Effects of oil shocks on stock markets in G7 countries

Abstract

This paper aims to assess the effects of oil price shocks on the stock markets of the G7 countries. We develop an oil sentiment indicator that measures the volatility of oil prices. We analyze oil shocks on the stock market of the G7 countries, using a structural VAR and Local Projection approach. Our results suggest that oil shocks explain 8% of the US stock market, 10% in Germany, and 7% in the UK. These results point out the possibility of using this sentiment variable for forecasting the stock market's volatility.

Keywords: Stocks volatility; Oil prices; Oil shocks; Structural VAR; Local Projection.
JEL Code: G15; Q41; Q43.

1. Introduction

The interaction between the oil market and stock market variables has received attention in more developed countries. Kilian (2009) and Kilian and Park (2009) show that oil price shocks cause fluctuations in stock market returns and volatility. For example, the authors indicate that aggregate and specific demand shocks have a greater impact on the behavior of the United States stock market when compared to global oil supply shocks.

Kang et al. (2016) disentangle the effects of oil supply shocks by country of origin. They show that a positive U.S. oil supply shock has a positive impact on U.S. real stock returns. They also find that oil demand and supply shocks are of comparable importance in explaining the variability of U.S. real stock returns. Bastianin et al. (2016) focus on the effects of oil market shocks on the G7 countries' stock market volatility. They show that aggregate demand and oil-specific demand shocks matter for the behavior of G7 countries-members stock market, while oil supply shocks do not.

In turn, Ahmadi et al. (2016) investigate the relationship between the oil market and the U.S. stock market. However, they go further when separating the effects of oil price shocks on corporate returns according to the industry classification of the enterprise. Bastianin and Manera (2018) find similar results for the U.S. stock market volatility. They assess the effects of aggregate demand, oil supply, and oil-specific demand shocks on the U.S. stock market volatility and show that volatility responds mostly to oil price shocks caused by unexpected changes in aggregate demand and oil-specific demand, whereas the impacts of supply-side shocks are negligible.

In this paper, we present evidence supporting the importance of a novel oil market shock, a textual sentiment shock.The idea is that the textual sentiment index captures the current mood of oil market analysts about the state and prospects of the future evolution of oil markets. Therefore, unexpected changes in the sentiment index might reflect the arrival of new information, changes in the interpretations of oil market performance, the mood of oil market analysts, waves of optimism or pessimism on the behavior of oil markets, among other things, as Tetlock (2007).

Thus, the objective of this study is to analyze the effects of oil shocks on the stock market volatility in the G7 countries. For that, we estimate structural vector autoregressive models (SVAR) for each country in our sample. The SVAR models include measures of global oil production, real economic activity, real oil prices, stock markets' realized volatility in the G7 countries, and our textual sentiment index. In addition to evaluating the effects of oil market shocks using a SVAR model, we also analyzed the effects of oil shocks using the Local Projection, method proposed by Jordà (2005). Following Kilian and Park (2009), we identify four oil price shocks: an oil-supply shock, an oil-demand shock, a demand-specific oil shock, and the textual sentiment shock.

This essay contributes to the literature on oil shocks by constructing a textual sentiment index to investigate its effects on stock market volatility. Most of the recent literature follows Kilian (2009) and Kilian and Park (2009) and shows that shocks arising in the oil markets are important drivers of fluctuations in stock markets. Degiannakis et al. (2014) assess the effects of oil market shocks on the European stock markets. They find that oil supply shocks and oil specific demand shocks do not affect volatility, whilst, aggregate demand shocks lower stock market volatility. de Medeiros et al. (2023) develop an indicator that captures oil market sentiment, however, evaluate oil prices shocks on economic activity in United States and Brazil.

In addition to this introduction, this essay is divided into four more sections. The Section 2 presents the methodology used for this study. Section 3 presents the results and discussions. Section 4 is dedicated for additional results (robustness). Finally, Section 5 shows the main conclusions.

2. Methodology

In this paper, we investigate whether unexpected changes in the mood of oil agency's reports affect stock market volatility. To do this, we extract the textual sentiment of crude oil market reports issued by the Energy International Agency using a Naive Bayes Classifier Algorithm. Then, we construct a textual sentiment index. Using monthly data on the oil market (prices and production), real economic activity, and stock market volatility for each of the G7 countries, we estimate structural vector autoregressive (SVAR) models. We use the estimates of the models to assess the effects of shocks to textual sentiment on stock market volatility. We also investigate the effects of oil supply shocks, aggregate demand shocks, and oil-specific demand shocks. As a robustness check, we perform a Local Projection Method to check the quality of the results.

