Event Study of Energy Price Volatility:
An Application of Distributional Event Response Model

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Abstract

We apply the Distributional Event Response Model (DERM), which is appropriate in studying relatively slowly-evolving information events, to nineteen years of daily crude oil futures returns and volatility to analyze the pattern of market responses to selected events. The results show that all the events considered have statistically significant effects on crude oil futures price volatility. The U.S. invasion of Iraq in 2003 and the bankruptcy filing of Lehman Brothers in 2008 are found to have the largest impacts on both daily returns and volatility. In addition, the location and duration of event windows vary across different event. Generally, the largest volatility response to an event is observed after several months following the event, suggesting that simply using an event-day dummy variable would hinder discovering the actual market responses to slowly-evolving events.

Key words: crude oil, distributional event response model (DERM), event study, returns, volatility
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Introduction

Energy prices have a major impact on 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 level, 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 USDA’s Cost of Production estimates 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 of 2008 during 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 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.

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). 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 volatility has been also found to be sensitive to major economic events, such as oil production cuts by OPEC (Lee and Zyren, 2007).

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 volatility caused by major global economic 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 four events considered (the Asian financial crisis, OPEC’s production cut, the U.S. invasion of Iraq, the bankruptcy filing of Lehman Brothers) have statistically significant effects on crude oil futures price volatility. In addition, the location and duration of the event windows are found to vary among these four events. While the impact of
OPEC’s production cut in 1999 on volatility has the longest duration, the impact of the U.S. invasion of Iraq in 2003 has the shortest duration. The largest impact on crude oil return series, a 4% decrease, is found following the Iraq invasion, whereas the largest effect on volatility, a 3.8% increase, is observed two months after the bankruptcy filing of Lehman Brothers in 2008. Generally, the largest volatility response to an event is observed after several months following the event. Only for the U.S. invasion of Iraq the market response peaked on the event day. Thus, simply using an event-day dummy prevents one to discover the actual market responses to slowly-evolving events.

**Literature Review**

Determinants of energy price and its volatility have been widely studied in the literature. Basic price determinants include demand and supply factors (Pindyck, 2001). Weather is one of the major determinants of demand for energy products. Demand for crude oil, heating oil, and natural gas increases in winter due to space heating, whereas demand for natural gas also increases in summer due to space cooling. The increase in demand results in upward pressure in prices, and thereby increasing price volatility. For instance, Suenaga, Smith, and Williams (2008) show that natural gas futures price volatility rapidly increases in the last three months of trading and is higher for winter contracts than it is for spring and summer contracts. Energy price volatility has been also explained by macroeconomic indicators in the literature. Macro effects are found to be more significant during exceptionally volatile periods (Karali and Power, 2013).

Event studies have been applied in energy markets to study the impact of major incidents. Zyren (2007), for example, show that price volatility of crude oil increased as a result of a structural shift to higher prices after April 1999 when Organization of the Petroleum Exporting
Counties (OPEC) signed an agreement to cut oil production. Olowe (2010) points out that while the Asian financial crisis of 1997 had an impact on the crude oil price return series, neither the Asian crisis nor the global financial crisis of 2008 accounted for the sudden change in volatility.

The objective of this study is to provide a time path of energy markets’ response to a set of major economic and political events. To this end, we build on the literature on energy volatility dynamics but incorporate a relatively new event study methodology to explicitly quantify the magnitude and duration of the impacts of major events on crude oil return and volatility.

