EVENT STUDY ON CRUDE OIL FUTURES MARKET

by

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(Under the Direction of Berna Karali)

ABSTRACT

This dissertation investigates the behavior of crude oil futures return and volatility and their response to short-term as well as long-term events. The primary objectives of this research are to estimate the direction, magnitude, and duration of an event's impact on crude oil futures and to relate the results to the nature of the events.

The first essay applies the Distributional Event Response Model (DERM), which is designed for examining relatively slowly-evolving information events, to twenty-five years of daily crude oil futures return and volatility in order to analyze the pattern of market responses to selected events. The results show that all ten events considered have statistically significant effects on crude oil futures return and volatility. The U.S. invasion of Iraq in 1991 and 9/11 terrorists' attacks are found to have the largest daily impacts on returns and volatility, respectively. In addition, the location and duration of event windows vary across different events. Generally, the largest return and volatility responses to an event are observed after several days or even months following the event, suggesting that simply using an event-day dummy variable would hinder discovering actual market responses to slowly-evolving events.

The second essay, published in *Energy Economics*, examines the behavior of intraday crude oil futures return and volatility and how they respond to weekly inventory announcements by the American Petroleum Institute (API) and Energy Information Administration (EIA). The informational content of API reports is measured relative to market analysts' expectations collected by Reuters, whereas that of EIA reports is measured relative to API reports. Results suggest that unexpected inventory changes in both API and EIA reports exert an immediate inverse impact on returns and a positive impact on volatility; but the duration and magnitude of EIA inventory shocks are longer and larger, with the largest impact observed when Reuters and API both err on the same side. While there are no instant asymmetric return responses to positive and negative API shocks, the return and volatility responses to cross-commodity inventory shocks in EIA reports exhibit asymmetry.

INDEX WORDS: API, crude oil futures, distributional event response model (DERM), EIA, event study, intraday, inventory shock, variance, volatility

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DEDICATION

I dedicate this dissertation to my loving wife, Chun Li, for her great love, selfless support, spurring and encouragement during all these years we have been through together; and to my parents, Bixia Peng and Zhao Ye, who have been giving me selfless love, spurring, courage and confidence ever since my childhood.

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INTRODUCTION

1.1 Background

1.1.1 Crude oil prices

Crude oil price fluctuations have a major impact on the global economy. A high crude oil price has been documented to have a negative effect on economic growth (e.g. Kilian, 2008). Crude oil price shocks in 1973-74, late 1970s/early 1980s, early 1990s, early 2000s and 2008 were all followed by economic recessions. Oil price is also a key signal in business activities because it constitutes a major portion of input costs in manufacturing, transportation, and agricultural production. Specifically, firm returns (e.g. Narayan and Sharma, 2011) and returns volatility (e.g. Narayan and Sharma, 2014) respond significantly to oil price shocks. The price slump beginning in June 2014 resulted in a laying off 200,000 employees of in the global oil and gas companies (Kristopher, 2015).

Crude oil futures prices have been more volatile since 1999. In 1999, there was a sudden increase in demand which, along with OPEC's production cut, raised oil prices to about $30 per barrel in 2000 but they fell in 2001. After March 2002, oil prices had been on an upward trend climbing to record levels due the Iraq war as well as increasing speculative trading. The nearby crude oil futures price reached a record level of $148 per barrel in July 2008 during global financial crisis and then dramatically dropped to $35 per barrel within six months (Kaufmann, 2011). With the global economy recovered and OPEC's production cut, the oil price went up again in 2011 and was kept at a high level until 2014. In the most recent period, the oil price declined dramatically due to supply and demand conditions such as shale gas revolution, China's slower economic growth, appreciation of U.S. dollar and OPEC's refusal to decrease oil supply.

In general, higher volatility depresses producers' fixed capital investments due to uncertainty of the price path, and encourages them to hedge the underlying assets. Specifically, in agricultural markets, higher volatility of energy prices induces uncertainty on agricultural production costs and thereby causes agricultural producers to face input price risk. On the other hand, higher volatility presents investors profit opportunities from buying energy products at lower prices and selling those at higher prices (Lee and Zyren, 2007). Given the importance of energy prices and its volatility, it is important to understand the determinants and dynamics of energy price volatility to make sound production, hedging and investment decisions in energy and agricultural markets, and manufacturing industries, as well as to facilitate the formulation and implementation of economic policies.

In this dissertation, I use crude oil futures prices rather than spot prices to construct return and volatility series, because spot prices significantly differ based on the location, physical base of trades and might generate adverse results such as manipulations, distortions and squeezes (Fattouh, 2006). Besides, as Kao and Wan (2012) indicate, when the transaction is small, the prices might be generated from assessment rather than the interaction of supply and demand fundamentals. More specifically, I use the West Texas Intermediate (WTI) futures contract traded at CME Group. WTI crude oil is of very high quality and excellent for making gasoline and it is the most influential benchmark for light crude oil in North America, the largest oil consumer in the world. Further, daily floor trading prices of WTI crude oil futures contract are used in the first essay where long-term events are examined, and 5-minute intraday WTI crude oil futures prices on CME Globex, the electronic trading platform of CME Group, are used in the second essay where short-term events are studied.

1.1.2 Event study

An event study is a standard statistical method in financial economics that has been widely used to assess impacts on the financial performance of firms from various events, such as mergers and acquisitions, earnings announcements, and changes in regulatory environments (Binder, 1998). The general procedure would be to (1) define the event of interest; (2) identify the event window (or observation interval) and estimation window; (3) determine an indicator (return of securities, return of futures contract, etc.); and (4) select a measure of the abnormal return.

The event window is the period over which the information involved in the event that will be examined. The estimation window, being used to calculate normal returns, is the period prior to event window and the two windows do not overlap (Mackinlay, 1997). The abnormal return is the actual ex post return of the security over the event window minus the normal return of the firm over the event window (Mackinlay, 1997). Traditionally, estimating abnormal returns has been done in two ways. The first is to use coefficient estimates from a market model, or a constant mean return model, or an asset pricing model to compute normal return within the event window, and then calculate the abnormal returns by subtracting normal return from actual return. The second method, being more straightforward, is to estimate the abnormal return for each event in the OLS regression or in Generalized Autoregressive Conditional Heteroskedasticity (GARCH) by the use of a dummy variable which takes the value of one during the event window and zero otherwise. The dummy variable technique is first used by Izan (1978). The first essay of the dissertation generalizes the second method by replacing the dummy variable with a specific distribution density (e.g. normal density) including a counter variable counting the number of trading days away from the event.

There are no universal rules in defining an event window. Theoretically it must be wide enough to capture all of the impacts from a specific event, but not so wide that it includes confounding effects unrelated to the event (Brown and Warner, 1985; McWilliams and Siegel, 1997). Empirical studies have shown that, very often, market tends to react to new information quite rapidly, often within one day. Therefore, a proper event window using daily data would be one day: the announcement day (Niquidet, 2008). However, for some other events, such as quarterly earnings announcements (Mackinlay, 1997) or even financial crises as discussed in this dissertation, the information content is slowly absorbed by public. Therefore, a longer event window needs to be specified. For example, Mackinlay (1997) employed an event window of 41 days, which has an additional 20 pre-event days and 20 post-event days. Because the event window starts just after the estimation window, without any justifiable approach, it is easy to include a potential event day into the estimation window or specify pre-event (post-event) days to be event days that would result in a difference or even contradiction concerning the conclusion on the impact of event. Therefore, more robust and testable methodology to define event window are desirable. There are several methods being discussed in the literature to allow the specification of event window to be more precise. The first is to run several regressions with varying window widths and locations, then choose the window with minimum sum of squared errors as the proper window (i.e. Niquidet, 2008). In addition, Bai and Perron (1998) propose a testing strategy that searches for the number and location of the breaks simultaneously. Essentially, it searches for the maximum value of the Chow (1960) test. The tests could be used to determine both whether a significant event occurred and when it occurred.

1.2 Objectives and Outline

This dissertation includes two manuscripts, investigating the behavior of crude oil futures return and volatility and how they respond to short-term event (e.g. weekly inventory announcements by Energy Information Administration (EIA)) as well as long-term event (e.g. 2008 global financial crisis). The primary objectives involve estimating the direction, magnitude, and duration of the impact of the event on the crude oil futures and relating the results to nature of the events (e.g. unexpected supply or demand changes). The motivation for this research is that crude oil prices remain a major influence on the global economy and have been more volatile since 1999. The primary procedures employed are time series models for detecting the dynamic linkage between crude oil return and volatility and supply and demand shocks.

The first manuscript studies ten slow-evolving events such as weather events, terrorists' attacks, Iraq wars, OPEC's production plan, and global financial crisis. It generalizes the second event study method and allows estimation of the exact days when the impact peaks and the dynamics of the impact. Specifically, dummy variables have been replaced by a specific distribution density (e.g. normal density) including a counter variable counting the number of trading days away from the event. The method is implemented using twenty-five years of daily crude oil futures returns and volatility to analyze the pattern of market responses to the selected events. The results show that all ten events considered have statistically significant effects on crude oil futures returns and their volatility. The duration of the impact depends on whether the event is exogenous or endogenous.

In the second manuscript, I examine more short-duration events; specifically, the inventory announcements released by American Petroleum Institute (API) and EIA. Using the dummy variable method and interacting them with the inventory shocks, I demonstrate that the impacts last for less than a few hours. The impact on crude oil futures and volatility depends on the sign and magnitude of inventory shocks, and the release time order of the two announcements. For example, the largest EIA impact is observed when Reuters and API both err on the same side. Further, both API and EIA shocks affect immediate returns inversely and volatility directly.

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CHATPER 2

EVENT STUDY OF CRUDE OIL FUTURES MARKET:

AN APPLICATION OF DISTRIBUTIONAL EVENT RESPONSE MODEL[1]

[1] Ye, S., B. Karali and O.A. Ramirez. To be submitted to *American Journal of Agricultural Economics*.

Abstract

We apply the Distributional Event Response Model (DERM), which is appropriate in studying relatively slowly-evolving information events, to twenty-five years of daily crude oil futures returns and volatility to analyze the pattern of market responses to selected events. The results show that all ten events considered have statistically significant effects on crude oil futures returns and volatility. The U.S. invasion of Iraq in 1991 and 9/11 terrorists' attacks are found to have the largest daily impact on returns and volatility, respectively. In addition, the location and duration of event windows vary across different events. Generally, the largest return and volatility responses to an event are observed after several days or even months following the event, suggesting that simply using an event-day dummy variable would hinder discovering actual market responses to slowly-evolving events.

2.1 Introduction

Energy prices have a major impact on the macro economy. Looking from the 1970s forward, the energy price shocks in 1973-74, late 1970s/early 1980s, early 1990s, early 2000s, and 2008 were all followed by economic recessions. Energy prices constitute a large portion of the Consumer Price Index (CPI), which significantly increased due to high energy prices after 2001. At industry and firm levels, energy prices constitute a major portion of input costs in manufacturing, transportation, and agricultural production. Gellings and Parmenter (2004) estimated that energy accounts for 70-80% of the total cost of fertilizer production, while the Cost of Production estimates of the U.S. Department of Agriculture (USDA) indicated that energy inputs accounted for 30% of the total U.S. corn production in 2008 (Hertel and Beckman, 2011).

In addition, energy futures prices have been noticeably more volatile since the summer of 2008. For example, the nearby crude oil futures price reached a record level of $148 per barrel in July 2008 during the global financial crisis and then dramatically dropped to $35 per barrel within six months (Kaufmann, 2011). In general, higher volatility depresses producers' fixed capital investments due to uncertainty of the price path, and encourages them to hedge the underlying assets. Specifically, in agricultural markets, higher volatility of energy prices induces uncertainty on agricultural production costs and thereby causes agricultural producers to face input price risk. On the other hand, higher volatility presents investors profit opportunities from buying energy products at lower prices and selling those at higher prices (Lee and Zyren, 2007). Given the importance of energy prices and its volatility, it is important to understand their determinants and dynamics to make sound production, hedging, and investment decisions in energy and agricultural markets, and manufacturing industries, as well as to facilitate the formulation and implementation of economic policies.

A massive literature has examined the determinants of energy volatility. The volatility has been explained by seasonality (Suenaga, Smith, and Williams, 2008), demand and supply factors (Pindyck, 2001, 2004), and macroeconomic variables (Karali and Power, 2013; Karali and Ramirez, 2014). Further, volatility spillover effects have been found between energy and agricultural markets (Hertel and Beckman, 2011; Serra, 2011) and among different energy products (Pindyck, 2001; Ewing, Malik, and Ozfidan, 2002; Brown and Yucel, 2008). Energy price volatility has been also found to be sensitive to major economic events, such as oil production cuts by OPEC (Lee and Zyren, 2007). Besides, weather-related and political events have also been found to be influential to energy price volatility. These events could be categorized into (1) exogenous to energy volatility (i.e. September 11 terrorist attacks, Hurricane Katrina), meaning that they are almost not predictable; and (2) endogenous (i.e. financial crisis, U.S. invasion of Iraq) indicating that people are capable of predicting it could happen. Both categories have something in common, which is that they might have huge impacts on energy volatility through demand and supply factors, macroeconomic factors, etc. Financial economists have long studied the impacts of information events on market prices and volatilities (e.g. Rucker, Thurman, and Yoder, 2005; Lee and Zyren, 2007; Karali and Ramirez, 2014). The standard method of measuring that impact is event study methodology. Event studies have been used for two major reasons: (1) to test the null hypothesis that the market incorporates information efficiently; and (2) under the maintained hypothesis of market efficiency, to study the impact of an event (Binder, 1998). Our paper builds on this extensive literature on volatility determinants and incorporates a relatively new event study methodology. Our main contribution is determining the magnitude and duration of the impacts on energy price return and volatility caused by major global economic, weather-related, and political events. Because the full market response to some of the events related to energy markets might evolve slowly and differ across the events, we apply the Distributional Event Response Model (DERM) developed in Rucker, Thurman, and Yoder (2005). Unlike a traditional event study with event-day dummy variables, which leads to model parameter estimates conditional on a specific event response structure and a specific event window specification, the DERM allows one to estimate, rather than to impose, the location and width of an event window as well as to have different response structures for different types of events.

Our results show that all ten events considered (9/11 terrorists' attacks, Hurricane Katrina, Iraq Wars in 1990, 1991 and 2003, OPEC's production change in 1990, 2003 and 2008, financial crises in 1997 and 2008) have statistically significant effects on crude oil futures return and volatility. In addition, the location and duration of the event windows are found to vary among these ten events. While the impact of the Asian financial crisis in 1997 on crude oil return has the longest duration, the impact of the OPEC's production increase announcement in 1990 has the shortest duration. The largest impact on crude oil return series, a 131% decrease, is found following the U.S. invasion of Iraq in 1991, whereas the largest effect on variance, a 53% increase, is observed after 9/11 terrorists' attacks in 2001. Generally, the largest return and variance responses to an event are observed several days or even months following the event. Only for the U.S. invasion of Iraq the market response on both crude oil returns and volatility peaked on the event day. Thus, simply using an event-day dummy variable prevents one from discovering the actual market responses to slowly-evolving events.

2.2 Literature Review

Three of the ten events in our study have already been explored in previous event study research. Olowe (2010) shows that the Asian financial crisis had a significant impact on crude oil return while the recent global financial crisis did not and both financial crises did not account for the variance change. Karali and Ramirez (2014) come to the same conclusion on the global financial crisis and further indicate that OPEC's oil production cut in 1999 led to an increase in crude oil futures volatility. Ye, Zyren and Shore (2002) concludes that Asian financial crisis and OPEC's oil production cut in 1999 brought about a significant decrease in crude oil returns.

However, in these previous studies, the correctness of the conclusions on event impact is conditioned on the right assumptions on event windows which haven't been tested. Rucker, Thurman, and Yoder (2005), on the other hand, developed the DERM, which not only solves the problem of the location and width of event window, but also allows for considerable flexibility in measuring the impacts of events and provides easily interpretable estimates of the time path of the market response to a set of events. The way the model is designed is to replace the event-day dummy variable with a probability density function. The authors utilize the model to measure the impact of three types of events on rate of return of lumber futures prices. In this article, we extend their idea into a GARCH model, and try to measure the impact of the selected events on crude oil rate of return and volatility simultaneously.

In a GARCH (Bollerslev, 1986) model, the variance of the current error term is a function of the squared past error term and a lagged value of the variance. It has been shown that futures prices exhibit time-varying volatility and can be effectively studied using GARCH models (Baillie and Myers, 1991; Goodwin and Schnepf, 2000). GARCH-type models have been widely used in event studies (i.e. Jong, Kemna, and Kloek, 1992; Park, 2000), since when the true data-generating process is better represented by models allowing for time variation in the conditional second moment and the distribution of returns is leptokurtic, GARCH-type model parameter estimates are more efficient than assuming a constant variance (Greene, 2000, p.798).

However, previous research only includes event-day dummy variables in the mean equation, and those dummy variables take the value of one on event days, and zero otherwise. In our research, we add in both the mean and variance equations, a probability density function accounting for the effect of different events on returns and volatilities, respectively. Further, we follow Baillie and Myers (1991) to use a GARCH model with a Student's t distribution (GARCH-T), because futures returns are commonly found to exhibit excess kurtosis. Research conducted by McKenzie, Thomsen, Dixon (2004) indicates that test statistic from GARCH (1, 1) model with a Student's t distribution is more powerful than OLS regression as well as GARCH (1, 1) model with normal distribution.

2.3 Empirical Model

Our paper builds on the study of Rucker, Thurman, and Yoder (2005) and studies the magnitude and duration of the impacts on crude oil return and volatility caused by major global economic and political events using the DERM. More specifically, the DERM allows one to measure the impacts of events in a flexible way and to obtain estimates of the time path of the market response. The model constrains market response patterns to correspond to shapes of specified probability distributions. The DERM involves both linear and nonlinear parts and is defined in our study as:

$$R_t = a + b_1 R_{t-1} + b_2 R_{t-2} + \sum_{i=1}^{k} \beta_i^R f\left(d_t^i;\, \boldsymbol{\theta}\right) + \varepsilon_t,$$

(2.1)
$$\varepsilon_t = z_t \sqrt{h_t}, \qquad z_t \sim t_\nu,$$

$$h_t = \omega + \alpha \varepsilon_{t-1}^2 + \gamma h_{t-1} + \sum_{i=1}^{k} \beta_i^V f\left(d_t^i;\, \boldsymbol{\varphi}\right),$$

where R_t is the daily return of crude oil futures contracts, R_{t-1} and R_{t-2} are the response variable lagged by one and two periods, respectively, k is the number of events, d_t^i is a counter variable indicating the difference (in trading days) between any given day t and the day event i occurred, ε_t is the regression error term, and z_t is a random variable that follows Student's t distribution with degrees of freedom ν. The count variable d_t^i is zero on the event day; and it takes negative values before the event day and positive values after the event day. We create d_t^i for each of the ten events we studied with d_t^{Iraq1}, d_t^{OPEC1}, d_t^{Iraq2}, d_t^{Asian}, d_t^{OPEC2}, d_t^{Sep11}, d_t^{Iraq3}, $d_t^{Katrina}$, d_t^{Global} and d_t^{OPEC3}. The term h_t is the conditional variance and h_{t-1} is the conditional variance lagged by one period. The function $f\left(d_t^i;\ \boldsymbol{\theta}\right)$ is a density function for d_t^i with parameter vector $\boldsymbol{\theta}$ and we specify it to be a normal density as:

$$(2.2) \qquad f\left(d_t^i;\ \boldsymbol{\theta}\right) = f\left(d_t^i;\ \mu_i, \sigma_i\right) = \frac{1}{\sigma_i\sqrt{2\pi}}\exp\left(-\frac{\left(d_t^i - \mu_i\right)^2}{2{\sigma_i}^2}\right).$$

Thus, the DERM becomes the Normal Event Response Model (NERM). While we assume the normal density function for each event i, the distribution parameters (mean μ and standard deviation σ) are allowed to vary across different events. $f\left(d_t^i;\ \boldsymbol{\varphi}\right)$ has the same formula with $f\left(d_t^i;\ \boldsymbol{\theta}\right)$ but includes different parameters (i.e. mean and standard deviation).

Figure 2.1 reproduces the figure 2 in Rucker, Thurman, and Yoder (2005) to illustrate the NERM. Consider three different events that occurred on days t_1, t_2, and t_3. As shown in the figure, the parameters μ_i and σ_i for $i = 1, 2, 3$ determine, respectively, the location and spreads of the response patterns for each event. Besides the distributional parameters, each event has its own scaling parameter β_i, which allows different magnitude and sign of each event's effect. From the figure, for instance, it can be seen that the second event has a negative effect and its magnitude is about two-thirds of the size of the first event's impact. In addition, the height of the density function for any given day shows the impact of the event on the daily returns. For instance, on day t_1, the impact of the first event on the daily return is R_1. As time goes by, the impact of this event increases until the day $t_1 + \mu_1$ and then diminishes.

Because the NERM is a nonlinear model, estimation through Ordinary Least Squares (OLS) is not feasible. Once the day counter variables, d_t^i, are plugged into the normal density functions given in equation (2.2), the means and standard deviations of the densities can be estimated along with the other model parameters using Maximum Likelihood Estimation (MLE). Our maximum likelihood estimation is based on the assumption of Student's t distributed disturbances.

