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What is the role of Emerging Asia in global oil prices?

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Abstract

This paper studies the effects of demand shocks caused by Emerging Asian (EMA) countries on oil prices over the past two decades, using vector autoregression models. The analysis builds on previous work done on identifying different types of oil shocks using structural time series methods. However, uniquely, this paper introduces a commodity demand indicator for EMA economies that is based on data independent of oil production and consumption data, thus properly accounting for oil demand pressures stemming from macroeconomic conditions in the EMA economies and the rest of the world. The analysis strongly suggests that EMA demand shocks have had a persistent and statistically significant effect on the level and variation of global oil prices over the past two decades. This result differs from some of the previous literature and hence proves that the choice of oil demand indicator in an oil-market VAR makes a material difference for the results. Furthermore, tentative evidence suggests that the effect of EMA demand is mainly driven by demand dynamics in China. The results of the benchmark model are robust to different sample periods and to variations in the definition of the oil demand indicators, as well as to an alternative identification strategy based on sign restrictions.

Keywords: macroeconomic shocks, oil markets, sign restrictions, vector autoregression
JEL Classification: C32, E32, Q43

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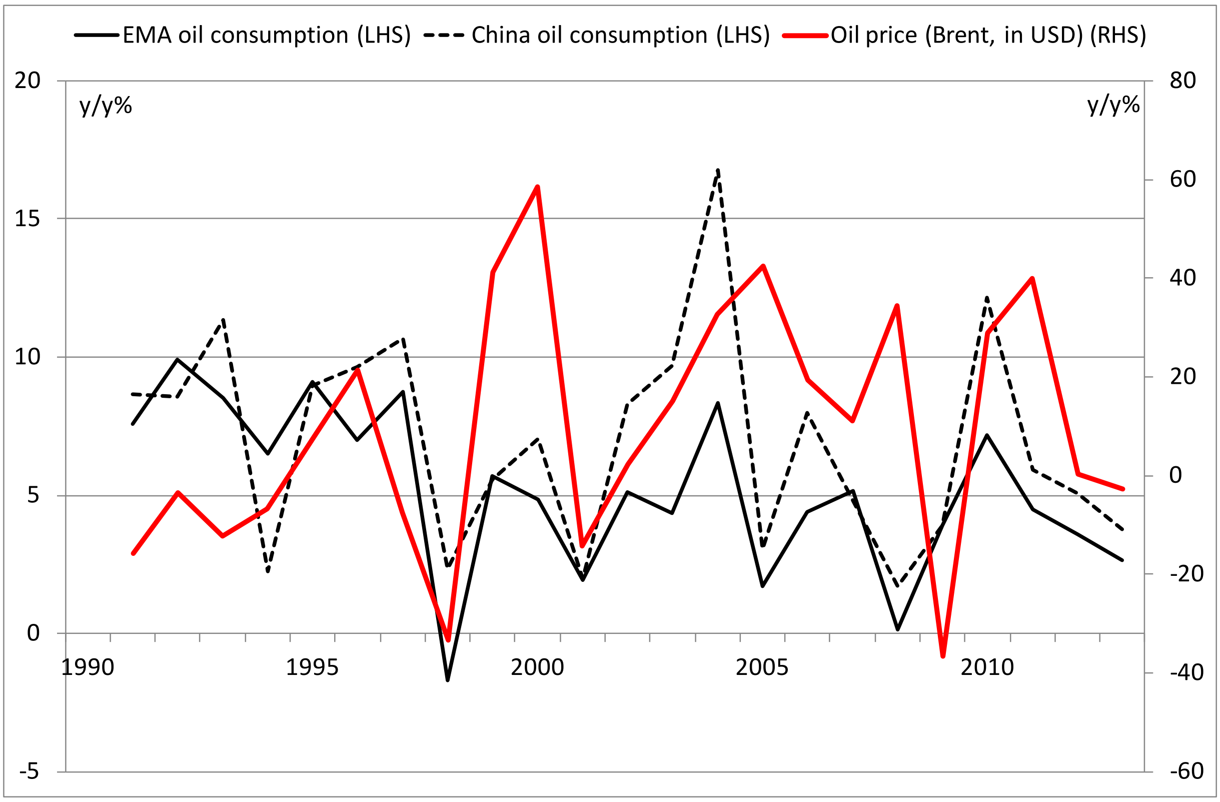
1 Introduction

The aim of this paper is to study the effects of demand shocks caused by Emerging Asian (EMA) countries[1] on oil prices over the past two decades. The rapid increase in economic activity and oil consumption of EMA countries, and especially China, has attracted considerable attention since the turn of the century up until the beginning of the global financial crisis in 2008. This dynamism of EMA economies coincided with a sharp rise in the global crude oil prices between 2002 and 2008 (Chart 1). Hence, at least intuitively, the increasing oil demand of EMA countries appear to have been an important driver of oil prices. However, correlation is of course not proof of causation. Other factors, related, for example, to the muted supply-side response to higher oil prices have also been assigned a role in the oil market narrative of the past decade. So clearly there is room for empirical analysis to shed light on the issue.

Chart 1 China/EMA oil consumption and oil price



Source: BP (2014)

[1] The countries included in the EMA aggregate for the purposes of the current study are China, Hong Kong, India, Indonesia, Republic of Korea, Malaysia, Pakistan, Philippines, Singapore, Taiwan and Thailand.

A number of studies have analysed the significance of Chinese and EMA demand for oil prices in recent years. Without estimating the size of this effect, Hamilton (2009) and Smith (2009) argued, based on anecdotal evidence and some theoretical oil market considerations, that Chinese and EMA demand dynamics were important factors in the surge in global oil prices in the 2000s. Turning to more formal methods of analysis, Mu and Ye (2011) used a vector autoregression (VAR) model to assess the importance of Chinese crude oil imports for global oil prices. The paper finds, perhaps somewhat surprisingly, that these imports have not been a significant driver of crude oil prices over the sample period (1997 to 2010), and China's oil demand only played a small role in the oil price rise that occurred prior to the global financial crisis. Niklaus and Inchauspe (2013) also cast doubt on the importance of EMA demand for oil prices, whereas Roache (2012), using a large VAR model, finds that Chinese demand has had a positive short-term effect on certain commodity prices (including crude oil) between 2002 and 2011. However, the longer-term effects are less relevant than those caused by demand shocks in the US. Overall, based on recent research, the importance of EMA demand for recent oil price dynamics appears to be ambiguous.

The approach taken in the current study differs from other recent empirical studies in the way it handles the EMA oil demand variable. In some of the existing studies (for example, Mu and Ye (2011)), EMA oil demand is defined in terms of oil consumption data. In contrast, I make an effort to model EMA oil demand by an oil demand indicator, which is not dependent on oil production and consumption data. By doing this, it should be possible to elicit responses to structural EMA oil demand shocks in a more realistic manner. The results of the study also confirm this. EMA demand shocks have been an important driver of global oil prices over the past two decades. The shocks have led to persistent effects on oil prices, much more so than has been the case for demand shocks emanating from other countries, or supply shocks. EMA demand shocks have also accounted for a significant share of oil price variation. Furthermore, there is tentative evidence for China being the main driver of the EMA demand shocks. These results are robust to alternative specifications of the demand indicator and to an identification strategy based on sign restrictions instead of the conventional Choleski ordering of the variables.

