Bachelor Thesis

Department of Economics

An event study approach for the terrorist attacks in Saudi Arabia

Elenidis Charalampos

Under the supervision of
Professor Panagiotidis Theodore

May 2020

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Acknowledgements

I would like to thank my family for the continuous support through all these years and especially my sister for being always there to motivate me.

Foremost, I would like to express my sincere gratitude to my supervisor, Professor Panagiotidis Theodore, for giving me the opportunity to conduct this thesis and for contributing to my development as a student and as a person.

Abstract

In this paper we capture the effects on the oil price due to the recent terrorist attacks in Saudi Arabia, on September 14, with the use of the event study methodology. Both the market model and the constant mean return model have been employed in order to measure the normal performance, while the parameter computation has been implemented not only with the OLS estimator but also with the Quantile regression and a GARCH model. The results signal the presence of the impact of the event under consideration, since we find several significant abnormal returns and cumulative abnormal returns, thus justifying its long-lasting influence. Finally, we estimate the changes in systematic risk with 3 distinct approaches and observe that the risk variation in commodity market is noteworthy, while the stock market seemed to be much more resilient to this exogenous shock.

JEL classification

Y40; C01; G14; Q40

1. Introduction

Although there is an intense discussion regarding who provoked the terrorist attack, since the Saudi Arabia and the USA blame the state of Iran while the Houthi rebels of Yemen have claimed responsibility for that fact, there is another great issue, related to the influence on capital markets. The idiosyncrasy of that event is attributed to the absence of any evidence that an action of that magnitude would take place. Casting a glance over similar cases in the past, one would encounter a long period of warnings between the two sides, before the perpetrator fulfilled his threats. That absence resulted in a much greater volatility among market participants, taking into consideration the sensitivity of that period, given that a few specialists have warned that another financial crisis might be on the way. At this point, we should refer to the great importance of two issues, one quite broad and another one more specific, that have regularly come up; oil-related events (expected and unexpected) and their spillover effects on other sectors.

Firstly, we cannot omit the fact that oil is still the most important commodity in terms of consumption volume, despite the repetitive efforts from environmentalists for a switch to renewable sources. Hence, the oil-related events and the subsequent oil price fluctuations have a significant impact on every economic entity. This causality is expected to prevail for many more years, as it is projected that only 12% of oil in place globally has been extracted to this date which equals to 1.1 trillion barrels. The reinforcement of that view comes from the reports which claim that oil is supplying 33% of all energy, thus a turnaround is highly unlikely to happen on the short or medium-term. The drivers of that scope might be pretty explicit for most individuals, no matter whether they possess economic background or not. The long-term extensive use of oil as the prime energy source has created a significant amount of economies of scale and cost synergies for the extracting and refining companies, providing them with enough margin to offer more inexpensive energy in comparison to the upcoming "green" companies. The contribution from governments and well-established organizations could be the solution for the convergence between the two energy resources, so that an affordable switch to renewable sources happens, but given that the economic environment is highly uncertain those expenditures might seem unnecessary for some prominent people.

Regarding the second topic, the interaction between different asset classes that are traded in exchanges, or over the counter (OTC), strongly affects the market as a whole. The so-called spillover effects, in this case, refer to the significantly higher cost for businesses due to oil price hike, as its use in industrial activities are still highly considerable. For instance, during the event-period under review it was observed a decline on the stock market, while both the Brent and WTI crude oil futures surged, insinuating a potential correlation between those two. The existence of this relationship will be further tested later on, when we will have concrete results so as to draw some reliable conclusions. However, we should note that we anticipate to observe a mechanism between those two, based on the findings of Malik and Ewing (2009) as for the spillover effects between WTI oil prices and equity sector returns and especially due to the work from Chiou and Lee (2009) on the asymmetric unexpected impact of oil prices on stock returns, given that our research is hinged on an unexpected event as well. Moreover, we should note that oil might also be a decisive factor for the development of the macroeconomic environment, considering that it strongly influences the headline inflation, which includes the often-volatile elements of food and energy and as a consequence the economic output as a whole.

Furthermore, the exogenous nature of that event makes it even more noteworthy, taking into account that investors had no information of what was about to happen, thus they could not speculate as for the event result before it took place. Keeping this scenario in mind, we are in quest of further variations that could be related to the attack and are grievous enough to be included in this work. To conduct that kind of tests we utilized the event study methodology (ESM), which was first introduced in 1969 by Fama et al. (1969) to check for the semi-strong form of market efficiency, by examining the stock splits effect on stock prices. After that, the number of papers that used this approach has been constantly increased (MacKinlay, 1997; Binder, 1998; Corrado, 2011), although only few of them studied the impact of exogenous events like the one we try to estimate in this thesis. The vast majority of them tried to capture the effects of expected facts, such as quarterly earnings announcements, stock splits and corporate deals, which are broadly known as mergers and acquisitions (M&A). Therefore, a further objective of this thesis is to contribute to the enrichment of the widely used event study methodology, providing the existent literature with a reliable work on an additional unexpected event such as the one under consideration. Besides, we researched thoroughly the papers that utilize this approach for exogenous shocks and found just few similar studies on oil futures contracts.

With regard to the structure of this Thesis, in Chapter 2 we examine the previous literature that is relevant to our methodology, terrorism or even oil price fluctuation and its potential spillovers. Afterwards, in Chapter 3 we lay the groundwork for the so-called event study methodology, mentioning many different versions of it, while reference is also made to the relative risk and the approaches that could quantify it in a dynamic way. In the Data Description section (Chapter 4), we observe the variability of price, returns and conditional variance with the use of graphs, whereas the necessary diagnostics and descriptive statistics are also included. The next step in Chapter 5 is to illustrate the results of the study and interpret the mechanism that led to those values. Finally, in Chapter 6 we summarize the main conclusion drew and try to come up with some more generic implications in order for this paper to be comparable with a greater amount of future studies.

2. Literature Review

2.1. Preface of Literature Review

Oil has been the dominant energy source for a long time, and it seems that this will be the case for plenty of years to come, despite the fact that a switch to renewable sources has been strongly promoted by market officials and environmental organizations. The serious cost of this switch, since the replacement of the current system is necessary, and the power of some of the oil-exporting countries such as Russia and the USA, are just two of the many reasons why this move is yet to be completed. Having clarified its long-term importance, the next step is to research the numerous papers published on oil price shocks and especially those driven by terrorist attacks in oil producing countries. In addition, attention is also paid to the literature using the event study methodology to capture the abnormal performance.

2.2. Impact of the Demand-Supply forces on oil price

Firstly, we look into fundamental factors that might influence the oil price variation, such as the forces of supply and demand, before emphasizing on more exogenous causes. Alquist and Kilian (2010) and Kilian and Murphy (2010) record that demand shocks motivated by shifts in expectations have been an important determinant of global oil price fluctuations, both of spot and futures value, during certain episodes. However, a year earlier Kilian (2009a) concluded to the substantial role of productivity shocks in explaining the increased oil price volatility in 2000s, providing an alternative perspective as for the key factor that drives the oil value. All the above-mentioned works are strengthened by the rejection of the standpoint that speculation has an important role in driving the oil prices by Fattouh et al. (2012), as this finding insinuates that variability in oil demand and supply have the most vital influence on oil price, therefore studying those events account for the greatest part of oil price variations.

2.3. Early studies on the association between output and oil shocks

One of the first relevant studies was conducted by Hamilton (1983), when he addressed the matter of the association between U.S. recessions since World War II and oil shocks over the same time frame. He justified that the latter were a contributing factor in at least some of the former events prior to 1972, thus confirming the importance of oil throughout the previous decades. Mork (1994) has also monitored the same relationship and concluded that, although oil price increases appear to hurt aggregate activity, price declines do not seem to help in a similar manner, in what could be a two-way causality. The reasoning on which those findings are based assumes that uncertainty along with some sectoral imbalances are responsible for these results.

2.4. OPEC's production policy since the U.S. shale rise

Recently, there were enormous developments in the field of oil extraction, a fact that is claimed to be a key driver of oil price. More specifically, the well-known U.S. shale boom was implied to be the driving force behind the huge drop of oil prices between 2014 and 2016, when crude oil value declined from $112 (June 2014) to $31 (January 2016). As a consequence, a variability of that magnitude could not be left without further analysis, but we only focus on a selected group of papers that is concerned with the pricing strategy of OPEC and its greater member, Saudi Arabia, along with the rise of shales. Ansari (2017) claimed that, based on an equilibrium model, OPEC tried not only to protect its market share against its new competitor, but also to test its ability to survive in a low-price environment, considering the higher production cost of shale extraction. The paper also notes that the organization could have even accepted low-prices, in order to adjust to what could be the norm from now on, due to the upcoming renewable energy sources, cost efficiencies in oil production and weaker demand. Behar and Ritz (2017) contributed to this debate, utilizing the same approach, and justified that OPEC rationally switched to a "market-share" regime as a response to shale. However, it is pointed out that other high-cost producers were affected as well, beyond those working with the U.S. shale, which in turn led them to invest less on future capacity, a suggestion similar to the one of Toews and Naumov (2015). Nevertheless, Prest (2018) observed that the decline in oil price since 2014 was probably a consequence of the weaker global oil demand rather the effect of the increased supply due to shale discoveries, while this evidence was also supported by Kilian and Zhou (2018).

2.5. Spillovers of oil shocks on stock market

With regard to the spillover effects, Sadorsky (1999) documented that high oil prices can depress stock market returns to an important degree, although the opposite case, that is when oil prices are low, does not hold. Similarly, Nandha and Faff (2008) suggested that oil price fluctuations have a negative influence on stock returns in all industries except for the mining and the oil and gas, while reference has also been done to the use of oil as a portfolio diversifier by investors. Additionally, Jones and Kaul (1996) provided evidence that stock market returns in the USA, Canada, Japan and the U.K. are negatively correlated with the impact of oil price shocks within those countries, while Papapetrou (2001) shows that movements in economic activity in Greece could be attributed to a large extent to oil prices, despite the fact that the country demonstrates tolerance to oil price changes. Assuming that worse economic and industrial activity translates to less amount for investments, it is normal to insinuate that this has negative influence on stock returns as well. Based on similar findings investors have been using commodities as a diversifier in their portfolios for a long time, taking for granted sometimes that this relationship will exist perpetually. However, the evolution of the index investing has probably given surge to the long-term strengthening of the integration between the oil and equity markets, as Tang and Xiong (2012) noted, especially during periods when the market is in turmoil, according to Silvennoinen and Thorp (2013). Subsequently, from the long-run perspective, the diversification value of oil derivatives has significantly reduced, signalling a need for amendment in the field of investment management, especially from individual investors. Slightly deviated are the implications of Kollias et al. (2011), when they examined the influence of terrorism and war on the oil price-stock connection and found that the covariance between shares and oil is significantly affected in each of the stock markets observed during war cases, while terrorism affects only the co-movement between CAC 40, DAX and oil returns. As a consequence, they imply that oil could be utilized as a portfolio diversifier over periods characterized by nonrecurring shocks, such as the terrorist attacks.

