Online Appendix

The macroeconomic effects of oil supply news: Evidence from OPEC announcements

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Contents

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A. Charts, tables and additional sensitivity checks

In this Appendix, I present additional tables and figures, and sensitivity checks that are not featured in the main body of the paper. The subappendices refer to the corresponding sections in the main text.

A.1. Diagnostics of the surprise series

As discussed in the paper, I perform a number of additional validity checks on the surprise series. In the main text, I already discussed the role of background noise in detail. A related concern is that there may be other news confounding the surprise series in a systematic way. Even though this seems unlikely given the rather irregular schedule of OPEC conferences, I checked whether any of the major U.S. news releases systematically occur on OPEC dates. Table A.1 confirms that no release systematically overlaps with OPEC announcements. For all these releases, there are only a few, random overlaps. Excluding the overlapping dates in constructing the instrument does also not change the results materially.[1]

Table A.1: U.S. macroeconomic news announcements

Announcement	Observations	Source	Dates	Frequency	Overlaps
GDP	114	BEA	4/1987-12/2017	quarterly	2
Unemployment rate	466	BLS	1/1983-12/2017	monthly	5
Nonfarm payrolls	405	BLS	2/1985-12/2017	monthly	5
Retail sales	385	BC	12/1986-12/2017	monthly	3
Industrial production	385	FRB	12/1986-12/2017	monthly	6
Durable goods orders	464	BC	4/1983-12/2017	monthly	10
Trade balance	384	BEA	12/1986-12/2017	monthly	8
CPI	467	BLS	1/1983-12/2017	monthly	3
PPI	385	BLS	12/1986-12/2017	monthly	5
FOMC	305	FED	3/1983-12/2017	six-week	4

Notes: The table shows information on major U.S. macroeconomic news announcements on activity, prices and monetary policy together with the number of instances in which they coincide with OPEC announcement days. The U.S. news data are from Kilian and Vega (2011), extended for the most recent period using Bloomberg.

I also investigate the autocorrelation and forecastability of the surprise series as well as the relation to other shocks from the literature. Figure A.1 depicts the autocorrelation function. We can see that there is no evidence that the series is serially correlated. I also perform a number of Granger causality tests. Table A.2 shows that the series is not forecastable by past macroeconomic or financial vari-

[1] This is in line with the findings by Kilian and Vega (2011), who found that energy prices do not to respond instantaneously to U.S. macroeconomic news.

ables. Finally, I look how the series correlates with other shock series from the literature and find that it is not correlated with other shocks such as global demand or uncertainty shocks (see Table A.3). Not surprisingly, I find that the series is significantly correlated with oil-specific demand shocks. This is consistent with the fact that oil-specific demand shocks capture among other things news about future supply. Finally, I find that the series is only weakly correlated with the previously identified unanticipated oil supply shocks.

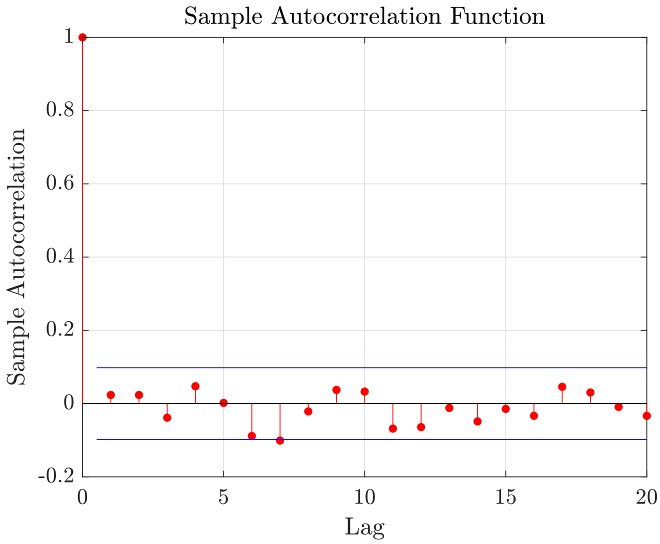


Figure A.1: The autocorrelation function of the oil supply surprise series

Table A.2: Granger causality tests

Variable	p-value
Instrument	0.3749
Oil price	0.4846
World oil production	0.7481
World oil inventories	0.6882
World industrial production	0.9502
US industrial production	0.9342
US CPI	0.7641
Fed funds rate	0.8849
S&P 500	0.1865
NEER	0.7282
Geopolitical risk	0.1526
Joint	0.7342

Notes: The table shows the p-values of a series of Granger causality tests of the oil supply surprise series using a selection of macroeconomic and financial variables. To be able to conduct standard inference, the series are made stationary by taking first differences where necessary. The lag order is set to 12 and in terms of deterministics, only a constant term is included.

Table A.3: Correlation with other shock measures

Shock	Source	ρ	p-value	n	Sample
Panel A: Oil shocks					
Oil price	Hamilton (2003)	0.06	0.17	492	1977M01-2017M12
Oil supply	Kilian (2008)	-0.05	0.38	369	1974M01-2004M09
	Caldara, Cavallo, and Iacoviello (2019)	-0.02	0.74	372	1985M01-2015M12
	Baumeister and Hamilton (2019)	-0.08	0.09	515	1975M02-2017M12
	Kilian (2009)	0.08	0.09	395	1975M02-2007M12
Global demand	Kilian (2009)	0.03	0.51	395	1975M02-2007M12
Oil-specific demand	Kilian (2009)	0.17	0.00	395	1975M02-2007M12
Panel B: Other shocks					
Productivity	Basu, Fernald, and Kimball (2006)	-0.04	0.66	152	1974Q1-2011Q4
	Smets and Wouters (2007)	-0.06	0.50	124	1974Q1-2004Q4
News	Barsky and Sims (2011)	-0.14	0.12	135	1974Q1-2007Q3
	Kurmann and Otrok (2013)	-0.03	0.76	126	1974Q1-2005Q2
	Beaudry and Portier (2014)	0.04	0.61	155	1974Q1-2012Q3
Monetary policy	Gertler and Karadi (2015)	0.07	0.20	324	1990M01-2016M12
	Romer and Romer (2004)	-0.00	0.99	276	1974M01-1996M12
	Smets and Wouters (2007)	0.04	0.64	124	1974Q1-2004Q4
Uncertainty	Bloom (2009)	0.01	0.87	522	1974M07-2017M12
	Baker, Bloom, and Davis (2016)	0.07	0.15	390	1985M07-2017M12
Financial	Gilchrist and Zakrajšek (2012)	0.02	0.70	498	1974M07-2015M12
	Bassett et al. (2014)	0.12	0.30	76	1992Q1-2010Q4
Fiscal policy	Romer and Romer (2010)	0.03	0.77	136	1974Q1-2007Q4
	Ramey (2011)	0.07	0.39	148	1974Q1-2010Q4
	Fisher and Peters (2010)	0.05	0.55	140	1974Q1-2008Q4

Notes: The table shows the correlation of the oil supply surprise series with a wide range of different shock measures from the literature. Panel A depicts the relationship with other oil shocks. Panel B shows the relationship to other types of shocks. For these shock measures, I draw on the shocks studied in Stock and Watson (2012) and Piffer and Podstawski (2017). ρ is the Pearson correlation coefficient, the p-value corresponds to the test whether the correlation is different from zero and n is the sample size. When the shock measure is only available at the quarterly frequency, the oil supply surprise series is aggregated by summing across months.

A.2. Effects on the oil market and the macroeconomy

A.2.1. Accounting for background noise

As discussed in the main text, background noise in the oil supply series may lead to unreliable inference and overstate the statistical precision of the estimates. Therefore, it is important to analyze the robustness of the results when accounting for background noise using the heteroskedasticity-based identification strategy.

As shown in the paper, accounting for background noise does not materially change the point estimates but leads to larger sampling uncertainty. This may be a bit surprising, given the non-trivial background noise documented in Figure 2 in the paper. Here, I provide some suggestive evidence for the potential explanations discussed in the main text.

One explanation is that the background noise may in fact largely reflect variation in market beliefs about future oil supply announcements. Studying the impulse responses using the control series as an external instrument provides some suggestive evidence for this explanation. As shown in the top panel of Figure A.2, the responses to the control series display quite some similarity to the baseline responses, even though the responses for inventories and industrial production turn out to be somewhat different. Interestingly, these are also the variables for which we observe the relatively largest differences between the external instruments and the heteroskedasticity-based approach in Figure 4 in the paper. These results are in line with the interpretation that a large part of the background noise is in fact oil supply news related and also accord well with the finding that oil supply news shocks account for the bulk of the fluctuations in oil prices, especially in the short run.

I also explored the explanation that most of the identification could come from large shocks. To this end, I dropped very large surprises (i.e. surprises larger than 7 percent in absolute value) from the treatment sample. From the bottom panel of Figure A.2, we can see that point estimates of the heteroskedasticity-based and the external instruments estimator differ slightly more in this case. However, the most striking difference arises for the confidence bands, which are now substantially wider for the heteroskedasticity-based estimator, consistent with the lower variance ratio. Thus, the large shocks appear to be quite important for the statistical precision of the estimates.

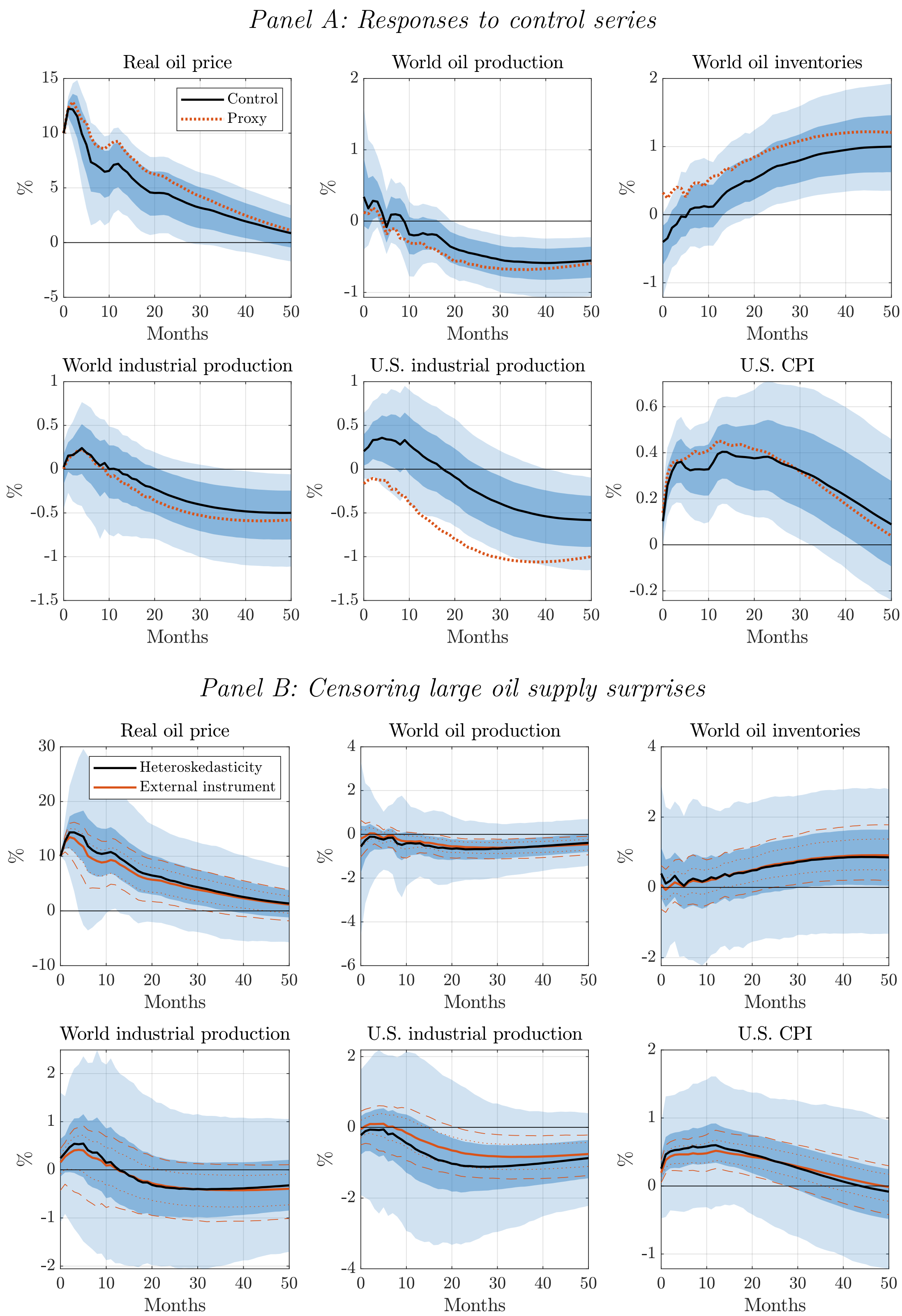


Figure A.2: Understanding heteroskedasticity-based identification

Notes: Investigating potential explanations for the similarity of the heteroskedasticity-based and the external instruments estimator. Panel A: Responses using the control series as an external instrument. Panel B: Responses from the two estimation approaches after censoring large values in the surprise series to zero. The shock is normalized to increase the real price of oil by 10 percent on impact. The solid lines are the point estimates and the shaded areas are 68 and 90 percent confidence bands, respectively.

To analyze the role of the dynamic VAR structure, I compute again the impulse responses to the identified shock from the heteroskedasticity-based VAR using local projections. The results are shown in Figure A.3. We can see that the VAR-based and the LP-based impulse responses are very similar but the LP responses are more erratic and less precisely estimated, in line with the findings for the external instruments approach.

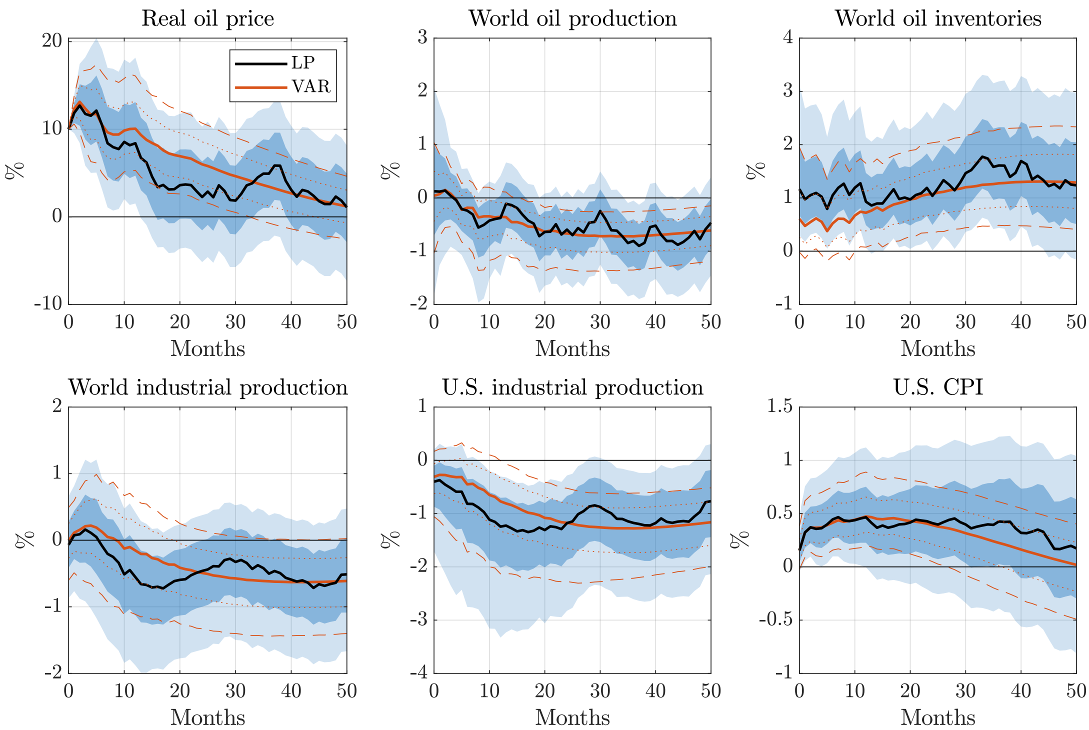


Figure A.3: Local projections on oil supply news shock (heteroskedasticity-based)

Notes: Impulse responses estimated from LPs on the oil supply news shock extracted from the heteroskedasticity-based VAR (black) together with VAR responses (red), normalized to increase the real price of oil by 10 percent on impact. The solid lines are the point estimates and the shaded areas and dashed/dotted lines are 68 and 90 percent confidence bands, respectively.

A.2.2. Local projections

An alternative approach would be to directly estimate the dynamic causal effects using local projections on the surprise series. However, directly estimating the *macroeconomic* effects of high-frequency surprises is challenging. As discussed in Nakamura and Steinsson (2018), the clean identification via the high-frequency approach often comes at the cost of lower statistical power. Intuitively, macroeconomic variables several months, quarters or even years out are hit by a myriad of shocks. At the same time, the oil price is an extremely volatile variable itself and the high-frequency surprises account only for a small part of the price fluctuations, rendering the signal-to-noise ratio low. This makes it challenging to directly estimate the macroeconomic effects of high-frequency oil supply surprises without imposing additional structure.

Furthermore, the high-frequency surprises are typically only available for a shorter sample than the outcome variables of interest, further reducing statistical power. The VAR approach allows one to estimate the reduced form over a longer sample even if the instrument is only available for a subperiod, improving efficiency at all horizons. By contrast, in the local projection framework there is less scope to improve efficiency (Stock and Watson, 2018).

