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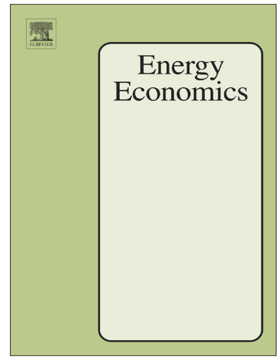

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Spillovers between the oil sector and the S&P500: The impact of information flow about crude oil

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Abstract

Crude oil is one of the most important commodities in the real economy and as such the relationship between oil prices and broader equity markets has attracted a lot of research attention. Recent work has considered directional spillovers or links between oil and equity markets. In recent times there has been a growing body of research into the impacts of news and media attention on asset returns, both in the context of oil and equity markets but also within each of these markets. This paper considers how news or information flows about crude oil influence the spillover links between these assets. Using realized volatility estimates based on high frequency data, the empirical analysis reveals a number of novel results in terms of the behavior of these linkages. Increased news flow about oil reduces the impact of the broader equity market on the oil sector, implying that it is driven more by oil specific shocks and less by more general financial market conditions. It also increases the impact of the oil sector on the broader equity market. These results have potential implications for hedging and portfolio allocation.

JEL Classification Numbers

C1, C58, G1, G14

Keywords

Investor attention, Google search volume, Google trends, Oil market, Stock market, Volatility, Spillovers

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Abstract

Crude oil is one of the most important commodities in the real economy and as such the relationship between oil prices and broader equity markets has attracted a lot of research attention. Recent work has considered directional spillovers or links between oil and equity markets. In recent times there has been a growing body of research into the impacts of news and media attention on asset returns, both in the context of oil and equity markets but also within each of these markets. This paper considers how news or information flows about crude oil influence the spillover links between these assets. Using realized volatility estimates based on high frequency data, the empirical analysis reveals a number of novel results in terms of the behavior of these linkages. Increased news flow about oil reduces the impact of the broader equity market on the oil sector, implying that it is driven more by oil specific shocks and less by more general financial market conditions. It also increases the impact of the oil sector on the broader equity market. These results have potential implications for hedging and portfolio allocation.

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1. Introduction

Given the central importance of crude oil to the broader economy, the link between oil and equity markets has attracted a great deal of research attention. The early work of Kling (1985) motivated a strand of literature, Huang et al. (1996), Jones and Kaul (1996), Sardosky (1999), Park and Ratti (2008), and Apergis and Miller (2009) among others considered the link between oil and equity returns. The overarching result from this work is that oil prices have an impact on equity returns. In more recent times, the focus of research has moved to links between the volatilities of oil and equity market returns. Malik and Hammoudeh (2007), Arouri et al. (2011), and Maghyereh and Awartani (2016) found significant spillovers from oil to equity volatility across a range of different equity markets, while Mancini (2009) found links in both directions. Maghyereh et al. (2016) employs the network connectedness measures of Diebold and Yilmaz (2014) to examine directional volatility spillovers between oil and a range of equity markets worldwide. While for many equity markets, the spillover is predominantly in the oil to equity direction, of central interest for this paper, in the context of the U.S. market there bi-directional have been identified. There is also a long standing strand of research linking information flows or arrivals to asset returns and volatility. In the context of oil markets, the recent work of Campos et al. (2017) and Afkhami et al. (2017) examined the impact of Google Search Volume (GSV) related to oil prices (and other energy related terms) on oil price volatility. Such analysis is normally univariate in nature with little understanding of how information flows may influence interactions between markets. Moving beyond the univariate setting, Drake et al. (2017) considered how comovements in investor attention to individual stocks (using GSV as one proxy) explain comovements in returns. This analysis was a low frequency annual analysis where only the contemporaneous comovements between stocks were considered. Drake et al. (2017) found that comovement in investor attention provides incremental explanatory power for return comovement beyond traditional explanatory factors such as industry membership, size and so forth. This study also moves beyond the univariate case, but in a higher frequency setting than Drake et al. (2017) and considers how the rate of news attention regarding oil markets influences the directional (not simply contemporaneous) linkages between the oil sector and the broader equity markets.

This analysis is based on two measures of information flow, GSV and an index of media attention. First, the influence of the rate of oil news flow on the level of volatility in both the oil sector and the equity market will be examined along with its impact on the correlation between the two. Moving beyond the level of volatility and or correlation, the impact of news flow on the strength of directional measures of spillovers is also considered. It is found that the past volatility of oil sector returns is significantly related to market level volatility, and vice-versa, indicating the presence of spillovers between the two. News flow is found to be related to the level of volatility in both the oil sector and broader equity market, even after controlling for past volatility of both markets, however, there is little impact on correlation, a directionless measure of association.

By moving beyond correlation to consider network based measures of directional spillovers within a rolling-window framework of high-frequency returns, new insights into the dynamic links between the oil sector and broader market are revealed. The network framework of Diebold and Yilmaz (2014) is used here to estimate directional spillovers which are asymmetric and directional (in contrast to correlation), revealing the strength of the spillovers moving in both directions between the equity and oil markets. Return and volatility spillovers from the broader market to the oil sector increase when equity returns are lower or volatility is higher. The impact of oil market activity on equities is less pronounced. A new result revealed here, is that the oil sector becomes insulated from shocks from the broader equity market as the rate of information flow about crude oil rises. This result implies that the oil market is driven more by oil specific shocks and less by general financial shocks. Greater information flow about oil also magnifies the spillovers from the oil sector to equities. Such patterns are not observed when simply examining correlation, a directionless measure of association. These results deepen our understanding of the impacts of news attention on the directional linkages between markets relative to those of Drake et al. (2017). While Drake et al. (2017) showed that contemporaneous movements in investor attention influences contemporaneous movements in returns, these novel results show that news attention asymmetrically influences directional spillovers between the oil and equity markets. It is shown that the effect of investor attention on directional spillovers is concentrated in the time outside of the unique period of the Global Financial Crisis (GFC) and possible oil price bubble of 2008.

The paper proceeds as follows. Section 2 outlines the data used, along with the volatility and correlation measures employed, and the two sources of information flow. Section 3 presents the methodology employed in terms of volatility and correlation regressions, and methodology relating to the directional spillovers. Section 4 presents the empirical results. Section 5 provides a summary of the results and suggests potential new directions for future research.

2. Data

The sample period considered here spans 3 January 2007 to 31 December 2016 containing 2507 daily observations. Intraday 5-minute returns on the United States Oil (USO) exchange-traded fund and the S&P 500 index were collected from Thomson Reuters Tick History. The USO ETF was chosen as it trades over the same time period as S&P500 index each day, which is important when aligning simultaneous trading across the two markets. Alternatives such as WTI futures were not used as they trade close to 24-hours a day, and the quality of the high-frequency prices was poorer in the early part of the sample where many missing observations were observed. Intraday 5-minute prices (9:30am to 4pm NY time) were collected and used to construct daily estimates of realized volatility (RV) for each market along with realized correlation (RC). Daily RV estimates for USO are shown in the top panel of Figure 1. Volatility increased markedly during the 2008-2009 GFC period, and rose again (but to lower levels) during the falls in oil prices during 2014-2016. Estimates of broad S&P500 RV in the second panel are broadly similar, with RV dominated by the period of the GFC, but did not rise dramatically in the latter part of the sample. Daily estimates of RC are shown in the lower panel and reveal that while there is clear variation in correlation, there is less persistence in RC certainly relative to RV.

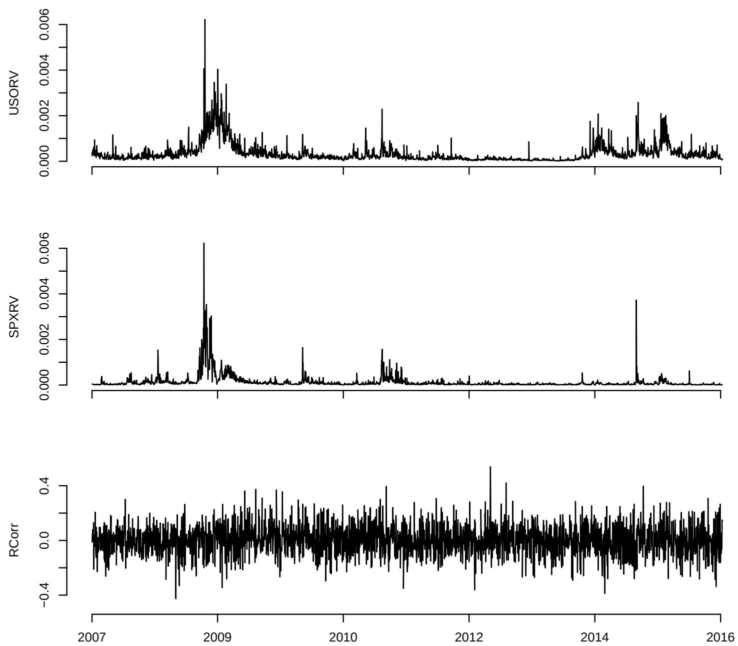

Figure 1: Top panel: Daily realized oil volatility, $USORV_t$. Middle Panel: Daily realized S&P500 volatility, $SPXRV_t$. Lower Panel: Daily realized correlation, RC_t.