2.6. Spillovers with dynamic correlation models

Moreover, the use of dynamic correlation is a really important and highly reliable measure in order to estimate the interaction and spillover effects between two markets and as a consequence the literature that is hinged on that is quite broad. Bharn and Nikolovann (2010) utilized a dynamic bivariate EGARCH model to examine the relationship between stock market and oil prices and detected three major events (i.e. 9/11 terrorist attack, war in Iraq 2003 and the civil war in Iraq in 2006) which caused a negative correlation between the Russian stock market and the oil prices. Additionally, Chang et al. (2013) utilized four dynamic multivariate GARCH models, namely CCC model of Bollerslev (1990), VARMA-GARCH model of Ling and McAleer (2003), VARMA-AGARCH model of McAleer et al. (2008), and DCC model of Engle (2002), in order to address the volatility spillovers between crude oil returns (spot, forward and futures prices) and stock market returns. They found that the conditional variance fluctuated significant over time, with the one between Brent forward returns and FTSE 100 to be the most obvious such case.

2.7. Terrorism in oil-exporters

Furthermore, another ever-expanding literature is the one related to terrorist attacks in its broadest form, or more specifically for similar events in the region of Middle East, which is where oil production facilities are most concentrated. Les Coleman (2012) addressed the matter of explaining oil prices using fundamental analysis and justified the conventional wisdom, that terrorist activity in the Middle East is among the factors that does have a significant influence on the long-term price of the commodity. Others drivers are the market share of OPEC, the global GDP and size of the oil futures market in comparison with the physical oil demand. In addition, Barsky and Killian (2004) showed that political upheavals in the Middle East is one of the factors that affect oil prices, which in turn, contributing to the recessions in developed countries, at least to some extent. Of course, there are several other drivers behind this outcome, however, terrorism in Middle East has also its share due to the magnitude of oil concentration there. Nevertheless, we ought to highlight that, at the time of this writing, those conditions have changed significantly with the upgrowth of the United States of America as a top-tier producer of oil.

Terrorism has a constantly increasing influence on capital markets as the markets become more and more integrated and that is why this issue is widely investigated for the last decades. In this context, Eldor and Melnick (2004) studied the influence of Palestinian terror attacks on stock market of Israel between 1990 and 2003 and found that they had indeed real economic cost and that they even compressed firms expected returns. In addition to that, they observed that markets incorporate the news of terrorist attacks efficiently, while also remaining resilient to those events to the same extent over time. Similarly, Johnston and Nedelescu (2005, p. 19) showed that "diversified, liquid, and sound financial markets" were effective in absorbing the shocks generated by terror events, although the actions of the authorities were a critical factor in order for the markets to be stabilized. They also noted the necessity for changes in the current regulatory framework, so that financing of terrorist activities to be more thoroughly examined, preventing future events from taking place.

2.8. Terrorism impact on capital markets

Moreover, Arin et al. (2008) suggested that there was evidence of causality effects between terrorism and stock market performance, both in mean and variance. However, this association depended on the specific country under consideration, given that stock exchanges of Spain and the UK were found to be less affected by those shocks, hence it seems that investors in those markets are not that sensitive to terrorist attacks. Charles and Darné (2006) focused on the influence of the 9/11 attack, in the U.S., on the international capital markets and proved the significance of the shocks that followed. Also, worth-mentioning was the justification that substantial improvements in modelling financial risk are presented when terror events are taken into account. Finally, Abadie and Gardeazabal (2008) have also examined investors' reactions to similar events and have shown that in an integrated world economy terrorism may induce substantial movements of capital across countries and as a consequence hurting the domestic economy.

2.9. Government response to terrorism

The number of terrorist attacks and primarily their impact could be regarded as the main drivers for the ever-expanding literature addressing the issue of whether governments should have a direct line with terrorists, so that they can negotiate with them and avoid some unfortunate events. To begin with, Lapan and Sandler (1988) suggested that this strategy cannot be effective when terrorists are likely to fulfill their goal and cost of failing is considerably low, although a perfect Bayesian equilibrium was found in a partial-cooperative strategy. Enders et al. (1990) concluded to the inference that the installation of metal detectors has been the most satisfactory choice to protect against terrorism, as measured by the frequency of such events, while Atkinson et al. (1987) proposed that when bargaining cost increases, because of negotiation about a switch of strategy by officials, the same holds for the duration of the attack.

2.10. Use of the Event Study Methodology – general studies

Event study methodology could be considered as the most common approach to estimate the impact of an event on the subject security regardless of the specific industry or event. In this context, Ramiah et al. (2016) produced a noticeable work in order to assess the effects of Brexit, based on the reaction of stock market indices following the announcement of the outcome of the referendum on 24th June 2016. The grouping of the abnormal returns (ARs) into industries to capture cross-sectoral results and the adjustment to the daily returns to obtain ex-post ARs were in accordance with Ramiah et al. (2013), and they were core elements that contributed to the inference drawn. In particular, they justified that Brexit will have mainly negative impact on most sectors, as expected by the academic community at large, although there were some exceptions such as the aerospace and defence, beverages and tobacco. Yu and Huarng (2019) proposed a new event study method to project stock returns of Facebook by utilizing news during the estimation period and the in-sample data to determine the thresholds based on which some firm-specific rules, that will be then used for forecasting purposes in the event period, will be built . The above-mentioned thresholds can be considered as the ARs, so as to detect whether the abnormal performance of the stock is due to the event under review.

2.11. Event Study Methodology and terrorism

ESM approach has also been employed to quantify the impact of accidents on the value of energy firms by Boersen and Scholtens (2011), while Chen and Siems (2004) used it to estimate the influence of terrorist attacks on global capital markets. More specifically, the latters concluded that terrorist attacks and military invasions have great potential to affect capital markets in a short period of time and that the U.S. markets seem to have become able to absorb shocks brought on by such events more effectively, thanks to their relatively robust banking sector. Similarly, the former study showed that the industry under review had reacted negatively to the corresponding accident, although the magnitude of this response was not important. Those two studies are greatly aligned with our subject, which could be articulated in its most general form as the impact of an exogenous event on oil price and the spillover effects derived from it, hence underpinning our work on that issue. Chesney et al. (2011) made use of three distinct methodologies namely, event-study, non-parametric and filtered GARCH-EVT, to compare the effect of terrorist events on capital markets with the effect of natural catastrophes and financial crashes. They detected that terrorist attacks and financial crashes cause an event-day return fluctuation, whose impact declining in the post-event period, whereas in cases of natural disasters the negative influence is more often observed in the post-event period. Moreover, they suggested some portfolio diversification strategies for investors, who should hold assets that have little or no correlation with terrorism risk such as US Government bond index or stocks from aero/defense and pharma/biotech industries. Hempel (2016) also used the event study methodology to investigate the behavior of bond and stock markets in response to terrorist attacks and realised that the equity returns of the estimation-window and fatalities are the only statistically significant predictors of bond and stock cumulative abnormal returns (CARs), respectively. Futhermore, Schuurman (2017) utilized the ESM approach to test the impact of 22 terrorist attacks, in 10 different countries, on the European and global financial markets and discovered that all of them had substantial negative influence on stock indices, while attacks in North America proved to have more enhanced immediate effect than those in Europe. Finally, reference has been made to the diminishing effect of such events over time, which is in accordance with Arin et al. (2008). This could be alternatively interpreted as the existence of short-term market inefficiencies, although the fast recovery indicates for somewhat of long-term efficiency.

In conclusion, there is a vast literature that examines the oil price fluctuation, its spillovers on other sectors and the impact of terrorism on capital markets. In addition, a great proportion of those studies utilize the event study methodology to check for the existence of any abnormalities due to such events, hence we infer that our work is well-supported based on past studies. In the Methodology Chapter that follows more details are incorporated for this model and its variations.

3. Methodology

3.1. Preface of Methodology

Event study methodology has long been recognized as a powerful tool to detect the influence of occurrences on the value of securities. In this context, it is still widely used to research the impact of events, such as earnings announcements, M&A, terrorist attacks and others, and that is why we opted for this specific approach. The papers by Ball and Brown (1968) and Fama et al. (1969) are considered to be the landmarks for the event study approach, although a great number of authors has tried to expand those by distinguishing their work with the use of additional assumptions. The common ingredient between the two papers is the utilization of the broadly known market model over other measures of normal performance. This domination will be partially maintained, in that we are about to implement the market model along with the constant mean normal return model. The above-mentioned choice constitutes the first decision we have to make in order to conduct the study under consideration, while the specification of the estimation and event window is also pronounced. In that manner we obtain the parameter computation needed to proceed to the econometric design, which includes the null hypothesis definition, both for the abnormal returns and the cumulative abnormal returns. Lastly, we present the empirical results, hoping for prolific diagnostics, and gauge the significance of the results by performing robustness check based on the importance of the cumulative abnormal returns, since a persistent deviation from the normal performance would support the findings of the abnormal returns.

At this point we need to refer to the calculation of abnormal returns, which is the difference between the actual ex post returns of the asset over the event window and the normal returns over the same period.

$$AR_{it} = R_{it} - E(R_{it}|Xt) \qquad (1),$$

where ARit, Rit and E(Rit|Xt) are the abnormal, actual and expected (normal) returns, respectively, for asset i and event date t.

3.2. Normal Return model

The choice over the estimation window length is highly associated with the one over the normal return model, hence the latter is really crucial in many aspects. Generally, there are four distinct models; the constant mean return model, the market model and other statistical and economic models, according to MacKinlay (1997). The constant mean return model assumes that the normal returns equal to the mean returns of a security and that they will remain constant through time, while the latter postulates that they derive from a linear relationship between the market and the actual returns, the so-called market model. In particular, the returns for period t and security i, according to constant mean return model, are assessed as follows:

$$ER_{i,t} = \mu_i + \zeta_{it} \qquad (2),$$

where μ_i is the constant mean for security i and ζ_{it} is the disturbance term for time period t and security i, whereas in market model the returns for period t and security i are estimated as follows:

$$ER_{i,t} = a_i + b_i R_{m,t} + e_{it} \qquad (3),$$

where a_i is the constant term, R_{mt} is the market returns for period t, b_i is market portfolio's coefficient and e_{it} and is the zero mean disturbance term.

