ONLINE APPENDIX TO

What drives oil prices?

Emerging versus developed economies

Knut Are Aastveit* Hilde C. Bjørnland† Leif Anders Thorsrud‡

May 28, 2014

*Norges Bank. Email: Knut-Are.Aastveit@norges-bank.no
†BI Norwegian Business School.Email: hilde.c.bjornland@bi.no
‡BI Norwegian Business School. Email: leif.a.thorsrud@bi.no

1 Introduction

In this on-line appendix we provide details on the data, sources and diagnostics of the model, including a discussion of the estimated factors and the implementation of sign restriction. Thereafter we report the estimated country responses in greater detail, and discuss various robustness tests in terms of the chosen estimation, specification and identification strategy.

2 Data, sources and oil market exposure

Our data set includes variables from 33 different countries, where we use real GDP growth and industrial production growth as measures of economic activity for each country. In total, our sample countries account for approximately 80 percent of world GDP, measured by purchasing-power-parity (authors calculations based on 2009 estimates from the IMF).

We determine a priori which countries should be considered developed and emerging economies. Countries that are members of the OECD at the beginning of our sample are considered developed economies. The remaining countries are considered emerging economies. Accordingly, the following 18 countries are considered developed economies: Australia, Belgium, Canada, Denmark, Finland, France, Germany, Italy, Japan, Luxembourg, Netherlands, New Zealand, Norway, Spain, Sweden, Switzerland, the UK and the US. The following 15 countries are considered emerging economies: Argentina, Brazil, Chile, China, Hong Kong, India, Indonesia, Korea, Malaysia, Mexico, Peru, Singapore, South Africa, Taiwan and Thailand. Of these countries, four developed countries (Canada, Denmark, Norway and the UK) and four emerging countries (Argentina, Indonesia, Malaysia and Mexico) are net oil exporters over the period (1991-2009). However, many other countries are commodity producers (e.g., Australia, New Zealand and Peru), where export prices may have been highly correlated with oil prices over the period (see Table 1 below). To these categorizations it is worth noting that Chile, Korea and Mexico are now members of the OECD, and although Brazil is not a net oil exporter over the entire period, in recent years Brazil has been a major producer and a net exporter.

Most of the data series were collected from Thomson Reuters Ecowin. Other series were collected from the following sources: Gross Domestic Product (GDP) in China and

Indonesia were found in the GVAR data set constructed by Pesaran et al. (2009). Industrial production (IP) in Argentina, Indonesia, Mexico and the Netherlands were collected from Datastream. Industrial production in Denmark and Portugal were taken from OECD, while industrial production in Norway was collected from Statistics Norway.

All GDP series are at constant prices. The industrial production series are volume indexes, and refer, with few exceptions, to the manufacturing industry. For Argentina, China, Indonesia, Italy, Norway, Peru and Portugal, we only found series for overall industrial production. Some of the activity series do not span the whole time period used in the analysis. To avoid excluding these variables from the sample, we have applied the EM algorithm, as described in Stock and Watson (2002), to construct the missing observations. However, experiments conducted on the data set excluding the series with missing observations, do not change our main conclusions.

To measure oil production and the real price of oil, we use world crude oil production, in millions of barrels per day, and US real refiner' acquisition cost for imported crude oil, respectively. The nominal oil price has been deflated using the US consumer price index. These are the same variables used in Kilian (2009) and many other papers.

3 Factors and correlations

Figure 1, Panels (a) and (b), display the two observable series: global oil production and the real price of oil. The figure shows significant growth in the real price of oil during the economic booms in 1999/2000 and 2006/2007 and a decrease in the real price of oil during the Asian crisis and the recent financial crisis, (see Panel (a)). The economic booms and busts are also evident in global oil production (see Panel (b)), where production slows down during the two recessions and increases during the two expansions. Furthermore, there is also evidence of a slowdown in global oil production during 2002/2003. The dates coincide with the Venezuelan unrest (strike) and US attack on Iraq (second Persian Gulf War).

Figure 1, Panels (c) and (d), display the two key activity variables used in the analysis: the emerging and developed economy factors. As the figure shows, the two factors capture features commonly associated with the business cycles in each region over the last 20 years.

Table 1: **Oil production and consumption by countries**

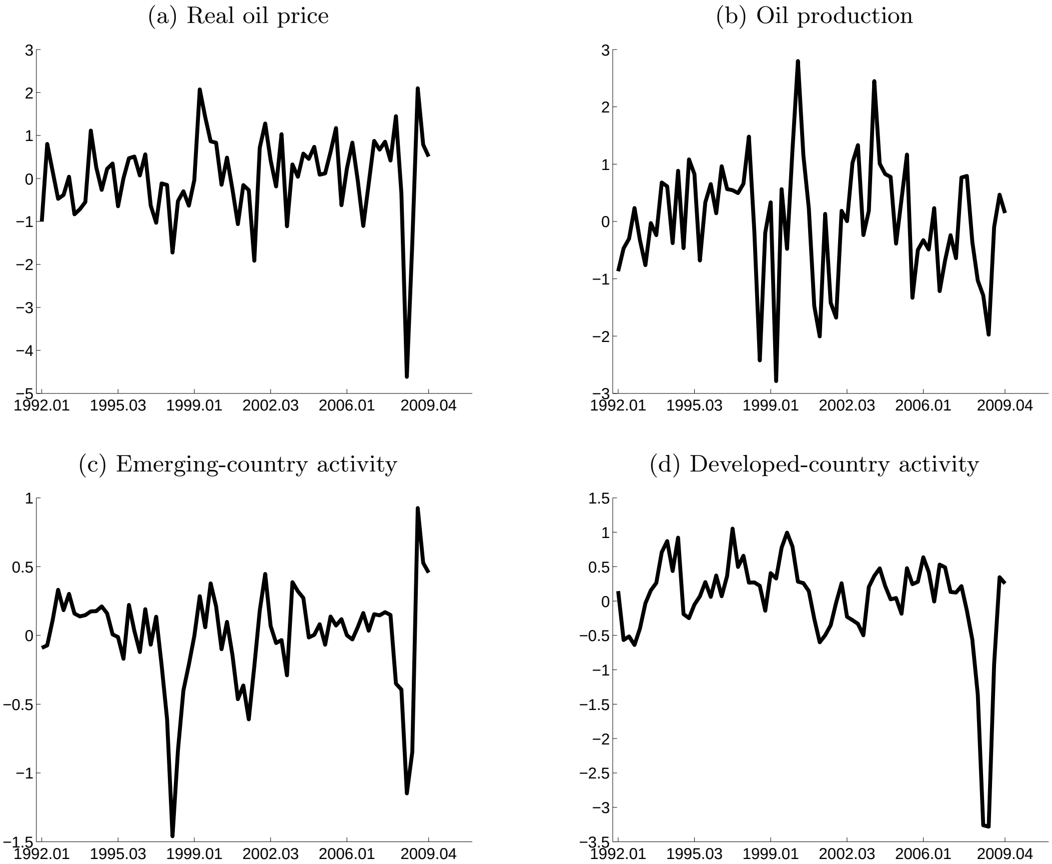
	Country	Production	Consumption	Net exporter
Developed	*Australia*	0.64	0.87	No
	Belgium	0.01	0.61	No
	Canada	2.83	2.03	Yes
	Denmark	0.29	0.20	Yes
	Finland	0.01	0.21	No
	France	0.09	1.97	No
	Germany	0.13	2.74	No
	Italy	0.14	1.83	No
	Japan	0.11	5.36	No
	Netherlands	0.06	0.89	No
	New Zealand	0.05	0.14	No
	Norway	2.93	0.22	Yes
	Portugal	0.00	0.31	No
	Spain	0.03	1.39	No
	Sweden	0.00	0.37	No
	Switzerland	0.00	0.27	No
	United Kingdom	2.32	1.78	Yes
	United States	9.04	19.19	No
Emerging	*Argentina*	0.80	0.50	Yes
	Brazil	1.59	2.06	No
	Chile	0.02	0.23	No
	China	3.45	5.17	No
	Hong Kong	0.00	0.25	No
	India	0.77	2.12	No
	Indonesia	1.38	1.04	Yes
	Korea, South	0.01	2.06	No
	Malaysia	0.75	0.46	Yes
	Mexico	3.42	2.00	Yes
	Peru	0.11	0.15	No
	Singapore	0.01	0.69	No
	South Africa	0.20	0.47	No
	Taiwan	0.00	0.83	No
	Thailand	0.21	0.77	No

Note: Column three to five reports oil production and oil consumption in millions of barrels per day, measured as averages for the period 1992-2009 (Source: EIA).