Two sources of information flow are used here. Following Campos et al. (2017) GSV related to the term 'oil prices' were downloaded from Google trends to capture the rate of investor attention to the oil sector. The rate of GSV is scaled relative to a maximum value of 100 within each period, irrespective of the length of the period or the frequency of the data requested. Over the full sample period considered here, if only one continuous sample is downloaded, only data at a monthly frequency is available directly from Google trends. If multiple, shorter periods of daily data are spliced together, each period will be scaled relative to its own maximum of 100. However, a longer period of daily data can be obtained by the rescaling method suggested by Johansson (2018). This involves using monthly observations over the full sample, and weekly and daily samples from within shorter periods to rescale a full, long sample of daily GSV data over the full sample period. Therefore, GSV for day t, is used as a measure of the rate at which information about oil markets is sought out by investors and will be denoted by G_t below. The second measure of information flow is an index of media attention on crude oil markets representing the rate at which information is available to investors. This is constructed using the Global Vectors (GloVe) approach of Pennington et al. (2014).

The construction of the index of media attention involves two steps: estimation of word vector representations and computation of word frequencies. In the first step, a natural language processing model, GloVe, is used to compute a numerical representation of words. The numerical representations are trained to capture as much information as possible regarding the pattern of word co-occurrences in the training corpus. The exercise can be understood as an implementation of a dimensionality reduction technique that summarizes relevant information regarding the way in which words are used. In particular, the method has been shown to efficiently summarize semantic information. The relatedness between different words is approximated through the distance between the computed word vector representations. In the second step, a list of words most closely related to 'oil' are identified using cosine similarity as a metric of distance. For any given period, the index of attention is given by the relative frequency of these words. That is, the index is equal to the number of times in which an oil-related word is detected as a fraction of the total number of words in the selected subset of news items. More formally, under the GloVe approach, word vectors are trained to capture information relating to word co-occurrences in the training corpus. The method is global in the sense that all vectors are computed in a single optimization exercise. Defining W as a dictionary and letting X_{ij} denote the number of times word i occurs in the context of word j. Then, word vector representations $\{v_i\}_{i \in W}$ solve:

$$\min_{\{v_i\}_{i \in W}} \sum_i \sum_j f(X_{ij}) \left[v_i \cdot \tilde{v}_j + b_i + \tilde{b}_j - log(X_{ij}) \right]^2$$

where v_i and $\tilde{v}_j$ are word vectors, $f(X_{ij})$ is a weighting function and b_i and $\tilde{b}_j$ are word biases.[1] This is a log-bilinear regression model. The weighting function $f(X_{ij})$ is increasing and concave.[2] The vector representations are trained using stochastic gradient descent (Duchi et al., 2011), with more details available in Pennington et al. (2014). A vector dimensionality of 100, and a window size of 5 are used to compute term co-occurrence, values which are commonly used in the natural language processing literature. The vocabulary used in the implementation is given by words with a frequency of 100 or higher in the training corpus. Robustness analyses indicate that the results are not sensitive to variations in these parameters. Vector representations of words are computed using package text2vec (Selivanov and Wang, 2018) available in R. The same package has been used in other related analysis (e.g. tokenization, term co-occurrence matrix).

In the second step, a subset of relevant words is identified using the trained vector representations and the index is built calculating their frequency. More formally, given the word oil and its respective numerical representation (v_{oil}), the set of S most closely related words is identified computing the cosine similarity: $\frac{v_{oil} \cdot v_j}{||v_{oil}|| ||v_j||}$.[3] Let n_{wt} denote the number of times word w is

[1]The vector representations used in applications are typically given by the sum of the two fitted word vectors: v_i and $\tilde{v}_j$. This practice is followed in the current implementation.

[2]More specifically, following Pennington et al. (2014), the weighting function equals $f(x) = (x/100)^{3/4}$ if $x < 100$, otherwise $f(x) = 1$.

[3]The list of the 50 most closely related words is reported in the Appendix.

observed in period t. Then, the news attention index for period t is given by:

$$N_t = \frac{\sum_{w \in S} n_{wt}}{\sum_{w \in W} n_{wt}}$$

That is, the index is given by the number of occurrences of words in S as a fraction of the total number of occurrences of words in the dictionary W.

The texts used in this exercise are extracted from a publicly available subset of content published in the Wall Street Journal (WSJ). The data can be found at `http://pqasb.pqarchiver.com/djreprints/`. For each article published in the newspaper, this website provides access to the headline, the lead and a fraction of the body. Two collections of texts are used in this exercise. The training corpus is given by content published between 1970 and 2006 upon which the 50 words in S are chosen.[4] The news attention index, N_t is then computed for each day using a second corpus of material published during the sample period.

Figure 2 plots both measures of information flow. The news attention index, N_t is shown in the top panel of Figure 2. A surge in N_t is evident around the peak and start of the fall in prices and onset of higher volatility in 2008, appearing to slowly subside as prices continue to fall. Periods of greater attention are also evident around the periods of higher volatility in 2014-2016 associated with large price falls. The bottom panel of Figure 2 plots the GSV, where G_t is scaled down to have a similar level as N_t. Broadly speaking, the patterns observed in G_t are very similar to those in N_t. G_t reaches its peak during 2008, and persists at higher levels for somewhat longer than N_t and rises again quite significantly during the latter part of the sample.

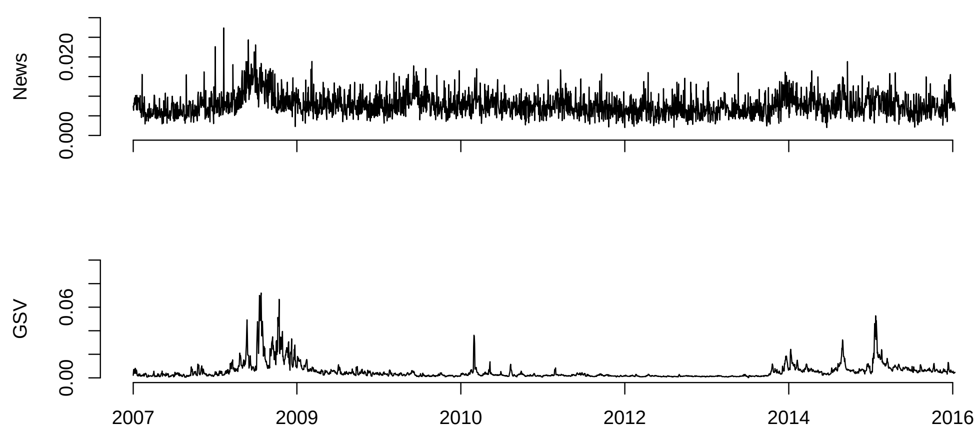

Figure 2: Top panel: Index of media attention N_t. Bottom panel: GSV relating to 'oil prices' G_t.