Local projections-IV. Despite these challenges, I present here the results from a local projections-instrumental variable (LP-IV) approach. To fix ideas, the responses are estimated by running the following set of IV-regressions:

$$y_{i,t+h} = \beta_0^i + \psi_h^i p_t + \boldsymbol{\beta}_h^{i\prime} \mathbf{x}_{t-1} + \xi_{i,t,h}, \tag{1}$$

using the oil supply surprise series z_t as an instrument for the oil price, p_t, where $y_{i,t}$ is the outcome variable of interest and $\mathbf{x}_{t-1}$ is a vector of controls. ψ_h^i is the impulse response to the oil supply news shock of variable i at horizon h.[2]

An important choice in this context concerns the selection of control variables. According to Stock and Watson (2018), there are three reasons for adding control variables. First, and most importantly, the instrument may satisfy the exogeneity condition only after controlling for some observable factors. Second, control variables can help to increase the instrument strength in the first stage by filtering out the effects of past shocks and thus increasing the signal-to noise ratio. Third, and

[2]To increase efficiency, I follow Stock and Watson (2018) and estimate the controls on the full sample and then use the residuals in the local projections for the subsample for which the instrument is available. An alternative would be just to censor the missing values in the instrument to zero and run the local projections including the controls on the full sample (see also Noh, 2019). In practice, I found that these two approaches produce similar results. To compute the bands, I use HAC standard errors with a lag length of 1 plus the horizon in question.

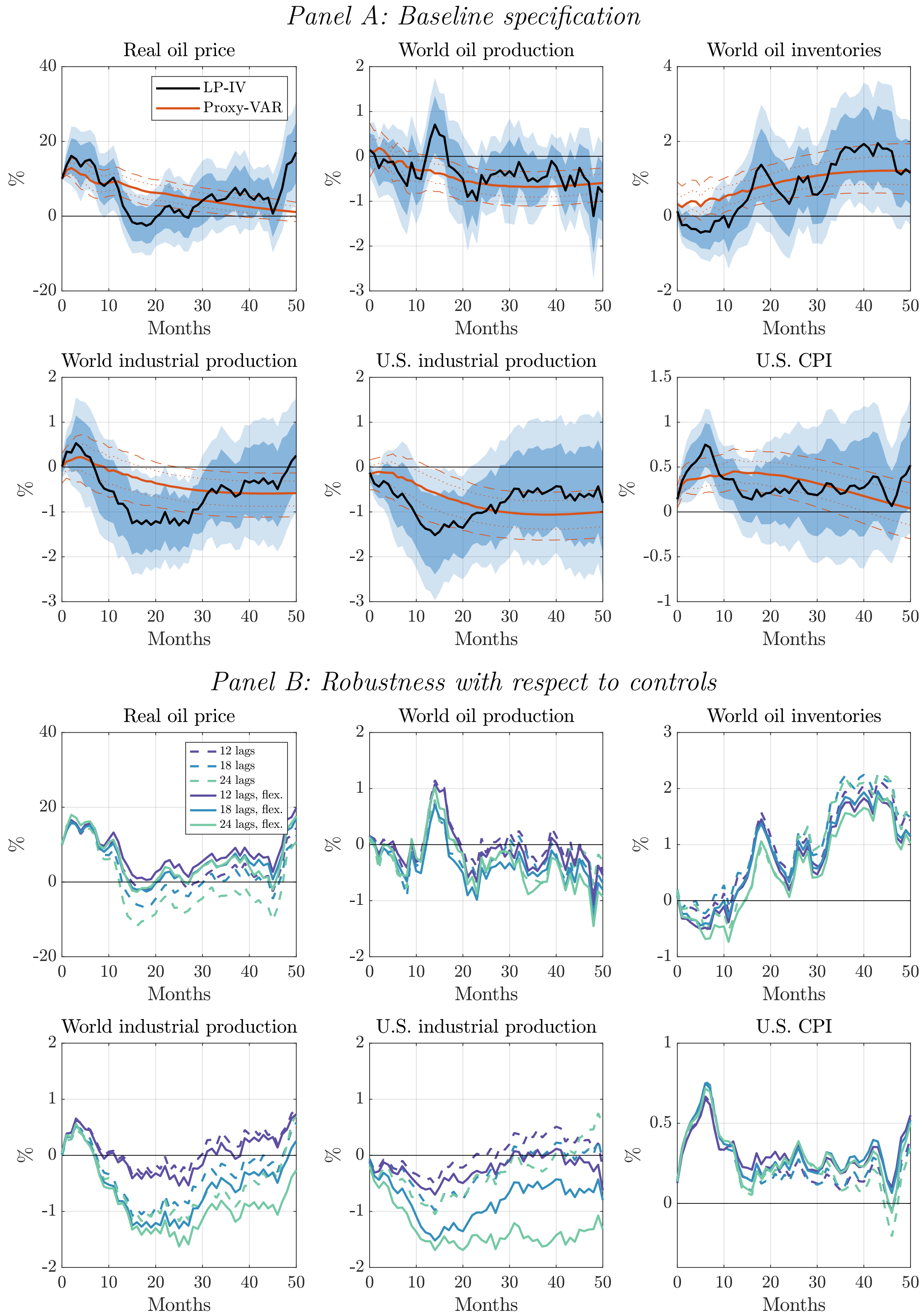


Figure A.4: Local projection-instrumental variable approach

Notes: Impulse responses to the oil supply news shock from LP-IVs. Panel A: Impulse responses from the baseline LP-IV (black) together with the responses from the external instruments VAR (red). The solid lines are the point estimates and the shaded areas and dashed/dotted lines are 68 and 90 percent confidence bands, respectively. Panel B: Robustness of LP-IV responses with respect to the selection of controls. I consider 12, 18, and 24 lags of all variables as well as the same number of lags in specifications with oil market and U.S. variable specific-controls.

relatedly, including control variables helps to reduce the sampling variance of the IV estimator by reducing the variance of the error term.

Because the oil market is known to feature persistent cycles (see e.g. Herrera and Hamilton, 2004), it is important to control for sufficient lags. However, when choosing the controls, there is always a trade-off between underfitting and overfitting. In light of this, I use a specification with 18 lags and oil market and U.S. variable specific controls as the baseline. For the oil market variables, I only use lags of the oil price, oil production, oil inventories and world industrial production. For the U.S. variables I also control for lags of industrial production and the CPI, respectively. This flexible specification allows to control for sufficient lags of the relevant variables while keeping the model degrees of freedom manageable.

The results are shown in the top panel of Figure A.4. The point estimates turn out to be reasonably similar to the VAR responses: the oil price rises significantly, world oil production tends to fall with a lag, oil inventories increase persistently, world and U.S. industrial production fall and the U.S. CPI increases significantly. However, compared to the VAR, all responses are much more erratic and the standard errors are substantially larger, especially at longer horizons. This had to expected to a certain extent as we impose less structure.

The bottom panel of Figure A.4 analyzes how the results depend on the controls used in the LP-IVs. In particular, I consider 12, 18, and 24 lags of all variables as well as the same number of lags in specifications with oil market and U.S. variable specific-controls. The main takeaway is that the results are not driven by one specific set of controls. Especially at shorter horizons, the responses are all very similar. At longer horizons there is more uncertainty, as is common in time series models. It should be noted, however, that given the relatively large standard errors, the differences across LP specifications are not statistically significant.

Heteroskedasticity-based local projections. We can also implement the heteroskedasticity-based identification strategy in the local projections framework. Define again a sample of treatment (R1) and control periods (R2) and compute the instrument z_t in both periods. As shown in Nakamura and Steinsson (2018), the heteroskedasticity-based estimator is then given by

$$\psi_h^i = \frac{\text{cov}_{R1}(y_{i,t+h}, z_t) - \text{cov}_{R2}(y_{i,t+h}, z_t)}{\text{var}_{R1}(z_t) - \text{var}_{R2}(z_t)}.$$

As in the LP-IVs, I first estimate the coefficients of the control variables on the full sample and then use the residuals $y_{i,t+h}^{\perp}$ in the heteroskedasticity-based estimator for the subsample for which z_t is available. As controls, I use the same set of variables as the baseline LP-IV specification. To compute the impulse responses, I use again the implementation through instrumental variables developed in Rigobon and Sack (2004).[3]

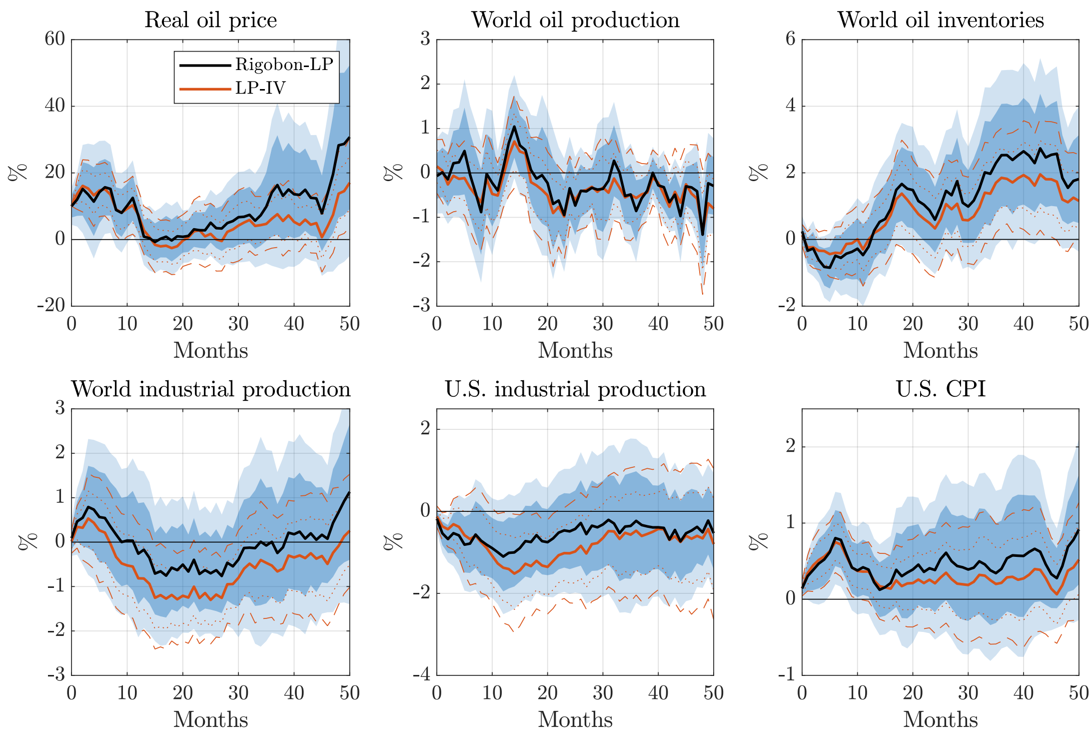


Figure A.5: Heteroskedasticity-based local projections

Notes: Impulse responses to the oil supply news shock from heteroskedasticity-based local projections (black) together with the LP-IV responses (red), normalized to increase the real price of oil by 10 percent on impact. The solid lines are the point estimates and the shaded areas and dashed/dotted lines are 68 and 90 percent confidence bands, respectively.

The results are shown in Figure A.5. We can see that most responses are qualitatively similar to the baseline LP-IVs. However, some of the responses, in particular the world and U.S. industrial production responses, turn out to be a bit weaker. The responses are also less precisely estimated and somewhat more erratic. This probably had to be expected to a certain extent, as the problems regarding statistical power discussed above are likely more acute in this context because the sample has to be further split into a treatment and control sample.

These results illustrate again the challenges of directly estimating the economic effects of high-frequency surprises. An elegant solution to this problem is to focus on variables that move contemporaneously, such as financial variables and survey expectations, as proposed by Nakamura and Steinsson (2018). However, if we are interested in macroeconomic variables, estimating the dynamic causal effects turns

[3]Given that the first-stage F-statistic confirmed that the change in variance is significant enough, I use standard HAC errors to compute the bands, as in the LP-IV regressions.

out to be challenging without imposing additional structure, as illustrated above.

A.2.3. Model uncertainty

To study in more detail how the modeling choice affects the results, I perform a systematic evaluation of the role of model uncertainty. In particular, I consider the following models:

1. External instruments VAR
2. LP using shock from external instruments VAR
3. LP-IV using oil supply surprise series
4. Heteroskedasticity-based VAR
5. LP using shock from heteroskedasticity-based VAR
6. Heteroskedasticity-based LP
7. Heteroskedasticity-based VAR (implementation as in Wright 2012)

For each model, I further consider a specification with 12, 18, and 24 lags as controls.[4]

The results are presented in Figure A.6. Depicted is the minimum and the maximum of the point estimates of all the models and specifications considered, together with the baseline responses from the external instruments VAR. We can see that qualitatively, the conclusions of the paper turn out to be robust with respect to the modeling choice. For the large majority of models, an oil supply news shock leads to an immediate increase in the oil price, a gradual decrease in world oil production, an increase in world oil inventories, a fall in world and U.S. industrial production, and an increase in U.S. CPI.[5] Quantitatively, however, the effects can differ quite a bit across the different models: some models are associated with somewhat weaker effects while other models feature effects that are more pronounced. Importantly, the baseline responses appear to lie mostly somewhere in between.

[4] For the LP specifications, I use both general and variable-specific controls as discussed above.

[5] The only qualitative difference emerges for world and U.S. industrial production, which according to a few specifications that impose very little structure merely changes or even tends to increase slightly. However, in light of the power problems discussed above and the large uncertainty around these estimates, these results should be interpreted with a grain of salt.

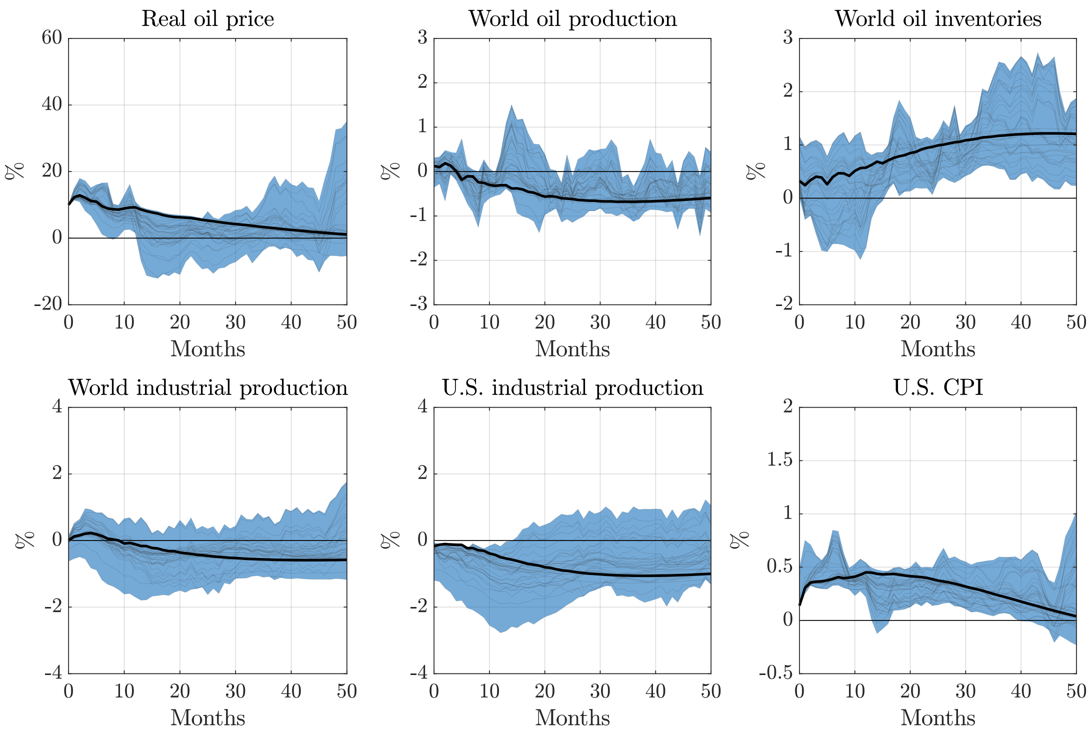


Figure A.6: The role of model uncertainty

Notes: The figure displays the model uncertainty for the results of oil supply news on the macroeconomy, as measured by the minimum and the maximum of the point estimates for a wide selection of different models and model specifications, including different specifications of the external instruments and heteroskedasticity-based VAR and LP models, together with the baseline responses (black line).

A.3. Wider effects and propagation channels

Below, I show the impulse responses of additional variables of interest, as discussed in the main text.