2.1. Database

We use monthly data covering the period from January 1998 to December 2018. Table 1 presents the source of the data.

Table 1: Source of variables

Variable	**Source**
Oil market reports' mood	U.S. Energy information Administration
Crude oil production (millions barrels)	U.S. Energy information Administration
Crude oil prices ($ per barrel)	U.S. Energy information Administration
Real Economic Activity Index	Kilian (2019)
G7 economies stock market indices S&P 500 , NIKKEY 225, DAX, FTSE 100, CAC 40,FTSE MIB, S&P/TSX	Investing

Differently from Bastianin et al. (2016), for each country in our sample, we add a fifth variable, which is the oil market reports' sentiment index. Thus, our vector of endogenous variables has the following structure $Z_t = [\Delta prod_t, rea_t, rpo_t, sent_t, RV_t]$, where $\Delta prod_t$ is the global oil production, rea_t denotes a measure of global real economic activity, rpo_t denotes the international real price of crude oil, $sent_t$ is the textual sentiment index captured from the EIA oil sector reports and RV_t is the realized stock market volatility for each country in our sample.

The textual sentiment is obtained using Jockers (2017)'s algorithm, which uses a routine to disentangle words according to its positive or negative cognitive aspects. This latter was previously classified by a dictionary, as in Deeney et al. (2015). Then, based on the count of positive and negative words present in the reports, we construct an index, this one representing the reports' tone, as described in the equation below:

$$sent_t = \frac{\sum PositiveWords - \sum NegativeWords}{\sum PositiveWords + \sum NegativeWords} \tag{1}$$

The index $sent_t$ lies in the range $[-1, 1]$ and the crude oil reports' tone is considered positive if the value of the index is greater than 0. On the other hand, if the index value is less than 0, the tone is negative.

To construct the measure of realized volatility, RV_t, we follow Schwert (1989) and compute the mean of the squares of daily real log-returns for each country index ($\mathrm{r_{j:t}}$):

$$RV_t = \sum_{i=1}^{N_t} \frac{r_{i:t}^2}{N_t} \tag{2}$$

where N_t is the number of trading days in month t and $r_{i:t}$ is the daily real log return of the i-th day of month t. For the U.S., we use the S&P 500, for Japan, the NIKKEY 225, for the U.K., the FTSE 100, for France CAC40, for Germany, DAX, for Italy, the FTSE MIB, and for Canada, the S&P/TSX index.

2.2. Structural VAR model specification and identification

The dynamic relationship between our endogenous variables can be represented as:

$$A_0 Z_t = \alpha + \sum_{i=1}^{13} A_i Z_{t-i} + \varepsilon_t, \tag{3}$$

where A_0 is a 5×5 matrix of contemporaneous impact, Z_t is 5×1 vector of endogenous variables, α is a 5×1 vector of constants, $\sum_{i=1}^{13} A_i$ is the matrix of lagged coefficients, ϵ_t is a vector of structural innovations.[1]

By left multiplying equation (3) by the inverse of A_0, we obtain

$$Z_t = B_0 + \sum_{i=1}^{13} B_i Z_{t-i} + \epsilon_t \tag{4}$$

where B_0 is a vector of constants, B_i denotes a matrix of lagged coefficients and ϵ_t is the reduced form SVAR residuals. As equation 4 is in the reduced form, we impose exclusion restrictions to recover the structural errors. As in Kilian and Park (2009), our identification strategy relies on exclusion restrictions on the A_0^{-1} matrix, as below:

$$\epsilon_t = \begin{pmatrix} \epsilon_t^{\Delta prod} \\ \epsilon_t^{rea} \\ \epsilon_t^{rpo} \\ \epsilon_t^{sent} \\ \epsilon_t^{RV} \end{pmatrix} = \begin{bmatrix} a_{11} & 0 & 0 & 0 & 0 \\ a_{21} & a_{22} & 0 & 0 & 0 \\ a_{31} & a_{32} & a_{33} & 0 & 0 \\ a_{41} & a_{42} & a_{43} & a_{44} & 0 \\ a_{51} & a_{52} & a_{53} & a_{54} & a_{55} \end{bmatrix}^{-1} \begin{pmatrix} \varepsilon_t^{\text{oil supply shock}} \\ \varepsilon_t^{\text{aggregate demand shock}} \\ \varepsilon_t^{\text{oil specific demand shock}} \\ \varepsilon_t^{\text{oil reports' sentiment shock}} \\ \varepsilon_t^{\text{other shocks to RV}} \end{pmatrix} \tag{5}$$