2.4 Data

2.4.1 Futures Returns and Volatility

We study crude oil futures contracts that are traded on CME Group from April 1990 to December 2014. Light Sweet Crude Oil (WTI) futures contract is the world's most actively traded energy product. WTI futures contracts play an important role in managing risk in the energy sector worldwide because it is the most liquid energy contract (CME, 2014). The contracts have expiry dates in every month of the year and are traded until the third business day prior to 25th calendar day of the month preceding the delivery month. A single price series is constructed by rolling over the first nearby contract on the 15th day of the expiration month (the month preceding the contract month).

Daily return on a futures contract is defined as $R_t = 100 \times (lnP_t - lnP_{t-1})$, where P_t is the closing price of the nearby contract on trading day t. Descriptive statistics of the return of crude oil futures contracts are summarized in table 2.1. There are 6,194 observations in the sample. The average return is 0.02% with a standard deviation of 2.16%. The average daily volatility, on the other hand, is 1.52% with a standard deviation of 1.53%. The largest return increase happened on December 17, 2008 which is after the announcement of OPEC's production cut and the largest return drop happened on January 17, 1991 when U.S. invaded Iraq. The returns are not normally distributed based on Kolmogorov-Smirnov and Jarque-Bera tests with significant left skewness and excess kurtosis. Figures 2.2 and 2.3, respectively, show the daily return and absolute return series for the entire sample. It can be seen that there is obvious volatility clustering during the Gulf War, after 9/11 terrorists' attacks and after OPEC's production cut in 2008.

2.4.2 Event Descriptions

Many events have potential impact on crude oil futures prices. We study only those slowly-evolving events in our analysis. The events can be categorized into four groups based on event nature and potential duration: (1) weather-related or terrorist attack events; (2) invasions or wars related to Middle East (i.e. Iraq); (3) OPEC's production change events; (4) financial crises. We expect the duration of an event's impact to be based on whether the event is exogenous and the difficulty of absorbing the information. The more exogenous or isolated an event is, the shorter the impact duration will be. For instance, hurricane Katrina and terrorist attacks were exogenous events that only influence prices in the short term. On the other hand, the more endogenous an event, the harder the information is to absorb, and the longer the duration will be. For instance, a financial crisis is endogenous, because, in general, the crisis can be related previous economic phenomenon (e.g. high default rate in the subprime home mortgage before global financial crisis). Further, people spare every effort to help the economy to recover from the crisis. So a financial crisis is highly complicated and it is hard to absorb the information. Other examples include OPEC's production cut, which is often announced during the OPEC meeting including specific countries and cutting amount. The event is highly related with the global economy and therefore endogenous. Furthermore, whether OPEC countries choose to follow the agreement is always uncertain because they have the incentive to keep their production high to gain more profit and market share. From this aspect, the information is hard to absorb and confirm in the short run. Therefore, the impact of OPEC events generally lasts a very long time. Event group (2) can also be considered as endogenous oil events in that part of the motivation of the military attacks is that the invaders are not satisfied with opponent's oil production and exports, and this dissatisfaction accumulates over time resulting in an invasion eventually. However, the impact of modern wars is often easy to be largely understood by the market because the duration of modern war period is often pretty short. In that sense, we expect the duration of event groups (3) and (4) to be longer than (1) and (2) in general.

In group (1), we include hurricane Katrina and 9/11 terrorists' attacks. Hurricane Katrina hit the U.S. Gulf coast on August 29, 2005. It is the costliest natural disaster, as well as one of the five deadliest hurricanes, in the history of the United States. Katrina damaged or destroyed 30 oil platforms. In addition, nine refineries were forced to close down for about six months and 24% of the annual oil production in the Gulf coast was lost. The variable $d_t^{Katrina}$ is created to count the trading days between any given day in our sample and August 29, 2005. The 9/11 terrorists' attacks happened on September 11, 2011. The trading stopped immediately after the attacks and started back again on September 17th. As a result of the attacks, the World Trade Center was destroyed, the Pentagon was heavily damaged, and thousands of people died. Aviation was halted in the U.S. and all major trading markets (including energy) were closed for the remainder of the week. The economic damage of these attacks was estimated to be in the billions. Markets reopened a week later, and futures prices of crude oil and petroleum products fell to their lowest levels in nearly two years, probably with the fears that a recession will reduce energy demand. The variable d_t^{Sep11} is created to count the trading days between any given day in our sample and September 17, 2011. These two events happened quickly and were considered to be isolated events that did not have a long-term impact and the impact on crude oil was straightforward and therefore, we expect their impacts to be relatively short.

There are three military invasions that involved Iraq in our sample period which are assigned to group (2). The military affairs events should not be considered exogenous. Since the pace of the war was generally slow and highly influenced by global politics and economy, it took time for the information to be fully absorbed. The first two events both happened during the Gulf War,[2] of which the first one happened on August 2, 1990 when Iraq invaded Kuwait. Oil production was expected to decline sharply because one of the motivations of the invasion was to prevent Kuwait from over-producing oil. Oil prices increased accordingly. The occupation was followed by direct military intervention by U.S.-led forces in the Gulf War happening on January 16, 1991. U.S. crude prices fell $10.56 a barrel in response to a U.S. decision to release stockpiles of crude from its massive Strategic Petroleum Reserve to compensate for supply shortfalls during Gulf War. However, with the increasing world oil supply, oil prices fell again until 1994. The third event is U.S. invasion of Iraq on March 19, 2003. The invasion was expected to stabilize global energy supplies as a whole by ensuring the free flow of Iraqi oil to world markets (Muttitt, 2011). The oil prices only decreased in a limited period of time, not preventing the long-term increasing trend. The variables d_t^{Iraq1}, d_t^{Iraq2}, and d_t^{Iraq3} are created to

[2] The Gulf War (August 2, 1990 – February 28, 1991), codenamed Operation Desert Shield (August 2, 1990 – January 17, 1991) for operations leading to the buildup of troops and defense of Saudi Arabia and Operation Desert Storm (January 17, 1991 – February 28, 1991) in its combat phase, was a war waged by coalition forces from 34 nations led by the United States against Iraq in response to Iraq's invasion and annexation of Kuwait.

count the trading days between any given day and the event days August 2, 1990, January 16, 1991, and March 19, 2003, respectively.

There are three production change decisions by OPEC that have significant and long-lasting impacts in our sample period which we include in event group (3). The first one happened on August 27 1990, when OPEC members gathered informally and announced their plan to raise oil production to help meet the supply shortfall caused by Iraq's invasion of Kuwait on August 2 1990. Unlike the first event, two other OPEC events are production cut decisions. On March 23, 1999, in an effort to raise oil prices which were at considerably low levels from late 1997 until early 1999 resulting in a 30% revenue loss, OPEC and non-OPEC countries agreed to cut oil output by a combined 2.104 million barrels (1.716 for OPEC members and 0.388 for non-OPEC members) per day during OPEC's 107th meeting in Vienna. This pledge was for one year, effective as of April 1, 1999. After that, on December 17, 2008, on its 151st meeting in Oran, Algeria, OPEC announced its decision to cut production by 2.2 million barrels a day in January 2009. The cut is the largest ever announced by OPEC. After OPEC's production change, the movement of crude oil prices should be straightforward by supply and demand theory, at least the direction. However, since the announcement was hard to implement to some extent, the duration of these events was still not short. The variables d_t^{OPEC1}, d_t^{OPEC2}, and d_t^{OPEC3} are created to count the trading days between any given day and the event days August 27, 1990, March 23, 1999, and December 17, 2008, respectively.

In group (4), we include the Asian financial crisis that lasted from July 1997 to February 1998. The crisis started in Thailand with the financial collapse of the Thai baht after the Thai government was forced to float the baht and it spread to many Asian countries thereafter. The Asian crisis led to economic slowdown in developing countries in many parts of world and therefore to a large decrease in the demand for oil. This reduced the price of crude oil to be as low as $10 per barrel, triggering OPEC to change its policy to restore oil prices to higher levels. A variable d_t^{Asian} is created to compute the difference (in trading days) between any given day in our sample and July 2, 1997 (taking into account time zone difference). There was no specific event marking the beginning of the 2007-2008 global financial crisis. But the major investment bank Lehman Brothers' announcement of its filing for bankruptcy on September 15, 2008 certainly precipitated the crisis which resulted in diminishing credit lines in financial markets creating a credit constraint for firms and consumers. This was followed by a substantial decrease in the demand for crude oil, gasoline, and other energy commodities. We create a variable, d_t^{Global}, that computes the trading days between any given day in the sample and September 15, 2008.

2.5 Results

Table 2.2 reports the results. All NERM parameter estimates are statistically significant at the 1% level. The estimated degree of freedom seen in table 2.2 is 7.99 and statistically significant at the 1% level, indicating the validity of assuming t-distributed errors. Coefficients on the autoregressive terms in the return equation indicate that daily returns exhibit negative and significant serial correlation (-0.02 and -0.03 for the first and second lags) which is consistent with Bu (2014) and Schmidbauer and Rosch (2012). In addition, the significant ARCH and GARCH terms shows that using GARCH model is appropriate. The LR test for the joint significance of the normal density terms in equation (2.4) is significant at the 1% level, indicating that we can reject the exclusion restriction on the normal density terms included in both the return and variance equations. Using the estimated β, μ and σ, table 2.3 demonstrates the impacts of events (i.e. the scaling factor β multiplied with the normal density function) on both the event day and the estimated peak day. Tables 2.4 and 2.5 present the estimated duration of event impacts on crude oil return and variance. We assume the impact of each event to start from 3σ days before estimated μ (after simple rounding) until 3σ after, for a total of 6σ days, so that more than 99.7% of the area under the normal curve is being captured. Besides, estimated normal event response patterns in the daily returns and variance are depicted in figures 2.4 through 2.7.

The event responses of 9/11 terrorists' attacks and hurricane Katrina are depicted in figure 2.4. It shows that 9/11 terrorists' attacks led to 17% drop in crude oil futures return about 5 trading days after the market reopened on September 17, 2001. This event's daily impact on crude oil futures return is the third largest in our sample period. Since the event is exogenous, its impact only lasted for less than a week and it did not form a long-term trend of decreasing oil prices. Similarly, the duration of hurricane Katrina is also estimated to have an impact that lasts 3 days for returns, indicating that the weather event did not have a long-term impact. Furthermore, the impact of hurricane Katrina is increases of 2.40% in return and 4.76% in variance on the peak day. Given the duration and the magnitude of the influence, the model does not provide evidence that hurricane Katrina was a significant event on crude oil futures markets as expected. Besides, we select the day when the hurricane struck the Gulf coast as the event day, therefore, a μ of -3 indicates that the peak impact was three days before the event day which was the day hurricane was formed. No impact was found on the event day.

The Iraq events are also found to have significant impact on the daily crude oil return and variance. The events' impacts are illustrated in figure 2.5. The first Iraq event was Iraq's invasion of Kuwait. The oil price returns increased by over 5%, because the market was expecting Kuwait's oil production to fall. The impact peaked on the next day of the event and lasted for 2 weeks. The impact on variance is also significant and over 46.85%, but it is only on the third day after the event. Two other events were both the invasion of Iraq by the U.S. The earlier one happened on January 1991 and resulted in a 130.76% drop in return on the peak day, which was the largest return drop in the entire sample period, but the impact only lasted for 2 days. It also resulted in a 11.6% decrease in variance. The later invasion happened on March 2003 and brought about a 5.65% decrease in return and lasted for more than 2 weeks. It also led to a 1% increase in variance around peak day. Interestingly, the peak impact for both return and variance appeared before the event day, indicating that the third Iraq event was expected by the market long before the actual invasion day on which the impact was relatively smaller.

As we expected, the lengths of the impact of the above five events were limited, because they were exogenous events and the information was not difficult to absorb. However, four out of the following five events, which are considered as endogenous events, generated long-term impacts on crude oil futures return and variance.

All three OPEC events are found to have significant impact on crude oil returns. However, signs, magnitudes, and durations of the impacts are different as shown in figure 2.6. The first OPEC event announced a production raise plan, and therefore resulted in a decrease in returns, while the last two were production cut announcement and brought about a price increase. Previous research only focus on the third OPEC event (e.g. Ye, Zyren, and Shore, 2002; Lee and Zyren, 2007; Karali and Ramirez, 2014), and the results (significant return drop and volatility increase) are consistent with ours. In addition, the last two OPEC production decisions would not become effective until weeks later, and each individual country did not have a strong incentive to reduce the production, so the returns and variance adjusted relatively slowly after the events. The estimated duration for the last two OPEC events were 76 and 60 trading days for returns and 600 and 112 days for variance, respectively, as shown in figure 2.6. While the estimated duration is only 2 (return) and 1 (variance) days for the first OPEC event, the estimated impacts on the peak day are -35.20% for returns and 14.37% for variance, as depicted in figure 2.6, which are both significantly larger than those for the last two OPEC events. Another interesting finding is the peak days, which are different among all three events. The peak day for the first OPEC event on crude oil futures return is on the event day. Negative peak day of 3 on variance indicates that the market started to be active before the information release. The peak day for the second OPEC event on return is about 5 days before the event, indicating obvious information leakage. However, impact of the third OPEC event on return peaks after 100 days, which indicates that the market made the most adjustment a few months later after it confirmed that the production was actually decreased.

For the Asian financial crisis, the estimated μ in the return equation indicates that the market response peaked about 156 trading days after the event occurred as seen in figure 2.7. Table 2.4 shows that the impact on the crude oil futures return is estimated to last for $6\sigma = 302$ trading days from July 10, 1997 to September 22, 1998. The scaling factor β in the return equation is negative and statistically significant which is in line with previous research (e.g. Olowe, 2010; Ye, Zyren, and Shore, 2002). Variance results, on the other hand, show that the scaling factor is positive and significant and not consistent with Olowe (2011) that does not find significant evidence. The variance response peaked about 141 trading days after the event, and lasted for about a trading day, and therefore, is considered to be trivia. Table 2.3 shows that the market response to this event is a decrease of 0.01% in the returns on the event day, and a 0.72% decrease on the peak day. Variance, on the other hand, is not affected on the event day itself, but increases by 10.05% on the peak day (i.e. 141 days after the event). Global financial crisis is found negatively affect the return and positively affect the variance which is in line with what we observe in figures 2.2 and 2.3, but not along with previous research (e.g. Olowe, 2010; Karali and Ramirez, 2014) that suggest that the 2008 global financial crisis had no impact on oil return and volatility. For the daily return, the largest impact is found 32 trading days after the event with an overall duration of 231 days. While the daily return decreased by 1.21% on the event day, it decreased by 1.72% on the peak day. The variance response peaked 18 trading days after the event, with a duration of 118 days (table 2.5). The variance increased by 0.97% on the peak day, and by 0.64% on the event day. The durations of both financial crises in returns were all over 200 trading days which are significantly longer than all other 8 events. This is consistent with our expectations because financial crises consist of multiple events and the information is hard to absorb in short run.

2.6 Conclusions

Our study investigates the impact of ten oil events on crude oil futures return and volatility. We use a DERM introduced by Rucker, Thurman, and Yoder (2005), which generalizes the traditional dummy variable method, to compare the direction, magnitude and duration of impact of those events. The ten events are categorized into four groups: (1) weather and terrorists' attack; (2) three Iraq events; (3) three OPEC events; (4) two financial crisis. The categorization is based on event nature.

Results show that the return and variance responses to all these ten events are statistically significant, and the location and duration of the event windows are different for each event. The duration is consistent with the exogenous and endogenous event assumption. Specifically, among the ten events, the impact of financial crises on crude oil return has the longest duration with more than 100 trading days, followed by OPEC events. On the other hand, the impact of 9/11 terrorists' attacks, hurricane Katrina, military attacks related to Iraq on crude oil futures return and variance lasted less than 16 trading days. The most delayed reaction in the returns and variance is found for the Asian financial crisis in 1997 and the OPEC's production cut in 2008, respectively. While the crude oil return decreased by 0.01% on the day the Asian financial crisis started, 156 days after the event this impact was amplified to a decrease of 0.72%. The impact of OPEC's production cut decision in 2008 on variance peaked 153 days after the event at 0.06%. Among the ten events considered, the largest market response in crude oil returns is found following the U.S. invasion of Iraq in 1991, a 130.76% decrease, followed by a 35.20% decrease after OPEC's announcement of production increase in 1990 and a 17% decrease after 9/11 terrorists' attacks in 2011. On the other hand, the largest positive effect on variance, is a 53.49% increase caused by the 9/11 terrorists' attacks in 2001, followed by a 46.85% increase after Iraq's invasion of Kuwait in 1990 and a 14.37% increase after the OPEC's announcement of production increase in 1990.

In general, a large market response to a slowly-evolving event is found to last for weeks, or even months after the event occurred. Therefore, if a traditional event study methodology with event day dummy variables were used, then actual market responses would not have been discovered.

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Table 2.1 Summary Statistics of Crude Oil Returns

	Return
Observations	6194
Mean	0.02
Median	0.07
Standard Deviation	2.16
Maximum	13.34
Minimum	-38.41
Skewness Coefficient	-1.17
	(<0.00)
Excess Kurtosis Coefficient	19.31
	(<0.00)
Kolmogorov-Smirnov Coefficient	0.13
	(<0.00)
Jarque-Bera Coefficient	100900
	(<0.00)

Note: Values in parentheses are two sided p-values for the skewness and kurtosis tests and one-sided p-values for the normality tests.

Table 2.2 Estimates of the Normal Event Response Model

	Return			Variance		
	β^R	μ^R	σ^R	β^V	μ^V	σ^V
Iraq1	24.97	0.66	1.79	17.82	3.29	0.15
	(0.78)	(0.03)	(0.05)	(0.23)	(0.05)	(0.02)
OPEC1	-24.67	-0.38	0.28	7.89	-2.99	0.22
	(0.64)	(0.03)	(0.03)	(0.14)	(0.04)	(0.04)
Iraq2	-84.68	0.40	0.26	-6.85	-0.07	0.24
	(4.26)	(0.01)	(0.01)	(0.14)	(0.01)	(0.03)
Asian financial crisis	-90.84	156.16	50.33	7.08	140.64	0.28
	(0.67)	(2.13)	(0.35)	(0.03)	(0.14)	(0.00)
OPEC2	40.30	-4.84	12.67	6.31	9.66	99.93
	(0.17)	(0.02)	(0.04)	(0.01)	(0.03)	(0.38)
September 11	-20.96	4.91	0.49	19.09	0.30	0.14
	(0.37)	(0.08)	(0.02)	(0.04)	(0.01)	(0.01)
Iraq3	-30.23	-2.12	2.13	6.08	-2.65	2.45
	(0.11)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Katrina	2.62	-2.92	0.44	3.66	-0.64	0.31
	(0.04)	(0.03)	(0.01)	(0.01)	(0.00)	(0.00)
Global financial crisis	-165.43	32.32	38.48	47.55	17.84	19.63
	(0.26)	(0.03)	(0.05)	(0.05)	(0.03)	(0.02)
OPEC3	31.74	103.47	10.05	2.65	152.55	18.65
	(0.04)	(0.18)	(0.02)	(0.00)	(0.20)	(0.02)
Intercept (a) (ω)	0.06			0.02		
	(0.00)			(0.00)		
Lagged dep. var. (b_1)	-0.02					
	(0.00)					
Lagged dep. var. (b_2)	-0.03					
	(0.00)					
ARCH (α)				0.04		
				(0.00)		
GARCH (γ)				0.96		
				(0.00)		
Degrees of Freedom (ν)	7.99					
	(0.01)					
LR test	215.57					

Note: All parameters are statistically significant at the 1% level. Standard errors are shown in parentheses.

Table 2.3 Impacts of Events

	Return		Variance	
	Event day [d_t=0]	Peak day [$d_t=\mu^R$]	Event day [d_t=0]	Peak day [$d_t=\mu^V$]
Iraq1	5.19	5.55	0.00	46.85
OPEC1	-13.94	-35.20	0.00	14.37
Iraq2	-38.42	-130.76	-11.05	-11.60
Asian financial crisis	-0.01	-0.72	0.00	10.05
OPEC2	1.18	1.27	0.03	0.03
September 11	0.00	-17.00	6.04	53.49
Iraq3	-3.44	-5.65	0.55	0.99
Katrina	0.00	2.40	0.55	4.76
Global financial crisis	-1.21	-1.72	0.64	0.97
OPEC3	0.00	1.26	0.00	0.06

Table 2.4 Estimated Duration of Event Impacts on Returns

	Duration [6σ]	Event date [base]	Start date [-3σ]	Peak date [μ]	End date [+3σ]
Iraq1	10.77 (0.28)	8/2/1990	7/27/1990	8/3/1990	8/10/1990
OPEC1	1.68 (0.18)	8/27/1990	8/24/1990	8/27/1990	8/28/1990
Iraq2	1.55 (0.05)	1/17/1991	1/16/1991	1/17/1991	1/18/1991
Asian financial crisis	302.00 (2.09)	7/2/1997	7/10/1997	2/17/1998	9/22/1998
OPEC2	76.04 (0.24)	3/23/1999	1/20/1999	3/16/1999	5/10/1999
September 11	2.95 (0.09)	9/17/2001	9/21/2001	9/24/2001	9/25/2001
Iraq3	12.80 (0.08)	3/20/2003	3/10/2003	3/18/2003	3/26/2003
Katrina	2.61 (0.05)	8/29/2005	8/23/2005	8/24/2005	8/25/2005
Global financial crisis	230.88 (0.33)	9/15/2008	5/16/2008	10/29/2008	4/16/2009
OPEC3	60.33 (0.13)	12/17/2008	4/3/2009	5/18/2009	6/30/2009

Note: All parameters are statistically significant at the 1% level. Standard errors are shown in parentheses. Start, peak, and end dates are determined after simple rounding of the estimated peak, μ.

