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Thomas S. Gundersen

NORWEGIAN BUSINESS SCHOOL

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Abstract

I examine the role of the U.S. shale oil boom in driving global oil prices. Using a structural vector autoregressive (SVAR) model that identifies separate oil supply shocks for the U.S. and OPEC, I find that U.S. supply shocks have exerted considerable negative pressure on the oil price. More specifically, U.S. supply shocks explain up to 13% of the oil price variation over the 2003–2015 period, considerably more than what has been found in other studies. However, the timing of the downward pressure on prices is delayed relative to the boom in U.S. shale oil production. This mismatch implies a temporary friction in the transmission of U.S. supply shocks to the rest of the world likely caused by logistical and technological challenges in the downstream supply chain.

JEL-codes: C32, Q33, Q35
Keywords: structural VARs, oil prices, demand and supply shocks, shale oil.

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†BI Norwegian Business School, Centre for Applied Macro-, Petroleum and Energy Economics (CAMP). Email: thomas.s.gundersen@bi.no.

1 Introduction

Few other commodities enjoy the same level of attention among economists as crude oil. It serves as an important input for a large share of production and is actively traded in the financial markets. It has been at the centre of wars and conflicts and can be a contributing factor to political turmoil and geopolitical tensions as well as leading to inflationary pressure and recessions (Hamilton 1983, 1985). Thus it is not surprising that a significant change in the price of oil spurs interest and debate.

During the summer of 2014, the oil price practically collapsed. From fluctuating around \$120 per barrel, the price hit the \$28 mark in January 2016, a decrease of more than 75 per cent. In the decade preceding the collapse, the United States saw an unprecedented surge in crude oil output after more than two decades of production decline. This sudden spurt was the result of innovations in shale oil extraction technology, as well as record high oil prices. Still, the role of U.S. shale oil in the subsequent collapse of the oil price is still debated. In particular, since the seminal paper by Kilian (2009), demand shocks have been commonly viewed as the main driver of oil price fluctuations (see e.g. Kilian and Murphy (2012) and Aastveit, Bjørnland and Thorsrud (2015)). While Baumeister and Kilian (2016) argue that slow growth in emerging markets may also have played a key role in the large oil price drop of 2014, it is hard to rule out oil supply shocks considering the unprecedented surge in oil production over the last decade, especially in the United States. This is also supported by the recent findings of Caldara, Cavallo and Iacoviello (2016) who attribute a larger role for supply. Yet none of the recent papers examine the role of the United States and the shale oil boom explicitly.

In this paper, I aim to rectify this shortcoming and explore the implications of increased U.S. self-sufficiency in crude oil for oil prices over the 2003:M01–2015:M12 period. The hypothesis is that additional oil production produced by the U.S. shale oil fields has put a downward pressure on prices. To analyse this hypothesis, I estimate a structural vector autoregression (SVAR) model which includes a measure of U.S. crude oil supply, OPEC production, a measure of global economic activity and the real price of oil. The model builds on Kilian (2009) in that oil supply and demand shocks are identified separately. Novel to my model, however, is the explicit distinction between U.S. and OPEC supply shocks. To quantify the role of changes in U.S. supply, I use a constructed U.S. imports variable. The variable is constructed as the residual from a regression of U.S. crude oil imports on measures of domestic and foreign demand for U.S. crude oil. The supply shock from the U.S. is interpreted as a sudden negative shift in U.S. demand for foreign crude oil due to higher domestic availability.

I find strong support for the hypothesis that the U.S. shale industry has put a downward pressure on global oil prices. In particular, following a positive U.S. supply shock that lowers U.S. imports by 1%, the real price of oil falls by almost 2%. U.S. supply shocks explain up to 13% of the variation in the real price of oil over the sample period. Taken together, U.S. and OPEC supply shocks account for a third of the variation in the real price of oil. This is considerably higher than what has been found by earlier studies in the literature and reintroduces supply as an important driver of oil prices.

The remainder of the paper is structured as follows. Section 2 gives a brief narrative of the U.S. shale oil boom and the plunge in the oil price during 2014 and 2015. Section 3 presents the SVAR model which includes an adjusted measure of U.S. crude oil imports to identify U.S. supply shocks. I present the results in section 4 while showing that a model in the spirit of Kilian (2009), including U.S. crude oil production instead of oil imports, fails to deliver satisfactory results. Section 5 discusses robustness with alternative identifying restrictions.

2 Data environment

2.1 The U.S. shale oil boom

Shale oil is petroleum found in rock formations of low permeability.[1] Primary recovery from conventional oil wells requires only drilling because the pressure differential brings the oil to the surface (Bret-Rouzaut and Favennec 2011). Shale oil, on the other hand, cannot be extracted by traditional methods as the sediment in which it is enclosed bars it from flowing freely. A combination of two technologies makes this extraction commercially viable: hydraulic fracturing (*fracking*) and horizontal drilling. The former allows the oil to escape the rocks and the latter lets more rock be fracked at the same time. The development of these technologies was fuelled by the period of high oil prices in the run-up to the financial crisis and subsequent years (Alquist and Guénette 2014; Kilian 2016; Maugeri 2013). Unconventional oil thus became competitive against conventional techniques, and investments in shale oil gained traction.

2.1.1 The Cushing glut

It is easy to justify an assertion that the fall in global oil prices, at least to some extent, was due to the U.S. shale oil boom. However, there are two caveats to consider relating to the timings of the boom and the fall in prices. The first is related to the lack of appropriate transportation infrastructure in shale oil rich regions of the United States and the second to the chemical properties of shale oil.

North Dakota has become a prominent shale producer, but has not been an important producer of conventional oil historically. For this reason, pipelines and rail capacity did not exist to accommodate the rapid expansion of oil production in the state, making it more costly for the producers to get the oil to the market. When shale oil production started, it was not evident that it was going to be a reliable new source of energy, something that hampered willingness in the sector to expand capacity in transportation (Wilkerson and Melek 2014).

Second, the chemical make-up of shale oil is different from that of conventional oil. In general, the chemical properties of shale oil are characterised as light and sweet, measured by API gravity and sulphur content respectively. These

[1] Shale oil should not be confused with *oil shale*, sedimentary rocks with high kerogen content. Liquid petroleum can be extracted from these rocks, but it is a costly and capital intensive process (Bret-Rouzaut and Favennec 2011). Because of this confusion, shale oil is often referred to as *tight oil*.