The paper is organised as follows. Section 2 introduces the oil demand indicator used in the model, with special emphasis on the definition of the EMA oil demand variable. Section 3 presents the results of the benchmark VAR analysis, and section 4 the results of an alternative specification based on a sign-restricted VAR. Section 5 concludes.

2 Oil demand indicator

Typically, a modern benchmark oil-market VAR consists of three variables measuring oil demand, oil supply and oil price. In this type of a VAR, defining the supply and oil price variables is relatively straightforward. As is customary in the literature, the supply of oil is defined as global oil production, and oil price is defined as one of the main benchmark oil prices (typically Brent or West Texas Intermediate (WTI)) deflated by a price index (typically the US Consumer Price Index), to obtain a measure of the real oil price.

In contrast, the definition of oil demand is more elusive. This is because there is no explicit measure available that can capture all the relevant factors affecting the dynamics of oil demand. However, some attempts have been made in the recent literature to define proxy variables for global oil demand. The motivation for designing such variables has been to make a distinction between demand and supply shocks in the oil markets. The pioneering study in this respect is Kilian (2009), which derives a measure of global commodity demand based on global shipping freight rates. Melolinna (2012), on the other hand, uses a factor model based on industrial production in emerging markets and the OECD as well as household consumption expenditures on oil to construct an oil demand indicator.

For purposes of the current study, the aim being to analyse the effects of EMA oil demand shocks, one needs a measure of EMA oil demand. To my knowledge, no such measure has been suggested in previous literature. When attempting to identify the effects of Chinese or EMA oil demand shocks, previous studies have usually resorted to oil consumption or net oil imports data as an indicator of oil demand. However, using this kind of a proxy for oil demand is highly problematic. This is because oil supply (global or regional oil production) is linked to oil consumption (global or regional) by an accounting identity; consumption during any given time period must be equal to production plus depletion of inventories. Therefore, it is very difficult to elicit an independent demand shock from the system, as it is not clear whether changes in consumption are linked to changes in demand or are driven by changes in production.

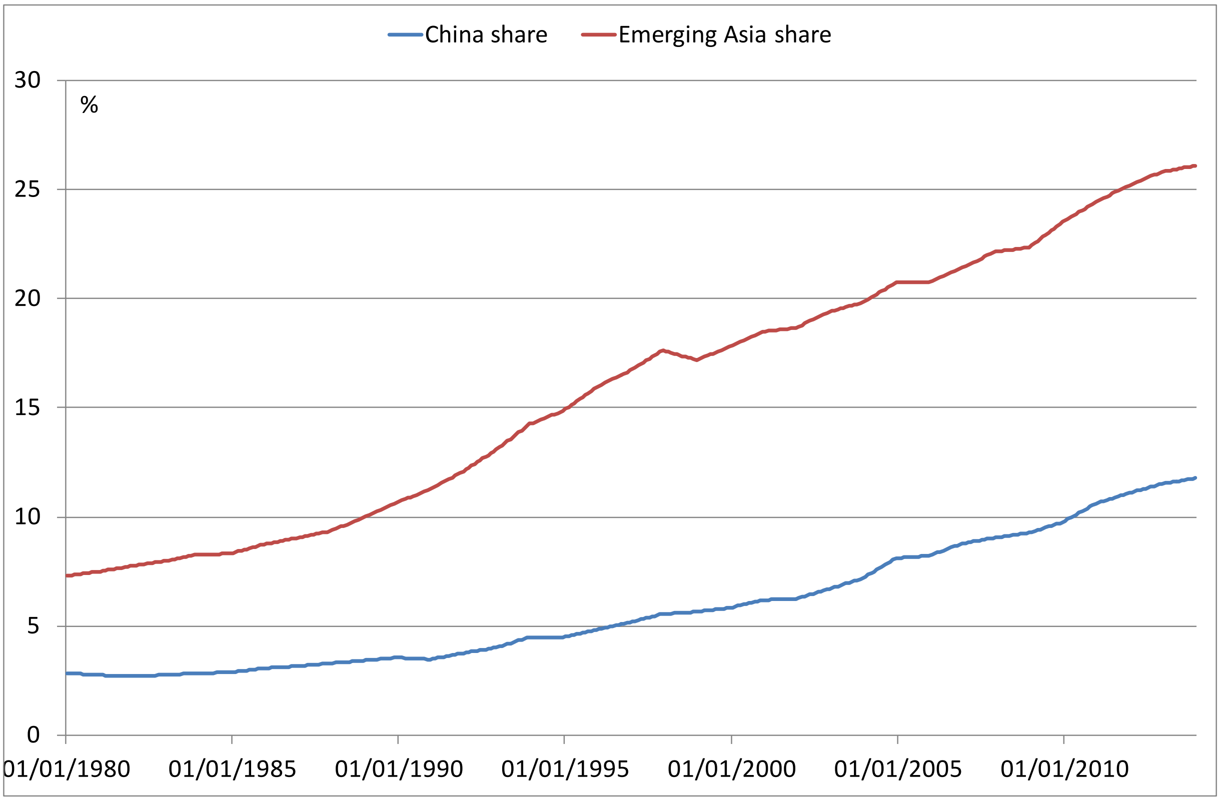
For my model, the aim is to find a general indicator measuring commodity demand that is driven by real economic activity. The approach taken is to use the only available internationally consistent statistic as a proxy for commodity and oil demand, namely industrial production. While industrial production does not directly measure demand for oil or other commodities, and while the share of industrial oil consumption on total oil consumption varies across countries[2], it nevertheless contains much relevant information, as there is a direct link between industrial production processes and the underlying need for commodities. Furthermore, industrial production data (unlike GDP statistics) are available at monthly frequency and are not subject to large revisions, facilitating the identification of shocks in the VAR model (see below). Comparable cross-country data (published by CPB Netherlands Bureau for Economic Policy Analysis) exist in a relatively long time-series for both world as well as EMA industrial production. Hence, in the spirit of the demand indicator used by Melolinna (2012), industrial production data for EMA countries and for other countries of the world (RoW henceforth) are used as a basis for the demand indicator. Unlike demand indicators based directly on oil consumption data, my demand indicator provides an accurate proxy of oil demand and cannot be driven by fluctuations in supply.

Because the viability of the VAR approach requires that the total global oil demand indicator be split into its contributions from the EMA and RoW, the industrial production data have to be weighted by a variable that reflects these relative shares. To complement the EMA demand indicator for oil market dynamics and to take into account the increasingly important role of EMA countries in global commodity (including oil) demand, the relevant industrial production time series are weighted by the share of EMA countries in global oil consumption. This share has been steadily increasing over recent decades, as shown in Chart 2, and these dynamics have been driven largely by oil consumption dynamics in China. Only by allowing the EMA oil demand indicator to account for this feature can one hope to get a realistic picture of the importance of EMA oil demand in recent decades. This choice of the weighting variable is also supported by the fact that the data are timely, readily available and not subject to revisions or exchange rate fluctuations[3].

[2] Based on data published by the US Energy Information Administration, and making certain simplifying assumptions on the consumption purposes of oil, this share has been slightly below 50% for the EMA countries between 1990 and 2010, and declined from approximately 40% to 35% for the RoW. Hence, while the share is lower for the RoW, the differences and changes are relatively small, and are not considered here to be a significant factor in the dynamics of the oil demand indicator.

