Price Discontinuities in Energy Spot and Futures Prices

Svetlana Maslyuk\(^a\), Kristian Rotaru\(^b\) and Alexander Dokumentov\(^c\)

Abstract
How often do jumps or price discontinuities occur on energy markets? What is the dynamics of the energy market sentiment (based on media coverage of economic fundamentals and other news events) that influence market behavior? How does the market sentiment affect the commodity returns? This study answers these questions by first, investigating jumping behavior of daily energy spot and nearest month futures returns for crude oil, natural gas, gasoline, heating oil and propane and second, by proposing a novel Cumulative Sentiment Index applied to the analysis of the detected jumps in returns. Our findings confirm previous studies that jumps are the common feature for all energy commodities studied. For some commodities such as gasoline spot and futures and heating oil futures, the average number of jumps per year has increased after the start of the Global Financial Crisis.

**JEL codes:** C14, G12

**Keywords:** jumps, energy prices, sentiment, nonparametric tests

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1. Introduction

In financial markets a subpopulation of market participants trades on sentiment and generates excess volatility (Dumas et al., 2009). From this subpopulation, a part of investors behave overconfidently giving too much credence to a public information signal (ibid.). This paper takes the view on investor sentiment suggested in Tetlock (2007) seeing the sentiment as the level of belief of noise traders, holding random beliefs about future dividends and beliefs, relative to rational arbitrageurs, holding Bayesian beliefs. Fluctuations in market sentiment subsequently cause prices to be more volatile than what would be justified by Market Efficiency Theory. This leads to a problem known as systematic market mispricing (Brown and Cliff, 2005) which manifests as price jumps, or discontinuities, driven by traders' "beliefs about asset values unwarranted by fundamentals" (Dorn, 2009, p.85). The relationship between sentiment analysis and the movement of financial markets has been examined in a whole range of studies. In relation to content analysed for traders' sentiment, the studies differentiate between formal channel that includes media coverage of the economic fundamentals though financial press releases and financial news (i.e. Tetlock, 2007); and user generated content (i.e. Antweiler & Frank, 2004; Das & Chen, 2007). Being specifically concerned with the impact of news on energy markets, this present paper relates to the former group of research studies, although its scope of the researched news items is significantly wider when compared to the above mentioned formal channel studies.

To date in the research literature the impact of the news on energy markets has been largely studied under the assumption of the continuous stochastic energy price process with smooth changes in prices (Wilmot and Mason, 2013, Alvarez-Ramirez, et al., 2010). Energy commodities are among the most important inputs contributing to the world economy. Hence, understanding the underlying stochastic process driving energy prices is of immense importance for investors, energy producing companies, governments and other market agents (Wilmot and Mason, 2013; Meade, 2010; Hamilton, 2008; Huntington, 2007; Jimenez- Rodriguez and Sanchez, 2005). The literature suggests that commodity prices in general, and energy commodities in particular, exhibit mean-reversion in the long run and price spikes and high volatility in the short run (Nomikos and Andriosopoulos, 2012). The mean-reversion in energy prices can be explained by the fact that in the long run the price of a commodity should be tied to its long run marginal production cost; that is it tends to revert back to a "normal" long-run equilibrium level (Nomikos and Andriosopoulos, 2012).

Meade (2010) suggested that there is a methodological discrepancy between theoretical and empirical asset pricing literature: while, arbitrage pricing theory literature suggests using geometric Brownian motion and mean reversion models, empirically driven literature favors ARMA–GARCH-type models. Although convenient, such models, either univariate or multivariate, often fail to reflect the so called jumps, or price discontinuities, which are inherent in prices of many assets, including energy. Following Meade (2010) and Liu and Tu (2012), price jumps are a common occurrence in the oil market. Such discontinuities can potentially arise after a news surprise including natural disasters, changes in geopolitical situation, actions of major players on energy markets, macroeconomic news announcements, geopolitical events and other events in countries consuming and producing energy (Kang et al., 2009). Since energy is an input in production, changes in energy prices are likely to spill over to other commodities and macroeconomic variables and also affect investment decisions.
The existence of jumps in energy prices suggests that assumption of normal distribution of log-returns which is typically used in the literature may not hold. The presence of jumps also implies that diffusion models are misspecified statistically (Lee and Cheng, 2007). The possibility of jumps may explain fat tails in many energy price returns. Understanding of jump behavior in energy prices after a particular news surprise is also important for derivative pricing, hedging and forecasting activities (Wilmot and Mason, 2013).

Although jump models proved to be a useful in capturing extreme price movements caused by news surprises (Gronwald, 2012), to date, the majority of researchers in energy literature have been focusing on modeling jumps in electricity prices and gave very limited attention to the prices of other energy resources. This can be partly explained by the availability of electricity data at high frequencies, special nature of electricity being non-storable seasonal commodity with uncertain and inelastic demand and a steep supply function (Deng and Oren, 2006). While comparing stock market returns and changes in electricity prices, Bierbrauer et al. (2007) argued that while stock market returns usually display daily standard deviations in the range of 1-2%, electricity price changes can have daily standard deviations of up to 40%. In addition, while jump identification has not yet been studied for other energy commodities, in electricity literature models involving jumps are used to better understand the possible causes behind discontinuities in electricity prices (Hellström et al., 2012) as well as to forecast future electricity prices (Chan et al., 2008; Haugom et al., 2011).