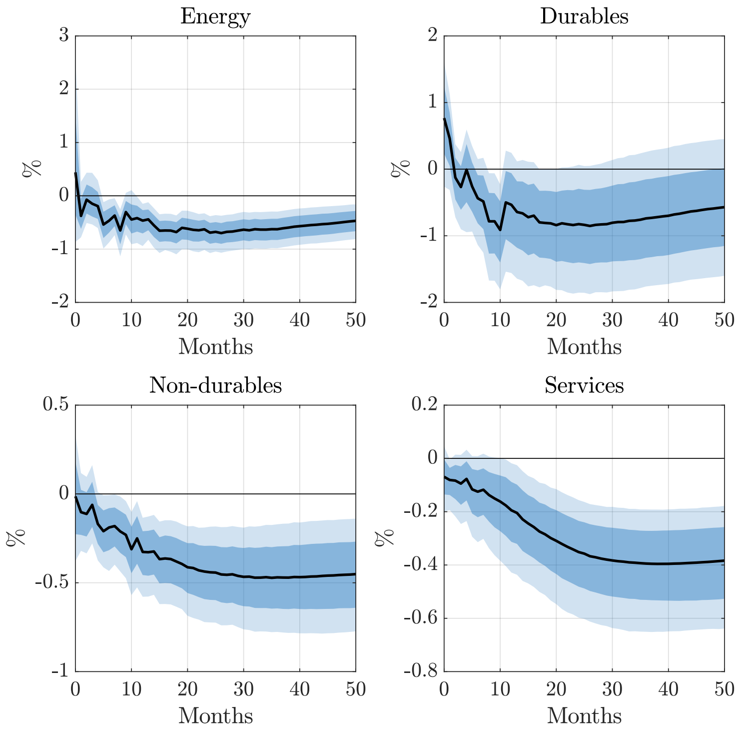


Figure A.7: Personal consumption expenditures

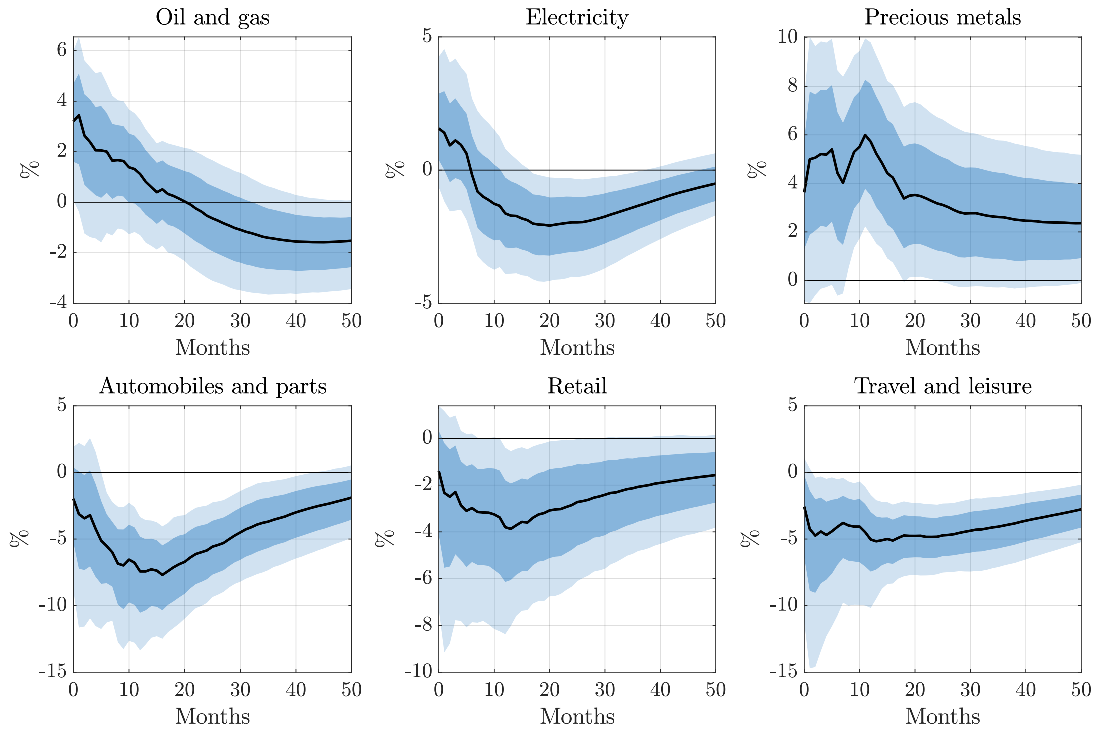
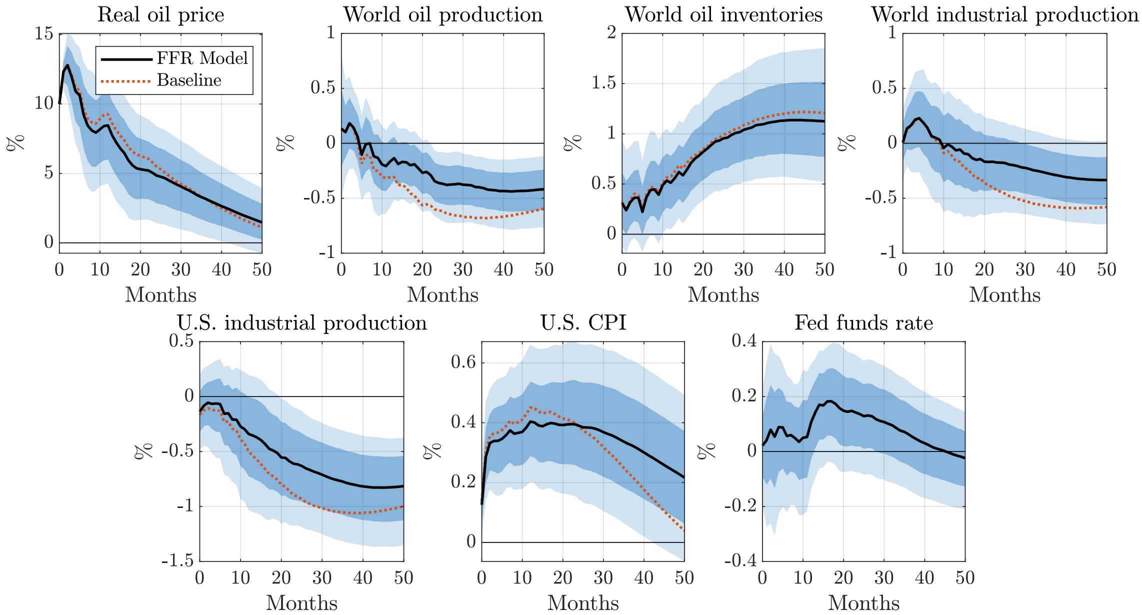


Figure A.8: Stock indices for different industries

To address the potential concern that monetary policy may contaminate the baseline results, I also study how the results are affected when controlling for the policy rate. Figure A.9 presents the responses from the model augmented by the federal funds rate together with the baseline responses. We can see that controlling for the federal funds rate does not affect the results materially.



First stage regression: F: 22.21, robust F: 10.23, R^2: 4.14%, Adjusted R^2: 3.96%

Figure A.9: Model with federal funds rate

Notes: Impulse responses from the model augmented with the federal funds rate. The shaded areas are 68 and 90 percent confidence bands, respectively. The red dotted lines are the responses from the baseline proxy VAR.

A.4. Sensitivity analysis

A.4.1. Identification

Announcements. The news coverage of OPEC meetings in the financial press is suggestive that there is no strong information channel confounding high-frequency oil supply surprises, as the focus is typically on whether OPEC could agree on production quotas or not. This is illustrated in Table A.4, which shows the headlines and main paragraphs of a selection of articles by the Financial Times on OPEC meetings.

Table A.4: News coverage on OPEC meetings by the Financial Times

Date	Headline	Main paragraph
Dec 4, 2019	OPEC and Russia agree deeper production cuts to prop up oil prices	The so-called OPEC+ alliance, which also includes Russia, agreed curbs of 500,000 barrels per day on Friday after two days of fraught meetings in Vienna, with Saudi Arabia pledging additional voluntary cuts of a further 400,000 b/d.
Dec 4, 2015	OPEC meeting ends in acrimony	OPEC will stick with its policy of not constraining output and has all but abandoned its official production target at its semi-annual meeting, risking a further drop in oil prices that are currently close to six-year lows.
Mar 17, 2010	OPEC keeps oil quota unchanged	The OPEC oil cartel on Wednesday kept its production quotas unchanged, as ministers flipped from worrying about oil prices falling too far to becoming wary of them rising too high.
Mar 16, 2005	OPEC agrees to raise oil production quotas	OPEC producers agreed a 2 per cent increase in oil supplies on Wednesday, raising production limits by 500,000 barrels a day to 27.5m b/d, the highest level since the quota system was introduced in 1987.

To address this concern more formally, I construct an informationally robust oil supply surprise series. Since 2001, OPEC publishes monthly oil market reports, including information about world oil demand, supply as well as stock movements. Importantly the report also includes OPEC's global demand forecasts and forecast revisions. Figure A.10 shows an excerpt of the oil market report from December 2006.

Table 10: World oil demand forecast for 2007, mb/d								
							Change 2007/06	
	2006	1Q07	2Q07	3Q07	4Q07	2007	Volume	%
North America	25.45	25.52	25.21	25.65	26.27	25.66	0.21	0.83
Western Europe	15.49	15.62	15.13	15.47	15.82	15.51	0.02	0.13
OECD Pacific	8.45	9.40	7.77	7.91	8.76	8.46	0.01	0.09
Total OECD	**49.40**	**50.54**	**48.12**	**49.04**	**50.85**	**49.64**	**0.24**	**0.48**
Other Asia	8.76	8.81	9.07	8.80	8.98	8.91	0.15	1.77
Latin America	5.16	5.12	5.23	5.36	5.28	5.25	0.09	1.75
Middle East	6.16	6.33	6.35	6.67	6.47	6.46	0.30	4.88
Africa	2.95	3.01	3.00	2.95	3.05	3.00	0.05	1.75
Total DCs	**23.03**	**23.26**	**23.65**	**23.79**	**23.78**	**23.62**	**0.60**	**2.59**
FSU	3.78	3.78	3.50	3.76	4.13	3.79	0.01	0.32
Other Europe	0.91	1.01	0.88	0.90	0.95	0.93	0.03	3.19
China	7.16	7.44	7.85	7.72	7.41	7.61	0.45	6.26
Total "Other Regions"	**11.84**	**12.23**	**12.23**	**12.39**	**12.49**	**12.33**	**0.49**	**4.13**
Total world	**84.27**	**86.04**	**84.00**	**85.21**	**87.12**	**85.59**	**1.33**	**1.57**
Previous estimate	84.26	85.99	84.01	85.20	87.13	85.58	1.33	1.57
Revision	0.01	0.05	-0.01	0.02	-0.01	0.01	0.00	0.00

Figure A.10: OPEC's world oil demand forecast for 2007

Source: OPEC Monthly Oil Market Report, December 2006.

I collected all world oil demand forecasts as well as forecast revisions from the reports for 2001-2017. This data is then used to construct a refined version of the oil supply surprise series, purged from potential confounding factors coming from global demand. A delicate issue here is the timing, i.e. when the reports are released for publication. For a large part of the OPEC announcements, these reports were published shortly after the OPEC meetings. For some meetings, in particular extraordinary ones taking place towards the end of a given month, the report is already available before the announcement. In these cases, the refinement should have no effect as this information is already known to markets. In this sense, the refinement does not control for all potential confounding demand factors but for a large part. In addition, I also analyze whether only using ordinary announcements in the construction of the instrument changes the results.

The results are displayed in Figures A.11-A.12. We can see that the responses based on the refined, informationally robust instrument are consistent with the responses using the raw instrument. Apart from a few minor, statistically insignificant differences, the responses are very similar. Note that the results based on the raw instrument are slightly different from the baseline in Section 4 of the paper because of the shorter identification sample. Likewise, using only ordinary announcements to construct the instrument yields very similar results to the baseline case.

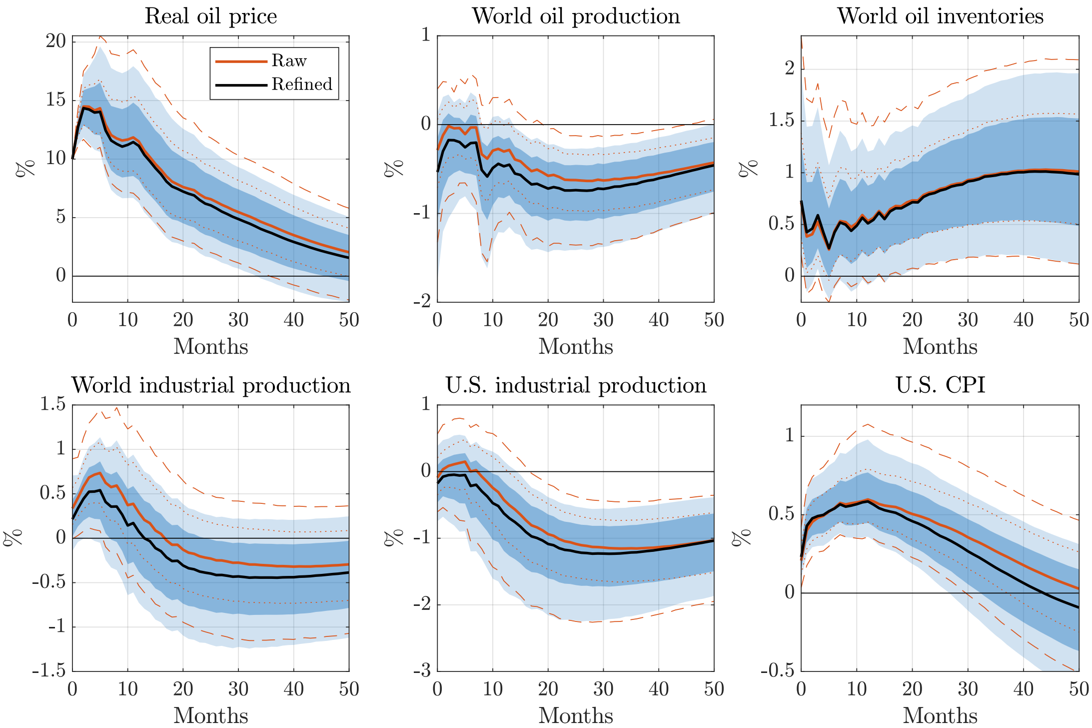
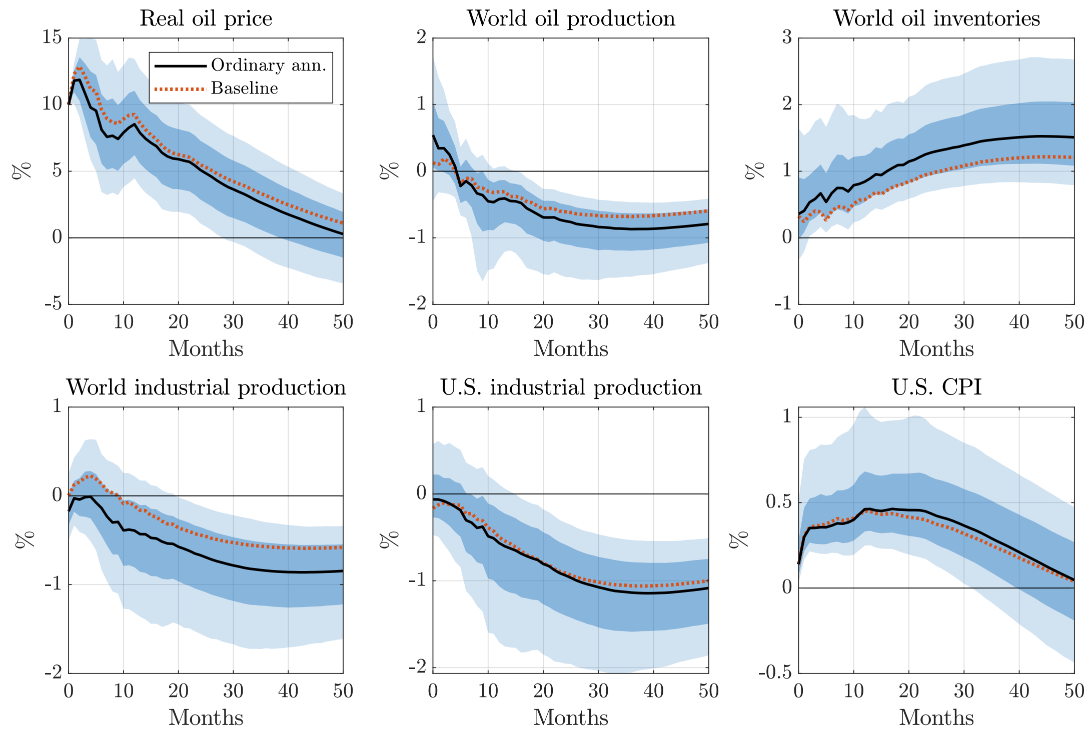


Figure A.11: Raw versus refined instrument

Notes: Impulse responses using the refined (black) and the raw oil supply surprise series (red). The solid lines are the point estimates and the shaded areas and dashed/dotted lines are 68 and 90 percent confidence bands, respectively.



First stage regression: F: 9.75, robust F: 4.46, R^2: 1.86%, Adjusted R^2: 1.67%

Figure A.12: Using ordinary announcements only

News and surprise shocks. Figure A.13 presents the IRFs from the two-shock proxy VAR introduced in the main text. The results suggest that we can identify the oil supply news shock without controlling for the oil supply surprise shock.