Both the booms and busts pre-dating and following the Asian crisis near the end of the 1990s, and the dot-com bubble around 2001 are evident in the emerging-country and the developed-country factors, respectively.

There is, however, a notable difference in how the recent financial crisis has affected the two factors. The decline in the activity factor representing the developed economies is much larger than any other previous decline in that factor. For the emerging-country activity factor, the recent financial crisis also caused large negative movements. However, compared to earlier downturns, the recent crisis does not seem particularly different. Ad-

Figure 1: **Observable variables and estimated factors**



Note: The figure shows the standardized values of the first differences of the logs of each observable variable, i.e. the real price of oil and global oil production, and the estimated activity factors (the median). The sample used in the VAR is 1992:Q1 to 2009:Q4, while we use information from 1991:Q1 to 2009:Q4 to estimate the unobserved factors.

ditionally, the recovery in the emerging-country activity factor has been stronger than in the developed-country economy factor.

Although the factors should capture common movements among the countries in each group, the various countries may still contribute differently to the factor estimate. In particular, some countries may be more correlated with their respective factor than others. To illustrate this (and to further interpret the factors), Table 2 displays the correlation between the activity variables in each country and the developed-country and emerging-country factors. First, regarding the developed-country factor, the table indicates that with the exception of Australia, Japan, New Zealand and Norway, all developed countries are highly correlated with the factor (as expected). For Japan and New Zealand, however, the correlation with the emerging-country factor (that contains many Asian countries) is slightly higher than with the developed-country factor. Clearly, location is important. For Norway, and to some extent Australia, the correlation between GDP and either the developed-country or the emerging-country factors is low, suggesting a more idiosyncratic pattern in these countries.

Regarding the emerging-country factor, the results for the Asian and the South American countries are more diverse. While the Asian countries are highly correlated with the emerging-country factor, three of the South American countries (Argentina, Chile, Mexico) and South Africa are slightly more correlated with the developed-country factor than with the emerging-country factor. This indicates that the Asian countries account for the majority of variation in the emerging-country factor.

Table 2: **Correlation with factors**

Developed				**Emerging**			
Country	**Var.**	*emeAct*	*devAct*	**Country**	**Var.**	*emeAct*	*devAct*
Australia	*GDP*	0.09 (0.12)	0.35 (0.12)	*Argentina*	*GDP*	0.20 (0.15)	0.25 (0.18)
	IP	0.34 (0.13)	0.48 (0.12)		*IP*	0.36 (0.13)	0.38 (0.13)
Belgium	*GDP*	0.41 (0.14)	0.78 (0.14)	*Brazil*	*GDP*	0.44 (0.12)	0.41 (0.12)
	IP	0.32 (0.12)	0.63 (0.12)		*IP*	0.51 (0.13)	0.41 (0.12)
Canada	*GDP*	0.16 (0.14)	0.75 (0.17)	*Chile*	*GDP*	0.24 (0.13)	0.32 (0.15)
	IP	0.32 (0.14)	0.70 (0.16)		*IP*	0.37 (0.13)	0.41 (0.13)
Denmark	*GDP*	0.19 (0.11)	0.56 (0.11)	*China*	*GDP*	0.36 (0.11)	0.14 (0.13)
	IP	0.04 (0.11)	0.43 (0.09)		*IP*	0.27 (0.11)	0.10 (0.10)
Finland	*GDP*	0.26 (0.14)	0.80 (0.16)	*Hong Kong*	*GDP*	0.78 (0.14)	0.47 (0.15)
	IP	0.15 (0.14)	0.62 (0.14)		*IP*	0.43 (0.13)	0.33 (0.14)
France	*GDP*	0.25 (0.15)	0.83 (0.16)	*India*	*GDP*	*N/A*	*N/A*
	IP	0.35 (0.15)	0.75 (0.15)		*IP*	0.19 (0.11)	0.24 (0.12)
Germany	*GDP*	0.29 (0.13)	0.74 (0.14)	*Indonesia*	*GDP*	0.54 (0.13)	-0.02 (0.14)
	IP	0.20 (0.14)	0.68 (0.15)		*IP*	0.58 (0.14)	0.01 (0.15)
Italy	*GDP*	0.42 (0.15)	0.80 (0.16)	*Korea*	*GDP*	0.59 (0.13)	0.49 (0.14)
	IP	0.43 (0.15)	0.83 (0.16)		*IP*	0.70 (0.13)	0.45 (0.13)
Japan	*GDP*	0.63 (0.12)	0.52 (0.13)	*Malaysia*	*GDP*	0.49 (0.11)	0.27 (0.11)
	IP	0.66 (0.14)	0.46 (0.15)		*IP*	0.69 (0.11)	0.48 (0.15)
Netherlands	*GDP*	0.17 (0.14)	0.78 (0.16)	*Mexico*	*GDP*	0.26 (0.14)	0.67 (0.14)
]	*IP*	0.29 (0.12)	0.56 (0.12)		*IP*	0.16 (0.15)	0.61 (0.15)
New Zealand	*GDP*	0.47 (0.14)	0.43 (0.16)	*Peru*	*GDP*	0.31 (0.12)	0.08 (0.11)
	IP	*N/A*	*N/A*		*IP*	0.45 (0.13)	0.33 (0.13)
Norway	*GDP*	0.08 (0.10)	0.33 (0.11)	*Singapore*	*GDP*	0.75 (0.13)	0.43 (0.14)
	IP	0.17 (0.12)	0.51 (0.13)		*IP*	0.54 (0.12)	0.32 (0.11)
Portugal	*GDP*	0.10 (0.12)	0.66 (0.15)	*South Africa*	*GDP*	0.24 (0.14)	0.56 (0.18)
	IP	-0.07 (0.10)	0.24 (0.10)		*IP*	0.40 (0.13)	0.61 (0.14)
Spain	*GDP*	-0.02 (0.15)	0.75 (0.19)	*Taiwan*	*GDP*	0.56 (0.12)	0.52 (0.13)
	IP	0.31 (0.13)	0.76 (0.13)		*IP*	0.61 (0.13)	0.27 (0.13)
Sweden	*GDP*	0.32 (0.14)	0.83 (0.16)	*Thailand*	*GDP*	0.48 (0.13)	0.22 (0.14)
	IP	0.32 (0.14)	0.78 (0.15)		*IP*	0.63 (0.13)	0.42 (0.14)
Switzerland	*GDP*	0.17 (0.15)	0.69 (0.16)				
	IP	0.33 (0.12)	0.62 (0.12)				
United Kingdom	*GDP*	0.23 (0.15)	0.84 (0.18)				
	IP	0.37 (0.14)	0.80 (0.15)				
United States	*GDP*	0.27 (0.14)	0.71 (0.16)				
	IP	0.36 (0.16)	0.81 (0.18)				
	Mean	***0.27***	***0.65***		***Mean***	***0.45***	***0.35***

Note: Column three to four, and seven to eight report the correlation between observable activity variables and the identified emerging-country and developed-country activity factors. IP is an abbreviation for industrial production. N/A are missing values. Standard errors in parenthesis.

