas Journal* (2015) reports that the country holds around 9% of the world's crude reserves and nearly 18% of proved reserves in the Middle East. In addition, more than 50% of the country's GDP emanate from petroleum resources, which are essentially dispersed along southern Shiite regions and northern Kurdish regions; areas that are constantly at risk from extremist terrorism. Beside the threatening presence of ISIS in Iraq, a shocking fact is reflected from the massive acts of terrorism in this country, including 12,073 attempts out of which 11,400 attacks were successful.

With reference to Iran and despite the recent sanctions that led to a reduction in its level of crude production (IMF, 2011), the country remains the fourth leading country with abundant oil

[18] According to the *Arab Oil and Gas Journal*, Abqaiq processes more than 70% of Saudi crude before export or delivery to refineries.

proved reserves. Iran benefits from the most important strategic chokepoint for oil transit: the Strait of Hormuz, which passes through its territorial waters in the southeastern coast. The Strait traded around 17 million barrels per day in 2013, the highest volume among all other maritime petroleum chokepoints, as reported by EIA (2014) which based its information on Lloyd's List Intelligence. Similarly to Saudi Arabia, Iran has few rebellious acts (217 successful attacks among 234); nevertheless, its instability and oil richness trigger us to detect the response of oil prices as a result of Iranian chaos.

As for the African continent, Nigeria hosts the biggest share of Africa's oil production. In 2013, it produced around 2,322,000 barrels per day according to the BP Statistical Review of World Energy June 2014, and was ranked as the fifth oil supplier to the US. Not only does the country face the menace of Islamic terrorist organizations such as Boko Haram recently and Al Qaeda previously, but also witnessed 1,531 terrorist attacks during the period mid-1987 till end of 2013 from which 1,406 attacks succeeded. The GTD reported officially 159 successful attacks in 2011 alone. Based on the ranking of the Global Terrorism Index (2012), Nigeria rose from rank 16 among 158 countries in 2008 to rank 6 by the end of 2011.

Angola as well is an interesting country to study. It is the second biggest oil producer in Africa behind Nigeria (see figure 3 in the appendix). It relies mostly on oil exports which accounted for approximately 97% of its total export revenues in 2012 (IMF, 2014). Likewise, it does not make an exception for terror; hosting 442 successful attacks out of 454 during our sample period.

Furthermore, Algeria has shown a remarkable level of violence with 2,687 terrorist acts over past years. The country is rich in oil, given its rank as the third largest carrier of crude reserves in Africa, hence our interest to include it in our model.

Last but not least, we will also consider Libya because it surpasses all African countries in proven oil reserves (see figure 1 in the appendix), and depends on a great deal on oil revenues to finance its budget (around 80% of export revenues in 2012 as reported by the IMF). In our sample period, the country witnessed 315 successful attacks out of 361. Hostilities affecting oil production occurred in the 2011 civil war, followed by protests hindering oil production and security at several oil ports and facilities by mid-2013.

3.3 Selected variables

3.3.1 The independent variables

We collect the data related to terrorism for the period June 1, 1987 till the end of December 2013 from the latest version of the Global Terrorism Database (GTD, 2014). This terrorism incident database is upheld by the National Consortium for the Study of Terrorism and Responses to Terrorism (START), and is based on several sources to increase the validity of data collection. These sources comprise the review of around one million media articles per day on any subject worldwide. Data gathering also includes available data sets, legal documents, books, journals and electronic news archives. The GTD defines terrorist attacks as "the threatened or actual use of illegal force and violence by a non-state actor to attain a political, economic, religious, or social goal through fear, coercion, or intimidation" (GTD codebook, 2014, 8). In other words, to include terrorist attacks in their database, the incidents must be deliberate, violent against people or properties and executed by sub-nationals rather than by states.

GTD (2014) collects information concerning each successful terrorist attacks. The latter is an attack that depends on the attack type. If any of the attack types take place, for example assassination, hijacking, kidnapping, bombings, assaults etc terrorism is therefore considered as successful except for assassination where the target must necessarily be killed. For each such attack, information concerning the target of the attack is reported. GTD considers twenty two target types:

1. Business
2. Government (General)
3. Police
4. Military
5. Abortion related
6. Airports & Aircraft
7. Government (Diplomatic)
8. Educational Institution
9. Food and Water Supply
10. Journalists & Media
11. Maritime
12. NGO
13. Other
14. Private and citizens & property
15. Religious figures/ institutions

16. Telecommunication
17. Terrorists/ Non-State militias
18. Tourists
19. Transportation (other than aviation)
20. Unknown
21. Utilities
22. Violent Political Parties

From which we only consider businesses that imply gas and oil, in addition to the utilities and the maritime field which entail oil.