The former model is, usually, implemented when limited data are available, given that it requires no parameter estimation based on the pre-event period, as model coefficients are prespecified. Under these circumstances, the potential biases resulted from the imposition of restrictions need to be taken into account. Jay Ritter (1991) investigates the underpricing of an IPO and provides such an example. On the other hand, the factor model, which is the statistical approach that is employed more often, reduces the variance of the AR due to the explanation more of the fluctuation in the normal return. We must highlight that the market model is a typical instance of a one factor model, since it utilizes a portfolio that assumes the market performance. Moreover, there has been plenty of work that is hinged on multifactor models, such as the ones of Sharpe (1970) and Sharpe et al. (1995), that includes industry indices in addition to the market. However, the gains deriving from those approaches might even be restricted because of the negligible explanatory power added. In order for this difficulty to be solved, the use of economic models as limitations on the statistical models have been devised and as a result more constrained normal return models were constructed. The Capital Asset Pricing Model of Sharpe (1964) and Lintner (1965), and the Arbitrage Pricing Theory of Ross (1976), are the most notorious and widely used of this kind, although their benefits have been under dispute. More specifically, the former was criticized as sensitive to the specific CAPM conditions whereas the latter is said to behave just like a market model, hence no significant improvement is made.

In our case, as it has already been established, we opted for the market model and the constant mean return model. Worth-mentioning is the fact that the former approach dominates the majority of the literature utilizing the event study methodology, while it is also intriguing that the normal returns measurement could be performed not only with the ordinary least squares (OLS), but also with other type of regressions such as the Quantile (median quantile) and GARCH(1,1). In this paper, we do employ each of these 3 kinds of estimators in order to compare their findings. Afterwards, we measure the abnormal returns by subtracting the expected returns estimated based on the market model, Equation (3), from the actual returns, where returns are calculated by dividing the closing prices of two consecutive trading days and subtracting one unit afterwards. The equations described are the following:

$$AR_{i,t} = A_{i,t} - ER_{i,t} \qquad (4),$$

$$A_{i,t} = (P_{i,t} / P_{i,t-1}) - 1 \qquad (5),$$

The Equations (4) and (5) are the very same for the constant mean model as well, but the expected returns ($ER_{i,t}$) in this case are the simple arithmetic mean of the asset under consideration during the estimation period.

3.3. Event and Estimation window

Regarding the estimation window we consider a period of 45 days to be the optimal, given that oil prices have undergone a correction just few days after the event has taken place, thus its short-term impact signals that there is no value in computing the parameters over a lengthier window. However, we should be aware of any significant shock not to have taken place in the meantime, so that the returns reflect the true normal returns instead of the influence of yet another event on oil price. On the other hand, a 7-day event window should be enough for the needs of the present work based on the fluctuations on oil prices that followed the attack on the facilities in Abqaiq and Khurais. More specifically, when the markets opened on Monday, September 16, and the officials observed how the investors responded a lot of interventions took place, with the one of the President Trump to be the most prevailing. He declared that the U.S.A. will supply the oil needed in order for the daily world production not to be reduced, a fact that provoked the immediate correction in oil prices. What is more, it is of paramount importance for the estimation and the event window not to overlap in order to avoid the influence of the event returns on the model parameters and, in turn, on the expected returns. Hence, we define the event day as t_0 so that the event window is; [t_0 , t_6], while the estimation window is; [t_{-45} , t_{-1}]. However, we should note that, theoretically, the event window could even start before the event day so as to test whether the market has already discounted the probability of the event's emergence. For instance, we could split our 7-day event window by setting the starting point two days prior to the event, so that the event period to be formulated as [t_{-4}, t_2]. This adjustment could be adopted in cases with expected events, such as earnings announcements, when the information leakage is highly likely to happen, thus it is considered to be an unnecessary action in exogenous events like the one under consideration.

Afterwards, we define that the null hypothesis is considered to be the case in which no abnormal returns are observed. In practice, this means that the event under review, which is the terrorist attacks in Saudi Arabia, does not affect oil returns, thus it could be marked as a fact of minor importance. On the contrary, in case of existence of abnormal returns, through the rejection of the Ho, our expectation will be justified as the short-term rally in oil prices in mid-September would, indeed, be induced due to the attack. Similarly, the null hypothesis of the cumulative abnormal returns concerns the absence of persistence of the shock, which could even suggest that the event under consideration was a daily abnormality of the market instead of the result of a substantial exogenous event. The process followed in order to verify the statistical significance of the event is described below, both for the ARs and the CARs.

3.4. Abnormal Returns and Significance computation

Another core issue is the sum of the abnormal returns, since for periods longer that one day, cumulative abnormal returns should be calculated, according to Bonekamp and Van Veen (2017). Hence, we sum the daily abnormal return of our 7-day event-window, for every security under consideration (Brent crude oil and WTI crude oil), in that: $CAR_{i,t} = \sum_{t=0}^{6} ARi,t$ (6)

Worth-mentioning is the fact that the statistical significance of this estimation is often utilized as a robustness check, although a simplistic one compared to non-parametric tests. In addition to that, the assumption that indices follow a normal distribution, noted by Brown and Warner (1980), allows us to compute a t-statistic with the use of the Abnormal Returns as numerator and the standard deviation of the returns during the estimation window as the denominator. According to the same work, the standardized abnormal returns could be aggregated so as to form an alternative test statistic, but that is anticipated to make little difference when the event study focus is short-horizon. As for CARs t-statistic we need to calculate the ratio of the CARs to their standard error, whose computation is given by the following equation:

$$S_{CAR} = \sqrt{(L_1 * S^2_{AR_t})} \quad (7),$$

where L_1 amounts to the difference between T_2 and T_1, with T_2 as the latest day of the event window and T_1 as the latest day of the estimation window.

Moreover, cumulative abnormal returns indicate the persistence of the event under review, in terms of impact on the financial markets, thus the inferences deriving from that measure are quite intriguing. For this reason, we test them on multiple dates after the event day, in order to monitor the resilience of each of the markets (stock market and oil market) and each of the commodities (Brent and WTI crude oil). In particular, just like in the case of ARs, we will estimate the CARs for all 7 days of our event window in order to detect whether the presence of abnormal performance was long-lasting or short-term.

3.5. Time-varying systematic risk measurement

Given that we make use of the market model beta coefficients are estimated, and taking into account that it is the most widely used indicator of relative risk it would be interesting to observe its fluctuations over time. For this purpose, plenty of approaches have been employed in the finance literature such as the Rolling regression, the Recursive regression, multivariate GARCH models and the Kalman Filter. In this paper, we are going to implement three of these measures in order to capture the changes in the systematic risk. Firstly, Rolling regression requires to set an estimation window, just like in the event study, during which the parameters needed are calculated. This window is kept constant in size through the calculation, but it is moved one observation forward in time and then the process is repeated. Moreover, necessary is also the definition of a step, that is the frequency we want to see the variations in beta, which allows for tailor-made analysis.

Similarly, Recursive regression is performed by applying the ordinary least squares (OLS) on the historical returns while increasing the size of the window by one observation each time. Alternatively, we run a Rolling regression once more but anchoring the window at start. This difference between the two approaches is responsible for the divergent results obtained, since the Rolling regression assigns equal weight to each observation in the rolling window, whereas Recursive regression assigns less weight to each subsequent observation.

Finally, the Kalman Filter is considered to be the most sophisticated methodology among those three and this is probably why it is the most widely used as well, since it entails a state space formulation of the problem. In particular, two equations are necessary in order for this approach to be conducted, the measurement and the transition equation.

The former should be in the form of: $Y_t = b^*X_t + e_t,$ (8)

where in the case of the market model the dependent variable is the asset under consideration and the explanatory variable is the market returns, as measured by a broad index such as the Standard & Poor's 500. On the other hand, the latter equation assumes that betas follow a random walk process according to Faff et al. (2000), thus the corresponding equation is given by the following relationship: $\beta_{it} = \beta_{it-1} + \eta_t$ (9)

What is also worth to be highlighted is the fact that the Kalman Filter is also a recursive algorithm, as it is actually hinged on a repeated and revised procedure, at each point in time. One of the most recent and well-known such observation was the one of Renzi-Ricci (2016) in his comparison of the ordinary least squares with the Kalman Filter.

In the next section we take a glance at the data employed in this paper, while some substantial properties are also monitored so that we implement the proper adjustments, if needed. Additionally, a variance analysis is conducted in order to capture the changes in volatility prior and post to the event.

4. Data Description

4.1. Preface of Data Description

We have already specified that the models selected in this paper, in order to capture the normal return, are the market model and the constant mean return model. In finance literature the most commonly used measure to reflect the market performance is the S&P 500 due to the substantial influence that large-cap companies have on the total market returns. On the other hand, given that our estimations will focus on Brent and WTI crude oil futures, we consider the Dow Jones Commodity Index (DJCI) to be a more appropriate benchmark, as the market under investigation is the oil market. However, we decided to calculate the Abnormal Returns both ways so that our analysis is not subjected to any benchmark-driven sensitivities. As for the DJCI, we need to point out that the commodities in this index are initially weighted by liquidity, based on the 5-year average total dollar value traded (TDVT), while at second stage adjustments are implemented so that only one of its components reaches the weight of 35% and no other exceeds the threshold of 20%. The final step for the index is related to the requirement of equal weighting for all sectors, meaning that one-third is attributed to each of the energy, metals and agriculture & livestock sectors. The above-mentioned commodity index was chosen due to its equal weighting approach in contrast to other indices, such as the S&P GSCI, that are heavily hinged on oil. This decision is partially aligned with that of Kutan and Demirer (2010), as the authors employed the Dow Jones AIG Commodity Index as market proxy as well. All data was retrieved from Investing.com at daily frequency and as a consequence the 15th of July is the first day of our estimation window (t= -45), while the event day (t= 0), on September 16, marks the starting point of the 7-day event window.

