The Impacts of Oil Price Shocks on Stock Market Volatility: Evidence from the G7 Countries

Andrea Bastianin
University of Milan, Italy and Fondazione Eni Enrico Mattei, Milan, Italy

Francesca Conti
Fondazione Eni Enrico Mattei, Milan, Italy

Matteo Manera
University of Milan-Bicocca, Italy and Fondazione Eni Enrico Mattei, Milan, Italy

October, 2015

Abstract: We study the effects of crude oil price shocks on the stock market volatility of the G7 economies. We rely on a structural VAR model to identify the causes underlying the oil price shocks and gauge the differential impact that oil supply and oil demand innovations have on financial volatility. We show that stock market volatility does not respond to oil supply shocks. On the contrary, demand shocks impact significantly on the variability of the G7 stock markets.

Key Words: Volatility, Oil Price Shocks, Oil Price, Stock Prices, Structural VAR

JEL Codes: C32, C58, E44, Q41, Q43.

Acknowledgments: Andrea Bastianin gratefully acknowledges financial support from the Italian Ministry of Education, Universities and Research (MIUR) research program titled "Climate change in the Mediterranean area: scenarios, economic impacts, mitigation policies and technological innovation" (PRIN 2010-2011, prot. n. 2010S2LHSE-001).

Corresponding author: Matteo Manera, Department of Economics, Management and Statistics, University of Milano-Bicocca, Via Bicocca degli Arcimboldi, 8, Building U7, 20126, Milan, Italy. Email: matteo.manera@unimib.it

1 Introduction

The relationship between stock markets and macroeconomic and financial variables has been widely investigated (see, for example, Engle and Rangel (2008), Güntner (2014), Kang and Ratti (2013) and Kilian and Park (2009)). One of the relevant topics in this area is the interaction between changes in the price of oil and stock market volatility (see Bastianin and Manera (2016), Degiannakis et al. (2014), Jung and Park (2011) and Kang et al. (2015)). Our paper examines and compares the features of this relationship in the G7 countries.

This study is based on the belief, shared by most academics (see, e.g. Kilian (2008b) and Hamilton (2013)), that the price of oil is endogenous and driven by innovations to both demand and supply. According to the work of Campbell (1991), unexpected returns are related to innovations to dividend growth rates and expected returns. If these two variables were observable, it would be possible to identify the relative contribution of each component to unconditional stock variance. In practice, innovations to dividend growth rates and expected returns are estimated through a regression on macroeconomic and financial variables, which implies that a relationship exists between volatility and macroeconomic and financial variables, including oil price shocks (see Engle and Rangel (2008)).

However, the impact of oil price shocks on stock markets is still unclear. The work of Kilian (2009) pointed out that the origin of shocks to the price of crude oil is a key determinant of its effects on financial and macroeconomic aggregates. Kilian (2009) shows that the price of crude oil is determined by three distinct structural shocks: innovations to global crude oil supply, to aggregate demand for all industrial commodities and to oil-specific demand, which could also be considered as precautionary demand.

We rely on a structural Vector Autoregressive (VAR) model which includes the equations describing the oil market, as modeled by Kilian (2009), and the realized volatility equation to represent the relationship between oil market and stock market.

This approach has already been used by some authors to investigate the impact of shocks to the price of crude oil on aggregate stock market volatility. Bastianin and Manera (2016) focused on the U.S. stock market; Degiannakis et al. (2014) considered the European market, while Jung and Park (2011) compared Norway and Korea. The aim of this work is to compare the responses of stock market volatility to oil price shocks across G7 economies.

It is well known that economies with different characteristics react differently to innovations to the price of crude oil (see Baumeister et al. (2010), Jiménez-Rodríguez and Sánchez (2005) and Kilian (2008a)). Among the G7 countries, three are oil producers (the U.S., Canada and the U.K.), but only one is a net-exporter (Canada). As of 2012, the U.S. and Japan were the first and third largest world net-importers of crude oil[1]. The U.K. became a net-importer in 2005, while from the early eighties to 2004 it was a net-exporter[2]. Therefore, the data at our disposal cover a variety of economies, allowing for a wide comparison.

We show that stock market volatility does not respond to oil supply shocks; on the contrary, demand shocks impact significantly on the variability of G7 stock markets. Aggregate demand shocks cause an initial volatility decrease in all countries, which lasts about five months. In the long-run the sign of the responses of volatility switches to positive in Canada, in the U.K. and in the U.S., but the positive response is statistically significant only in the case of Canada. Shocks to oil-specific demand depress volatility on impact, but are followed by a rise of volatility that lasts for about ten months in most countries. Robustness checks proved that these results are not affected by changes in the volatility proxy or in the sampling frequency of the data.