Another literature gap includes the use of the low frequency data in studying the jumping behavior of asset prices. In addition, in the literature it is customary for modeling energy prices to use either Generalized Autoregressive Conditional Heteroskedastic (GARCH)-type methodologies (Gronwald, 2012) or time series methods such as Autoregressive Moving Average (ARMA). Unfortunately both approaches fail to uncover jumps and lack explanatory power to investigate the potential root causes of the past jumps (Deaton and Laroque, 1992; Wirl, 2008; Ennio and Olivares, 2011). Following Ennio and Olivares (2011), the reason for this lies in the inability of both ARMA and GARCH models to meet all conditions and assumptions required in modeling energy prices which include time-varying volatilities and heavy tails.

The purpose of this study is two-fold: (1) to investigate the jumping behavior of daily energy spot and futures prices including crude oil, natural gas, gasoline, heating oil and propane; and (2) to propose a Cumulative Sentiment Index, a novel index of market sentiment which is based on the data provided in the Linfonics/Lexalytics developed Thomson Reuters NewsScope Sentiment Engine (RNSE) database which was renamed Thomson Reuters News Analytics (TRNA) database. This database is an explanatory tool for asset markets dynamics offering historical coverage for 40 commodities and over 25000 equities from 2003. In addition, it allows continuous flow of information to the market and provides broad coverage of publicly available news, which can be both macroeconomic and company specific (Lechthaler and Leinert, 2012).

The contributions of this paper are as follows. First, while in this paper we study price discontinuities or jumps in prices of a wide range of energy commodities (crude oil, propane, coal and natural gas) at daily data frequency. The majority of studies investigating jumps in the energy literature focus on electricity markets and more recently on crude oil, paying very limited attention to other non-electricity energy commodities. Second, contrary to previous studied which focused either on
spot and futures prices, we analyze both spot and near maturity futures contracts and consider large history of daily data from January 2003 to January 2013. Third, we use state-of-art econometric methodology including jump detection tests of Lee and Mykland (hereafter LM, 2008) which have superior jump detection properties. Fourth, we propose a novel measure of market sentiment which is specifically applied to energy market in general and to each spot and futures commodity under investigation.

The structure of the paper is as follows. In Sections 2 and 3, we discuss recent literature studying jumps in energy commodities and describe the data used in the paper. We review jump detection and sentiment index measurement methodologies used in this study in Section 4. In Section 5, we present estimation results, which are subsequently discussed in Section 6 followed by conclusions.

2. Jumps in the energy literature

Among those few researchers who investigated jumps in energy commodities are Askari and Krichere (2008), Bernard et al. (2008), Lee et al. (2010), Gronwald (2012), Wilmot and Mason (2013). Askari and Krichere (2008), who applied a time-invariant jump diffusion processes in daily oil prices from 2002 to 2006, found that oil prices were highly sensitive to news, subject to high volatility and were exhibiting high intensity of jumps. When detecting jumps in daily crude oil prices, Lee et al. (2010) proposed an innovative auto-regressive jump-intensity (ARJI) model, which allowed for price jumps and decomposed conditional variance into transitory and permanent components. They argued that while permanent component is important, transitory component could be caused by the news. Gronwald (2012) applied a combined jump GARCH model to study the behavior of daily, weekly and monthly crude oil prices. He found that WTI spot prices at all frequencies were characterized by both GARCH and conditional jump behaviour. He also found that although a considerable part of the variance was attributed to jumps, in more recent years the portion of the variance caused by jumps has decreased which could be explained by the general increase in the volatility of oil prices. Wilmot and Mason (2013) investigated the presence of jumps and time-varying volatility in spot and futures prices for crude oil at daily, weekly and monthly frequencies. They found that allowing for jumps at daily and weekly frequencies helps to explain oil prices better at these frequencies, but not at a monthly level.

While most of the studies in the literature are univariate, very few studies analyzed co-jumping between the energy prices. For example, Lee and Cheng (2007) applied bivariate jump models to study the relationship between the volatility of WTI and New York conventional gasoline spot prices. They found that although larger jumps occurring in crude oil returns are likely to simultaneously appear in gasoline returns, the magnitude of co-movements in volatility is likely to fall because the volatility of gasoline is less sensitive. Using event risk model, Liu and Tu (2012) studied jump spillovers of five energy futures contracts including Brent crude oil, natural gas, heating oil, gasoline and fuel oil which are traded on the InterContinental Exchange in Europe. They calculated two types of jump spillovers, namely, the simultaneous jump intensities for pairs of energy futures contracts and the conditional jump spillovers. They found strong evidence in support of jump spillovers and based on the simultaneous jump intensities investigation they concluded that both good and bad news events can potentially cause a jump spillover.

Several studies used jumps for predicting future movements in prices. For example, Bernard et al. (2008) compared forecasting accuracy of random-walk
models with (GARCH) effects, models with Poisson jumps and (G)ARCH effects and mean-reverting models. They found that although jumps in oil futures prices are significant, mean reverting model had the best performance.