The independent variables are continuous variables rather than dummies. This way of constructing the variables intend to highlight the level of responsiveness related to oil returns and their volatility subject to the status of terrorist attacks. We expect that successful attacks will have a higher impact on the return and the volatility of oil prices than unsuccessful attacks. We also expect successful attacks targeting the oil industry to have a higher effect on oil returns and volatility than other attacks.

These variables will be constructed as follows:

Success is a variable equals to 0 in case of no terrorist attack. It will take value 1 if the attack was unsuccessful and 2[19] if the attack was successful as per the GTD definition here above.

Oil_targ is another variable taking value 0 if there were no terrorist attacks in general or at the other hand attacks took place but not on oil. It will be equal to 1 if the terrorist attack aimed to damage the oil industry including oil utilities, gas/oil businesses and maritime oil tankers but was not successful. It will be equal to 2 if the attack targeted the oil industry and was successful at the meantime.

We also disaggregate the successful attacks into levels of intensity: high and low intensity terrorist attacks. *Intensity* is a variable that will take value 0 in case of no attacks, 1 if the attacks were not successful, 2 if successful attacks had a low intensity which means that the number of casualties (killed and wounded victims) is less than the country's average casualties (casualties caused by all the terrorist attacks), and 3 in case successful attacks had a high intensity, where the number of casualties is greater than the country's average.

[19] The choice of 0, 1 and 2 intend to highlight the level of responsiveness related to oil returns and their volatility subject to the status of terrorist attacks.

Similarly, we disaggregate the successful attacks targeting the oil industry into two levels of intensity: high and low. The construction of the variable *oil_int* will take value 0 in case there were no terrorist attacks or attacks took place but not on the oil industry. It will take value 1 in case attacks on oil facilities were not successful, 2 if attacks targeting the oil industry were successful with low intensity and 3 if attacks on oil facilities were successful with high intensity.

3.3.2 The dependent variables

When it comes to the international oil prices, there are three global leading benchmarks for crude: the Europe Brent crude oil produced in the North Sea and quoted on International Oil Exchange in London (ICE), the West Texas Intermediate- Cushing Oklahoma (WTI) quoted on the New York Mercantile Exchange, and Dubai/Oman crudes which are typically used to quote crude oil produced in the Middle East and exported to Asia. These benchmarks are very close; however, they report small spreads as a result of differences in the production base, transportation/ delivery costs, oil quality and trading times (Matar et al. 2013).

In this thesis, we use the returns of the Europe Brent as the dependent variable because they are more prone to fluctuate subject to chaos and geopolitical situation in the Middle East and North Africa compared to the WTI produced and traded mostly in the United Sates (Zhang and Zhang, 2015). The Europe Brent spot prices (measured in dollars per barrel) are imported from the database of EIA (2015). They are drawn from mid-1987 till end of 2013, on a daily basis except for weekends and at other times when markets close for trading. Prices are then converted to returns (taken in natural logarithm) totaling a number of 6,743 observations. Because terrorist attacks were omnipresent even during weekends and holidays; we manipulated the data related to those attacks by adding them to the last trading day of the week. That way, we avoid attributing any influence of terrorism on transactions for crude oil taking place off exchange over-the-counter[20] (OTC) markets, leading thereby to significantly different prices from where the market closed.

[20] Where transactions are not subject to market rules and regulations required on the actual exchange market.

3.4 Methodology

We estimate four regression models. Each model includes an indicator for terrorism occurring in all the seven countries: Algeria, Angola, Iran, Iraq, Libya, Nigeria and Saudi Arabia.
The mean and conditional variance can be written as:

1. $y_t = \lambda_0 + \lambda_1 \text{success\_i}_t + \varepsilon_t$
   $h_t = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 h_{t-1} + \lambda'_1 \text{success\_i}_t$

2. $y_t = \lambda_0 + \lambda_2 \text{oil\_targ}_t + \varepsilon_t$
   $h_t = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 h_{t-1} + \lambda'_2 \text{oil\_targ}_t$

3. $y_t = \lambda_0 + \lambda_3 \text{intensity}_t + \varepsilon_t$
   $h_t = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 h_{t-1} + \lambda'_3 \text{intensity}_t$

4. $y_t = \lambda_0 + \lambda_4 \text{oil\_int}_t + \varepsilon_t$
   $h_t = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 h_{t-1} + \lambda'_4 \text{oil\_int}_t$

where y_t represents the returns of daily Brent crude oil. *Success_i* and *oil_targ* are the variables referred to earlier that will capture the existence of successful attacks as well as those targeting the oil industry in all studied countries. The use of the variable *intensity* will help us track the significance of each incident by identifying the responsiveness of successful attacks with low and high intensity. The variable oil_int_t captures the impact of successful terrorist incidents carried out against the oil industry while identifying the attacks with low intensity from those with high intensity. The conditional variance equation is a GARCH(1,1) model where h_t measures the volatility of the Brent crude oil return assumed to be function of lagged values of the variance itself (h_{t-1}), some news contained in the square of the errors (ε_{t-1}^2), and terrorist attacks. The variance intercept (α_0), the coefficient on the lagged squared residual (α_1) and the coefficient on the lagged conditional variance (β_1) should all be greater than zero to obtain a positive variance. In addition, if $\alpha_1 + \beta_1 \geq 1$, this implies that shocks to the conditional variance will be highly persistent.