The rest of the paper is organized as follows. Section 2 describes data and methods,

---

[1] We calculated net-exports as the difference between exports and imports of crude oil, including lease condensate, reported in the International Energy Statistics published by the U.S. Energy Information Administration (EIA). Using these data, the four most important net-importers of crude oil in 2012 were: the U.S. (9413 thousand barrels/day), China (3978 thousand barrels/day), Japan (3724 thousand barrels/day), India (3185 thousand barrels/day). Net-imports of Germany, Italy, France and the U.K. amounted to 1884, 1493, 1158 and 512 thousand barrels/day, respectively. The 2012 ranking of net-exporters is as follows: Saudi Arabia (6250 thousand barrels/day), Russia (4835 thousand barrels/day), Iran (2297 thousand barrels/day), United Arab Emirates (2181 thousand barrels/day). Canada was ranked eighth and its net-exports totaled 1734 thousand barrels/day.

[2] Source: Crude oil and petroleum: production, imports and exports 1890 to 2014, published by the Department of Energy & Climate Change of the U.K. Government (https://www.gov.uk/government/statistical-data-sets/crude-oil-and-petroleum-production-imports-and-exports-1890-to-2011).

while the results are discussed in Section 3. Some robustness checks are reported in Section 4, while Section 5 concludes.

2 Data and methods

2.1 Data

We rely on a structural VAR model for $\boldsymbol{z}_t = [\Delta prod_t, rea_t, rpo_t, RV_t]^T$ for each of the G7 countries, namely Canada, France, Germany, Italy, Japan, the U.K. and the U.S.. We estimate the model using monthly data over the sample February 1973-January 2015.

The first three equations describe the global market of crude oil through the annualized percent change in world crude oil production, $\Delta prod_t$, an index of real economic activity, rea_t, and the real price of crude oil, rpo_t[3]. The last equation investigates the relationship between oil market shocks and stock price volatility.

To measure the volatility of stock markets in the G7 countries we compute realized volatility, RV_t, using the Morgan Stanley Capital International (MSCI) country indices. Following Schwert (1989), we calculate monthly realized volatility as the mean of the squares of daily real log-returns[4]:

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

where N_t is the number of trading days in month t and $r_{j:t}$ is the daily real log return of the

[3] $\Delta prod_t$ is defined as $1200 \times \ln(prod_t/prod_{t-1})$. Monthly world oil production is available starting from January 1973 in the EIA Monthly Energy Review (Table 11.1b). rea_t was introduced by Kilian (2009) and is available on the author's website. It is based on dry cargo ocean shipping rates. The refiners' acquisition cost of imported crude oil, available from the EIA, is used to calculate rpo_t. Since the MSCI indices are based on the price returns in local currency, while the price of crude oil is denominated in U.S. dollars, we take the fluctuations of exchange rates into account. In doing so we follow Güntner (2014) and convert the refiners' acquisition cost of crude oil from U.S. dollars to domestic currency using bilateral exchange rates, as reported by the exchange rates archives of the Bank of Italy. The price is deflated using the CPI for all Urban Consumers of each country, available from OECD. rpo_t is the logarithm of the deflated price expressed in deviations from its sample average.

[4] Real returns are based on interpolated CPI as suggested by Lunde and Timmermann (2005).

j-th day of month t. The annualized realized standard deviation, $(252 \times RV_t)^{1/2}$, is used for the analysis.

2.2 Identification and construction of the structural VAR model

The structural VAR representation is

$$\boldsymbol{A}_0 \boldsymbol{z}_t = \boldsymbol{\alpha} + \sum_{i=1}^{24} \boldsymbol{A}_i \boldsymbol{z}_{t-i} + \boldsymbol{\varepsilon}_t \tag{2}$$

where $\boldsymbol{\varepsilon}_t$ is a vector of serially and mutually uncorrelated structural innovations. Reduced-form VAR residuals, $\boldsymbol{e}_t$, are given by: $\boldsymbol{e}_t = \boldsymbol{A}_0^{-1} \boldsymbol{\varepsilon}_t$. Following Kilian (2009) and Kilian and Park (2009), the identification of the model is achieved by imposing the following restrictions on $\boldsymbol{A}_0^{-1}$:

$$\boldsymbol{e}_t \equiv \begin{pmatrix} e_t^{\Delta prod} \\ e_t^{rea} \\ e_t^{rpo} \\ e_t^{RV} \end{pmatrix} = \begin{bmatrix} a_{11} & 0 & 0 & 0 \\ a_{21} & a_{22} & 0 & 0 \\ a_{31} & a_{32} & a_{33} & 0 \\ a_{41} & a_{42} & a_{43} & a_{44} \end{bmatrix} \begin{pmatrix} \varepsilon_t^{oil\, supply\, shock} \\ \varepsilon_t^{aggregate\, demand\, shock} \\ \varepsilon_t^{oil-specific\, demand\, shock} \\ \varepsilon_t^{other\, shocks\, to\, RV} \end{pmatrix} \tag{3}$$

The first three rows of the model are based on the hypothesis of a global crude oil market characterized by a vertical short-run supply curve and a downward sloping short-run demand curve.