[3] For robustness analysis with different weighting variables, see the next section.

Chart 2 Shares of China and EMA countries of global oil consumption



Source: BP (2014), author's calculations

The benchmark EMA oil demand indicator is defined as

$$emaindic_t = \left(\frac{emaip_t}{emaip_{t-12}} - 1\right) * emaoil_t \tag{1}$$

and the oil demand indicator for RoW is then calculated as follows:

$$rowindic_t = \left(\frac{worldip_t}{worldip_{t-12}} - 1\right) - emaindic_t \tag{2}$$

where $emaindic_t$ is the EMA oil demand indicator at month t, $emaip_t$ is EMA industrial production index, $emaoil_t$ is the share of EMA oil consumption of total world, $rowindic_t$ is the RoW oil demand indicator and $worldip_t$ is world industrial production. Hence, the EMA demand indicator can be seen as the contribution of EMA countries to world industrial production growth[4], weighted by the EMA oil consumption share.

[4] The y/y growth rates are used in line with previous literature to ensure the stationarity of the time series for the VAR models (see next section).

The EMA and RoW demand indicators are shown in Chart 3, together with the Kilian demand indicator[5]. The chart suggests that global oil demand has been driven mainly by RoW dynamics, although EMA has gained in importance since the early 2000's. This is also intuitive based on anecdotal and other evidence on global oil markets. The global recession led to a severe drop in the RoW oil demand indicator, while the EMA indicator was slightly less affected. As expected, there is also a strong positive correlation between the Kilian indicator and world industrial production growth, again emphasising the importance of industrial production in commodity demand dynamics.

One could argue that the Kilian demand indicator should somehow be taken into account in the EMA/RoW oil demand indicators. For this purpose, a simple alternative demand indicator was also tested in the model. This is derived by first splitting the Kilian indicator into its EMA/RoW-consumption share weighted components:

$$k1\_emaindic_t = (kilian_t) * emaoil_t \tag{3}$$

and

$$k1\_rowindic_t = kilian_t - k1\_emaindic_t \tag{4}$$

where $k1\_emaindic_t$ and $k1\_rowindic_t$ are intermediate indicators for EMA and RoW, and $kilian_t$ is the Kilian oil demand indicator. Then, a simple average is taken of the benchmark indicators (1) and (2) and these intermediate indicators:

$$k\_emaindic_t = (k1\_emaindic_t + \ emaindic_t)/2 \tag{5}$$

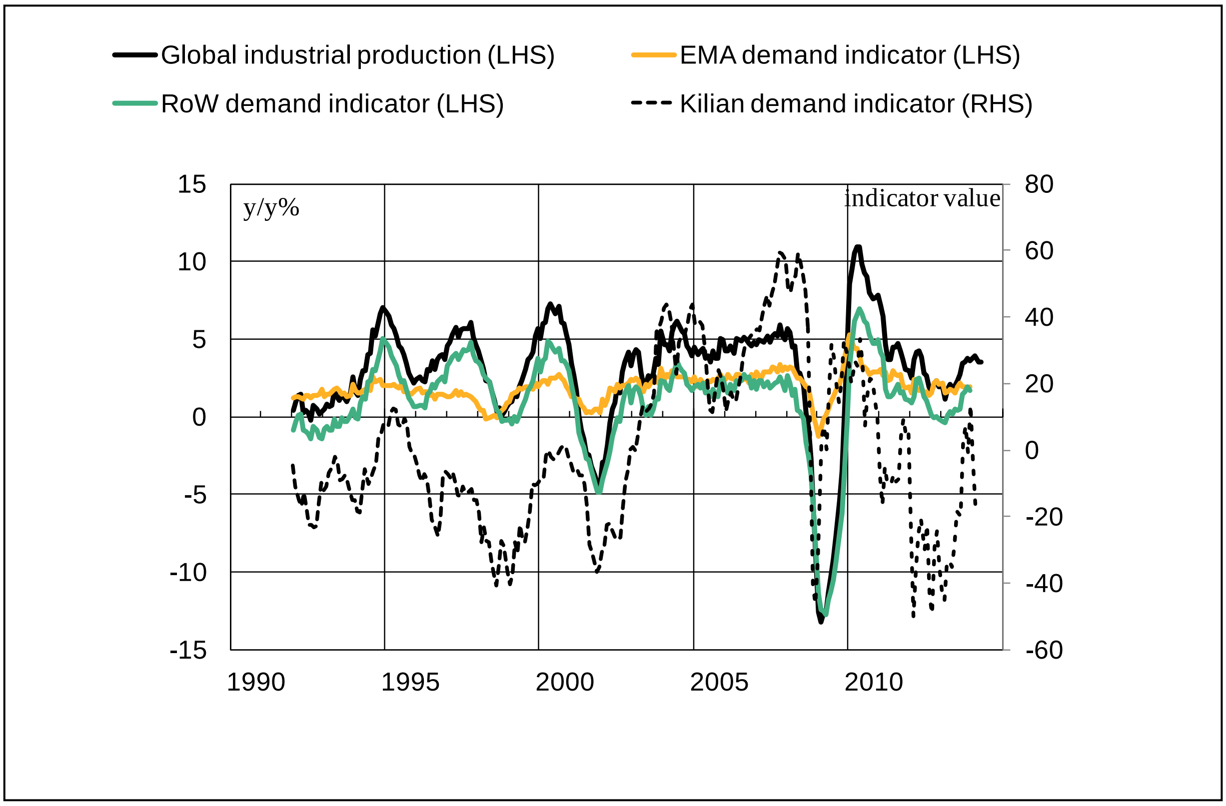
and

$$k\_rowindic_t = (k1\_rowindic_t + \ rowindic_t)/2 \tag{6}$$

This is a simple and transparent way of taking account of information in the Kilian indicator in making the split between EMA and RoW oil demand.

[5] This series can be obtained from http://www-personal.umich.edu/~lkilian/reaupdate.txt.

Chart 3 Oil and global commodity demand indicators



Source: CPB, Lutz Kilian, author's calculations

3 VAR model specification and results

As noted above, the benchmark VAR model used in the analysis includes variables for oil market supply, demand and prices. This means that the model has four variables; monthly change in global oil production (prodmm), the RoW and EMA demand indicators developed above (rowindic and emaindic, respectively) as well as the real oil price (rpo, defined as Brent oil price in USD, deflated by the US CPI). As is conventional in the literature, the variables are included in the model in stationary form. I follow Kilian (2009) and include the production data in monthly changes (as the level data display a strong non-stationary upward trend) and the real price as logarithmic level (see Appendix 1 for data charts). Given the data availability, the sample period is 1992M1 to 2013M12. This is considerably shorter than traditional oil market models for the US economy, but longer than most models in the previous literature on the EMA/Chinese economy.

The following subsections describe the VAR model and its identification strategy, as well as the estimation results in more detail.

3.1 VAR model and identification strategy

The structural form VAR model used to study the effects of oil shocks is

$$B_0 Y_t = A_0 + \sum_{i=1}^{L} B_i Y_{t-i} + \epsilon_t \tag{7}$$

where Y_t is an Nx1 vector of endogenous variables (hence, in the benchmark case, N=4), A_0 is an Nx1 vector of constants, L is the lag length of the VAR, the B_i are the NxN coefficient matrices, and ϵ_t is a vector of mutually and serially uncorrelated structural error terms. Based on established convention in the oil market VAR literature as well as standard information criteria, I set L=12 (although the results are quite similar for shorter lag lengths).