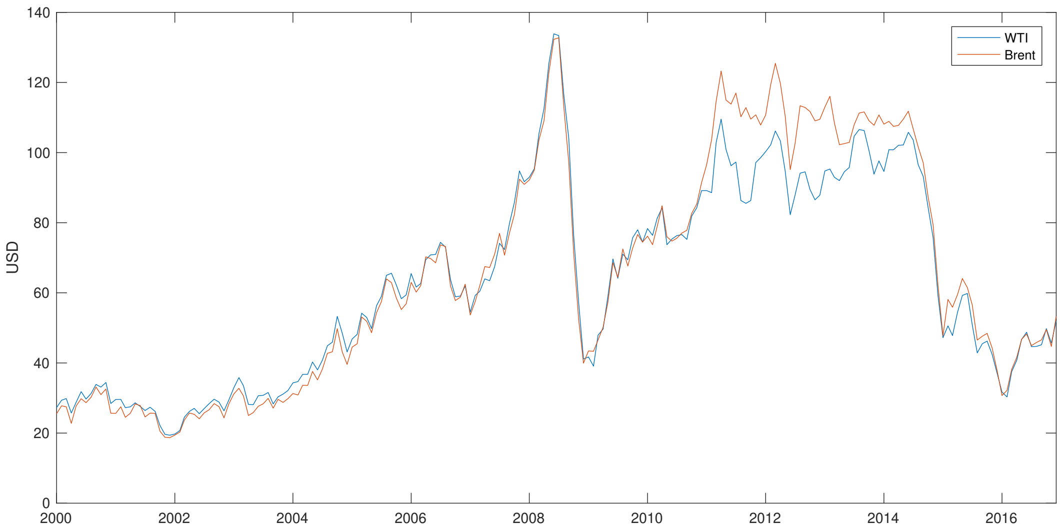

Figure 1: West Texas Intermediate and Brent Blend benchmark prices, 2000–2016, at monthly frequency
Source: Federal Reserve Bank of St. Louis Economic Data (FRED)

are similar to the properties of crude oil that has been produced in the U.S. traditionally. However, because of declining crude oil production from conventional wells since the 1970s, refineries along the Gulf Coast have been relying on imports from the Middle East to cover petroleum product demand. This oil, however, is characterised as heavy and sour. These refineries were fitted accordingly and have been mostly unable to process lighter oil without further investments in new or upgraded equipment.[2] Several obstacles related to the processing of shale oil have also been reported by the industry, namely that shale oil differs chemically, not only from conventional oil, but also from sample to sample extracted from the same shale play (Baker Hughes 2013; Benoit and Zurlo 2014). These developments spawned a glut of light sweet crude oil in Cushing, Oklahoma. The emergence of this glut can be seen in Figure 1 as a price spread widening between the Brent Blend and the West Texas Intermediate (WTI) benchmarks. The persistent spread in prices created incentives for refineries to adapt to the new opportunities in shale oil refining. Over time and in addition to the use of trucks, rail and river barges, pipelines were constructed from the storage facilities in Cushing to the refineries along the Gulf Coast (see Wilkerson and Melek 2014). The closing of the Brent–WTI spread later on is an indication that U.S. oil to a larger extent was adopted by the domestic refining industry.

The implication of this glut in Cushing was a temporary friction in the trans-

[2] While refining plants on the East Coast which typically import light and sweet North Sea oil could use the shale oil as feedstock, the necessary infrastructure to transport the oil is not in place. Some refineries on the Gulf Coast had the necessary equipment to process shale oil, but the lack of southbound pipelines from the Midwest hindered the adoption (Kilian 2016).

mission of booming shale oil supply in the U.S. to the oil prices globally. While the inventories of shale oil continued to build in Cushing, the refineries had to continue importing crude from abroad in order to satisfy demand for petroleum products. In other words, as the U.S. oil supply was booming, the impact on global prices was cushioned by the glut until downstream buyers were able to adapt their refining processes and utilise domestic shale oil to a greater extent, thereby reducing the need for foreign imports. This mechanism will be modelled explicitly in the next section.

3 A Structural VAR with U.S. imports of crude oil

In this section, I present the empirical model that I use in my analysis. Novel to my approach is that in order to capture U.S. oil supply, I construct a measure of U.S. imports of crude oil. I then analyse the effects of U.S. oil supply shocks, along with the other shocks, on the global oil market using a structural VAR model.

3.1 U.S. imports of crude oil

Since I am interested in how developments in the U.S. oil industry have affected the global oil market, a U.S. centric model design with an appropriate measure of U.S. oil supply is needed. A key point is that any increase in U.S. supply of crude oil only transmits to prices globally if it displaces foreign sources of oil. Hence, the only way the U.S. can affect the global oil price is by changing their net exports. The idea is therefore to capture shifts in U.S. demand for foreign crude oil that occur due to a higher availability of domestic supply, i.e. shifts in imports due to higher U.S. oil production.

Equation 1 explains the relationship between U.S. self-sufficiency, net exports and changes in inventories.

$$\text{U.S. Production} - \text{U.S. Consumption} = \text{Exports} - \text{Imports} + \Delta\text{Inventories} \quad (1)$$

In this context, consumption refers to the number of barrels of crude oil U.S. refineries use as input to produce petroleum products. After the enactment of the Energy Policy and Conservation Act of 1975, the U.S. government banned

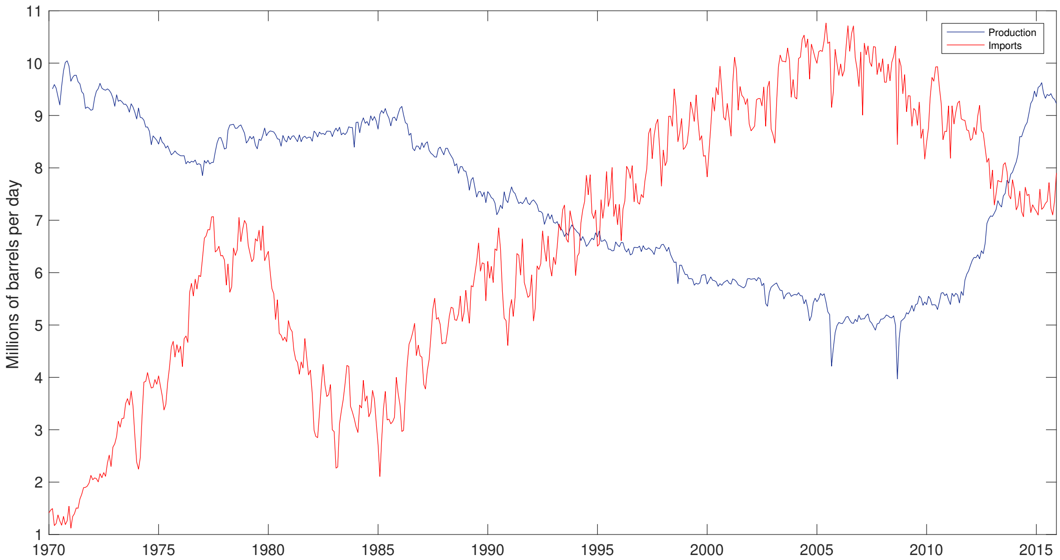

Figure 2: U.S. crude oil production and imports, 1970–2015. Source: EIA

exports of crude oil and natural gas.[3] While, given the appropriate permissions, some export could take place, the extent of this flow is negligible relative to total U.S. oil production.[4].

Moreover, holding inventories are likely only to be done to smooth out gluts and shortfalls in the flow of oil. Therefore, build-ups of inventories are likely to be transitory and even out over time.[5] By setting exports and the change in inventories equal to zero and re-arranging, equation 1 can be simplified to:

$$\text{Imports} = \text{U.S. Consumption} - \text{U.S. Production} \tag{2}$$

The demand for oil that is not satisfied by domestic production thus has to be covered by changes in imports.

Figure 2 shows a clear negative correlation between U.S. oil production and imports over the long run. Tropical storms and hurricanes are temporary shocks to both variables causing the series to co-move. Most of these shocks hit during the August–October hurricane season. Hurricane Katrina (2005) and Hurricane Ike (2008) are by far the most devastating in terms of volumes and

[3]This clause was repealed in the Consolidated Appropriations Act of 2016, signed into law in January 2016. Crude oil exports are once again legal in the United States. This will restrict the sample size used in the analysis to end in December 2015.