Our literature analysis reveals that another gap to date research devoted to the analysis of market sentiment on energy prices is limited. In the analysis of causal relationship between investor's positions and price movements for crude oil, gasoline, heating oil and natural gas from 1992 to 1999, Sanders et al. (2004) came to conclusion that investor commitments do not cause movements in prices. Using position-based sentiment index, Choi (2010) studied the causality between the investor sentiment and weekly NYMEX crude oil, heating oil and natural gas futures returns from 1995 to 2007. Based on the Granger-causality tests, he concluded that causality runs from futures prices to investor sentiment and particular speculator's (hedger's) sentiment increases (decreases) as the previous returns increase (Choi, 2010, p. 47). Therefore, it was concluded that sentiment is not useful in predicting future movements in the NYMEX energy futures market. This finding is in contrast to Lechthaler and Leinert (2012), who used TRNA sentiment values to demonstrate that between February 2003 and February 2010, crude oil prices and the news sentiment have shown a high degree of co-movement and positive correlation between the prices and the news sentiment. Using event studies methodology Borovkova and Lammiman (2012) investigated the response of oil futures prices of various maturities to positive and negative sentiment in news based on the daily aggregated news sentiment. They found that over the period from 2003 to the end of 2008 positive sentiment causes the price of distant futures to rise more than that of nearby futures and are likely to reduce (deepen) the degree of backwardation (contango). In addition, similar to previous news studies they found that market responds asymmetrically to positive and negative news events with news events being accompanied with much greater losses as compared to neutral events than the gains of positive events as compared to neutral days.

3. Data

In this paper we use daily spot and futures prices for two benchmark crudes: West Texas Intermediate (WTI) and Brent, Henry Hub Gulf Coast natural gas, Mont Belvieu, TX Propane, New York Harbor No. 2 Heating Oil, New York Harbor Reformulated RBOB Regular Gasoline. Although time period of analysis is January 2003 to January 2013, the exceptions are NYMEX propane futures (data was available until September 2009) and gasoline futures (data starts in October 2005). Futures for all commodities are taken at one month to maturity. All sample prices were converted in to the natural lags and further transformed into the daily percentage nominal logarithmic return series using the following approach

\[ r_t = \ln \left( \frac{p_t}{p_{t-1}} \right) \times 100\%, \]

Where \( r_t \) is return in time \( t \) and \( p \) is the futures or spot price. Table 1 contains the description of data used in this study.

Descriptive statistics of the price and return series are summarized in Tables 1 and 2 below. All spot and futures series exhibit similar characteristics: relatively small sample mean of returns with larger unconditional volatility of return series as indicated by their standard deviations. Both skewness and kurtosis values for all series indicate that the return series are not normal, which is further confirmed by the results of the Jarque-Bera test for normality. In fact, all series exhibit significant excess kurtosis meaning that as compared to normal distribution all return series have higher
and shaper central peak and longer fatter tails. The results of the conventional unit root tests (Augmented Dickey Fuller and Phillips Perron) indicate all return series are stationary variables, which means that the impact of a shock on the series is likely to be transitory and over time the series will revert to their respective means.

Table 1
Sample statistics for the spot returns

<table>
<thead>
<tr>
<th></th>
<th>WTIS</th>
<th>BrentS</th>
<th>NGS</th>
<th>HOS</th>
<th>PS</th>
<th>GS</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
</tr>
<tr>
<td>Median</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
</tr>
<tr>
<td>Maximum</td>
<td>0.16</td>
<td>0.18</td>
<td>0.58</td>
<td>0.11</td>
<td>0.17</td>
<td>0.22</td>
</tr>
<tr>
<td>Minimum</td>
<td>-0.15</td>
<td>-0.17</td>
<td>-0.57</td>
<td>-0.11</td>
<td>-0.50</td>
<td>-0.19</td>
</tr>
<tr>
<td>Skewness</td>
<td>-0.10</td>
<td>0.00</td>
<td>0.66</td>
<td>-0.05</td>
<td>-4.29</td>
<td>0.15</td>
</tr>
<tr>
<td>Kurtosis</td>
<td>7.42</td>
<td>7.91</td>
<td>28.99</td>
<td>3.97</td>
<td>86.47</td>
<td>7.37</td>
</tr>
<tr>
<td>JB</td>
<td>1310.00***</td>
<td>1613.28***</td>
<td>70595.02***</td>
<td>63.92***</td>
<td>7348.00***</td>
<td>1969.87***</td>
</tr>
<tr>
<td></td>
<td>(0.00)</td>
<td>(0.00)</td>
<td>(0.00)</td>
<td>(0.00)</td>
<td>(0.00)</td>
<td>(0.00)</td>
</tr>
<tr>
<td>ADF</td>
<td>-51.36***</td>
<td>-50.35***</td>
<td>-41.72***</td>
<td>-51.72***</td>
<td>-36.66***</td>
<td>-48.53***</td>
</tr>
<tr>
<td></td>
<td>(0.00)</td>
<td>(0.00)</td>
<td>(0.00)</td>
<td>(0.00)</td>
<td>(0.00)</td>
<td>(0.00)</td>
</tr>
<tr>
<td>PP</td>
<td>-51.44***</td>
<td>-50.35***</td>
<td>-49.08***</td>
<td>-51.70***</td>
<td>-36.45***</td>
<td>-48.54***</td>
</tr>
<tr>
<td></td>
<td>(0.00)</td>
<td>(0.00)</td>
<td>(0.00)</td>
<td>(0.00)</td>
<td>(0.00)</td>
<td>(0.00)</td>
</tr>
</tbody>
</table>

Note: Abbreviations: WTIS – West Texas Intermediate spot, BrentS – spot Brent, NGS- natural gas spot, HOS – heating oil spot, PS – propane spot, GS – gasoline spot. JB is the Jarque-Bera test for normality. ADF and PP are the Augmented Dickey Fuller and Phillips Perron Unit root tests. *** denotes a rejection of normality (unit root) null hypothesis at 1% significance level.