4.2. Descriptive statistics and Asset illustration

Table 1. Descriptive Statistics of the Assets used

	Brent Returns	WTI Returns	SP500 Returns	DJCI Returns
Mean	(0.000625)	(0.000377)	(0.000316)	(0.000437)
Median	0.000900	0.000200	0.000100	(0.001050)
Maximum	0.146100	0.146800	0.018800	0.037200
Minimum	(0.071700)	(0.079000)	(0.029800)	(0.026700)
Std. Dev.	0.030628	0.031688	0.010107	0.009505
Skewness	1.728127	1.591281	(0.862954)	0.910138
Kurtosis	11.92258	10.67799	4.486908	7.279994
Jarque-Bera	198.3758	149.6739	11.24425	46.86879
Probability	0.000000	0.000000	0.003617	0.000000

As expected, *Table 1* indicates that the returns of Brent oil, WTI crude oil and DJCI do not follow the normal distribution, given that Skewness does not amount to 0, Kurtosis does not equal to 3 and Jarque-Bera is much greater than the benchmark of 5.99. Additionally, the fact that the mean of all four assets approaches the null territory even after taking into account the abrupt and intense hike on September 16 signals that there was an overall downward tendency before the occurrence of the event under review, except for the case of the S&P 500 index in which the trend was actually even more upward. Moreover, worth-mentioning is the fact that the outputs of this index returns approach the thresholds of what is consider to be normally distributed, as far as mean, skewness and kurtosis are concerned. All these are perfectly aligned with the returns graphs below.

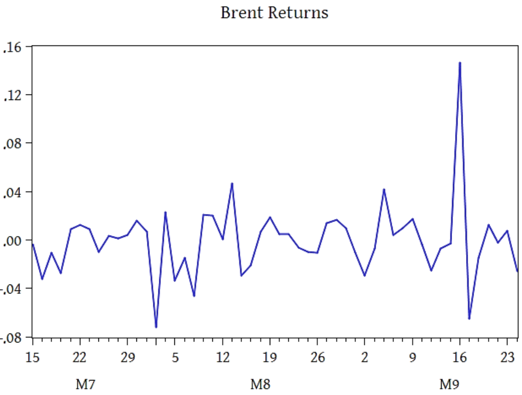

Figure 1. Returns of Brent oil

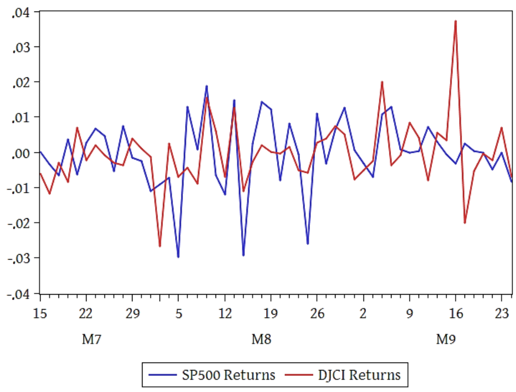

Figure 2. Returns of market indicators

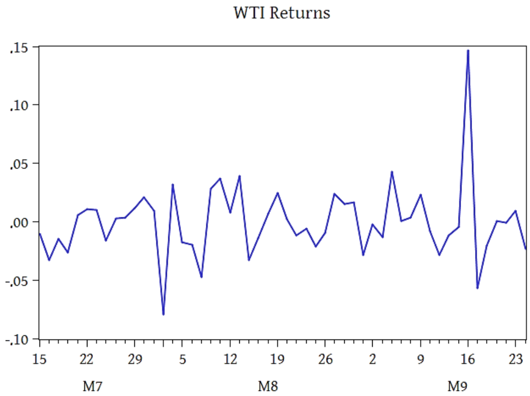

Figure 3. Returns of WTI crude oil

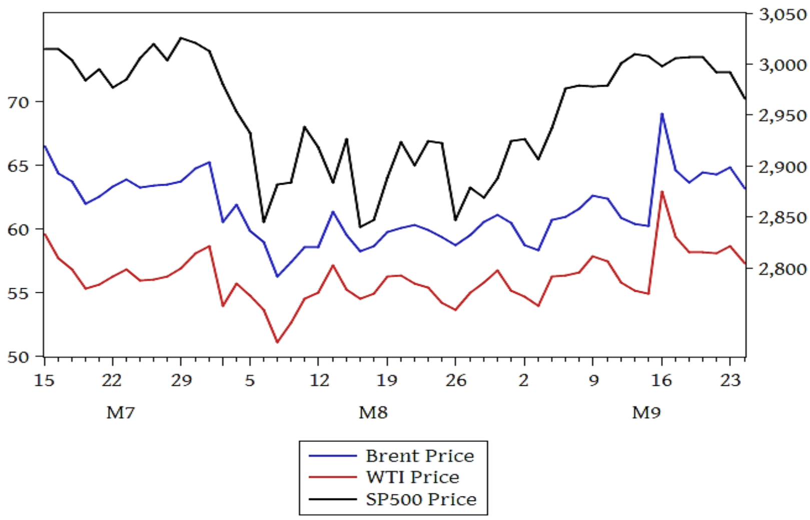

Figure 4. Oil futures prices (left) Vs S&P 500 price (right)

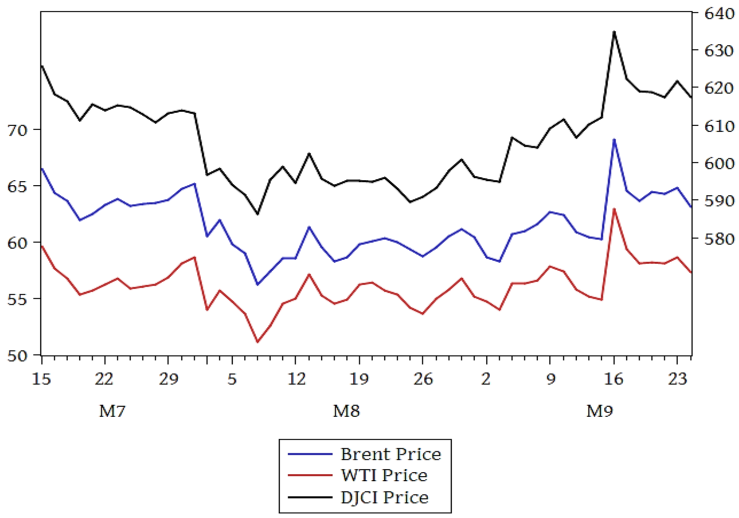

Figure 5. Oil futures prices (left) Vs DJCI price (right)

The figures above *(Figure 1, 2, 3, 4, and 5)* indicate that both WTI and Brent crude oil seriously impact the commodities market through Dow Jones Commodity Index, whereas the effect on stock market is disputable at first glance. This could be attributed to the weighting that high-tech companies have in market indices like the S&P 500, given that they are not that hinged on cost of energy compared to other industrial and manufacturing businesses. In addition to that, one can notice the immediate absorption of the shock by the market, taking into account that both futures representing the oil price significantly declined the second trading day of our event window, although still remaining above the level that they were trading before the attack took place.

4.3. Unit-root test

Table 2. Unit-root test on the Assets used

ADF test statistic	Brent Returns	WTI Returns	SP500 Returns	DJCI Returns
t-Statistic	(8.792828)	(8.366491)	(8.170316)	(8.771403)
Probability	0.0000	0.0000	0.0000	0.0000

Firstly, in order to conduct the market model we need to estimate the parameters that will be utilized in the normal performance projection (intercept and beta) and the standard deviation in our estimation window as well, so that we calculate the t-Statistic that will decide the existence, or not, of abnormal returns. Thus, four regressions should be run with our four variables, in which each oil indicator (Brent and WTI) will be the dependent variable twice. Before proceeding with the regressions, we need to ascertain the stationarity of our assets, or else no regression is allowed to be implemented. Indeed, *Table 2* proves that the returns of Brent and WTI crude oil, DJCI and S&P 500 index are stationary in every level of statistical significance, since the p-values extracted from the Augmented Dickey-Fuller test amount to zero.

4.4. Diagnostics

Table 3. Autocorrelation test of first and second order

Autocorrelation	Brent ~ SP500	Brent ~ DJCI	WTI ~ SP500	WTI ~ DJCI
Durbin-Watson	2.0954	1.717502	2.049088	1.702997
Breusch-Godfrey	0.7546 ˣ 0.7550 ˣˣ	0.4186 ˣ 0.4015 ˣˣ	0.8623 ˣ 0.8567 ˣˣ	0.3705 ˣ 0.3534 ˣˣ

ˣ → **F-statistic, Prob. F(1,49)**

ˣˣ → **Obs*R-squared, Prob. Chi-Square(1)**

Table 3 presents the results of first and second-order autocorrelation tests, according to which it is clear that there is no second-order Autocorrelation, taking into consideration that p-values of

Breusch-Godfrey are beyond the 0.1 (10%) level of economic significance. This translates into accepting the null hypothesis of no autocorrelation. However, regarding the first-order Autocorrelation the results are more controversial, since the value of 2 is considered to be the equivalent of no autocorrelation, but we observe that in the regression of both WTI and Brent crude oil on DJCI there is a substantial deviation which might even indicate positive autocorrelation. At this point, we should refer to the rule of thumb for Durbin-Watson test, according to which an output of less than 1 is generally a cause for alarm, while values between 1.5 and 2 are relatively normal.

Table 4. White's heteroskedasticity test

Heteroskedasticity White test	**Brent ~ SP500**	**Brent ~ DJCI**	**WTI ~ SP500**	**WTI ~ DJCI**
F-statistic	0.6697 ˣ	0.9148 ˣ	0.4978 ˣ	0.7130 ˣ
Obs*R-squared	0.6535 ˣˣ	0.9092 ˣˣ	0.4794 ˣˣ	0.6981 ˣˣ
Scaled explained SS	0.5664 ˣˣ	0.9512 ˣˣ	0.3846 ˣˣ	0.7924 ˣˣ

ˣ → **Probability F(2,41)**

ˣˣ → **Probability Chi-Square(2)**

Another crucial property of every regression is the one related to the variability of the standard errors, given that adjustments might be needed in case that this property exists. In order to check for this issue we employed the White test, which is one of the most prevailing tests for Heteroskedasticity and we concluded that our sample does not have to address this problem, since the p-values in *Table 4* are well above the 0.1% level of statistical significance in each of the four regressions run and that the null hypothesis assumes stable variance.