Table 2.5 Estimated Duration of Event Impacts on Variance

	Duration [6σ]	Event date [base]	Start date [-3σ]	Peak date [μ]	End date [+3σ]
Iraq1	0.91	8/2/1990	8/7/1990	8/7/1990	8/7/1990
	(0.14)				
OPEC1	1.31	8/27/1990	8/21/1990	8/22/1990	8/23/1990
	(0.26)				
Iraq2	1.41	1/17/1991	1/16/1991	1/17/1991	1/18/1991
	(0.19)				
Asian financial crisis	1.69	7/2/1997	1/23/1998	1/26/1998	1/27/1998
	(0.03)				
OPEC2	599.60	3/23/1999	1/26/1998	4/7/1999	6/16/2000
	(2.26)				
September 11	0.85	9/17/2001	9/17/2001	9/17/2001	9/17/2001
	(0.06)				
Iraq3	14.71	3/20/2003	3/6/2003	3/17/2003	3/26/2003
	(0.04)				
Katrina	1.84	8/29/2005	8/25/2005	8/26/2005	8/29/2005
	(0.01)				
Global financial crisis	117.78	9/15/2008	7/17/2008	10/9/2008	1/5/2009
	(0.13)				
OPEC3	111.89	12/17/2008	5/8/2009	7/29/2009	10/16/2009
	(0.12)				

Note: All parameters are statistically significant at the 1% level. Standard errors are shown in parentheses. Start, peak, and end dates are determined after simple rounding of the estimated peak, μ.

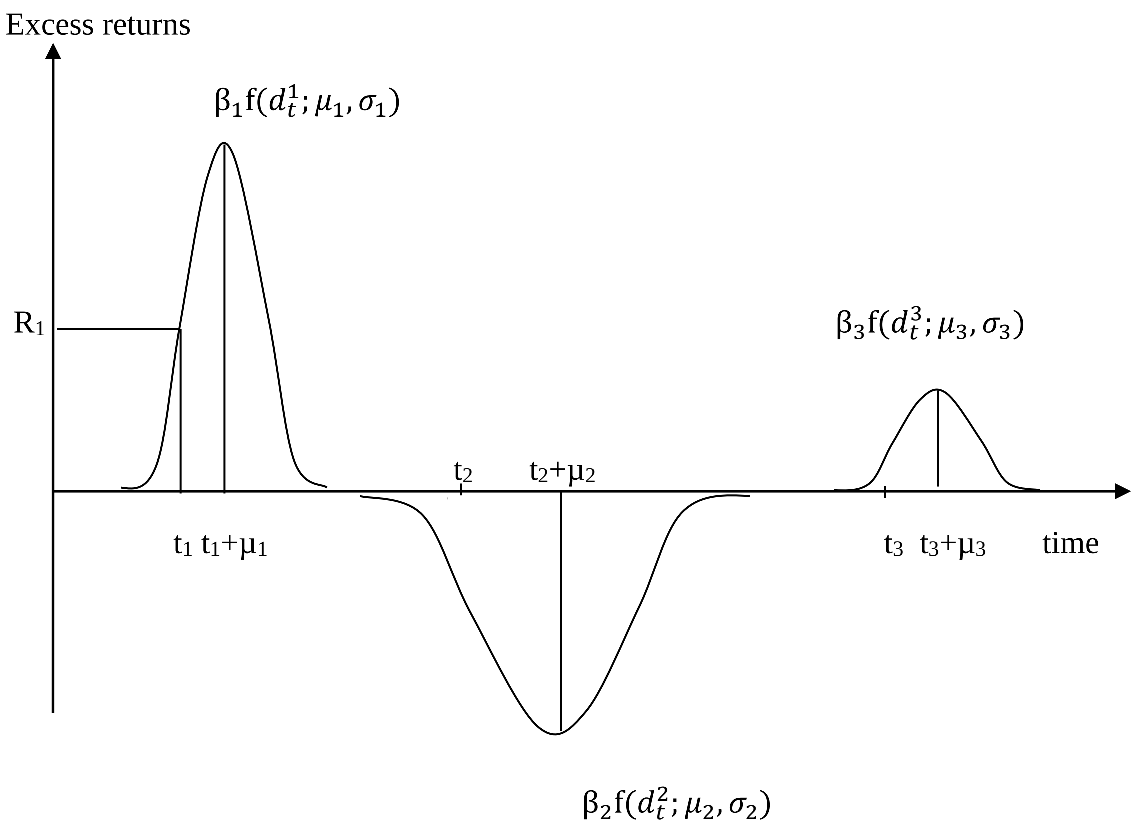

Figure 2.1 The Normal Event Response Model

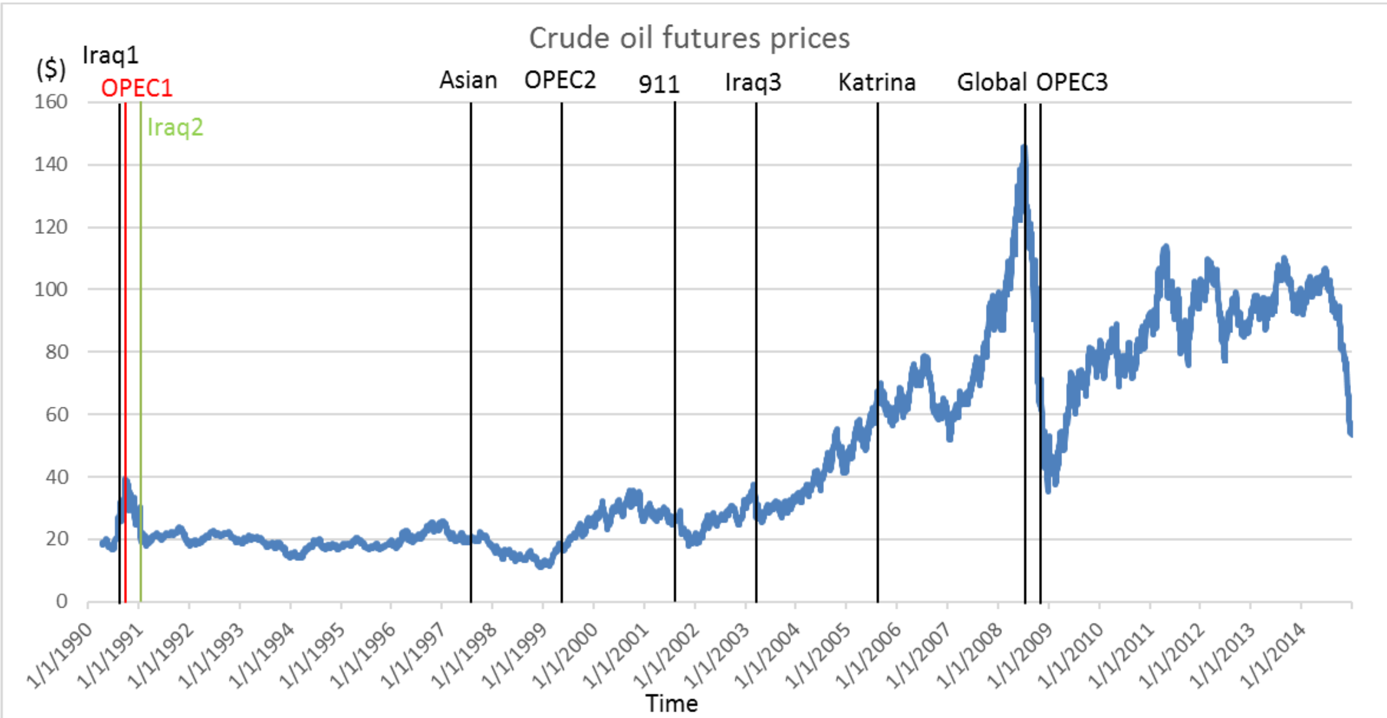

Figure 2.2 Crude oil Futures Prices from April 1990 to December 2014

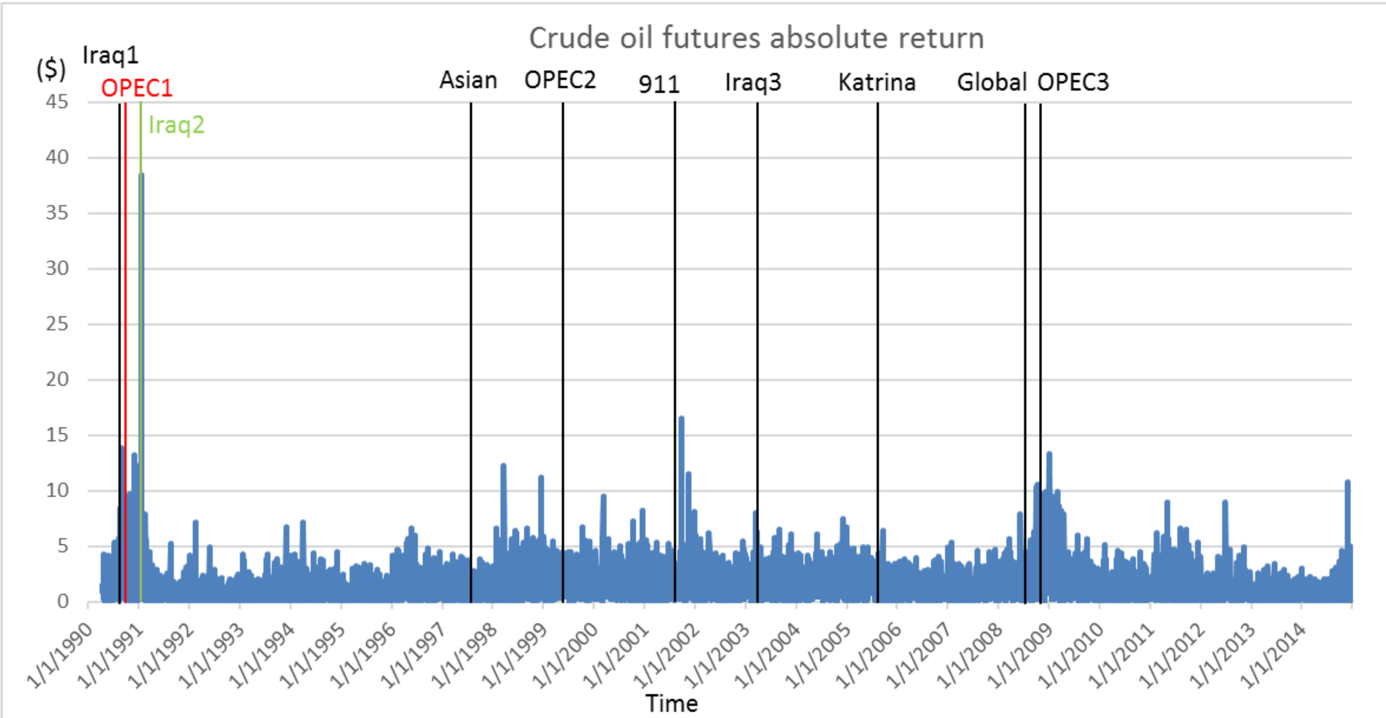

Figure 2.3 Crude Oil Futures Absolute Returns from April 1990 to December 2014

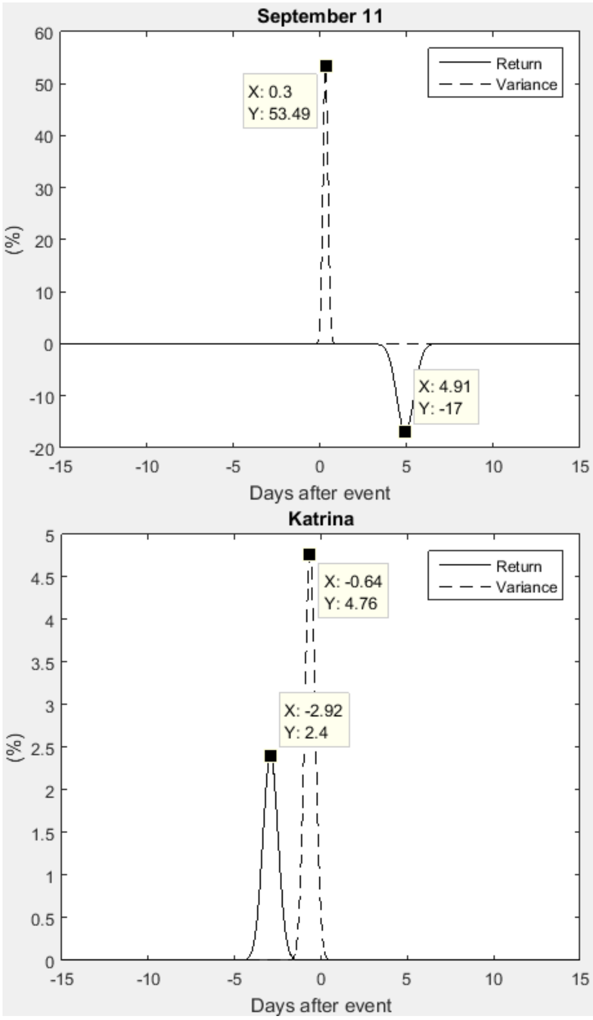

Figure 2.4. Event response of September 11 Terrorists' Attacks (September 17, 2001) and Hurricane Katrina (August 29, 2005) on Crude Oil Futures Return and Variance

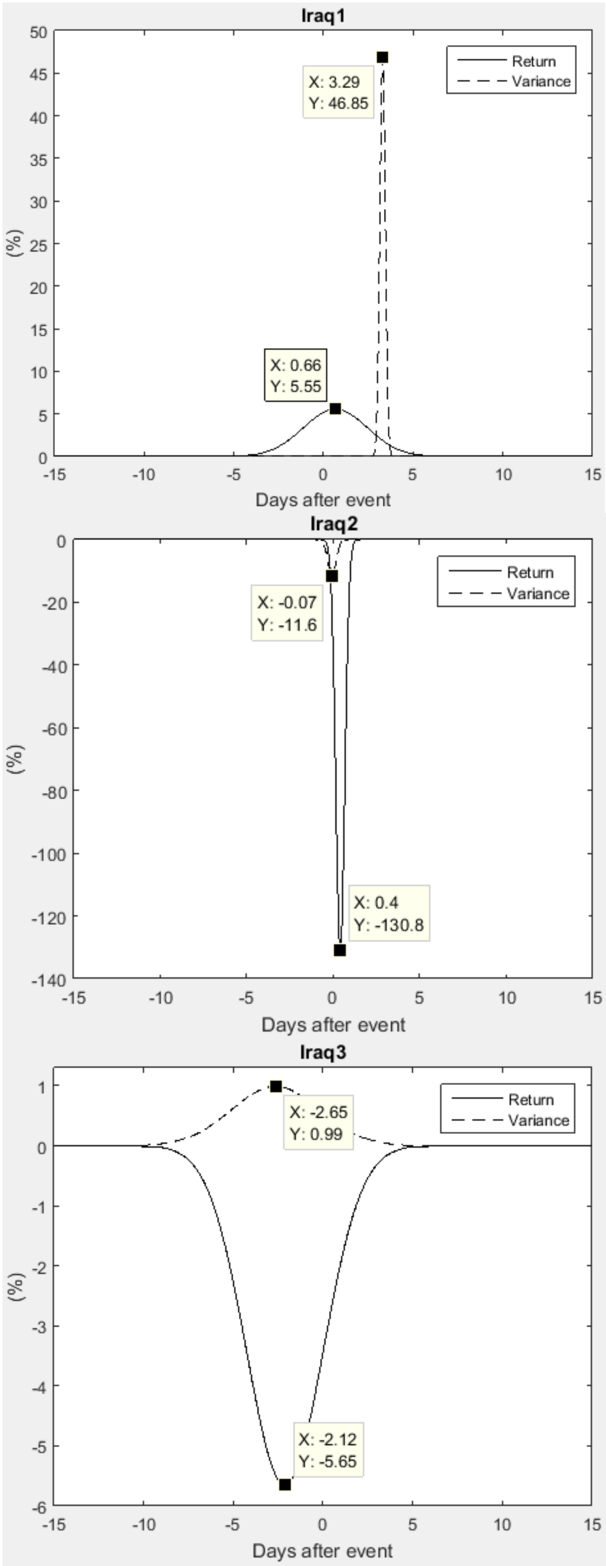

Figure 2.5 Event Response of Iraq1 (August 2, 1990), Iraq2 (January 17, 1991) and Iraq3 (March 20, 2003) on Crude Oil Futures Return and Variance

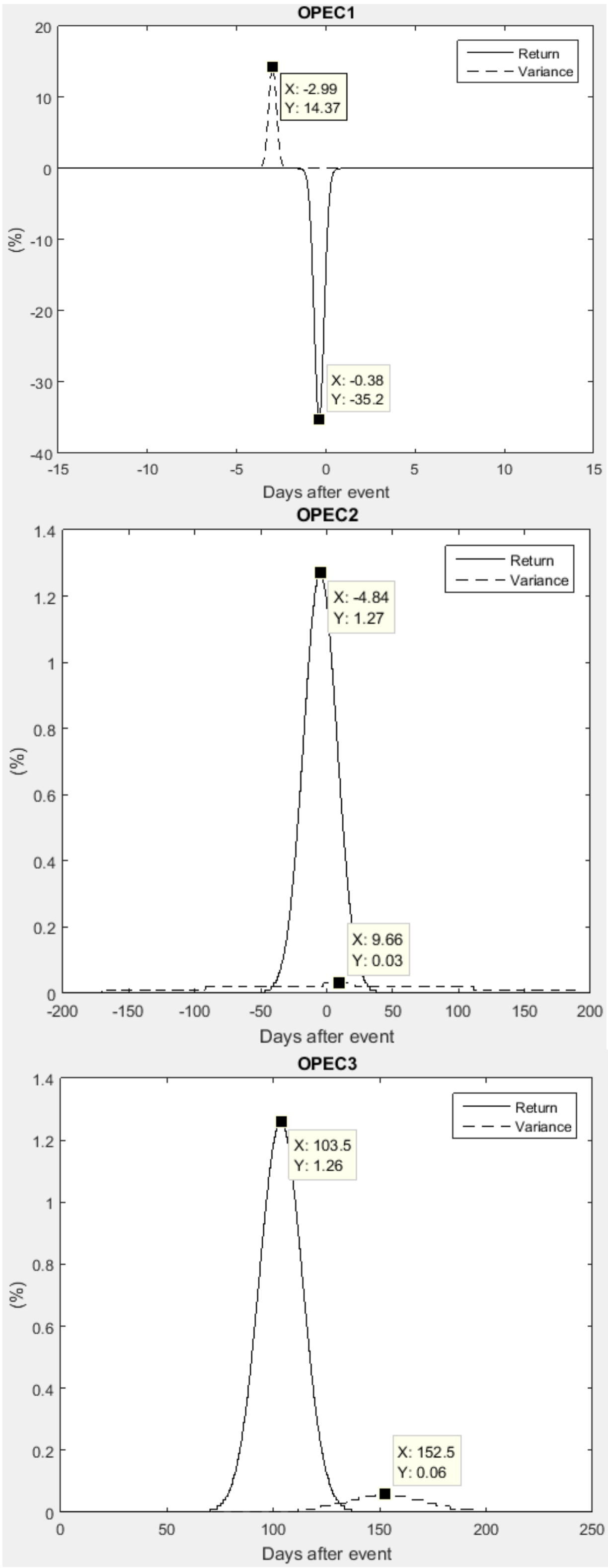

Figure 2.6 Event Response of OPEC1 (August 27, 1990), OPEC2 (March 23, 1999), and OPEC3 (December 17, 2008) on Crude Oil Futures Return and Variance

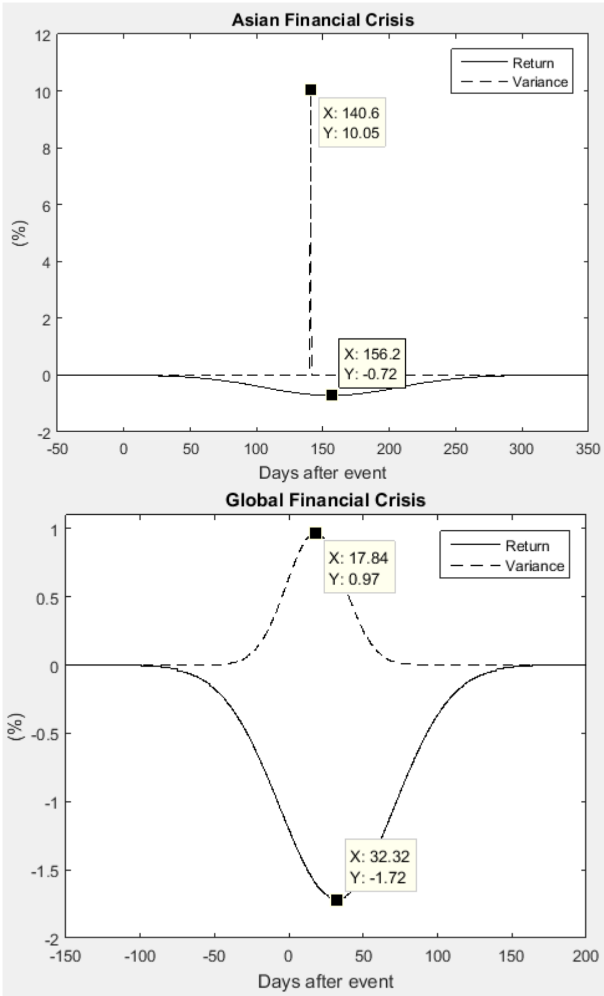

Figure 2.7 Event Response of Asian Financial Crisis (July 2, 1997) and Global Financial Crisis (September 15, 2008) on Crude Oil Futures Return and Variance

CHAPTER 3

THE INFORMATIONAL CONTENT OF INVENTORY ANNOUNCEMENTS: INTRADAY EVIDENCE FROM CRUDE OIL FUTURES MARKET[3]

[3] Ye, S. and B. Karali, 2016. *Energy Economics*. 59(2016): 349-364
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Abstract

This paper examines the behavior of intraday crude oil futures return and volatility and how they respond to weekly inventory announcements by the American Petroleum Institute (API) and Energy Information Administration (EIA). The informational content of API reports is measured relative to market analysts' expectations collected by Reuters, whereas that of EIA reports is measured relative to API reports. Results suggest that unexpected inventory changes in both API and EIA reports exert an immediate inverse impact on returns and a positive impact on volatility; but the duration and magnitude of EIA inventory shocks are longer and larger, with the largest impacts observed when Reuters and API both err on the same side. While there are no instant asymmetric return responses to positive and negative API shocks, the return and volatility responses to cross-commodity inventory shocks in EIA reports exhibit asymmetry.