Pre-multiplying (7) by B_0^{-1} and letting u_t denote the corresponding reduced-form error terms produces $u_t = B_0^{-1}\epsilon_t$, which allows for identifying the structural shocks from the reduced-form error terms (see, for example, Lutkepohl (2005) for more details). Adopting a similar identification strategy to the one deployed by Kilian (2009), I use the following Cholesky decomposition to identify the structural shocks in the model:

$$\boldsymbol{u}_t = \begin{bmatrix} u_t^{prodmm} \\ u_t^{rowindic} \\ u_t^{emaindic} \\ u_t^{rpo} \end{bmatrix} = \begin{bmatrix} b_{11} & 0 & 0 & 0 \\ b_{21} & b_{22} & 0 & 0 \\ b_{31} & b_{32} & b_{33} & 0 \\ b_{41} & b_{42} & b_{43} & b_{44} \end{bmatrix} \begin{bmatrix} \epsilon_t^{oil\ supply\ shock} \\ \epsilon_t^{RoW\ demand\ shock} \\ \epsilon_t^{EMA\ demand\ shock} \\ \epsilon_t^{other\ oil\ demand\ shock} \end{bmatrix} \tag{8}$$

The ordering of the variables is largely based on existing literature and can be intuitively justified as follows. The model implies a vertical short-run oil supply curve, since supply can only react to demand shocks with a lag. This restriction is plausible, because oil producers are typically slow to respond to changes in oil market conditions. The RoW and EMA demand shocks are ordered next in the model. Hence, demand in RoW and EMA reacts contemporaneously to oil supply shocks, but not to other, oil-market-specific demand shocks. As shown in the existing literature (see, for example, Kilian (2009)), real activity and commodity demand typically react very sluggishly to oil-market demand shocks, which justifies this restriction. With regard to the ordering of the RoW demand shock before the EMA demand shock, this restriction implies that RoW demand does not react to an

EMA demand shock during the same month, whereas EMA demand can react to RoW demand shocks. This is intuitive due to the larger size of the RoW economy compared to EMA, which is also more dependent on economic activity in the RoW. Nevertheless, this restriction is not crucial for the model, and all the results below remain qualitatively similar even if the relative ordering of RoW and EMA demand shocks is reversed. Finally, oil prices are allowed to react contemporaneously to all the shocks in the model, which is intuitive given the speed with which news is incorporated into oil market prices. The fourth, "residual" shock includes, for example, precautionary demand shocks of the type introduced by Kilian (2009).

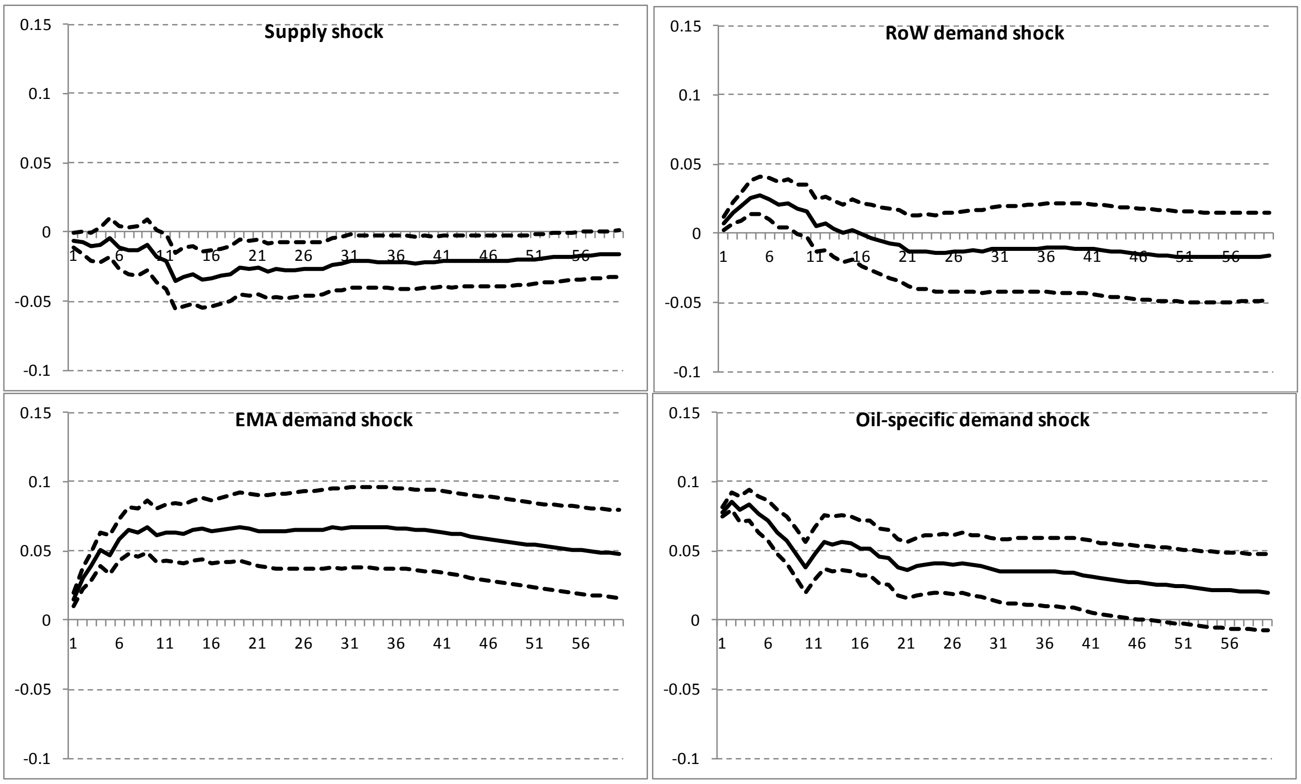
3.2 Results

The results of the VAR model estimation are presented in Chart 4. The impulse response functions suggest that EMA demand shocks have had a much more positive and persistent effect on oil prices than RoW demand shocks. Furthermore, statistical analysis of the results also shows that EMA demand shocks Granger-cause the real oil price with 95% statistical significance, whereas no such causality can be found for RoW or supply shocks. These results are at odds with some previous studies (see, for example, Mu and Ye (2011)) and hence suggest that accounting properly for demand variables in an oil market model makes a crucial difference[6]. The results for the supply and oil-market specific demand shocks are consistent with the findings of Kilian (2009). Oil-specific demand shocks have a large immediate effect on oil price, which is also intuitive given that oil prices can be expected to be driven strongly by shocks affecting the market directly. As also evidenced by Alquist and Kilian (2010), there are signs of overshooting in oil prices caused by precautionary demand shocks (which would be included in the oil-market-specific demand shock in the current study). Furthermore, the relatively muted response of oil prices to supply shocks is also in line with previous literature, as oil supply disruptions in one part of the world typically tend to generate an increase in supply from other oil producers[7].