4 Implementation of sign restrictions

We implement the following algorithm for each draw of the reduced form covariance matrix Ω:

1. Let $\Omega = PP'$ be the Cholesky decomposition of the VAR covariance matrix Ω, and $\tilde{A}_0 = P$.

2. Draw an independent standard normal 2×2 matrix J. Let $J = QR$ be the "economy size" QR decomposition of J with the diagonal of R normalized to be positive.

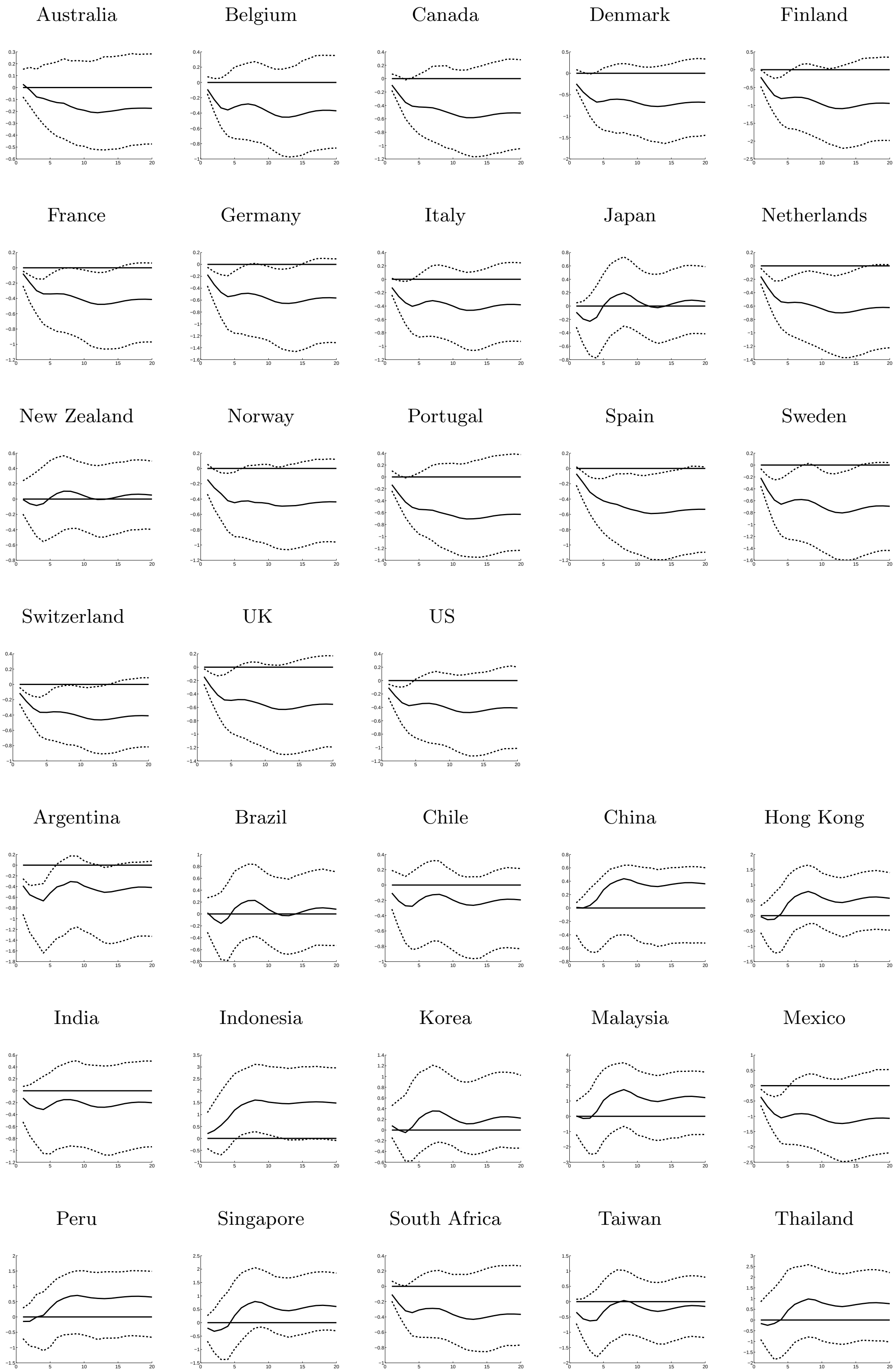
3. Compute a candidate structural impact matrix $A_0 = \tilde{A}_0 \tilde{Q}$, where $\tilde{Q}$ is constructed from a 4×4 identity matrix, with the 2×2 matrix Q placed in the 2nd and 3rd row and column of $\tilde{Q}$.

If the candidate matrix satisfies the sign restrictions, we keep it. Otherwise the procedure above is repeated. The imposed signs can also be restricted to hold for many periods, in which case the candidate matrix must be past into the impulse response function before validation.

5 Country details

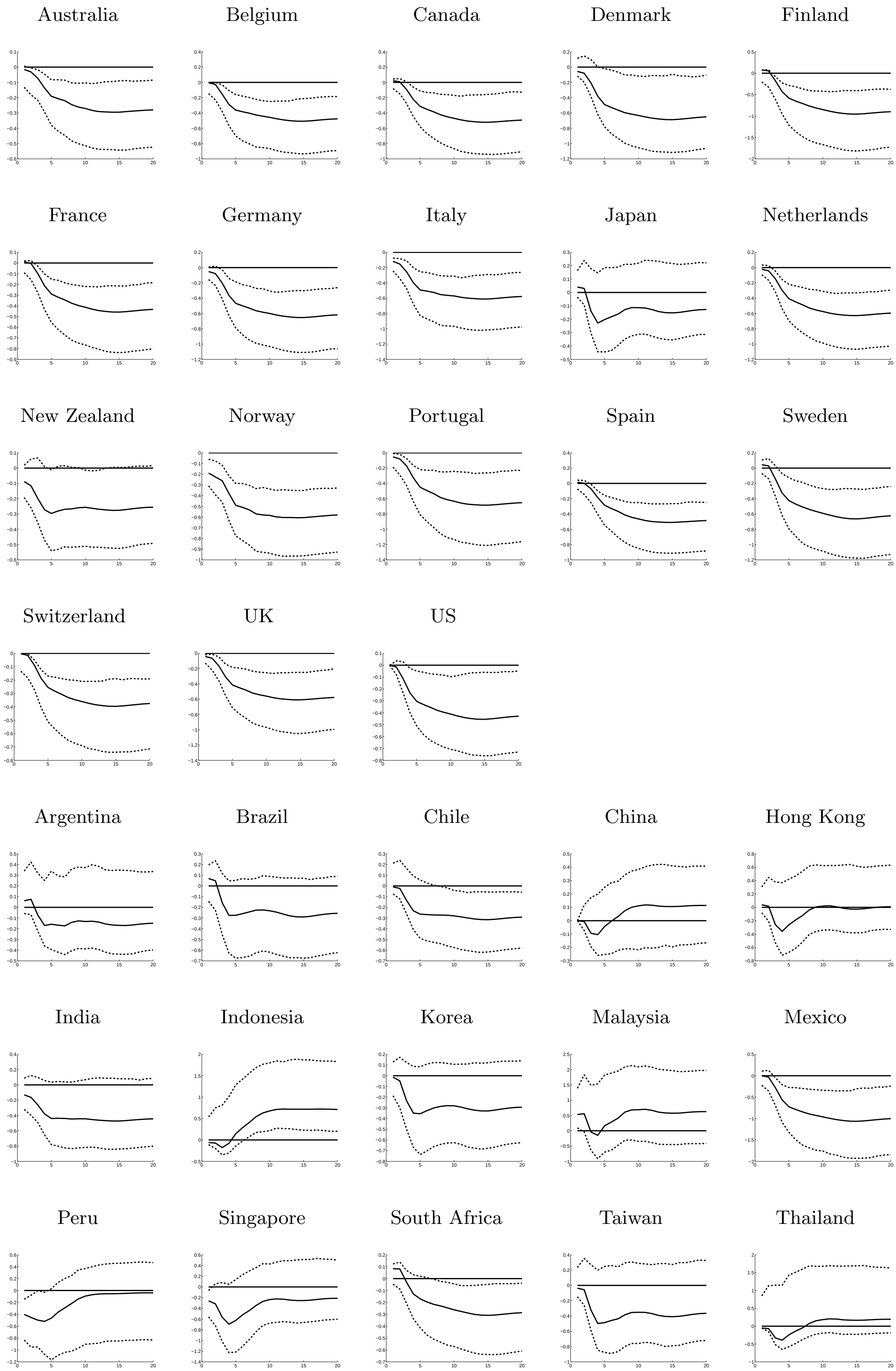
In the paper we report the median response at the two year horizon across countries within the same geographical region: Asia, Europe, North America (NA) and South America (SA), respectively. Here, Figures 2 and 3 report the country specific details. That is, the individual countries' responses to a oil supply and oil-specific demand shock.