3.1 Introduction

While there is still an ongoing debate on whether commodity fundamentals or speculative trading drive the volatility of commodity prices (Buyuksahin and Harris, 2011; Sanders and Irwin, 2011; Tang and Xiong, 2012; Kilian and Murphy, 2014), after the dramatic decline in oil prices since June 2014 the focus, at least for the energy markets, has shifted to supply and demand conditions. These factors include, for instance, the shale gas revolution, China's slower economic growth, appreciation of the US dollar, and OPEC's refusal to decrease oil supply. We analyze the effect of a fundamental factor, namely inventories of crude oil and key petroleum products, in crude oil futures markets to shed more light on this discussion.

Inventory information is of critical importance in price discovery of a storable commodity, such as crude oil. Uncertainty in future demand and supply fundamentals induces storage,[4] which, in turn, plays a stabilizing role in consumption, production, and prices. However, since the US demand and supply of crude oil are inelastic in the short run, any deviations from equilibrium storage levels could have an immediate impact on futures prices and volatility (Ye et al., 2005; Hamilton, 2009; Bu, 2014; Halova et al., 2014).

In efficient markets, asset prices reflect all publicly available information and instantly adjust to incorporate new information. Assuming futures markets are efficient, crude oil futures prices should react to the unexpected deviations in inventory levels embedded in public announcements, and the adjustment should be fairly quick. Measuring the effect of unexpected inventory levels on prices and volatility is important for several reasons. First, it would allow indirect inferences about demand and supply elasticities (Halova et al., 2014). Second, higher

[4] Even though economists differ in how they measure benefits and costs, they generally agree that the marginal benefit from the last unit stored should equal to the marginal cost of storing that unit. For papers on the theory of storage, see, for example, Brennan (1958), Telser (1978), Scheinkman and Schechtman (1983), Thurman (1988), Williams and Wright (1991), and Peterson and Tomek (2005).

volatility would discourage investments in fixed capital as producers face higher uncertainty about future conditions. Third, the knowledge of volatility changes could create arbitrage opportunities for traders since volatility is a key in pricing of derivatives (Lee and Zyren, 2007).

To this end, we measure the magnitude and the duration of crude oil futures return and volatility responses to unexpected changes in inventory levels. Specifically, our paper investigates and compares the impact of two major inventory reports on crude oil and key petroleum products (distillate fuel and gasoline), released by the American Petroleum Institute (API) and Energy Information Administration (EIA), on crude oil return and volatility using intraday futures data. Previous studies focus on the informational content of EIA reports and define inventory surprises, or shocks, as the differences between the inventory levels released in EIA reports and the market expectations, represented by either Reuters' (Bu, 2014) or Bloomberg's survey (Halova Wolfe and Rosenman, 2014). However, the API report, which is released before the EIA report, might contain new information on commodity fundamentals beyond those analysts' survey results, and therefore should be incorporated in an analysis of EIA announcement effects on oil futures markets.

We contribute to the existing literature by showing varying price and volatility impacts of these reports after decomposing commonly used inventory shock (i.e. the difference between EIA and market survey) into two separate informational shocks (differences between the API and market survey, and between the EIA and API reports).[5] We also include cross-commodity inventory shock effects (Halova Wolfe and Rosenman, 2014; Halova et al., 2014), and allow positive and negative shocks to have asymmetric impacts on both futures return (Bu, 2014) and volatility (Bu, 2014; Halova Wolfe and Rosenman, 2014). Further, the use of high-frequency

[5] Even though Bu (2014) investigates the relationship between API reports and Reuters' surveys in terms of forecast unbiasedness, she only considers EIA inventory shocks, measured as the difference between EIA and Reuters' survey, in her analysis of daily crude oil futures returns and volatility.

data enables us to model the intraday volatility pattern observed during a trading day (Andersen and Bollerslev, 1997), and to determine the exact duration of inventory shock effects.

Our results show that unexpected crude oil inventory changes in both API and EIA reports exert an immediate inverse impact on crude oil futures returns although the instantaneous response to API report is generally smaller. While we do not find asymmetric responses in returns to positive and negative API shocks immediately after the report release, the cumulative effects after 20 minutes exhibit asymmetric effects. The return responses to EIA shocks differ substantially based on the relative rankings of the inventory changes published in these reports. We find that, in general, the impact on returns is exacerbated when market analysts' and API reports both under- or overstate the inventory changes to be released in the successive reports. While asymmetric responses in returns to EIA shocks are not pronounced for crude oil inventory shocks, both distillate fuel and gasoline inventory shocks exhibit asymmetric effects in crude oil return. Our study further shows that intraday crude oil volatility increases following the report releases. While we find no evidence of cross-commodity effects in volatility following the API reports, both distillate fuel and gasoline shocks embedded in EIA reports exert an immediate increase in crude oil volatility. In addition, we find that the duration of inventory shocks on both return and volatility is longer following the EIA reports, lasting about 60 minutes (compared to 25 minutes after API reports).

3.2 Literature review

Possible impacts of petroleum and natural gas inventory reports released by EIA on energy futures returns and volatility have been widely studied in the literature. Linn and Zhu (2004), for instance, find that intraday volatility of natural gas futures prices around the release time of

EIA's weekly natural gas storage reports is considerably greater than its normal level. Chang et al. (2009), by employing analysts' forecasts from Bloomberg, find a significant response of intraday crude oil futures returns to unexpected inventory changes immediately after the EIA's crude oil inventory report releases, and that the price reaction is greater when the inventory forecasts were made by analysts with forecast accuracy in the past. Gay et al. (2009) study the impact of EIA's natural gas inventory reports on intraday natural gas futures returns by regressing intraday returns around the report time on both anticipated and unanticipated components of the reports and find that only the surprise component has statistically significant impact. Halova et al. (2014) investigate the effect of the unexpected part in EIA's crude oil inventory reports on intraday crude oil returns and volatility implementing both ordinary least squares (OLS) and identification-through-censoring (ITC) methods and find that energy returns are strongly influenced by unexpected changes in inventory levels. Bu (2014) employs a generalized autoregressive conditional heteroskedasticity (GARCH) model to investigate the effect of the unexpected part in EIA's crude oil inventory reports on daily crude oil returns and volatility and finds that inventory shocks have negative impacts on returns but no effect on return variance on report release days. In addition to inventory reports, the impact of OPEC announcements on energy futures markets has also been studied in the literature (Demirer and Kutan, 2010; Schmidbauer and Rösch, 2012; Karali and Ramirez, 2014).

Our study is most closely related to Halova Wolfe and Rosenman (2014), in which the impact of inventory surprises measured as the difference between EIA reports and Bloomberg's survey on intraday crude oil and natural gas volatility is investigated. Similar to their study, we also include cross-commodity inventory shock effects and test for asymmetric responses to shortage and surplus. However, our study differs in several ways. First, we incorporate the possible impact of additional information that becomes available to market participants by the release of API reports. To the best of our knowledge, our study is the first to analyze the impact of API report releases, and to disaggregate the informational content in EIA reports based on the information shock in API reports. Second, we model both futures return and volatility and investigate the impact of inventory shocks on both, whereas Halova Wolfe and Rosenman (2014) model only volatility. Third, we condition the return and volatility responses in pre- and post-announcement periods on inventory shocks. Lastly, we account for a possible pronounced sinusoidal pattern in intraday volatility as shown in Andersen and Bollerslev (1997) for foreign exchange and equity markets.[6] The intraday periodicity observed in those financial markets could also exist in crude oil futures market, and therefore should be incorporated in high-frequency volatility models.

3.3 Data

3.3.1 Inventory reports and market expectations

There are two important weekly reports providing information on the inventory levels of crude oil, distillate fuel, and gasoline in the US. One is released on Tuesdays at 4:30pm EST by the industry-backed API and called "Weekly Statistical Bulletin." The other is released on Wednesdays at 10:30am EST (or on Thursdays at 11:00am EST due to holidays) by the US Department of Energy's agency EIA and called "Weekly Petroleum Status Report." Both reports

[6] More specifically, Andersen and Bollerslev (1997) show that intraday periodicity in the return volatility in foreign exchange and equity markets have a strong impact on the dynamic properties of high-frequency data. In addition, Andersen and Bollerslev (1998) demonstrate that incorporating a periodic function along with a daily heteroskedasticity component to account for persistence at lower frequencies reveal interesting patterns in the correlograms of absolute returns (proxy for volatility) that are invisible prior to the periodic filtering. Harju and Hussain (2011) employ a similar method to study the impact of US macroeconomic news on the high frequency European equity returns and volatility and further include autoregressive and moving average terms in the volatility equation to account for volatility clustering.

provide inventory levels of these energy commodities as of the previous Friday. Although the surveys conducted to prepare these two reports are similar, participation in the EIA survey is government mandated while participation in the API survey is voluntary. Therefore, the EIA report is often viewed as the main market mover.[7]

Reuters conducts a weekly survey among many energy market investors, analysts, and economists to collect their expectations of inventory changes in the upcoming inventory reports. Reuters then reports the median of these forecasts (after taking out the maximum and the minimum) on Mondays and Tuesdays.[8] The release time of these survey results vary each week but, it is generally around 2:00pm EST.[9] Figure 3.1 shows the timing of inventory report releases as well as the Reuters' survey in a typical week.

To determine whether Reuters' survey can be used as a measure of "expected" inventory changes, we perform forecast unbiasedness tests by estimating the regression equation (Andersen et al., 2003; Bu, 2014):

$$\Delta Inv_{API,m,w} = \alpha_0 + \alpha_1 \Delta Inv_{R,m,w} + \alpha_2 \Delta P_t^{API-R} + e_{API,m,w} \tag{3.1}$$

for $m = \{\text{crude oil, distillate fuel, gasoline}\}$ and $w = 1, 2, \cdots, W$ (weeks). The variable $\Delta Inv_{API,m,w}$ is the inventory change in API report in week w for commodity m, $\Delta Inv_{R,m,w}$ is the inventory change in Reuters' survey released in week w for commodity m, and ΔP_t^{API-R} is the change in crude oil futures price between the releases of Reuters' survey and API report. If Reuters' survey is an unbiased forecast of API reports, then we should have $\alpha_0 = 0$ and $\alpha_1 = 1$.

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[7] More specifically, the EIA report is the most useful for non-institutional investors looking for a full breakdown report as it is free to access. While the EIA report is often considered the main market mover, the API report still moves the market as it gives an early indication of what the EIA numbers are likely to be (Brown, 2013).

[8] Forecasts released on Mondays include a smaller set of survey participants and therefore are less accurate than the forecasts released on Tuesdays. For that reason, we use the survey results released on Tuesdays in our analysis.

[9] Only two out of 70 reports in our sample are released as early as 12:23pm EST and as late as 2:54pm EST. Among the remaining 68 reports, 33 are released during the 1:45pm-2:15pm EST interval.

Further, if analysts' expectations are revised after the survey but before the API release, then $\alpha_2 \neq 0$. Table 3.1 presents the results of equation (3.1), estimated both with and without the variable ΔP_t^{API-R}. As can be seen in columns (1)-(6), the hypothesis $\alpha_1 = 1$ cannot be rejected for any of the commodities, indicating that Reuters' survey provides unbiased forecasts of inventory changes listed in API reports. The coefficients on the price change variables are not statistically different form zero, implying that there were no forecast revisions between the two releases.

We apply the same analysis to EIA reports and estimate the following equation:

(3.2) $$\Delta Inv_{EIA,m,w} = \alpha_0 + \alpha_1 \Delta Inv_{R,m,w} + \alpha_2 \Delta P_t^{EIA-R} + e_{EIA,m,w},$$

where $\Delta Inv_{EIA,m,w}$ is the inventory change in EIA report in week w for commodity m and ΔP_t^{EIA-R} is the change in crude oil futures price between the releases of Reuters' survey and EIA report. Results are presented in columns (7)-(12) of table 3.1. An important difference compared to API results emerges for crude oil inventory changes. While column (7) shows statistical evidence of biasedness of Reuters' survey at 10% significance level, this evidence disappears in column (8) when we include the price change variable. However, it is seen that the price change variable is statistically significant and negative, implying that forecasts are revised from the release of Reuters' survey to the EIA release. This result is not surprising. Because the API reports are released after the Reuters' survey but before the EIA reports, they might contain new information for market participants. Thus, inventory changes in EIA reports could be compared to those in API reports. We perform the above analysis in equations (3.1)-(3.2) to establish the relationship between the EIA and API reports by estimating $\Delta Inv_{EIA,m,w} = \alpha_0 + \alpha_1 \Delta Inv_{API,m,w} + \alpha_2 \Delta P_t^{EIA-API} + e_{EIA,m,w}$, where $\Delta P_t^{EIA-API}$ is the change in crude oil futures price between the releases of API and EIA reports. As seen in table 3.2, unbiasedness of API reports for EIA reports is rejected in all cases, implying that, on average, EIA reports provide additional information.[10] In addition, there is significant and negative price change between the two reports, suggesting market participants might have revised their forecast after the API report.

3.3.2 Inventory shocks

Since Reuters' survey results are shown to be unbiased forecasts of the inventory changes in API reports above, we use these median forecasts released on Tuesdays as our measure of "expected" inventory changes. We define "API inventory shock" as the difference between actual inventory changes released in the API reports and the expected inventory changes released by Reuters. We follow Halova et al. (2014) and divide this difference by the inventory levels to obtain standardized inventory shocks. Thus, inventory shock contained in API reports in our study, $S_{API,m,w}$, is given by:

$$(3.3) \qquad S_{API,m,w} = 100 \times \left(\frac{\Delta Inv_{API,m,w} - \Delta Inv_{R,m,w}}{Inv_{API,m,w}} \right)$$

where $m = \{\text{crude oil, distillate fuel, gasoline}\}$ and $w = 1, 2, \cdots, W$ (weeks). Because the information in API report becomes available before the EIA report is released (and based on our results in tables 3.1-3.2) we define "EIA inventory shock" as the standardized difference between the inventory changes in EIA and API reports. Specifically, inventory shock contained in EIA reports in our study, $S_{EIA,m,w}$, is given by:

$$(3.4) \qquad S_{EIA,m,w} = 100 \times \left(\frac{\Delta Inv_{EIA,m,w} - \Delta Inv_{API,m,w}}{Inv_{EIA,m,w}} \right)$$

where $m = \{\text{crude oil, distillate fuel, gasoline}\}$ and $w = 1, 2, \cdots, W$(weeks).

[10] The simple correlation coefficients between inventory changes in API and EIA reports are 0.80 for crude oil, 0.76 for distillate fuel, and 0.79 for gasoline (all significant at 1% level).

Table 3.3 provides summary statistics of the inventory shocks computed in equations (3.3) and (3.4). Sample period spans from August 26, 2012 to December 30, 2013, resulting in a total of $W = 70$ observations for each report. Inventory shocks, on average, are close to zero. However, when positive and negative inventory shocks are distinguished, the averages are in the range of 0.63% to 1.26% for positive shocks, and -0.50% to -1.17% for negative shocks. The proportions of positive and negative shocks in the sample are approximately the same. On average, crude oil inventory shocks are smaller in magnitude compared to distillate fuel shocks, which have larger standard deviations in both reports compared to the other two shocks.

Given the timing of the report releases and the information that becomes available before the EIA release, categorizing EIA shocks into positive and negative requires consideration of six possible scenarios. Denoting Reuters, API, and EIA with “R,” “A,” and “E,” respectively, positive EIA shocks are realized when (1) R>E>A; or (2) E>R>A; or (3) E>A>R. On the other hand, negative EIA shocks are realized when (4) R>A>E; or (5) A>E>R; or (6) A>R>E. Even though the cases listed in (1)-(3) all result in a positive EIA shock computed as in equation (3.4), the impact on prices and volatility might differ based on the relative ranking of the inventory changes released in Reuters’ survey and the two reports. Similarly, price and volatility reaction might differ for a negative EIA shock based on the relative rankings listed in (4)-(6). Table 3.4 presents summary statistics of positive and negative EIA inventory shocks for each of these six scenarios. For positive shocks, the case with E>A>R in column (3) slightly dominates in terms of frequency in the sample, while R>A>E in column (4) occurs slightly more often in the case of negative shocks. On average, positive EIA shocks are greater in magnitude when E>R>A (column (2)), while negative shocks are greater in magnitude when A>R>E (column (6)).

3.3.3 Futures prices

We use intraday prices of crude oil futures contracts traded at CME Globex, the electronic trading platform of CME Group. Crude oil electronic trading takes place from Sunday 6:00pm EST until Friday 5:15pm EST with a 45-minute break on each day from 5:15pm to 6:00pm EST. Figure 3.2 shows both the electronic and floor trading hours of crude oil futures contracts in a typical week. In our sample, we removed fixed holidays, including Christmas (December 24-26), New Year's (December 31- January 2), 4th of July, as well as moving holidays such as Martin Luther King Day, Presidents' Day, Good Friday, Easter Monday, Memorial Day, Labor Day, and Thanksgiving and the day after. Although the exact days of these holidays do not account for all the associated market slowdowns, they represent the most important holiday effects. To be consistent with the electronic trading hours throughout the sample period and to keep the intraday periodicity intact, we exclude observations starting from 6:00pm EST the night before a holiday until 5:15pm EST of that holiday evening. After excluding holidays, we are left with intraday price data for 330 days.

In our analysis, we use crude oil futures prices measured at 5-minute intervals to compute 5-minute return as:

(1) $$R_t = 100 \times \ln(P_t / P_{t-1})$$

where P_t is the nearby futures price at the t^{th} 5-minute interval. Nearby futures series are obtained by rolling over to the second nearby contract once that next contract has a trade volume exceeding the most nearby contract. Each trading day consists of N = 279 5-minute intervals, resulting in a total of T = 92,070 (= 279 × 330) observations. Table 3.5 presents descriptive statistics of 5-minute returns and absolute returns. While the average 5-minute return is basically zero, the average absolute return, a commonly used volatility proxy, is 0.05%. Normality of and unit root in both return and absolute return series are rejected based on the Jarque-Bera and augmented Dickey-Fuller tests, respectively. Ljung-Box statistics indicate existence of serial correlation in both series. Autocorrelation functions of both series are shown in figure 3.3. The return series display small but statistically significant serial correlation at the very shortest lags, presumably due to microstructure effects (Andersen et al., 2003). However, the sample autocorrelations of absolute returns display very slow decay and pronounced periodicity (i.e. strong regular cyclical pattern) which is in line with Andersen and Bollerslev (1998) and Andersen et al. (2003).

3.3.4 Preliminary analysis

To investigate the intraday pattern of 5-minute returns and their volatility we compute the averages of those specific intervals across all trading days in our sample. Figure 3.4 presents the average return in each of the 5-minute interval on the days with API report releases, separated for positive (panel a) and negative (panel b) crude oil inventory shocks.[11] During the 5-minute interval immediately following the API report release at 16:30, the average return is negative (-0.08%) when there is a positive inventory shock, whereas it is positive and similar in magnitude (0.06%) when there is a negative inventory shock. This inverse relationship between inventories and returns is expected as decreases (increases) in inventories indicate price increases (decreases) in the future. Similarly, figure 3.5(a) shows that during the immediate 5-minute interval after the EIA report release at 10:30, the average return is negative (-0.23%) when there is a positive inventory shock.[12] Figure 3.5(b) shows that when there is a negative shock the average return is positive but smaller in magnitude (0.04%) at 10:30 and becomes negative shortly after. The

[11] The labels on the horizontal axis represent the starting time of the 5-minute interval.
[12] In figure 5, EIA shocks are categorized as positive and negative as in table 3; thus ignoring those six possible cases shown in table 4.

difference in the magnitude of the average returns suggests a possible asymmetric impact of positive and negative shocks on intraday returns.

Figures 3.6 and 3.7 display, respectively, average returns and average absolute returns in each 5-minute interval during a trading day, separated for non-report days and days with API and EIA report releases.[13] Figure 3.6(b) illustrates a clear drop in average returns to 0.09% on EIA days at 10:30, which is the report release time. On EIA days, there is also an increase in average return reaching to 0.06% around 14:30, the time floor trading closes. On non-report days presented in figure 3.6(c), there is a decrease in average return to 0.04% at 18:00, the opening of electronic trading.