**Empirical Model**

A traditional event study methodology is performed by constructing dummy variables for event days. However, this method with event-day dummy variables leads to model parameter estimates conditional on a specific event response structure and a specific event window specification (Rucker, Thurman, and Yoder, 2005). Even if the date of the event is known with certainty, the timing and pattern of the market response might be unknown and possibly distributed across multiple days surrounding the event. Rucker, Thurman, and Yoder (2005) introduced a Distributional Event Response Model (DERM) to address this issue. Their model allows one to estimate, rather than impose, the location and width of the event window. Further, their model allows for different response structures for different types of events. Our paper builds on the study of Rucker, Thurman, and Yoder (2005) and studies the magnitude and duration of the impacts on energy 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:

\[
y_t = \alpha + \delta y_{t-1} + \sum_{i=1}^{k} \beta_i f(d^i_t; \theta) + \varepsilon_t,
\]

where \(y_t\) is either the daily return, \(R_t\), or the volatility, \(V_t\), on crude oil futures contracts, \(\alpha\) is the intercept, \(y_{t-1}\) is the response variable lagged by one period, \(k\) is the number of events, \(d^i_t\) is a counter variable indicating the difference (in trading days) between any given day \(t\) and the day event \(i\) occurred, and \(\varepsilon_t\) is the regression error term. The variable \(d^i_t\) is zero on the event day; and it takes negative values before the event day and positive values after the event day. The function \(f(d^i_t; \theta)\) is a density function for \(d^i_t\) with parameter vector \(\theta\) and we specify it to be a normal density as:

\[
f(d^i_t; \theta) = f(d^i_t; \mu_i, \sigma_i) = \frac{1}{\sigma_i \sqrt{2\pi}} \exp\left(-\frac{(d^i_t - \mu_i)^2}{2\sigma_i^2}\right).
\]

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 \(\mu\) and standard deviation \(\sigma\)) are allowed to vary across different events.

Figure 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 \(\mu_i\) and \(\sigma_i\) 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 \(\beta_i\), 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 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 usual Ordinary Least Squares (OLS) is not feasible. Once the day counter variables, $d_i^t$, are plugged into the normal density functions given in equation (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 an assumption of normally distributed disturbances.

**Data**

*Futures Returns and Volatility*

We study crude oil futures contracts that are traded on the New York Mercantile Exchange from January 1995 to December 2013. Light Sweet Crude Oil (WTI) futures are the world's most actively traded energy product. WTI futures play an important role in managing risk in the energy sector worldwide because it is the most liquid energy contract (CME, 2014). They 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 $R_t = 100 \times (\ln P_t - \ln P_{t-1})$, where $P_t$ is the closing price of the nearby contract on trading day $t$. The volatility is then defined as $V_t = 100 \times |\ln P_t - \ln P_{t-1}|$. Descriptive statistics of the return and volatility of crude oil futures contracts are summarized in table 1. There are 4,224 observations in the sample. The average daily return is 0.04% with a standard deviation of 2.23%. The average daily volatility, on the other hand, is 1.64% with a standard deviation of 1.52%. Figures 2 and 3, respectively, show the daily return and volatility series for the entire sample. It can be seen that there is obvious volatility clustering during the sample period.

**Event Descriptions**

We consider the following events in our analysis. (1) 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 spread to many Asian countries thereafter. The Asian crisis led to economic slowdown in several developing countries, followed by 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 1, 1997. (2) In an effort to raise oil prices which were at considerably low levels from late 1997 until early 1999 resulting in a 30 percent revenue loss, OPEC and non-OPEC countries agreed to cut oil output by a combined 2.104 million barrels per day, announcing on March 23, 1999. This pledge was for one year, effective as of April 1, 1999. OPEC members have pledged to cut 1.716 million barrels per day, while several non-OPEC countries have pledged total reductions of 0.388 million barrels per day. Our variable $d_t^{OPEC}$ counts the trading
days between any given day in the sample and March 23, 1999. (3) The U.S. invasion of Iraq on March 19, 2003. On that day, Iraq launched several conventional missiles at Kuwait, but it was reported that this had no effect on Kuwaiti oil production because of Kuwaiti’s implementation of an emergency plan to protect its workers and facilities (The Financial Express, 2003). To count the trading days between any given day and March 19, 2003 we create the variable $d_{t}^{Iraq}$.