Table 2
Descriptive statistics for the futures returns

<table>
<thead>
<tr>
<th></th>
<th>WTIF</th>
<th>BrentF</th>
<th>NGF</th>
<th>HOF</th>
<th>PF</th>
<th>GF</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
</tr>
<tr>
<td>Median</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
</tr>
<tr>
<td>Maximum</td>
<td>0.16</td>
<td>0.13</td>
<td>0.32</td>
<td>0.10</td>
<td>0.09</td>
<td>0.15</td>
</tr>
<tr>
<td>Minimum</td>
<td>-0.13</td>
<td>-0.11</td>
<td>-0.20</td>
<td>-0.19</td>
<td>-0.25</td>
<td>-0.13</td>
</tr>
<tr>
<td>Std. Dev.</td>
<td>0.03</td>
<td>0.02</td>
<td>0.04</td>
<td>0.03</td>
<td>0.02</td>
<td>0.03</td>
</tr>
<tr>
<td>Skewness</td>
<td>0.03</td>
<td>-0.11</td>
<td>0.94</td>
<td>-0.25</td>
<td>-1.53</td>
<td>-0.17</td>
</tr>
<tr>
<td>Kurtosis</td>
<td>7.31</td>
<td>5.66</td>
<td>10.13</td>
<td>5.82</td>
<td>19.26</td>
<td>6.38</td>
</tr>
<tr>
<td>JB</td>
<td>1239.28***</td>
<td>477.45***</td>
<td>5678.61***</td>
<td>548.82***</td>
<td>18295.84***</td>
<td>875.94***</td>
</tr>
<tr>
<td></td>
<td>(0.00)</td>
<td>(0.00)</td>
<td>(0.00)</td>
<td>(0.00)</td>
<td>(0.00)</td>
<td>(0.00)</td>
</tr>
<tr>
<td>ADF</td>
<td>-53.14***</td>
<td>-54.28***</td>
<td>-53.02***</td>
<td>-51.06***</td>
<td>-33.60***</td>
<td>-42.29***</td>
</tr>
<tr>
<td></td>
<td>(0.00)</td>
<td>(0.00)</td>
<td>(0.00)</td>
<td>(0.00)</td>
<td>(0.00)</td>
<td>(0.00)</td>
</tr>
<tr>
<td>PP</td>
<td>-53.28***</td>
<td>-54.27***</td>
<td>-52.98***</td>
<td>-51.06***</td>
<td>-48.60***</td>
<td>-42.28***</td>
</tr>
<tr>
<td></td>
<td>(0.00)</td>
<td>(0.00)</td>
<td>(0.00)</td>
<td>(0.00)</td>
<td>(0.00)</td>
<td>(0.00)</td>
</tr>
</tbody>
</table>

Note: Abbreviations: WTIF – West Texas Intermediate crude oil futures, BrentF – Brent crude oil futures, NGF- natural gas futures, HOF – heating oil futures, PF – propane futures, GF – gasoline futures. JB is the Jarque-Bera test for normality. ADF and PP are the Augmented Dickey Fuller and Phillips Perron Unit root tests. *** denotes a rejection of normality (unit root) null hypothesis at 1% significance level.

4. Methodology
In this paper we use Lee and Mykland (LM) (2008) non-parametric jump detection tests. The main advantage of non-parametric tests is elimination of risk of incorrect
specification of the functionals which is inherent in model selection while performing parametric tests. LM (2008) jump detecting procedure was chosen because of the following advantages over the alternative tests:

a) Model-free tool for characterizing jumps in individual asset returns
b) Solves low detection rates issue: allows determining the jump intensity and jump size distribution.
c) Allows identifying timing and magnitude of the jump.
d) Tests can be applied to all kinds of financial variables (wide spectrum of use).

Several studies (Audrino and Hu, 2011; Pukthuanthong and Roll, 2012; Erdenlioglu et al., 2012; Będowska-Sójka, 2010; Zhou and Zhu, 2011a, 2011b; Lahaye et al., 2011) have applied LM (2008) test and its modifications to financial data, but not to energy.

In this study we also introduce a Cumulative Sentiment Index (CSI), a novel index of sentiment which is based on the data provided in the TRNA database. TRNA is a resilient server system that performs complex linguistic processing on multiple news sources the equities and commodities covered.

Results show that TRNA data feed provides measurable, multidimensional news-sentiment induced input which can be useful for price forecasting and algorithmic trading. It is shown by cumulative covariance graphs between energy commodity returns and daily change in the respective CSIs.

In TRNA each news item is scored individually for each asset based on its relevance, novelty, sentiment, volume and other measures. Both sentiment and relevance scores are based on the qualitative news and market information. While relevance reflects the likelihood that the given story is about this particular asset, novelty is a measure of repetition among the news articles (novelty=0) and the repetition or similarity of this news item to previously seen news items (novelty>0). The score for relevance is calculated in the [0, 1] interval. The score for volume corresponds to the number of recent news items mentioning the asset. Sentiment measure reflects whether the news item talks about the asset in a positive, neutral or negative manner, calculates the value for each in order to determine the prevailing market sentiment score which takes the values +1; 0 and -1 respectively.