[4]These exports have mainly come from production sites in California and Alaska (EIA 2014; 2015). On average, exports relative to U.S. production have been around 1% from 2003 to 2015 with a peak at 6% in April 2015. The vast majority of U.S.-sourced crude goes to Canada (EIA 2014b), but starting in 2014, some crude leaving the Gulf was shipped to Europe and Asia. However, this is Canadian oil re-exported by the United States (EIA 2014a). This might help explain the growth in U.S. exports relative to U.S. production starting in 2014.

[5]The monthly changes in U.S. inventories resemble a covariance stationary process with mean close to zero. See Appendix B for details.

clearly visible in Figure 2. Further, the decline in imports after 2005 precedes the boom in domestic supply, indicating that the initial fall in imports was due to lower U.S. consumption. This poses a challenge for representing U.S. oil supply with U.S. imports as variations in imports would need to be orthogonal to shifts in domestic demand while at the same time being correlated with domestic supply. To ensure that the orthogonality condition is satisfied, I therefore regress U.S. imports on variables that reflect demand for oil. I then use the residual from this regression as a proxy for U.S. oil supply.

Two variables with the appropriate monthly frequency and sample availability were chosen for the regression. *Vehicle miles travelled* captures domestic demand for petroleum products through the use of road vehicles. It includes cars and larger diesel vehicles used in freight transportation. More traffic on U.S. roads implies a higher demand for petroleum products which induces demand for crude oil from refineries. The refineries can choose to import the oil or use what is produced domestically. However, the mileage on the U.S. vehicles each month does not affect the amount of oil extracted from the ground directly. *Petroleum product exports* captures demand for American crude oil abroad through exports of refined products from U.S. refineries.[6] Again, the refineries have to make use of imports or domestic supply. How much is refined and exported does not directly determine how much crude oil is taken up from the ground. See Appendix A for more information about the dataset.

$$\Delta usimp_t = \underset{(0.28^{***})}{0.843}\,\Delta vmt_t + \underset{(0.03^{***})}{0.12}\,\Delta petrolexp_t + \hat{e}_t \quad \bar{R}^2 = 0.17 \qquad (3)$$

Equation 3 describes the regression that I estimate on the sample 2003:M01–2015:M12. All variables are in log-differences and the standard errors are shown in parentheses. The residual is the measure of U.S. oil supply that I will later include in the structural VAR model (explained in the next section). The variable (residual) is orthogonal to demand innovations and therefore captures the supply effects of oil imports. In other words, a negative shock to the modified U.S. imports variable can be interpreted as a decision by refineries to import less crude because of a sudden abundance of domestic supply. This will hold as long as U.S. refineries always prefer to use domestic supply rather than imports. A positive shock will then reflect the need for more imports because of less domestic production.

[6] The U.S. became a net exporter of petroleum products in 2011 (EIA 2015)

3.2 The Structural VAR model

I will now include my constructed measure of U.S. imports in a Structural VAR model. Having a U.S.-specific variable in the model necessitates the use of OPEC production as an alternative measure of foreign supply. The reason for this is twofold. The first is due to a possible simultaneity issue, as U.S. oil production is a component of global production. The second reason has to do with the data itself. Aggregate global production exhibits low variation relative to more disaggregated measures, possibly reflecting that a shortfall of production in one location is met by an increase somewhere else thereby neutralising fluctuations. While the same can be said about the producers within OPEC, the member countries as a group account for most of the short-run fluctuations in the global output (see e.g. Almoguera, Douglas and Herrera 2011). OPEC production is an interesting candidate as it represents a large bulk of global production and possibly captures some interesting dynamics between itself and the U.S. Adding separate supply-equations for different oil producers has been done by Kang, Ratti and Vespignani (2016; 2017) with U.S. and non-U.S. production, Ratti and Vespignani (2015) and Kolodzeij and Kaufmann (2014) with OPEC and non-OPEC production. Common to these papers is the argument that aggregate global production leads to underestimation of the influence of supply shocks on oil prices.

This model is an augmentation of the Kilian (2009) 3-variable model that includes aggregate global oil production, the measure of global activity and the real price of oil.

Consider the following reduced form VAR model

$$\mathbf{Y}_t = \boldsymbol{\mu} + \sum_{p=1}^{P} A_p \mathbf{Y}_{t-p} + \mathbf{e}_t \tag{4}$$

where $\mathbf{Y}_t$ is the vector of variables, OPEC crude oil production, adjusted U.S. crude oil imports, an index of real economic activity (Kilian 2009) and the real price of oil. $\boldsymbol{\mu}$ is a vector of intercept terms and $\mathbf{e}_t \overset{iid}{\sim} N(0, \Sigma_{\mathbf{e}})$ where $\Sigma_{\mathbf{e}}$ is positive semi-definite and symmetric. To identify the structural shocks, let the reduced form errors be decomposed such that $\mathbf{e}_t = S\boldsymbol{\varepsilon}_t$ where matrix S is the lower triangular component of the Cholesky decomposition of $\Sigma_{\mathbf{e}}$ and $\boldsymbol{\varepsilon}_t$ is the structural shocks with the property that $\mathbb{E}\left[\varepsilon_t \varepsilon_t'\right] = I$. The way S is identified implies that a recursive structure is imposed where the responses of the variables ordered at the top in $\mathbf{Y}_t$ will be restricted to zero contemporaneously.

Now, consider equation 5, which shows the structural representation of the same model now specified with 18 lags. Hamilton and Herrera (2004) demonstrated with their replication of the Bernanke, Gertler and Watson (1997) model that a rich lag structure is needed to capture oil price shocks. An *ex ante* choice of 1.5 years worth of lags rather than the use of information criteria is in line with the recommendations of Kilian and Lütkepohl (2017).

$$\begin{bmatrix} \Delta opecprod \\ \Delta usimp^S \\ rea \\ lrpo \end{bmatrix}_t = \begin{bmatrix} \nu_1 \\ \nu_2 \\ \nu_3 \\ \nu_4 \end{bmatrix} + \begin{bmatrix} \theta_{11} & 0 & 0 & 0 \\ \theta_{21} & \theta_{22} & 0 & 0 \\ \theta_{31} & \theta_{32} & \theta_{33} & 0 \\ \theta_{41} & \theta_{42} & \theta_{43} & \theta_{44} \end{bmatrix} \begin{bmatrix} \varepsilon^{\Delta opecprod} \\ \varepsilon^{\Delta usimp^S} \\ \varepsilon^{rea} \\ \varepsilon^{lrpo} \end{bmatrix}_t + lags \tag{5}$$

Supply variables are ordered at the top, followed by global demand and, lastly, the oil price. OPEC supply shocks are defined as unexpected changes in oil production in OPEC member countries. A U.S. import shock is a sudden change in the importing decision of U.S. refineries reflecting the availability of domestically produced crude oil. By placing OPEC on top, a short-run vertical supply curve is imposed. Hence, OPEC cannot adjust their production within a month after shocks to aggregate demand, nor after shifts in beliefs about the state of the future oil markets (oil-specific demand shocks). Taking into consideration the adjustment costs of changing their production schedules, necessary cartel coordination among OPEC members, but also lack of information regarding business cycle movements in real time, oil producers are likely to respond to these innovations with a lag. Additionally, OPEC cannot respond to U.S. import shocks contemporaneously, reflecting OPEC's inability to observe what the United States imports from abroad in real time. This information is published by the EIA later on.[7] Finally, the refineries in the U.S are assumed not to react to aggregate demand and oil-specific demand shocks instantly. Although oil prices are observed in the market daily, the American suppliers are slow to ramp up their production due to adjustment costs. Hence, the effect of higher oil prices on imports when the U.S. supply situation is taken into account is delayed. Still, the United States is ordered beneath OPEC production as there is evidence which suggests that shale producers are more flexible than conventional producers (see e.g. Bjørnland, Nordvik and Rohrer 2017).[8]

An abrupt change in global real activity is here represented by a shock to the demand of industrial commodities, henceforth called an aggregate demand shock (see Kilian 2009). Innovations to the real price of oil that are not explained by either supply or demand are called oil-specific demand shocks and

[7] Since the structural shock to U.S. imports reflects domestic supply conditions, it is even tougher for OPEC to monitor.