The two sources of information used here are very different, GSV is a result of individuals

[4]As a robustness check, the subsequent analysis has been conducted on different indices of attention based on different assumptions for S and the dimension for the word vector representations. The results are qualitatively the same leading to the same conclusions drawn here.

consciously searching and can be viewed as a measure of direct attention, and news or media attention is more passive from the point of view that individuals are not actively searching for information. GSV has been used as a measure of investor attention by a wide range of studies across different asset classes and countries. Amongst many other studies, Da et al. (2011) consider U.S. equities, Aouadi et al. (2013) French equities, and as mentioned earlier, Campos et al. (2017) the oil market. While Da et al. (2011) points out that GSV likely reflects the attention of retail investors, it has been found that GSV is related to future asset returns and volatility, behaviour around IPOs and future option implied volatilities. While GSV may not be a complete picture of investor (certainly all types of) attention, it is certainly been found to be important in a range of different contexts and hence worthy of consideration in this context. The index of media attention used, is clearly only based one publication. This choice however, is motivated by the fact that all the WSJ articles are freely, and publicly available. Such a rich data source with the associated text of each article is not freely available from any other news source. While in this case, it is more difficult to link one group of investors to this news source, it is clearly a publication followed by a broad spectrum of participants in the financial sector. That said, it is clear again in this case, that index of media attention from the WSJ is not a complete picture of news flow. While there are clear shortcomings associated with both measures, they are both available to a broad audience, and both lead to nearly identical empirical results. This indicates that either index plays an important role in explaining the links between oil and equity markets and that they both reflect broadly similar underlying information.

3. Methodology

3.1. Impact of news attention on volatility and correlation

The first issue considered is how both measures of information flow are related to the level of volatility in both markets along with the correlation between the markets. To achieve this, the role of N_t and G_t will be examined within the context of the Heterogeneous Auto-Regressive (HAR) framework of Corsi (2009). HAR style regressions are a very simple tool to capture much of the long-term persistence in RV (and related measures) and have become somewhat of a benchmark in the financial econometrics literature.

To consider how news attention is related to both oil sector and market level volatility, a range of HAR regressions that include the lags of news attention are estimated:

$$\begin{aligned} ln(RV_{t+1\to t+k}) &= \beta_0 + \beta_1 ln(RV_{1,t}) + \beta_2 ln(RV_{5,t}) + \beta_3 ln(RV_{22,t}) + \varepsilon_t \\ ln(RV_{t+1\to t+k}) &= \beta_0 + \beta_1 ln(RV_{1,t}) + \beta_2 ln(RV_{5,t}) + \beta_3 ln(RV_{22,t}) + \beta_4 ln(NA_{1,t}) + \varepsilon_t \\ ln(RV_{t+1\to t+k}) &= \beta_0 + \beta_1 ln(RV_{1,t}) + \beta_2 ln(RV_{5,t}) + \beta_3 ln(RV_{22,t}) + \beta_5 ln(NA_{22,t}) + \varepsilon_t \quad (1) \end{aligned}$$

where $RV_{t+1\to t+k}$ is the average realized volatility over the k-day horizon based on either $USORV_t$ or either $SPXRV_t$ and where $RV_{1,t}$, $RV_{5,t}$ and $RV_{22,t}$ are lagged 1, 5 and 22 day moving averages of the respective RV series (USO or SP). $NA_{1,t}$ and $NA_{22,t}$ are used to denote 1 and 22 day lagged moving averages in both measures of news attention. Therefore in all of the subsequent analysis, $NA_{1,t} = N_{1,t}$ or $G_{1,t}$ and $NA_{22,t} = N_{22,t}$ or $G_{22,t}$. Results below are reported for β_4 (for both $N_{1,t}$ and $G_{1,t}$) and β_5 (for both $N_{22,t}$ and $G_{22,t}$). Here the logarithm of volatility is used given the highly skewed nature of RV with $\ln(RV)$ being close to normally distributed. All subsequent results are based on HAC standard errors.

Next, the focus moves to whether the rate of news attention regarding oil markets influences the degree of association between the oil sector and broader market by employing the estimated realized correlation, RC_t. Again, a similar HAR structure is employed:

$$\begin{aligned}
RC_{t+1\to t+k} &= \beta_0 + \beta_1 RC_{1,t} + \beta_2 RC_{5,t} + \beta_3 RC_{22,t} + \varepsilon_t \\
RC_{t+1\to t+k} &= \beta_0 + \beta_1 RC_{1,t} + \beta_2 RC_{5,t} + \beta_3 RC_{22,t} + \beta_4 NA_{1,t} + \varepsilon_t \\
RC_{t+1\to t+k} &= \beta_0 + \beta_1 RC_{1,t} + \beta_2 RC_{5,t} + \beta_3 RC_{22,t} + \beta_6 NA_{22,t} + \varepsilon_t \qquad (2)
\end{aligned}$$

where $RC_{t+1\to t+k}$ is the average realized correlation over the k-day horizon and $RC_{1,t}$, $RC_{5,t}$ and $RC_{22,t}$ are lagged 1,5 and 22 day moving averages of the RC_t in this instance. $NA_{1,t}$ and $NA_{22,t}$ are defined in the same way again. RC_t is not transformed given that it is symmetric and close to normally distributed in the first place. Again, all subsequent results for these correlation regressions are based on HAC standard errors.

3.2. Impact of news attention on directional spillovers

To provide a deeper examination of the spillovers between the oil sector and the broader market, the network framework of Diebold and Yilmaz (2014) is used here to provide measures of directional spillovers. Diebold and Yilmaz (2014) show how the traditional vector autoregressive (VAR) model and associated generalized variance decompositions provide a natural and insightful framework to measure network connectedness of a panel of financial time series. In contrast to correlation, these spillovers are asymmetric and directional and reveal the strength of the spillovers moving in both directions.

This modeling framework allows estimates of connectedness between either returns or volatilities in USO or S&P500 to be generated by assessing the shares of forecast error variation due to shocks arising from each other. This is related to the familiar econometric notion of variance decomposition in which the forecast error variance of variable i is decomposed into parts attributable to other variables in the system. Denoting the $ijth$ H-step variance decomposition by d_{ij}^H that measures the fraction of variable $i's$ H-step forecast error variance due to shocks in variable j, d_{ij}^H takes the form:

$$d_{ij}^H = \frac{\sigma_{jj}^{-1}\sum_{h=0}^{H-1}(e_{i,t}' A_h \Sigma e_{j,t})^2}{\sum_{h=0}^{H-1}(e_{i,t}' A_h \Sigma A_h' e_{i,t})}, \qquad (3)$$

where $e_{j,t}$ is a selection vector with $j-th$ element unity and zeros elsewhere at time t, A_h is the coefficient matrix of the h-lagged shock vector in the infinite moving-average representation of the VAR model, Σ is the covariance matrix of the shock vector in the VAR, and σ_{jj} is the $jj-th$ diagonal element of Σ.

As shocks are correlated here, sums of forecast error variance contributions are not necessarily unity. Therefore, d_{ij}^H is normalized to $\tilde{d_{ij}^H}$ by:

$$\tilde{d_{ij}^H} = \frac{d_{ij}^H}{\sum_{j=1}^{N} d_{ij}^H}. \tag{4}$$

The structure in the network can be summarised in a number of connectedness measures which can be constructed from $\tilde{d_{ij}^H}$. Here, the oil sector (USO) will be defined as market 1 and the broad market (S&P500) defined as 2. Thus two directional spillover measures are constructed, $\tilde{d}_{USO \leftarrow SP}$ ($\tilde{d}_{12}$) and $\tilde{d}_{SP \leftarrow USO}$ ($\tilde{d}_{21}$), dropping the H forecast horizon for ease of notation in the following discussion. There is no accepted method for testing the significance of the spillovers obtained from this method. However, this is a question that has just started to attract research attention. While there are standard tests of significance available for spillovers in variance, see for instance Comte and Lieberman (2000) and Hafner and Herwartz (2006), these are based on the Mutlivariate GARCH framework and hence not relevant to RV, nor are they suited to the variance decomposition framework of Diebold and Yilmaz (2014).

To identify how the directional spillovers change through time and respond to the rate of news attention, the directional spillover measures will be estimated from short rolling windows of high-frequency intraday returns. Rolling windows of 1 week (390 5 minute observations) and 2 weeks (780 5 minute observations) are used to estimate the VAR and construct $\tilde{d}_{t,USO \leftarrow SP}$ and $\tilde{d}_{t,SP \leftarrow USO}$. Spillovers in returns are based on 5 minute returns from within each rolling window, and spillovers in volatility are based on squared 5 minute returns. The diurnal pattern in volatility is removed prior to estimating the connectedness measures. Here t is used to denote each rolling window.