We are interested in four structural shocks: i) an oil supply shock, which consists in an unexpected increase in crude oil production; 2) an aggregate demand shock, which can be a result of any unexpected macroeconomic policy change that raises

1 We follow Kilian and Park (2009) and use 13 lags in the SVARs. However, using information criteria such as the Akaike Information Criteria - AIC resulted in the same lag specification, except for Italy, where the AIC indicated 12 lags. Notwithstanding, using 12 lags does not change the results.

oil consumption; 3) an oil-specific demand shock, which can be considered as an unexpected increase in the precautionary demand for crude oil; and finally 4) an oil market reports' sentiment shock. This is defined as an unexpected change in the sentiment (mood) in the EIA's oil market report.

The first three identifying assumptions are consistent with a vertical short-run supply curve of crude oil, a downward sloping demand curve, and the inter-relation between macroeconomic variables and the oil market (Kilian and Park, 2009). The oil market reports' sentiment shock and its effect on the stock market rely on a new strand of crude oil market studies that attempts to relate changing in sentiments of online news, such as Twitter and big data to financial volatility (Li et al., 2015; Deeney et al., 2015; Ding et al., 2017).

All variables are in levels, except for the crude oil production which presents a stochastic trend, according to Augmented Dickey-Fuller, KPSS, and Phillip Perron tests.

2.3. Local Projection Method

To check the quality of the results when using the oil market sentiment as a shock to the stock market volatility for the seven largest economies in the world, we used the method proposed by Jordà (2005). This method consists of estimating impulse response functions through local projections. This method has some advantages in relation to the autoregressive vector method, described in section 2.3, we highlight two: a) it can be estimated by ordinary least squares (OLS); and b) robust to specification errors.

For each period h, the equation 6 is estimated considering monthly data.

$$x_{t+h} = \alpha_h + \psi_h(L)y_{t-1} + \beta_h S_t + \epsilon_{t+h} \tag{6}$$

with $h = 0,\ldots,20$ and where x_t is the variable of interest, α is a constant; ψ is a lag operator polynomial; y represents a set of lagged variables used as control; β is the response of x in time $t+h$ given the time shock t; S is the variable that represents the sentiment (tone) of the oil market.

3. Results and discussion

This section presents the results of our analysis. Subsection 3.1 presents the impulse response functions to a negative oil supply shock, a positive aggregate demand rise shock, a positive oil demand shock, and a negative shock in the tone of EIA reports for the countries in our sample. Although our focus is on the effects on stock market volatility to sentiment shocks, we briefly discuss the responses to the other oil market shocks. Then, in subsection 3.2, we present the results of the forecast error variance decomposition.

3.1. Impulse Response Functions

Figure 1 presents the impulse response functions for each country in our sample. As in Bastianin et al. (2016), we estimate the responses for 18 steps ahead, based on a recursive-design wild bootstrap with 1000 replications and 0.68 confidence interval (Horowitz, 2019). First, we discuss the effects of oil supply shocks, aggregate demand, and oil-specific demand shocks on stock market volatility in the G7 countries. Then, we turn to the effects of the sentiment shock on stock market volatility.

The results show that, for most countries, an oil supply shock raises stock market volatility. In the United States, stock market volatility increases in the 4th and 5th periods and again at the 10th, 11th, and 17th periods after the shock. Similar results hold for the remaining G7 countries, except for the impact responses in Canada and Japan where volatility displays a decline following an oil supply shock. Kilian and Park (2009) and Bastianin et al. (2016) present similar results for the United States and G7 countries.