From figure 3.7, clear volatility spikes are observed at around 9:00, 14:30, and 18:00, which correspond to the opening and closing of floor trading and the opening of electronic trading, respectively. What distinguishes API days from non-report days is the volatility spike, with average volatility reaching to 0.09%, at around 16:30 when the API report is released as seen in figure 3.7(a). On EIA days shown in figure 3.7(b), there is a dramatic volatility spike at around 10:30 when the EIA report is released, with average intraday volatility reaching to 0.26%. This is about three times larger than the increased volatility following API reports.

3.4 Methodology

We follow the two-step econometric methodology proposed by Andersen and Bollerslev (1998), which was also used in Andersen et al. (2003) and Harju and Hussain (2011), to investigate the impact of unexpected inventory changes inherent in API and EIA reports on the intraday return and volatility of crude oil futures contracts. Specifically, we first estimate conditional mean of

[13] Among the 70 EIA reports in our sample period, 57 were released on Wednesdays at 10:30 and the remaining 13 were released on Thursdays at 11:00. In figures 6 and 7, the averages are calculated by excluding those 13 EIA reports released at 11:00. However, all 70 EIA reports are included in the empirical analysis.

returns and use the predicted residuals from the estimation to fit a conditional volatility model. The fitted conditional volatility is then used in a weighted least squares (WLS) procedure to obtain heteroscedasticity-robust standard errors in the conditional mean equation.

3.4.1 Return model

We model the 5-minute crude oil futures return, R_t, as follows:

$$R_t = \alpha + \sum_{p=1}^{P} \gamma_p R_{t-p} + \sum_{q=1}^{Q} \delta_q \varepsilon_{t-q} + \sum_{k} \sum_{m} \sum_{l} \sum_{j=-1}^{J} \beta_{k,m,l,j} S_{k,m,l,t-j} + \sum_{g=1}^{G} \theta_g D_g + \varepsilon_t, \tag{3.5}$$

$$\begin{aligned} t &= 1, \dots, T \; (T = 92{,}070); \\ k &= \{\text{API}, \text{EIA}\}; \\ m &= \{\text{crude oil}, \text{distillate fuel}, \text{gasoline}\}; \\ l &= \{\text{positive}, \text{negative}\}; \end{aligned}$$

where R_t is continuously compounded return in interval t from equation (3.5); $S_{k,m,l,t-j}$ is inventory shock computed as in equations (3.3) and (3.4) for API and EIA reports, respectively; D_g is a set of dummy variables indicating opening and closing of floor and electronic platforms, each taking the value of one in the respective 5-minute interval, and zero otherwise, during the day; [14] and ε_t is the random error term. The first two summation terms on the right-hand side represent autoregressive and moving average terms, respectively. In order to determine the duration of inventory news, we allow the inventory shock effects to last for J periods (i.e. 5-minute intervals from $j = -1$ to $j = J$) after the report release. With this notation, $j = 0$ refers to the 5-minute interval within which the report is released, while $j = -1$ refers to the 5-minute interval right before the report release (i.e. [-5,0] interval), which is included to test for any report leakage effects (Balduzzi et al., 2001; Andersen et al., 2003; Halova Wolfe and Rosenman, 2014). We further allow the inventory impacts to vary between positive and negative

[14] We also estimated the model with interaction terms between the dummy variables for floor opening and closing hours and the inventory shock variables to capture the spikes in average returns seen around 9:00 and 14:30 in figure 6 but did not find any statistical significance.

shocks.[15] Based on the Akaike information criterion and likelihood ratio tests, we set $P = 2$, $Q = 0$, $J = 4$ for API reports, and $J = 11$ for EIA reports.[16]

Following Andersen et al. (2003), we first estimate the conditional mean model (6) by OLS to obtain the residuals, $\hat{\varepsilon}_t$. We then approximate the time-varying volatility of these residuals by a linear model explained below to use in the WLS estimation of equation (3.6).

3.4.2 Volatility model

Based on the preliminary analysis presented in figure 3.3, we allow futures return variance to be heteroskedastic. We approximate the 5-minute return volatility, $|\hat{\varepsilon}_t|$, using the model:

$$|\hat{\varepsilon}_t| = \mu + \sum_{p=1}^{P'} \gamma'_p |\hat{\varepsilon}_{t-p}| + \sum_{q=1}^{Q'} \delta'_q u_{t-q} + \Psi \frac{\hat{\sigma}_{d(t)}}{\sqrt{N}} + \sum_k \sum_m \sum_l \sum_{j=-1}^{J'} \beta'_{k,m,l,j} |S_{k,m,l,t-j}|$$

(3.6)

$$+ \sum_{h=1}^{H} \left(\Omega_h^S \sin\left(\frac{h2\pi th}{N}\right) + \Omega_h^C \cos\left(\frac{h2\pi t}{N}\right) \right) + \sum_{g=1}^{G} \theta'_g D_g + u_t.$$

The dependent variable, $|\hat{\varepsilon}_t|$, in equation (3.7) is the absolute value of the estimated residuals from (6), which proxies the time-varying 5-minute volatility; $|S_{k,m,l,t-j}|$ is the absolute value of inventory shock computed as (3) for API and as (4) for EIA reports; D_g is the same set of dummy variables in equation (3.6) to capture possible impacts of opening and trading hours of both floor and electronic platforms on volatility seen in figure 3.7; and u_t is the random error term. As before, the first two summation terms on the right-hand side, represent autoregressive and moving average terms, respectively. The term, $\hat{\sigma}_{d(t)}/\sqrt{N}$, is the average volatility over trading day d containing the 5-minute interval t in question, and computed from a simple

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[15] Note that positive and negative EIA inventory shocks consist of three separate variables each, representing those six possible cases shown in table 4.
[16] To simplify comparison, we do not allow J to differ between positive and negative inventory shocks, or among inventory shocks in different commodities. $J = 4$ and $J = 11$correspond to the intervals from the 20th to the 25th minute and from the 55th to the 60th minute after the report release, respectively.

GARCH(1,1) model using daily data (Andersen et al., 2003). The cyclical intraday pattern observed in the high-frequency data is captured by the trigonometric functions in equation (3.7), of which sum provides a periodic function with a period of one trading day (Gallant, 1981, 1982; Andersen and Bollerslev, 1997, 1998). As in the return equation, the coefficients on the inventory shock variables are allowed to differ between positive and negative shocks;[17] and the impact of shocks are allowed to last for J' periods to determine the impact duration. Based on the Akaike information criterion, we set $P' = 6$, $Q' = 1$, $H = 10$, $J' = 4$ for API reports, and $J' = 11$ for EIA reports.[18]

3.5 Results

3.5.1 Return model

Results from the return model (6) estimated via WLS are presented in two parts in tables 3.6 and 3.7. Table 3.6 presents the coefficient estimates (except for the inventory shocks) along with the model diagnostics test results. Coefficients on the autoregressive terms indicate that 5-minute returns exhibit negative and significant serial correlation (-0.038 and -0.012 for the first and second lags).[19] Only the coefficients of floor closing and electronic opening dummies are statistically significant. While the former increases 5-minute returns by 0.020, the latter decreases the returns by 0.016, which are consistent with figure 3.6. The F-test statistics for the joint significance of model parameters are significant at the 1% and 5% levels, confirming that

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[17] Since we incorporate negative inventory shocks in absolute value, their coefficients are expected to be positive, indicating an increase in volatility. Note also that positive and negative EIA inventory shocks consist of three separate variables each, representing those six possible cases shown in table 4.
[18] To facilitate comparison, we do not allow J' to vary between positive and negative shocks, or among inventory shocks associated with different commodities. $J' = 4$ and $J' = 11$ correspond to the intervals from the 20th to the 25th minute and from the 55th to the 60th minute after the report release, respectively.
[19] Note that based on the Akaike information criterion, the return model does not include moving average terms and therefore, table 3.6 does not contain δ estimates.

we can reject the exclusion restriction on the independent variables included in the return equation.

Coefficient estimates and corresponding p-values of the inventory shock variables are presented in table 3.7. For crude oil, all shock coefficients are statistically significant and negative during the first 5-minute interval following the report releases (interval [0,5] in table). This is consistent with the theory of storage that if inventories are lower (higher) than expected, the price of crude oil is likely to increase (decrease), and therefore futures returns are likely to increase (decrease). For example, if crude oil inventories in API report is 2% lower than the Reuters' survey (a negative shock with our definition) this leads to a 0.158 ($= -2 \times -0.079$) increase in return, while a positive shock of 2% results in a -0.196 ($= 2 \times -0.098$) decrease.

In order to analyze the time pattern of inventory shock effects, figure 3.8 plots the cumulative impacts calculated by adding up the coefficient estimates presented in table 3.7 for each successive time interval. The labels on the horizontal axes correspond to the starting point of the time interval (e.g., zero indicates the time interval [0,5] in table 3.7, which is the first 5-minute interval after the report release). The black circles represent cumulative effects that are statistically significant at the 10% level and the blank circles represent those that are insignificant.

Insignificant estimates corresponding to the [-5,0] interval in figure 3.8(a) suggest that there is no evidence of pre-report effects for the API reports except for positive gasoline shocks. However, both positive and negative crude oil inventory shocks have significant effects in the following time intervals. For instance, a 1% positive (negative) crude oil inventory shock in API reports will result in a total of 0.094 (0.074) drop (increase) in the futures returns in the first five minutes. Based on the t-test, these effects are not significantly different from each other at the

10% level (t-value of -0.67), indicating no asymmetric effects of positive and negative crude oil inventory shocks in the first 5-minute interval. However, the impact of positive shocks lasts for another 20 minutes with a cumulative effect of -0.171, whereas the impact of negative shocks accumulates to -0.104, resulting in a statistically significant difference (t-value of -9.46). Even though the coefficient on positive API distillate fuel shock is negative and statistically significant at 10% (table 3.7), the successive movements in crude oil returns are small and mostly insignificant, resulting in an insignificant cumulative response pattern shown in 8(a). On the other hand, the cumulative effect is significant in the [0,5] and [20,25] intervals when the distillate fuel shock is negative. Negative gasoline inventory shocks also result in significant negative effects on crude oil futures returns lasting for 25 minutes after the API report release. Although the impact in the [0,5] interval is smaller compared to that of crude oil shock, it keeps increasing in magnitude in the following intervals.

Figure 3.8(b) presents the same analysis for the EIA reports. Pre-report effect is observed in several cases. For crude oil, for instance, this effect exists for both positive and negative EIA shocks, when there was a positive API shock the day before (A>R). In the first 5-minute interval after the EIA report release, a 1% positive shock leads to a total of 0.131 decrease in crude oil futures returns when R>E>A, 0.274 when E>R>A, and 0.488 when E>A>R. This finding shows that the market reaction to a positive shock differs substantially depending on the relative rankings of the inventory changes released in these reports, with largest impact observed when both Reuters and API underestimate the successive report release (i.e. when Reuters' survey underestimates API and when API underestimates EIA). A 1% negative shock in crude oil inventories results in a 0.395 cumulative increase in returns in the [0,5] interval when R>A>E, 0.180 when A>E>R, and 0.229 when A>R>E, again with the largest impact observed when

Reuters and API both err on the same side (when they both overestimate the successive report). The impact of positive (negative) shocks decreases in magnitude to -0.343 when E>A>R (-0.102 when R>A>E) in the following 5-minute interval, implying that there are positive price corrections after the initial shock. The cumulative impact of negative shocks becomes mostly insignificant in the following intervals, suggesting that successive positive and negative price adjustments average out to zero quickly when there is a negative shock, while it takes a little more time for the market to adjust to a positive shock when both API and Reuters underestimate crude oil inventories. These initial effects are somewhat smaller than the OLS (-0.48) and ITC (-1.06) estimates provided in Halova et al. (2014). However, the authors do not distinguish positive and negative shocks in their study, and use the same 15-minute intraday intervals on non-report days to calculate normal returns. Our normal return, on the other hand, is computed by modeling all intraday return series while taking into account the intraday volatility. As our study controls for more factors, the finding of smaller impacts is not surprising.

In addition, there is statistical evidence that crude oil futures returns inversely react to positive shocks (E>A>R) in distillate fuel inventories contained in EIA reports. On the other hand, the cumulative effect is positive when there is a negative distillate fuel shock (A>R>E) resulting in a decrease in crude oil returns, which is contrary to our expectation. However, it should be noted that this case also coincides with a positive API shock the day before. Further, both positive and negative gasoline shocks inversely affect crude oil futures returns, especially when Reuters' surveys and API reports both over- or under-forecast gasoline inventories. The cumulative effects on returns amount to -0.368 in the [35,40] interval when E>A>R, and to -0.554 in the [55,60] interval when R>A>E.

3.5.2 Volatility model

Results from the volatility model (7) obtained via maximum likelihood estimation are presented in tables 3.8 and 3.9. In table 3.8, autoregressive terms are mostly significant and except for the first lag they are negative. Moving average term is also statistically significant at the 1% level. In addition, highly significant coefficients on the trigonometric terms indicate that the pronounced intraday volatility pattern in financial markets described in Andersen and Bollerslev (1997) also exists in intraday volatility of crude oil futures returns. There is no surprise that the daily volatility term is positively correlated with the 5-minute intraday volatility within that day. Moreover, intraday volatility increases at the times of opening and closing of both floor and electronic trading platforms, consistent with figure 3.7. The likelihood ratio tests shown at the bottom of table 3.8 indicate that the exclusion restrictions on the independent variables included in the volatility equation can be rejected at the 1% level.

Table 3.9 presents the coefficient estimates and corresponding p-values of the inventory shock variables in the volatility model. Results show that crude oil inventory shocks, both API and EIA, increase volatility (whenever statistically significant) during the [0,5] interval following the report releases. The impact of positive crude oil inventory shocks in the EIA reports (ranging from 0.038 to 0.082) is greater than the impact of positive API shocks (0.025). Similarly, the impact of negative EIA shocks in crude oil inventories (0.071) is larger compared to that of API shocks (0.022). While the impacts in the following intervals are statistically insignificant for API shocks, there are several intervals with significant estimates following the EIA shocks. For example, the initial impact of 0.059 in the [0,5] interval when a positive EIA shock (E>A>R) occurs, is followed by a correction of -0.086 in the [10,15] interval.

In the case of inventory shocks in distillate fuel, there is no statistical evidence for volatility effects in the first 5-minute interval right after the API report releases, but an increase of 0.013 is observed in the [5,10] interval following negative API shocks. On the other hand, both positive and negative distillate fuel inventory shocks in EIA result in higher volatility ranging from 0.077 to 0.094 in the [0,5] interval. While gasoline inventory shocks in API reports do not affect the crude oil volatility, the positive gasoline shocks in EIA reports when both API and Reuters underestimate gasoline inventories (that is, E>A>R) increase volatility by 0.106 during the [0,5] interval. However, when both API and Reuters overestimate gasoline inventories (R>A>E), the crude oil volatility decreases by 0.087 in the [0,5] interval followed by an increase of 0.091 in the following 5-minute interval, [5,10].

The cumulative effects of inventory shocks on intraday volatility are presented in figure 3.9. Panel (a) shows that the impact of crude oil inventory shocks in API is very limited in terms of duration and magnitude. Specifically, a 1% positive crude oil inventory shock in API reports will result in a total of 0.046 volatility increase 15 minutes after the report release.

Figure 3.9(b), on the other hand, portrays a different time pattern for crude oil intraday volatility in response to the inventory shocks in EIA reports. The cumulative volatility impacts last for about an hour, generally with an upward trend. This is similar to the findings of Halova Wolfe and Rosenman (2014), in which intraday crude oil volatility is shown to remain higher than usual for approximately 60 minutes following the EIA reports.[20] For a 1% negative crude oil inventory shock, for instance, the volatility increases by a total of 0.558 in the [55,60] interval when both Reuters' survey and API reports overestimate successive inventories (R>A>E). In contrast, when API and Reuters underestimate inventories in the upcoming EIA reports (E>A>R)

[20] Because the authors use dummy variables for the intervals before and after the announcement, and do not interact those with the inventory shocks, we are not able to compare the magnitude of volatility impacts between the two studies.

a 1% positive EIA shock results in a cumulative decrease of -0.102 in volatility by the 15th minute after the report release. This suggests that, after controlling the volatility increase following the positive API shock the day before, additional inventories in EIA reports beyond the API levels counteract the immediate positive reaction in volatility.

While the volatility impact of positive distillate fuel shocks is not much pronounced except for the case E>A>R where it reaches to -0.160 at the [55,60] interval, negative shocks have a steady impact during the first hour after the report release reaching to 0.177 when R>A>E and an increasing effect accumulating to 0.392 when A>E>R. An increasing pattern is observed for the positive shocks in gasoline inventories, resulting a total of 0.280 increase in crude oil volatility at the [55,60] interval when E>A>R, and a 0.352 volatility increase in the [50,55] interval is observed following negative gasoline shocks when A>E>R.

3.6 Conclusions

Our study investigates the intraday behavior of crude oil futures returns and volatility and how they react to the unexpected inventory changes inherent in weekly API's Weekly Statistical Bulletin and EIA's Weekly Petroleum Status Report. We measure the informational content of API reports relative to market analysts' expectations collected by Reuters, and that of EIA reports relative to API reports published a day before. Using a two-step procedure to estimate both return and volatility, we compare and contrast the magnitude and duration of the inventory surprises in these reports while allowing for asymmetric responses to positive and negative shocks. Inventory shocks (positive and negative) in EIA reports are further classified into subcategories based on the relative ranking of the inventory changes released in Reuters' survey, API, and EIA reports. We also incorporate the impact of market opening and closing hours as well as intraday volatility periodicity in our analysis.

We find that unexpected crude oil inventory changes in both API and EIA reports exert an immediate inverse impact on crude oil futures returns. The instantaneous response to the shocks inherent in API reports is generally smaller and does not exhibit asymmetric effects. However, the cumulative effects of API shocks on returns, which last about 25 minutes, show asymmetric effects. Inventory surprises in API reports are found to affect volatility only when Reuters' survey underestimates crude oil inventories (i.e. a positive shock).

Our study shows the importance of using the most recent available information market participants have when measuring announcement effects. We show that the crude oil return responses to EIA shocks differ substantially depending on the information shock observed with the release of API report the day before. In general, the response in returns is larger when inventory forecasts in Reuters fall short of API levels, and when API inventory levels fall short of EIA levels. Asymmetric effects of EIA reports on returns are only found for inventory surprises in distillate fuel and gasoline. We find cross-commodity effects in crude oil futures, with distillate fuel and gasoline inventory shocks in EIA reports (in addition to crude oil shocks) resulting in an immediate increase in intraday crude oil volatility. We also find that the duration of return and volatility responses to inventory shocks in EIA reports is longer, with the impact lasting as long as one hour.

Overall, our results provide clear evidence of how differently market participants perceive the information contained in two similar, yet different reports. We provide the first empirical evidence that the government-based EIA report conveys additional information to the markets beyond the industry-backed API report and that the market response varies with the direction of the surprise experienced the day before with the API report release.

Our results are of great importance to energy market participants. While our findings support the efficient markets hypothesis in that prices move in response to unexpected news, the adjustment process is rather slow, especially following the EIA reports. However, new information is still absorbed within an hour in a trading day. Our study also suggests that the traders involved in high-frequency trading in crude oil markets should account for the pronounced intraday periodicity. Our model could be used by traders to predict futures return and volatility moves based on their forecasts of inventory levels. Additionally, our results suggest crude oil market participants to utilize all relevant information on petroleum products (i.e. distillate fuel and gasoline inventories), not just on crude oil, and take into consideration the asymmetric impact of the positive and negative inventory shocks in their hedging and risk management decisions. Last but not least, our results also reveal that intraday volatility of crude oil futures prices can be partly explained by news on commodity fundamentals.

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Table 3.1 Unbiasedness Tests of Reuters' Forecasts.

	API ($\Delta \boldsymbol{Inv_{API}}$)						EIA ($\Delta \boldsymbol{Inv_{EIA}}$)					
Variable	Crude oil		Distillate fuel		Gasoline		Crude oil		Distillate fuel		Gasoline	
(Parameter)	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Intercept	-0.13	-0.18	-0.00	-0.01	0.06	0.07	-0.17	-0.24	-0.03	-0.02	0.19	0.19
($\boldsymbol{\alpha_0}$)	(0.75)	(0.68)	(0.99)	(0.98)	(0.81)	(0.78)	(0.68)	(0.55)	(0.90)	(0.93)	(0.47)	(0.49)
$\Delta \boldsymbol{Inv_R}$	1.12***	1.17***	0.81***	0.81***	0.99***	0.99***	1.39***	1.24***	1.05***	1.04***	1.08***	1.08***
($\boldsymbol{\alpha_1}$)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
$\boldsymbol{\Delta P}$		2.08		0.13		-0.51		-0.71**		0.08		-0.05
($\boldsymbol{\alpha_2}$)		(0.38)		(0.92)		(0.72)		(0.05)		(0.73)		(0.84)
Test of	0.31	0.60	0.60	0.61	0.00	0.00	3.31*	1.10	0.04	0.02	0.09	0.10
$\boldsymbol{\alpha_1}$=1	(0.58)	(0.44)	(0.44)	(0.44)	(0.98)	(0.98)	(0.07)	(0.30)	(0.85)	(0.88)	(0.76)	(0.75)
F-stat for	28.66***	14.86***	10.88**	6.24**	14.69***	7.95***	41.20***	22.57***	14.33***	7.40***	18.34***	9.08***
$\forall \boldsymbol{\alpha_j}$=0, $\boldsymbol{j}$>0	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Obs.	70	70	70	70	70	70	70	70	70	70	70	70
Adj-R^2			0.17	0.17	0.21	0.22	0.37	0.41	0.23	0.23	0.24	0.24

Notes. The regression equation is $\Delta Inv_{k,m,w} = \alpha_0 + \alpha_1 \Delta Inv_{R,m,w} + \alpha_2 \Delta P_t^{k-R} + e_{k,m,w}$, where $\Delta Inv_{k,m,w}$ is the inventory change in report k={API, EIA} in week w for commodity m, $\Delta Inv_{R,m,w}$ is the inventory change in Reuters' survey, and ΔP_t^{k-R} is the change in crude oil futures price between the releases Reuters' forecast and report k. Estimation results in (3)-(12) are based on heteroscedasticity-consistent standard errors, while results in (1)-(2) are based on Newey-West standard errors. P-values are presented in parentheses. *, **, and *** denote statistical significance at 10%, 5%, and 1% levels, respectively

Table 3.2 Relationship between API and EIA Reports.