Here, a large number of bivariate VARs (between the USO and SP returns or volatilities) need to estimated, 503 1-week and 251 2-week rolling windows. Given the large number of VARs needing to be estimated, a pragmatic view to model selection is taken. Autocorrelations in a number of rolling windows were examined. The 5 minute returns exhibited very little significant autocorrelation. For 5 minute volatilities, after controlling for the diurnal pattern in the volatility in each market (which are of course very similar) a small amount of autocorrelation was evident, out to 2 to 5 lags were observed depending on the window. Therefore given the large number of rolling windows, set lag length of 5 periods was chosen.

To examine the impact of news flow on the strength of the directional spillovers, the following set of return or volatility regressions are estimated:

$$
\begin{aligned}
&\text{Return} \\
\ln(\tilde{d}_{t,USO\leftarrow SP}) &= \beta_0 + \beta_1 \ln(NA_t) + \varepsilon_t \\
\ln(\tilde{d}_{t,SP\leftarrow USO}) &= \beta_0 + \beta_1 \ln(NA_t) + \varepsilon_t \\
&\text{Volatility} \\
\ln(\tilde{d}_{t,USO\leftarrow SP}) &= \beta_0 + \beta_1 \ln(NA_t) + \varepsilon_t \\
\ln(\tilde{d}_{t,SP\leftarrow USO}) &= \beta_0 + \beta_1 \ln(NA_t) + \varepsilon_t \qquad (5)
\end{aligned}
$$

for each combination of returns or volatility, and 1- or 2-week rolling window. Here NA_t denotes the average news attention (N_t) or GSV (G_t) within period t. The results presented below are also robust to including lagged spillovers.

4. Results

This section presents the empirical results, first relating to the links between news attention and volatility and correlation, and then news attention and directional spillovers.

4.1. Impact of news attention on volatility and correlation

To begin, Table 1 reports the estimation results for equation 1 based on $USORV_t$ at an horizon of $k = 22$. The coefficients on lagged RV, β_1, β_2 and β_3 are all highly significant, a standard result in HAR models. The coefficients on lagged N_t, β_4 and β_5 are significant (β_5 only at 10%) indicating the rate of media attention to crude oil contains relevant information for the level of volatility of oil sector returns. While the coefficients on news may be significant, there is little change in explanatory power relative to the base HAR model. In the case of GSV, both β_4 and β_5 are significant at 1%. In contrast to N_t, G_t appears to help account for a degree of the persistence in volatility as the estimates of β_2 and β_3 fall significantly after GSV is included, and explanatory power increases by up 3%.

Table 2 reports the estimation results for equation 1 based on $SPXRV_t$ at a horizon of $k = 22$. While not of central interest here, again the coefficients on lagged volatility are significant. The interesting result here, is that the coefficients β_4 and β_5 on lagged N_t are significant indicating that the rate of news attention is also relevant to the level of market wide S&P500 volatility. In this case of lagged G_t, only the short 1-day lag is significantly related to broader market volatility. These results together may imply that the rate of media based news attention may reflect broader information about the condition of the economy that may also be reflected in the equity market.

Table 3 reports estimation results for the RC HAR regression in equation 2 based on RC_t at a horizon of $k = 22$. In contrast to RV, there is very little persistence in RC. While the

	Dependent variable: $ln(USORV_{t\rightarrow t+22})$				
β_1	0.1033***	0.1018***	0.0998***	0.0441***	0.0903***
	(0.0143)	(0.0144)	(0.0148)	(0.0139)	(0.0137)
β_2	0.3368***	0.3280***	0.3191***	0.2354***	0.2540***
	(0.0609)	(0.0862)	(0.0916)	(0.0749)	(0.0859)
β_3	0.4617***	0.4615***	0.4333***	0.4338***	0.3353***
	(0.0716)	(0.0928)	(0.1045)	(0.0919)	(0.1206)
$\beta_4(N_{1,t})$		0.1036***			
		(0.0327)			
$\beta_5(N_{22,t})$			0.4541*		
			(0.2605)		
$\beta_4(G_{1,t})$				0.2513***	
				(0.0453)	
$\beta_5(G_{22,t})$					0.2771**
					(0.1379)
Adj R^2	0.8283	0.8301	0.8356	0.8597	0.8499

Table 1: Regression results for equation 1 based on $USORV_t$ at a horizon of $k = 22$. HAC standard errors are reported in parentheses. *p<0.1; **p<0.05; ***p<0.01

	Dependent variable: $ln(SPXRV_{t\rightarrow t+22})$				
β_1	0.1683***	0.1654***	0.1588***	0.1504***	0.1646***
	(0.0198)	(0.0188)	(0.0188)	(0.0199)	(0.0193)
β_2	0.2532***	0.2497***	0.2400***	0.2410***	0.2424***
	(0.0568)	(0.0558)	(0.0509)	(0.0532)	(0.0526)
β_3	0.3630***	0.3564***	0.3183***	0.3501***	0.3284***
	(0.0615)	(0.0612)	(0.0691)	(0.0621)	(0.0708)
$\beta_4(N_{1,t})$		0.1860***			
		(0.0633)			
$\beta_5(N_{22,t})$			0.8870		
			(0.2259)***		
$\beta_4(G_{1,t})$				0.1268*	
				(0.0661)	
$\beta_5(G_{22,t})$					0.1314
					(0.0867)
Adj R^2	0.6421	0.6469	0.6670	0.6539	0.6522

Table 2: Regression results for equation 1 based on $SPXRV_t$ at a horizon of $k = 22$. HAC standard errors are reported in parentheses. *p<0.1; **p<0.05; ***p<0.01

strength of the coefficients on lagged RC increase out to β_3, they are still not significant. The rate of news attention appears to play relatively little role in relation to RC, with only the β_4 coefficient on $N_{1,t}$ significant at 5%. This result contrasts those revealed by examining the behaviour of RV above in that news flow was related to the level of volatility in both markets. However, correlation is a directionless measure of association and a deeper examination of the links between news flow and directional spillovers between the oil sector and the broader market may reveal further insights in to the role played by the rate of news flow. This analysis is undertaken in the following section.

	Dependent variable: $RC_{t\to t+22}$				
β_1	-0.0012	-0.0012	-0.0013	-0.0012	-0.0012
	(0.0016)	(0.0017)	(0.0016)	(0.0016)	(0.0016)
β_2	0.0187	0.0190	0.0169	0.0187	0.0187
	(0.0192)	(0.0172)	(0.0178)	(0.0173)	(0.0173)
β_3	0.1074*	0.1075*	0.1069*	0.1074*	0.1075*
	(0.0635)	(0.0565)	(0.0548)	(0.0582)	(0.0579)
$\beta_4(N_{1,t})$		0.0048**			
		(0.0028)			
$\beta_5(N_{22,t})$			0.0109		
			(0.0113)		
$\beta_4(G_{1,t})$				-0.00004	
				(0.0019)	
$\beta_5(G_{22,t})$					0.0002
					(0.0022)
Adj R^2	0.0153	0.0203	0.0220	0.0172	0.0189

Table 3: Regression results for equation 2 based on RC_t at a horizon of $k = 22$. HAC standard errors are reported in parentheses. *p<0.1; **p<0.05; ***p<0.01

4.2. Impact of news attention on directional spillovers

Figure 3 shows the spillovers in both returns (top 2 panels) and volatilities (lower 2 panels) in the 1-week rolling windows based on the network methodology of Diebold and Yilmaz (2014) described in Section 3.2. In terms of the return spillovers, on the whole, $\tilde{d}_{t,SP\leftarrow USO}$ is stronger than $\tilde{d}_{USO\leftarrow SP}$. While there is less variation in $\tilde{d}_{USO\leftarrow SP}$, it rises during the middle of the sample when spillovers in the opposite direction are at their lowest. $\tilde{d}_{t,SP\leftarrow USO}$ clearly dominates increasing noticeably during the latter part of the sample. Volatility spillovers on the whole behave quite differently, but do share common features with the return spillovers. The volatility spillovers are more variable (and more skewed) than the return spillovers. Again, $\tilde{d}_{t,SP\leftarrow USO}$ is stronger than $\tilde{d}_{USO\leftarrow SP}$ though the difference is not as great as between the return spillovers. Again, $\tilde{d}_{USO\leftarrow SP}$ reaches its peaks during the middle of the sample, while $\tilde{d}_{t,SP\leftarrow USO}$ is again higher during both the earlier and latter parts of the sample. Overall, these results share common patterns with those of Maghyereh et al. (2016) in that the there are bi-directional spillovers between the oil sector and the broader market, and that the strength of the spillover from oil to equities is stronger than in the reverse direction.