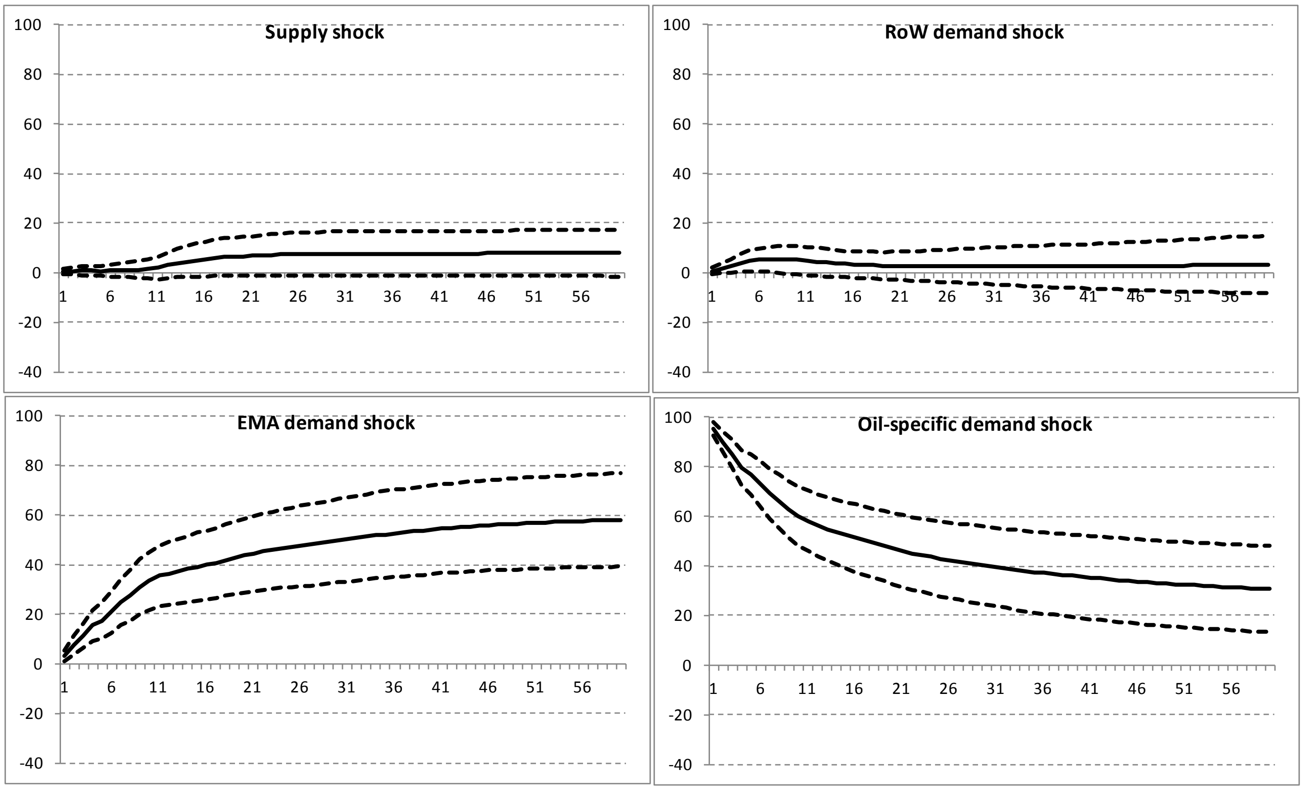
[6] This difference also exists if one uses the shorter sample period of 1998M1 to 2010M6 of Mu and Ye (2011). The latter study concentrates solely on the effects of Chinese demand shocks, while the current study covers the whole EMA. However, since the EMA oil demand dynamics have largely been driven by China over the past few decades, this is unlikely to be a decisive difference between the two studies.

[7] It is also possible that the limited importance of supply shocks is at least partly due to the relatively short sample available for the model, as the significant supply shocks experienced in the late 1970s and early 1980s are excluded from the analysis.

Chart 4 Innovation accounting for real oil price – benchmark model
(32^{nd}, 50^{th} and 68^{th} percentiles)



(1) Impulse responses (to 1-standard deviation shock)



(2) Forward error variance decompositions (in %)

The forward error variance decompositions for the benchmark model are presented in the lower panel of Chart 4. The results suggest that the variance of the real oil price has been mainly explained by oil-specific demand shocks at short horizons (as is typical in Choleski type identification schemes, and as is also suggested by the previous literature), but then EMA demand shocks quickly gain in importance as drivers of oil price variance. In contrast, neither oil supply nor RoW demand shocks have been particularly important drivers of oil price variance. This further supports the conclusions from the impulse response functions; over the sample period, EMA demand shocks have been an important driver of real crude oil prices.

One question arising from the results is to what extent the results are driven by country-specific dynamics, most notably those related to China. Unfortunately, results for China cannot be estimated in similar fashion, as there is no comparable, publicly available industrial production data available for China[8]. Nevertheless, the model was replicated using Chinese industrial production instead of EMA, as well as China's share in global oil consumption. While the results can only be interpreted tentatively due to the data issues, it would appear that the significant role of EMA oil demand in oil price dynamics is indeed largely due to Chinese oil demand, as the response of oil price to Chinese oil demand shocks account for large proportion of the size of the EMA demand shock in the benchmark model (Chart 5).

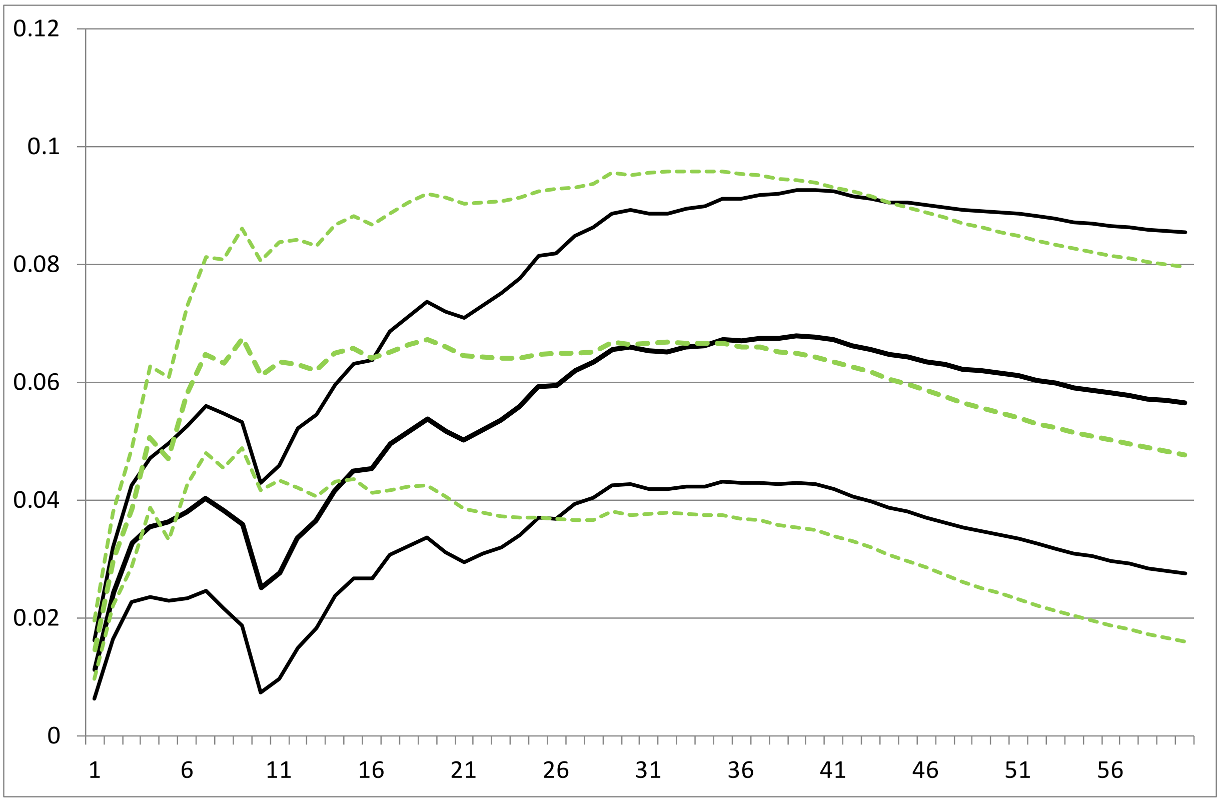
Looking at the results in Chart 4, it is perhaps surprising to see that the RoW demand shocks have had such a limited effect on oil prices over the sample period. Given that the RoW – and OECD countries in particular – still accounts for the majority of global oil demand, one would maybe intuitively expect these demand shocks to carry more weight as a driver of global oil prices. One potential explanation for the muted response of oil prices to RoW demand shocks is that oil supply has reacted more to RoW demand shocks than EMA demand shocks, thus limiting the price effect of the former. It is conceivable that due, for example, to historical oil market links and geopolitical considerations, OPEC countries have responded relatively rapidly to unexpected demand shocks in OECD countries and most notably the US. Indeed, there is some tentative evidence that this has been