3.5 Hypotheses

In order to provide evidence of whether terrorist attacks affect individually the Brent return and its volatility, we test individually the significance of the coefficients λ and λ' using a standard student test.

For example, if we reject the null hypothesis $H_0: \lambda_1 = 0$, the conclusion would be that Brent oil returns are affected by successful terrorist attacks taking place in the studied countries; and that successful terrorist attacks have a higher impact on oil returns than unsuccessful attacks. The same applies to volatilty; if we reject the null hypothesis $H_0: \lambda'_1 = 0$, this means that successful terrorism impact oil returns volatility; and that successful terrorist attacks have a higher impact on oil volatility than unsuccessful attacks.

For each research question, the functional forms of the hypothesis are given by:

RQ1

$$\begin{cases} H_0: \lambda_1 = 0 \\ H_1: \lambda_1 > 0 \end{cases} \qquad \begin{cases} H_0: \lambda'_1 = 0 \\ H_1: \lambda'_1 > 0 \end{cases}$$

RQ2

$$\begin{cases} H_0: \lambda_2 = 0 \\ H_1: \lambda_2 > 0 \end{cases} \qquad \begin{cases} H_0: \lambda'_2 = 0 \\ H_1: \lambda'_2 > 0 \end{cases}$$

RQ3

$$\begin{cases} H_0: \lambda_3 = 0 \\ H_1: \lambda_3 > 0 \end{cases} \qquad \begin{cases} H_0: \lambda'_3 = 0 \\ H_1: \lambda'_3 > 0 \end{cases}$$

RQ4

$$\begin{cases} H_0: \lambda_4 = 0 \\ H_1: \lambda_4 > 0 \end{cases} \qquad \begin{cases} H_0: \lambda'_4 = 0 \\ H_1: \lambda'_4 > 0 \end{cases}$$

Chapter 4: Findings

4.1 Descriptive statistics

A summary of descriptive statistics for Brent crude oil returns is presented in table (1). The average returns measured by the mean is about 0.026, different from the median where half of the returns are below 0.038 and the other half higher than this value. This difference between mean and median can be a first indicator of the distribution non-normality. In terms of the standard deviation, the value 2.297 reflects a high variation from the mean. The negative skewness provides evidence of the extent to which the distribution of oil returns is asymmetric with low values (long tail to the left). In addition, kurtosis indicates divergence from normality. It is positive and significantly different from zero implying that the distribution is leptokurtic due to volatility clustering around the mean. It is worth mentioning that leptokurtic distributions involve fat tails which suggest a frequent occurrence for risks arising mostly from exogenous and unexpected events. The Jarque-Bera test confirms the non-normality of the distribution with p-value less than 0.05. Thus, employing GARCH model to capture the effect of terrorism on oil returns and volatility appears to be suitable with oil characteristics. We also provide evidence using the Augmented Dickey-Fuller (ADF) test that the dependent variables are stationary in level. We considered the ADF model without a constant or a trend. The ADF test statistic (-79.6226) is less than the critical values at 1%, 5% and 10% (-2.5653, -1.9409 and -1.6167 respectively). Thus, we reject the null hypothesis of a unit root and confirm the stationarity of the time series.

Table 1: Descriptive statistics

	Brent crude oil returns
Mean	0.026
Median	0.038
Standard deviation	2.297
Skewness	-0.666
Kurtosis	18.035
Jarque-Bera	64013.20 (0.000)
Augmented Dickey-Fuller	-0.9693 [-79.6226]

Note: For significance tests, p-values are presented between parentheses and t-statistics between brackets.

Panel (a) of table (2) illustrates a summary of descriptive statistics for successful terrorist attacks. During the sample period from June 1987 till end of 2013, around 56,000 victims were killed and 100,000 injured from 16,363 successful attacks carried against the seven sample countries. Iraq suffered the most from those incidents leading to 36,566 killed persons and 83,828 injured victims. Algeria and Nigeria were also subject to a high frequency of successful attacks where the killed victims summed to nearly 11,000 and 5,377, and the injured to 9,000 and 3,000 respectively. The rest of the countries also witnessed a high omnipresence for killed and injured victims caused by successful attacks. However, in terms of importance, casualties were most importantly victims of low intensity successful attacks rather than of high intensity.