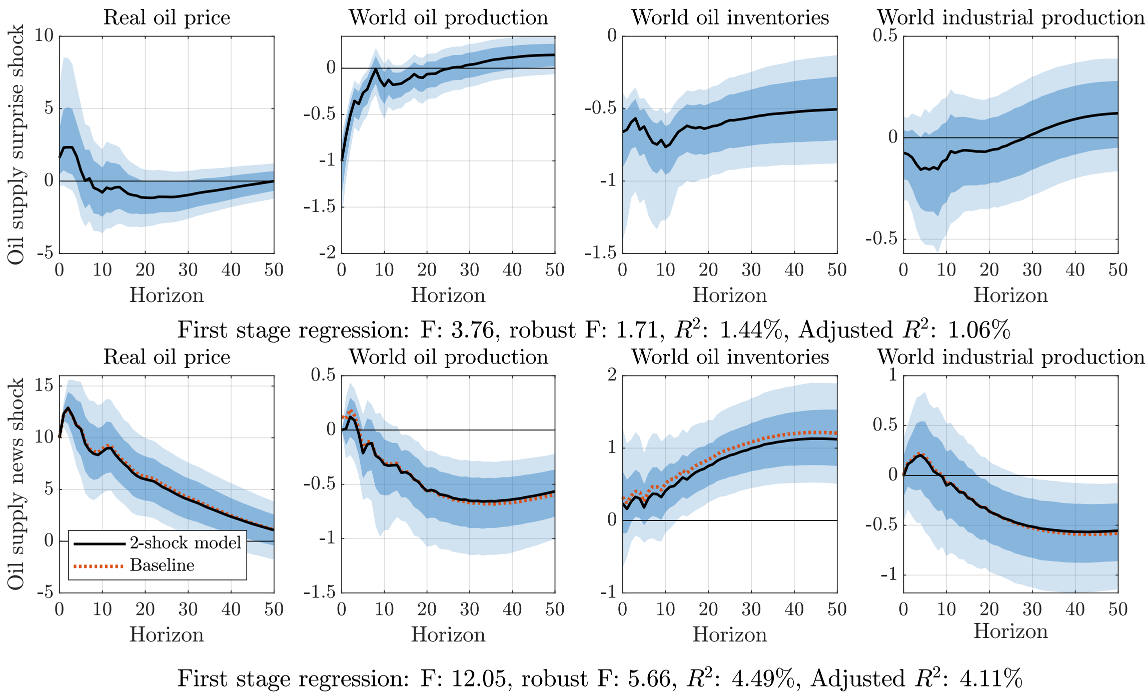


Figure A.13: Two-shock proxy VAR

Notes: The top panel is the oil supply surprise shock and the bottom panel is the oil supply news shock. The shocks are identified using Kilian's (2008) production shortfall series, extended by Bastianin and Manera (2018), and the oil supply surprise series as instruments. The surprise shock is normalized to decrease oil production by 1 percent and the news shock to increase the oil price by 10 percent on impact.

Invertibility. To be able to identify the shock of interest, the VAR has to span all relevant information. As a robustness check, I analyze how the information contained in the VAR affects the results. In the context of news shocks, Ramey (2016) argues that using high-frequency surprises as instruments can be problematic without including them in the VAR. Thus, as an alternative to the external instruments approach, I include the oil supply surprise series as the first variable in a recursive VAR. This is the so-called internal instruments approach (Ramey, 2011; Plagborg-Møller and Wolf, 2019).[6] The results are shown in Figure A.14. Overall, the responses are less precisely estimated. Furthermore, the responses of the industrial production indicators turn out to be less pronounced. However, none of these differences are statistically significant.

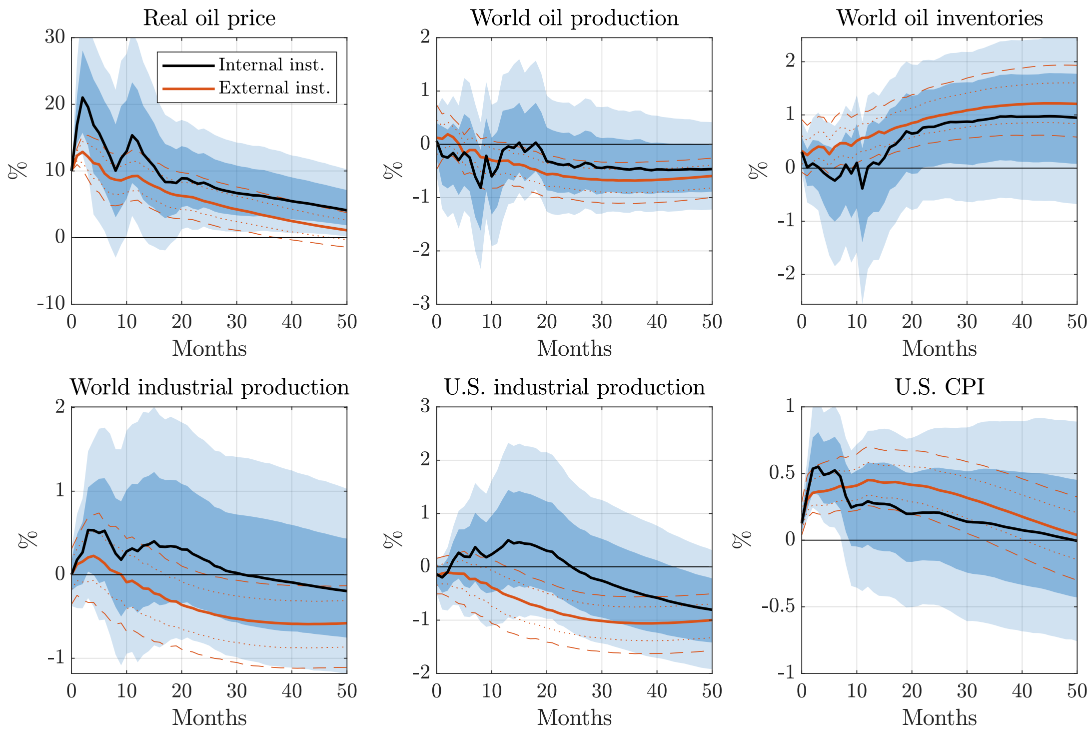


Figure A.14: Internal versus external instruments approach

I also analyze how the inclusion of additional variables in Section 4.4 in the paper affects the baseline results. Figure A.15 shows the impulse responses of the baseline variables from all the augmented VAR models. The responses of the baseline variables appear to be robust to the inclusion of additional variables. In particular, the impact responses turn out to be quite stable, supporting the validity of the baseline proxy VAR. As Miranda-Agrippino and Ricco (2018) show, unstable im-

[6] A disadvantage of this approach is that we cannot easily accommodate instruments that are only available for a shorter sample than the variables in the VAR, which is relevant for the application at hand. Following Noh (2019), I censor the missing values to zero.

pact responses are an indication that the instrument is contaminated by other past structural shocks that are not filtered out by the VAR model. I also augmented the VAR by factors estimated from the FRED-MD database. The results turn out to be robust, indicating that there is no problem of informational insufficiency. These results are available upon request.

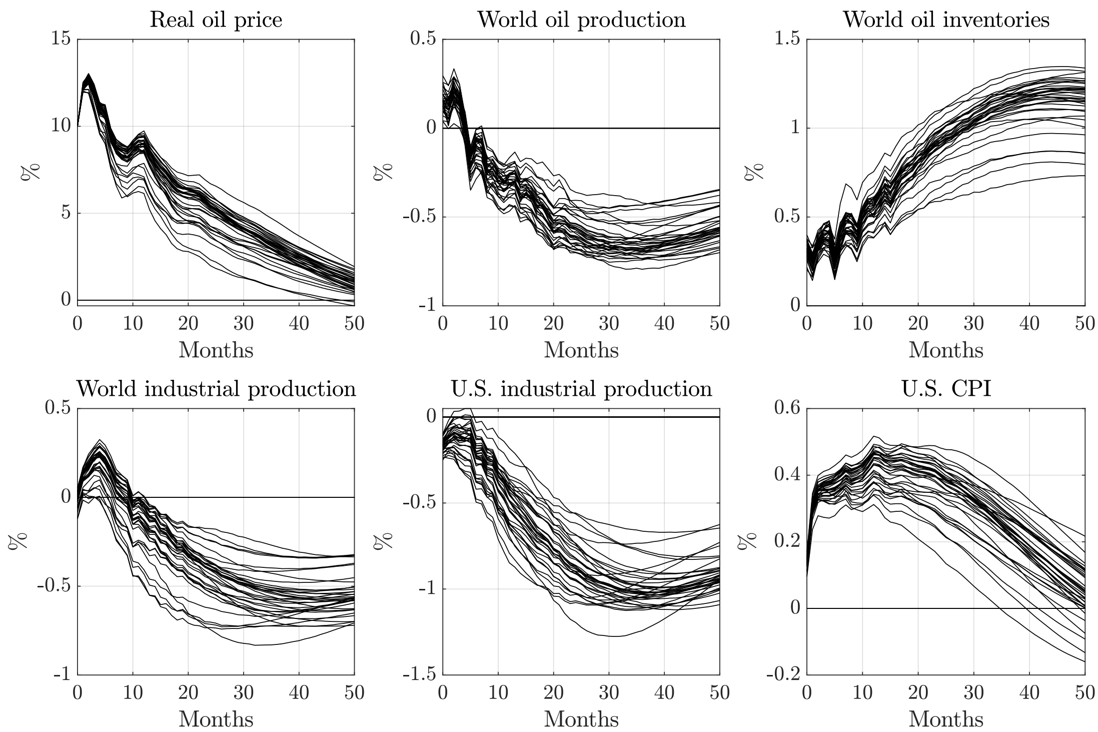


Figure A.15: Responses from the extended models in Section 4.4

Additional robustness checks:

Constructing the instrument. To construct a time series of oil supply surprises, I look at how oil futures prices change around OPEC announcements. In particular, I use a composite measure, spanning the first year of the term structure. However, in principle, we can use any asset price that is sufficiently responsive, such as single futures contracts or the spot price. Figure A.16 presents responses based on instruments constructed using the 1-month, 3-month, 9-month, and 12-month futures and an extended composite measure (COMP+), which also includes the spot price and the front contract, together with the response using the baseline composite measure. The results do not change materially, illustrating that the crucial feature of my identification strategy is OPEC's institutional framework and not the specific asset used to measure the impact of OPEC announcements. The fact that the responses do not differ much using different maturities also suggests that the results are not severely affected by changes in risk premia.

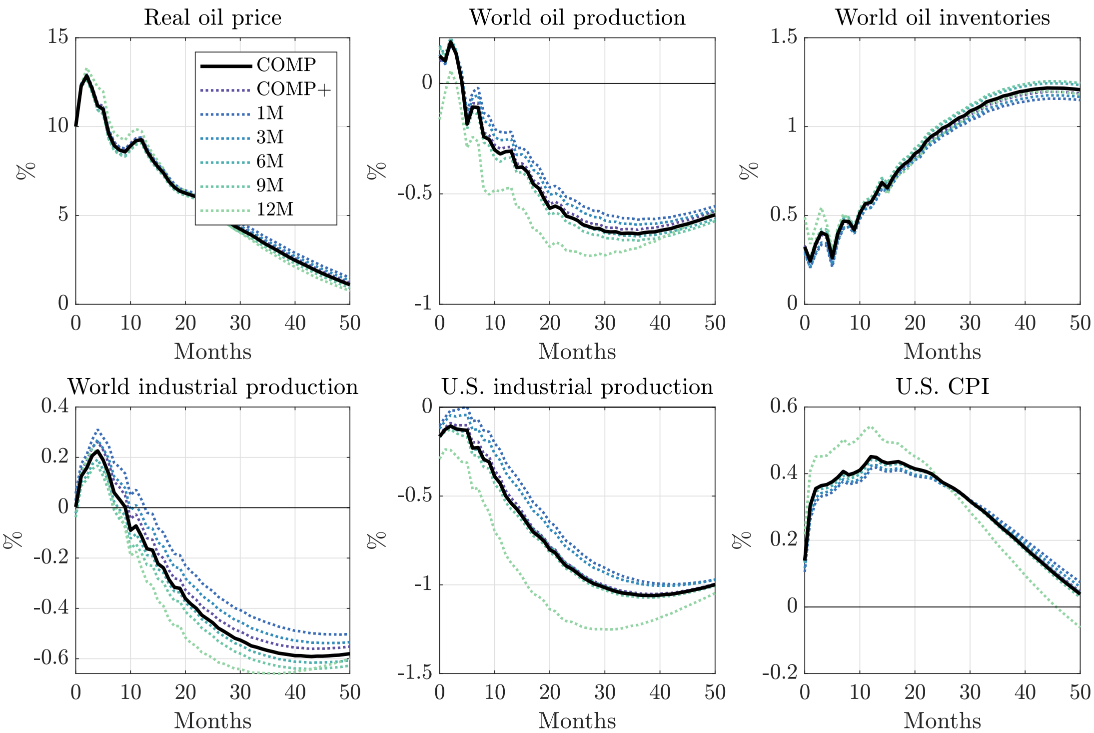
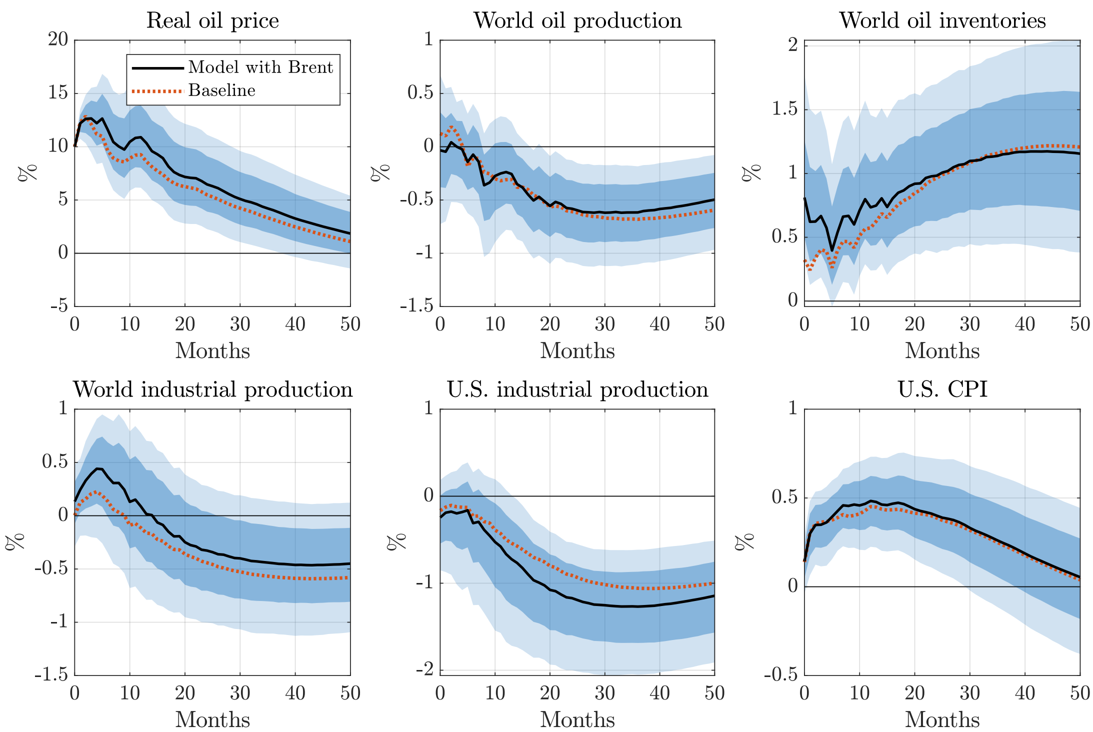


Figure A.16: Instruments based on different futures contracts



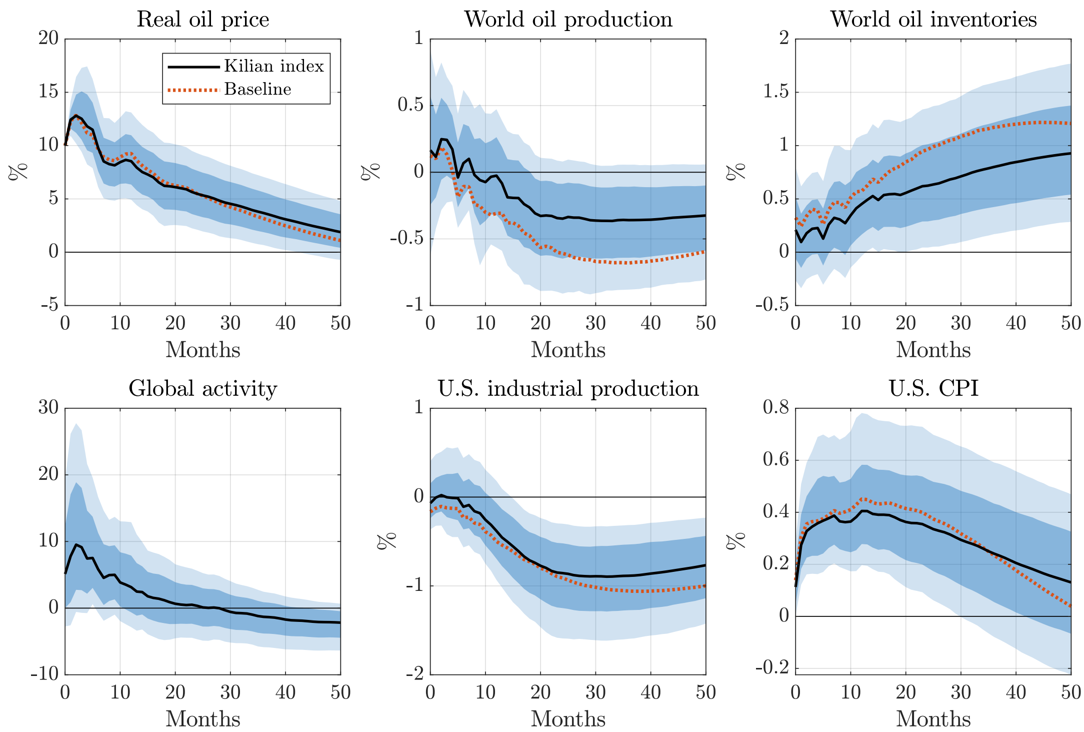
First stage regression: F: 10.27, robust F: 5.56, R^2: 1.96%, Adjusted R^2: 1.77%

Figure A.17: Using Brent as oil price indicator and to construct instrument

A related issue is the choice of the relevant oil price measure. As a benchmark, I rely on WTI. However, in the most recent part of the sample, WTI has become less representative for the global price of oil because of the shale oil boom (Baumeister and Kilian, 2016). For this period, Brent is probably the better measure. However, Brent futures only started trading in the late 1980s and were less liquid at the beginning, making the instrument sample even shorter. Figure A.17 presents the IRFs using a composite instrument spanning the first year of the Brent futures term structure and using the Brent spot price as the oil price indicator in the VAR. The results turn out to be robust.