(4) The global financial crisis precipitated on September 15, 2008 when the major investment bank Lehman Brothers announced that it will be filing for bankruptcy. The crisis 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, $d_{t}^{Lehman}$, that computes the trading days between any given day in the sample and Sept 15, 2008.

Results

Table 2 reports the NERM results for both the daily returns and volatility. Using these estimates, table 3 demonstrates the overall event impacts (i.e. the scaling factor $\beta$ multiplied with the normal density function) on both the event day and the day the market response peaked. Estimated normal event response patterns in the daily returns and volatility are depicted in figures 4 and 5, respectively.

For the Asian financial crisis, the estimated $\mu$ in the return equation indicates that the market response to the Asian financial crisis peaked about 145 trading days after the event occurred. The overall impact of this event on the crude oil futures return is estimated to last for $3\sigma = 292$ trading days. The scaling factor $\beta$ in the return equation is negative but insignificant. Volatility results, on the other hand, show that the scaling factor is positive and significant. The
volatility response peaked about 207 trading days after the event, and lasted for about 96 trading days. Table 3 shows that the market response to this event is a decrease of 0.13% in the returns on the event day, and a 0.39% decrease on the peak day. Volatility, on the other hand, is not affected on the event day itself, but increases by 0.68% on the peak day (i.e. 207 days after the event).

OPEC’s production cut is found not to have any impact on crude oil returns. However, its impact on volatility has the longest duration, about 1,076 trading days, among the four events considered. The volatility response to this event, which is estimated to peak 457 trading days after the event, is an increase of 0.63%. The volatility response on the event day itself is only 0.28%.

The U.S. invasion of Iraq is found to have a negative and significant impact on the daily returns, and positive and significant impact on volatility. While the return response peaks on the event day ($\mu = 0.12$), the volatility return peaks after 3.5 days. The overall impacts of this event on the returns and volatility are estimated to last for about 4 and 14 days, respectively. Table 3 shows that, for the returns, the overall impact is the same on the event day and the peak day, as the peak day is estimated to be the event day. The 4% decrease in the returns is considerably large compared to the average daily return of 0.04% during the sample period. For volatility, the impact is an increase of 1.76% on the event day and 2.34% on the peak day. Again, compared to the average volatility of 1.64% in the sample, these estimated effects are economically large.

Global financial crisis, which is elevated by Lehman Brothers’ bankruptcy filing, is found negatively affect the return and positively affect the volatility. For the daily return, the largest impact is found 27 trading days after the event with an overall duration of 89 days. While the daily return decreases by 1.20% on the event day, the impact is a decrease of 1.79% on the peak
day. The volatility response peaks 62 trading days after the event, with an overall duration of 138 days. The volatility is estimated to increase by 3.82% on the peak day, and by 1.55% on the event day.

**Conclusions**

In a traditional event study, researchers often construct dummy variables for event days. The parameters are conditional on a specific event response structure and event window specification, which is very restrictive. In order to solve these problems, Rucker, Thurman, and Yoder (2005) introduced a Distributional Event Response Model (DERM), which includes a nonlinear probability density function in the usual linear regression model. The model allows estimation of the location and width of the event window and therefore is appropriate when studying relatively slowly-evolving information events.

We implement this methodology to nineteen years of daily returns on crude oil futures contracts and its volatility to analyze the pattern of the market responses to four major events (the Asian financial crisis in 1997, OPEC’s production cut in 1999, the U.S. invasion of Iraq in 2003, the bankruptcy filing of Lehman Brothers in 2008), of which effects are considered to persist for a long period of time rather than a one-day jump.