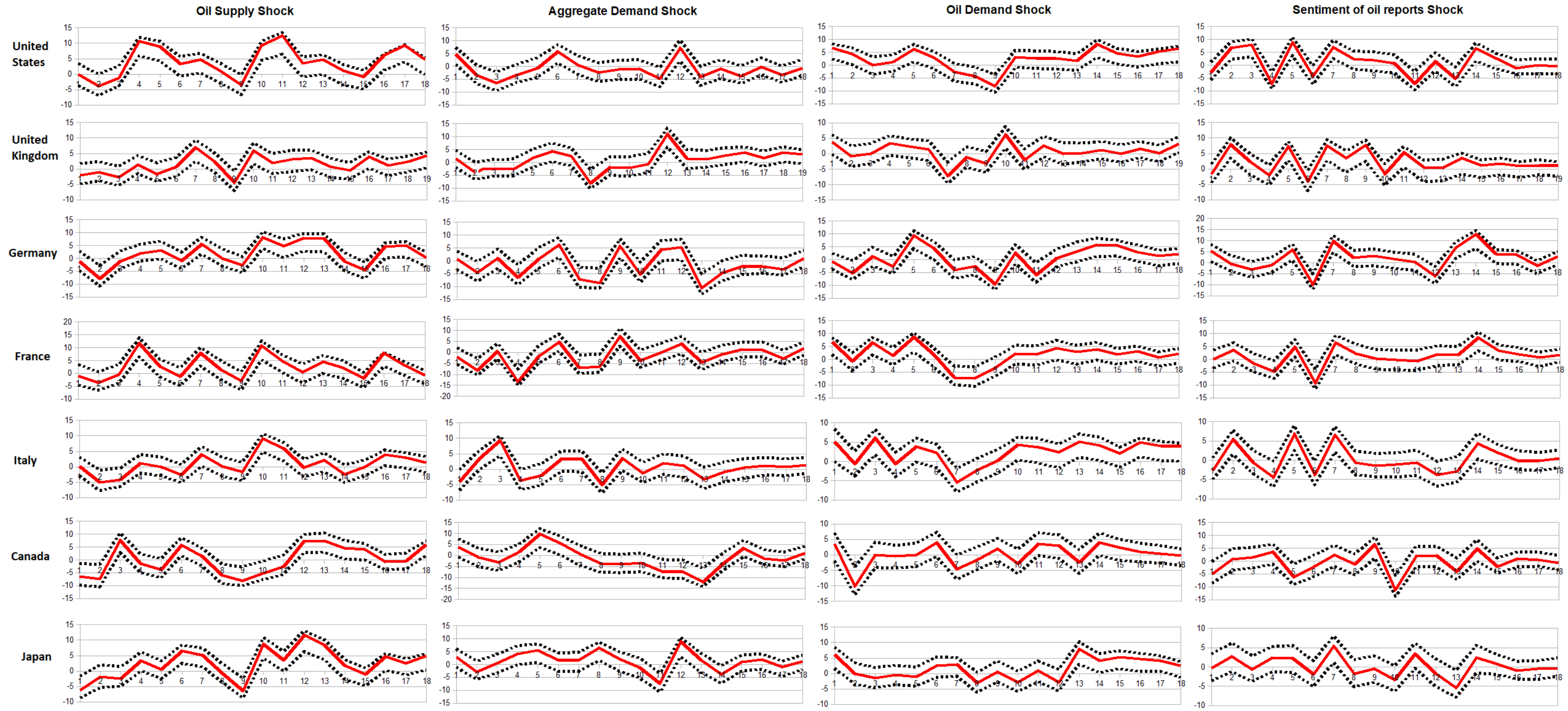

Figure 1: **G7 countries impulse response functions to structural oil market shocks.** Each panel shows the response of the stock market volatility of each country to a one standard deviation structural shock (continuous line), as well as one standard error bands (dotted line). Estimates are based on a recursively identified five-variable structural VAR model of order 13. Confidence bands are based on a recursive-design wild bootstrap with 1000 replications and 68% confidence interval.

The effects of aggregate demand shocks on the stock market volatility do not show a clear pattern in the responses across countries. While in the United States, the aggregate demand shock raises volatility, in the United Kingdom, Germany, Canada, and Japan, the responses alternate into increases and declines in volatility following the shock.

Bastianin et al. (2016) also report mixed responses (increases and decreases) in volatility following an aggregate demand shock in G7 countries. According to Kilian and Park (2009), the response pattern is unclear because increases in global real activity also boost the real price of oil, hence increasing production costs and lowering corporate dividends.

The third column in Figure 1 presents the responses to an oil-specific demand shock. In the United States, there is an increase in stock market volatility in the 1st period and again at the 14th following the shock. In the United Kingdom, there are positive effects at the 1st and 10th periods. In Germany, positive effects occur at the 5th, 14th, and 15th periods. In Japan, there are positive effects in the 1st and 13th periods.