[8] While monthly year-on-year industrial production data for China is available from Chinese statistical authorities, the problem is the timing of the Chinese New Year in January or February of each year. This timing causes large fluctuations in the year-on-year growth rates, which cannot be rectified with normal seasonal adjustment algorithms. The estimations for China in the current study are done with data adjusted by averaging the January and February growth rates for each year. This procedure mitigates the fluctuations, but does not completely eradicate the problem.

the case during the sample period; RoW demand shocks have Granger-caused year-on-year changes in oil production with 99% statistical significance, whereas there is no statistically significant causality between EMA demand shocks and oil production. Therefore, it would appear possible that EMA demand shocks have come as more of a surprise to oil producers than RoW demand shocks, and the reactions of oil producers have been driven more by demand signals received from the RoW – most probably OECD – countries.

It is worth emphasising that the muted response of oil prices to the RoW demand shocks does not imply that the actions of oil market participants in advanced economies have no significance for oil prices. In particular, when considering modern-day oil market dynamics, the importance of oil-specific demand shocks must be kept in mind. As the results of the current and also several previous studies suggest, oil price reacts mostly to shocks specific to oil markets. These markets are to a large extent located in and connected with advanced economies, especially the US, and actions taken by oil market participants, for example in relation to precautionary demand shocks, are still very important drivers of oil price dynamics.

Chart 5 Impulse responses of real oil price to EMA and China demand shocks



Note: Responses with 32nd, 50th and 68th percentiles for 1-standard deviation shock. The solid lines indicate a China demand shock, the dashed lines the EMA demand shock from Chart 4.

3.3 Robustness checks

To study the effects of different assumptions and choices, several robustness checks were carried out on the benchmark model. First, the results are qualitatively robust to changes in the sample period. Most importantly, the results are not dependent on the inclusion of the recent global financial crisis period, as the effect of the EMA demand shock is even more pronounced during the pre-crisis sample period of 1992 to 2007. One interesting experiment would be to split the sample in half to take into account the lesser significance of EMA and China in global oil consumption in the early part of the sample. Unfortunately this leads to very short sub-samples, so no firm conclusions can be drawn regarding the results. Nevertheless, there is tentative evidence in the results from such shorter models for a less significant reaction of oil price to the EMA demand shock in the earlier sample period.

The decision to use oil consumption shares as weights in the demand indicators (equations (1) and (2)) is open to criticism. While the choice is intuitively rational, one might ask why this weighting scheme should be preferred to any other choice. It needs to be kept in mind that the industrial production growth rates need to be weighted with something that allows for the summing to one of the RoW and EMA shares, as the objective is to find the *relative* contributions of the two regions to the total global demand indicator. This naturally restricts the choice of variables that can be used as weights in the indicators[9]. One natural option would be to use the shares of RoW/EMA in global (nominal) GDP. This data is available annually from the IMF (although some of the data for 2013 are still based on forecasts), and was used (after interpolating to monthly data) as an alternative for the oil-consumption-based weights in the model. Since the EMA share of global (purchasing power parity weighted) GDP shows a very similar trend to its share of oil consumption, the results of this alternative estimation are virtually unchanged from the benchmark model.

Another potential criticism of the benchmark model is the fact that some proportion of the EMA crude oil demand is derived from an increased demand for end-products by the RoW economies, and hence the demand indicators used in the benchmark model do not capture the “true” source of commodity and oil demand. On the other hand, this criti-

[9] This rules out using variables like net exports (which sum to zero globally, at least in theory), or any type of oil consumption intensity indicators (like oil consumption per GDP).

cism can be levelled against any basic oil-market model, with which it will inevitably be very difficult to capture the effects of commodity demand driven by final consumption demand. Nevertheless, the benchmark model was modified in an attempt to take into account the true domestic demand for commodities instead of total demand driven by both domestic and export usage. This was done by defining the part of oil consumption used for transport as domestic and the part used for industry as export-driven[10], then summing the domestic oil consumption data for the EMA and the RoW and using these EMA/RoW weights in the oil demand indicators in equations (1) and (2). Again, the results for the available sample (1992 to 2010) are qualitatively similar to those for the benchmark model, suggesting that final consumption demand for oil in the EMA, and not just indirect EMA demand driven by RoW final demand, has been an important driver of oil prices.

The estimation was also replicated for the alternative demand indicator introduced in equations (5) and (6). The results are qualitatively similar to those for the benchmark model, with the exception that the RoW demand shock is even more muted than in the benchmark model (see Appendix 2). Hence, the results with regard to the importance of EMA demand shocks are robust to the different demand indicators considered in the analysis.

4 Alternative identification with sign restrictions

To study the robustness of the benchmark results to the model identification scheme, a VAR model analysis based on sign restrictions[11] was also carried out. For this analysis, the four-variable benchmark model is not viable, as it is not possible to make a distinction in the sign restrictions between the RoW and the EMA demand shocks. In other words, restricting the demand indicator reaction to be positive and the oil price reaction also to be positive is not enough to render the RoW/EMA demand shock unique in a statistical sense. Hence, the following relative demand indicator, based on the demand indicators and industrial production data presented above, is introduced:

[10] This split is allowed by the detailed annual, country-specific statistics on oil consumption purpose published by the US Energy Information Administration (available for 1992 to 2010). Of course, some part of petrol consumption used for transport is also ultimately driven by exports, and some part of industrial oil consumption is also used for domestic purposes, but based on more detailed consumption purpose data available for the US, the split used in the model is a very good proxy.