Exclusion restrictions may be motivated as follows. Crude oil production is only driven by exogenous shocks to oil supply; due to the costs of adjusting the production level, it responds to demand shocks only with delay. Real economic activity immediately reacts to aggregate demand shocks, which identify shifts in the demand of all commodities, including crude oil. The innovations specific to the oil market, which can be considered as precautionary demand shocks, do not influence the global business cycle within the same month. Restrictions in the third row indicate that changes in the real price of oil instantly reflect supply shocks and both aggregate and oil-specific demand shocks. Finally, realized volatility responds to all the structural shocks related to the oil market, as well as to the residual category capturing other innovations to stock market volatility. We assume that innovations to the variables describing the global oil market are predetermined with respect to domestic stock markets, which implies that stock price volatility has no instantaneous impact on the real price of oil. This assumption has been used by several authors (see e.g. Kilian (2008b), Kilian and Park (2009), Degiannakis et al. (2014) and Güntner (2014)) and is supported by empirical evidence in Kilian and Vega (2011).

3 Results

3.1 Impulse Response Functions

Figure 1 shows the responses of realized volatility to different oil shocks in each of the G7 countries. The shocks presented are expected to generate an increase in the price of crude oil. Thus, we consider a negative oil supply shock, which represents an unpredictable decrease of oil production, and positive shocks to aggregate and oil-specific demand.

The leftmost column shows that oil supply shocks do not have a significant impact on volatility. In all countries the response is close to zero and statistically insignificant. On average, during the period 1975-2015, stock market volatility has not responded to oil price shocks originating from the supply side, neither in oil-importing nor in oil-exporting G7 countries.

From the second column we see that a positive aggregate demand shock immediately reduces volatility in all G7 countries. This decrease is significant at the 68% level and lasts up to six months. Eleven months after the shock the sign of the response becomes positive for Canada, the U.K. and the U.S., although it is significant at the 68% confidence level only for Canada, where the higher level of volatility is persistent.

This pattern might be explained considering the two simultaneous effects of an unexpected increase in aggregate demand. On the one hand, this innovation could be interpreted as good news by stock markets and reduce volatility, since a positive shock to aggregate demand implies increased economic activity and lower uncertainty about future cash flows. On the other hand, higher aggregate demand could trigger a rise in the price of oil and slowdown the economy, causing an increase in volatility.

The impulse response functions for the G7 economies indicate that initially the first effect prevails and volatility decreases in all countries, while in the medium-run the second effect is stronger and boosts volatility in the U.K., the U.S. and Canada. The fact that an oil net-exporter, such as Canada, experiences a significant increase in volatility after a year might be due to its high degree of energy intensity[5], which implies that if the price of crude rises industry costs will undergo a major increase and thus boost volatility.

The third column presents the response of volatility to oil-specific demand shocks. The countries showing significant responses are Canada and the U.S.. They follow a similar path, which consists of an initial decrease in volatility and a switch to positive response after three to four months. The positive sign is significant at the 68% level for the U.S. for seven months. In Canada, the positive sign is significant at the 95% level from the fifth until the eleventh month after the shock, then its significance decreases to 68% until the fifteenth month. After more than a year the response returns close to zero. The initial decrease in volatility might be due to the fact that when an oil-specific demand shock occurs investors are not sure whether it is caused by higher aggregate demand or by higher precautionary demand. The volatility increase in the next months could indicate that higher precautionary demand, which being strictly related to expectations about future oil supply shortages, reflects macroeconomic uncertainty and therefore higher stock market volatility.

The responses of volatility in the U.K., France and Germany are similar to those above, but the effect is only significant at the 68%.

In Japan a positive oil-specific demand shock causes a permanent decrease in volatility that on impact is also statistically significant at the 68% level.

Lastly, also in Italy the initial response of volatility to an oil-specific demand shock is negative and statistically significant using the 68% confidence interval only for the third month, while it remains close to zero the following months.

Overall, the initial response of stock market volatility to a positive oil-specific demand

[5]Energy intensity is given by total primary energy consumption per dollar of GDP, as published by the EIA. In 2011 energy intensity in Canada was 10884 BTU per (2005) U.S. Dollars, the highest among the G7 countries (France 4840 BTU/USD, Germany 4457 BTU/USD, Italy 4284 BTU/USD, Japan 4574 BTU/USD, U.K. 3588 BTU/USD, U.S. 7328 BTU/USD).

shock is negative in all G7 countries, with slightly different timing. In a few months the sign switches from negative to positive and remains above zero for almost a year in all countries but Japan and Italy, where the response reverts close to zero in five months.

In conclusion, the interpretation of the estimated impulse response functions highlights two main results. First, as pointed out by several related studies (see Bastianin and Manera (2016), Jung and Park (2011) and Kilian and Park (2009) among others), the impact of oil price shocks on stock market volatility depends on the origin of the shock. In particular, we found that volatility is primarily driven by oil price shocks originating from the demand side of the market. Second, the stock markets in the G7 countries, despite the differences in their economies, have very similar reactions to oil shocks. The analysis does not identify substantial contrasts in the responses of volatility in oil importing and exporting countries.

These results differ from those of the study by Jung and Park (2011), which compared the relationship between stock market volatility and oil price shocks in Norway and South Korea, a net exporter and a net importer of oil respectively. They found that reactions to oil price shocks are different in oil-exporting and oil-importing countries, but this could be due to some discrepancies between our analysis and their study. For instance they considered data of two different sample periods, January 1980 - December 2008 for Norway and September 1987 - December 2008 for South Korea. Instead, we have relied on data with a common sample period (February 1973 - January 2015).