Finally, the last column in Figure 1 shows the responses of stock market volatility to unexpected changes in the oil market reports' sentiment. In most countries, stock market volatility increases (with a lag) after a negative sentiment shock. Among the G7 members, the initial response is null (except for a small increase in Germany), but after a lag, the stock market volatility increases in most countries.

In the United States, stock market volatility increases in five periods after the shock (2nd, 3rd, 5th, 7th, and 14th periods). A similar pattern occurs in the United Kingdom, where stock market volatility increases at the 2nd, 5th, 7th and 9th periods. There are no negative responses in any period. In Germany, volatility also increases in the 7th, 13th, and 14th periods. A negative response occurs in the 6th period. In France, stock market volatility increases in the 7th and 14th periods. As in Germany, there is a decline in volatility in the 6th period. In Italy, there is an increase in volatility in the 2nd, 5th, and 7th periods.

In Canada, most periods do not show any clear response to the sentiment shock. The exception occurs in the 10th period, where there is a decline in volatility. In Japan, in most periods, there is no statistically significant response at the 68% confidence level. The only exception is in the 7th period.

These results present evidence that pessimism in the tone of the EIA oil reports increases financial market volatility in the G7 countries. We also implement a Forecast Error Variance Decomposition (FEVD) exercise to investigate the quantitative importance of oil market shocks to stock market volatility in each country. The next section presents these results.

3.2. Forecast error variance decomposition

Our results show that the contribution of oil market shocks to volatility in the first month is almost null in all countries. However, as time increases, the share of the variance explained by these shocks increases. Altogether the four oil market shocks explain 41% of stock market volatility in the U.S. at the 5 years horizon. These shocks also do matter for volatility in the other G7 countries. They account for 26% of the variation in volatility in the UK, 35% in France, 38% in Germany, 29% in Italy, 27% in Japan, and, finally, 30% in Canada. Table 2 presents the results of the FEVD exercise.

The contribution of oil supply shocks to volatility is non-negligible in most G7 countries. For instance, in the U.S. this shock accounts for 11% of the variation in volatility in the first year and reaches roughly 16% after 5 years. This differs from the results of Bastianin et al. (2016) for the U.S. They show that oil supply shocks explain less than 2% of the stock market volatility, while aggregate demand and oil specific-demand shocks explain a larger share.[2] An oil supply shock is also the single

2 Bastianin and Manera (2018) also argue that oil supply shocks do not matter for the U.S. stock market volatility. Although, they did not implement a variance decomposition exercise.

most important shock in Canada, France, and Germany, where it accounts for 14%, 12% and 10% of the stock market volatility at the five years horizon.