As can be shown in panel (b) of table 2, out of 16,363 successful terrorist attacks, 316 targeted the oil industry. Iraq and Nigeria witnessed the highest number of successful attacks (most of them had low intensity) targeting the oil pipelines, utilities and businesses. The number of casualties in the two countries exceeded that of the rest of countries.

Furthermore, panel c of table 2 shows that the mean of successful attacks is large. On average, 94% of all terrorist attacks hitting the oil-rich countries over the period of study are successful with a 0.248 standard deviations implying high deviations from the mean. Likewise, around 95% of the terrorist attacks aiming to destroy the oil industry are successful with a quite high standard deviation indicating significant variations from the mean. It is worth noting that nearly 20% of the successful attacks were powerful leading to an elevated number (above the mean) of killed and wounded people, while 80% of the successful attacks were low in intensity. Hence, it is of great interest to examine the impact of each terrorist attack on oil returns and its volatility.

Table 2: Number of terrorist events

Panel a: Terrorist attacks

Country	Number of total attacks	Number of killed	Number of wounded	Number of successful attacks	Attacks with high intensity	Attacks with low intensity
Algeria	2,687	11,024	9,011	2,520	616	2,071
Angola	454	2,426	1,532	442	104	350
Iran	234	542	1,541	217	30	204
Iraq	12,073	36,566	83,828	11,400	2,520	9,553
Libya	361	278	659	315	46	315
Nigeria	1,531	5,377	2,984	1,406	319	1,212
Saudi Arabia	69	178	1,051	63	8	61
Total	**17,409**	**56,391**	**100,606**	**16,363**	**3,643**	**13,766**

Note: The number of killed and wounded is related to all attacks. High and low intensity attacks are related to successful attacks only.

Panel b: Terrorist attacks on the oil industry

Country	Number of total attacks	Number of killed	Number of wounded	Number of successful attacks	Attacks with high intensity	Attacks with low intensity
Algeria	11	13	9	11	3	8
Angola	14	11	1	12	1	11
Iran	7	0	0	6	0	6
Iraq	165	218	445	157	34	123
Libya	2	0	2	2	0	2
Nigeria	132	286	102	125	17	108
Saudi Arabia	3	36	59	3	3	0
Total	**334**	**564**	**618**	**316**	**58**	**258**

Note: The number of killed and wounded is related to all attacks. High and low intensity attacks are related to successful attacks only.

Panel c: Attacks statistics

	Mean	Standard deviation
Number of successful attacks	0.940	0.248
Number of successful attacks targeting the oil industry	0.946	0.117
Successful attacks with low intensity	0.792	0.396
Successful attacks with high intensity	0.208	0.396
Successful attacks on oil with low intensity	0.816	0.107
Successful attacks on oil with high intensity	0.184	0.048

4.2 Main results

Table (3) reports the estimated results of mean and conditional variance equations according to the GARCH(1,1) model. The results of the mean equation show that terrorist attacks against the seven selected countries have a positive and significant impact at a 5% significance level on the returns of Brent oil (see λ_1 and λ_3). An increase in successful terrorist attacks in Saudi Arabia, Iran, Iraq, Libya, Algeria, Nigeria and Angola would lead to a 4.25% increase in oil returns compared to unsuccessful terrorist attacks (see λ_1). Moreover, an increase in the number of terrorist attacks by one additional attack from low intensity to high intensity will lead to a 3 % increase in

Brent returns (see λ_3). However, the impact of successful attacks hitting gas/oil businesses, oil utilities and maritime on Brent returns is not significant; neither is the impact of an increase in the intensity level of successful attacks hitting oil (see λ_2 and λ_4). It appears that an increase in the number of terrorist attacks against oil platforms and facilities by one additional attack from low intensity to high intensity will not lead to any change in Brent returns.

Moreover, table (3) shows that the conditional variance for successful attacks is persistent since $\alpha_1 + \beta_1$ is approximately equal to 1. In all the cases, the estimated half-life[21] period of terrorist shocks confirms the high volatility persistence. It takes 117.136 days (around 4 months) for oil returns to decay for half of their initial value after successful terrorist attacks, and 109.676 days after successful terrorist attacks targeting oil tankers, utilities and businesses.

According to GARCH(1,1), the estimated results of the conditional variance equation reveal a negative relationship between terrorist attacks and oil returns volatility. The impact is significant at a 5% significance level for RQ1 and RQ3. It is not significant for RQ2 and RQ4 implying that successful terrorist attacks targeting especially the oil industry in the selected countries and regardless of their intensity do not have a higher impact on the volatility of crude oil than unsuccessful attacks targeting the oil industry.