Results show that volatility response to all these four events is statistically significant, and the location and duration of the event windows are different for each event. Among the four events, the impact of OPEC’s production cut on volatility has the longest duration with about 1,076 trading days. On the other hand, the impact of the invasion of Iraq on volatility lasted only 14 trading days. The most delayed reaction in the returns and volatility is found for the Asian financial crisis and the OPEC’s production cut, respectively. While the crude oil return decreased
by 0.13% on the day the Asian financial crisis started, 145 days after the event this impact was amplified to a decrease of 0.39%. The impact of OPEC’s production cut on volatility peaked 458 days after the event at 0.63%. Among the four events, the largest market response in the returns is found following the Iraq invasion, a 4% decrease, followed by a 1.79% decrease after the bankruptcy filing of Lehman Brothers. On the other hand, the largest effect on volatility, a 3.82% increase, is found after the Lehman Brothers’ bankruptcy filing, followed by a 2.34% increase caused by the Iraq invasion.

In general, the largest market response to a slowly-evolving event is found several months after the event occurred. Therefore, if a traditional event study methodology with event-day dummy variables were used, the actual market responses would not have been discovered.
References


### Table 1. Summary Statistics

<table>
<thead>
<tr>
<th></th>
<th>N</th>
<th>Mean</th>
<th>Standard deviation</th>
<th>Minimum</th>
<th>Maximum</th>
</tr>
</thead>
<tbody>
<tr>
<td>Crude oil returns</td>
<td>4,224</td>
<td>0.04</td>
<td>2.23</td>
<td>-16.54</td>
<td>13.34</td>
</tr>
<tr>
<td>Crude oil volatility</td>
<td>4,224</td>
<td>1.64</td>
<td>1.52</td>
<td>0</td>
<td>16.54</td>
</tr>
</tbody>
</table>

### Table 2. Estimates of the Normal Event Response Model

<table>
<thead>
<tr>
<th>Event</th>
<th>Returns</th>
<th>Volatility</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>$\beta$</td>
<td>$\mu$</td>
</tr>
<tr>
<td>Asian financial crisis</td>
<td>-95.43</td>
<td>144.49*</td>
</tr>
<tr>
<td>OPEC</td>
<td>99.25</td>
<td>115.03</td>
</tr>
<tr>
<td>Iraq war</td>
<td>-14.71***</td>
<td>0.12</td>
</tr>
<tr>
<td>Lehman Brothers</td>
<td>-133.33***</td>
<td>26.54***</td>
</tr>
<tr>
<td>Intercept ($\alpha$)</td>
<td>0.08*</td>
<td></td>
</tr>
<tr>
<td>Lagged dep. var. ($\delta$)</td>
<td>-0.03*</td>
<td></td>
</tr>
</tbody>
</table>

Note: *, **, and *** denote significant at 10%, 5%, and 1% levels, respectively.

### Table 3. Overall Impacts of Events

<table>
<thead>
<tr>
<th>Event</th>
<th>Returns</th>
<th>Volatility</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Event Day</td>
<td>Peak Day</td>
</tr>
<tr>
<td></td>
<td>(d=0)</td>
<td>(d=m)</td>
</tr>
<tr>
<td>Asian financial crisis</td>
<td>-0.13</td>
<td>-0.39</td>
</tr>
<tr>
<td>OPEC</td>
<td>0.20</td>
<td>0.29</td>
</tr>
<tr>
<td>Iraq war</td>
<td>-4.03</td>
<td>-4.05</td>
</tr>
<tr>
<td>Lehman Brothers</td>
<td>-1.20</td>
<td>-1.79</td>
</tr>
</tbody>
</table>
Excess returns

\[ \beta_1 f(d_{t_1}; \mu_1, \sigma_1) \]

\[ \beta_2 f(d_{t_2}; \mu_2, \sigma_2) \]

\[ \beta_3 f(d_{t_3}; \mu_3, \sigma_3) \]

Figure 1. The normal event response model
Figure 2. Crude oil futures returns from January 1995 to December 2013

Figure 3. Crude oil futures volatility from January 1995 to December 2013
Figure 4. Estimated normal event response pattern for returns

Figure 5. Estimated normal event response pattern for volatility