Table 5. Ramsey Reset test

Ramsey RESET test	**Brent ~ SP500**	**Brent ~ DJCI**	**WTI ~ SP500**	**WTI ~ DJCI**
t-Statistic	0.7234	0.1439	0.7374	0.1361
F-statistic	0.7234	0.1439	0.7374	0.1361
Likelihood ratio	0.7125	0.1302	0.7270	0.1207

Probabilities

Ramsey RESET test is a general specification test and it is utilized for linear regressions, so that we obtain an evidence related to whether this relationship is good enough for the regression. If it is not, transformation into a more complex, non-linear type is necessary. Given that the null hypothesis signals for a well-specified model, and the p-values in each of the regressions are above the critical value (10% or 0.1), we do accept the null hypothesis which means that there is no value in modifying the current type of the equation.

4.5. Variance overview

Having estimated the necessary diagnostics in our estimation window, it might be productive to take a glance at the variance. For this reason, we performed a GARCH (1,1) test based on Bollerslev (1986) on each of the variables during the period of July 15 and September 24, in order to check for the existence of volatility clustering and leverage effect. We did include the event day in our estimation on purpose, so that we see if there are any substantial changes after this occurrence. Firstly, Mandelbrot (1963) observed the tendency of big changes to be followed by big changes, and vice versa for small changes, a fact that implies the deviation from the average variance for longer than just one observation. When referring to securities, this is probably explained by the subsequent correction after a huge shock. We expect this property to have an inversed relationship with the capitalization, given that finance theory teaches us that the smallest the capitalization the greatest the volatility.

Table 6. GARCH model estimation

Variance Equation	**Brent Returns**	**WTI Returns**	**SP500 Returns**	**DJCI Returns**
C	7.89E-06 ˣ 0.0804 ˣˣ	2.10E-05 ˣ 0.0018 ˣˣ	5.02E-06 ˣ 0.4046 ˣˣ	1.22E-06 ˣ 0.0620 ˣˣ
RESID(-1)^2	(0.155587)ˣ 0.0000 ˣˣ	(0.158962) ˣ 0.0000 ˣˣ	0.337229 ˣ 0.1027 ˣˣ	(0.172556) ˣ 0.0000 ˣˣ
GARCH(-1)	1.167583 ˣ 0.0000 ˣˣ	1.152523 ˣ 0.0000 ˣˣ	0.682801 ˣ 0.0000 ˣˣ	1.162857 ˣ 0.0000 ˣˣ

ˣ → **Coefficient**

ˣˣ → **Probability**

The economic significance of the square of Residuals coefficient (of the previous period) signals the existence of the above-mentioned phenomenon, hence we deduce that there was an evidence of volatility clustering in every case except for the S&P 500 index, which is in accordance with our anticipation, since this index reflects the performance of blue chips with major capitalization. Moreover, of paramount importance is also the significance of the GARCH (-1) coefficient, because this translates into volatility dependence, the claim that history does matter. *Table 6* indicates that this was true for both oil futures and market indices, thus all variables presented persistent behaviour across that time frame.

All these inferences are better illustrated in *Figure 6 & Figure 7* below, where we observe the fluctuation in the conditional variance as measured by the above-mentioned GARCH model. We see that the movements of WTI and Brent crude oil were almost identical, as anticipated, whereas noteworthy is the negligible rise in volatility in the DJCI index compared to the oil futures. Certainly, one would expect an even greater increase, considering that this specific index reflects the commodity market, thus includes oil assets. As for the S&P 500 index, it was probably most affected by the Trade War between the U.S. and China that took place around the same period.

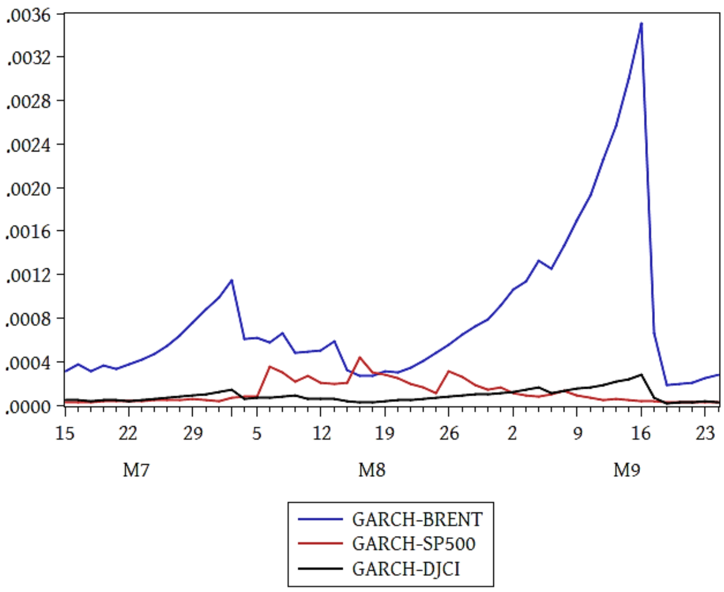

Figure 6. Conditional Variance; Brent oil Vs market indicators

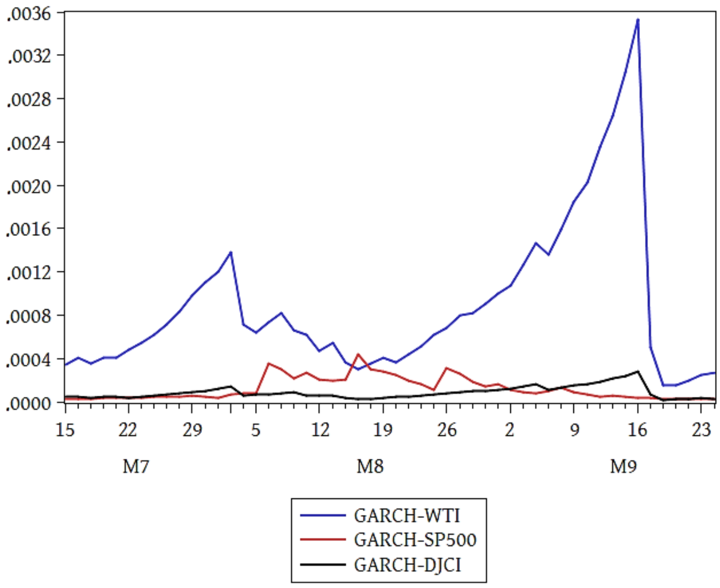

Figure 7. Conditional Variance; WTI crude oil Vs market indicators

Finally, we checked for the existence of the so-called leverage effect, which refer to the greater extent that negative shocks influence future volatility, compared to the positive ones. In our case the attack on the Saudi Arabia oil facilities is considered to be a positive shock for all oil-related assets utilized, namely WTI crude oil, Brent oil and DJCI index, while the opposite holds for S&P 500 index. We assessed this fact with the use of an EGARCH model, based on Nelson (1991), since this approach allows for asymmetries in the structure of the variance, hence avoiding the need for any parametric constraints. Profound attention is paid to the C(4) coefficient below (*Equation 10)* as it captures the evidence regarding the leverage effect.

$$\text{EGARCH}(1,1,): \ln(\sigma^2_t) = C(2) + C(3) * |u_{t-1}|/\sigma_{t-1} + \gamma + C(4) * u_{t-1}/\sigma_{t-1} + C(5) * \ln(\sigma^2_{t-1}) \qquad (10),$$

We discern three distinct cases: I) C(4) is negative, in turn, justifying the presence of the leverage effect, II) C(4) is positive, which translates to greater impact of the positive shocks on the volatility, and III) C(4) coefficient amounts to zero, insinuating the absence of asymmetries in volatility.

Table 7. EGARCH model estimation

Variance Equation	**Brent Returns**	**WTI Returns**	**SP500 Returns**	**DJCI Returns**
C	(5.730076) ˣ 0.2347 ˣˣ	(1.040749) ˣ 0.0000 ˣˣ	(0.485495) ˣ 0.0000 ˣˣ	(2.437513) ˣ 0.0000 ˣˣ
|Resid (-1)|/Garch (-1)	(0.407358) ˣ 0.0563 ˣˣ	(0.922879) ˣ 0.0000 ˣˣ	(0.549444) ˣ 0.0005 ˣˣ	(1.251180) ˣ 0.0000 ˣˣ
Resid (-1)/Garch (-1)	0.382765 ˣ 0.1186 ˣˣ	0.187247 ˣ 0.0918 ˣˣ	(0.601593) ˣ 0.0187 ˣˣ	0.294063 ˣ 0.0000 ˣˣ
ln Garch (-1)	0.154628 ˣ 0.8224 ˣˣ	0.758330 ˣ 0.0000 ˣˣ	0.905045 ˣ 0.0000 ˣˣ	0.647423 ˣ 0.0000 ˣˣ

ˣ → **Coefficient**

ˣˣ → **Probability**

It is clear that the leverage effect is detected solely in the S&P 500 index in our sample, an outcome that was likely anticipated, given that events like the one under consideration negatively impact only the stock market and as a consequence increasing its volatility. On the other hand, the potentially positive association between oil prices and terrorist events resulted in the suggestion that positive shocks induce more volatility in commodities market, through the DJCI index. Nevertheless, this relationship is probably more complicated, since both the Brent and WTI crude oil were found to be highly resilient based on the statistically insignificance of the C(4) coefficient at 5% level of importance. However, there are differences even between those two, since in the case of the WTI returns economic significance is observed in 10% level, in contrast with the outcome of Brent returns.

4.6. Quantile Regression

In econometrics the quantile regression is used because of the existence of outliers, and taking into account that we do examine a sample that includes one major outlier the results could be fruitful. This method was first introduced by Koenker and Bassett (1978) as an extension of the ordinary least squares, but instead of calculating the conditional mean of the response variable it estimates the conditional median. Thorough attention will be paid to the 0.500 quantile, since it should approach the values of the OLS estimator.