Table 3: GARCH (1,1) for terrorist attacks - Normal distribution

Coefficient	RQ1	RQ2	RQ3	RQ4
	Mean equation			
λ_0	0.0025 (0.9360)	0.0444 (0.0378)	0.0039 (0.9006)	0.0450 (0.0355)
λ_1	0.0425** (0.0455)	-	-	-
λ_2	-	0.0590 (0.2551)	-	-
λ_3	-	-	0.0301** (0.0456)	-
λ_4	-	-	-	0.0473 (0.2954)

[21] We calculate the half-life of terrorist shocks in days using $\ln(0.5)/\ln(\alpha_1+\beta_1)$.

	Conditional variance equation			
α_0	0.0543* (0.0000)	0.0467* (0.0000)	0.0551* (0.0000)	0.0471* (0.0000)
α_1	0.0759* (0.0000)	0.0763* (0.0000)	0.0757* (0.0000)	0.0762* (0.0000)
β_1	0.9182* (0.0000)	0.9174* (0.0000)	0.9182* (0.0000)	0.9175* (0.0000)
λ'_1	-0.0082** (0.0453)	-	-	-
λ'_2	-	0.0027 (0.9181)	-	-
λ'_3	-	-	-0.0063** (0.0223)	-
λ'_4	-	-	-	-0.0020 (0.9312)
Jarque-Bera	979.2512 (0.0000)	1010.583 (0.0000)	976.8384 (0.0000)	1008.577 (0.0000)

Note: p-values are between brackets. *, ** and *** indicate the significance at 1%, 5% and 10% levels.

However, as can be deduced from the Jarque-Bera normality test, residuals do not follow a normal distribution (as p-values below 1%, 5% or 10% provide evidence against the null hypothesis of a normal distribution) implying that the inferences we made about the coefficient estimates could be wrong. Accordingly, to avoid bias, a t-distribution for the errors is essential rather than a normal distribution. Here under in table (4), we interpret the results of GARCH (1,1) using a student distribution for the errors.

Table 4: GARCH (1,1) for terrorist attacks - Student distribution

Coefficient	RQ1	RQ2	RQ3	RQ4
	Mean equation			
λ_0	0.0182 (0.5492)	0.0536 (0.0101)	0.0202 (0.5014)	0.0542 (0.0092)
λ_1	0.0391*** (0.0575)	-	-	-
λ_2	-	0.0768 (0.1224)	-	-

λ_3	-	-	0.0272*** (0.0631)	-
λ_4	-	-	-	0.0624 (0.1506)
	Conditional variance equation			
α_0	0.0447* (0.0000)	0.0407* (0.0000)	0.0460* (0.0000)	0.0411* (0.0000)
α_1	0.0633* (0.0000)	0.0628* (0.0000)	0.0631* (0.0000)	0.0627* (0.0000)
β_1	0.9296* (0.0000)	0.9302* (0.0000)	0.9298* (0.0000)	0.9302* (0.0000)
λ'_1	-0.0007 (0.9130)	-	-	-
λ'_2	-	0.0305 (0.4005)	-	-
λ'_3	-	-	-0.0015 (0.7048)	-
λ'_4	-	-	-	0.0228 (0.4712)
Shape parameter	6.2871* (0.0000)	6.2676* (0.0000)	6.2912* (0.0000)	6.2691* (0.0000)

Note: p-values are between brackets. *, ** and ***indicate the significance at 1%, 5% and 10% levels.

Because the shape parameter is significant for all variables, this validates the use of a t-distribution for our GARCH model. In accordance with expectations, the effect on Brent returns is consistent with the result of a supply shock resulting from terrorist attacks, where the supply of oil might decrease or get interrupted leading to higher prices. Successful terrorist attacks in the sample countries have a higher impact on the return Brent crude oil than unsuccessful attacks. This can be seen in the positive and significant coefficients λ_1 and λ_3 at a 10% significance level. On the other hand and similarly to the results in table (3), the coefficients of λ_2 and λ_4 are not significant. This shows that the impact of terrorist attacks on oil returns does not depend on the target of the terrorist attacks (316 successful attacks on oil) but rather on the number of terrorist attacks in the selected Middle Eastern and African countries (16,363 successful attacks). Hence, an increase in the number of successful attacks will positively affect oil returns.

Similar to the results of table (3), crude Brent volatility is found to be persistent with the sum of α_1 and β_1 equals nearly 1, but the half-life is reduced to 97.279 days. Negative shocks on Brent returns do not seem short-lived but permanent. It takes around three months for the terrorist attacks to lose half of their initial impact. This confirms that the discontinuous moves in oil returns subject to unforeseen terrorism is not mean reverting.