Table 2: FEVD – Stock Market Volatility – G7 countries

	Shock	US	UK	France	Germany	Italy	Japan	Canada
t =1	Oil supply	0.0000	0.0019	0.0003	0.0005	0.0000	0.0092	0.0126
	Aggregate demand	0.0083	0.0010	0.0012	0.0001	0.0069	0.0035	0.0028
	Oil-specific demand	0.0162	0.0054	0.0141	0.0001	0.0104	0.0030	0.0117
	Sentiment index	0.0030	0.0015	0.0000	0.0072	0.0035	0.0054	0.0000
	Volatility	0.9725	0.9902	0.9844	0.9921	0.9792	0.9789	0.9729
t =3	Oil supply	0.0053	0.0045	0.0038	0.0177	0.0151	0.0318	0.0152
	Aggregate demand	0.0248	0.0084	0.0197	0.0063	0.0415	0.0057	0.0056
	Oil-specific demand	0.0203	0.0052	0.0256	0.0081	0.0232	0.0243	0.0120
	Sentiment index	0.0372	0.0237	0.0045	0.0093	0.0149	0.0058	0.0024
	Volatility	0.9124	0.9583	0.9465	0.9586	0.9053	0.9323	0.9648
t =6	Oil supply	0.0576	0.0057	0.0370	0.0197	0.0164	0.0401	0.0296
	Aggregate demand	0.0329	0.0160	0.0654	0.0253	0.0472	0.0301	0.0197
	Oil-specific demand	0.0300	0.0102	0.0407	0.0363	0.0280	0.0262	0.0137
	Sentiment index	0.0701	0.0434	0.0355	0.0411	0.0384	0.0169	0.0064
	Volatility	0.8094	0.9248	0.8214	0.8777	0.8700	0.8867	0.9306
t =12	Oil supply	0.1116	0.0326	0.0736	0.0542	0.0502	0.0690	0.0933
	Aggregate demand	0.0455	0.0595	0.0905	0.0680	0.0548	0.0530	0.0595
	Oil-specific demand	0.0507	0.0357	0.0642	0.0622	0.0436	0.0328	0.0195
	Sentiment index	0.0831	0.0705	0.0411	0.0660	0.0497	0.0474	0.0184
	Volatility	0.7091	0.8018	0.7306	0.7496	0.8017	0.7978	0.8093
t = 24	Oil supply	0.1488	0.0507	0.1016	0.0821	0.0666	0.0893	0.1296
	Aggregate demand	0.0496	0.0762	0.0902	0.0890	0.0526	0.0842	0.0620
	Oil-specific demand	0.0969	0.0378	0.0811	0.0885	0.0810	0.0369	0.0616
	Sentiment index	0.0877	0.0707	0.0569	0.1009	0.0508	0.0514	0.0254
	Volatility	0.6172	0.7646	0.6702	0.6395	0.7490	0.7381	0.7215
t =60	Oil supply	0.1597	0.0591	0.1196	0.1014	0.0774	0.0933	0.1411
	Aggregate demand	0.0482	0.0906	0.0889	0.0883	0.0526	0.0854	0.0638
	Oil-specific demand	0.1155	0.0374	0.0861	0.0912	0.1136	0.0372	0.0691
	Sentiment index	0.0850	0.0690	0.0566	0.0982	0.0471	0.0511	0.0248
	Volatility	0.5916	0.7438	0.6488	0.6209	0.7093	0.7330	0.7011

Note: the table shows the Forecast Error Variance Decomposition for each country stock market volatility. Thus, each column represent how much each kind of shock affects it, given the period.

However, demand shocks are also important for volatility. Both demand-side shocks explain roughly 16% of volatility at the 5 years horizon in the U.S. This is similar to the results of Bastianin et al. (2016). They show that demand-side shocks explain approximately 12% of the variation of the U.S. stock market volatility. A similar result holds for other G7 countries. The two demand-side shocks jointly explain a larger share of the stock market volatility in Germany (17%), France (17%), Italy (13%), and Japan (12%) in the five years horizon.

The novelty in our results is to show that the contribution of the sentiment shock is non-negligible. At the 12th horizon, this shock accounts for 8% of the variation of volatility in the U.S. stock market, 7% in the United Kingdom, 7% in Germany, 4% in France, 5% in Italy and Japan, and 2% in Canada. At latter horizons, the share of the volatility explained by the sentiment shock reaches 10% in Germany and 8.5% in the U.S. at the five years horizon.

These results present evidence of the importance of a new structural shock in the oil market, a textual sentiment index related to unexpected changes in textual sentiments in EIA oil market reports.

4. Robustness test

In this section we carry out an additional test to verify the robustness of a shock in the oil sentiment variable on the volatility of the stock market of the G7 member countries. For that, we used the method of local projection, of Jordà (2005), to analyze the impulse-responses through local projections.

In this robustness exercise, we compare the result obtained from a structural VAR, described in the last column of the figure 1, with the impulse-responses of the Location Projection method. In general, we found that the results of the estimation by local projection corroborate the answers obtained by the VAR, from the shock in the oil market. Among the results, we highlight the positive response of the German stock market to the oil shock. In turn, it is also worth noting that the US stock market reacts negatively to the negative shock, despite not having been significant in the result obtained by the structural VAR. This last result was expected given that the construction of oil market sentiment was derived from the International Energy Agency of the United States. Additional impulse responses can be seen in Figure 2.