Table 3
TRNA news items: quantity, relevance and valence

<table>
<thead>
<tr>
<th>TRNA RIC</th>
<th>Relevant news</th>
<th>Relevant positive news</th>
<th>Relevant negative news</th>
</tr>
</thead>
<tbody>
<tr>
<td>Crude oil</td>
<td>345805</td>
<td>170795</td>
<td>175010</td>
</tr>
<tr>
<td>Natural gas</td>
<td>171328</td>
<td>90853</td>
<td>80475</td>
</tr>
<tr>
<td>Heating oil and diesel</td>
<td>74717</td>
<td>35569</td>
<td>39148</td>
</tr>
<tr>
<td>LPG</td>
<td>1447</td>
<td>748</td>
<td>699</td>
</tr>
<tr>
<td>Gasoline</td>
<td>61212</td>
<td>30067</td>
<td>31145</td>
</tr>
</tbody>
</table>

Table 3 shows quantity, relevance and valence of news items retrieved from the TRNA database and used for the calculation of the CSI for five energy markets. For convenience reasons, this table represents the number of relevant news items, which is broken down into the relevant positive and relevant negative news items. Herein, we consider a relevant news item positive if the probability of the positive sentiment of this news item associated with a given commodity market is greater or
equal to the probability of negative sentiment. On the contrary, a news item is considered negative if the probability of the positive sentiment of this news item associated with a given commodity is lesser than the probability of negative sentiment. It should also be noted that some news items can overlap for several commodities. Table 3 demonstrates that for crude oil, heating oil and gasoline the number of relevant negative news is greater than the number of relevant positive news, while it is the opposite for natural gas and LPG.

4.1 LM (2008) jump detection technique
Suppose that \( S(t) \) is the oil price and \( d\log S(t) \) is continuously compounded return for \( t \geq 0 \). Provided there are no jumps on the market, oil price can be represented as a standard Brownian motion \( W(t) \) and a drift \( \mu(t) \)

\[
d\log S(t) = \mu(t) dt + \sigma(t) dW(t),
\]

(1)

where \( \sigma(t) \) is a spot volatility.

If there are no jumps in the market, \( S(t) \) is given by standard Brownian motion \( W(t) \) which can be described as \( \Delta W(t) = W(t) - W(t - \Delta) \sim N(0, \Delta) \), a drift \( \mu(t) \) and a \( \Upsilon(t) \), which is a counting process independent of \( W(t) \).

\[
d\log S(t) = \mu(t) dt + \sigma(t) dW(t) + \Upsilon(t) dJ(t),
\]

(2)

where \( J(t) \) is the jump size, which can be predicted.

LM test makes following assumptions:
1) Jump sizes \( \Upsilon(t) \) are independent of each other, identically distributed and are also independent of other random components \( W(t) \) and \( J(t) \).
2) The drift and diffusion coefficients not changing dramatically over a short time interval and are allowed to depend on the process itself.

LM (2008) test compares realized return at any given time to a continuously estimated instantaneous volatility \( \sigma(t_i) \), a measure that explains local variation arising from the continuous part of the process. \( \sigma(t_i) \) is estimated using a modified version of realized bipower variation calculated as the sum of products of consecutive absolute returns in the local window (Barndorff-Nielsen and Shephard, 2004). Then, jump detection statistic \( \mathcal{L}(i) \) testing for jump in returns occurring at time \( t_i \) within a window size \( K \) is calculated as the ratio of realized returns to estimated instantaneous volatility:

\[
\mathcal{L}(i) \equiv \frac{\log S(t_i)/S(t_{i-1})}{\hat{\sigma}(t_i)}
\]

(3)

where

\[
\hat{\sigma}(t_i)^2 \equiv \frac{1}{K-2} \sum_{j=i-K+1}^{i-1} |\log S(t_j)/S(t_{j-1})||\log S(t_{j-1})/S(t_{j-2})|
\]

(4)

The advantages of using bipower variation as the estimator for the instantaneous volatility is in the denominator of the statistic are that this technique is robust to the presence of jumps in the previous periods and does not affect consistency of estimation (Lee and Mykland, 2008, p. 2541). In order to take advantage of bipower variation, the choice of local window size \( K \) is very important. For instance, in time of high volatility not every high return would imply a jump and conversely, in low volatility time abnormal return doesn’t need to be specially high.
to be detected as a jump (Będowska-Sójka, 2010). K should be large enough so that the effect of jumps on estimating instantaneous volatility disappears but smaller than number of observations $n$ (Lee and Mykland, 2008, p. 2542). Lee and Mykland suggest that the choice of sampling frequency $\Delta t$ determines the window size which is calculated as $K = O_p(\Delta t^\alpha)$ with $-1 < \alpha < -0.5$. For daily data, which we use in this study Lee and Mykland suggested $K=16$.

The behaviour of jump detection statistic $L(i)$ differs depending on whether there is a jump in the data. If there is no jump, $L(i)$ test statistic follows approximately a normal distribution. However, if there is a jump in the data, the value of $L(i)$ becomes very large. Lee and Mykland (2008) propose selecting the rejection region for $L(i)$ statistic based on the distribution of maximums of the statistics. Assuming no jumps in a particular time interval $[t_{i-1}, t_i]$ and a small distance between two consecutive observations in this interval ($\Delta \rightarrow 0$) this maximum converges to a Gumbel variable,

$$\max_{i \in A_n} |L(i)| - C_n \overset{S_n}{\rightarrow} \xi$$

Where $n$ is the number of observations and $\xi$ has a cumulative distribution function $P(\xi \leq x) = \exp(-e^{-x})$, $A_n$ is the set of $i \in \{1, 2, \ldots, n\}$ so that there is no jump in $[t_{i-1}, t_i]$ and $C_n$ and $S_n$ are defined as follows

$$C_n = \frac{(2 \log n)^{1/2}}{c} - \frac{\log n + \log \log n}{2c(2 \log n)^{1/2}} \quad \text{and}$$

$$S_n = \frac{1}{c(2 \log n)^{1/2}}$$

where $c$ is a constant calculated as $c = E \left[ \frac{1}{\sqrt{\Delta t}} (W_{t_i} - W_{t_{i-1}}) \right]$.