According to theory and previous literature, measuring volatility reflects the trading activity in most financial markets where the increase in volatility is associated with low asset returns and vice versa (Davidson *et al*, 2001). Thus, an increase in volatility can be interpreted as a result of fear and uncertainty among traders especially after shocks such as terrorism and wars. For RQ1 and RQ3, table (4) shows an inverse relationship between successful terrorist attacks and the variation of Brent returns (see $\lambda'_1$and λ'_3) but the latter relationship is not significant. For the four hypotheses, we do not reject the null hypotheses that terrorism in Saudi Arabia, Iraq, Iran, Nigeria, Angola, Algeria, and Libya does not affect the volatility of Brent returns nor create any form of panic and chaos in the international commodity market.

Chapter 5: Conclusions and Recommendations

Crude oil is not only the most traded physical commodity globally, but its importance relies also on encompassing the biggest volume of futures trading in the world. While numerous OPEC countries depend largely on crude oil production and revenues to fund their fiscal budgets, most of these countries have suffered from violent terrorist defeats such as infrastructure and facility attacks, bombings, armed assaults, hijacking, kidnapping and assassinations, leading thereby to adverse repercussions on their economies. In this thesis, we analyzed the influence of terrorism on the dynamics of crude oil returns and volatility in OPEC countries that are the wealthiest in oil reserves and are the most vulnerable to terrorism; namely Saudi Arabia, Iran, Iraq, Libya, Algeria, Nigeria and Angola. Whereas the frequency of terrorist attacks hitting oil-dependent countries has been mounting in the last decades, there is a narrow literature on the impact of terror on the movements of crude oil, and practically no evidence on how terrorist attacks hitting oil wells, pipelines and facilities affect the response of oil returns and its variations. Using GARCH(1,1) model, we find evidence for a positive and significant impact of terrorism on the returns of Brent crude oil. Interestingly, evidence shows that this effect is only significant when successful attacks are carried out randomly in these countries and not when targeting the oil industry. However, both sorts of attacks (those hitting randomly and those targeting the oil industry) were found to lead to a statistically insignificant impact on the volatility of Brent returns when the non-normality of the residuals is taken into consideration in the estimation of the GARCH(1,1) model. In contrast to our expectations regarding a low half-life for shocks, our findings suggest a high persistency of terrorist shocks on the volatility of oil returns.

We concluded that exogenous terrorist events lead primarily to negative supply shocks. Because such events would induce disruptions in the flow of oil supply, especially when the number of successful terrorist incidents is large, they would decrease supply and raise crude oil returns. We also notice that hitting oil-related targets such as businesses, utilities and maritime does not lead to a significant effect on the returns and volatility of Brent crude oil. On the contrary, it is the high number of successful attacks that matters, leading to higher Brent returns. Furthermore, the sensitivity of oil volatility to terrorism is minimal. In other words, traders will not rush in their buying or selling activities nor be alarmed subject to recurrent attacks in the selected OPEC member countries. This kind of behavior reflects the absence of fear and troublesome reactions of oil-traders to the terrorist shocks and expectations of shocks.

Our findings have crucial economic implications because achieving good investment decisions in the oil industry requires the understanding of political risk and uncertainty. Although studies have examined the impact of terrorism on commodity prices, this thesis can be beneficial for researchers exploring the oil-terrorism relationship, especially because our innovation relies on disaggregating terrorism into several components (attack status, intensity of attack, and target of terrorism) and assessing them on the volatility of oil returns.

The results necessitate strong support against terrorism. Policymakers and authorities in both OPEC and non-OPEC countries that rely heavily on oil production and had long suffered from terrorism must tighten their country's security and address their strategic deficiencies in combating national and global terrorism. It is also recommended that each country gives much attention and priority to defend its oil fields, refineries, tankers and pipelines as terrorists primarily hit oil targets to undermine the economic and internal stability of the countries they are fighting. Policymakers need to protect oil hubs and resources by implementing systematic investigations against terror as well as detection measurement systems. That way, despite the maneuvers and endurance of terrorists, the protective measures would prevent or minimize the outcomes of those unpredictable shocks. Furthermore, if crude oil prices continue to rise as a result of frequent terrorist attacks, then meaningful increases in energy prices might lead to inflation and adverse economic outcomes for oil importing countries. Consequently, the biggest losers from rising oil prices will have to execute assertive policy decisions to curb the substantial downside risks to growth. Moreover, it is of great importance for investors to observe the volatility of crude oil returns in order to make the right trading decisions and or take appropriate actions. This happens through identifying the time points at which structural breaks occur, the periods of volatility clustering and periods of volatility persistence.