[11] A so-called pure sign-restrictions approach (PSR) is used. For technical details, see Appendix 3.

$$relindic_t = \left(\frac{emaoil_t * emaip_t}{rowoil_t * rowip_t}\right) \tag{9}$$

where $relindic_t$ is the relative indicator, $rowoil_t$ is the RoW share in oil consumption and $rowip_t$ is the RoW industrial production. In other words, the relative demand indicator gives the relative importance of EMA compared to RoW in global commodity and oil demand. For time series stability, the monthly change in the indicator is used in the model below.

Table 1 Sign restrictions for relative oil demand shocks with pure sign restriction approach

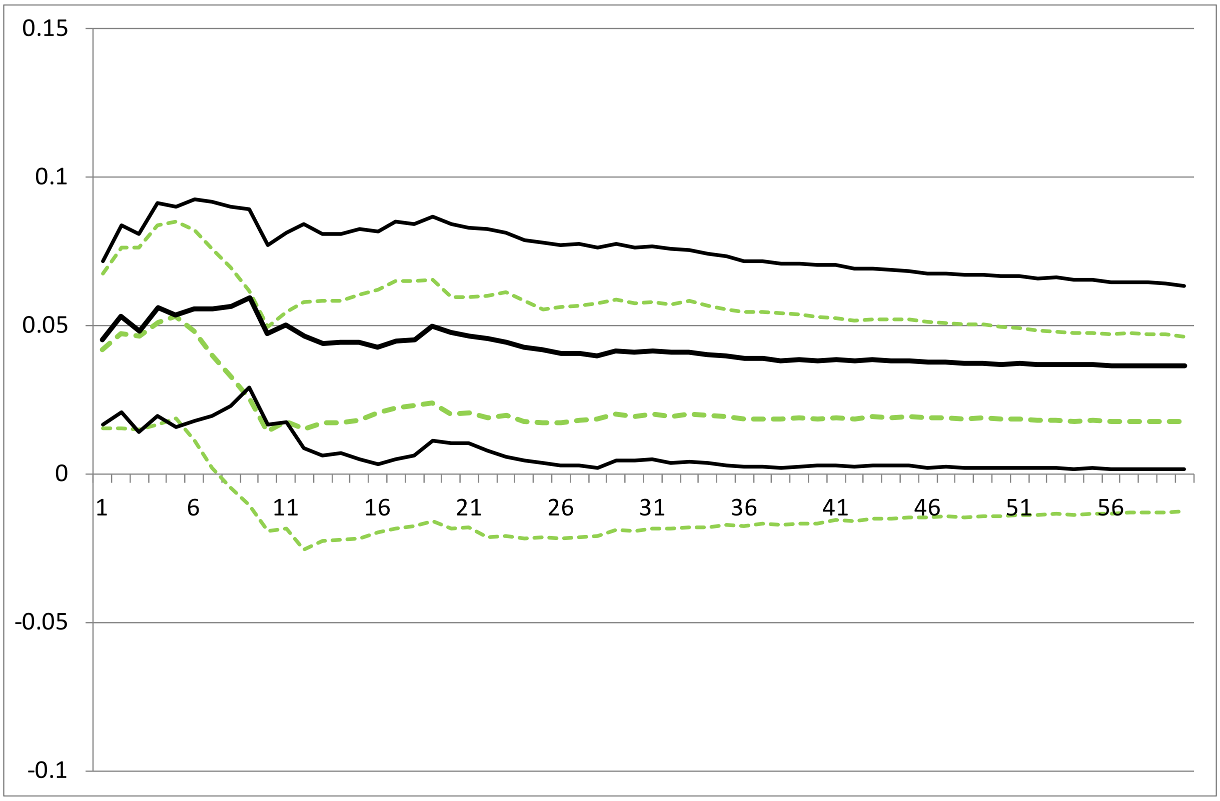
Shock\variable	Oil production	Relative demand	Real oil price
Oil supply shock	–		+
EMA/RoW demand shock	+	+/–	+
Oil-specific demand shock			+

Note: an empty cell means that the sign is not restricted. All restrictions also include a zero response.

The sign restrictions used in the PSR approach, which are similar in spirit to those used by Kilian and Murphy (2012), are presented in Table 1. Oil supply shocks are defined as shocks that cause a cut in production and an increase in the oil price. Relative demand shocks are defined as shocks that cause either an upward or downward reaction in the relative demand indicator (depending on whether demand increases in RoW or EMA), a positive reaction in the oil price, and (if anything), a positive reaction in oil supply. Finally, all other shocks specific to the oil market are included in a residual shock causing an upward reaction to the oil price. For this shock, I am agnostic on the effects on the other two variables, as this shock is not a focal points of the current study. All sign restrictions in the model are forced on the impact period only, although the relevant results are also robust to longer periods. Other details of the model (sample period and lag length) are the same as in the benchmark model.

The results of the PSR approach are qualitatively quite similar to the benchmark approach. Chart 6 depicts the shocks of interest to the current study, namely the effect of the two different demand shocks on the oil price. The results suggest that relative (positive) EMA shocks have caused much more pronounced reactions of the oil price than have relative RoW shocks. EMA shocks have also been considerably more persistent than RoW shocks. Hence, this alternative approach to the model identification also supports the relative results of the benchmark model; EMA demand shocks have been an important driver of real oil prices over the sample period.

Chart 6 Impulse responses of real oil price to relative demand shocks



Note: Responses with 32nd, 50th and 68th percentiles for 1-standard deviation shock. The solid lines indicate a relative EMA shock, the dashed lines a relative RoW shock.