3.2 Forecast Error Variance Decomposition

Table 1 shows the percentage contributions of each oil market shock to the overall variability of stock market volatility, based on the forecast error variance decomposition of the structural VAR models presented earlier.

The results indicate that in the first month the contribution of oil market shocks to volatility is close to zero. As the horizon increases, the effects of shocks to aggregate demand and oil-specific demand gain a little more importance, while the contribution of oil supply shocks is negligible over the whole period considered.

In a year and a half the contribution of aggregate demand shocks to volatility is about 6%

in all countries, except in France where is less than 5%. This percentage increases through time, exceeding 8% in Canada, the U.K. and the U.S. after five years.

As for the influence of oil-specific demand shocks, it also grows over the years, always remaining lower than the contribution of aggregate demand shocks. The only exception is Canada, for which the contribution of precautionary oil demand shocks is higher than that of aggregate demand shocks during the second year (twelfth and eighteenth months).

At a five-year horizon we can see that in Canada, France, Italy and the U.S. the oil-specific demand shocks explain $5.5-6.5\%$ of stock market volatility, a magnitude that is close to the contribution of aggregate demand shocks. In the remaining countries the percentage is slightly lower, $3.5-4\%$, and the difference with the contribution of aggregate demand innovations is more noticeable.

At a five-year horizon aggregate demand shocks and oil-specific demand shocks jointly explain at least 10% of stock market volatility in G7 countries, ranging from a minimum of 10.17% in Germany to a maximum of 14.93% in Canada.

Overall, the results of the variance decomposition confirm the findings in the previous subsection, namely that volatility in all the G7 countries is mainly influenced by innovations to the demand side, especially to aggregate demand.

4 Robustness checks

The structural VAR model was specified relying on realized volatility as a volatility proxy. To verify the robustness of our results, we have estimated the same model using two different volatility proxies.

The first alternative proxy considered is the logarithm of RV. This measure was chosen because stock return volatility is positively skewed and leptokurtic and hence researchers often replace it with its logarithm (see Andersen et al. (2001)). Figure 2 shows that the impulse response functions of the logarithm of realized volatility do not differ from those presented earlier.

Another common proxy for stock market volatility is conditional volatility estimated with a first-order Generalized Autoregressive Conditional Heteroskedasticity model, GARCH(1,1).

The results, shown in Figure 3, are qualitatively similar to those obtained by considering realized volatility.

The last robustness check considers a quarterly sampling frequency, which is often used by central banks in the specification of macroeconomic models. We estimated a structural VAR model of order 8 with quarterly data. From the impulse response functions in Figure 4 we can see that the results are robust to alternative sampling frequencies.

5 Conclusions

Understanding the relationship between oil price shocks and stock market volatility is important to handle market uncertainty. On this respect, additional useful insights can be gained by comparing the reactions of stock markets in different economies.

Our paper investigated the relationship between oil market shocks and volatility with a structural VAR model for each of the G7 countries.

Disentangling the causes of oil price shocks proved crucial in understanding the response of volatility. We found that in all countries shocks to the supply of crude oil do not affect volatility, while demand-side shocks, especially aggregate demand shocks, do influence volatility and in the long-run they explain at least 10% of its total variability.

G7 countries react very similarly on impact to aggregate demand shocks and oil-specific demand shocks, while the long-run responses present some differences. With respect to oil-specific demand shocks, we can notice a common movement in the responses of volatility in all countries but Japan and Italy, where they appear more erratic.

These findings have important implications that must be considered while building both macroeconomic and financial models to support the decisions of policy makers and investors.

References

Andersen, T. G., Bollerslev, T., Diebold, F. X., and Ebens, H. (2001). The distribution of realized stock return volatility. *Journal of Financial Economics*, 61(1):43–76.

Bastianin, A. and Manera, M. (forthcoming). How does stock market volatility react to oil price shocks? *Macroeconomic Dynamics*.

Baumeister, C., Peersman, G., and Robays, I. V. (2010). The economic consequences of oil shocks: differences across countries and time. In Fry, R., Jones, C., and Kent, C., editors, *Inflation in an Era of Relative Price Shocks*, pages 91–128. Reserve Bank of Australia, Sidney.

Campbell, J. Y. (1991). A variance decomposition for stock returns. *The Economic Journal*, 101(405):157–179.

Degiannakis, S. A., Filis, G., and Kizys, R. (2014). The effects of oil price shocks on stock market volatility: evidence from european data. *The Energy Journal*, 35(1):35–56.

Engle, R. F. and Rangel, J. G. (2008). The Spline-GARCH model for low-frequency volatility and its global macroeconomic causes. *Review of Financial Studies*, 21(3):1187–1222.

Gonçalves, S. and Kilian, L. (2004). Bootstrapping autoregressions with conditional heteroskedasticity of unknown form. *Journal of Econometrics*, 123(1):89–120.