Variable (Parameter)	EIA ($\Delta \boldsymbol{Inv_{EIA}}$) Crude oil (1)	(2)	Distillate fuel (3)	(4)	Gasoline (5)	(6)
Intercept	0.03	-0.05	-0.07	-0.19	0.16	0.17
($\boldsymbol{\alpha_0}$)	(0.91)	(0.86)	(0.70)	(0.85)	(0.41)	(0.37)
$\Delta \boldsymbol{Inv_{API}}$	0.76***	0.71***	0.86***	0.86***	0.80***	0.80***
($\boldsymbol{\alpha_1}$)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
$\boldsymbol{\Delta P}$		-0.58*		0.23		0.10
($\boldsymbol{\alpha_2}$)		(0.06)		(0.14)		(0.63)
Test of	9.03***	11.71***	2.80*	3.05*	5.62**	5.14**
$\boldsymbol{\alpha_1}$=1	(0.00)	(0.00)	(0.10)	(0.09)	(0.02)	(0.03)
F-stat for	90.25***	53.85***	98.42***	57.80***	88.19***	43.46***
$\forall \boldsymbol{\alpha_j}$=0, $\boldsymbol{j}$>0	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Obs.	70	70	70	70	70	70
Adj-R^2	0.64	0.66	0.58	0.59	0.62	0.62

Notes. The regression equation is $\Delta Inv_{EIA,m,w} = \alpha_0 + \alpha_1 \Delta Inv_{API,m,w} + \alpha_2 \Delta P_t^{EIA-API} + e_{EIA,m,w}$, where $\Delta Inv_{EIA,m,w}$ and $\Delta Inv_{API,m,w}$ are the inventory changes reported in EIA and API reports, respectively, in week w for commodity m and $\Delta P_t^{EIA-API}$ is the change in crude oil futures price between the releases of API and EIA reports. Estimation results based on heteroscedasticity-consistent standard errors are presented with p-values in parentheses. *, **, and *** denote statistical significance at 10%, 5%, and 1% levels, respectively.

Table 3.3 Summary Statistics of Inventory Shocks.

		API shocks (%)			EIA shocks (%)		
		Crude oil	Distillate fuel	Gasoline	Crude oil	Distillate fuel	Gasoline
All shocks	Mean	-0.03	0.01	0.02	0.00	-0.05	0.07
	Std. dev.	1.02	1.60	1.04	0.72	1.31	0.77
	Min.	-3.36	-4.79	-2.97	-1.64	-3.39	-1.56
	Max.	2.44	4.26	2.50	1.77	2.83	2.01
	Obs.	70	70	70	70	70	70
Positive shocks	Mean	0.68	1.26	0.83	0.63	0.94	0.64
	Std. dev.	0.55	1.02	0.62	0.48	0.79	0.50
	Min.	0.03	0.01	0.05	0.01	0.00	0.00
	Max.	2.44	4.26	2.50	1.77	2.83	2.01
	Obs.	37	34	35	31	36	37
Negative shocks	Mean	-0.83	-1.17	-0.78	-0.50	-1.10	-0.56
	Std. dev.	0.83	1.03	0.70	0.43	0.85	0.46
	Min.	-3.36	-4.79	-2.97	-1.64	-3.39	-1.56
	Max.	-0.05	-0.03	0.00	-0.04	-0.04	0.00
	Obs.	33	36	35	39	34	33

Notes. The sample period is August 26, 2012-December 30, 2013. API inventory shocks are computed as the difference between the inventory changes reported in API and Reuters' survey, divided by the inventory level reported in API. EIA inventory shocks are computed as the difference between the inventory changes reported in EIA and API, divided by the inventory level in EIA

Table 3.4 Summary Statistics of Categorized EIA Inventory Shocks.

		Positive shock (%)			Negative shock (%)		
		(1)	(2)	(3)	(4)	(5)	(6)
		R>E>A	E>R>A	E>A>R	R>A>E	A>E>R	A>R>E
Crude oil	Mean	0.60	0.97	0.51	-0.31	-0.52	-0.75
	Std. dev.	0.52	0.34	0.45	0.34	0.42	0.45
	Min.	0.06	0.53	0.01	-1.17	-1.64	-1.48
	Max.	1.77	1.49	1.67	-0.04	-0.11	-0.26
	Obs.	12	6	13	15	14	10
Distillate fuel	Mean	0.68	1.54	0.85	-0.86	-0.76	-1.87
	Std. dev.	0.81	0.57	0.75	0.69	0.47	0.99
	Min.	0.00	0.52	0.03	-2.27	-1.71	-3.39
	Max.	2.50	2.13	2.83	-0.06	-0.04	-0.49
	Obs.	12	8	16	16	9	9
Gasoline	Mean	0.52	0.92	0.56	-0.38	-0.33	-1.03
	Std. dev.	0.42	0.62	0.44	0.24	0.33	0.49
	Min.	0.00	0.13	0.01	-0.79	-0.91	-1.56
	Max.	1.62	2.01	1.41	-0.06	0.00	-0.21
	Obs.	12	9	16	14	9	10

Notes. The sample period is August 26, 2012-December 30, 2013. EIA inventory shocks are computed as the difference between the inventory changes reported in EIA and API, divided by the inventory level in EIA. R, E, and A represent inventory changes released in Reuters's survey, EIA report, and API report, respectively.

Table 3.5 Summary Statistics of Futures Returns.

	5-minute Return (%)	5-minute Absolute Return (%)
Mean	-0.00004	0.04908
Median	0.00000	0.03144
Std. dev.	0.07694	0.05925
Min.	-3.18141	0.00000
Max.	1.50551	3.18141
Interquartile range	0.06287	0.05334
Jarque-Bera	7.68×10^{6}	4.80×10^{7}
normality test	(<.001)	(<.001)
Augmented Dickey-	-114.97	-27.65
Fuller unit root test	(<.001)	(<.001)
Ljung Box serial	1.84×10^{3}	1.08×10^{6}
correlation test	(<.001)	(<.001)
Obs.	92,070	92,070

Notes. The sample period is August 26, 2012-December 30, 2013. Interquartile range is the difference between the 75th and 25th percentiles. Null hypothesis of the Jarque-Bera test is the normality of the series in investigation. Null hypothesis of the Augmented Dickey-Fuller unit root test is the existence of a unit root. Null hypothesis of the Ljung Box test is no serial correlation. The p-values of the test statistics are reported in parentheses.

Table 3.6 Return Equation Parameters.

Variable	Parameter	Estimate	p-value
Intercept	α	0.000	0.762
$\boldsymbol{R_{t-1}}$	γ_1	-0.038^{***}	0.001
$\boldsymbol{R_{t-2}}$	γ_2	-0.012^{***}	0.004
Opening of floor trading	θ_1	-0.002	0.865
Closing of floor trading	θ_2	0.020^{***}	0.042
Opening of electronic trading	θ_3	-0.016^{**}	0.018
Closing of electronic trading	θ_4	0.001	0.842
Joint F-tests:			
$\boldsymbol{\beta_{k,m,l,j}} = 0$		51.150^{***}	0.000
$\boldsymbol{\theta_g} = 0$		2.460^{**}	0.044
$\boldsymbol{\beta_{k,m,l,j}} = \boldsymbol{\theta_g} = 0$		50.440^{***}	0.000

Notes. The parameter estimates (except for inventory shocks) from WLS estimation of the return equation (3.6) are presented. Null hypotheses of the F-tests are that the parameters in question are jointly zero. *, **, and *** denote statistical significance at 10%, 5%, and 1% levels, respectively.

Table 3.7 Inventory Shock Effects on Intraday Crude Oil Returns.

		API		EIA					
		Positive	Negative	Positive			Negative		
	Interval (Parameter)	A>R	R>A	(1) R>E>A	(2) E>R>A	(3) E>A>R	(4) R>A>E	(5) A>E>R	(6) A>R>E
Crude oil	[-5,0]	0.004	0.004	0.065	0.005	-0.070*	-0.004	0.046**	0.000
	(β_{-1})	(0.510)	(0.172)	(0.118)	(0.766)	(0.066)	(0.943)	(0.045)	(0.998)
	[0,5]	-0.098***	-0.079***	-0.196*	-0.278***	-0.418***	-0.391***	-0.226**	-0.229**
	(β_0)	(0.000)	(0.000)	(0.063)	(0.001)	(0.000)	(0.000)	(0.015)	(0.028)
	[5,10]	-0.056***	-0.007	0.006	-0.089	0.146***	0.292	0.180***	0.028
	(β_1)	(0.002)	(0.479)	(0.903)	(0.155)	(0.007)	(0.105)	(0.000)	(0.656)
	[10,15]	-0.018**	0.007	0.099	0.148***	-0.001	0.025	-0.147***	0.060
	(β_2)	(0.036)	(0.158)	(0.099)	(0.046)	(0.973)	(0.809)	(0.001)	(0.218)
	[15,20]	-0.021***	-0.012**	-0.034	0.031	-0.081*	-0.019	0.053	0.000
	(β_3)	(0.000)	(0.036)	(0.629)	(0.494)	(0.079)	(0.815)	(0.245)	(0.997)
	[20,25]	0.018***	-0.018***	0.010	0.002	-0.073	0.051	0.092***	-0.065
	(β_4)	(0.003)	(0.000)	(0.810)	(0.925)	(0.399)	(0.526)	(0.003)	(0.101)
	[25,30]			-0.040	-0.057	-0.068***	0.033	-0.086**	0.017
	(β_5)			(0.115)	(0.132)	(0.002)	(0.784)	(0.018)	(0.455)
	[30,35]			0.048	0.062	0.204***	-0.129	-0.065	-0.091**
	(β_6)			(0.159)	(0.394)	(0.000)	(0.215)	(0.159)	(0.049)
	[35,40]			-0.023	0.030	0.005	-0.083	-0.057*	-0.023
	(β_7)			(0.731)	(0.483)	(0.932)	(0.163)	(0.094)	(0.455)
	[40,45]			0.011	-0.014	-0.059	-0.029***	0.008	0.126***
	(β_8)			(0.670)	(0.550)	(0.188)	(0.000)	(0.884)	(0.000)
	[45,50]			-0.033	0.011	-0.074	0.150***	0.002	-0.003
	(β_9)			(0.429)	(0.830)	(0.343)	(0.008)	(0.959)	(0.885)
	[50,55]			0.064***	0.107***	0.070	0.088	0.017	-0.064***
	(β_{10})			(0.006)	(0.000)	(0.188)	(0.208)	(0.845)	(0.000)
	[55,60]			0.031	-0.093***	0.008	-0.090	-0.085	0.003
	(β_{11})			(0.557)	(0.003)	(0.884)	(0.196)	(0.396)	(0.919)
Distillate fuel	[-5,0]	0.004	-0.002	-0.048**	0.001	-0.050*	-0.007	0.062**	0.013
	(β_{-1})	(0.129)	(0.565)	(0.040)	(0.890)	(0.072)	(0.576)	(0.021)	(0.572)
	[0,5]	-0.016*	0.018***	0.004	-0.047	-0.035	0.139*	0.004	0.007
	(β_0)	(0.072)	(0.002)	(0.965)	(0.535)	(0.491)	(0.076)	(0.962)	(0.794)
	[5,10]	-0.003	0.000	0.079***	0.078**	0.068*	-0.027	0.050	0.054**
	(β_1)	(0.643)	(0.992)	(0.000)	(0.014)	(0.088)	(0.443)	(0.321)	(0.016)
	[10,15]	0.004	-0.005*	0.094***	-0.053***	-0.089	-0.011	-0.055	0.056***
	(β_2)	(0.304)	(0.014)	(0.000)	(0.000)	(0.104)	(0.774)	(0.517)	(0.002)
	[15,20]	-0.001	0.003	-0.106***	-0.079***	0.000	0.044	-0.001	0.033
	(β_3)	(0.730)	(0.461)	(0.005)	(0.000)	(0.999)	(0.147)	(0.991)	(0.137)
	[20,25]	-0.006*	0.015**	-0.042	-0.018	-0.094***	0.016	-0.084	0.046***
	(β_4)	(0.066)	(0.010)	(0.244)	(0.529)	(0.003)	(0.617)	(0.280)	(0.000)

	[25,30]			-0.001	-0.051**	0.028	-0.031	-0.039	-0.021*
	(β_5)			(0.924)	(0.029)	(0.207)	(0.272)	(0.385)	(0.059)
	[30,35]			0.093**	0.037*	-0.050	-0.022	-0.097	0.007
	(β_6)			(0.097)	(0.077)	(0.132)	(0.505)	(0.345)	(0.403)
	[35,40]			0.042	-0.006	-0.006	0.008	-0.096	0.005
	(β_7)			(0.263)	(0.668)	(0.737)	(0.754)	(0.118)	(0.750)
	[40,45]			-0.016	0.029**	0.042*	-0.033	-0.071*	-0.014
	(β_8)			(0.626)	(0.027)	(0.098)	(0.217)	(0.060)	(0.416)
	[45,50]			-0.002	-0.026	0.031*	0.002	-0.061*	0.009
	(β_9)			(0.944)	(0.264)	(0.077)	(0.925)	(0.071)	(0.725)
	[50,55]			-0.018	-0.006	-0.043*	-0.003	-0.012	-0.025***
	(β_{10})			(0.738)	(0.385)	(0.064)	(0.943)	(0.786)	(0.006)
	[55,60]			-0.050	-0.023	-0.004	-0.014	0.054	-0.004
	(β_{11})			(0.196)	(0.297)	(0.886)	(0.644)	(0.140)	(0.798)
Gasoline	[-5,0]	-0.010***	0.006	0.136***	0.002	0.034	-0.029	-0.244***	-0.002
	(β_{-1})	(0.001)	(0.265)	(0.000)	(0.929)	(0.199)	(0.603)	(0.000)	(0.947)
	[0,5]	0.024**	-0.036**	0.034	-0.157**	-0.223*	-0.207**	0.164	-0.171***
	(β_0)	(0.046)	(0.037)	(0.751)	(0.015)	(0.065)	(0.014)	(0.415)	(0.004)
	[5,10]	0.001	-0.047***	-0.060	0.052**	-0.090	-0.071	-0.043	0.078***
	(β_1)	(0.886)	(0.000)	(0.203)	(0.054)	(0.155)	(0.581)	(0.664)	(0.001)
	[10,15]	-0.014***	-0.018**	-0.004	-0.106**	-0.222***	-0.085	-0.297	0.046*
	(β_2)	(0.005)	(0.018)	(0.956)	(0.045)	(0.009)	(0.262)	(0.243)	(0.084)
	[15,20]	0.010*	-0.005	0.170***	0.106**	0.026	-0.129*	-0.169***	-0.091
	(β_3)	(0.087)	(0.390)	(0.000)	(0.024)	(0.556)	(0.092)	(0.000)	(0.137)
	[20,25]	-0.005	-0.007	0.016	0.068***	0.192***	-0.074	0.014	-0.133***
	(β_4)	(0.136)	(0.134)	(0.799)	(0.000)	(0.005)	(0.296)	(0.934)	(0.003)
	[25,30]			-0.014	-0.108***	-0.060	-0.139*	0.029	-0.019*
	(β_5)			(0.697)	(0.009)	(0.109)	(0.071)	(0.407)	(0.058)
	[30,35]			-0.247***	-0.128***	-0.022	0.155**	-0.071	0.124**
	(β_6)			(0.000)	(0.000)	(0.712)	(0.010)	(0.312)	(0.013)
	[35,40]			0.049	-0.058***	-0.002	0.150**	-0.016	0.030
	(β_7)			(0.207)	(0.009)	(0.966)	(0.036)	(0.808)	(0.507)
	[40,45]			0.009	-0.046***	0.058	-0.115**	0.101*	0.074**
	(β_8)			(0.839)	(0.001)	(0.155)	(0.047)	(0.095)	(0.029)
	[45,50]			-0.025	0.003	-0.010	-0.043	0.092	-0.022
	(β_9)			(0.534)	(0.947)	(0.657)	(0.409)	(0.330)	(0.530)
	[50,55]			-0.051	-0.009	0.020	0.114**	-0.012	-0.019
	(β_{10})			(0.476)	(0.693)	(0.635)	(0.032)	(0.940)	(0.622)
	[55,60]			-0.028	0.002	0.062	-0.082	0.005	-0.003
	(β_{11})			(0.665)	(0.941)	(0.211)	(0.112)	(0.867)	(0.909)

Notes. The estimates of the inventory shock coefficients from WLS estimation of the return equation (3.6) and their p-values (in parenthesis) are presented. R, A, and E represent inventory changes released in Reuters's survey, API report, and EIA report, respectively. *, **, and *** denote statistical significance at 10%, 5%, and 1% levels, respectively.

Table 3.8 Volatility Equation Parameters.

Variable	Parameter	Estimate	p-value
Intercept	μ	0.006**	0.039
$\lvert\hat{\varepsilon}_{t-1}\rvert$	γ_1'	1.057***	0.000
$\lvert\hat{\varepsilon}_{t-2}\rvert$	γ_2'	-0.042***	0.000
$\lvert\hat{\varepsilon}_{t-3}\rvert$	γ_3'	0.001	0.832
$\lvert\hat{\varepsilon}_{t-4}\rvert$	γ_4'	-0.014***	0.005
$\lvert\hat{\varepsilon}_{t-5}\rvert$	γ_5'	-0.003	0.490
$\lvert\hat{\varepsilon}_{t-6}\rvert$	γ_6'	-0.012***	0.001
u_{t-1}	δ_1'	0.964***	0.000
$\sin_1$	Ω_1^S	-0.026***	0.000
$\cos_1$	Ω_1^C	-0.009***	0.000
$\sin_2$	Ω_2^S	0.001***	0.010
$\cos_2$	Ω_2^C	-0.010***	0.000
$\sin_3$	Ω_3^S	0.005***	0.000
$\cos_3$	Ω_3^C	0.000**	0.534
$\sin_4$	Ω_4^S	-0.004***	0.000
$\cos_4$	Ω_4^C	-0.004***	0.000
$\sin_5$	Ω_5^S	0.005***	0.000
$\cos_5$	Ω_5^C	-0.001***	0.000
$\sin_6$	Ω_6^S	0.002***	0.000
$\cos_6$	Ω_6^C	0.001***	0.000
$\sin_7$	Ω_7^S	0.000	0.898
$\cos_7$	Ω_7^C	0.003***	0.000
$\sin_8$	Ω_8^S	0.001*	0.069
$\cos_8$	Ω_8^C	0.003***	0.000
$\sin_9$	Ω_9^S	-0.003***	0.000
$\cos_9$	Ω_9^C	0.000	0.098
$\sin_{10}$	Ω_{10}^S	-0.002***	0.000
$\cos_{10}$	Ω_{10}^C	-0.001***	0.006
Daily volatility	Ψ	0.564***	0.000
Opening of floor trading	θ_1'	0.081***	0.000
Closing of floor trading	θ_2'	0.055***	0.000
Opening of electronic trading	θ_3'	0.061***	0.000
Closing of electronic trading	θ_4'	0.010**	0.000
Likelihood ratio tests:			
$\Omega_h^S = \Omega_h^C = 0$		3,194***	0.000
$\beta_{k,m,l,j}' = 0$		890***	0.000
$\theta_g' = 0$		1,582***	0.000
$\Omega_h^S = \Omega_h^C = \beta_{k,m,l,j}' = \theta_g' = 0$		6,027***	0.000

Notes. The parameter estimates (except for inventory shocks) from MLE estimation of the volatility equation (3.7) are presented. Null hypotheses of the likelihood ratio tests are that the parameters in question are jointly zero. *, **, and *** denote statistical significance at 10%, 5%, and 1% levels, respectively.

Table 3.9 Inventory Shock Effects on Intraday Crude Oil Volatility.