Table 8. Quantile regression of Brent oil against S&P500

Quantile Regression	Quantile	C Coefficient	SP500 Coefficient	Prob. (C)	Prob. (SP500)
	0.111	(0.028052)	0.396135	0.0000	0.3472
	0.222	(0.016947)	0.558824	0.0007	0.1196
	0.333	(0.006288)	0.799054	0.1076	0.0125
	0.444	(0.003621)	0.737589	0.3575	0.0249
Brent ~ SP500	0.500	(0.001636)	0.748344	0.6756	0.0247
	0.556	0.003384	0.505181	0.4004	0.2102
	0.667	0.008414	0.642857	0.0336	0.1141
	0.778	0.012122	0.551913	0.0015	0.2146
	0.889	0.019135	1.113333	0.0000	0.0010

Table 9. Quantile regression of Brent oil against DJCI

Quantile Regression	Quantile	C Coefficient	DJCI Coefficient	Prob. (C)	Prob. (DJCI)
	0.111	(0.016713)	2.416431	0.0000	0.0000
	0.222	(0.008426)	2.482014	0.0014	0.0000
	0.333	(0.005950)	2.462541	0.0328	0.0000
	0.444	(0.002842)	2.578947	0.3164	0.0000
Brent ~ DJCI	0.500	0.000205	2.694118	0.9433	0.0000
	0.556	0.001397	2.801527	0.6376	0.0000
	0.667	0.007887	2.980769	0.0237	0.0000
	0.778	0.012434	3.151079	0.0011	0.0000
	0.889	0.016487	3.347826	0.0000	0.0000

Table 10. Quantile regression of WTI crude oil against S&P 500

Quantile Regression	Quantile	C Coefficient	SP500 Coefficient	Prob. (C)	Prob. (SP500)
	0.111	(0.028486)	0.143813	0.0000	0.6929
	0.222	(0.016292)	0.560000	0.0006	0.1294
	0.333	(0.010583)	0.413793	0.0211	0.2738
	0.444	(0.003931)	0.670635	0.3923	0.0867
WTI ~ SP500	0.500	(0.000823)	0.564103	0.8567	0.1512
	0.556	0.002586	0.670683	0.5792	0.0889
	0.667	0.008195	0.858896	0.0728	0.0161
	0.778	0.013194	0.808824	0.0029	0.0198
	0.889	0.023607	1.073826	0.0000	0.0024

Table 11. Quantile regression of WTI crude oil against DJCI

Quantile Regression	Quantile	C Coefficient	DJCI Coefficient	Prob. (C)	Prob. (DJCI)
	0.111	(0.013492)	2.453488	0.0000	0.0000
	0.222	(0.008470)	2.560714	0.0014	0.0000
	0.333	(0.007049)	2.490000	0.0145	0.0000
	0.444	(0.000807)	2.928571	0.7949	0.0000
WTI ~ DJCI	0.500	0.001201	3.003788	0.7292	0.0000
	0.556	0.001732	2.934911	0.6087	0.0000
	0.667	0.006434	3.167539	0.0725	0.0000
	0.778	0.013316	3.513369	0.0001	0.0000
	0.889	0.015988	3.552083	0.0000	0.0000

We observe that the outcomes of the quantile regressions above are almost identical between the two crude oil futures, thus we could refer to them as a group in order to interpret the results in a more concise way. In this context, we commence with the economic significance of the beta coefficient in both cases when S&P 500 is the explanatory variable, in which we see statistical insignificance of betas at 5% level in 5 and 6 quantiles respectively, for Brent and WTI futures. This could be attributed to the fitting of the S&P 500 as the indicator of the market performance, when our dependent variables are oil futures rather than shares. Additionally, at the top quantile in *Tables 8 and 10,* where the returns of our event day are captured, the beta exceeds the threshold of 1, hence the relative risk is greater than that of the S&P 500. On the other hand, when DJCI index represents the market we get statistically significant betas in all quantiles, in turn, contributing to our suitability theory. In parallel, the magnitude of coefficients highlights a relative risk that is two or three times greater than the one of the commodity market, which means that the two oil futures are much more risky than the corresponding commodity market index. This might be explained by the presence of the gold in the index, an asset that is less volatile than most of the investment products, except for periods of massive turmoil such as financial crises.

In the next chapter we present our findings of both the event studies performed and the systematic risk analysis, based on the framework that has already described in the Methodology section.

5. Empirical Results

5.1. Preface of Empirical Results

In this section we present the results of the methodology applied, so that we draw some inferences regarding the existence of abnormal returns at first stage and the persistence of this fact afterwards, assuming that there is abnormal performance. Given that we have conducted four event studies with the use of the market model, as we had to work with both crude oil futures and detect the normal returns when considering two distinct assets as market, and two event studies with the use of the constant mean model, we decided to structure the section accordingly. In particular, we present the findings of the market models, for each of the oil futures separately and based on 3 distinct estimators of the normal performance (OLS, Quantile regression and GARCH), followed by those of the constant mean model. The outcomes can be observed both with the use of graphs and quantified on tables, so that t-Statistic is included as well. Finally, we chose to illustrate the effect of the event under review on the systematic risk through the beta coefficient of the so-called market model. We accomplished that with three distinct methodologies, namely Rolling regression, Recursive regression and Kalman Filter, so as to have more robust results that are not subjected to any approach-driven sensitivities.

5.2. Market Model

In this sub-section the findings extracted from the market model are demonstrated, starting with the two cases when the Brent crude oil is considered to be the dependent variable, and presenting the corresponding cases for the WTI crude oil afterwards. Thus, the whole interpretation is conducted based on comparative analysis between the same approach (i.e., the market model) but with different market indicators.

5.2.1. Brent crude oil Vs Market indicators

Table 12. Event study results: Brent oil against S&P 500

OLS	Brent - SP500			
Event Date	ARs	t-Statistic	CARs	t-Statistic
0	14.62%	7.18 ***	-	-
1	(6.47%)	(3.18) ***	8.14%	4.00 ***
2	(1.46%)	(0.72)	6.68%	2.32 **
3	1.27%	0.62	7.95%	2.25 **
4	(0.18%)	(0.09)	7.76%	1.91 *
5	0.77%	0.38	8.53%	1.87 *
6	(2.57%)	(1.26)	5.95%	1.19
Quantile Regression				
Event Date	ARs	t-Statistic	CARs	t-Statistic
0	15.01%	7.36 ***	-	-
1	(6.51%)	(3.20) ***	8.49%	4.17 ***
2	(1.33%)	(0.65)	7.17%	2.49 **
3	1.42%	0.70	8.59%	2.43 **
4	0.34%	0.17	8.93%	2.19 **
5	0.93%	0.46	9.86%	2.16 **
6	(1.79%)	(0.88)	8.07%	1.62
GARCH (1,1)				
Event Date	ARs	t-Statistic	CARs	t-Statistic
0	15.11%	7.42 ***	-	-
1	(6.45%)	(3.16) ***	8.67%	4.25 ***
2	(1.25%)	(0.61)	7.42%	2.57 **
3	1.51%	0.74	8.93%	2.53 **
4	0.46%	0.23	9.39%	2.30 **
5	1.02%	0.50	10.40%	2.28 **
6	(1.64%)	(0.81)	8.76%	1.75 *

Table 12 indicates that the impact of the attacks on the oil facilities of Saudi Aramco was substantial over the first two days of our 7-day event window, as measured by the abnormal returns t-Statistic of Brent against the S&P 500 at 10% level of economic significance in each of the three cases. Additionally, the persistent influence of this event is detected through the

cumulative abnormal returns, given that they were important at the level of 5% in all but one observation of our event window according to the Quantile and the GARCH estimators, while the same holds for the ordinary least squares but at the level of 1%. The duration that this event affected the Brent oil price might be connected with the expectations of the investors that a response was about happen, a possibility that was indeed under review by the U.S. officials, as stated, thus still affecting investors' sentiment.

Table 13. Event study results: Brent oil against DJCI

OLS		Brent - DJCI		
Event Date	ARs	t-Statistic	CARs	t-Statistic
0	5.75%	5.00 ***	-	-
1	(1.69%)	(1.47)	4.06%	3.53 ***
2	(0.17%)	(0.15)	3.89%	2.39 **
3	1.37%	1.19	5.26%	2.64 ***
4	0.39%	0.34	5.65%	2.46 **
5	(0.86%)	(0.74)	4.79%	1.86 *
6	(0.87%)	(0.76)	3.92%	1.97 **
Quantile Regression				
Event Date	ARs	t-Statistic	CARs	t-Statistic
0	5.58%	4.78 ***	-	-
1	(1.32%)	(1.13)	4.26%	3.64 ***
2	0.06%	0.05	4.32%	2.61 ***
3	1.55%	1.32	5.87%	2.90 ***
4	0.59%	0.51	6.46%	2.76 ***
5	(0.74%)	(0.63)	5.72%	2.19 **
6	(0.63%)	(0.54)	5.09%	1.78 *
GARCH (1,1)				
Event Date	ARs	t-Statistic	CARs	t-Statistic
0	6.24%	5.40 ***	-	-
1	(1.99%)	(1.72) *	4.25%	3.68 ***
2	(0.27%)	(0.23)	3.99%	2.44 **
3	1.34%	1.16	5.32%	2.66 ***
4	0.34%	0.29	5.66%	2.45 **
5	(0.78%)	(0.68)	4.88%	1.89 *
6	(0.99%)	(0.86)	3.89%	1.37

On the other hand, the results are slightly deviated when considering the DJCI as the market indicator since we detect important abnormal returns only on the first day, except for the case of the GARCH model which insinuates a two-day effect at 1% of economic importance. The reason behind this difference compared to the same study with S&P 500 as the market proxy, is probably the inclusion of the oil in the index, thus the correction happens in both variables but to a different extent. As mentioned before, the immediate adjustment of the oil market could be attributed to the statements of President Donald Trump, according to which the United States would release an undetermined amount of oil from its emergency reserve to fill the global supply gap. The rise of the U.S. as the greatest oil producer the last few years, due to advancements in shale extraction technologies, has offered the ability to the country to act as price-setter, a role that had completely been under the control of OPEC+. As for the CARs, we observe substantial values throughout our event window at 1% according to the OLS and the 0.5 Quantile. Furthermore, we note that the divergent outcome between the significance of abnormal returns and cumulative abnormal returns is associated with the magnitude of the daily variation, meaning that despite the relative stability of Brent after the second trading day of our event window, the residuals of the abnormal performance of the first days were still well presented and taken into account by the CARs. Finally, we highlight that the correction that took place was not enough in order for the oil market, as observed by the international benchmark (i.e. Brent crude oil), to revert to its ordinary levels, hence the trading price was still beyond the pre-event levels.

5.2.2. WTI crude oil Vs Market indicators

Of course, we anticipate the evidence of the same process but with WTI crude oil as the dependent variable to be quite close to the ones observed above, given that the two futures are fluctuating in a manner almost identical most of the time. However, it would still be intriguing to examine whether this hypothesis holds or the fact that the U.S. might react to those assaults in Saudi Arabia impacted the WTI crude oil more than the Brent.