The test can be conducted by comparing $L(i)$ statistic standardized as max $L(i)$ as described in Equation (5) to the critical values from the Gumbel distribution (Dimitru and Urga, 2012). The null hypothesis of no jump is rejected when

$$L(i) > G^{-1}(1 - \alpha)S_n + C_n.$$  

4.2 Cumulative Sentiment Index (CSI)

The idea to develop a proxy of market sentiment based on the news is not new in the financial literature, but it is relatively new in the energy literature. Moreover, not many studies developed an alternative measure of sentiment using the TRNA database. The exception is Son et al. (2012) who were first in the literature to suggest three sentiment indices on TRNA. Each of the suggested indices used only the news items with the relevance score greater than or equal to 0.9 in order to filter the most important news items. The first sentiment index (Index-1) is the average value of most relevant sentiment values from the previous three months. The second sentiment index (Index-2) is a normalized index based on the ratio between SENT_POS (probabilistic measure of positive Sentiment contained in the news item) and SENT_NEG (probabilistic measure of negative sentiment contained in the news item) averaged over three month period. The third sentiment index (Index-3) is similar to Index-2 apart from the fact that each Index-2 value is multiplied by the absolute value of the TRNA sentiment score. Hence, Index-3 is equal to zero if the sentiment score is zero. The major limitation associated with the proposed indices relates to the arbitrary
choice of the relevance score which is used to filter out the majority of events, even though their volume and level of relevance assure that they influence price dynamics.

The Cumulative Sentiment Index (CSI) was suggested as an alternative to the above mentioned TRNA-based indices of market sentiment. The CSI is calculated using the following TRNA measures: (1) the amount of the news items; (2) relevance of the news to a particular energy commodity; and (3) the measure of sentiment of the news associated to this commodity. The latter is calculated as the difference between probability that the sentiment of the news item was positive and the probability that sentiment of the news item was negative. The CSI is calculated as follows:

\[ CSI(t) = \sum_{\tau=t_0}^{t} R_\tau (SP_\tau - SN_\tau), \]

where \( CSI(t) \) is value of CSI at time \( t \), \( R_\tau \) is the measure of how relevant the news item is to the given commodity at moment in time \( \tau \), \( SP_\tau \) is the probability that the sentiment of the news item was positive at moment \( \tau \) and \( SN_\tau \) is the probability that the sentiment of the news item was negative at moment \( \tau \). In this study we use full history of the TRNA data, from 2003 to January 2013.

For propane, due to the absence of the relevant RIC code, or more specifically, "STOCK_RIC" code in TRNA database we used Liquefied Petroleum Gas (LPG) news field as the basis for identification of relevant news items for CSI calculation. For all other commodities CSI was calculated based on the relevant TRNA news fields.

Figure 1 represents an Aggregated CSI (ASCI) measure based on crude oil, natural gas, gasoline and LPG related news for the period of January 2003 - January 2013. ACSI can be interpreted as the general market sentiment or the general market’s attitude about the state of energy markets. One can see that prior to 2004 and after mid-2008 ACSI was in the steep decline. If the former is likely to be connected to the second war in Iraq and tightness in oil and natural gas supply in the coming months, the latter can be explained as the reflection of market pessimism due to GFC. From 2004 till the start of 2006 the market sentiment was positive and increasing, which can be a reflection of positive economic conditions. Interestingly, during 2006 and early 2007, prior to the start of the Global Financial Crisis (GFC), the sentiment did not change much and was fluctuating around its mean value over this period of time. On this diagram GFC can be shown as a small sharp dip in 2007, after which the sentiment has recovered and responded by a period of strong growth until it reached its peak in the mid-2008. Such growth in the ACSI could be a reflection of positive market beliefs about potential economic recovery, but as it did not happen after 2008 the sentiment values were in deep decline indicating general market pessimism about the economy overall and energy markets in particular. Notice that this index has to be interpreted with caution because of the black box nature of the original measures of sentiment and relevance of the news items provided by TRNA upon which this index is constructed.
In addition, we have calculated cumulative covariance between the same day returns and the individual market CSIs, cumulative covariance between the returns and CSI one day prior and cumulative covariance between the returns one day before and the same-day CSI. Herein, cumulative covariance at moment \( t \) (\( CCov(t) \)) is defined as:

\[
CCov(t) = \sum_{t=t_0}^{t} Return_{Instrument\_1}(\tau) \times Return_{Instrument\_2}(\tau)
\]

for some starting time \( t_0 \). Cumulative covariance for CIS and log price is calculated and presented as a graph (i.e. Figure 2) to visualize possible relation between CSI returns and log price returns. Cumulative covariance for one day delayed CSI and log price is calculated and presented as a graph to visualize possible influence of CSI returns on log prices. Cumulative covariance for one day delayed log price and CSI is calculated and presented as a graph to visualize possible influence of log price returns on CSI.