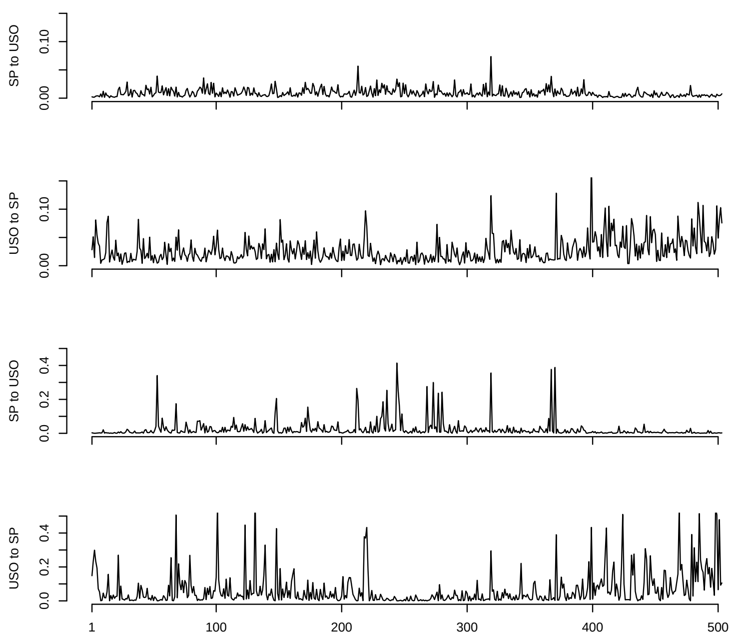

Figure 3: Top 2 panels: spillovers in returns. Bottom 2 panels: spillovers in volatilities. Spillover measures are based on a 1-week rolling window of 390 5 minute returns.

Figure 4 reports the spillovers based on the 2-week rolling window. These spillovers exhibit the same temporal patterns as the 1-weeks spillovers shown in reported in Figure 3. Again, in terms of return spillovers, $\tilde{d}_{t,SP\leftarrow USO}$ is stronger than $\tilde{d}_{USO\leftarrow SP}$ on the whole. $\tilde{d}_{USO\leftarrow SP}$ rises during the middle of the sample when spillovers in the opposite direction are at their lowest. Again, volatility spillovers are more variable than the return spillovers. Again, $\tilde{d}_{t,SP\leftarrow USO}$ is stronger than $\tilde{d}_{USO\leftarrow SP}$ though the difference is not as great as between the return spillovers. As with the 1-week spillovers, $\tilde{d}_{USO\leftarrow SP}$ reaches its peaks during the middle of the sample, while $\tilde{d}_{t,SP\leftarrow USO}$ is again higher during both the earlier and latter parts of the sample.

Table 4 reports the estimation results for the regressions in equation 5 based on both return and volatility spillovers, and a 1-week window (top panel) and 2-week window (lower panel). The discussion begins with the spillovers in the 1-week windows. Increases in the rate of information flow relating to oil markets in terms of G_t reduce the $\tilde{d}_{USO\leftarrow SP}$ spillover. Hence as the rate of information flow regarding crude oil increases, the broader equity market has less of an impact

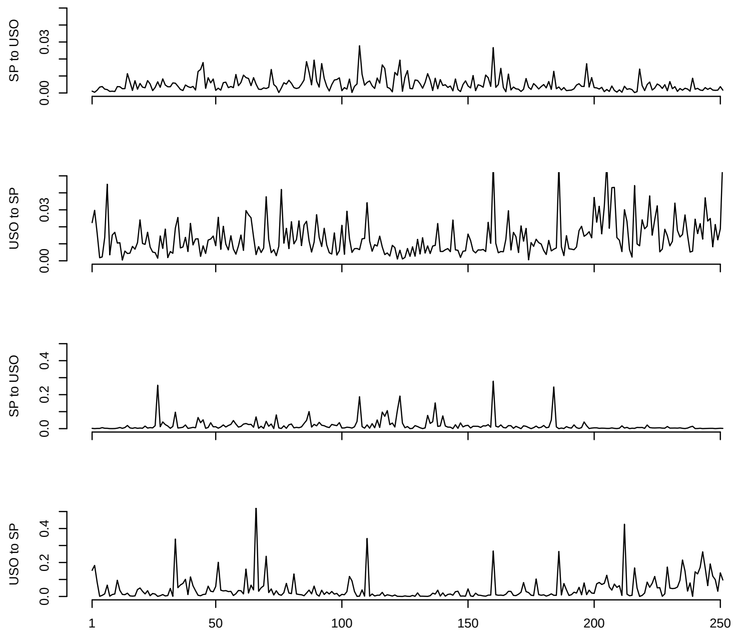

Figure 4: Top 2 panels: spillovers in returns. Bottom 2 panels: spillovers in volatilities. Spillover measures are based on a 1-week rolling window of 390 5 minute returns.

on the oil sector. This implies the oil sector behaves less like a general equity asset and will be left to be more heavily influenced by oil market specific information flow. This result is not evident when information flow is captured by N_t. In the context of the spillovers in the other direction, $\tilde{d}_{SP \leftarrow USO}$, increased information flow in terms of either N_t or G_t is associated with stronger links, meaning that the oil market has a greater influence on the broader equity market. Results based on the 2-week windows reveal broadly similar results. The effect of G_t remains the same, though the negative effect on $\tilde{d}_{USO \leftarrow SP}$ in the case of returns remains, it is not significant. The role of N_t is less pronounced in the 2 week windows. Overall, it seems the link between news and investor attention is more pronounced at the shorter 1-week horizon.

4.3. Robustness check: Market conditions and the role of news

This section considers how the impact of news attention on directional spillovers is influenced by prevailing market conditions. First, the regressions in equation 5 are extended to control for the conditions prevailing in the market from where the spillover originates. To examine the impact of news flow on the strength of the directional spillovers, this new set of return or

		$\ln(N_t)$	$\ln(G_t)$
1-week window			
Returns	$\ln(\tilde{d}_{USO \leftarrow SP})$	0.1052 (0.1629)	
	$\ln(\tilde{d}_{SP \leftarrow USO})$	0.3037** (0.1620)	
Volatility	$\ln(\tilde{d}_{USO \leftarrow SP})$	0.0442 (0.2501)	
	$\ln(\tilde{d}_{SP \leftarrow USO})$	0.3889** (0.2241)	
Returns	$\ln(\tilde{d}_{USO \leftarrow SP})$		−0.0933*** (0.0414)
	$\ln(\tilde{d}_{SP \leftarrow USO})$		0.2187*** (0.0403)
Volatility	$\ln(\tilde{d}_{USO \leftarrow SP})$		−0.1990*** (0.0632)
	$\ln(\tilde{d}_{SP \leftarrow USO})$		0.2671*** (0.0561)
2-week window			
Returns	$\ln(\tilde{d}_{USO \leftarrow SP})$	0.3347 (0.2712)	
	$\ln(\tilde{d}_{SP \leftarrow USO})$	0.5671*** (0.2606)	
Volatility	$\ln(\tilde{d}_{USO \leftarrow SP})$	0.3704 (0.4106)	
	$\ln(\tilde{d}_{SP \leftarrow USO})$	0.4100 (0.3266)	
Returns	$\ln(\tilde{d}_{USO \leftarrow SP})$		−0.0702 (0.0622)
	$\ln(\tilde{d}_{SP \leftarrow USO})$		0.2288*** (0.0586)
Volatility	$\ln(\tilde{d}_{USO \leftarrow SP})$		−0.1779*** (0.0936)
	$\ln(\tilde{d}_{SP \leftarrow USO})$		0.2382** (0.0736)

Table 4: Results for return and volatility spillover regressions in equation 5. *p<0.1; **p<0.05; ***p<0.01

volatility regressions are estimated,

$$
\begin{aligned}
&\text{Return} && \\
\ln(\tilde{d}_{t,USO\leftarrow SP}) &= \beta_0 + \beta_1 SP_{r_t} + \beta_2 \ln(NA_t) + \varepsilon_t \\
\ln(\tilde{d}_{t,SP\leftarrow USO}) &= \beta_0 + \beta_1 USO_{r_t} + \beta_2 \ln(NA_t) + \varepsilon_t \\
&\text{Volatility} && \\
\ln(\tilde{d}_{t,USO\leftarrow SP}) &= \beta_0 + \beta_1 \ln(SPRV_t) + \beta_2 \ln(NA_t) + \varepsilon_t \\
\ln(\tilde{d}_{t,SP\leftarrow USO}) &= \beta_0 + \beta_1 \ln(USORV_t) + \beta_2 \ln(NA_t) + \varepsilon_t \qquad (6)
\end{aligned}
$$

again for each combination of returns or volatility, and 1 or 2 week rolling window. Again, NA_t denotes the average news attention (N_t) or GSV (G_t) within period t, and SP_{r_t} and USO_{r_t} are the equity and oil market returns within each window. The level of return or volatility in the market from where the spillover originates is included to identify whether the rate of information flow has an influence on the directional spillovers beyond that simply due to the prevailing market conditions. Returns or volatilities are included as opposed to correlation, as correlation is not directional, and here it is necessary to control for whether shocks originating in one market influence the strength on the directional spillovers from that market to other market.