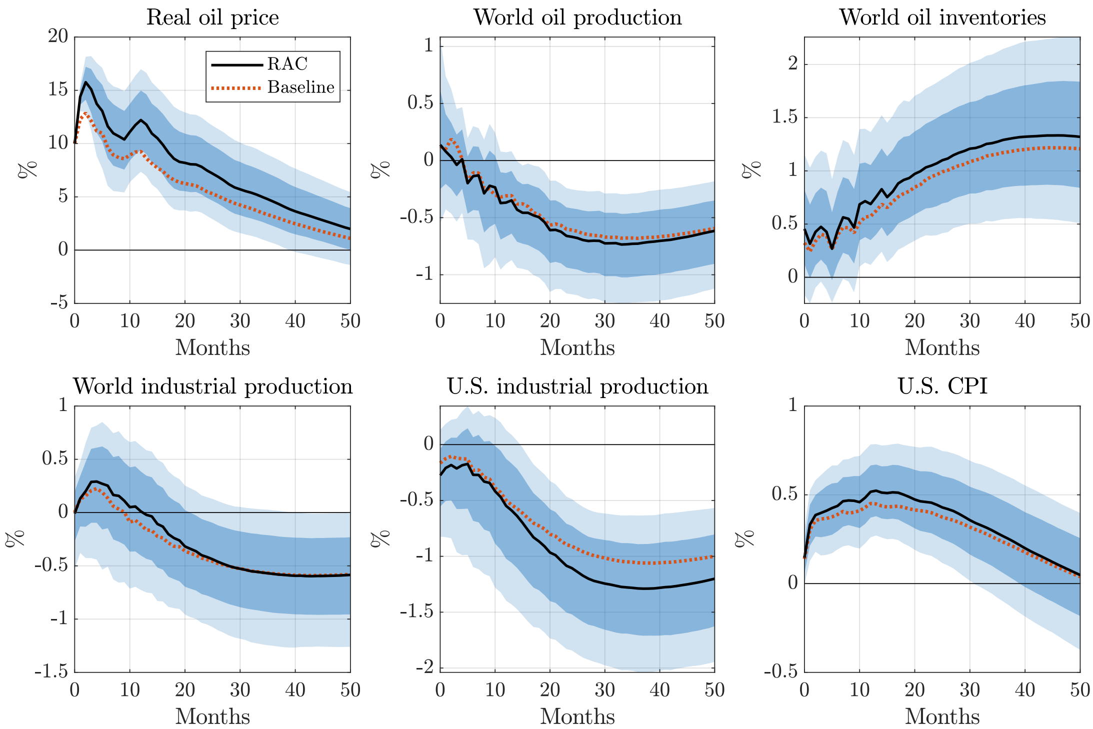
A.4.2. Specification and data choices

Model specification. Figures A.18-A.19 show the responses using Kilian's (2009) index as the global economic activity indicator and the responses using the real refiner acquisition cost as the oil price indicator. The results are robust to using these alternative indicators.



First stage regression: F: 22.05, robust F: 13.63, R^2: 4.41%, Adjusted R^2: 4.21%

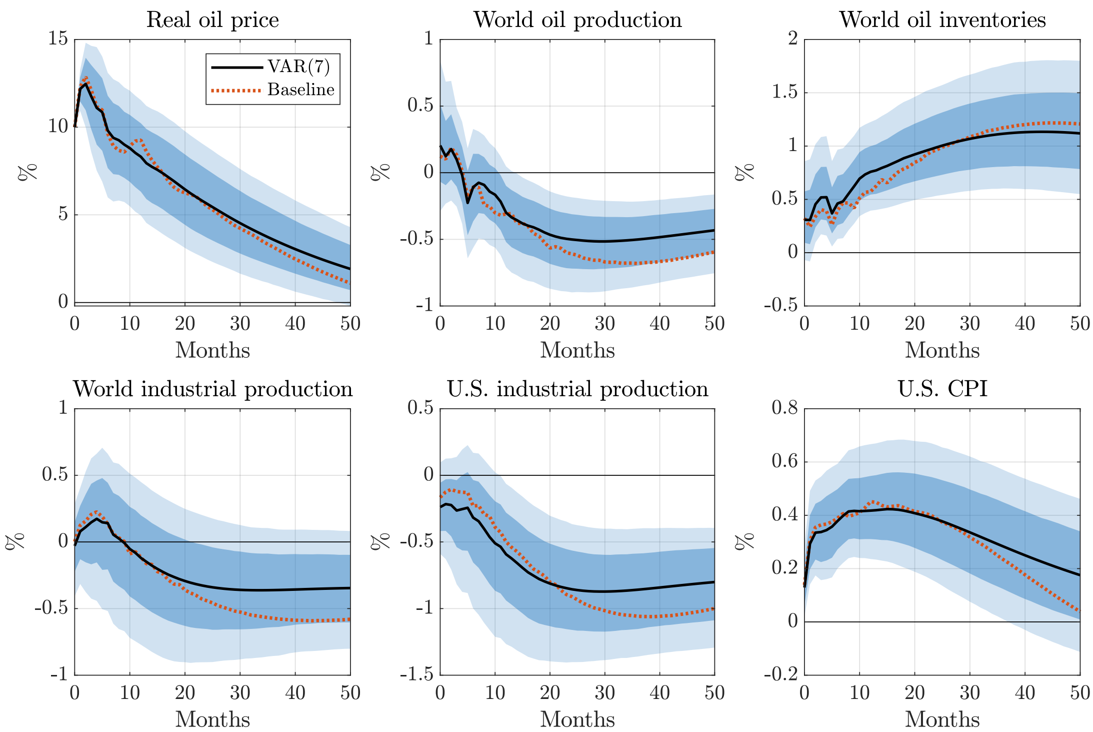
Figure A.18: Model with Kilian's (2009) global activity indicator



First stage regression: F: 15.19, robust F: 9.55, R^2: 2.87%, Adjusted R^2: 2.68%

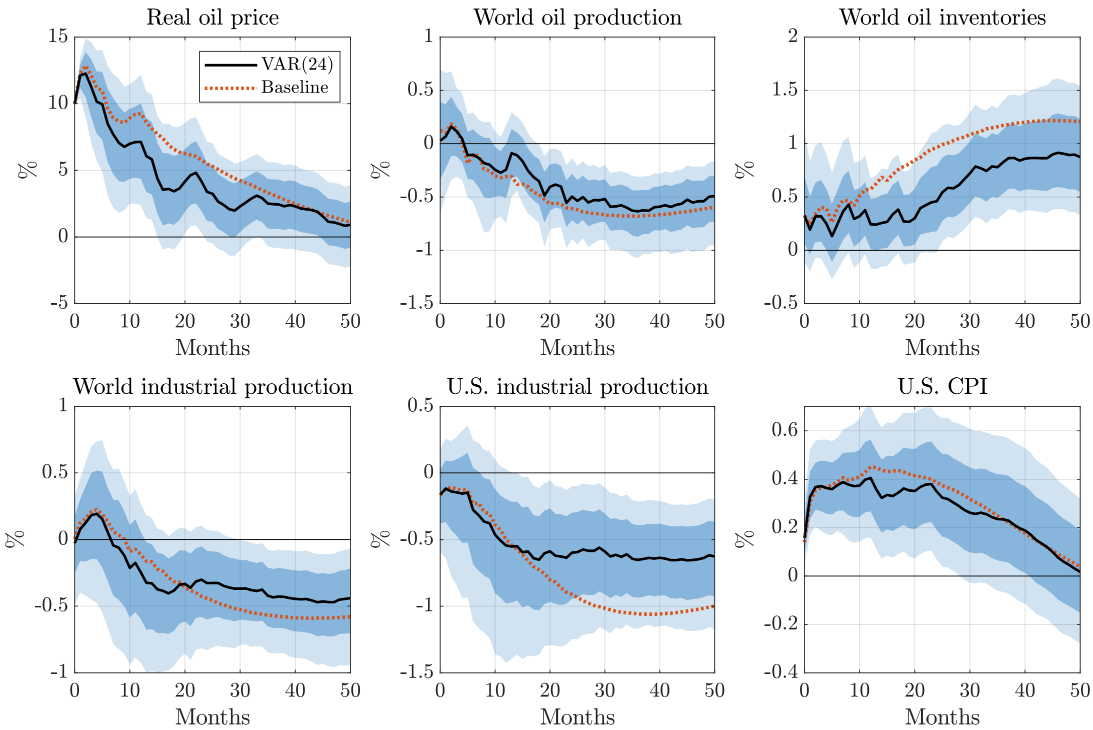
Figure A.19: Model with real refiner acquisition cost as oil price indicator

I also perform a number of robustness checks with respect to the lag order, the deterministics included in the model as well as the treatment of non-stationary variables. In particular, I vary the lag order according to information criteria and other popular choices in the literature, estimate a VAR without a constant as well as VAR with a constant and a linear trend. Furthermore, I estimate a stationary VAR in the real price of oil, world oil production growth, the change in world oil inventories, world industrial production growth, U.S. industrial production growth and U.S. CPI inflation. From Figures A.20-A.24, we can see that the results are robust with respect to all these choices. Finally, in Figures A.25-A.26, I rely on the exact same specification as in Kilian and Murphy (2014) and Baumeister and Hamilton (2019), respectively. Again, the results turn out to be robust.



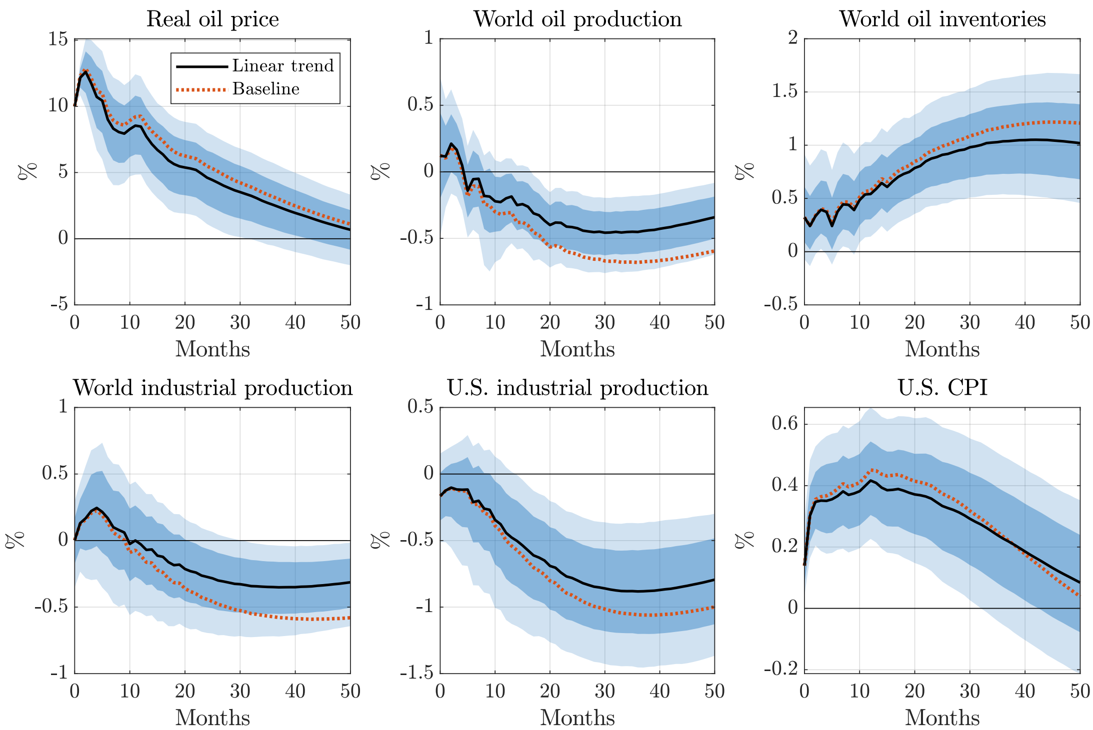
First stage regression: F: 20.75, robust F: 9.06, R^2: 3.84%, Adjusted R^2: 3.66%

Figure A.20: Results from a VAR(7), selected by AIC



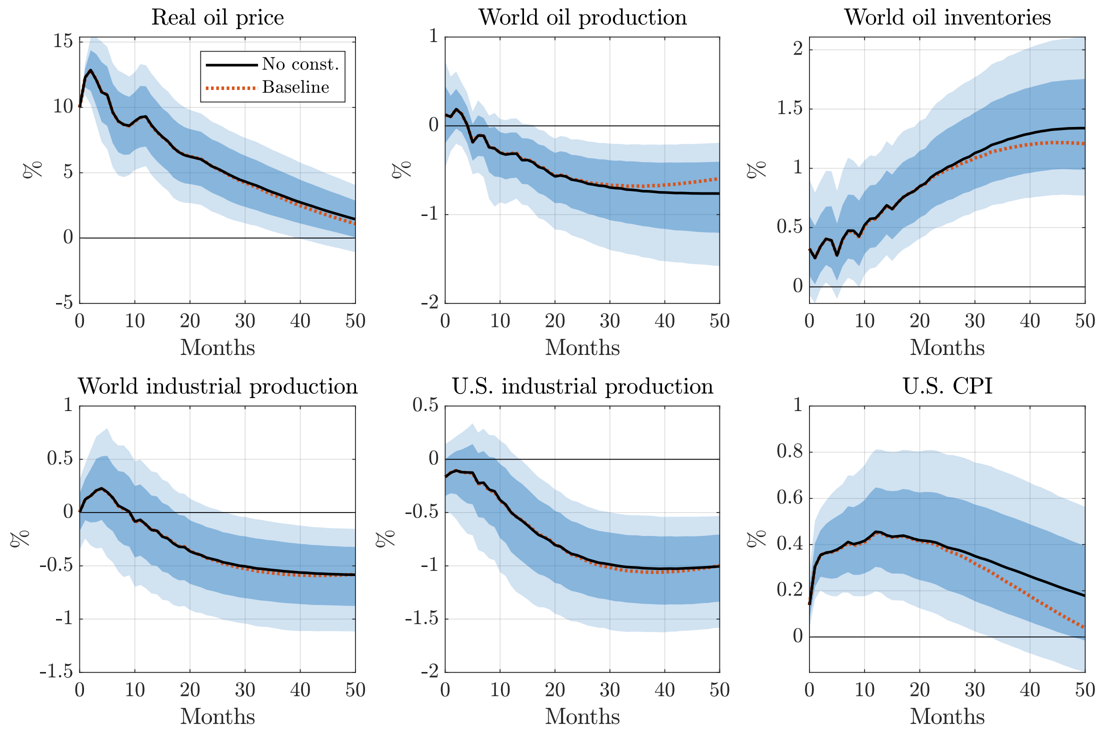
First stage regression: F: 20.98, robust F: 11.17, R^2: 4.01%, Adjusted R^2: 3.82%

Figure A.21: Results from VAR(24)



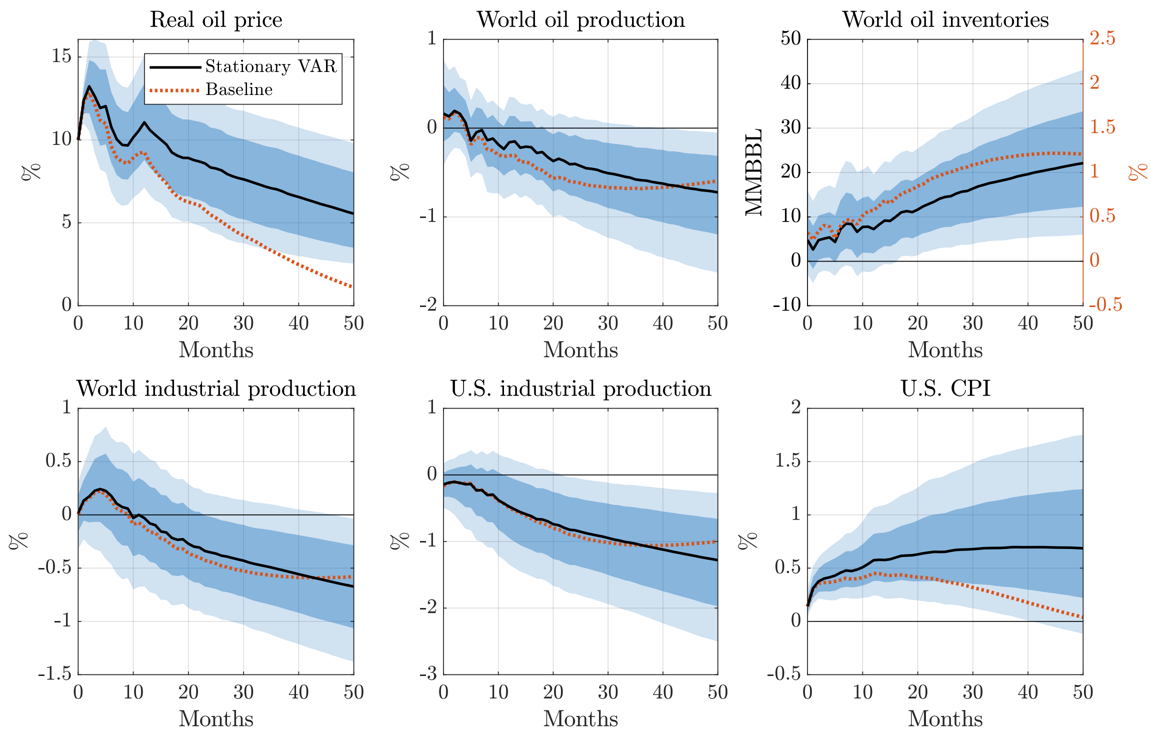
First stage regression: F: 23.08, robust F: 11.11, R^2: 4.30%, Adjusted R^2: 4.11%