Potential extensions of this thesis would be to detect the existence of structural breaks in volatility of Brent crude oil using formal tests such as modified iterated cumulated sums of squares (ICSS) algorithm. Ignoring the presence of potential jumps and discontinuities in the pricing process might have been the reason behind the high level of volatility persistence. Furthermore, we can capture more explicitly the extent to which the fluctuations of oil returns are time-varying and stochastic as a result of terrorism using intraday terrorist events. We can also employ asymmetric

GARCH models such as the E-GARCH(1,1) to gauge for the unequal changes of the volatility. Because the volatility of oil returns is categorized by the leverage effect, using the E-GARCH can demonstrate whether the negative shocks caused by terrorist attacks tend to have a bigger impact on volatility. Moreover, we can check the order of GARCH at which residuals are not autocorrelated and have no ARCH effects so that the estimation of standard errors will not be biased. Finally, dummy variables instead of continuous variables can be constructed in order to isolate different terrorist attack and assess their marginal impacts on oil return and volatility. In spite of the importance of these extensions, they remain outside the scope of the paper.

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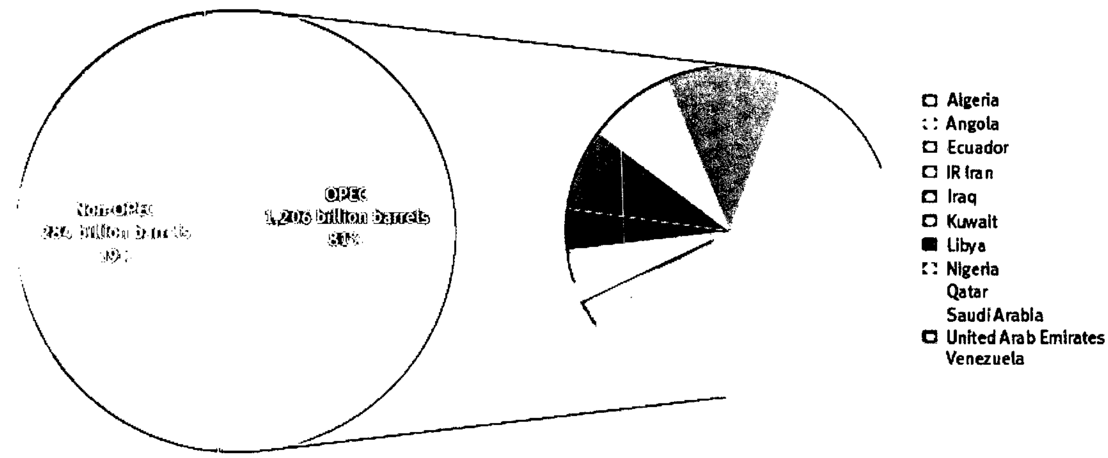
Appendices

B. Figures



OPEC proven crude oil reserves, at end of 2013 ***(billion barrels, OPEC share)***

Venezuela	298.4	24.7%	Iraq	144.2	12.0%	Libya	48.4	4.0%	Algeria	12.2	1.0%
Saudi Arabia	265.8	22.0%	Kuwait	101.5	8.4%	Nigeria	37.1	3.1%	Angola	9.0	0.7%
IR Iran	157.8	13.1%	UAE	97.8	8.1%	Qatar	25.2	2.1%	Ecuador	8.8	0.7%

Figure 1: OPEC share of world crude oil reserves, 2013
(Source: OPEC Annual Statistical Bulletin 2014)

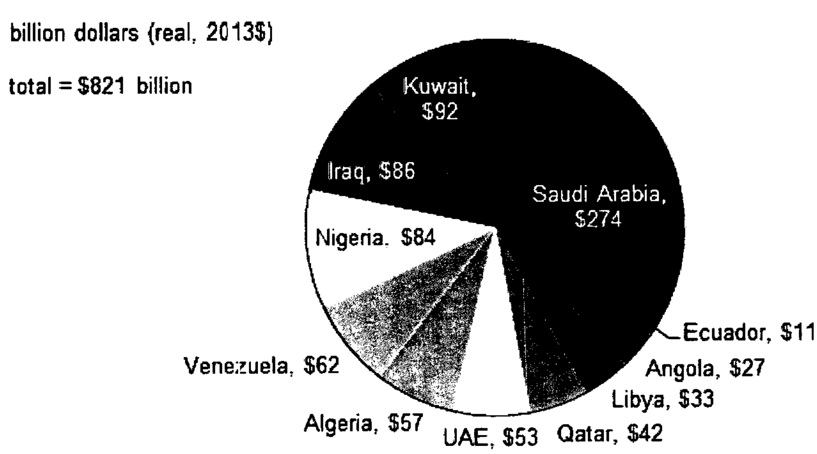


Figure 2: OPEC net oil export revenues (excluding Iran), 2013
(Source: U.S. Energy Information Administration, *Short-Term Energy Outlook 2014*)