[8] A specification where this ordering is flipped is included in Appendix D.

reflect primarily precautionary demand for crude oil related to expectations of future supply shortfalls (see Kilian 2009).[9] The exclusion restriction implies that global real activity takes one month to adjust to oil-specific demand shocks. While oil prices are observable daily, economic agents are slow to change their behaviour, and the effect on the level of real activity is therefore delayed. This is consistent with the historical relationship between oil prices and business cycle movements (see e.g. Hamilton (1985)). The real price of oil equation is left unrestricted. These identifying restrictions are similar to those first imposed by Kilian (2009). In section 5, I show that the results are robust to alternative restrictions.

4 Empirical results

The sample period used for the estimation is 2003:M01–2015:M12. As shown by Baumeister and Peersman (2013), parameter instability is a prevalent feature of oil market models over the commonly estimated sample beginning in the early 1970s. The choice of sample period is ultimately motivated by the research question. Shale oil production in the U.S. did not begin to catch on before 2003 and the U.S. export ban on exports was lifted in December 2015. Extending the sample backwards, however, does not affect the main results until 1997 when statistical significance is lost. Estimated impulse responses are shown in Figure 3.

Starting with the supply shocks (left columns), a sudden innovation to OPEC supply growth leads to a persistent increase in their level of production. The United States begins to import more on impact and periodically so over the next year. The response of global activity is clearly negative and statistically significant over time. The real price of oil initially increases, but turns negative within 6 months.

The second column shows the responses to the U.S. import shock. A negative shock to U.S. imports, reflecting a sudden abundance of domestically produced crude oil, does not change OPEC production nor global activity. Interestingly, U.S. imports exhibit a very low degree of persistence as it returns to pre-shocks levels within two months. Still, the oil price exhibits a persistent but gradual decrease. When the U.S. reduces its imports by 1%, the oil price falls by almost 2% after ten months and is significantly negative after eight months.

Turning to the demand side, the third column shows the responses to the aggregate demand shock that increases global activity. The shock leads OPEC

[9] The interpretation of this shock should not be taken too literally however, as it will reflect all residual variation in the oil price not explained by the other endogenous variables.

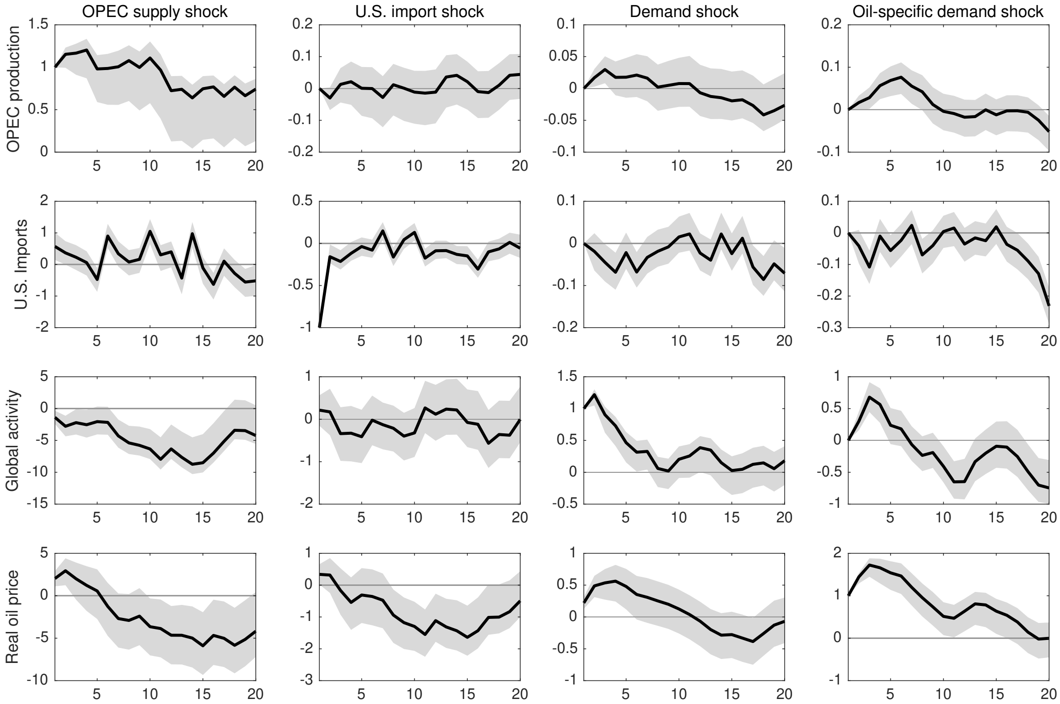

Figure 3: Impulse responses generated from the model described in equation 5. The sample is 2003:M01–2015:M12. They are all in levels of the variables. Shocks are normalised so that the response of the variables is 1 on impact, i.e. 1% for the OPEC supply shock, U.S. supply shock and aggregate demand shock while one log unit for the oil price. The shaded areas represent 68% confidence bands calculated using a bootstrap with 10,000 draws.

and the United States to produce more (imports less) crude oil, but only temporarily. The oil price responds by increasing on impact and follows a hump-shaped trajectory back to zero as expected.

Following an oil-specific demand shock (right column), both OPEC and the U.S. follow sound trajectories. OPEC starts to produce more while the Americans import less, implying that their domestic supply is higher. For OPEC, the response is slow, but it is much more persistent than that of the U.S. and lasts for almost eight periods. A puzzling result is that of global activity, which initially increases following the shock to oil prices. This is a similar result as that seen in Kilian (2009), later attributed to not allowing emerging and developed economies to respond differently to oil market shocks (see Aastveit et al. 2015).

The historical decomposition of the real price of oil is presented in Figure 4. The cumulative effect of the U.S. import shock has since late-2013 contributed to pushing oil prices down. OPEC, on the other hand, seems to have been working to increase prices following the 2014 fall. Oil-specific demand has also contributed, possibly reflecting the expectations of an oversupply in the oil markets. Caldara et al. (2016) find similar results for the 2014–15 episode, but do not identify separate U.S. and OPEC supply shocks. Baumeister and