Figure A.22: VAR with linear trend



First stage regression: F: 22.67, robust F: 10.54, R^2: 4.22%, Adjusted R^2: 4.04%

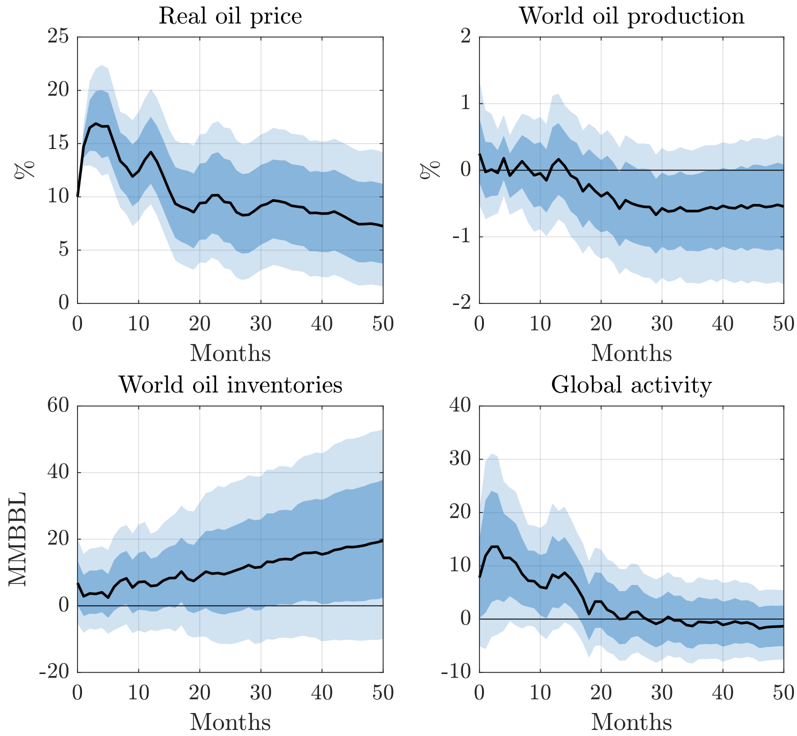
Figure A.23: VAR without a constant



First stage regression: F: 22.89, robust F: 11.60, R^2: 4.26%, Adjusted R^2: 4.08%

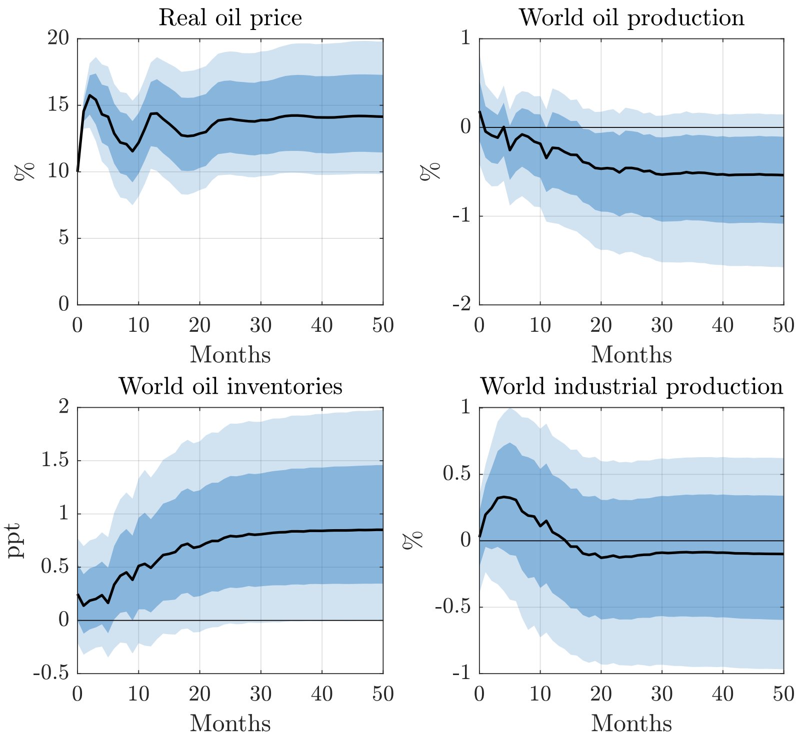
Figure A.24: Stationary VAR

Notes: (Cumulative) responses from stationary VAR in real oil price, world oil production growth, change in world oil inventories, world IP growth, U.S. IP growth, and U.S. CPI inflation.



First stage regression: F: 15.78, robust F: 15.19, R^2: 3.28%, Adjusted R^2: 3.07%

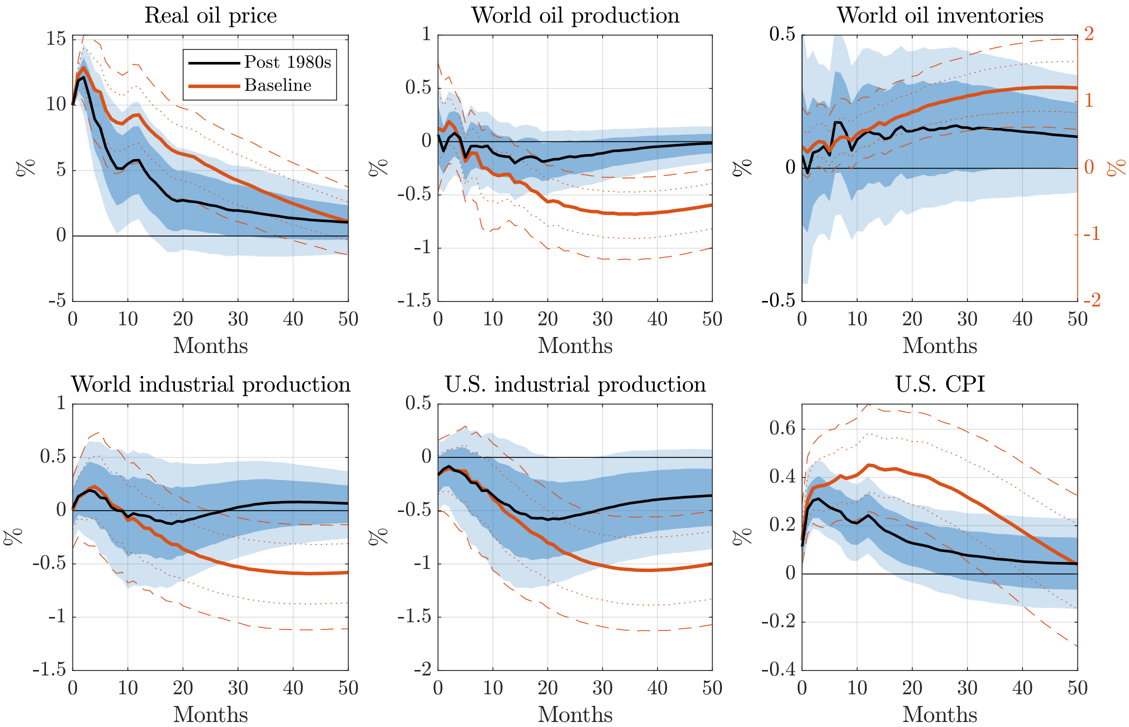
Figure A.25: Kilian and Murphy's (2014) model specification



First stage regression: F: 15.33, robust F: 11.18, R^2: 3.04%, Adjusted R^2: 2.84%

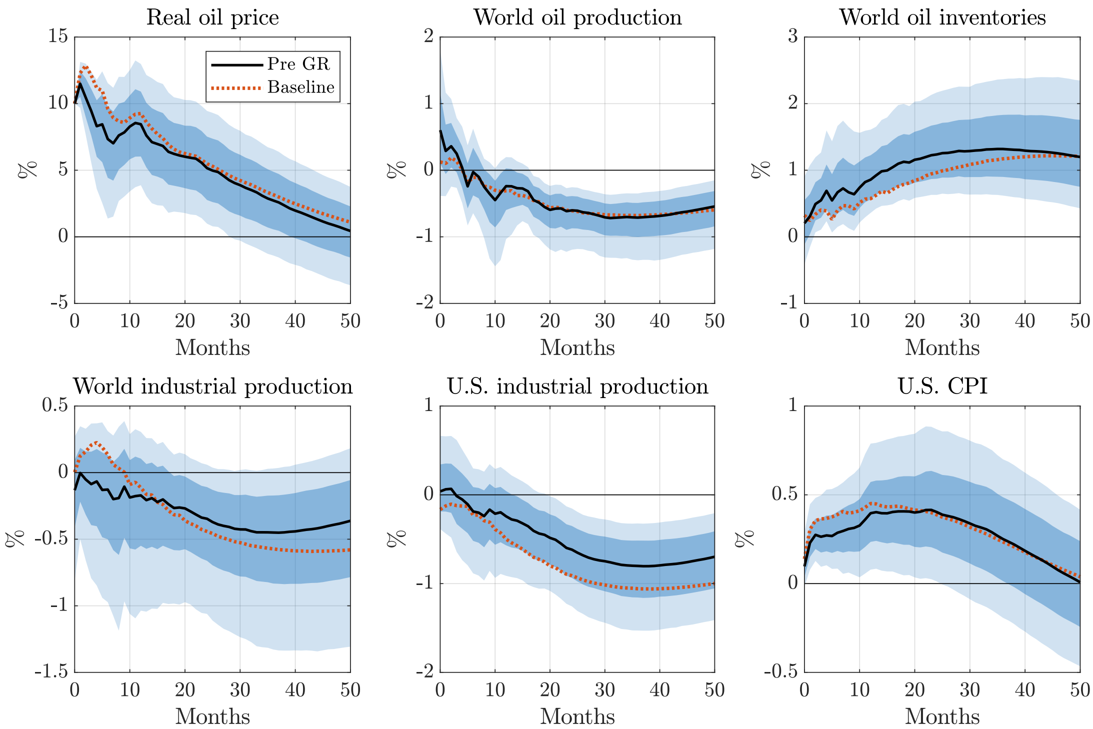
Figure A.26: Baumeister and Hamilton's (2019) model specification

Sample and data frequency. Figures A.27-A.29 present the results from the subsample analyses. It turns out that the results do not seem to be driven by a specific sample choice.



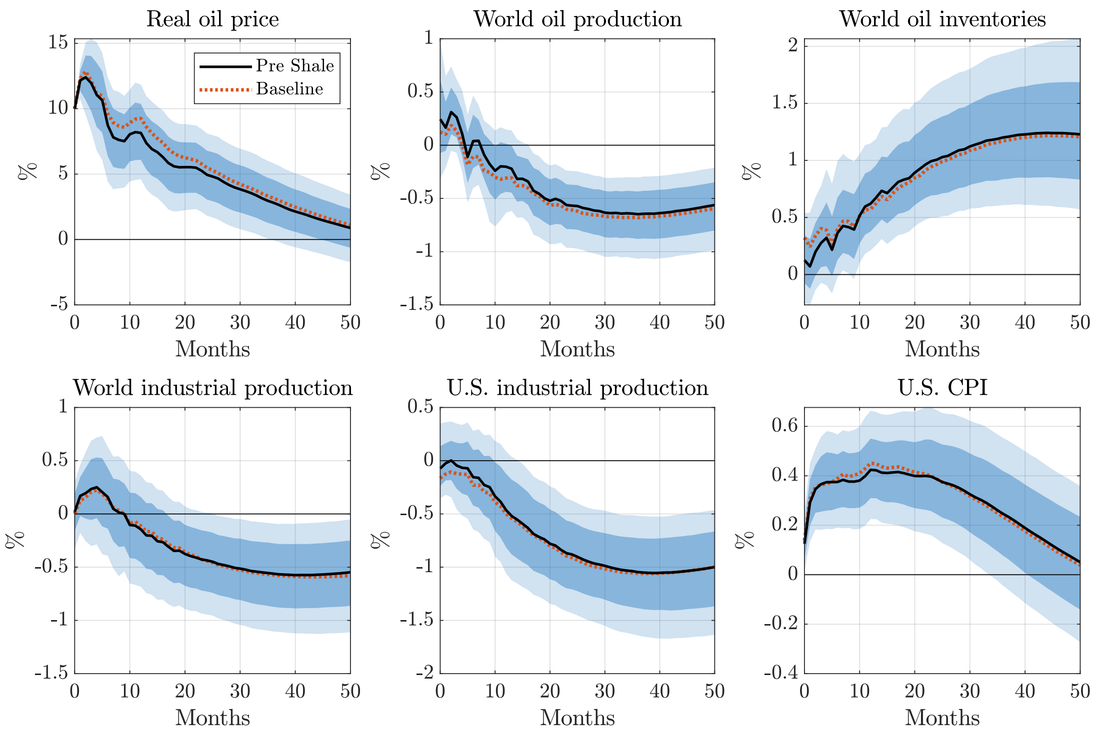
First stage regression: F: 19.78, robust F: 11.51, R^2: 4.55%, Adjusted R^2: 4.32%

Figure A.27: Shorter estimation sample: 1982M4-2017M12.



First stage regression: F: 15.79, robust F: 8.66, R^2: 3.85%, Adjusted R^2: 3.61%

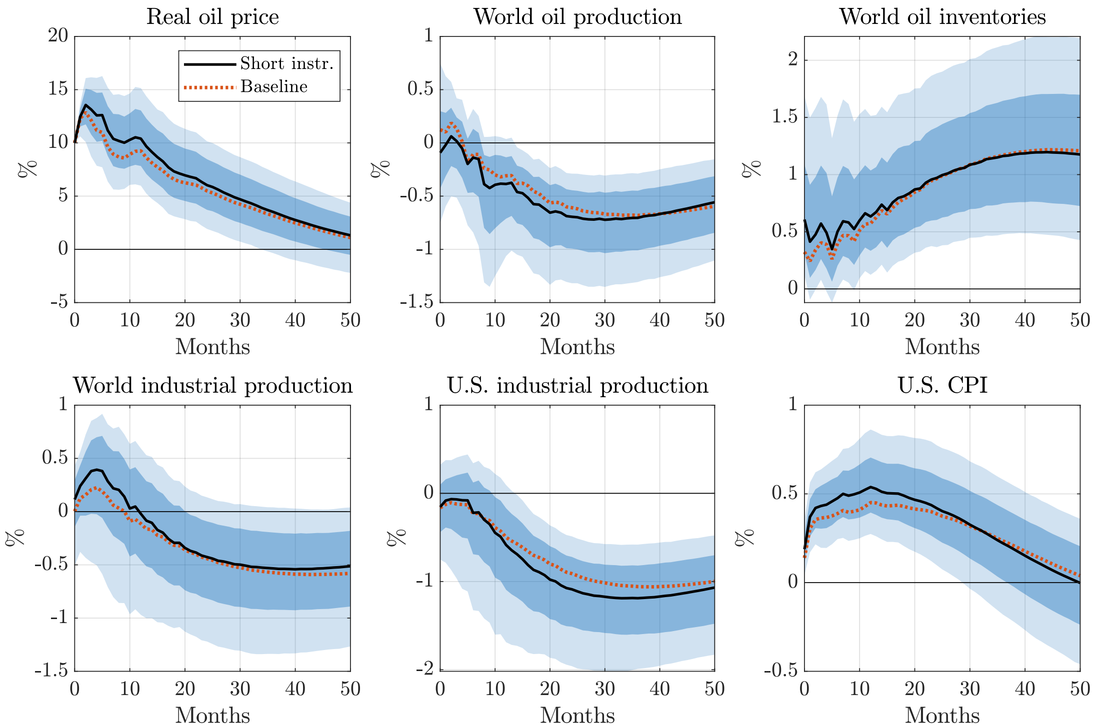
Figure A.28: Pre Great Recession: 1974M1-2007M12.



First stage regression: F: 29.13, robust F: 18.65, R^2: 6.35%, Adjusted R^2: 6.13%

Figure A.29: Pre shale oil revolution: 1974M1-2010M12.

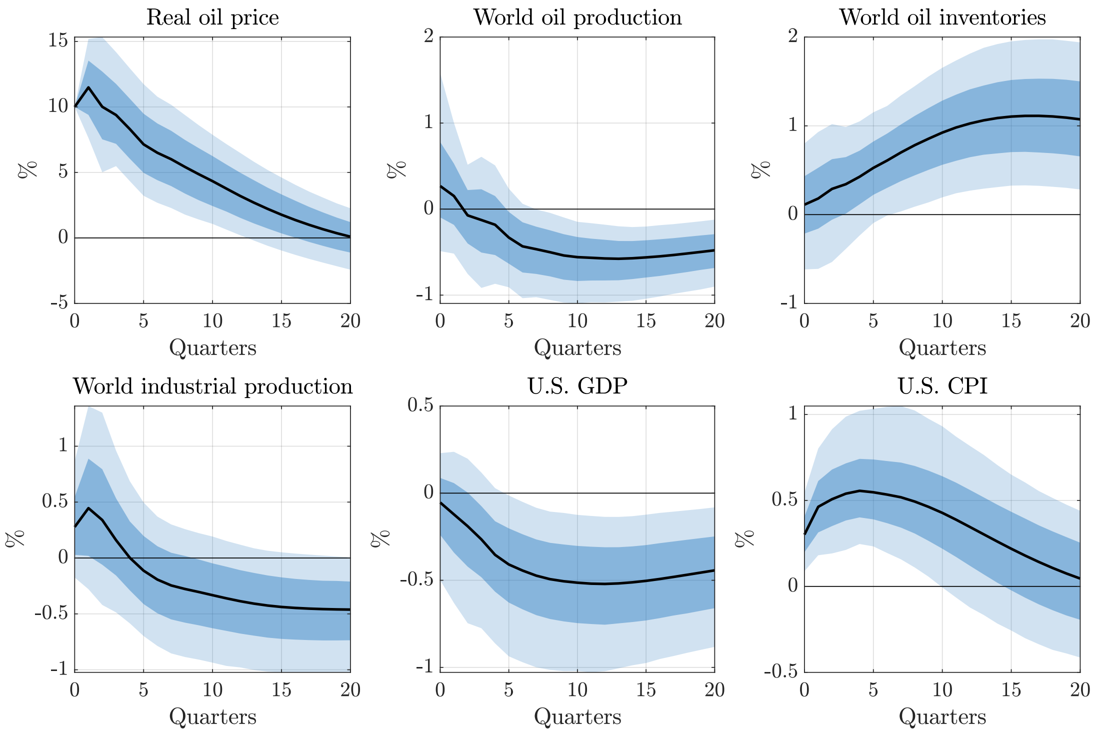
I also check the sensitivity with respect to the instrument sample. In particular, I test whether the results are robust if I exclude the first years of the instrument when the futures markets were not as liquid. Figure A.30 depicts the IRFs using an instrument that starts in 1990. Again, the results are robust.