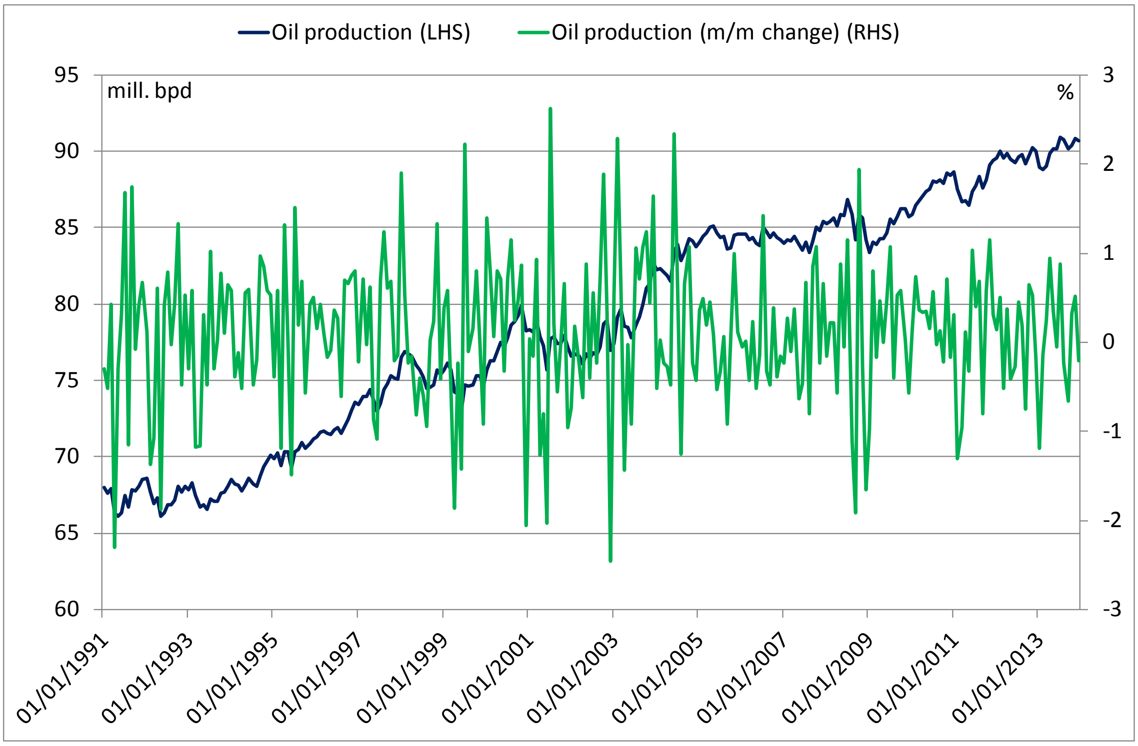
5 Conclusions

The analysis carried out in the current study strongly suggests that EMA demand shocks have had a persistent and statistically significant effect on the level and variation of global oil prices over the past two decades. This result is not consistent with some of the previous literature, but proves that properly accounting for commodity and oil demand in an oil-market VAR makes a material difference for the results. Tentative evidence suggests that the effect of EMA demand is mainly driven by demand dynamics in China. The results of the benchmark model are robust to different sample periods, variations in the definition of the oil demand indicators, as well as to an alternative identification strategy based on sign restrictions.

The study also leaves open some avenues for future research. First, much of the data available for the EMA, and especially China, is not of the same quality or sample length as data for most advanced economies, and so better data coverage would hopefully facilitate future research efforts. Second, the relative roles of emerging and advanced economies in global oil markets and oil price formation requires further work. The current study suggests that as regards the demand for crude oil emanating from the real economy, EMA demand shocks have been much more important drivers of oil price than have RoW demand shocks over the past two decades. There is also tentative evidence of oil producers reacting more strongly to unexpected RoW than EMA demand shocks, which has mitigated the price effects of the former. Clearly, however, there is room for more complex models and different shock identification approaches to further investigate the issue. From a global macroeconomic perspective, the source of final consumption demand ultimately driving commodity demand in emerging economies is a key topic, for which different approaches and data than those used in the current study could be deployed.

Appendix 1

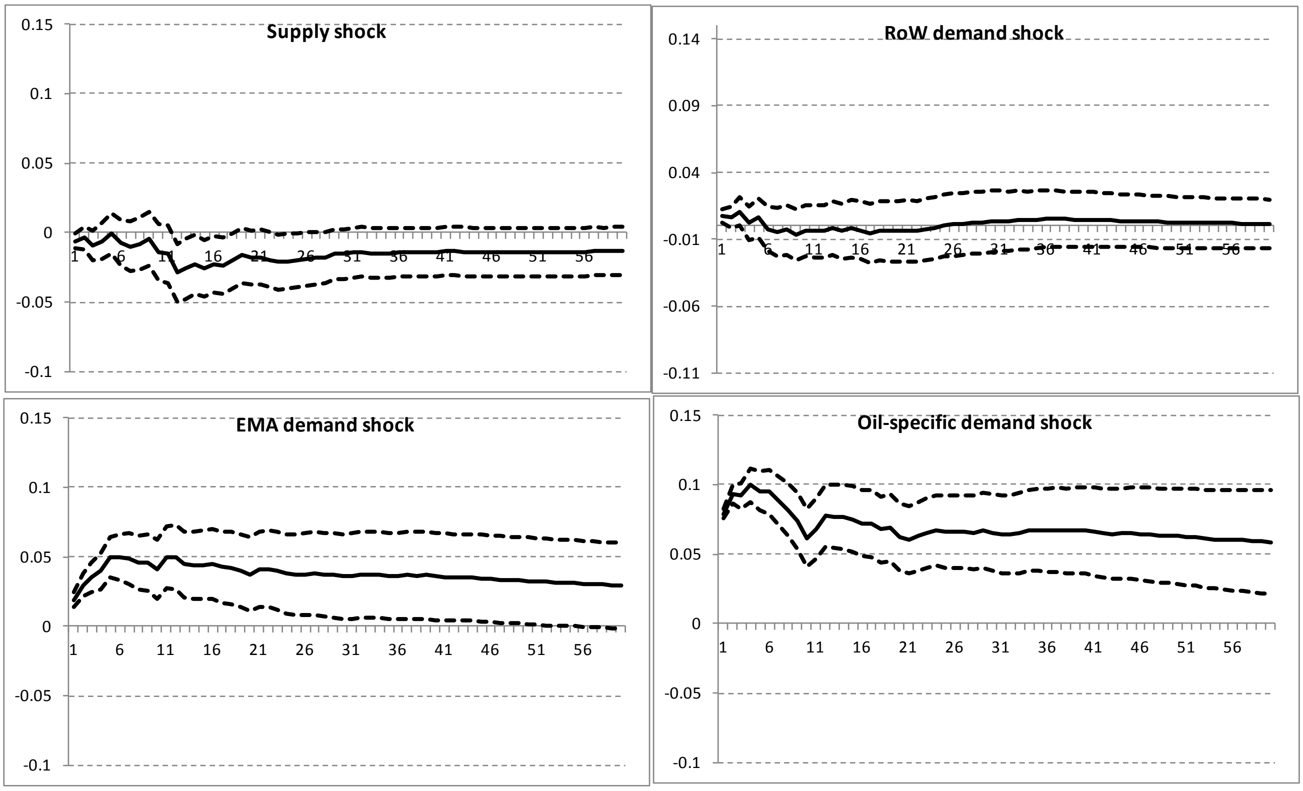
Oil production and real oil price



Source: Bloomberg, EIA, Macrobond

Appendix 2

Impulse responses for the alternative model (32nd, 50th and 68th percentiles)



Impulse responses (to 1-standard deviation shock)

Appendix 3[12]

Let ε_t denote the (Kx1) vector of structural VAR model innovations derived from equation (7) in the main text. To construct structural impulse responses, one needs an estimate of the KxK matrix C in $u_t = C\varepsilon_t$.

Let $\Sigma_u = P\Lambda P$ and $C = P\Lambda^{1/2}$ such that C satisfies $\Sigma_u = CC'$. Then C = BD (where B is a matrix of structural parameters obtained via a Choleski decomposition of the reduced form parameters) also satisfies $\Sigma_u = CC'$ for any orthonormal KxK matrix D.

It is possible to examine a wide range of possibilities for C by repeatedly drawing at random from the set **D** of orthonormal rotation matrices D. Following Rubio-Ramirez et al (2010), I construct the set **C** of admissible models by drawing from the set **D** of rotation matrices and discarding candidate solutions for C that do not satisfy a set of a priori sign restrictions on the implied impulse response functions. The procedure follows these steps:

1. Draw a KxK matrix K of NID(0,1) random variables. Derive the QR decomposition (to produce an orthonormal matrix and an upper-triangular matrix) of K such that K = QR with the diagonal of R normalised to be positive.
2. Let D = Q. Compute impulse responses using the orthogonalisation C = BD. If all implied impulse response functions satisfy the sign restrictions, keep D. Otherwise, discard D.
3. Repeat the first two steps a large number of times, recording each D (and the corresponding impulse response functions) that satisfy the restrictions. The resulting **C** comprises the set of admissible structural VAR models.

[12] This section draws on Rubio-Ramirez et al. (2010).

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