Figure 2: **Impulse responses: Oil supply shock**



Note: The figures show the responses of GDP (in percent) in a given country after a oil supply shock that is normalized to decrease oil production by one percent. The responses are displayed in levels of the variables. The dotted lines represent 68 percent confidence bands (bootstrapped), while the black solid lines are the point estimates.

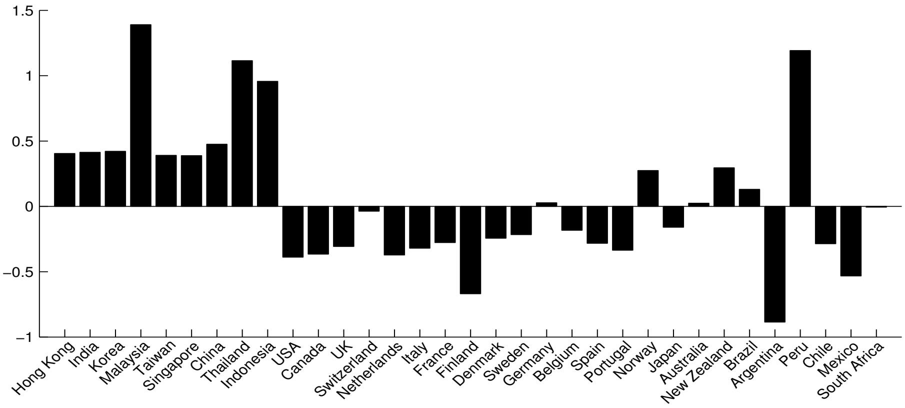
Figure 3: **Impulse responses: Oil-specific demand shock**



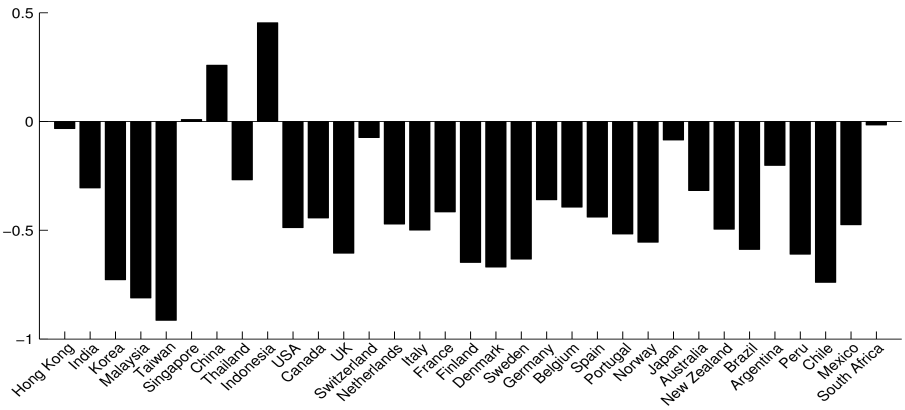
Note: The figures show the responses of GDP (in percent) in a given country after a oil-specific demand shock that increases oil prices with 10 percent. The responses are displayed in levels of the variables. The dotted lines represent 68 percent confidence bands (bootstrapped), while the black solid lines are the point estimates.

Figure 4: **Regression of oil shocks on observable GDP**

(a) Oil supply



(b) Oil-specific demand



Note: The bars show for each country the accumulated regression coefficients from the following regressions:

$$\Delta X_{t,i} = \alpha_i + \sum_{p=1}^{4} \beta_{p,i} s_{t-p} + e_{t,i}$$

where $\Delta X_{t,i}$ is the observable GDP growth in country i at time t, α and β are coefficients, and s_{t-p} are lags of the structural shocks (oil supply or oil-specific demand) identified in our model.

One concern with our modeling strategy, and therefore the identified country specific responses, is related to the idiosyncratic part of our model. That is, the factors might explain very different proportions of the variance in each individual country's activity measure. For example, the correlation between Norwegian GDP and the developed-economy activity factor is only 0.3, while the correlation between US GDP and the developed-economy activity factor is as high as 0.7, see Table 2 above. Thus, to avoid a direct dependence on the factor loading structure imposed in the FAVAR, we regress the structural oil supply and oil-specific demand shocks estimated in the model on the individual countries' GDP growth rates using standard OLS. The results are plotted in Figure 4. This also serves as a robustness check for the individual countries' impulse responses, plotted in Figures 2 and 3.

The findings confirm the baseline results that oil supply shocks (that temporarily increase the oil price) stimulate GDP in all emerging countries in Asia as well as in Brazil and Peru, while for the remaining countries in South America and for most of the developed countries, GDP instead falls. There are, however, a few exceptions to this picture: In Australia, Germany, New Zealand and Norway, GDP also increases temporarily (as in Asia).

Regarding the oil-specific demand shock, most countries respond negatively as expected. However, as seen using the FAVAR model, some Asian countries (most notably Indonesia) respond positively, implying that the average response for the Asian countries is less severe than for the other countries.