Güntner, J. H. F. (2014). How do international stock markets respond to oil demand and supply shocks? *Macroeconomic Dynamics*, 18(8):1657–1682.

Hamilton, J. D. (2013). Historical oil shocks. In Parker, R. E. and Whaples, R., editors, *Routledge Handbook of Major Events in Economic History*, pages 239–265. Routledge Taylor and Francis Group, New York.

Jiménez-Rodríguez, R. and Sánchez, M. (2005). Oil price shocks and real GDP growth: empirical evidence for some OECD countries. *Applied Economics*, 37(2):201–228.

Jung, H. and Park, C. (2011). Stock market reaction to oil price shocks: a comparison between an oil-exporting economy and an oil-importing economy. *Journal of Economic Theory and Econometrics*, 22(3):1–29.

Kang, W. and Ratti, R. A. (2013). Oil shocks, policy uncertainty and stock market return. *Journal of International Financial Markets, Institutions and Money*, 26:305–318.

Kang, W., Ratti, R. A., and Yoon, K. H. (2015). The impact of oil price shocks on the stock market return and volatility relationship. *Journal of International Financial Markets, Institutions and Money*, 34:41–54.

Kilian, L. (2008a). A comparison of the effects of exogenous oil supply shocks on output and inflation in the G7 countries. *Journal of the European Economic Association*, 6(1):78–121.

Kilian, L. (2008b). The economic effects of energy price shocks. *Journal of Economic Literature*, 46(4):871–909.

Kilian, L. (2009). Not all oil price shocks are alike: disentangling demand and supply shocks in the crude oil market. *American Economic Review*, 99(3):1053–1069.

Kilian, L. and Park, C. (2009). The impact of oil price shocks on the U.S. stock market. *International Economic Review*, 50(4):1267–1287.

Kilian, L. and Vega, C. (2011). Do energy prices respond to U.S. macroeconomic news? A test of the hypothesis of predetermined energy prices. *The Review of Economics and Statistics*, 93(2):660–671.

Lunde, A. and Timmermann, A. (2005). Completion time structures of stock price movements. *Annals of Finance*, 1(3):293–326.

Schwert, W. G. (1989). Why does stock market volatility change over time? *Journal of Finance*, 44(5):1115–1153.