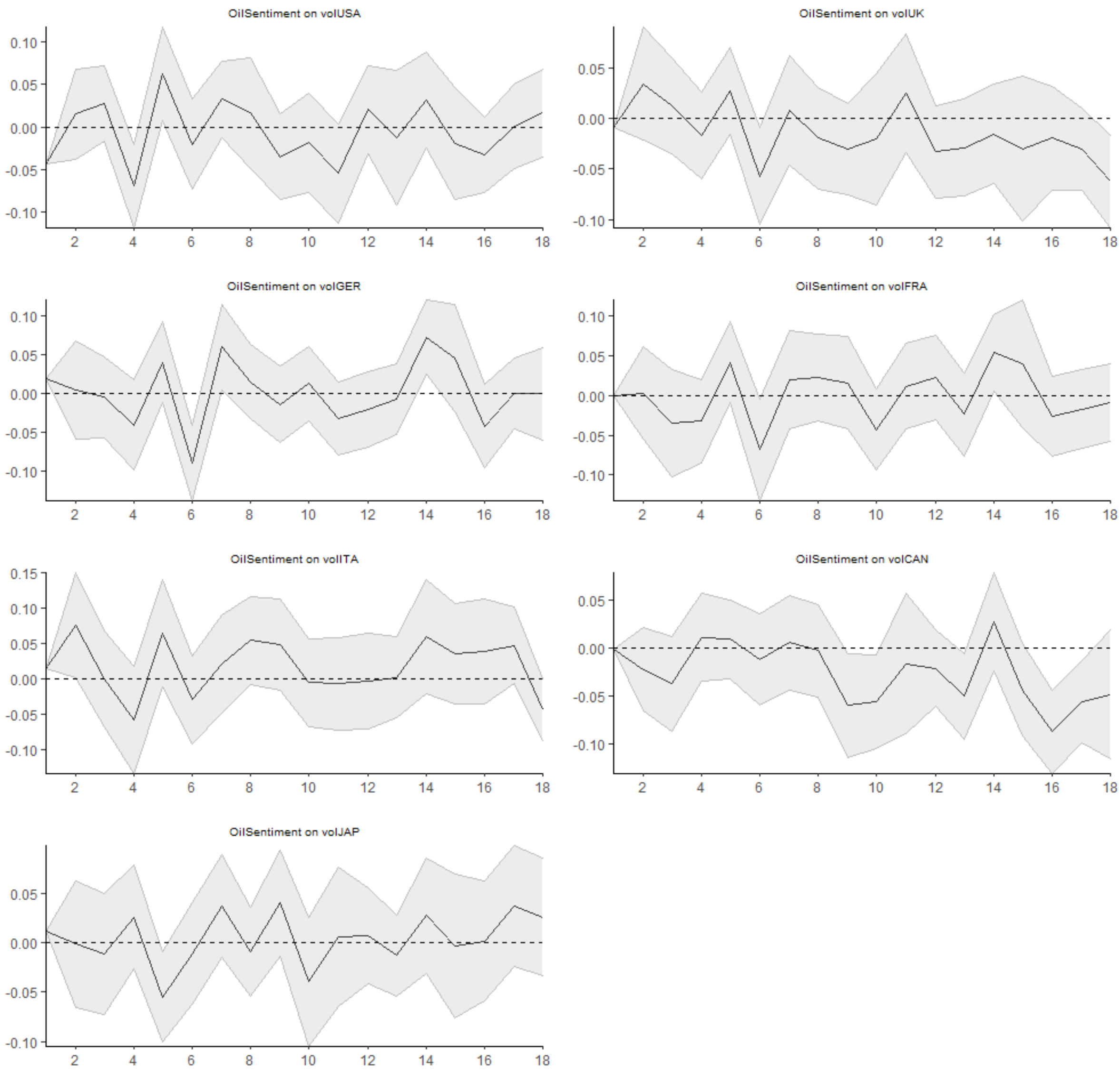

Figure 2: Responses to a shock in oil market sentiment

Note: 18 periods were used for the shock response.
Note: The confidence interval is 95%.

5. Conclusion

This paper investigates the effects of oil market reports' sentiment shocks on stock market volatility in the G7 countries over the period from January 1998 to December 2018. We use a computational algorithm of textual sentiment classification to build a tone/sentiments index based on oil market reports issued by Energy International Agency. We estimate structural vector autoregressive models using the oil reports sentiment index for each country in our sample.

Differently from previous papers, we construct a sentiment index based on official oil market reports instead of twitters or google search trend-lines, which can contain random information emitted by ordinary users of social media. We use this new index to analyze the effects of oil market reports' sentiment shocks on stock market volatility in each country in our sample.

Our findings show that after a negative sentiment shock, volatility increases in most countries in our sample. Therefore, our results highlight the importance of a new structural oil market shock, a shock related to unexpected changes in textual sentiments in EIA oil market reports.

Therefore, we recommend the use of the sentiment index for financial analysis purposes by analysts, policymakers, and traders, as its inclusion may reduce asymmetries of information and augment the accuracy of forecasting models.

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