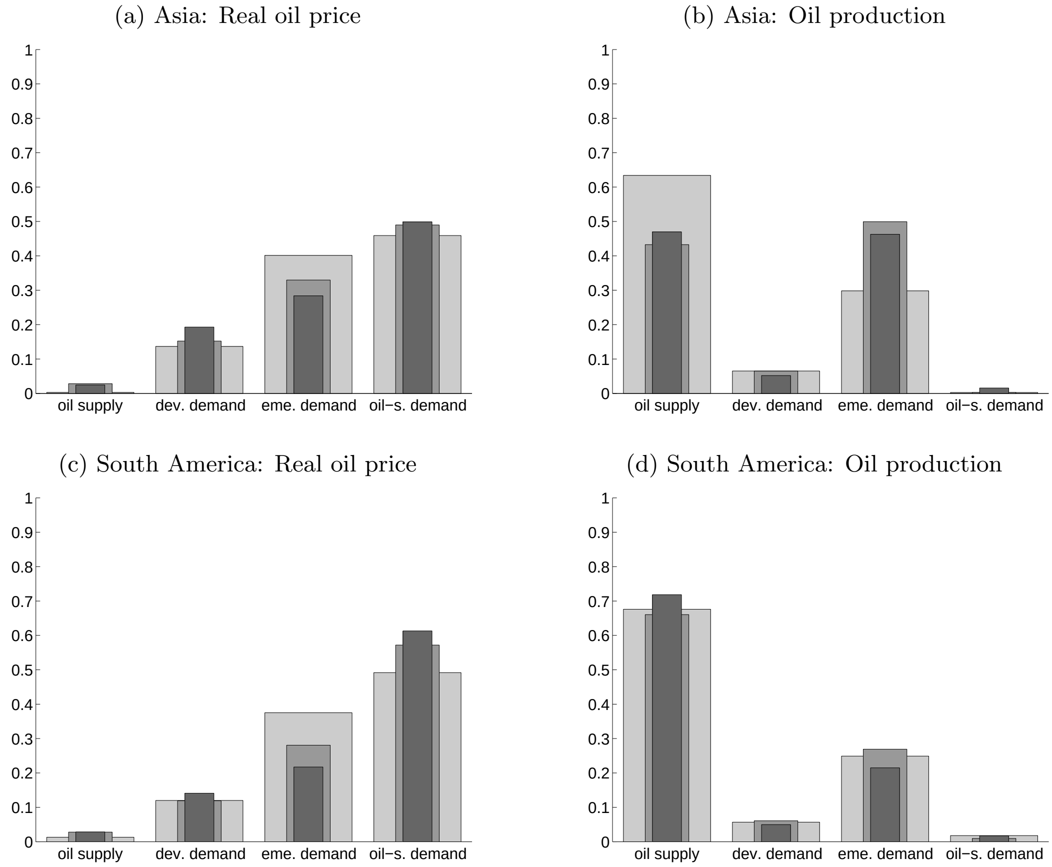
6 Robustness

Our main results are not particularly sensitive to the number of lags used in the transition equation. In fact, when we estimate the model with two lags instead of four, the results are slightly stronger, implying that the emerging-country factor explains an even larger share of the variation in the real price of oil and oil production. Below we discuss in greater detail the results for a number of additional robustness checks.

6.1 Asia or South America?

We examine whether Asia or South America (or a combination of both) drives the relationship between the oil-market and the macro economy presented in our paper. To do so, we split the sample of emerging countries into two blocks and estimate two different factors: one consisting of emerging Asian countries and one consisting of emerging South American countries (including South Africa). When estimating the South American factor we use GDP growth in Brazil to normalize the factor loadings. Then, we sequentially use these new factor estimates in our main model, as a replacement for the original emerging-country factor.

Figure 5: **Variance decomposition: Asia and South America separately**



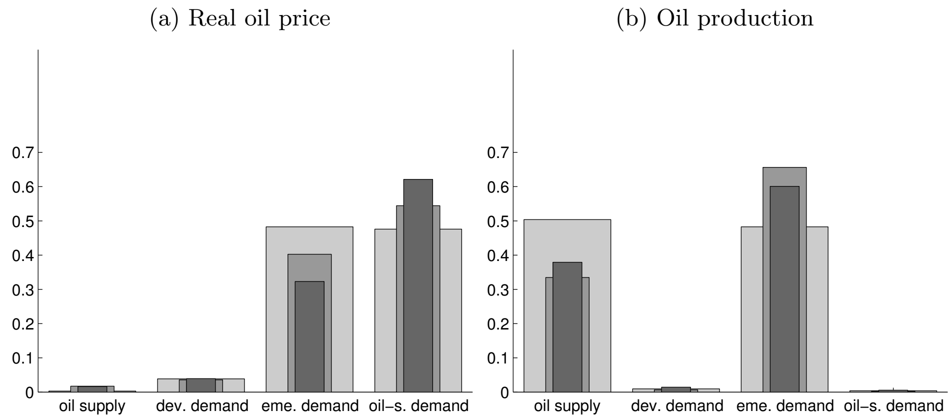
Note: In the model for Asia, only Asia is contained in the emerging factor, while in the model for South America, only South America is contained in the emerging factor. The bars display the variance decomposition with respect to the shocks for horizons 4, 8 and 12 quarters. The widest bars correspond to the shorter horizon.

The results using the emerging Asian factor are similar to our baseline results, while the results change when we use the emerging South American factor, see Figure 5. In particular, the emerging South American demand shock explains slightly less of the variance in oil prices and almost half of the variance in oil production compared to the results reported in the paper. This confirms that Asia is the main driver of the emerging factor, but the role of South America is far from negligible.

6.2 The impact of US demand and monetary policy

In this section we do two separate exercises. First, we exclude demand from the US altogether from the baseline model and second, we augment the model with the US interest rate. The exercises are motivated by the fact that many recent studies have argued that US

Figure 6: **Variance decomposition: Without the US**



Note: The bars display the variance decomposition with respect to the shocks for horizons 4, 8 and 12 quarters. The widest bars correspond to the shorter horizon.

monetary policy could be an important driver of commodity prices, see, e.g. Anzuini et al. (2013), who analyze the effect of expansionary US monetary policy shocks on commodity prices.

Excluding the US from the analysis gives an even smaller role to developed countries in explaining the oil price, see the variance decomposition in Figure 6.[1] This is not very surprising, given the importance of the US for developed countries, and given the importance of the US as the major consumer of oil.

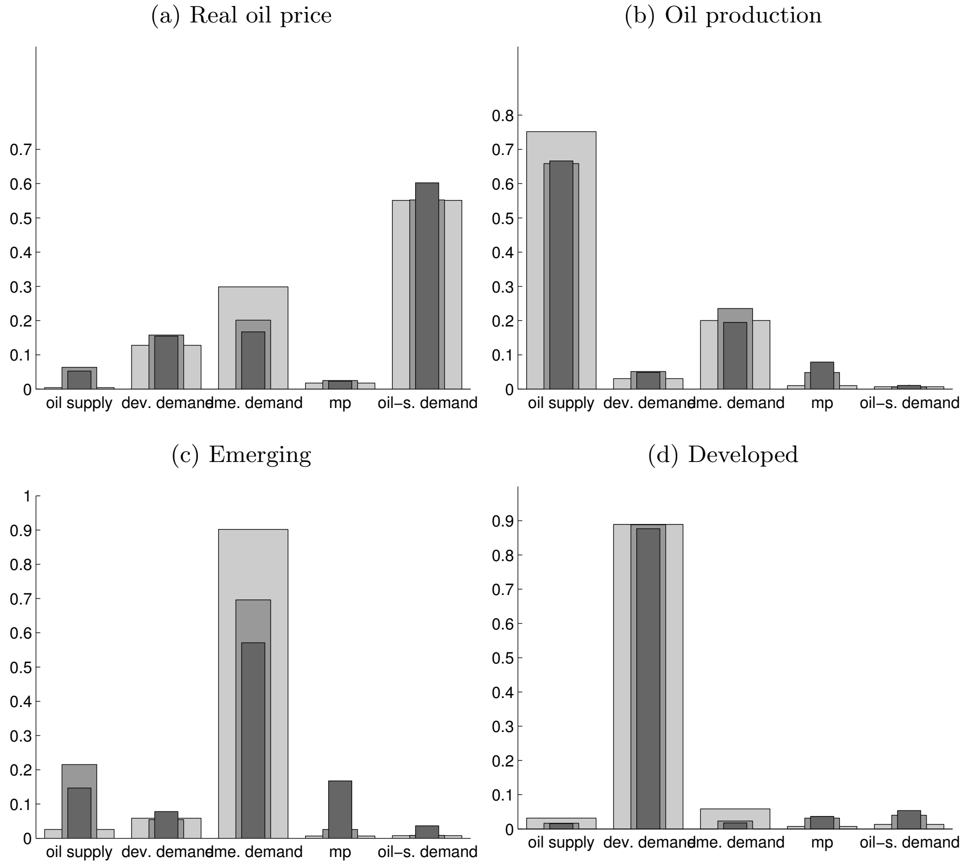
Second, we find that augmenting the model with the US Federal Funds rate (the interest rate is ordered second to last to allow monetary policy to affect the oil price on impact) does not alter the main results.[2] Emerging countries are still the main drivers of the oil price, see Figure 7. The small effects of US monetary policy shocks on oil prices is also consistent with the findings in Anzuini et al. (2013).