Table 5 reports the estimation results for the regressions in equation 6 based on both return and volatility spillovers, and a 1-week window (top panel) and 2-week window (lower panel). The discussion begins with the spillovers in the 1-week windows. In both the return and volatility cases, lower equity market returns or higher volatility increase the $\tilde{d}_{USO\leftarrow SP}$ spillover meaning that changes the equity market conditions influence its impact on the oil sector. There is much less evidence of a link between oil market conditions and spillovers from oil to broader equities. In addition to market conditions, consistent with the earlier results in Table 4, information flows continue to have an influence on the directional spillovers.

A very interesting result is that increases in the rate of information flow relating to oil markets (either N_t or G_t) reduce the $\tilde{d}_{USO\leftarrow SP}$ return spillover even after controlling for equity returns. In terms of the spillovers in the other direction, the rate of N_t does not have any significant effect on $\tilde{d}_{SP\leftarrow USO}$, however, increases in G_t lead to significantly stronger spillovers meaning that the oil market has a greater influence on the broader equity market controlling for USO returns. Volatility spillovers at the 1-week horizon exhibit broadly similar patterns with the role of news attention robust to the inclusion of oil or equity volatility. Increases in SPRV increase the strength of the $\tilde{d}_{USO\leftarrow SP}$ spillover revealing that again, activity in the equity market influences the spillover to the oil sector. Similar to the return case, increases in N_t or G_t reduce the $\tilde{d}_{USO\leftarrow SP}$ spillover to the oil sector, with G_t again significantly increasing the spillover from oil to equities. Results based on the 2-week windows reveal broadly similar results. Equity market conditions influence the oil to equity spillovers in most cases. The effect of N_t and G_t in the 2-week windows are a little less pronounced. N_t only has a role to play in terms of reducing the oil to equity volatility spillover. GSV continues to play more of an important role in the 2-week windows relative to N_t. Increases in G_t decrease (increase) the $\tilde{d}_{USO\leftarrow SP}$ ($\tilde{d}_{SP\leftarrow USO}$) volatility (return) spillover. The effect of G_t on the final two spillovers, $\tilde{d}_{USO\leftarrow SP}$ for returns and $\tilde{d}_{SP\leftarrow USO}$ for volatility still exhibit the same sign as the 1-week case but the effect is not significant. Overall, it seems the link between news and investor attention is more pronounced at the shorter 1-week horizon.

		$\ln(SPRV_t)/SP_{r_t}$	$\ln(USORV_t)/USO_{r_t}$	$\ln(N_t)$	$\ln(G_t)$
1-week window					
Returns	$\ln(\tilde{d}_{USO\leftarrow SP})$	-5.6333^{***} (1.4726)		-0.1790^{**} (0.1439)	
	$\ln(\tilde{d}_{SP\leftarrow USO})$		0.0459^{***} (0.0106)	-0.0306 (0.0431)	
Volatility	$\ln(\tilde{d}_{USO\leftarrow SP})$	0.7073^{***} (0.0563)		-1.1878^{***} (0.2659)	
	$\ln(\tilde{d}_{SP\leftarrow USO})$		-0.1175^{***} (0.0379)	-0.1239 (0.1531)	
Returns	$\ln(\tilde{d}_{USO\leftarrow SP})$	-5.3599^{***} (1.6658)			-0.1149^{***} (0.0416)
	$\ln(\tilde{d}_{SP\leftarrow USO})$		-0.2684 (0.8611)		0.2168^{***} (0.0408)
Volatility	$\ln(\tilde{d}_{USO\leftarrow SP})$	0.9099^{***} (0.0502)			-1.1472^{***} (0.0806)
	$\ln(\tilde{d}_{SP\leftarrow USO})$		0.1583^{*} (0.0824)		0.1440^{**} (0.0851)
2-week window					
		$\ln(SPRV_t)/SP_{r_t}$	$\ln(USORV_t)/USO_{r_t}$	$\ln(N_t)$	$\ln(G_t)$
Returns	$\ln(\tilde{d}_{USO\leftarrow SP})$	-4.8583^{***} (1.4795)		-0.2144 (0.2119)	
	$\ln(\tilde{d}_{SP\leftarrow USO})$		0.1974 (0.2023)	0.0478 (0.0621)	
Volatility	$\ln(\tilde{d}_{USO\leftarrow SP})$	0.6849^{***} (0.0845)		-1.1501^{***} (0.4289)	
	$\ln(\tilde{d}_{SP\leftarrow USO})$		0.0092 (0.0536)	-0.1627 (0.2378)	
Returns	$\ln(\tilde{d}_{USO\leftarrow SP})$	-2.5831 (1.9387)			-0.0887 (0.0637)
	$\ln(\tilde{d}_{SP\leftarrow USO})$		0.9006 (0.8464)		0.2403^{***} (0.0595)
Volatility	$\ln(\tilde{d}_{USO\leftarrow SP})$	0.7647^{***} (0.0772)			-0.5941^{***} (0.0898)
	$\ln(\tilde{d}_{SP\leftarrow USO})$		0.1878^{*} (0.1127)		0.0916 (0.1146)

Table 5: Results for return and volatility spillover regressions in equation 6. *p<0.1; **p<0.05; ***p<0.01

The results in Table 5 show that the impact of news attention on spillovers is generally robust to the prevailing market conditions. An alternative way to examine how the impact of news attention might vary with market conditions is to examine if the results of the regressions in equation 5 change across different sub-samples of data. Here, the regressions in equation 5 are estimated across two subsamples of 1-week windows. The subsamples cover the first and second half of the 1-week windows. The two halves of the full sample period are very different which is evident in the plots of the RV for both markets shown in Figure 1. The first half of the sample contains quite a unique set of market conditions. Historically high levels of volatility were experienced in S&P500 RV which was associated with the GFC. As evidenced in the USO RV plot in Figure 1, volatility in the first half of the sample was also at historical highs, in some part due to the GFC, but also heavily influenced by the possible bubble in oil prices when they rose to a record high of $147 a barrel on July 11 2008, before collapsing to less than $40 a barrel by the end of the year. The second half of the full sample period was very different. The S&P 500 volatility was relatively stable during this period as market steadily recovered post GFC. The oil market behaved very differently with USO RV rising again later in the sample associated with large price falls in 2014-2016. Given the contrasting market conditions across these periods, splitting the full sample period into two appears a logical choice to examine the role of varying market conditions on the role of news attention.

Table 6 reports the regression results for equation 5 estimated within the first (top panel) and second (lower panel) halves of the 1-week windows. It is immediately apparent that during the first half of the sample, during the GFC and oil price bubble, neither measure of news attention is related to the return or volatility spillovers. In contrast, during the second half of the sample, there are very strong and consistent links from both news attention measures to both return and volatility spillovers. Increases in N_t or G_t decrease (increase) the $\tilde{d}_{USO \leftarrow SP}$ ($\tilde{d}_{SP \leftarrow USO}$) spillovers. These effects are more significant and consistent than the full sample results reported in Table 4. Moving beyond the unique set of circumstances associated with the GFC, and the oil price bubble, measures of news attention clearly have an influence on the interactions between the oil market and the broader equity market.