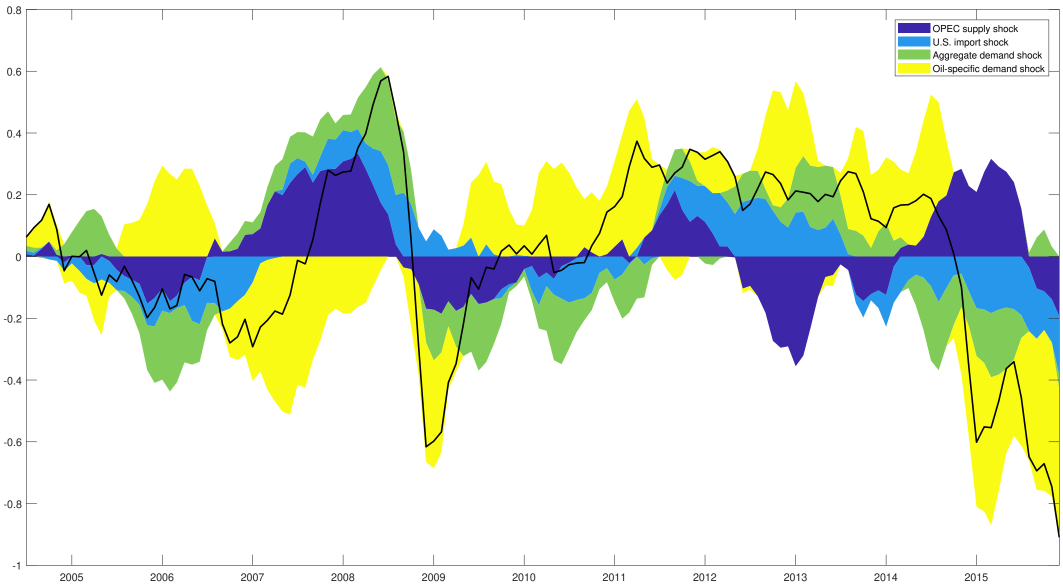

Figure 4: Historical decomposition of the real price of oil derived from the model described in equation 5. The shaded areas correspond to the cumulative effects of the different shocks on the oil price.

Kilian (2016) find evidence that prior to the slump in oil prices, movements in oil supply could predict parts of the decline that would occur, later which is consistent with the findings here. In contrast to the U.S. import shocks, aggregate demand shocks did not influence prices negatively until 2014 and only did so for the first of the two dips in prices that occurred between 2014 and 2016. Overall, the influence of demand factors in the historical decomposition is reduced compared to e.g. Kilian (2009).

Variance decomposition of the real price of oil

	Shocks			
	OPEC supply	U.S. imports	Aggregate demand	Oil-specific demand
1	7.73	2.12	7.15	83.00
	[2.41;16.06]	[0.22;7.58]	[2.31;13.51]	[70.10;87.98]
5	3.07	1.03	14.44	81.45
	[1.89;11.37]	[1.12;8.60]	[4.53;27.01]	[60.50;85.41]
10	5.83	5.16	12.05	76.96
	[4.11;20.97]	[2.93;17.32]	[4.75;25.73]	[48.15;77.08]
15	13.53	11.60	10.14	64.73
	[6.82;32.33]	[5.10;22.79]	[5.99;24.57]	[36.51;66.84]
20	19.87	13.18	10.45	56.50
	[8.94;39.33]	[5.34;23.52]	[6.93;26.59]	[30.19;60.37]

Table 1: Variance decomposition (in percentages) of the real price of oil for different time horizons, generated from the imports model described in equation 5. The confidence intervals (in brackets) are at the 68% level and computed using a bootstrapping method with 10,000 draws.

The variance decomposition of the real price of oil is presented in table 1. U.S.

supply-side innovations explain up to 13% of the variation in the oil price. OPEC and the United States together account for 33% of the fluctuations in the oil price at the 20-months forecast horizon according to the model. In recent years, the literature has been giving supply-side explanations of oil price fluctuations an increasingly smaller role. The current results, together with Caldara et al. (2016), however, provide evidence of the importance of supply.

In particular, the results presented here suggest that the U.S. shale oil boom has contributed significantly to lowering oil prices during 2014 and 2015. While this result might seem surprising considering the rapid growth in U.S. shale oil output began as early as 2011, it is consistent with the accounts of frictions in the supply-chain delaying the adoption of shale oil by U.S. refineries (see section 2.1.1). The closing of the Brent–WTI spread in late 2013 and early 2014 lines up with the emergence of the negative cumulative effect U.S. import shocks had on the oil price as can be seen by comparing Figure 1 and 4. This suggests that the adoption of shale oil in the domestic refining sector finally displaced foreign crude oil imports and the price spread narrowed as a result.[10]

The choice of representing the U.S. supply side of the oil market with (adjusted) U.S. imports was motivated by the research question. However, it has been customary in this literature to have a supply equation where the endogenous variable is the quantity of crude oil produced. The conclusion commonly drawn from these models is that oil supply shocks cannot explain oil-price fluctuations. The results from a model identical to the one presented above, but where U.S. imports are replaced by U.S. crude oil production, are presented in Appendix C. The gains from identifying the U.S. supply shocks by exploiting the relationship between domestic production and imports rather than with the quantity produced directly are evident. The response of OPEC to a positive U.S. supply shock, as seen in Figure 6, is sensible in that they increase output, consistent with attempting to keep their market share. The responses of global activity and the oil price – which both get a temporary boost – are however, puzzling. In particular, one would not expect oil prices to increase when both the U.S. and OPEC expand output. The estimated response eventually turns negative, but is not significantly different from zero.[11] In addition, the model fails at explaining the 2014 fall in oil prices as illustrated by the historical decomposition in Figure 7. Specifically, the oil-specific demand shock (a residual shock) explains the lion's share of the movements in the real price

[10] As has been pointed out earlier, U.S. imports and U.S. crude oil production have been sensitive to hurricanes and tropical storms in the Gulf Region. However, the 2013 Atlantic Hurricane season was the least active in two decades (NOAA 2014) so these disruptions are not driving the results in this period.

[11] Kilian (2009) also found that the response of global activity moves in the same direction as oil production following a supply shock. However, his results also showed that the real price of oil moves in the opposite direction, contrary to the results here.

of oil past mid-2014 suggesting that the supply (and demand) shocks are not well identified. Hence, a model that includes U.S. crude oil production rather than U.S. imports does not shed light upon the research question or reaffirm results from previous studies.

5 Robustness and sensitivity checks

To check the robustness of the results I impose different identifying restrictions. The details are given in Appendix D, so a brief summary will suffice here.

First, I rearrange the ordering of the variables so that the U.S. is placed on top and OPEC second. The results do not change compared to those of the main baseline ordering. Second, I re-estimate the baseline model using Bayesian methods with flat priors. For identification, I impose a mix of sign and zero restrictions on the contemporaneous impact matrix. In particular, the zero-restriction on the θ_{12} parameter is relaxed to be negative on impact. This implies that following a shock that lowers U.S. imports, OPEC will respond by increasing their output. The main results from the baseline model remain robust to the chosen identification strategy.

6 Conclusion

In this paper I analyse the impact of the U.S. shale oil boom on global oil prices. In doing so, I estimated a structural VAR based on Kilian (2009) with OPEC production, a modified U.S. crude oil import variable, a measure of real economic activity and the real price of oil. The use of crude oil import data in a structural VAR to model the case of the United States directly is to my knowledge new to the literature. It is modified so as only to capture U.S. supply innovations. This approach is the most sensible given the institutional framework in place in the United States up until December 2015 as it gives a clear transmission mechanism of domestic supply shocks to oil prices abroad.

Firstly, the findings show that a 1% reduction in U.S. imports causes the oil price to decrease by almost 2% after ten months. The U.S. import shock, reflecting the domestic supply environment, explains up to 13% of the variation in the oil price over the sample period 2003–2015. The U.S. and OPEC together account for a third of the variation in the oil price. This is significantly more than what has been found in earlier studies. Secondly, the results show that the developments in the U.S. oil industry had no significant effect on global prices until the end of 2013.