Table 14. Event study results: WTI crude oil against S&P 500

OLS		WTI - SP500		
Event Date	ARs	t-Statistic	CARs	t-Statistic
0	15.06%	6.55 ***	-	-
1	(5.68%)	(2.47) **	9.38%	4.08 ***
2	(1.93%)	(0.84)	7.45%	2.29 **
3	0.19%	0.08	7.64%	1.92 *
4	0.44%	0.19	8.09%	1.76 *
5	1.12%	0.49	9.21%	1.63
6	(1.54%)	(0.67)	7.66%	1.36
Quantile Regression				
Event Date	ARs	t-Statistic	CARs	t-Statistic
0	14.94%	6.48 ***	-	-
1	(5.72%)	(2.48) **	9.21%	4.00 ***
2	(2.00%)	(0.87)	7.21%	2.21 **
3	0.11%	0.05	7.32%	1.83 *
4	0.29%	0.13	7.61%	1.65 *
5	1.04%	0.45	8.65%	1.68 *
6	(1.74%)	(0.76)	6.90%	1.22
GARCH (1,1)				
Event Date	ARs	t-Statistic	CARs	t-Statistic
0	15.28%	6.61 ***	-	-
1	(5.56%)	(2.40) **	9.72%	4.21 ***
2	(1.77%)	(0.76)	7.96%	2.43 **
3	0.36%	0.16	8.32%	2.08 **
4	0.69%	0.30	9.00%	1.95 *
5	1.29%	0.56	10.29%	1.99 **
6	(1.24%)	(0.54)	9.05%	1.60

Indeed, the results of the WTI crude oil against the market seem to be entirely similar to those of the Brent oil against the same indices, as far as the importance of the abnormal returns are concerned. In particular, we find substantial abnormal returns at least at 5% level of significance for two consecutive trading days following the event when considering the S&P as the market. These outcomes are just like in the event study of Brent against the same index *(Table 12)*, whereas the results of the cumulative abnormal returns provide somewhat differentiated values. On the one hand, the long-lasting effect of this incidence is partially justified, as we find importance at the level of 1% in each but one of the days in our event window with the Quantile and the GARCH approaches. On the other hand, we detect no significance of the cumulative abnormal returns for the last two observations with the use of the OLS estimator despite the fact that we get slightly greater values of the CARs, compared to those of *Table 12*. This led us to conclude that the standard deviation of the WTI futures contracts was lower than that of the Brent futures over the period under review.

Table 15. Event study results: WTI crude oil against DJCI

OLS		WTI - DJCI		
Event Date	ARs	t-Statistic	CARs	t-Statistic
0	5.04%	3.86 ***	-	-
1	(0.53%)	(0.41)	4.51%	3.45 ***
2	(0.72%)	(0.55)	3.80%	2.06 **
3	0.09%	0.07	3.89%	1.72 *
4	0.51%	0.39	4.39%	1.68 *
5	(0.85%)	(0.65)	3.54%	1.21
6	(0.51%)	(0.39)	3.04%	0.95
Quantile Regression				
Event Date	ARs	t-Statistic	CARs	t-Statistic
0	5.65%	4.33 ***	-	-
1	(0.50%)	(0.39)	5.15%	3.94 ***
2	(0.54%)	(0.41)	4.61%	2.50 **
3	0.32%	0.24	4.93%	2.18 **
4	0.71%	0.55	5.64%	2.16 **
5	(0.55%)	(0.42)	5.09%	1.74 *
6	(0.35%)	(0.27)	4.74%	1.48
GARCH (1,1)				
Event Date	ARs	t-Statistic	CARs	t-Statistic
0	5.28%	4.03 ***	-	-
1	(0.50%)	(0.38)	4.78%	3.65 ***
2	(0.63%)	(0.48)	4.15%	2.24 **
3	0.19%	0.15	4.34%	1.91 *
4	0.60%	0.46	4.94%	1.89 *
5	(0.72%)	(0.55)	4.22%	1.44
6	(0.43%)	(0.33)	3.79%	1.18

The outcome extracted from the event study of WTI against the DJCI is almost identical to that of the Brent against the same market indicator, in that both the OLS and the Quantile regression signal for substantial abnormal returns only on the event day, just like the GARCH estimator.

Regarding the duration of the effect we observe several significant CARs at the level of 1%, especially when focusing on the Quantile regression. This justifies that the event affected the markets beyond the event date, a fact that has been visible in all of our findings above.
What is also intriguing is the adjustment of the CARs of WTI during the event window, compared to the CAR_1, as we notice a decline of 22.45% and 48.36% against the SP500 and DJCI, respectively, based on the OLS outputs. At the same time, the corresponding values for Brent oil are 2.27% and 3.57% against the market indicators. Alternatively, one might interpret this gap as the persistent hesitation of those investing on Brent regarding the consequences that could be triggered as a response to the attack, in contrast with those betting on the West Texas Intermediate.

5.3. Constant Mean Model

Table 16. Event study results: Constant mean model

Constant Mean		Brent		
Event Date	ARs	t-Statistic	CARs	t-Statistic
0	14.81%	6.85 ***	-	-
1	(6.28%)	(2.90) ***	8.54%	3.95 ***
2	(1.27)	(0.59)	7.27%	2.38 **
3	1.46%	0.68	8.73%	2.33 **
4	0.01%	0.01	8.75%	2.02 **
5	0.96%	0.45	9.71%	2.01 **
6	(2.38)	(1.10)	7.33%	1.39
Constant Mean		WTI		
Event Date	ARs	t-Statistic	CARs	t-Statistic
0	14.85%	6.26 ***	-	-
1	(5.49%)	(2.32) **	9.35%	3.95 ***
2	(1.90%)	(0.80)	7.45%	2.22 **
3	0.20%	0.08	7.65%	1.86 *
4	0.10%	0.04	7.75%	1.63
5	1.12%	0.47	8.86%	1.67 *
6	(2.13%)	(0.90)	6.73%	1.16

Table 16 check for the existence of abnormal behavior utilizing the constant mean model, so as to capture what is considered to be the normal returns. As mentioned in the *Methodology* section, we calculate the simple arithmetic mean during our estimation window for each of the crude oil futures and the standard deviation needed to form the t-Statistic for the ARs and the CARs. The results for the Brent are quite similar to the ones of the corresponding market model approach, given that we observe important abnormal performance at 10% level of economic significance during the first and the second day of the event window. Furthermore, we verify that the event had an impact on the Brent over a span of 6 days, according to the cumulative abnormal returns significance at the level of 5%, which is similar to the findings of the Brent oil against the S&P 500 market model study. What is also close to the output of the market model, is the inference drawn about the WTI crude oil as we observe merely two important CARs at 5% and another two at 1% level of significance. However, abnormal returns are detected during the first two days on WTI, instead of just one based on the market model with the DJCI, a negligible deviation though if we consider that the rest of the findings are in accordance with each other. With regard to the magnitude of the ARs and CARs, we notice that the constant mean return model presents values which approach the ones of the market model when considering the S&P 500 as the market indicator. This could be explained by the common movements, at least to some extent, of the stock market and the oil futures across the estimation window as far as the magnitude of the fluctuations is concerned, a fact that is also depicted in *Figure 4.* This implication should not be translated into positive relationship of the two asset classes, rather a proportional variability, which leads the average return of the oil futures to be close to the normal performance measured by the market model.

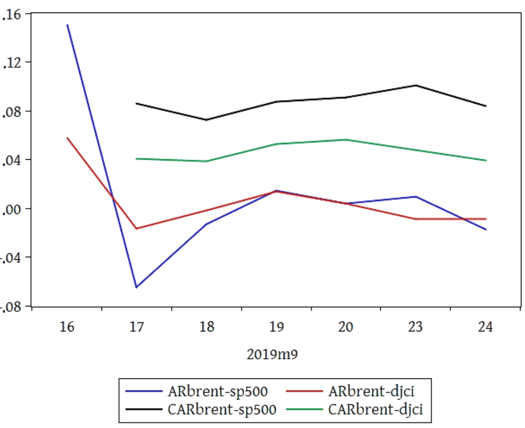

Figure 8. Results of Market model event study with Brent oil and OLS estimator

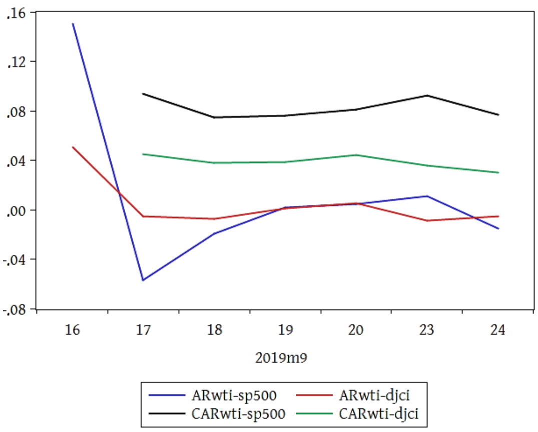

Figure 9. Results of Market model event study with WTI crude oil and OLS estimator

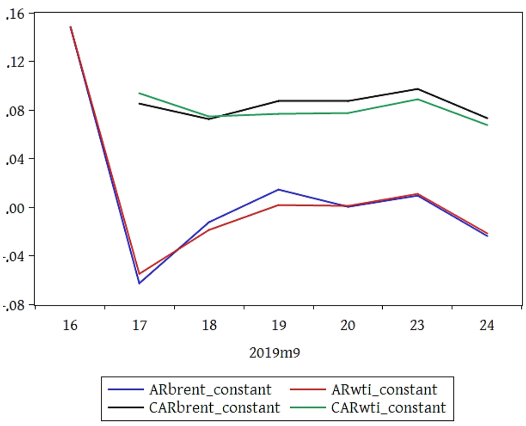

Figure 10. Results of Constant mean event study with OLS estimator

5.4. Time-varying changes in risk

Having already established the groundwork for the process needed in order to monitor the fluctuations in the relative risk of each asset, in comparison with the corresponding market indicator, further reference on this issue has to be done. In our case, we opted for a one-observation step for both the Rolling and the Recursive approach, so that we obtain the daily variation in betas. Additionally, the window selected for the former model is 39 days, which means that based on the Rolling model we get the values of beta one week prior to the event day and a week after. We note that the latter time-frame constitute our event window.