However, although we find US monetary policy to have only a trivial effect on the oil price, we still find US monetary policy to explain a considerable share of economic activity in emerging countries on longer horizons. The latter finding is consistent with Canova (2005) and Maćkowiak (2007), analyzing the impact of US monetary policy shocks on some emerging countries.

[1] We now choose Germany to have a loading with one on the developed factor.

[2] Results are robust to alternative measures of US monetary policy (i.e., the US Treasury Bill rate) and to alternative orderings of the US monetary policy.

Figure 7: **Variance decomposition: US monetary policy included**



Note: The bars display the variance decomposition with respect to the shocks for horizons 4, 8 and 12 quarters. The widest bars correspond to the shorter horizon.

6.3 Recursive identification

An advantage with our identification strategy is that we can identify distinct demand shocks that affect both the developed and the emerging factors simultaneously. If simultaneity was unimportant, however, then the FAVAR model could be identified using a standard recursive identification strategy, ordering the developed-economy factor above the emerging-economy factor or vice versa. Identifying such a recursive model, however, yields as expected, very different results from our baseline model. In particular, now the activity factor that is ordered first will always explain more of the variation in the oil price than the activity factor that is ordered second. Thus, simultaneity matters, which a standard recursive identification strategy does not adequately capture. Despite this, recursive identification strategies nonetheless reveal that the emerging-country factor plays an important role, see Table 3. First, the emerging-country activity factor will always explain

Table 3: Variance decompositions: Alternative identification schemes

Horizon	**VAR A - Cholesky**		**VAR B - Cholesky**		**VAR C - Sign**	
& demand shock	dev.	eme.	dev.	eme.	dev.	eme.
Real price of oil						
4	0.02	0.58	0.34	0.22	0.13	0.43
8	0.03	0.50	0.31	0.17	0.13	0.36
12	0.04	0.43	0.31	0.14	0.15	0.30
Oil production						
4	0.00	0.41	0.12	0.25	0.03	0.36
8	0.00	0.58	0.13	0.41	0.03	0.55
12	0.02	0.52	0.11	0.39	0.02	0.50

Note: VAR A contains the variables: $\left[\Delta prod \quad F^{eme} \quad F^{dev} \quad \Delta rpo\right]$, *and is identified using the Cholesky decomposition, i.e., a recursive ordering. VAR B is equal to VAR A, except from the ordering of the variables:* $\left[\Delta prod \quad F^{dev} \quad F^{eme} \quad \Delta rpo\right]$. *VAR C is identical to our main model, except that we only enforce the sign restriction to hold for one period.*

relatively more of the variation in the oil price than the developed-country activity factor, irrespective of where it is ordered. That is, when the emerging-country factor is ordered first, it explains nearly twice as much of the variation in the real oil price compared to when the developed-country factor is ordered first. Similarly, when the emerging-country factor is ordered last, it explains more than twice as much of the variation in the real oil price compared to what the developed-country factor does when ordered last. Second, the emerging-country factor always explain more of the variance in oil production than the developed-country factor, independent of the ordering of the emerging-country and the developed-country factors.

6.4 Set identification and alternative estimation strategies

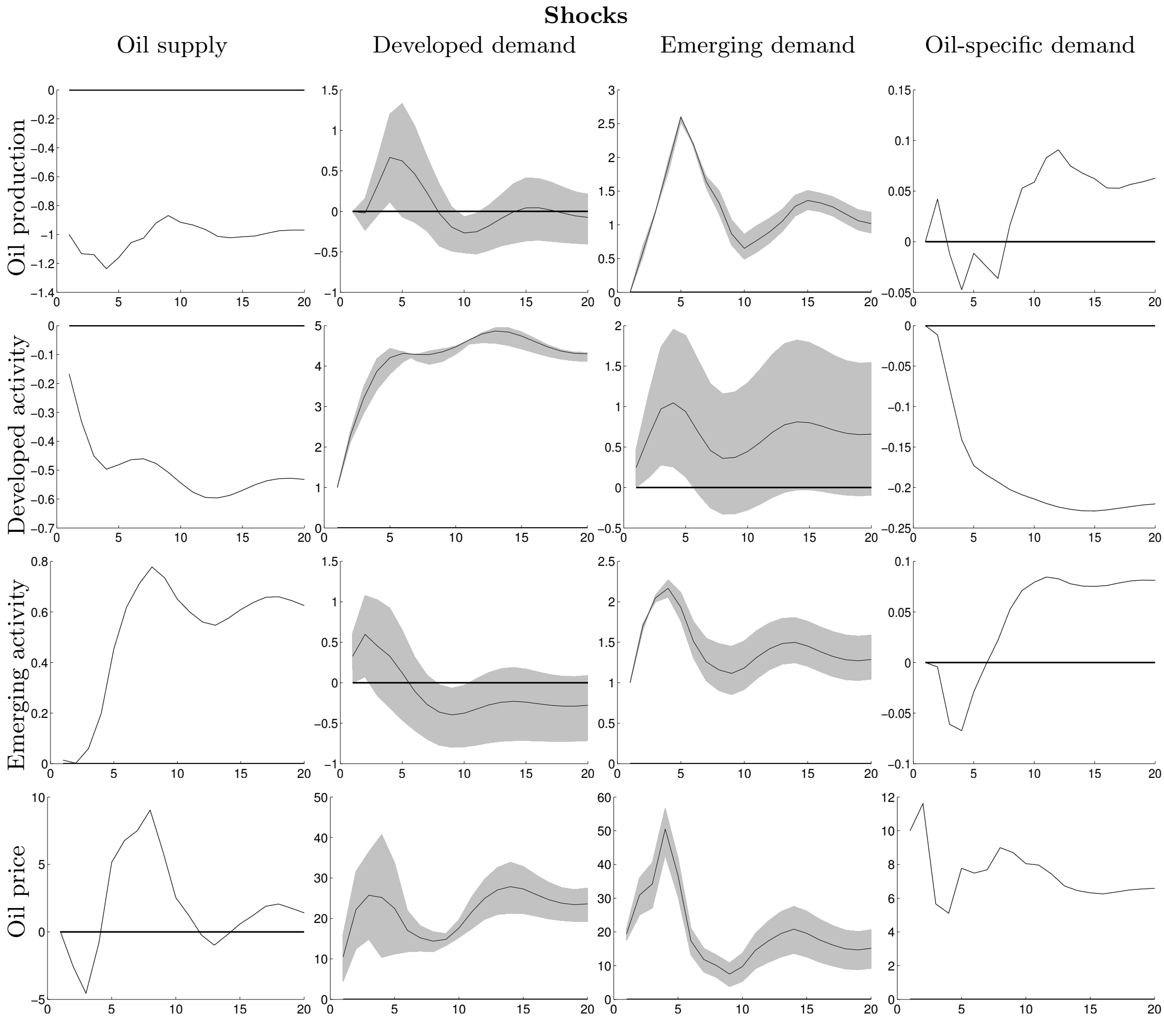
Neither the frequentist nor the Bayesian theory is conclusive on how confidence bands should be presented when structural disturbances are generated from sign restrictions. Moon et al. (2011) analyze the problem for classical VARs, in a frequentist setting. This do not apply directly to us, as we estimate a FAVAR where uncertainty in both parameter and factor estimates should be taken into account. Further, the sign restrictions we employ are not those that are studied in Moon et al. (2011).