These results suggest that the U.S. shale oil boom *has* in fact been able to affect global oil prices negatively. However, the analysis shows that oil prices were not affected until the end of 2013. The cause of the delay is puzzling considering the length of time U.S. production figures had been on the rise. A possible explanation for the lagged transmission of U.S. supply shocks to the rest of the world is the oil glut in Cushing, Oklahoma caused by the postponed adoption of shale oil by the domestic refining industry, indirectly observable in the WTI–Brent price spread.

The results put forward in this paper add to the discussion of the role of the U.S. in the oil price fall of 2014/2015. Contrary to earlier studies, I find an increased importance of supply side factors in explaining oil price fluctuations. Further, they also show that the United States' role in the market has fundamentally changed and will have implications for oil prices globally going forward as a result of the boom in the U.S. shale oil industry.

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A Data

Variable	Description	Source
$\Delta opecprod$	Log-change in total OPEC crude oil production in thousands of barrels per day. Datastream identifier: OPPCOBD.P	Thomson Reuters Datastream – EIA
$\Delta usimp^S$	Log-change in U.S. crude oil imports in millions of barrels per day. Adjusted for demand factors (see text for details).	Energy Information Administration
Δvmt	Log-change in the Vehicle Miles Travelled index compiled from automatic roadside traffic monitors. Seasonally adjusted.	Federal Highway Administration. Retrieved from FRED database, St. Louis Fed. `https://fred.stlouisfed.org/series/TRFVOLUSM227SFWA`
$\Delta petrolexp$	Log-change in U.S. petroleum products exports in million barrels per day.	Energy Information Administration.
$\Delta usprod$	U.S. field production of crude oil in thousands of barrels per day.	Energy Information Administration (EIA)
rea	Measure of global real economic activity based on dry cargo bulk freight rates. Monthly deviations from trend. Introduced in Kilian (2009).	`http://www-personal.umich.edu/~lkilian/paperlinks.html`
$lrpo$	Log of refiner's acquisition cost of crude oil imports deflated by the U.S. CPI.	Energy Information Administration. U.S. CPI retrieved from the FRED database, St. Louis Fed.
$\Delta gprod$	Global crude oil production in thousands of barrels per day. Datastream identifier: WDPCOBD.P	Thomson Reuters Datastream – EIA

Commonly quoted oil prices such as Brent or WTI are not used in the analysis the reason being that these prices reflect market outcomes on particular exchanges for particular types of oil. While they serve as benchmarks for the pricing of oil produced elsewhere, they do not reflect the cost refineries actually pay. For this reason, the U.S. refiner's acquisition cost of imported crude oil is the closest proxy to a true global oil price. It is a volume-weighted price series based on the crude oil imported to the United States. Using this price in oil market VAR models is not uncommon in the literature (see e.g. Aastveit, Bjørnland and Thorsrud 2015; Baumeister and Hamilton 2015; Kilian 2009). For a discussion on the different oil prices and their uses, see Alquist, Kilian and Vigfusson (2013) and Kilian and Vigfusson (2011).

B Augmented Dickey-Fuller test of U.S. Inventories

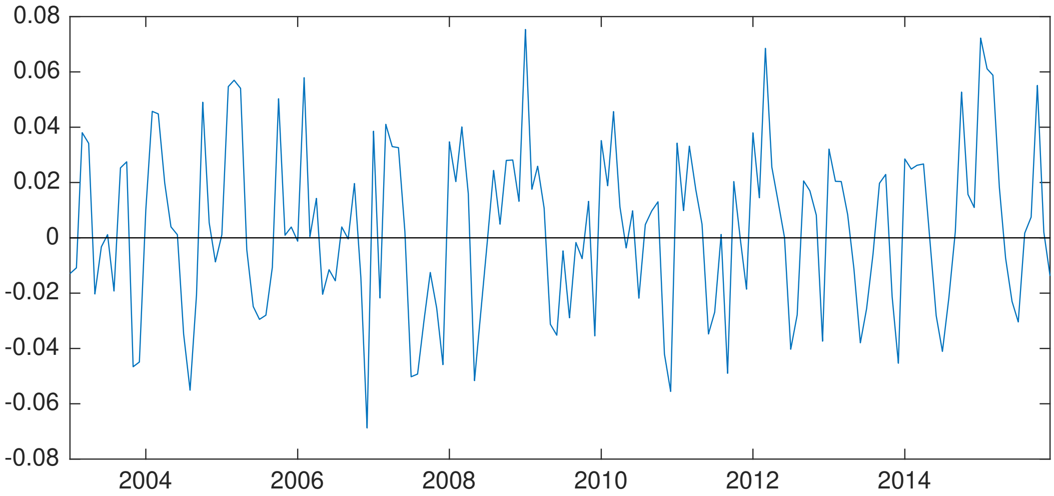

Figure 5: Plot of the log change in U.S. inventories over the sample 2003:M01–2015:M12. Data is retrieved from EIA.

Testing for stationarity: Augmented Dickey-Fuller

Variable	**Lags**	**Test statistics**
ΔU.S. inventories	2	-8.09^{***}
	4	-6.55^{***}
	6	-6.03^{***}
	8	-6.03^{***}
	10	-4.34^{***}
		Critical values
1%		-3.47
5%		-2.88
10%		-2.58

Table 2: An Augmented Dickey-Fuller test, checking for stationarity in U.S. inventory data. The series is tested with a constant term and in first differences after taking the natural logarithm. The sample range is 2003:M01–2015M12 with monthly observations. The null hypothesis is that the series is not stationary. The null hypothesis is rejected.

C Alternative SVAR model with U.S. crude oil production

In section 3.2, a new way of identifying supply shocks was implemented with U.S. crude oil imports. A relevant question is what the results would be if an alternative model that included U.S. crude oil production rather than imports was estimated. The only difference from earlier is the inclusion of U.S. crude oil production instead of oil imports.

The variable ordering is similar to the previous model with supply variables on top and United States production also with a short-run vertical supply curve.

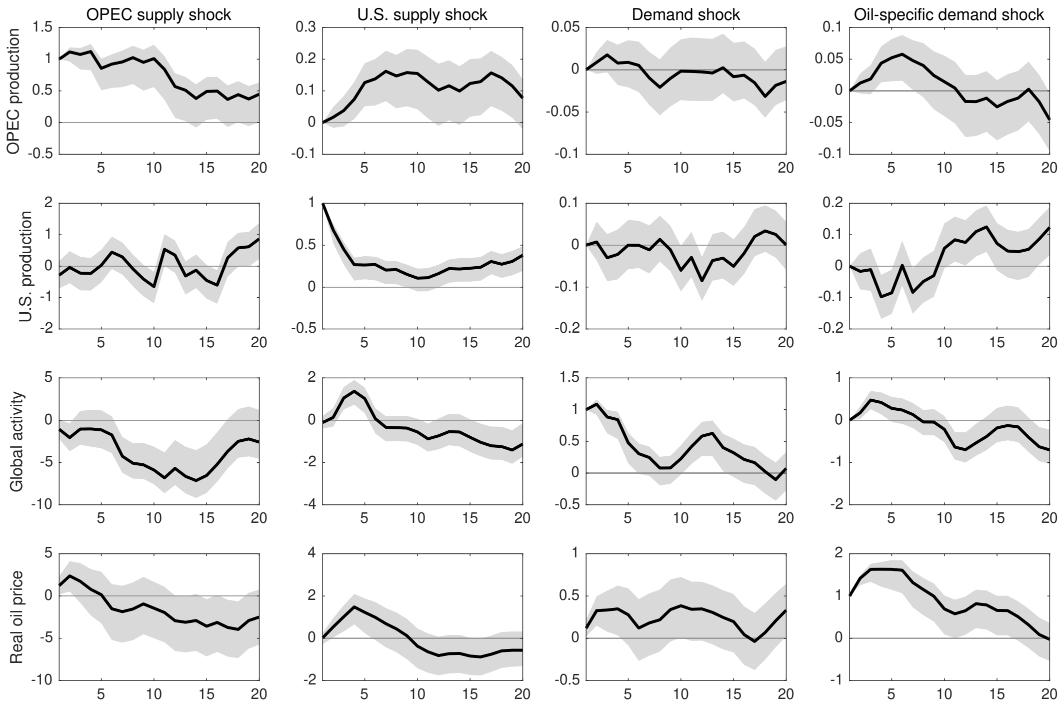

Figure 6: Impulse responses generated from the alternative SVAR model with U.S. production and the sample 2003:M01–2015:M12. They are all in levels of the variables. Shocks are normalised so that the response of the variables is 1 on impact, i.e. 1% for the OPEC supply shock, U.S. supply shock and aggregate demand shock while one log-unit for the oil price. The shaded areas represent 68% confidence bands calculated using a bootstrap with 10,000 draws.