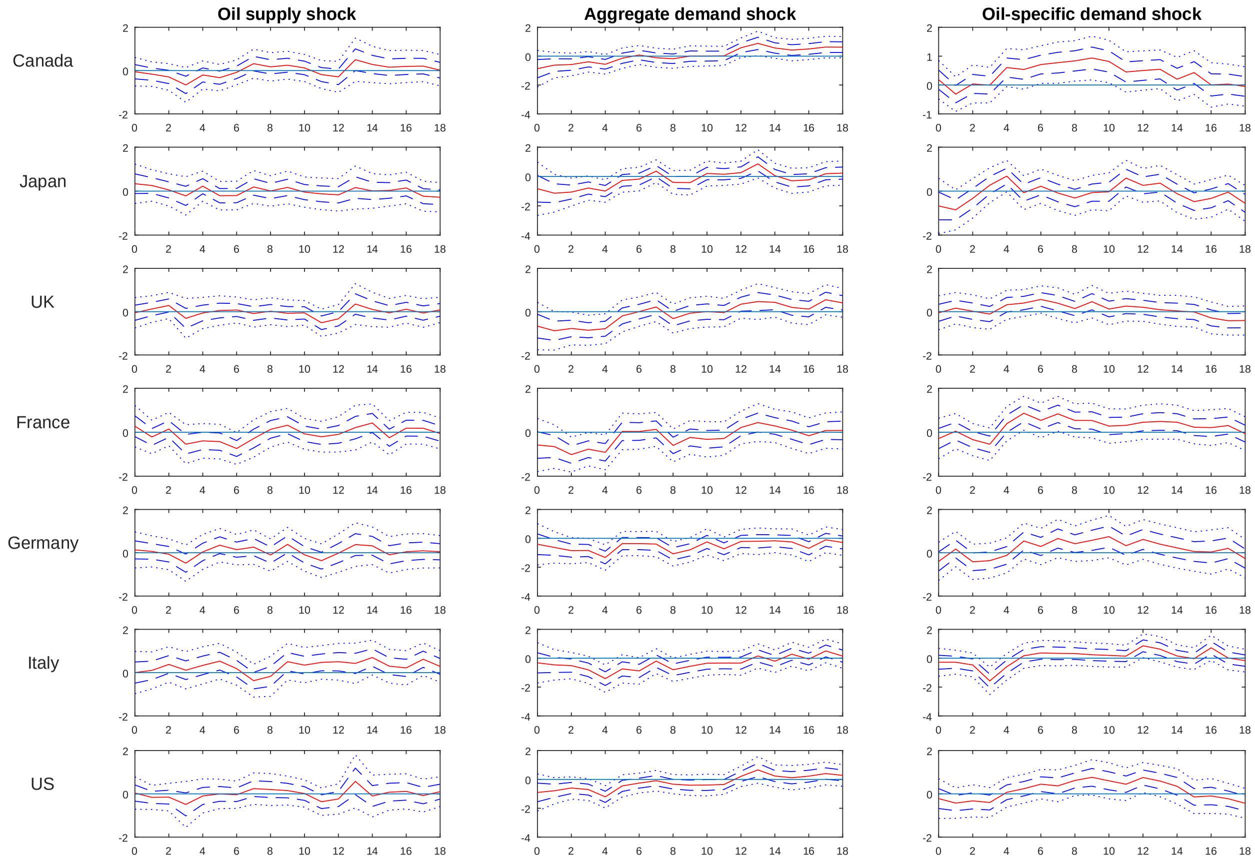
Tables and Figures

Table 1: Variance Decomposition - Realized volatility

	Shock	Canada	France	Germany	Italy	Japan	UK	US
t=1	Oil supply	0.067	0.186	0.030	0.015	0.259	0.037	0.051
	Aggregate demand	2.532	1.171	0.806	0.435	2.911	2.550	2.632
	Oil-specific demand	0.299	0.129	0.266	0.215	1.712	0.060	0.424
	Volatility	97.102	98.514	98.898	99.336	95.119	97.353	96.893
t=3	Oil supply	0.975	0.578	0.306	0.189	0.300	0.344	0.440
	Aggregate demand	2.858	3.168	2.386	1.395	4.933	4.549	3.461
	Oil-specific demand	0.238	0.657	0.589	3.229	1.783	0.074	0.753
	Volatility	95.930	95.597	96.719	95.187	92.984	95.033	95.346
t=6	Oil supply	1.131	1.588	0.432	0.617	0.437	0.337	0.424
	Aggregate demand	3.142	3.878	4.361	4.737	5.843	5.267	5.636
	Oil-specific demand	2.059	2.016	0.959	3.488	2.260	1.012	1.064
	Volatility	93.668	92.518	94.248	91.158	91.460	93.384	92.877
t=12	Oil supply	1.395	1.786	0.699	1.573	0.503	0.913	0.775
	Aggregate demand	3.172	4.401	5.995	5.751	5.801	5.378	5.853
	Oil-specific demand	6.172	3.760	2.594	4.316	2.558	1.729	3.789
	Volatility	89.262	90.053	90.711	88.359	91.138	91.981	89.583
t=18	Oil supply	1.832	2.123	0.893	2.724	0.666	1.118	1.171
	Aggregate demand	5.806	4.627	6.303	5.972	6.574	6.541	6.397
	Oil-specific demand	6.359	4.354	2.746	5.098	3.275	2.308	4.411
	Volatility	86.003	88.896	90.057	86.207	89.484	90.034	88.021
t=24	Oil supply	2.697	2.361	1.229	3.288	0.944	1.555	1.611
	Aggregate demand	7.123	5.122	6.560	6.085	6.672	6.648	6.787
	Oil-specific demand	6.482	5.199	3.325	5.197	3.436	3.328	5.995
	Volatility	83.698	87.317	88.886	85.430	88.948	88.469	85.606
t=60	Oil supply	2.772	2.616	1.320	3.392	1.064	1.849	1.774
	Aggregate demand	8.491	5.704	6.738	7.560	6.624	8.459	8.275
	Oil-specific demand	6.443	5.358	3.432	5.666	4.260	3.532	6.202
	Volatility	82.294	86.322	88.510	83.383	88.051	86.161	83.750