5. Conclusion

There has been a long history of research linking information flows and asset return volatility, mostly in a univariate sense, as has been the case in the context of crude oil markets. However, there is little understanding of how the rate of information arrival influences the linkages between assets. This paper has considered how the rate of information flow regarding the crude oil market, in the form of both internet search activity, or media attention influences links between the oil sector and the broader equity market along a number of dimensions. The influence of the rate of information flow relating to oil on the volatility of both the oil sector and broader market was considered, along with its impact on the correlation between the two. Moving beyond the level of volatility, the impact of news flow on the strength of directional measures of spillovers were also considered.

Initial results revealed that past volatility of the oil sector returns were significantly related to

1-week windows: Period 1

		$\ln(N_t)$	$\ln(G_t)$
Returns	$\ln(\tilde{d}_{USO\leftarrow SP})$	0.2273 (0.2063)	
	$\ln(\tilde{d}_{SP\leftarrow USO})$	0.2235 (0.1881)	
Volatility	$\ln(\tilde{d}_{USO\leftarrow SP})$	0.2829 (0.2936)	
	$\ln(\tilde{d}_{SP\leftarrow USO})$	0.3139 (0.2657)	
Returns	$\ln(\tilde{d}_{USO\leftarrow SP})$		0.0254 (0.0602)
	$\ln(\tilde{d}_{SP\leftarrow USO})$		0.1158 (0.0545)
Volatility	$\ln(\tilde{d}_{USO\leftarrow SP})$		0.0559 (0.0856)
	$\ln(\tilde{d}_{SP\leftarrow USO})$		0.0180 (0.0776)

1-week windows: Period 2

		$\ln(N_t)$	$\ln(G_t)$
Returns	$\ln(\tilde{d}_{USO\leftarrow SP})$	-0.5591^{**} (0.2767)	
	$\ln(\tilde{d}_{SP\leftarrow USO})$	0.9244^{***} (0.2966)	
Volatility	$\ln(\tilde{d}_{USO\leftarrow SP})$	-1.2749^{***} (0.4442)	
	$\ln(\tilde{d}_{SP\leftarrow USO})$	1.2377^{***} (0.4015)	
Returns	$\ln(\tilde{d}_{USO\leftarrow SP})$		-0.2567^{***} (0.0549)
	$\ln(\tilde{d}_{SP\leftarrow USO})$		0.3692^{***} (0.0575)
Volatility	$\ln(\tilde{d}_{USO\leftarrow SP})$		-0.5401^{***} (0.0862)
	$\ln(\tilde{d}_{SP\leftarrow USO})$		0.5816^{***} (0.0755)

Table 6: Results for return and volatility spillover regressions in equation 5 based on the first half (top panel) and second half (lower panel) of 1-week windows. *p<0.1; **p<0.05; ***p<0.01

market level volatility, and vice-versa, indicating the presence of spillovers between the two. Importantly, it was also found that the rate of information flow about the oil market was significantly related to the level of both oil sector and broader equity market volatility, even after controlling for past volatility of both markets. However, there was little impact from news flow to correlation, a directionless measure of association. By moving beyond correlation to consider network based measures of directional spillovers, new insights into the dynamic links between the oil sector and broader market were revealed. An important result is that the oil sector becomes insulated from shocks from the broad market as the rate of information flow about crude oil rises. This implies that the oil sector is more heavily influenced by oil specific shocks and less by those relating to broader financial conditions as more information arrives. In addition, the link from the oil sector to equities strengthens with higher rates of information flow. This result is broadly robust to the market conditions prevailing in both the oil and equity markets. Lower equity returns and higher volatility increase the directional link from equity to the oil sector, where activity in the oil market has little consistent effect in the opposite direction. A final robustness check showed that the effect of news attention on directional spillovers is concentrated in the period outside of the GFC and possible oil price bubble of 2008.

These results open up a potentially interesting avenue of research that may harness the changes in spillovers and the role of information flow for the purposes of hedging, or more generally portfolio allocation. Peralta and Zareei (2016) propose a method for using centrality (though based on a different measure than here) to compute optimal portfolio weights. This approach may be adapted to the directional spillovers used here. However, to implement a time-varying network, a time-varying VAR structure such as the Bayesian approach of Geraci and Gnabo (2018) might be used, again adapted to include exogenous news attention measures. This is a potentially valuable avenue for future research that is well beyond the scope of the current paper.

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7. Appendix: words related to oil

50 words selected by proximity of vector representation: alaskan, Alberta, amoco, arabia, ashland, barrel, barrels, calgary, chevron, crude, crude-oil, discovered, discovery, drilling, energy, exploration, exporting, exxon, field, gas, gasoline, glut, gulf, houston, husky, indonesia, leases, marathon, mexico, mobil, natural, naturalgas, offshore, oil, oils, opec, petroleum, pipeline, producing, properties, refineries, refinery, refining, saudi, sea, shell, tankers, texaco, well and wells.

Spillovers between the oil sector and the S&P500: The impact of information flow about crude oil

Highlights

- Spillovers between the oil and equity markets are considered here.
- Information flow about crude oil influences oil and equity volatility.
- Information flow does not influence correlation between the markets.
- Information flows influence directional spillovers.
- Spillovers from equity to oil decrease (oil to equity, increase) with more information flow.

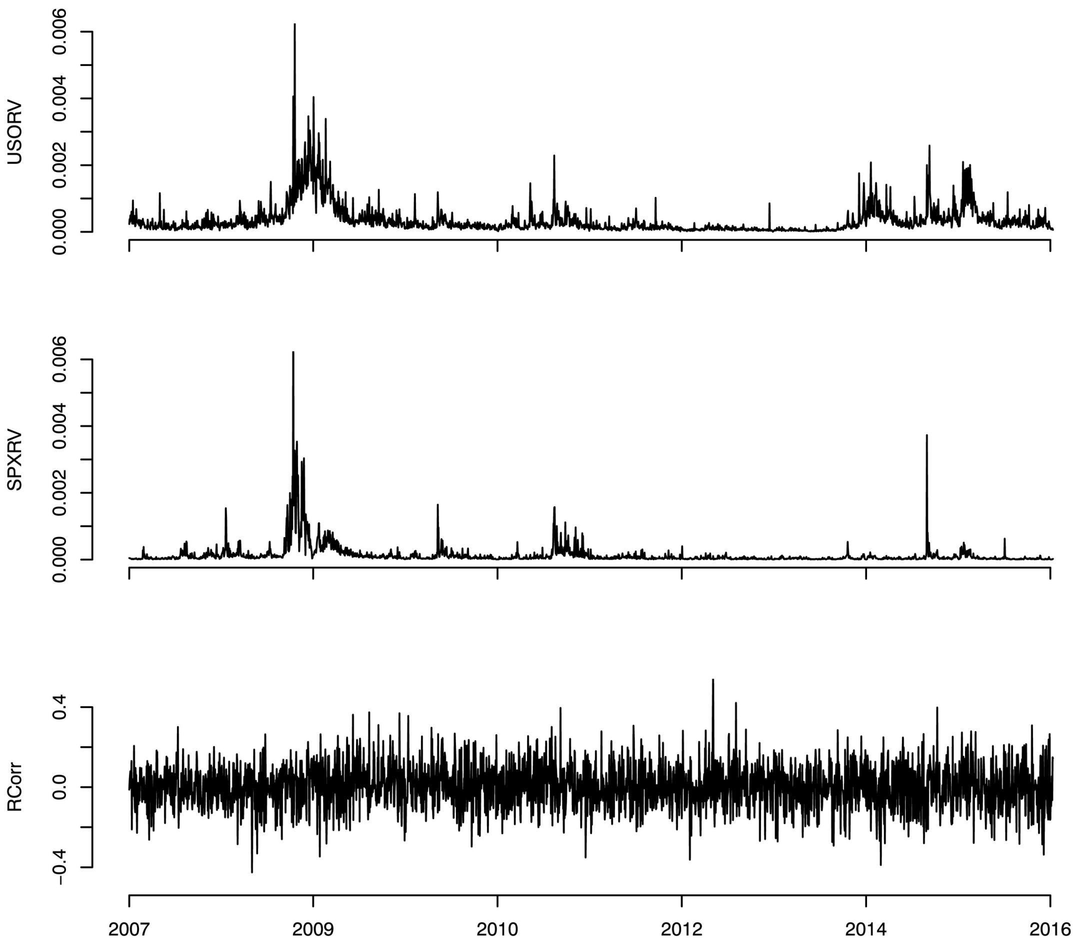

USORV
0.000
0.002
0.004
0.006
SPXRV
0.000
0.002
0.004
0.006
RCorr
−0.4
0.0
0.4
2007
2009
2010
2012
2014
2016