First stage regression: F: 12.93, robust F: 6.68, R^2: 2.45%, Adjusted R^2: 2.26%

Figure A.30: Shorter instrument sample: 1990M1-2017M12.

Finally, I check the robustness with respect to the data frequency. Figure A.31 presents the results based on the quarterly VAR. To aggregate the instrument to the quarterly frequency, I sum it over the respective months. The results are very similar to the monthly evidence.



First stage regression: F: 10.92, robust F: 6.96, R^2: 6.03%, Adjusted R^2: 5.48%

Figure A.31: Quarterly VAR

B. Data

This Appendix gives more details on the historical OPEC announcements used to construct the instruments as well as an overview of the data sources.

B.1. OPEC announcements

Table B.1 lists all OPEC announcements over the period 1983-2017. Starting from 2002, the press releases are available in the archive on the official OPEC webpage.[7] Before that, I used OPEC resolutions (OPEC, 1990) and Bloomberg news to collect the announcement dates. Note that some conferences ended on a weekend or a holiday. Similarly, some conferences ended after the market close of the NYMEX. For these conferences, the date of the next trading day is used to compute the surprise. The table also includes the trading days in the control sample used for the heteroskedasticity-based identification.

Table B.1: OPEC announcement dates over the period 1983–2017

Month	Announcement date	Control date	Additional information
1983M04		19/04/1983	
1983M05		17/05/1983	
1983M06		21/06/1983	
1983M07	19/07/1983		68th meeting of the OPEC conference
1983M08		12/08/1983	
1983M09		09/09/1983	
1983M10		07/10/1983	
1983M11		11/11/1983	
1983M12	09/12/1983		69th meeting of the OPEC conference
1984M01		11/01/1984	
1984M02		08/02/1984	
1984M03		14/03/1984	
1984M04		11/04/1984	
1984M05		09/05/1984	
1984M06		13/06/1984	
1984M07	11/07/1984		70th meeting of the OPEC conference
1984M08		29/08/1984	
1984M09		26/09/1984	
1984M10	31/10/1984		71st (extraordinary) meeting of the OPEC conference
1984M11		28/11/1984	
1984M12	29/12/1984		72nd meeting of the OPEC conference
1985M01	30/01/1985		73rd meeting of the OPEC conference
1985M02		11/02/1985	
1985M03		11/03/1985	
1985M04		08/04/1985	
1985M05		06/05/1985	
1985M06		10/06/1985	
1985M07	07/07/1985, 25/07/1985		Consultative meeting of the OPEC conference, 74th meeting of the OPEC conference
1985M08		02/08/1985	
1985M09		06/09/1985	
1985M10	04/10/1985		75th (extraordinary) meeting of the OPEC conference
1985M11		11/11/1985	
1985M12	09/12/1985		76th meeting of the OPEC conference
1986M01		20/01/1986	
1986M02		18/02/1986	
1986M03		24/03/1986	
1986M04	21/04/1986		77th meeting of the OPEC conference
1986M05		06/05/1986	
1986M06		03/06/1986	

[7]See http://www.opec.org/opec_web/en/press_room/28.htm

Month	Announcement date	Control date	Additional information
1986M07		08/07/1986	
1986M08	05/08/1986		78th meeting of the OPEC conference
1986M09		24/09/1986	
1986M10	22/10/1986		79th meeting of the OPEC conference
1986M11		24/11/1986	
1986M12	20/12/1986		80th meeting of the OPEC conference
1987M01		26/01/1987	
1987M02		23/02/1987	
1987M03		30/03/1987	
1987M04		27/04/1987	
1987M05		26/05/1987	
1987M06	27/06/1987		81st meeting of the OPEC conference
1987M07		13/07/1987	
1987M08		17/08/1987	
1987M09		14/09/1987	
1987M10		12/10/1987	
1987M11		16/11/1987	
1987M12	14/12/1987		82nd meeting of the OPEC conference
1988M01		12/01/1988	
1988M02		16/02/1988	
1988M03		15/03/1988	
1988M04		12/04/1988	
1988M05		17/05/1988	
1988M06	14/06/1988		83rd meeting of the OPEC conference
1988M07		25/07/1988	
1988M08		29/08/1988	
1988M09		26/09/1988	
1988M10		31/10/1988	
1988M11	28/11/1988		84th meeting of the OPEC conference
1988M12		07/12/1988	
1989M01		04/01/1989	
1989M02		08/02/1989	
1989M03		08/03/1989	
1989M04		05/04/1989	
1989M05		10/05/1989	
1989M06	07/06/1989		85th meeting of the OPEC conference
1989M07		26/07/1989	
1989M08		30/08/1989	
1989M09	27/09/1989		3rd meeting of the 8 ministerial monitoring committee
1989M10		31/10/1989	
1989M11	28/11/1989		86th meeting of the OPEC conference
1989M12		29/12/1989	
1990M01		26/01/1990	
1990M02		23/02/1990	
1990M03		30/03/1990	
1990M04		27/04/1990	
1990M05		25/05/1990	
1990M06		29/06/1990	
1990M07	27/07/1990		87th meeting of the OPEC conference
1990M08		16/08/1990	
1990M09		13/09/1990	
1990M10		18/10/1990	
1990M11		15/11/1990	
1990M12	13/12/1990		88th meeting of the OPEC conference
1991M01		15/01/1991	
1991M02		12/02/1991	
1991M03	12/03/1991		3rd meeting
1991M04		02/04/1991	
1991M05		07/05/1991	
1991M06	04/06/1991		89th meeting of the OPEC conference
1991M07		24/07/1991	
1991M08		28/08/1991	
1991M09	25/09/1991		4th meeting of the ministerial monitoring committee
1991M10		23/10/1991	
1991M11	27/11/1991		90th meeting of the OPEC conference
1991M12		17/12/1991	
1992M01		21/01/1992	
1992M02	15/02/1992		6th meeting of the ministerial monitoring committee
1992M03		24/03/1992	
1992M04		28/04/1992	
1992M05	22/05/1992		91st meeting of the OPEC conference
1992M06		18/06/1992	
1992M07		16/07/1992	
1992M08		20/08/1992	
1992M09	17/09/1992		9th meeting of the ministerial monitoring committee
1992M10		26/10/1992	
1992M11	27/11/1992		92nd meeting of the OPEC conference

Month	Announcement date	Control date	Additional information
1992M12		16/12/1992	
1993M01		20/01/1993	
1993M02	16/02/1993		10th meeting of the ministerial monitoring committee
1993M03		11/03/1993	
1993M04		08/04/1993	
1993M05		13/05/1993	
1993M06	10/06/1993		93rd meeting of the OPEC conference
1993M07		29/07/1993	
1993M08		26/08/1993	
1993M09	29/09/1993		94th (extraordinary) meeting of the OPEC conference
1993M10		25/10/1993	
1993M11	24/11/1993		95th meeting of the OPEC conference
1993M12		27/12/1993	
1994M01		31/01/1994	
1994M02		28/02/1994	
1994M03	26/03/1994		12th meeting of the ministerial monitoring committee
1994M04		14/04/1994	
1994M05		19/05/1994	
1994M06	16/06/1994		96th meeting of the OPEC conference
1994M07		19/07/1994	
1994M08		23/08/1994	
1994M09		20/09/1994	
1994M10		25/10/1994	
1994M11	22/11/1994		97th meeting of the OPEC conference
1994M12		20/12/1994	
1995M01		17/01/1995	
1995M02		21/02/1995	
1995M03		21/03/1995	
1995M04		18/04/1995	
1995M05		23/05/1995	
1995M06	20/06/1995		98th meeting of the OPEC conference
1995M07		19/07/1995	
1995M08		23/08/1995	
1995M09		20/09/1995	
1995M10		25/10/1995	
1995M11	22/11/1995		99th meeting of the OPEC conference
1995M12		08/12/1995	
1996M01		05/01/1996	
1996M02		09/02/1996	
1996M03		08/03/1996	
1996M04		12/04/1996	
1996M05		10/05/1996	
1996M06	07/06/1996		100th meeting of the OPEC conference
1996M07		29/07/1996	
1996M08		26/08/1996	
1996M09		30/09/1996	
1996M10		28/10/1996	
1996M11	28/11/1996		101st meeting of the OPEC conference
1996M12		26/12/1996	
1997M01		23/01/1997	
1997M02		27/02/1997	
1997M03		27/03/1997	
1997M04		24/04/1997	
1997M05		29/05/1997	
1997M06	26/06/1997		102nd meeting of the OPEC conference
1997M07		07/07/1997	
1997M08		04/08/1997	
1997M09		08/09/1997	
1997M10		06/10/1997	
1997M11		03/11/1997	
1997M12	01/12/1997		103rd meeting of the OPEC conference
1998M01		26/01/1998	
1998M02		23/02/1998	
1998M03	30/03/1998		104th (extraordinary) meeting of the OPEC conference
1998M04		22/04/1998	
1998M05		27/05/1998	
1998M06	24/06/1998		105th meeting of the OPEC conference
1998M07		27/07/1998	
1998M08		31/08/1998	
1998M09		28/09/1998	
1998M10		26/10/1998	
1998M11	26/11/1998		106th meeting of the OPEC conference
1998M12		22/12/1998	
1999M01		19/01/1999	
1999M02		23/02/1999	
1999M03	23/03/1999		107th meeting of the OPEC conference
1999M04		21/04/1999	

Month	Announcement date	Control date	Additional information
1999M05		26/05/1999	
1999M06		23/06/1999	
1999M07		21/07/1999	
1999M08		25/08/1999	
1999M09	22/09/1999		108th meeting of the OPEC conference
1999M10		27/10/1999	
1999M11		24/11/1999	
1999M12		29/12/1999	
2000M01		26/01/2000	
2000M02		23/02/2000	
2000M03	29/03/2000		109th meeting of the OPEC conference
2000M04		19/04/2000	
2000M05		24/05/2000	
2000M06	21/06/2000		110th (extraordinary) meeting of the OPEC conference
2000M07		10/07/2000	
2000M08		14/08/2000	
2000M09	11/09/2000		111th meeting of the OPEC conference
2000M10		16/10/2000	
2000M11	13/11/2000		112th (extraordinary) meeting of the OPEC conference
2000M12		13/12/2000	
2001M01	17/01/2001		113th (extraordinary) meeting of the OPEC conference
2001M02		20/02/2001	
2001M03	17/03/2001		114th meeting of the OPEC conference
2001M04		03/04/2001	
2001M05		08/05/2001	
2001M06	05/06/2001		115th (extraordinary) meeting of the OPEC conference
2001M07	03/07/2001, 25/07/2001		116th (extraordinary) meeting of the OPEC conference
2001M08		30/08/2001	
2001M09	27/09/2001		117th meeting of the OPEC conference
2001M10		17/10/2001	
2001M11	14/11/2001		118th (extraordinary) meeting of the OPEC conference
2001M12	28/12/2001		Consultative meeting of the OPEC conference
2002M01		11/01/2002	
2002M02		15/02/2002	
2002M03	15/03/2002		119th meeting of the OPEC conference
2002M04		24/04/2002	
2002M05		29/05/2002	
2002M06	26/06/2002		120th (extraordinary) meeting of the OPEC conference
2002M07		18/07/2002	
2002M08		22/08/2002	
2002M09	19/09/2002		121st meeting of the OPEC conference
2002M10		10/10/2002	
2002M11		14/11/2002	
2002M12	12/12/2002		122nd (extraordinary) meeting of the OPEC conference
2003M01	12/01/2003		123rd (extraordinary) meeting of the OPEC conference
2003M02		11/02/2003	
2003M03	11/03/2003		124th meeting of the OPEC conference
2003M04	24/04/2003		Consultative meeting of the OPEC conference
2003M05		14/05/2003	
2003M06	11/06/2003		125th (extraordinary) meeting of the OPEC conference
2003M07	31/07/2003		126th (extraordinary) meeting of the OPEC conference
2003M08		27/08/2003	
2003M09	24/09/2003		127th meeting of the OPEC conference
2003M10		02/10/2003	
2003M11		06/11/2003	
2003M12	04/12/2003		128th (extraordinary) meeting of the OPEC conference
2004M01		13/01/2004	
2004M02	10/02/2004		129th (extraordinary) meeting of the OPEC conference
2004M03	31/03/2004		130th meeting of the OPEC conference
2004M04		01/04/2004	
2004M05		06/05/2004	
2004M06	03/06/2004		131st (extraordinary) meeting of the OPEC conference
2004M07		14/07/2004	
2004M08		18/08/2004	
2004M09	15/09/2004		132nd meeting of the OPEC conference
2004M10		08/10/2004	
2004M11		12/11/2004	
2004M12	10/12/2004		133rd (extraordinary) meeting of the OPEC conference
2005M01	30/01/2005		134th (extraordinary) meeting of the OPEC conference
2005M02		16/02/2005	
2005M03	16/03/2005		135th meeting of the OPEC conference
2005M04		13/04/2005	
2005M05		18/05/2005	
2005M06	15/06/2005		136th meeting of the OPEC conference
2005M07		19/07/2005	
2005M08		23/08/2005	

Month	Announcement date	Control date	Additional information
2005M09	20/09/2005		137th meeting of the OPEC conference
2005M10		10/10/2005	
2005M11		14/11/2005	
2005M12	12/12/2005		138th (extraordinary) meeting of the OPEC conference
2006M01	31/01/2006		139th (extraordinary) meeting of the OPEC conference
2006M02		08/02/2006	
2006M03	08/03/2006		140th meeting of the OPEC conference
2006M04		06/04/2006	
2006M05		04/05/2006	
2006M06	01/06/2006		141st (extraordinary) meeting of the OPEC conference
2006M07		10/07/2006	
2006M08		14/08/2006	
2006M09	11/09/2006		142nd meeting of the OPEC conference
2006M10	20/10/2006		Consultative meeting of the OPEC conference
2006M11		09/11/2006	
2006M12	14/12/2006		143rd (extraordinary) meeting of the OPEC conference
2007M01		18/01/2007	
2007M02		15/02/2007	
2007M03	15/03/2007		144th meeting of the OPEC conference
2007M04		10/04/2007	
2007M05		08/05/2007	
2007M06		12/06/2007	
2007M07		10/07/2007	
2007M08		14/08/2007	
2007M09	11/09/2007		145th meeting of the OPEC conference
2007M10		03/10/2007	
2007M11		07/11/2007	
2007M12	05/12/2007		146th (extraordinary) meeting of the OPEC conference
2008M01		04/01/2008	
2008M02	01/02/2008		147th (extraordinary) meeting of the OPEC conference
2008M03	05/03/2008		148th meeting of the OPEC conference
2008M04		09/04/2008	
2008M05		07/05/2008	
2008M06		04/06/2008	
2008M07		09/07/2008	
2008M08		06/08/2008	
2008M09	10/09/2008		149th meeting of the OPEC conference
2008M10	24/10/2008		150th (extraordinary) meeting of the OPEC conference
2008M11		19/11/2008	
2008M12	17/12/2008		151st (extraordinary) meeting of the OPEC conference
2009M01		12/01/2009	
2009M02		09/02/2009	
2009M03	15/03/2009		152nd meeting of the OPEC conference
2009M04		30/04/2009	
2009M05	28/05/2009		153rd (extraordinary) meeting of the OPEC conference
2009M06		11/06/2009	
2009M07		09/07/2009	
2009M08		13/08/2009	
2009M09	10/09/2009		154th meeting of the OPEC conference
2009M10		20/10/2009	
2009M11		24/11/2009	
2009M12	22/12/2009		155th (extraordinary) meeting of the OPEC conference
2010M01		13/01/2010	
2010M02		17/02/2010	
2010M03	17/03/2010		156th meeting of the OPEC conference
2010M04		15/04/2010	
2010M05		13/05/2010	
2010M06		10/06/2010	
2010M07		15/07/2010	
2010M08		12/08/2010	
2010M09		16/09/2010	
2010M10	14/10/2010		157th meeting of the OPEC conference
2010M11		15/11/2010	
2010M12	11/12/2010		158th (extraordinary) meeting of the OPEC conference
2011M01		05/01/2011	
2011M02		09/02/2011	
2011M03		09/03/2011	
2011M04		06/04/2011	
2011M05		11/05/2011	
2011M06	08/06/2011		159th meeting of the OPEC conference
2011M07		13/07/2011	
2011M08		10/08/2011	
2011M09		14/09/2011	
2011M10		12/10/2011	
2011M11		16/11/2011	
2011M12	14/12/2011		160th meeting of the OPEC conference
2012M01		12/01/2012	