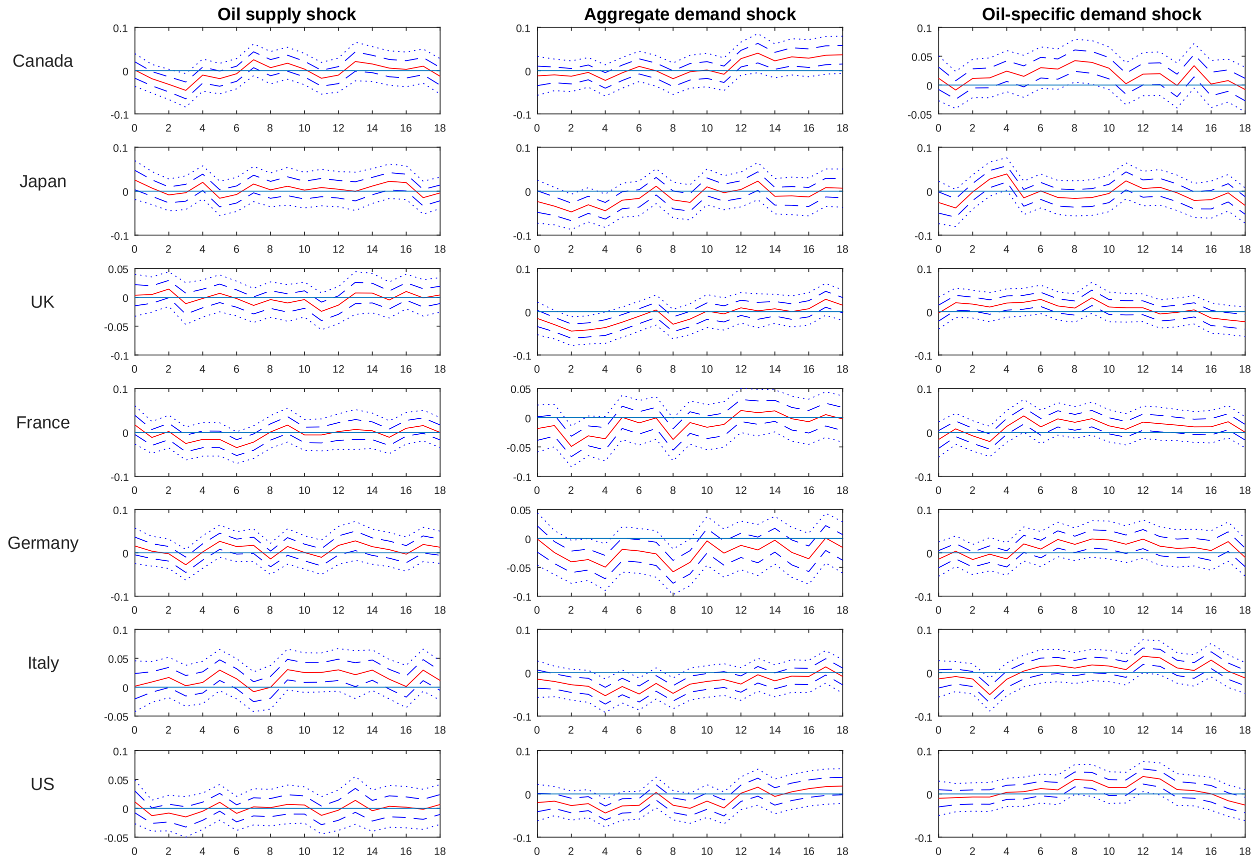
Notes: for each lag, reported on the left, the table compares the forecast error variance decomposition of the structural VAR models of the seven countries. Each row shows the percentage contribution of a shock to the variability of stock market volatility at a chosen lag.

Figure 1: Responses of realized volatility to structural shocks (Feb. 1975-Jan. 2015)



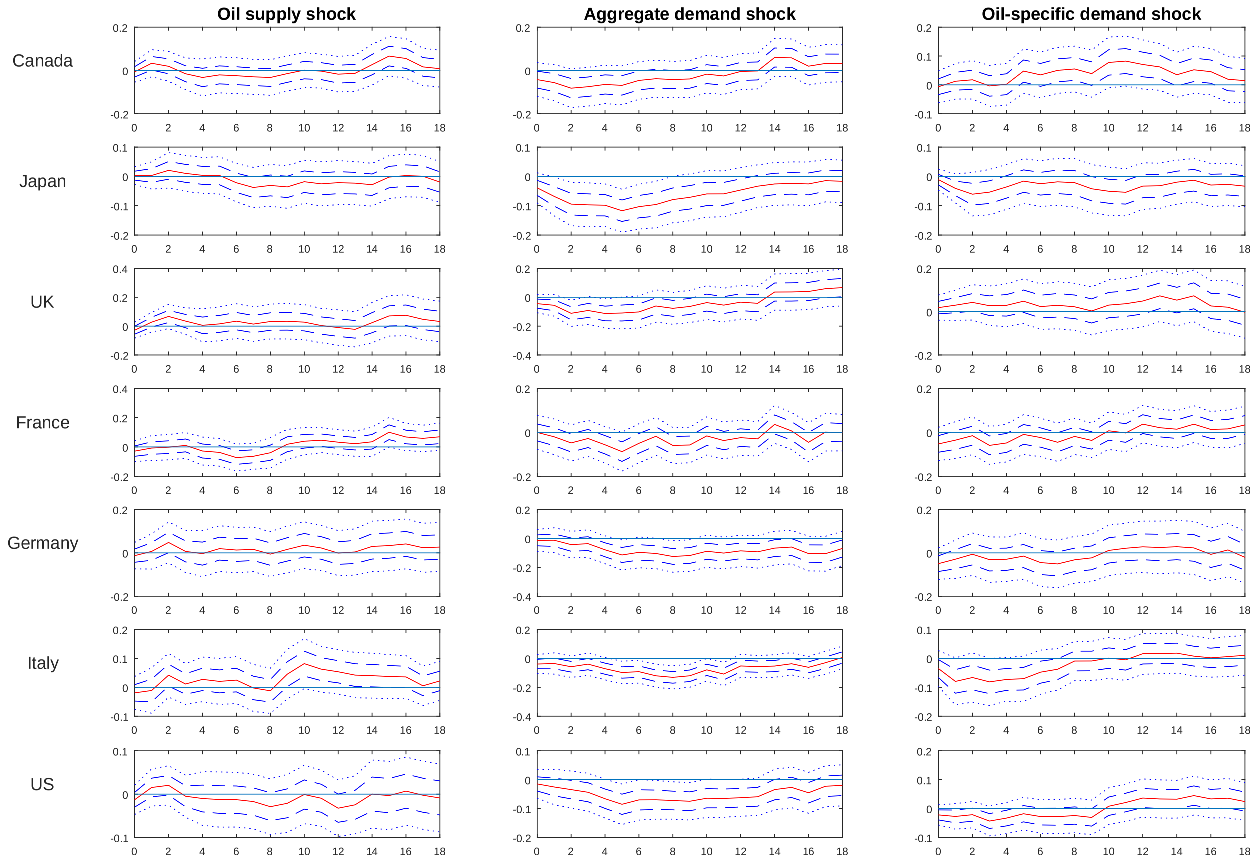
Notes: each row shows the estimated response of the realized volatility of the MSCI index of the country, indicated on the left, to a one-standard deviation shock reported at the top of each column. The dashed and dotted lines represent the one and two-standard error bands, corresponding to 68% and 95% confidence intervals. They are based on a recursive-design wild bootstrap with 2000 replications (Gonçalves and Kilian (2004)).