		API		EIA					
		Positive	Negative	Positive			Negative		
	Interval			(1)	(2)	(3)	(4)	(5)	(6)
	(Parameter)	A>R	R>A	R>E>A	E>R>A	E>A>R	R>A>E	A>E>R	A>R>E
Crude oil	[-5,0]	-0.001	-0.001	-0.013	-0.021	-0.038	-0.012	-0.012	-0.028
	(β'_{-1})	(0.912)	(0.882)	(0.561)	(0.350)	(0.133)	(0.722)	(0.650)	(0.182)
	[0,5]	0.025**	0.022**	0.082***	0.038*	0.059**	0.034	-0.011	0.071***
	(β'_0)	(0.031)	(0.024)	(0.000)	(0.092)	(0.021)	(0.311)	(0.663)	(0.001)
	[5,10]	0.019	0.004	0.031	0.026	-0.036	0.245***	-0.029	0.033
	(β'_1)	(0.103)	(0.710)	(0.181)	(0.256)	(0.156)	(0.000)	(0.261)	(0.119)
	[10,15]	0.004	0.001	-0.020	0.045**	-0.086***	0.037	-0.069***	0.016
	(β'_2)	(0.730)	(0.919)	(0.395)	(0.045)	(0.001)	(0.265)	(0.008)	(0.440)
	[15,20]	-0.009	0.003	0.067***	0.042*	0.000	0.099***	-0.009	0.052**
	(β'_3)	(0.447)	(0.755)	(0.004)	(0.062)	(0.985)	(0.003)	(0.715)	(0.014)
	[20,25]	-0.005	-0.002	-0.001	-0.029*	0.040*	0.002	-0.048*	-0.016
	(β'_4)	(0.658)	(0.845)	(0.977)	(0.206)	(0.118)	(0.944)	(0.064)	(0.461)
	[25,30]			-0.019	-0.023	-0.047*	0.132***	-0.020	-0.038*
	(β'_5)			(0.405)	(0.322)	(0.069)	(0.001)	(0.450)	(0.071)
	[30,35]			-0.012	0.052**	0.000	0.060*	-0.008	0.019
	(β'_6)			(0.608)	(0.022)	(0.998)	(0.075)	(0.742)	(0.366)
	[35,40]			0.052**	0.014	0.002	-0.011	-0.033	0.008
	(β'_7)			(0.024)	(0.537)	(0.932)	(0.735)	(0.207)	(0.699)
	[40,45]			-0.041*	-0.032	-0.025	-0.063*	0.012	-0.016
	(β'_8)			(0.078)	(0.158)	(0.329)	(0.059)	(0.643)	(0.453)
	[45,50]			0.015	0.024	0.042*	0.024	-0.004	-0.044**
	(β'_9)			(0.521)	(0.283)	(0.098)	(0.478)	(0.868)	(0.036)
	[50,55]			-0.025	-0.006	0.008	0.013	0.086***	-0.002
	(β'_{10})			(0.285)	(0.776)	(0.752)	(0.687)	(0.001)	(0.943)
	[55,60]			0.033	0.005	0.033	0.023	0.126***	-0.004
	(β'_{11})			(0.155)	(0.832)	(0.191)	(0.491)	(0.000)	(0.858)
Distillate fuel	[-5,0]	-0.001	-0.001	-0.014	-0.029**	0.012	-0.017	-0.011	0.014
	(β'_{-1})	(0.894)	(0.902)	(0.454)	(0.017)	(0.429)	(0.211)	(0.593)	(0.122)
	[0,5]	-0.002	-0.002	0.078***	0.077***	-0.002	0.094***	0.028	0.008
	(β'_0)	(0.834)	(0.756)	(0.000)	(0.000)	(0.893)	(0.000)	(0.199)	(0.352)
	[5,10]	0.001	0.013*	-0.023	-0.001	-0.048***	0.016	0.019	0.005
	(β'_1)	(0.927)	(0.068)	(0.223)	(0.944)	(0.002)	(0.252)	(0.387)	(0.570)
	[10,15]	-0.003	-0.004	-0.022	-0.031**	0.021	0.024*	0.064***	0.005
	(β'_2)	(0.738)	(0.529)	(0.244)	(0.011)	(0.173)	(0.080)	(0.003)	(0.560)
	[15,20]	-0.004	-0.003	-0.064***	-0.024*	-0.039***	0.006	0.041**	0.004
	(β'_3)	(0.596)	(0.635)	(0.001)	(0.054)	(0.010)	(0.670)	(0.056)	(0.687)
	[20,25]	0.002	0.005	-0.019**	0.013	-0.008	0.016	0.051**	-0.003
	(β'_4)	(0.818)	(0.449)	(0.319)	(0.302)	(0.586)	(0.260)	(0.017)	(0.709)

	[25,30]			-0.010	0.005	-0.025*	0.019	0.026	-0.015*
	(β'_5)			(0.582)	(0.701)	(0.093)	(0.179)	(0.219)	(0.095)
	[30,35]			0.016	-0.012	-0.013	0.011	0.117***	-0.014
	(β'_6)			(0.403)	(0.340)	(0.383)	(0.446)	(0.000)	(0.113)
	[35,40]			-0.014	-0.022*	-0.021	0.006	0.033	0.000
	(β'_7)			(0.452)	(0.070)	(0.170)	(0.653)	(0.127)	(0.993)
	[40,45]			-0.004	-0.007	0.016	0.003	0.029	0.009
	(β'_8)			(0.828)	(0.550)	(0.276)	(0.856)	(0.185)	(0.313)
	[45,50]			-0.038**	0.006	-0.033**	-0.006	-0.013	0.010
	(β'_9)			(0.042)	(0.635)	(0.030)	(0.676)	(0.539)	(0.252)
	[50,55]			0.017	-0.027**	-0.018	0.009	-0.001	-0.017*
	(β'_{10})			(0.369)	(0.028)	(0.226)	(0.520)	(0.971)	(0.057)
	[55,60]			0.018	0.002	-0.002	-0.003	0.011	-0.005
	(β'_{11})			(0.322)	(0.899)	(0.909)	(0.847)	(0.611)	(0.579)
Gasoline	[-5,0]	-0.006	-0.002	-0.007	-0.012	-0.031	0.009	-0.008	-0.003
	(β'_{-1})	(0.577)	(0.865)	(0.798)	(0.528)	(0.153)	(0.821)	(0.854)	(0.860)
	[0,5]	0.005	0.016	-0.056**	0.011	0.106***	-0.087**	0.080*	-0.001
	(β'_0)	(0.639)	(0.123)	(0.047)	(0.566)	(0.000)	(0.024)	(0.053)	(0.953)
	[5,10]	0.001	-0.004	0.001	-0.009	0.040*	0.091**	-0.006	-0.016
	(β'_1)	(0.919)	(0.708)	(0.985)	(0.630)	(0.066)	(0.019)	(0.894)	(0.368)
	[10,15]	-0.001	0.003	0.040	0.032*	0.084***	0.030	0.235***	-0.007
	(β'_2)	(0.910)	(0.767)	(0.153)	(0.080)	(0.000)	(0.429)	(0.000)	(0.692)
	[15,20]	0.003	0.002	-0.004	0.006	0.000	-0.049	-0.099**	0.059***
	(β'_3)	(0.760)	(0.861)	(0.888)	(0.760)	(0.986)	(0.204)	(0.017)	(0.001)
	[20,25]	-0.007	-0.008	0.012	-0.021	0.065***	-0.029	0.122**	0.011
	(β'_4)	(0.501)	(0.467)	(0.663)	(0.249)	(0.003)	(0.457)	(0.003)	(0.529)
	[25,30]			-0.015	0.034*	0.011	0.048	-0.057	-0.035*
	(β'_5)			(0.605)	(0.062)	(0.629)	(0.210)	(0.166)	(0.053)
	[30,35]			-0.018	-0.020	0.023	-0.053	-0.052	0.014
	(β'_6)			(0.531)	(0.215)	(0.303)	(0.167)	(0.212)	(0.446)
	[35,40]			-0.025	-0.020	0.014	-0.037	-0.010	0.019
	(β'_7)			(0.373)	(0.278)	(0.529)	(0.331)	(0.816)	(0.298)
	[40,45]			-0.010	-0.040**	-0.013	-0.009	0.009	-0.003
	(β'_8)			(0.715)	(0.031)	(0.568)	(0.810)	(0.826)	(0.888)
	[45,50]			0.029	0.011	-0.016	-0.024	0.019	0.009
	(β'_9)			(0.300)	(0.564)	(0.465)	(0.531)	(0.648)	(0.620)
	[50,55]			0.026	-0.025	-0.001	-0.041	0.118***	-0.002
	(β'_{10})			(0.349)	(0.165)	(0.972)	(0.284)	(0.004)	(0.897)
	[55,60]			0.007	-0.039**	-0.003	-0.099**	-0.080*	-0.033*
	(β'_{11})			(0.808)	(0.032)	(0.906)	(0.010)	(0.052)	(0.068)

Notes. The estimates of the inventory shock coefficients from MLE estimation of the volatility equation (3.7) and their p-values (in parentheses) are presented. R, A, and E represent inventory changes released in Reuters's survey, API report, and EIA report, respectively. *, **, and *** denote statistical significance at 10%, 5%, and 1% levels, respectively.

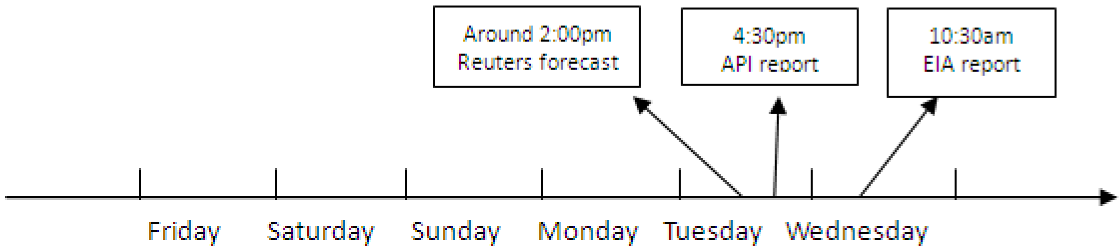


Figure 3.1 Release Times of Inventory Reports and Reuters' Forecasts.

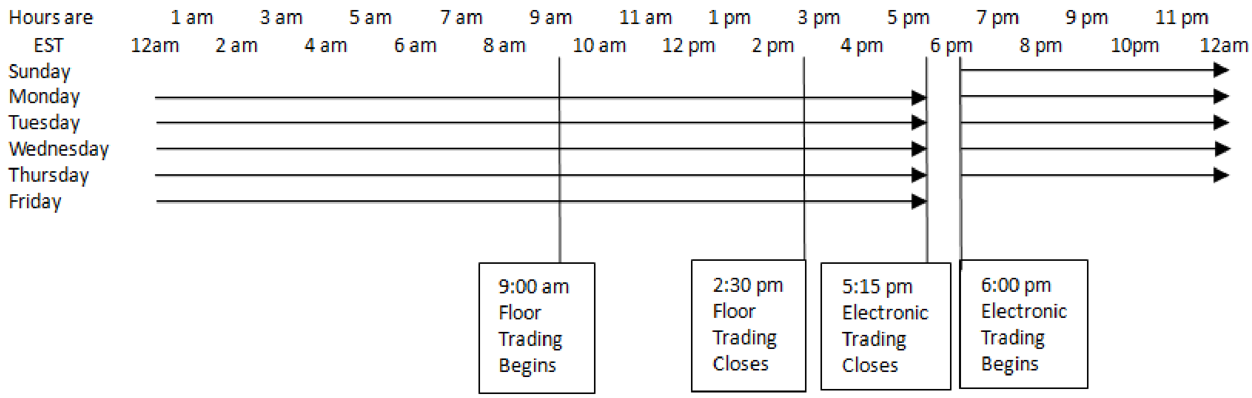


Figure 3.2 CME Crude Oil Trading Hours.

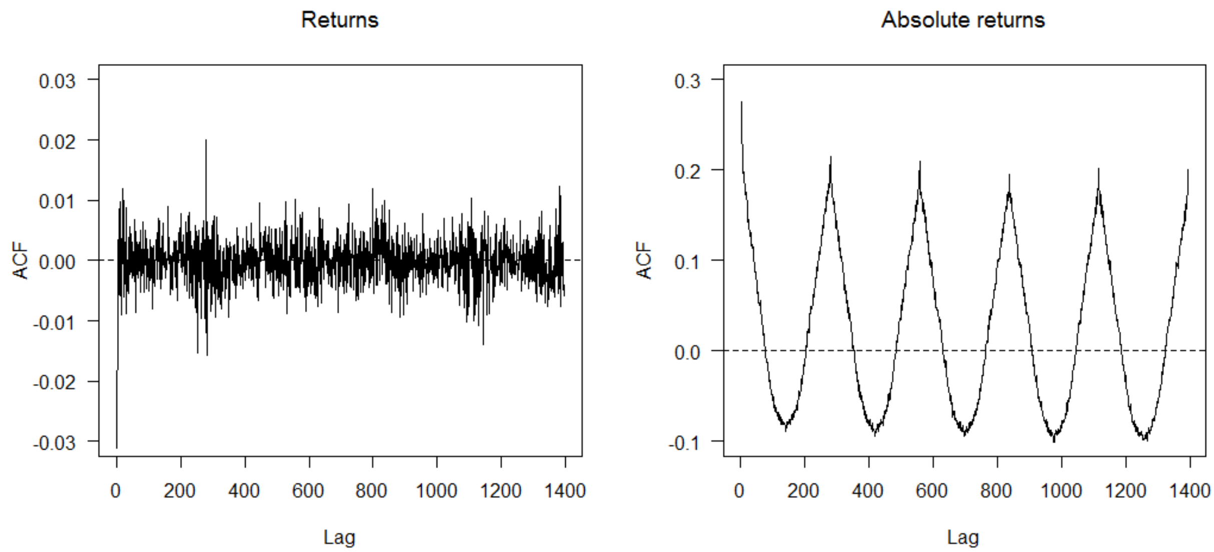
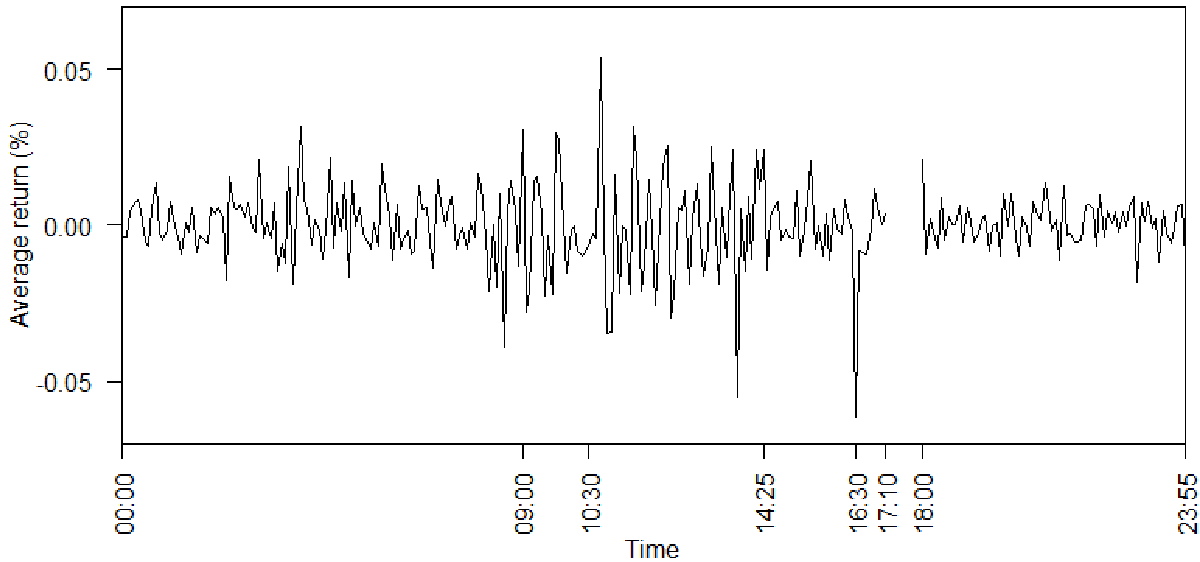
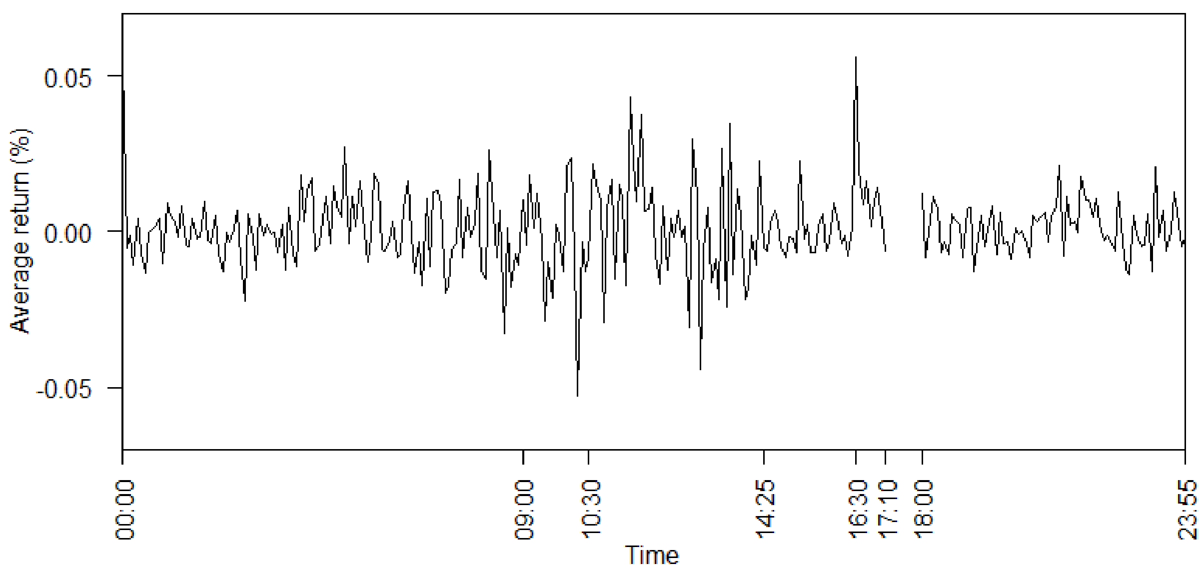


Figure 3.3 Sample Autocorrelation Runctions.

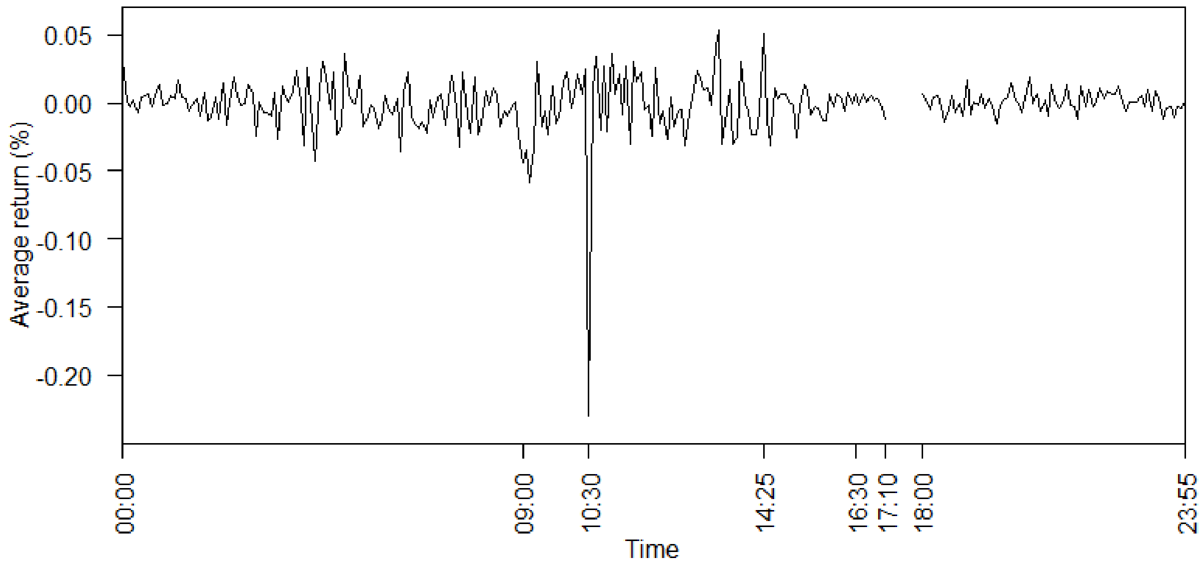


(a) Positive crude oil inventory shocks

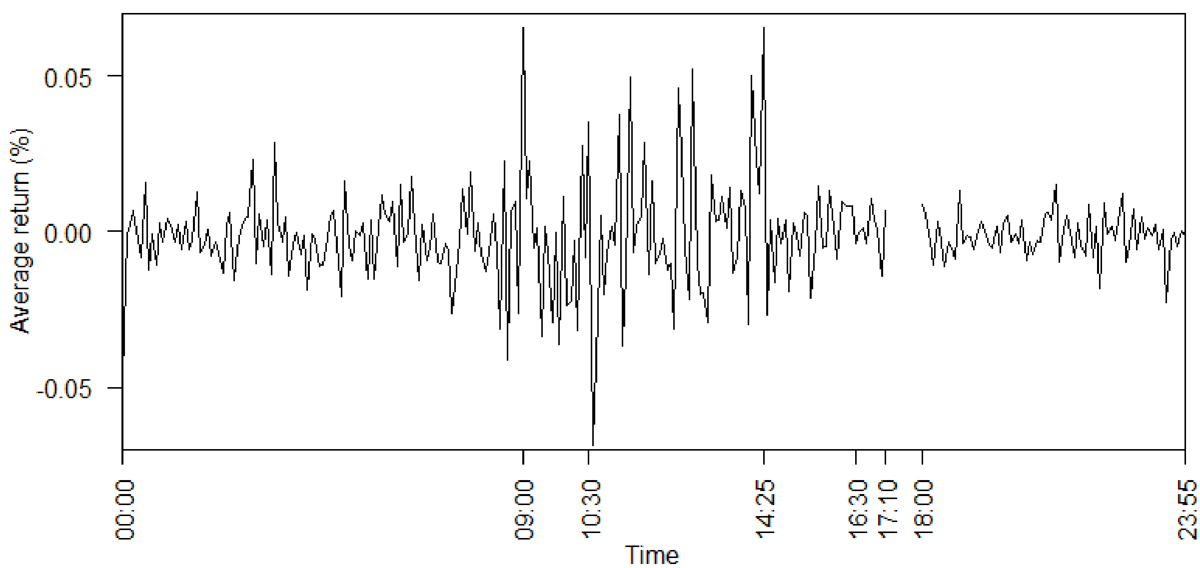


(b) Negative crude oil inventory shocks

Figure 3.4 Average Returns on API Report Release Days.