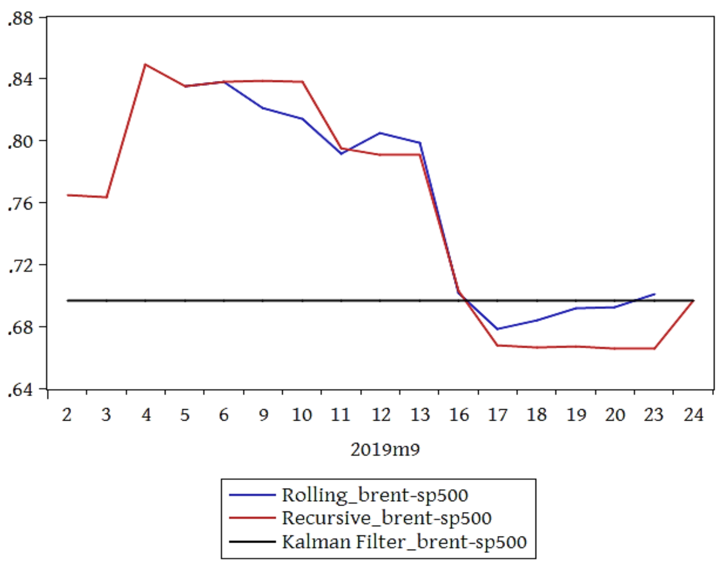

Figure 11. Changes in Brent oil risk relative to S&P 500

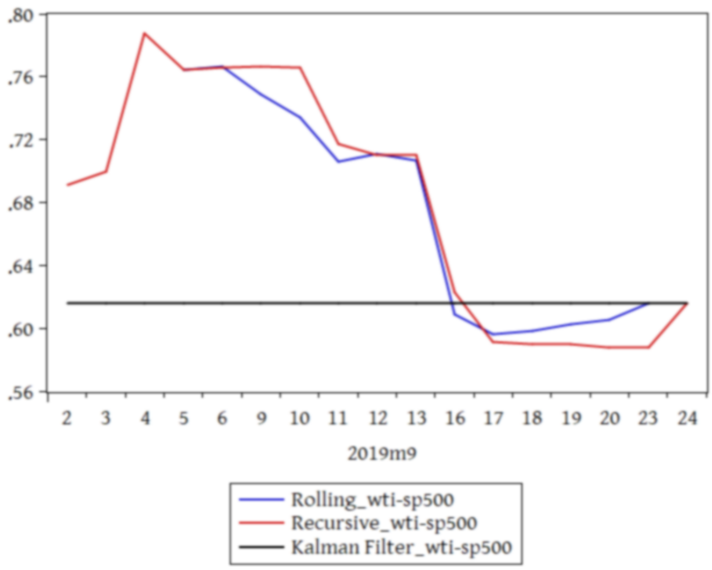

Figure 12. Changes in WTI crude oil risk relative to S&P 500

Plenty of significant facts are illustrated in *Figures 11 and 12*, as we see that although the relative risk between the two oil futures and the stock market fluctuates in a similar way, the one of the WTI crude oil is lower than the Brent oil. Moreover, we observe that the Kalman Filter approach produces a straight line which implies that the systematic risk is constant, a scenario that does not seem to be a realistic one. This result is in accordance with the work of Groenewold and Fraser (1999), in which they justify that the Kalman Filter shows the least variability, especially when the coefficient in the transition equation is near to zero. Lastly, the substantial decline depicted in each of the Rolling and Recursive regression outcomes is another intriguing finding, since the anticipated effect of a terrorist attack is the increased market turmoil. However, this result is probably mainly attributed to the diminishing correlation between oil and stock market, and to a lesser extent due to decreasing systematic risk, as illustrated in the S&P 500 condition variance in the Data Description section.

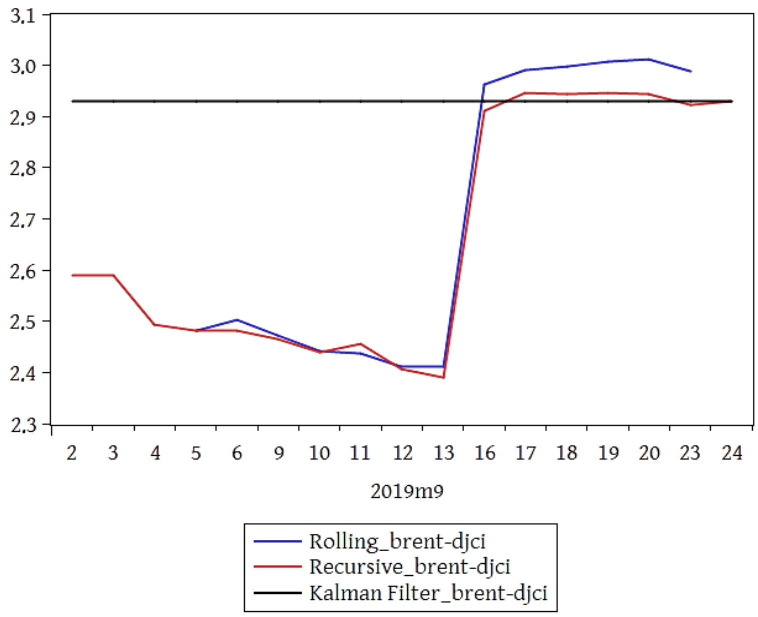

Figure 13. Changes in Brent oil risk relative to DJCI

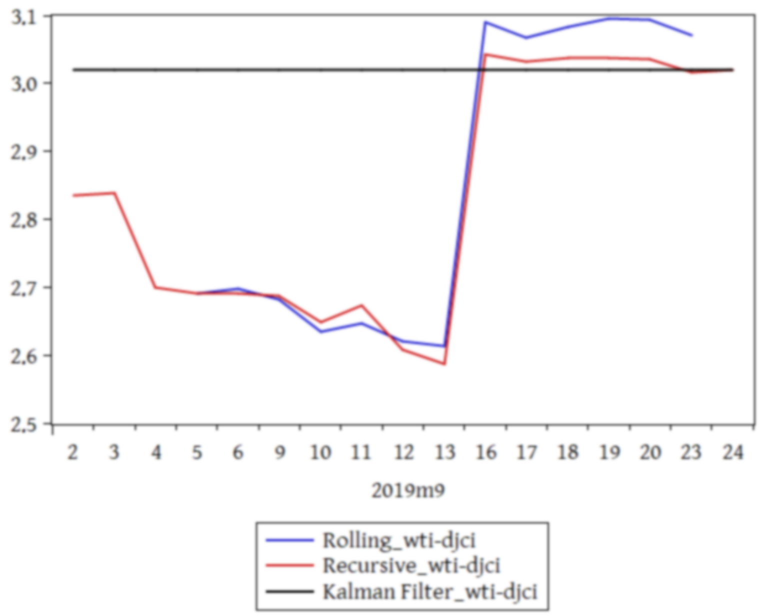

Figure 14. Changes in WTI crude oil risk relative to DJCI

Prolific enough are also the findings of the beta variations when we consider the DJCI as the market indicator, where we observe somewhat divergent estimates. On the one hand, the Kalman Filter demonstrates once more its superior resilience to changes since in both cases we get a fixed beta, which indicates a coefficient close to zero in the transition equation. On the other hand, the Rolling regression generates more extreme fluctuations than the Recursive regression during the first days of our event window. We need to point out the fact that the outcome of the *Figures 13 and 14* is perhaps the most sensible, given that we do see a sudden hike in the systematic risk as a response to the terrorist activity in Saudi Arabia. Finally, greater seem to be the correction of the Recursive approach after the event, whereas the Rolling model presents more stability. This is in contrast with the evidence provided in *Figures 11 and 12* and is due to the fact that the Recursive approach assigns more weighting in the past, while the Rolling model assigns the same weighting to each observation.

6. Concluding Remarks

In this paper we utilize the well-known event study methodology in order to justify the effect of the terrorist attack in Saudi Arabia, in mid-September, on the oil prices. Both market model and constant mean return model were employed as normal performance indicators so that we produce robust results. In this context, we considered not only the S&P 500 index as the market proxy but also the Dow Jones Commodity Index, in addition to the implementation of the market model with the Quantile regression (0.5 quantile) and the GARCH estimator as well, beyond the typical computation with the ordinary least squares (OLS). What is intriguing in the indices comparison is that the former is mainly used when the asset under consideration is a listed company and as a consequence the findings between the two are expected to be contradicting. Additionally, we conduct the methodology both with Brent and WTI crude oil, hence we believe that our work is not subjected to any sensitivities, caused by benchmark, estimator or asset under review selection.

The outcome of the market model signals that the influence of the attack was important for two consecutive days when the S&P 500 index is assumed to be the market indicator, while the corresponding results from DJCI indicate for noteworthy effect only on the event day. Regarding the duration of this occurrence, it is pretty interesting that we draw divergent inferences between the Brent and WTI crude oil, given that we mainly observe six important cumulative abnormal returns with the former and four with the latter futures, whereas previously the differences were detected between the benchmarks rather than between the oil futures. Moreover, the constant mean model led us to similar conclusions, empowering the view of Brown and Warner (1985) that more sophisticated models do not necessarily generate more accurate results. In particular, we found AR_0 and AR_1 to be statistically significant for both oil futures contracts, in addition to six out of seven important CARs for Brent oil and five for the West Texas Intermediate.

Another prolific discussion is produced based on the time-varying betas of the market model, as they measure the relative risk compared to the market. The fact that we utilized two very different indices as market indicators might require that we estimate the time-varying beta coefficients, so that we get an insight as for the suitability of each of the indices when the dependent variable is an oil futures contract. For this purpose, we conducted three different approaches; the Rolling regression in ordinary least squares, the Recursive regression (i.e. rolling regression anchored at start) and the Kalman Filter. The diminishing values of beta with S&P 500 as the market proxy following the attack could imply that this is not the most appropriate measure to capture the market performance, considering that the risk of the dependent variable, in our case the Brent or WTI crude oil, should increase as a response to this event, especially due to the fact the assault took place in oil facilities of Saudi Aramco, thus hurting the global oil production. On the other hand, a substantial increase in systematic risk was observed with the use of DJCI as market proxy, given that both the Rolling and the Recursive regressions presented a hike in betas in the range of 20 to 25%. Last but not least, worth-mentioning is the fact that Kalman Filter indicated for stable relative risk, based on the flat line of beta coefficients, a result that seem a bit implausible in reality.

To sum up, event study methodology has been primarily utilized in order to detect the abnormal performance of stock returns, which in turn imposed the use of stock market indices as the market proxy, while limited is the literature addressing the same issue on oil prices, through the oil futures contracts or spot prices. For this reason, our suggestion is that an index that incorporates oil assets is more suitable to implement such studies, although the weightings should be taken into account as well, considering that an index which is heavily hinged on oil would probably present very similar fluctuations to those of the individual oil derivatives, hence the absence of abnormal returns might be mistakenly found.

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