Figure 2: Responses of log-volatility to structural shocks (Feb. 1975-Jan. 2015)



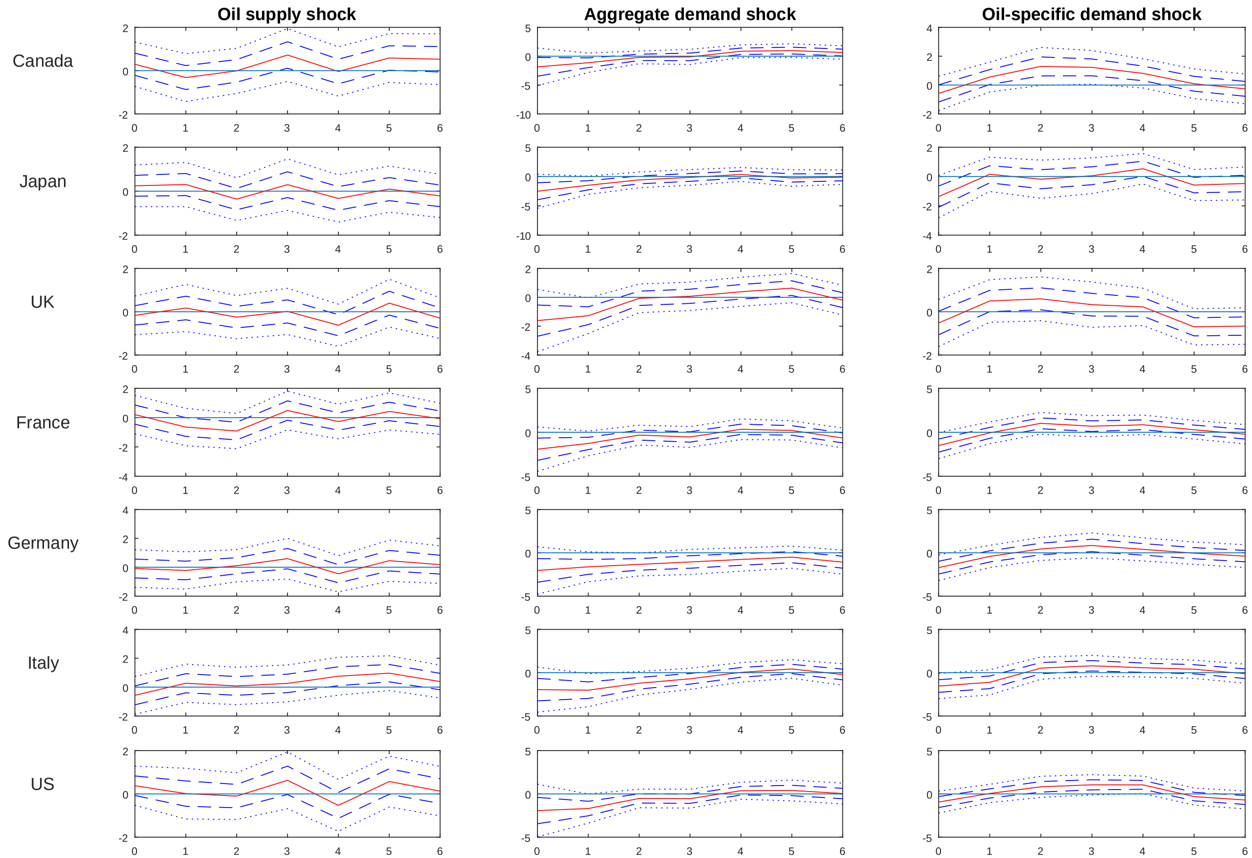
Notes: each row shows the estimated response of the natural logarithm of realized volatility to a one-standard deviation shock reported at the top of each column.

Figure 3: Responses of conditional volatility to structural shocks (Feb. 1975-Jan. 2015)



Notes: each row shows the estimated response of conditional volatility, estimated with a GARCH(1,1) model, to a one-standard deviation shock reported at the top of each column.

Figure 4: Responses of realized volatility to structural shocks. Quarterly data (Q2 1975-Q4 2014)



Notes: each row shows the estimated response of quarterly realized volatility to a one-standard deviation shock reported at the top of each column. Quarterly data were obtained by aggregation of monthly data.