Generally, our sign restrictions are very informative, meaning that the set of admissible impulse responses is rather narrow. This is illustrated in Figure 8. The figure reports the set of admissible impulse responses for 5000 draws based on the point estimates of β and Σ.

Importantly, variance decompositions of the set of impulse responses reported in Figure 8 are highly conclusive and supportive of the results already reported. Demand shocks originating in developed economies never explain more than 0.15 percent of the variation in global oil production. At horizons exceeding 5 quarters ahead, demand shocks originating in emerging economies never explain less than around 40 percent of the same variation. Further, for horizons up to 12 quarters ahead, demand shocks originating in emerging economies are almost unambiguously more important than demand shocks originating in developed economies in explaining the variation in the real price of oil. For example, at horizon 4, the set of variance decompositions attributed to emerging demand is in the range 20 to 60 percent, while the same range for developed demand is 0.02 to 30 percent.

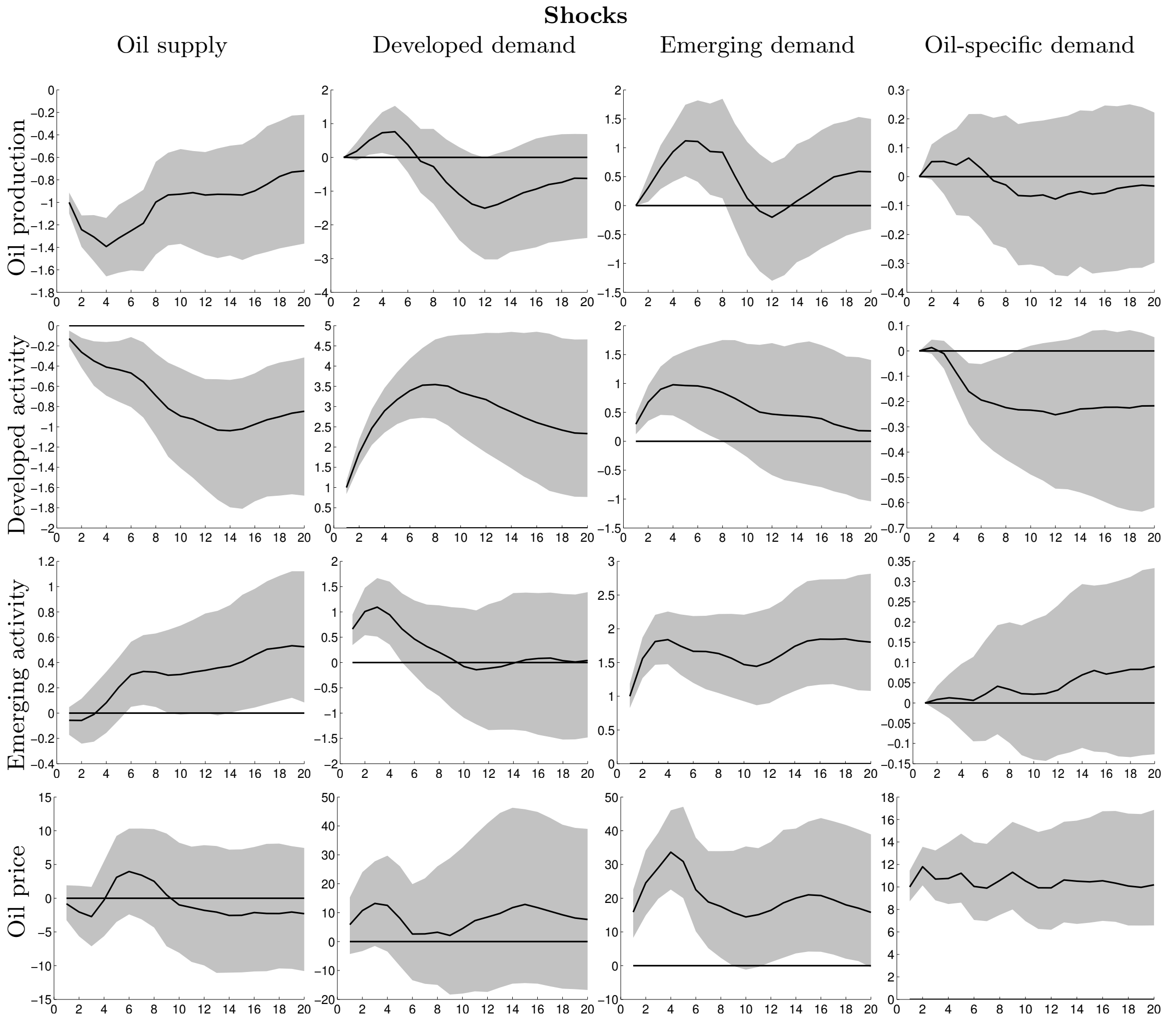
We stress that for a particular (bootstrapped) parameter set, β and Σ, any draw of the sign-restricted structural disturbances will not cause the impulse responses in columns one and four in Figure 8 to change. Only impulse responses in columns two and three are affected. Thus, these are set identified, while the former are point identified. That is, the confidence bands reported in columns one and four of the impulse response figure in the main text are purely a function of parameter and factor uncertainty.

Figure 8: **Impulse responses: Point estimates and admissible sets**



Note: The responses are displayed in levels of the variables. The developed-country and emerging-country demand shocks are normalized to increase activity in developed and emerging countries by one percent, respectively. To facilitate comparison with earlier studies, the oil supply shock is normalized to decrease oil production by one percent, while the oil-specific demand shock is normalized to increase the real oil price by 10 percent. The grey shaded areas represent the whole set of admissible impulse responses simulated, while the solid lines are the point estimates.

Figure 9: **Impulse responses: Bayesian estimates**



Note: The responses are displayed in levels of the variables. The developed-country and emerging-country demand shocks are normalized to increase activity in developed and emerging countries by one percent, respectively. To facilitate comparison with earlier studies, the oil supply shock is normalized to decrease oil production by one percent, while the oil-specific demand shock is normalized to increase the real oil price by 10 percent. The grey shaded areas represent 68 percent probability bands, while the black solid lines are the median estimates.