Figure 1

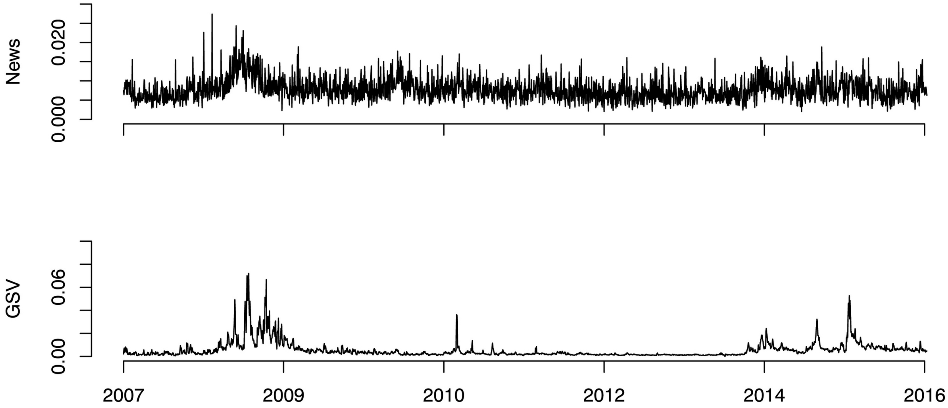


Figure 2

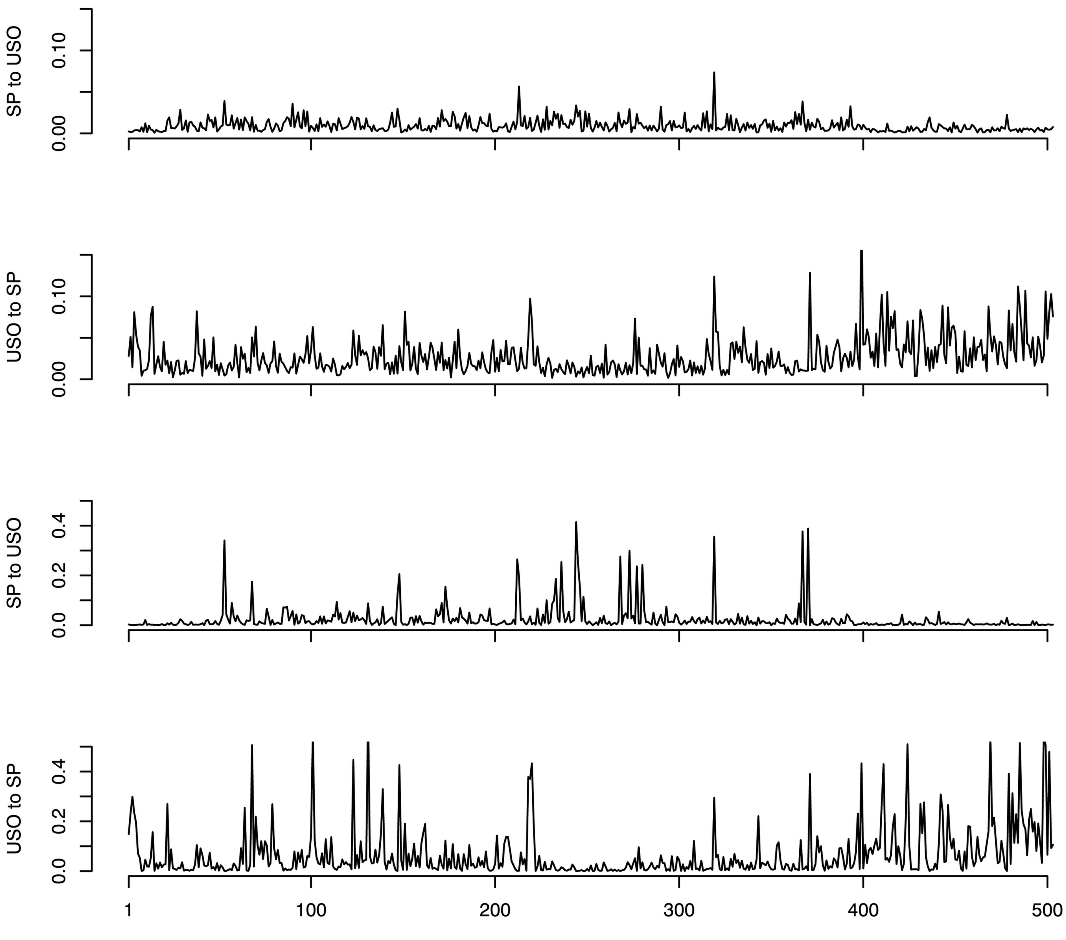
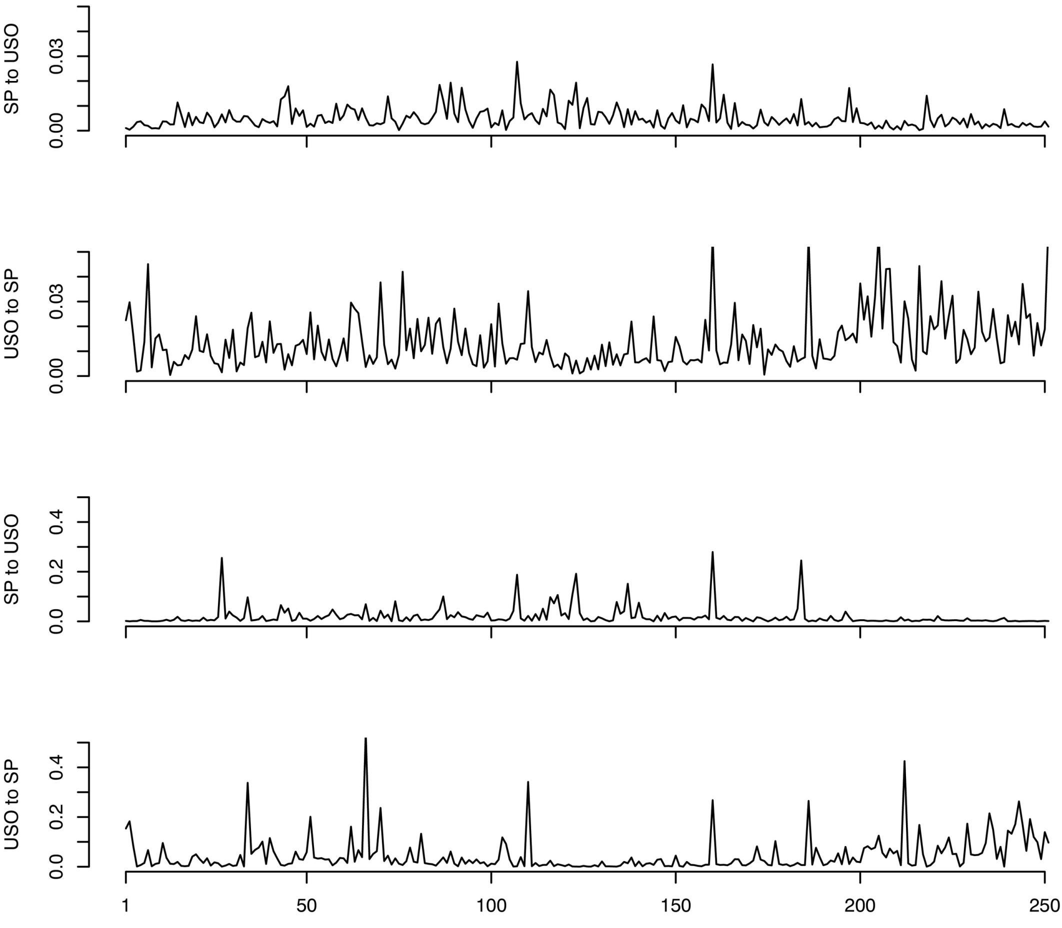

SP to USO
0.00
0.10
USO to SP
0.00
0.10
SP to USO
0.0
0.2
0.4
USO to SP
0.0
0.2
0.4
1
100
200
300
400
500

Figure 3



SP to USO
0.00
0.03
USO to SP
0.00
0.03
SP to USO
0.0
0.2
0.4
USO to SP
0.0
0.2
0.4
1
50
100
150
200
250

Figure 4