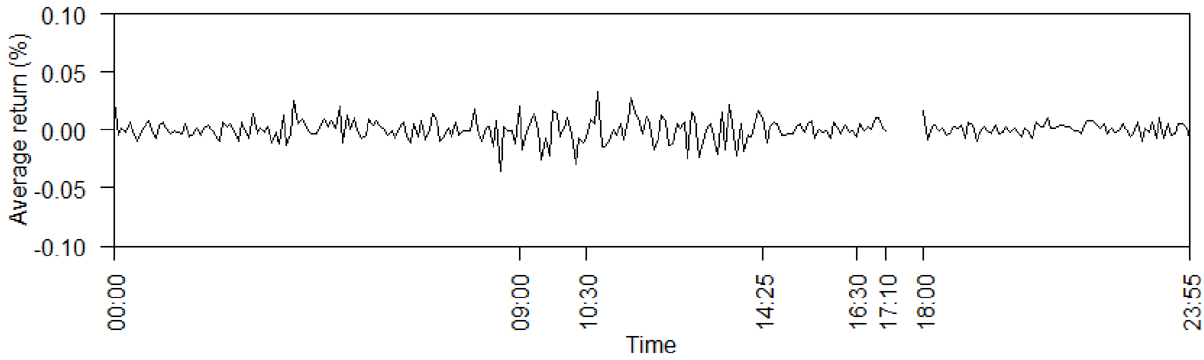


(a) Positive crude oil inventory shocks

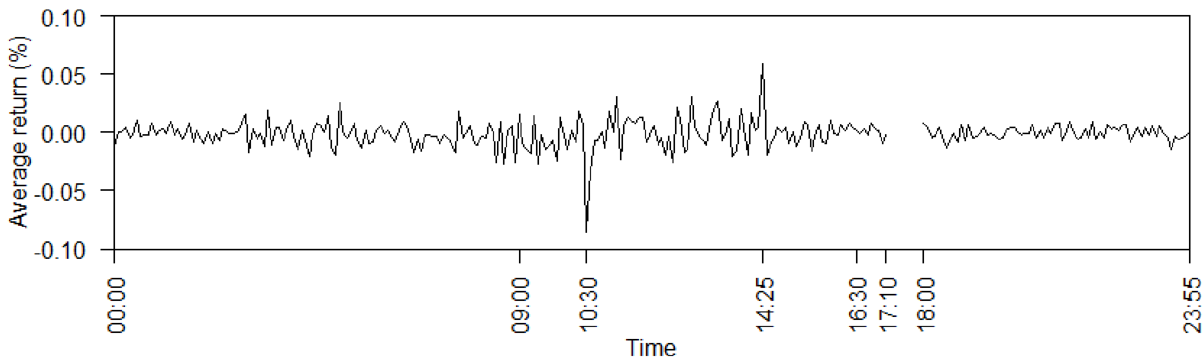


(b) Negative crude oil inventory shocks

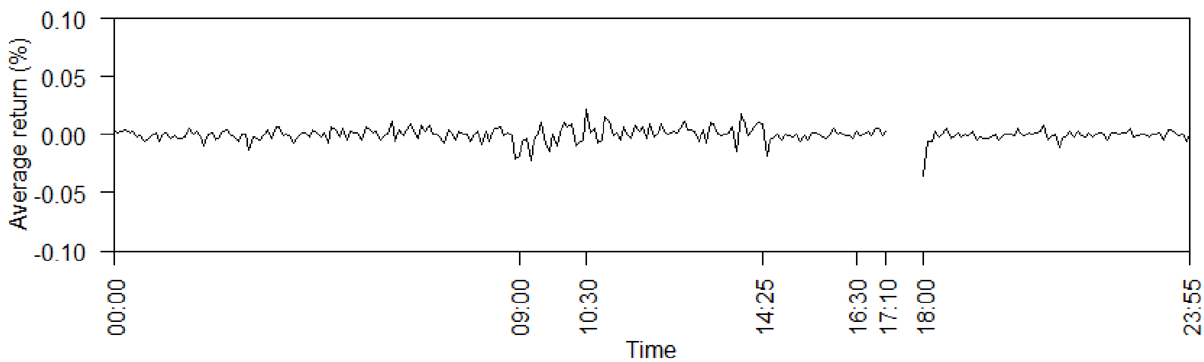
Figure 3.5 Average Returns on EIA Report Release Days.



(a) API days

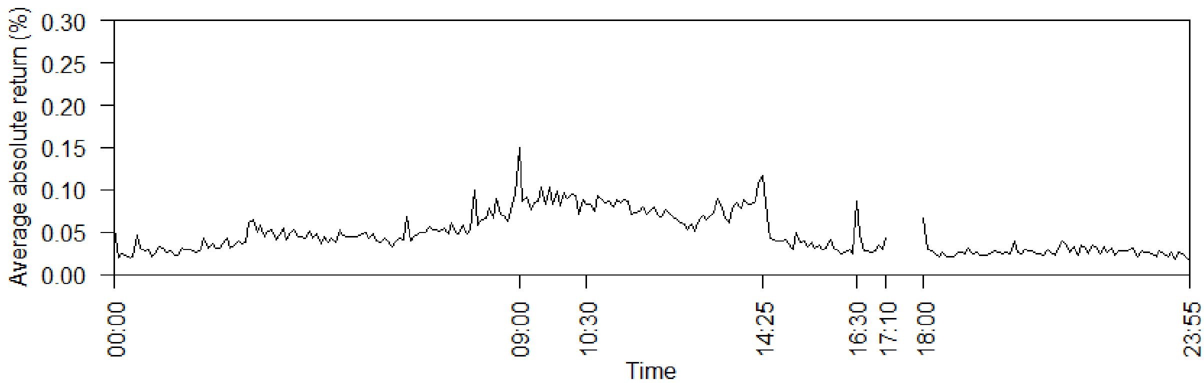


(b) EIA days

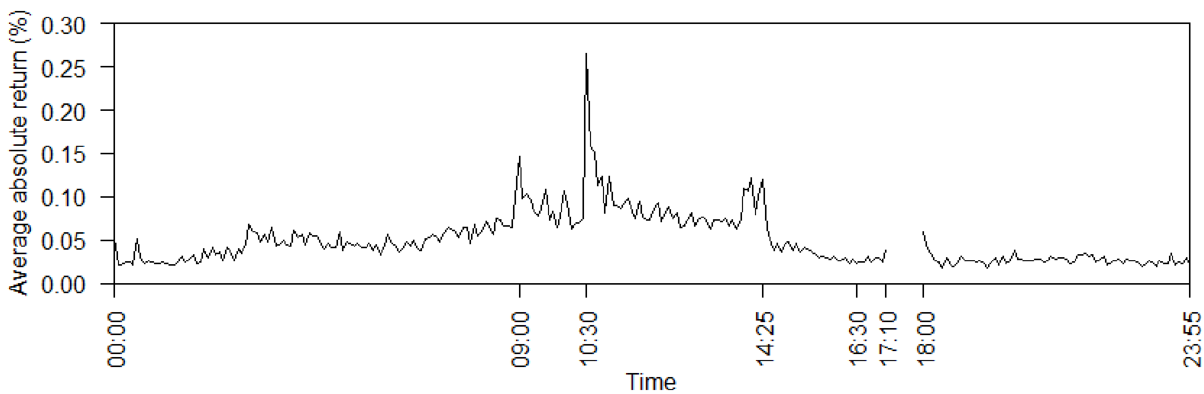


(c) Non-report days

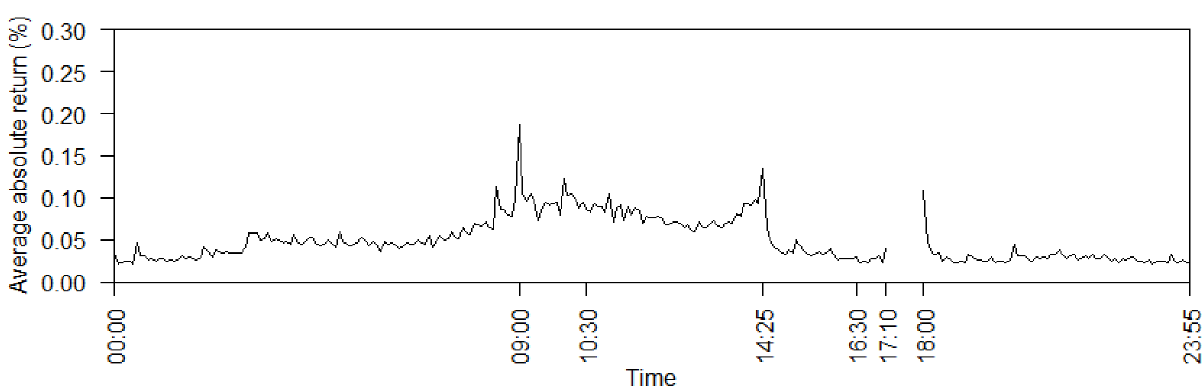
Figure 3.6 Average Returns on Report and Non-report Days.



(a) API days

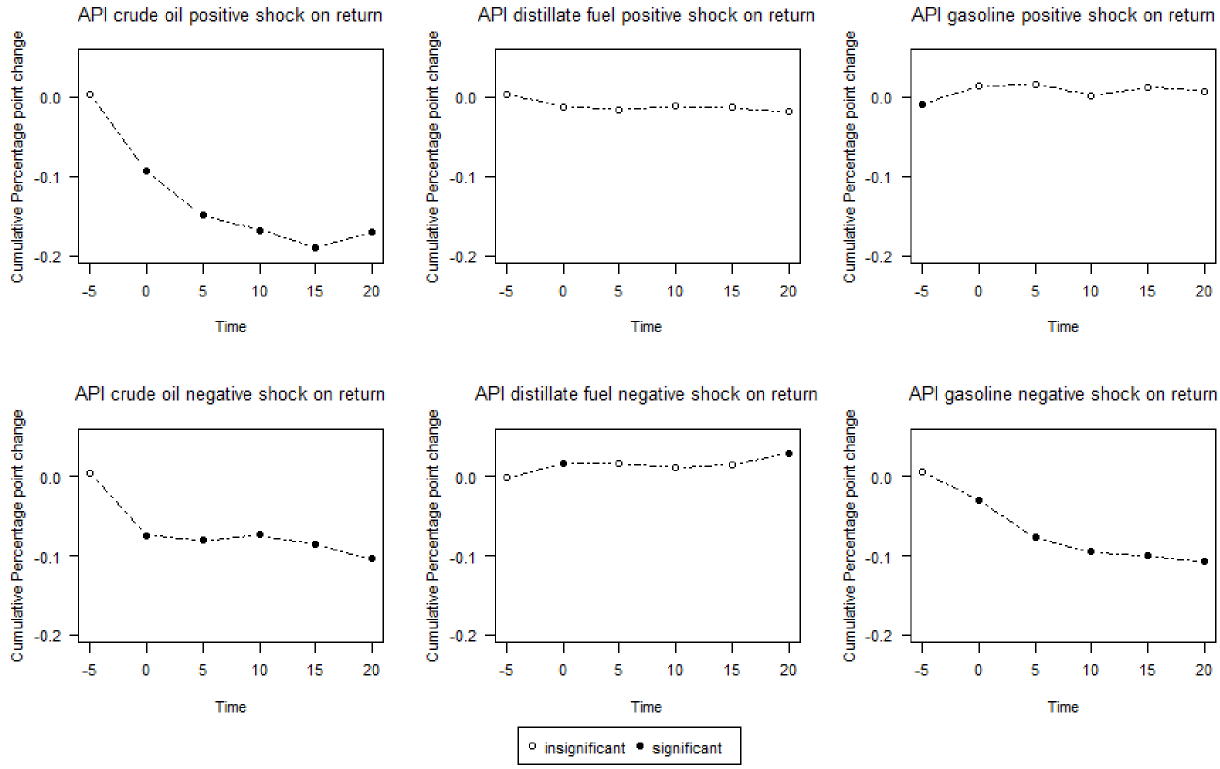


(b) EIA days

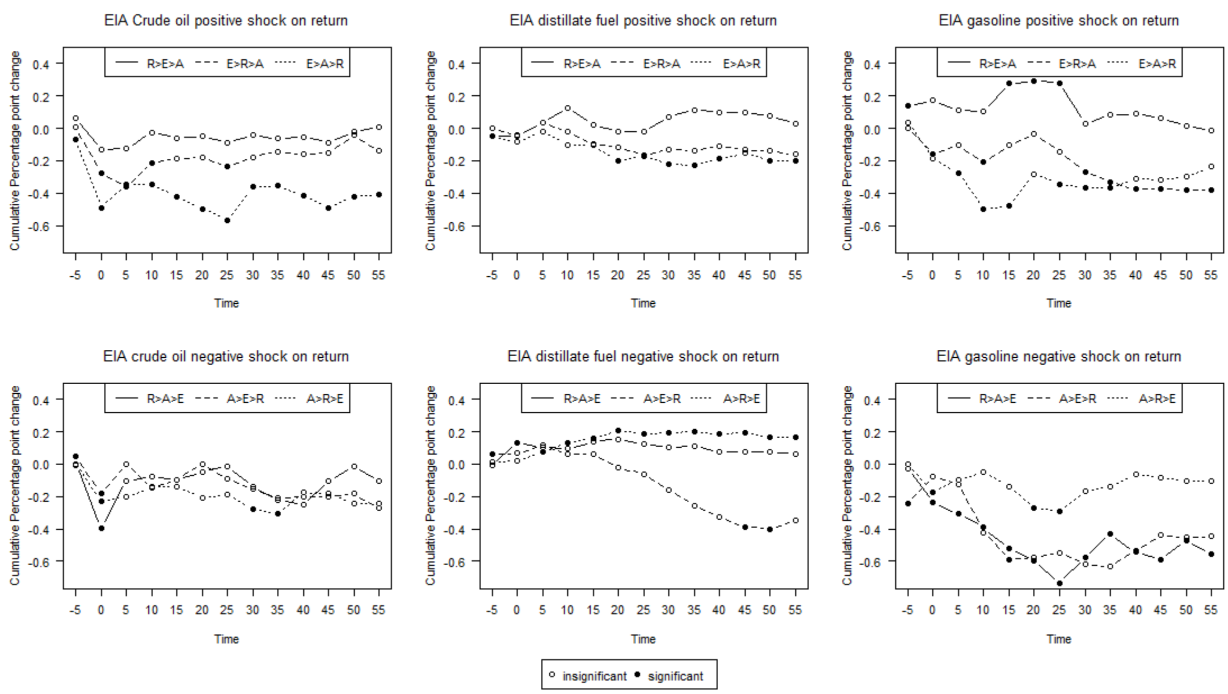


(c) Non-report days

Figure 3.7 Average Absolute Returns on Report and Non-report Days.

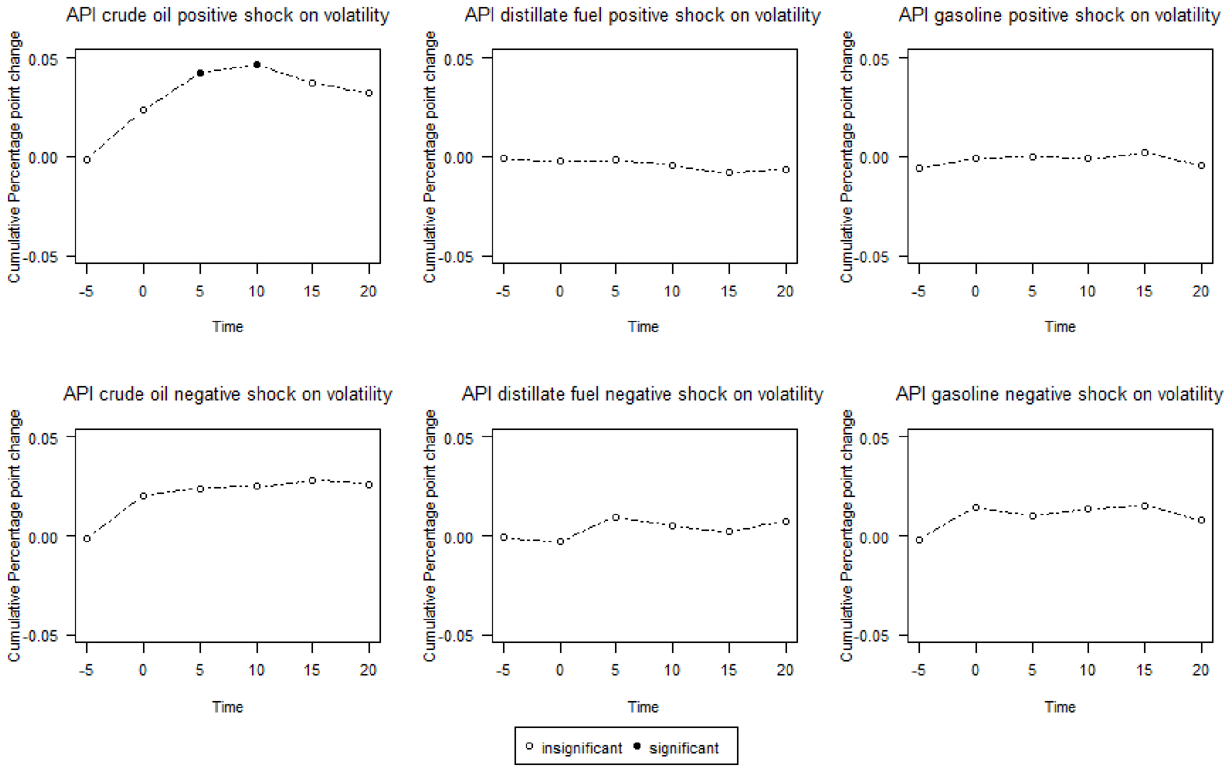


(a) API reports

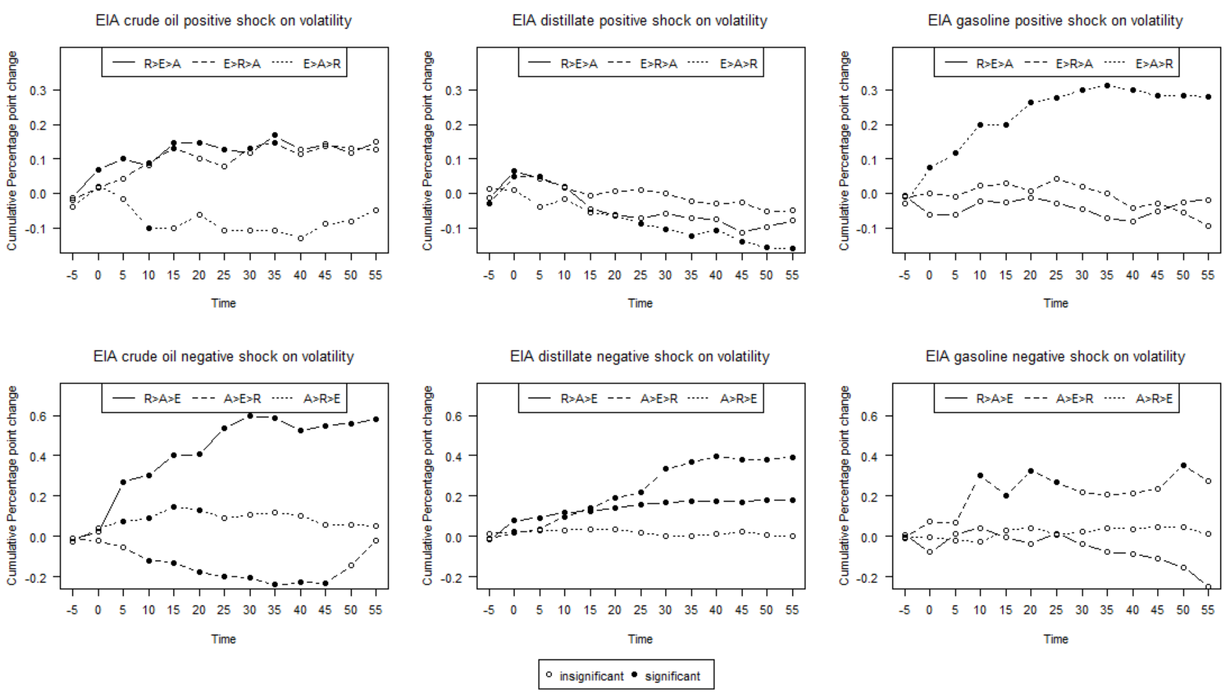


(b) EIA reports

Figure 3.8 Cumulative Effects of Inventory Shocks on Intraday Returns.



(a) API reports



(b) EIA reports

Figure 3.9 Cumulative Effects of Inventory Shocks on Intraday Volatility.