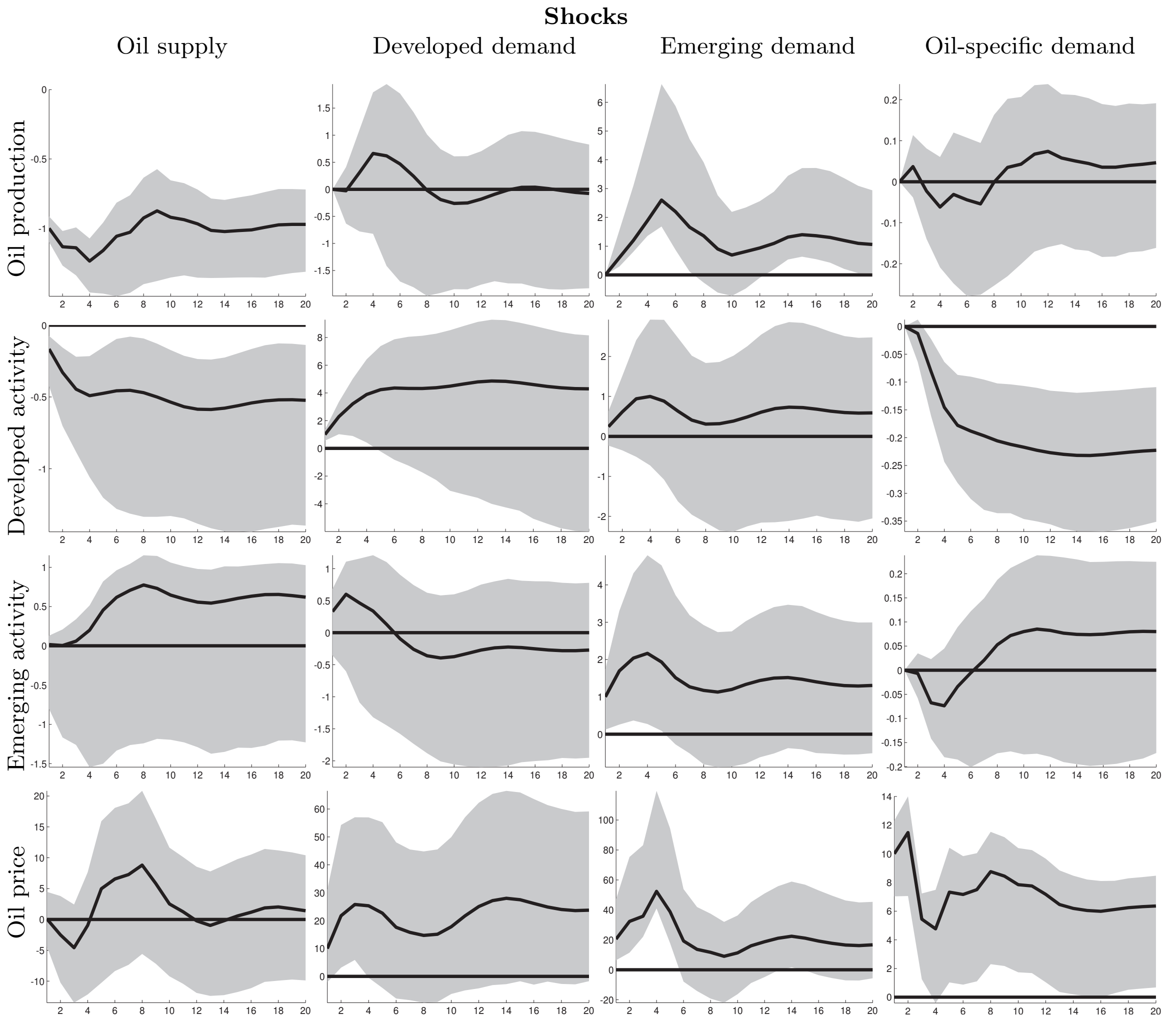
We have also estimated the FAVAR model using Bayesian techniques. Bernanke et al. (2005) show that a joint estimation of a related factor model, using likelihood-based Gibbs sampling techniques, yields very similar results to the ones applying a two-step procedure. This also holds in our application, when we specify and estimate the model as a Bayesian Dynamic Factor Model (BDFM). In particular, as shown in Figure 9, the impulse responses and the uncertainty estimates from the BDFM are very similar to the once presented in the main paper.

In this application we still prefer the FAVAR specification because of its simplicity, as estimating, identifying and simulating the FAVAR model requires only a few lines of Matlab code and takes less than 120 seconds. On the other hand, the BDFM is much more time consuming. Furthermore, the distributional assumptions (on, e.g., the error terms in the model) that are needed to estimate the BDFM using likelihood-based Gibbs sampling techniques are much more restrictive than in our FAVAR case, where the simulation is non-parametric.

6.5 Using the nominal price of oil

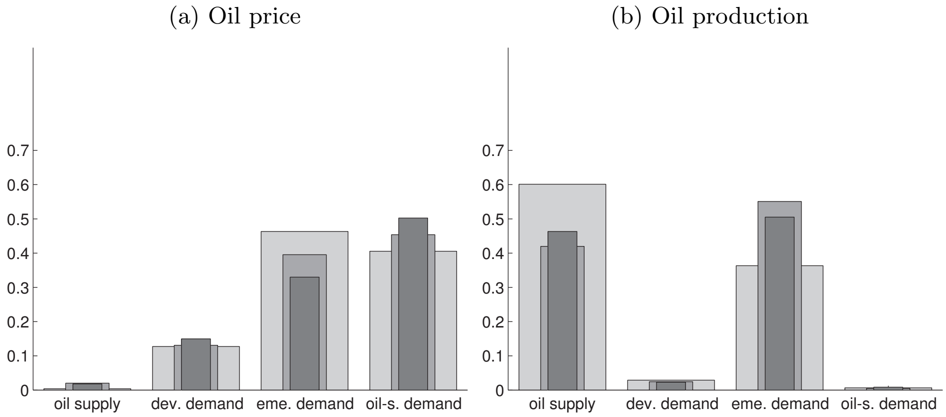
One concerns is that the relative weak response in the real price of oil to the developed demand shock is due to the fact that CPI also increases (since we deflate the price of oil with US CPI). This is not the case. In fact, when we run the model using the nominal price of oil, the model predicts an even larger role for the emerging-country demand shocks. See, Figures 10 and 11.

Figure 10: **Impulse responses: Using the nominal price of oil**



Note: The responses are displayed in levels of the variables. The developed-country and emerging-country demand shocks are normalized to increase activity in developed and emerging countries by one percent, respectively. To facilitate comparison with earlier studies, the oil supply shock is normalized to decrease oil production by one percent, while the oil-specific demand shock is normalized to increase the real oil price by 10 percent. The grey shaded areas represent 68 percent confidence bands, while the black solid lines are the point estimates.

Figure 11: **Variance decomposition: Using the nominal price of oil**



Note: The bars display the variance decomposition with respect to the shocks for horizons 4, 8 and 12 quarters. The widest bars correspond to the shorter horizon.

References

Anzuini, A., M. J. Lombardi, and P. Paganoa (2013). The impact of monetary policy shocks on commodity prices. *International Journal of Central Banking 9*, 119–144.

Bernanke, B., J. Boivin, and P. S. Eliasz (2005). Measuring the effects of monetary policy: A factor-augmented vector autoregressive (FAVAR) approach. *Quarterly Journal of Economics 120*(1), 387–422.

Canova, F. (2005). The transmission of US shocks to Latin America. *Journal of Applied Econometrics 20*(2), 229–251.

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.

Maćkowiak, B. (2007). External shocks, US monetary policy and macroeconomic fluctuations in emerging markets. *Journal of Monetary Economics 54*(8), 2512–2520.

Moon, H. R., F. Schorfheide, E. Granziera, and M. Lee (2011). Inference for VARs identified with sign restrictions. Working Papers 11-20, Federal Reserve Bank of Philadelphia.

Pesaran, M. H., T. Schuermann, and L. V. Smith (2009). Rejoinder to comments on forecasting economic and financial variables with global VARs. *International Journal of Forecasting 25*(4), 703–715.

Stock, J. H. and M. W. Watson (2002). Macroeconomic forecasting using diffusion indexes. *Journal of Business & Economic Statistics 20*(2), 147–162.