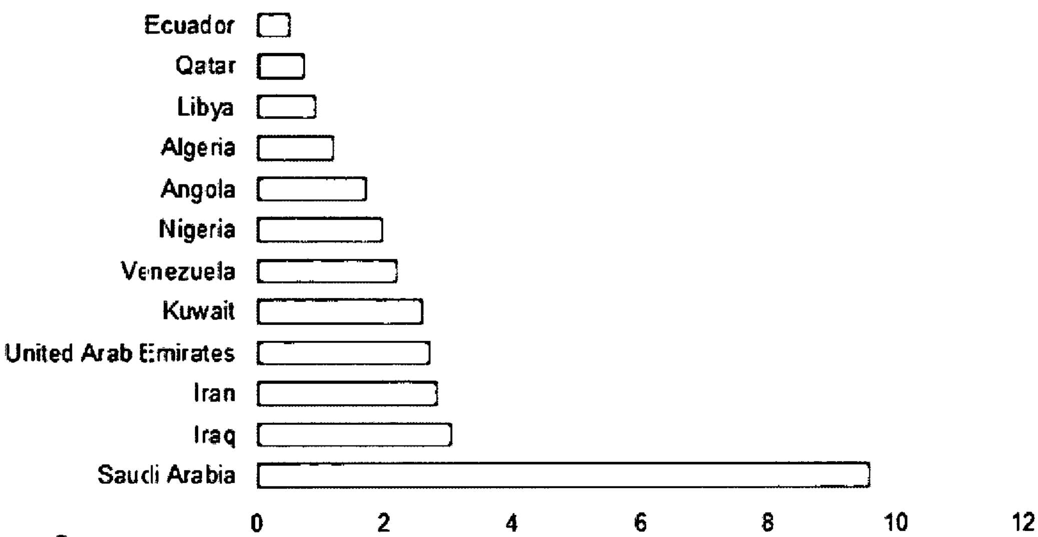


Figure 3: OPEC crude oil production, 2013 (million barrels per day)
(Source: U.S. Energy Information Administration, *Short-Term Energy Outlook 2014*)

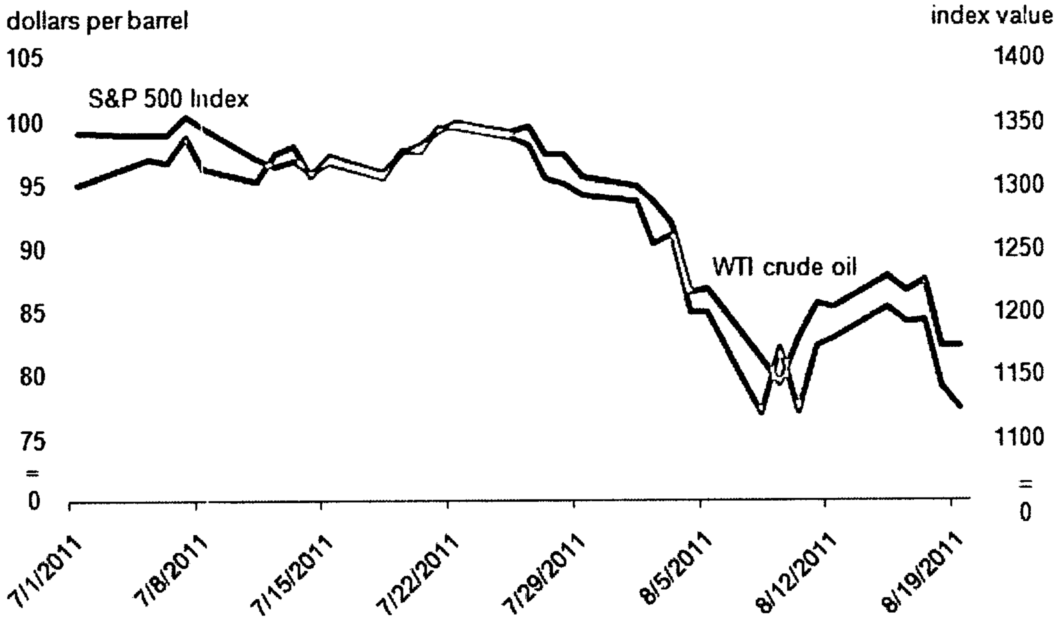


Figure 4: S&P 500 Index and WTI crude oil futures, July 1 - August 19
(Source: U.S. Energy Information Administration based on Bloomberg data)