5. Estimation results

In line with previous studies, we have found that jumps are indeed inherent feature of the energy commodity market. Moreover, daily returns for spot (futures) commodities tend to jump together although in some instances jumps in one commodity are not translated to other commodities. In case of a common jump, the direction of the jump (i.e. upward or downward movement in return) tends to be shared by the commodities. For example, second war in Iraq or the MENA civil unrest caused a negative swing in all commodities returns, both spot and futures, while a start of the second Iraq war cased an upward movement in the returns. This implies that energy commodities are likely to respond together to some news event which affects them all in a similar way.
Table 4 shows the number of jumps identified with 99% probability for each commodity return\(^1\). The largest number of jumps was identified in WTI future (119), spot propane (105) and heating oil future (100), while the smallest number of jumps was detected in gasoline future (15). For most of the series, LM test detected more jumps per year before the 2007 – a year when the GFC has started. The exception is gasoline spot and 1 month futures, where the amount of discontinuities after the start of the GFC was greater than before.

<table>
<thead>
<tr>
<th>Commodity</th>
<th>Total number of jumps</th>
<th>Average number of jumps before 2007</th>
<th>Average number of jumps after 2007</th>
</tr>
</thead>
<tbody>
<tr>
<td>Spot</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>WTI</td>
<td>77</td>
<td>3</td>
<td>3</td>
</tr>
<tr>
<td>BrentS</td>
<td>72</td>
<td>3</td>
<td>3</td>
</tr>
<tr>
<td>NGS</td>
<td>34</td>
<td>2</td>
<td>2</td>
</tr>
<tr>
<td>HOS</td>
<td>105</td>
<td>5</td>
<td>5</td>
</tr>
<tr>
<td>PS</td>
<td>54</td>
<td>2</td>
<td>2</td>
</tr>
<tr>
<td>GS</td>
<td>30</td>
<td>0.5</td>
<td>4</td>
</tr>
<tr>
<td>Futures</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>WTI</td>
<td>119</td>
<td>4</td>
<td>3</td>
</tr>
<tr>
<td>BrentF</td>
<td>76</td>
<td>4</td>
<td>2</td>
</tr>
<tr>
<td>NGF</td>
<td>47</td>
<td>3</td>
<td>2</td>
</tr>
<tr>
<td>HOF</td>
<td>85</td>
<td>4</td>
<td>5</td>
</tr>
<tr>
<td>PF</td>
<td>100</td>
<td>3</td>
<td>2</td>
</tr>
<tr>
<td>GF</td>
<td>15</td>
<td>1</td>
<td>3</td>
</tr>
</tbody>
</table>

Source: Authors calculations.

As per Table 4, the average number of jumps (most drastic jumps) in oil futures has decreased, while the average number of jumps per year was not affected by the GFC. The largest number of average jumps per year belongs to heating oil spot. The number of jumps has increased after the GFC for gasoline spot and futures and heating oil futures.

Figures 2-6 show the price series for each spot commodity with the news induced CSI, covariance lead CSI (covariance between CSI values 1 day prior and today’s return) and the covariance lead return (covariance between return values 1 day ahead and today’s CSI). The CSI graphs are scaled to assure their visibility when placed on the top of the existing pricing graphs. As it does not represent absolute value but rather the shape of CSI graph which is important when comparing it to the price logs, linearly scaling the CSI graphs does not result in the loss of any useful information. Similar figures were produced for futures commodities and to preserve space are available from authors upon request.

Similar to Lechthaler and Leinert (2012), we have found that energy spot and futures returns have shown high degree of co-movement with the suggested sentiment indices for the large part of the sample. This co-movement have broken down in March 2011 for crude oil, gasoline and heating oil. For these commodities market sentiment went on a downward trend, while the actual prices were fluctuating around their respective means from March 2011 onwards.

\(^1\) The number of jumps increases with the probability interval and is higher for 95%, 80% and lower intervals.
First half of March 2011 hit hard the energy sector with Tohoku earthquake and tsunami on the 8th of March 2011 and spread of the Middle East and North Africa (MENA) civil unrest to Egypt, Bahrain and Libya on the 11th of March onwards. From that time, investor sentiment was consistently negative reflecting market concerns about the availability of supply for these commodities.

Market sentiment was on increasing trend for the natural gas throughout the sample. In fact, the sentiment was rising even when the natural gas prices were declining (for example, from June 2008 to March 2009). This was due to a number of reasons. First of all, natural gas represents a cleaner alternative to other sources of energy in terms of greenhouse gas emissions, which is an important consideration for public policy in a climate change domain. In addition, given the increased uncertainty with the supply of oil, the supply of natural gas in the US is abundant.

Prior 2006, the propane news induced sentiment indicator was relatively stable. Similar to natural gas, the sentiment values associated with propane were increasing since the beginning of 2006, after the US government introduced several incentives to promote the use of propane, including the Alternative Fuel Infrastructure Tax Credit scheme.