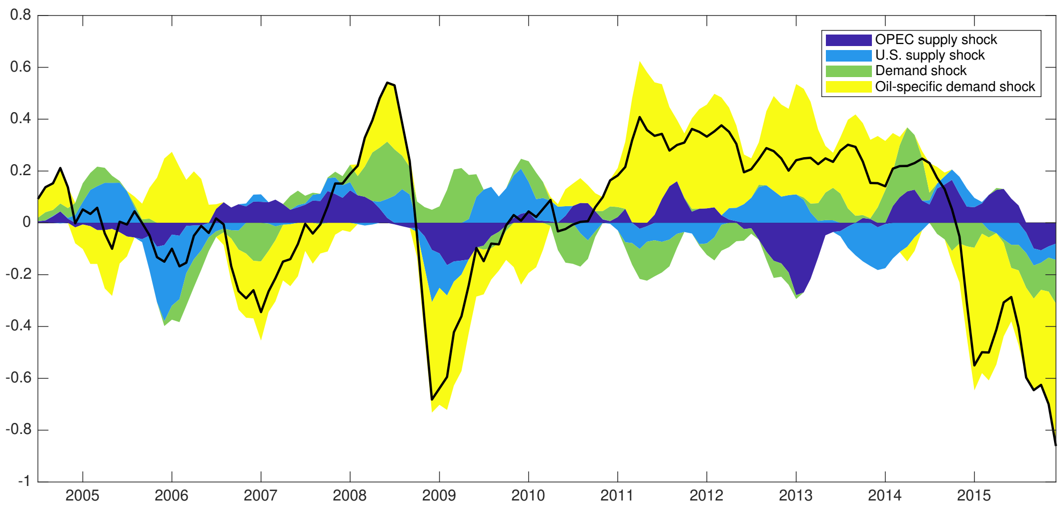

Figure 7: Historical decomposition of the real price of oil derived from the alternative SVAR model with the 2003:M01–2015:M12 sample. The shaded areas correspond to the cumulative effects of the different shocks on the oil price.

Variance decomposition of the real price of oil

	Shocks			
	OPEC supply	U.S. supply	Aggregate demand	Oil-specific demand
1	2.53	0.01	2.09	95.37
	[0.32;8.78]	[0.07;3.15]	[0.26;6.85]	[84.28;96.76]
5	1.47	9.46	5.09	83.98
	[1.15;9.11]	[2.06;22.20]	[1.37;15.64]	[61.41;87.80]
10	1.81	7.87	5.70	84.62
	[2.36;15.26]	[3.75;22.37]	[2.78;20.10]	[52.12;82.37]
15	4.43	9.14	7.26	79.18
	[3.91;21.82]	[5.83;25.40]	[3.64;22.98]	[42.70;75.35]
20	7.37	10.32	7.48	74.84
	[5.35;26.62]	[6.66;26.60]	[4.76;23.50]	[37.06;70.37]

Table 3: Variance decomposition (in percentages) of the real price of oil for different time horizons, generated from the alternative SVAR model with sample 2003:M01–2015:M12. The confidence intervals (in brackets) are at the 68% level and computed using a bootstrapping method with 10,000 draws.

D Section 5 — Robustness and sensitivity checks

D.1 Alternative restrictions

In my baseline model I assume that OPEC oil production cannot respond contemporaneously to U.S. supply shocks. To investigate whether my results are sensitive to this assumption, I report results for two alternative identification schemes.

D.1.1 Alternative ordering

A simple check of whether the results are sensitive to the restriction on θ_{12} is to re-arrange the equations so that θ_{12} now corresponds to the contemporaneous OPEC parameter in the United States imports equation. While often perceived as an infeasible exercise without any prior considerations and in large systems (see Kilian and Lütkepohl 2017), only two different models (orderings) are considered here as the other restrictions are taken as given following Kilian (2009). The results from this model are reported in figure 8. The first two columns show that the main results are insensitive to the ordering of the equations. The main differences are either in terms of statistical significance or the magnitude of the responses to the shocks. The qualitative interpretation of the results remains unchanged.

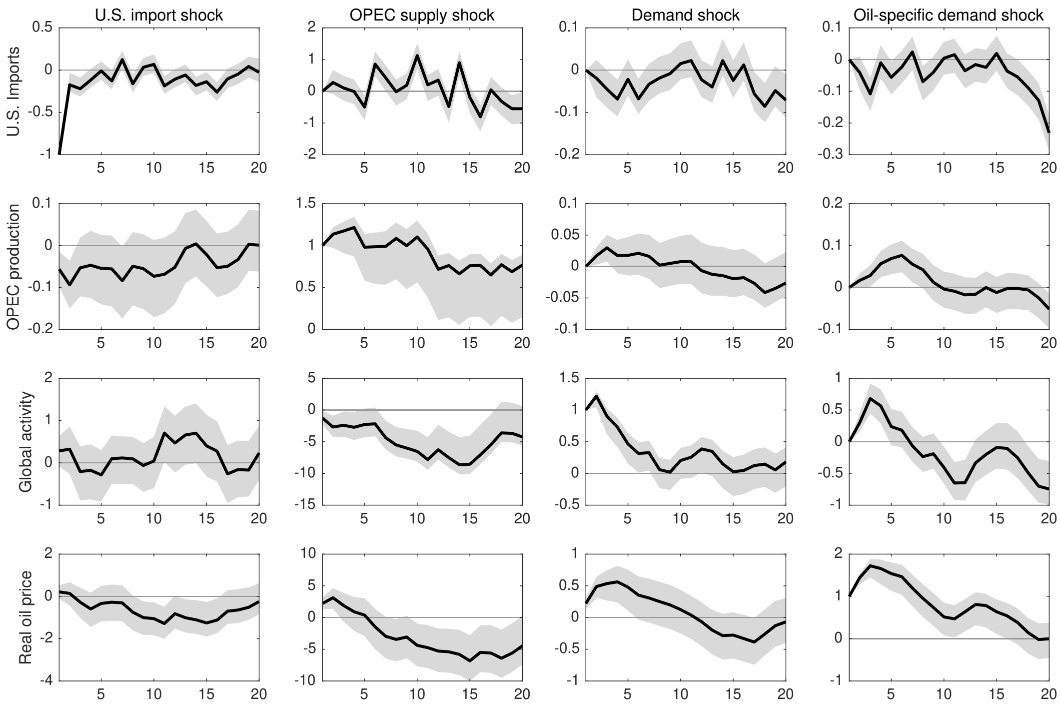

Figure 8: Impulse responses generated from the baseline model but where the ordering of the supply variables have been interchanged. The sample is 2003:M01–2015:M12. They are all in levels of the variables. Shocks are normalised so that the response of the variables is 1 on impact, i.e. 1% for the OPEC supply shock, U.S. supply shock and aggregate demand shock while one log-unit for the oil price. The shaded areas represent 68% confidence bands calculated using a bootstrap with 10,000 draws.

D.1.2 Mixed restrictions

One limitation of using a recursive identification scheme is that OPEC oil production and U.S. imports cannot both affect each other contemporaneously. To allow for this, I identify shocks using a combination of sign and zero-restrictions. Estimation of the reduced form model is done by applying Bayesian methods with diffuse priors.[12]

Sign restrictions have become a popular way of identifying structural shocks and date back to Faust (1998), Canova and De Nicolò (2003) and Uhlig (2005). For simplicity, only the zero restriction on θ_{12} will be relaxed. While not very common, imposing a mix of identifying restrictions has been done previously in Aastveit et al. (2015). Behar and Ritz (2017) show that a shift to a market-share strategy by OPEC can be optimal when facing competition from high-cost suppliers. OPEC thus will respond with the opposite sign to a change in U.S. imports. In other words, following a negative U.S. import shock reflecting a higher domestic supply of crude oil, OPEC will respond by increasing their own production. The restriction is imposed only on impact following Canova and Paustian (2011) to not to be more restrictive than necessary.

$$\begin{bmatrix} \Delta opecprod \\ \Delta usimp^S \\ rea \\ lrpo \end{bmatrix}_t = \begin{bmatrix} \nu_1 \\ \nu_2 \\ \nu_3 \\ \nu_4 \end{bmatrix} + \begin{bmatrix} + & - & 0 & 0 \\ \times & + & 0 & 0 \\ \times & \times & + & 0 \\ \times & \times & \times & + \end{bmatrix} \begin{bmatrix} \varepsilon^{\Delta opecprod} \\ \varepsilon^{\Delta usimp^S} \\ \varepsilon^{rea} \\ \varepsilon^{lrpo} \end{bmatrix}_t + lags \tag{6}$$

To produce impulse response functions that are consistent with the restrictions described in equation 6 a procedure based on the Rubio-Ramirez, Waggoner and Zha (2010) algorithm is implemented.

First, the Cholesky decomposition of the covariance matrix of the reduced form model is computed, $\Sigma_{\mathbf{e}} = SS'$. Thus far the procedure is no different from that of the uniquely identified model described above. This step provides orthogonal structural shocks. Then a 2×2 matrix $W \sim \mathrm{MN}(0_{2\times2}, I_2)$ is drawn and decomposed such that $W = QR$ with the property that $QQ' = I$. Following Binning (2013) to preserve normality, if the diagonal elements of matrix R are negative, the sign of the corresponding columns of matrix Q are flipped. Then $P_{4\times4} = \begin{bmatrix} Q_{2\times2} & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix}$ is constructed and the matrix SP computed as the candidate draw of the contemporaneous impact matrix. $\mathbb{E}\left[\mathbf{e}_t\mathbf{e}_t'\right] = \mathbb{E}\left[SP\varepsilon_t\left(SP\varepsilon_t\right)'\right] = \Sigma_{\mathbf{e}}$ and $\mathbb{E}\left[\boldsymbol{\varepsilon}_t\boldsymbol{\varepsilon}_t'\right] = I$ still hold because of the properties of P and S. Impulse response functions are then calculated and checked against the sign-restrictions posited in equation 6. If the restrictions are not satisfied, the draw is discarded and a new matrix W is drawn. This

[12] The posterior distribution is then dominated by the likelihood function. Further, assuming normally distributed reduced form errors, the posterior will be Normal-Inverse-Wishart with mean and variance parameters corresponding to the OLS estimates of the parameters and covariance matrix of the reduced form model. See Kadiyala and Karlsson (1997) and Canova (2007) for details.

procedure is repeated until the restrictions are satisfied and the corresponding impulse response functions are stored. Among all the accepted draws, the mean impulse response function is calculated.

The results are shown in figure 9. Note that because of the identification strategy implemented, only the responses of the OPEC supply and the U.S. import shocks will differ from the main model. The responses to the OPEC supply shock are mostly unchanged. This is to be expected as the responses to this shock were not restricted in the baseline model. The main difference is that the response of the real oil price is now insignificant. OPEC responds to a negative U.S. import shock by increasing output. However, this increase is very small in magnitude. Global real activity responds negatively, but is only significant from zero in some periods. The main result from the baseline model is robust to the identifying restrictions as the oil price decreases following a negative U.S. import shock in a similar way as with a pure recursive identification scheme.

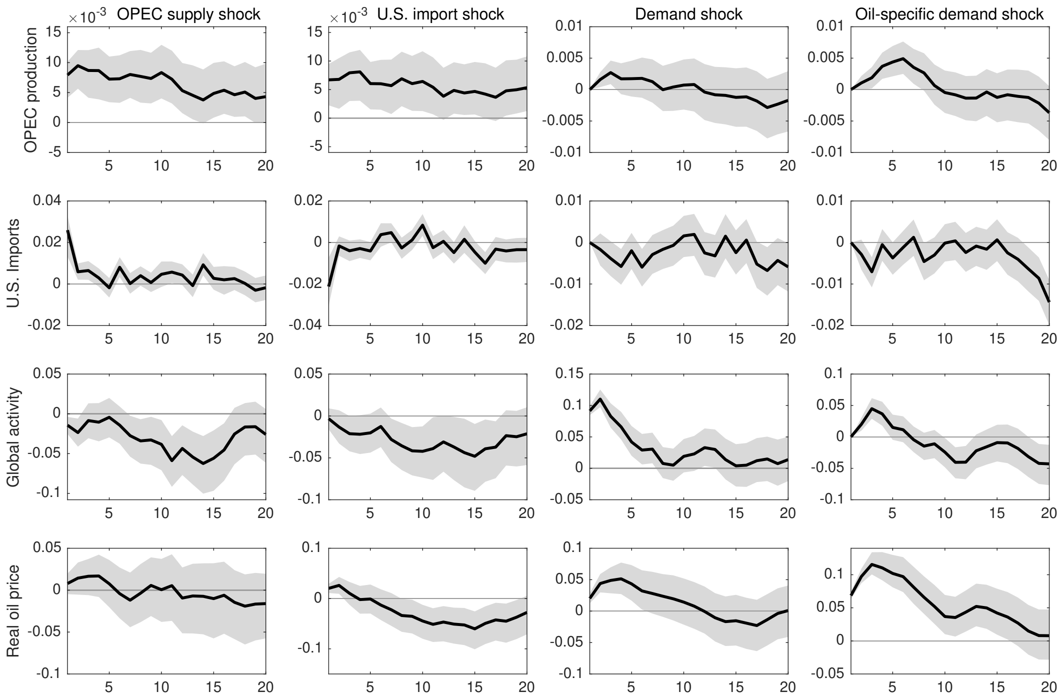

Figure 9: One standard deviation impulse responses generated from the imports model described in equation 6. The sample is 2003:M01–2015:M12. They are all in levels of the variables. The U.S. import shock is normalised to be negative. The solid line represents the median response at each horizon and the shaded areas represent 68th posterior probability regions of the estimated impulse responses.

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