Table 5
Number of identified jumps in CSI: 2003 -2013

<table>
<thead>
<tr>
<th>CSI feed types</th>
<th>Total number of jumps</th>
<th>Average number of jumps before 2007</th>
<th>Average number of jumps after 2007</th>
</tr>
</thead>
<tbody>
<tr>
<td>Energy commodity</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Crude oil</td>
<td>107</td>
<td>4</td>
<td>8</td>
</tr>
<tr>
<td>Natural gas</td>
<td>109</td>
<td>4</td>
<td>9</td>
</tr>
<tr>
<td>Heating oil and diesel</td>
<td>105</td>
<td>3</td>
<td>9</td>
</tr>
<tr>
<td>LPG</td>
<td>107</td>
<td>3</td>
<td>9</td>
</tr>
<tr>
<td>Gasoline</td>
<td>96</td>
<td>1</td>
<td>9</td>
</tr>
</tbody>
</table>

Source: Authors calculations.

Comparing the number of identified jumps in the commodity returns and CSI (Table 5), it is worth noting that the number of jumps in the same-day CSI has been greater than the number of the identified jumps in the respective commodity returns. In addition, not all jumps coincided.

In relation to the dates of the jumps in returns and jumps in the CSI, we have found that not all jumps in returns and the CSI correspond. The results show that market often overreacts with jump in CSI happening before the identified jump in the commodity return.

Our results show high level of correlation between same-day CSI and all commodity returns. Interestingly, covariance lead news induced CSI one day prior the trading day was more relevant for the return for all series that same-day CSI. This implies that a lot of trading decisions are made based on the previous sentiment and the previous news. Covariance lead returns were highly correlated with the current CSI values for all commodities implying that expectations about future do impact current market sentiment. Overall, our results show that both same-day CSI and its the previous value are the significant determinants of both future spot and futures returns for all energy commodities.
In addition, Figures 2-6 show that positive jumps in returns are more likely when market sentiment is positive which could be due to the arrival of positive and optimistic news. Similarly, negative jumps are more likely when the CSI is negative.
Figure 2: Detected jumps for the crude oil Brent oil spot price, crude oil CSI, covariance log price and CSI, covariance CSI leads and covariance log price leads: January 2003 to January 2013
Figure 3: Detected jumps for the crude oil WTI oil spot price, crude oil CSI, covariance log price and CSI, covariance CSI leads and covariance log price leads: January 2003 to January 2013
Figure 4: Detected jumps for the natural gas spot price, natural gas CSI, covariance log price and CSI, covariance CSI leads and covariance log price leads: January 2003 to January 2013
Figure 5: Detected jumps for the heating oil spot price, heating oil and diesel CSI, covariance log price and CSI, covariance CSI leads and covariance log price leads: January 2003 to January 2013
Figure 6: Detected jumps for the gasoline spot price, gasoline CSI, covariance log price and CSI, covariance CSI leads and covariance log price leads: January 2003 to January 2013
Figure 7: Detected jumps for the propane spot price, LPG CSI, covariance log price and CSI, covariance CSI leads and covariance log price leads: January 2003 to January 2013
6. Discussion and Conclusions

Trading on financial markets is strongly influenced by the information flows including company-specific, macroeconomic or political information which could arrive at the regular and irregular time intervals (Groß-Klußmann and Hautsch, 2011) as well as the perception of the market participants about these information events (Baker and Wurgler, 2007). Traditional financial models assume rational behavior from investors when they receive any new information so that asset prices always reflect true fundamental asset values (Asgharian et al., 2011). The purpose of the paper was to identify jumps in energy returns. Having a substantial understanding of the energy price dynamics and, in particular, about price discontinuities, is important for short term hedging strategies, portfolio optimization and understanding investors’ behavior (Gronwald, 2012). Our paper extends current literature by analyzing a wide range of energy commodities, out of which jump detection was performed only for crude oil and studying the impact of sentiment on arrival of jumps.

To detect jump events, in this study we use a nonparametric jump detection procedure developed by Lee and Mykland (LM, 2008) applied to daily energy spot and futures prices. LM (2008) test compares realized return at any given time to a continuously estimated instantaneous volatility. We have found that such news events are likely to create jumps, or discontinuities, in returns. Moreover, our findings show that market attitude to these events as proxied by the news induced CSI is highly correlated to the return series for five energy spot and futures markets including crude oil, gasoline, propane, heating oil and natural gas. This finding is in line with Elder et al. (2012) who studied the relationship between news and the precious market returns, we found that a strong relationship between the news and the spot and futures market commodity returns.

We see two major limitations of this study, which are associated with the design of the proposed index. First, at the moment CSI uses only a limited number of TRNA fields, which may restrict its explanatory power when investigating the price dynamics of a particular commodity. Even though this matter is outside the scope of this study, the addition of other parameters of the news item, such as novelty, might add to the explanatory power of the cumulative index. The second limitation relates to the black box nature of the sentiment data provided by the TRNA database. This means that, being part of the Thomson Reuters’s ‘know how’, the algorithm used for calculating the probabilistic measures of sentiment and relevance of the news items may not be empirically tested researchers.

The future research might address these limitations by: a) including other factors into the design of CSI, such as the novelty types of the news items (found in TRNA database); using other text mining algorithms to extract the measure of sentiment directly from the news items (i.e. using Thompson Reuters Global News Archive) and comparing its explanatory power to the CSI indicator. Another potential extension of the current study is to investigate the relationship between jump dynamics and measures of sentiment based not only on the formal channel, such as media coverage but also the user generated content (i.e. Antweiler & Frank, 2004; Das & Chen, 2007). Finally, this research would further benefit from the analysis of the news and jump magnitude, duration and direction.
Ng, A. and H. Donker "Purchasing Reserves and Commodity Market Timing as Takeover Motives in the Oil and Gas Industry." Energy Economics (0).