Month	Announcement date	Control date	Additional information
2012M02		16/02/2012	
2012M03		15/03/2012	
2012M04		12/04/2012	
2012M05		17/05/2012	
2012M06	14/06/2012		161st meeting of the OPEC conference
2012M07		11/07/2012	
2012M08		15/08/2012	
2012M09		12/09/2012	
2012M10		10/10/2012	
2012M11		14/11/2012	
2012M12	12/12/2012		162nd meeting of the OPEC conference
2013M01		25/01/2013	
2013M02		22/02/2013	
2013M03		22/03/2013	
2013M04		26/04/2013	
2013M05	31/05/2013		163rd meeting of the OPEC conference
2013M06		05/06/2013	
2013M07		03/07/2013	
2013M08		07/08/2013	
2013M09		04/09/2013	
2013M10		02/10/2013	
2013M11		06/11/2013	
2013M12	04/12/2013		164th meeting of the OPEC conference
2014M01		08/01/2014	
2014M02		12/02/2014	
2014M03		12/03/2014	
2014M04		09/04/2014	
2014M05		14/05/2014	
2014M06	11/06/2014		165th meeting of the OPEC conference
2014M07		25/07/2014	
2014M08		29/08/2014	
2014M09		26/09/2014	
2014M10		31/10/2014	
2014M11	27/11/2014		166th meeting of the OPEC conference
2014M12		05/12/2014	
2015M01		02/01/2015	
2015M02		06/02/2015	
2015M03		06/03/2015	
2015M04		10/04/2015	
2015M05		08/05/2015	
2015M06	05/06/2015		167th meeting of the OPEC conference
2015M07		10/07/2015	
2015M08		07/08/2015	
2015M09		04/09/2015	
2015M10		02/10/2015	
2015M11		06/11/2015	
2015M12	04/12/2015		168th meeting of the OPEC conference
2016M01		07/01/2016	
2016M02		04/02/2016	
2016M03		03/03/2016	
2016M04		07/04/2016	
2016M05		05/05/2016	
2016M06	02/06/2016		169th meeting of the OPEC conference
2016M07		28/07/2016	
2016M08		25/08/2016	
2016M09	28/09/2016		170th (extraordinary) meeting of the OPEC conference
2016M10		26/10/2016	
2016M11	30/11/2016		171st meeting of the OPEC conference
2016M12	10/12/2016		OPEC and non-OPEC ministerial meeting
2017M01		26/01/2017	
2017M02		23/02/2017	
2017M03		23/03/2017	
2017M04		27/04/2017	
2017M05	25/05/2017		172nd meeting of the OPEC conference
2017M06		29/06/2017	
2017M07		27/07/2017	
2017M08		31/08/2017	
2017M09		28/09/2017	
2017M10		26/10/2017	
2017M11	30/11/2017		173rd meeting of the OPEC conference
2017M12		28/12/2017	

B.2. Data sources

Table B.2 gives details on the data used in the paper, including information on the coverage and data sources.

Table B.2: Data description, sources, and coverage

Variable	Description	Source	Sample	Trans.
Instrument				
NCLC.hh (PS)	WTI crude oil futures *hh*-month contract (settlement price)	Datastream	30/03/1983-31/12/2017	100*Δlog
Baseline variables				
OILPRICE	WTI spot crude oil price (WTISPLC) deflated by U.S. CPI (CPIAUCSL)	FRED	1974M1-2017M12	100*log
EIA1955	World oil production	Datastream	1974M1-2017M12	100*log
OECD+6IP	Industrial production of OECD + 6 (Brazil, China, India, Indonesia, Russia and South Africa) from Baumeister and Hamilton (2019)	Baumeister's webpage	1974M1-2017M12	100*log
OECDSTOCKS	OECD crude oil inventories, calculated based on OECD petroleum stocks (EIA1976) and U.S. crude oil and petroleum stocks (EIA1533, EIA1541), as in Kilian and Murphy (2014)	Datastream/own calculations	1974M1-2017M12	100*log
INDPRO	U.S. industrial production index	FRED	1974M1-2017M12	100*log
CPIAUCSL	U.S. CPI for all urban consumers: all items	FRED	1974M1-2017M12	100*log
Additional variables				
Expectations and uncertainty				
BKEXP12M	Oil price expectations (12-month) from Baumeister and Kilian (2017), extended using futures prices	Baumeister's webpage/ own calculations	1983M4-2017M12	100*log
MICH	University of Michigan: inflation expectation	FRED	1981M7-2017M12	Level
CPI6	SPF median inflation expectations (1 year horizon)	Philadelphia FED	1981Q3-2017Q4	Level
VXOCLS	CBOE S&P 100 volatility index: VXO, extended as in Bloom (2009)	FRED/own calculations	1974M1-2017M12	100*log
GPR	Geopolitical risk index from Caldara and Iacoviello (2018)	Iacoviello's webpage	1985M1-2017M12	100*log
Prices				
CPILFESL	U.S. CPI for all urban consumers: all items less food and energy	FRED	1974M1-2017M12	100*log
CPIENGSL	U.S. CPI for all urban consumers: energy	FRED	1974M1-2017M12	100*log
CUSR0000SAN	U.S. CPI for all urban consumers: nondurables	FRED	1974M1-2017M12	100*log
CUSR0000SAD	U.S. CPI for all urban consumers: durables	FRED	1974M1-2017M12	100*log
CUSR0000SAS	U.S. CPI for all urban consumers: services	FRED	1974M1-2017M12	100*log
Activity				
UNRATE	Civilian unemployment rate	FRED	1974M1-2017M12	Level
RPCE	U.S. personal consumption expenditures (PCE), deflated by chain-type price index (PCEPI)	FRED	1974M1-2017M12	100*log
GDPC1	U.S. Real Gross Domestic Product	FRED	1974Q1-2017Q4	100*log
GPDIC1	U.S. Real Gross Private Domestic Investment	FRED	1974Q1-2017Q4	100*log
PCECC96	U.S. Real Personal Consumption Expenditures	FRED	1974Q1-2017Q4	100*log
Financial variables				
FF	Effective federal funds rate	FRED	1974M1-2017M12	Level
EBP	Excess bond premium from Gilchrist and Zakrajšek (2012)	Gilchrist's webpage	1974M1-2017M12	Level
SPCOMP	S&P 500 composite price index (monthly average)	Datastream/ own calculations	1974M1-2017M12	100*log
Exchange rates and trade				
TWEXBMTH	Trade Weighted U.S. Dollar Index: Broad	FRED	1974M1-2017M12	100*log
TWEXMMTH	Trade Weighted U.S. Dollar Index: Major Currencies	FRED	1974M1-2017M12	100*log
–	Bilateral exchange rates, domestic currency per U.S. dollar	IFS	1974M1-2017M12 RUS starts 1995M6	100*log
USTOTPRCF	U.S. terms of trade	Datastream	1974M1-2017M12	100*log
USBALGDSB	U.S. merchandise trade balance, as a share of nominal GDP (GDP from FRED)	Datastream/FRED	1974Q1-2017Q4	Level

Table B.3: Description of data in online appendix

Variable	Description	Source	Sample	Trans.
Wider effects				
RDNRGRC1M027SBEA	U.S. PCE energy goods and services (DNRGRC1M027SBEA), deflated by DNRGRG3M086SBEA	FRED	1974M1-2017M12	100*log
RPCEND	U.S. PCE nondurable goods (PCEND), deflated by DNDGRG3M086SBEA	FRED	1974M1-2017M12	100*log
RPCEDG	U.S. PCE durable goods (PCEDG), deflated by DDURRG3M086SBEA	FRED	1974M1-2017M12	100*log
RPCES	U.S. PCE services (PCES), deflated by DSERRG3M086SBEA	FRED	1974M1-2017M12	100*log
OILGSUS	Oil & Gas stock price index (monthly average)	Datastream/own calculations	1974M1-2017M12	100*log
ELECTUS	Electricity stock price index (monthly average)	Datastream/own calculations	1974M1-2017M12	100*log
MNINGUS	Mining stock price index (monthly average)	Datastream/own calculations	1974M1-2017M12	100*log
AUTOSUS	Automobiles stock price index (monthly average)	Datastream/own calculations	1974M1-2017M12	100*log
RTAILUS	Retail stock price index (monthly average)	Datastream/own calculations	1974M1-2017M12	100*log
TRLESUS	Travel & Leisure stock price index (monthly average)	Datastream/own calculations	1974M1-2017M12	100*log
Sensitivity				
LLCC.hh (PS)	Brent crude oil futures *hh*-month contract (settlement price)	Datastream	24/06/1983-31/12/2017	100*Δlog
BRENTP	Brent spot crude oil price (DCOILBRENTEU, extended using POILBREUSDM and WTISPLC) deflated by U.S. CPI (CPIAUCSL)	FRED/own calculations	1974M1-2017M12	100*log
REFINERCOST	U.S. refiners acquisition cost of imported crude oil (USCOCOIMA) deflated by U.S. CPI (CPIAUCSL)	Datastream	1974M1-2017M12	100*log
GLOBALACT	Kilian's (2009) index of global real economic activity	Kilian's webpage	1974M1-2015M12	Level

Figure B.1 shows the series included in the baseline VAR over the sample period 1974-2015. All the variables are depicted in logs.

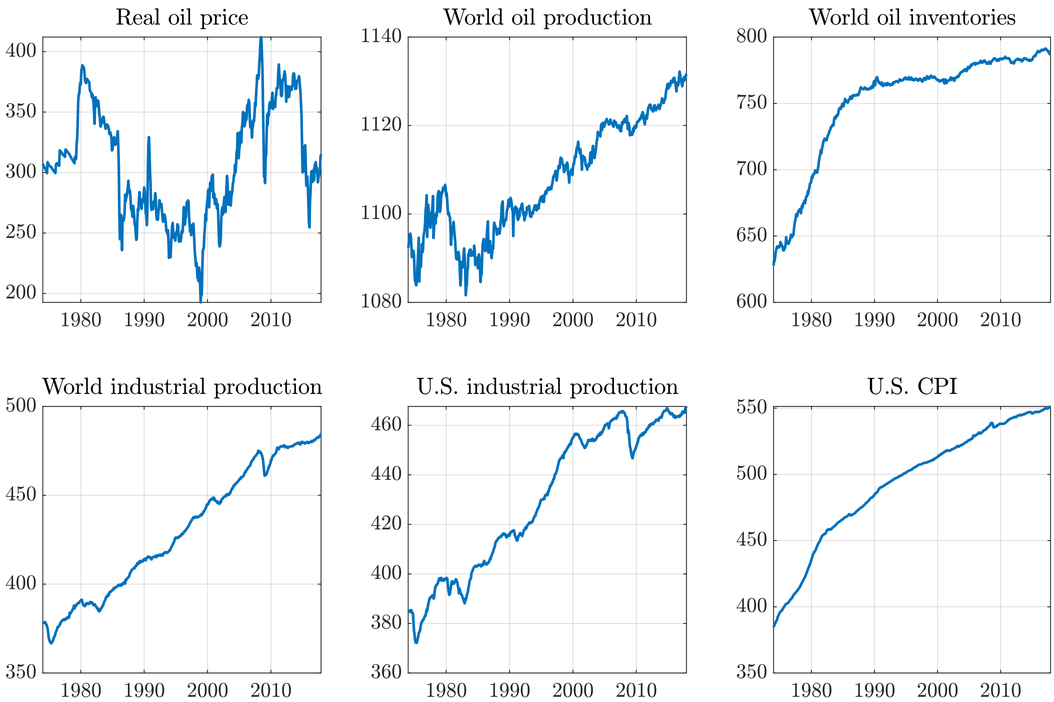


Figure B.1: Transformed data series in the baseline VAR

C. Identification using external instruments

This Appendix shows how to identify the structural impact vector using external instruments for the simple case with one instrument and one shock as well as the general case with k instruments and k shocks.

C.1. Simple case with one shock and one instrument

In the following, I derive the structural impact vector for the simple case with one instrument and one shock. Recall, the moment conditions for the external instrument were given by

$$\begin{aligned}\mathbb{E}[z_t \varepsilon_{1,t}] &= \alpha \neq 0 \\ \mathbb{E}[z_t \boldsymbol{\varepsilon}_{2:n,t}] &= \mathbf{0}.\end{aligned}$$

Under these assumptions, $\mathbf{s}_1$ is identified up to sign and scale. To see this, note that

$$\mathbb{E}[z_t \mathbf{u}_t] = \mathbf{S}\,\mathbb{E}[z_t \boldsymbol{\varepsilon}_t] = \begin{pmatrix}\mathbf{s}_1 & \mathbf{S}_{2:n}\end{pmatrix}\begin{pmatrix}\mathbb{E}[z_t \varepsilon_{1,t}] \\ \mathbb{E}[z_t \boldsymbol{\varepsilon}_{2:n,t}]\end{pmatrix} = \mathbf{s}_1 \alpha.$$

By partitioning this equation, one can write

$$\mathbb{E}[z_t \mathbf{u}_t] = \begin{pmatrix}\mathbb{E}[z_t \mathrm{u}_{1,t}] \\ \mathbb{E}[z_t \mathbf{u}_{2:n,t}]\end{pmatrix} = \begin{pmatrix}\mathrm{s}_{1,1}\alpha \\ \mathbf{s}_{2:n,1}\alpha\end{pmatrix}$$

Combining the two equations yields

$$\tilde{\mathbf{s}}_{2:n,1} \equiv \mathbf{s}_{2:n,1}/\mathrm{s}_{1,1} = \mathbb{E}[z_t \mathbf{u}_{2:n,t}]/\,\mathbb{E}[z_t \mathrm{u}_{1,t}], \tag{2}$$

provided that $E[z_t \mathrm{u}_{1,t}] \neq 0$. This condition is satisfied iff $\alpha \neq 0$ and $\mathrm{s}_{1,1} \neq 0$. Thus, $\mathbf{s}_1$ is identified up to scale, provided that these conditions hold.

The scale of $\mathbf{s}_1$ is then set by a normalization subject to

$$\boldsymbol{\Sigma} = \mathbf{S}\boldsymbol{\Omega}\mathbf{S}'.$$

One approach is to impose that $\boldsymbol{\Omega} = \mathbf{I}_n$. This implies that a unit positive value of $\varepsilon_{1,t}$ has a one standard deviation positive effect on $\mathrm{y}_{1,t}$. $\mathrm{s}_{1,1}$ can then be recovered as follows. In a first step, partition $\boldsymbol{\Sigma}$ and $\mathbf{S}$ as

$$\boldsymbol{\Sigma} = \begin{pmatrix}\sigma_{1,1} & \boldsymbol{\sigma}_{1,2} \\ \boldsymbol{\sigma}_{2,1} & \boldsymbol{\Sigma}_{2,2}\end{pmatrix}, \text{ and } \qquad \mathbf{S} = \begin{pmatrix}\mathrm{s}_{1,1} & \mathbf{s}_{1,2} \\ \mathbf{s}_{2,1} & \mathbf{S}_{2,2}\end{pmatrix}.$$

To economize on notation, parameters pertaining to the variables $i \in \{2, \dots, n\}$ are indexed by 2 instead of $2{:}n$.

From the covariance restrictions $\boldsymbol{\Sigma} = \mathbf{S}\mathbf{S}'$, we then have

$$\begin{pmatrix} \mathrm{s}_{1,1} & \mathbf{s}_{1,2} \\ \mathbf{s}_{2,1} & \mathbf{S}_{2,2} \end{pmatrix} \begin{pmatrix} \mathrm{s}_{1,1} & \mathbf{s}'_{2,1} \\ \mathbf{s}'_{1,2} & \mathbf{S}'_{2,2} \end{pmatrix} = \begin{pmatrix} \mathrm{s}_{1,1}^2 + \mathbf{s}_{1,2}\mathbf{s}'_{1,2} & \mathrm{s}_{1,1}\mathbf{s}'_{2,1} + \mathbf{s}_{1,2}\mathbf{S}'_{2,2} \\ \mathbf{s}_{2,1}\mathrm{s}_{1,1} + \mathbf{S}_{2,2}\mathbf{s}'_{1,2} & \mathbf{s}_{2,1}\mathbf{s}'_{2,1} + \mathbf{S}_{2,2}\mathbf{S}'_{2,2} \end{pmatrix} = \begin{pmatrix} \sigma_{1,1} & \boldsymbol{\sigma}_{1,2} \\ \boldsymbol{\sigma}_{2,1} & \boldsymbol{\Sigma}_{2,2} \end{pmatrix}.$$

Note that $\boldsymbol{\Sigma}$ is a covariance matrix and thus symmetric, i.e. $\boldsymbol{\sigma}'_{1,2} = \boldsymbol{\sigma}_{2,1}$. Thus, this system yields three equations (one is redundant):

$$\begin{aligned} \mathrm{s}_{1,1}^2 + \mathbf{s}_{1,2}\mathbf{s}'_{1,2} &= \sigma_{1,1} \\ \mathrm{s}_{1,1}\mathbf{s}_{2,1} + \mathbf{S}_{2,2}\mathbf{s}'_{1,2} &= \boldsymbol{\sigma}_{2,1} \\ \mathbf{s}_{2,1}\mathbf{s}'_{2,1} + \mathbf{S}_{2,2}\mathbf{S}'_{2,2} &= \boldsymbol{\Sigma}_{2,2}. \end{aligned}$$

By substituting out $\mathbf{s}_{2,1} = \tilde{\mathbf{s}}_{2,1}\mathrm{s}_{1,1}$, one can obtain

$$\mathrm{s}_{1,1}^2 + \mathbf{s}_{1,2}\mathbf{s}'_{1,2} = \sigma_{1,1} \tag{3}$$

$$\mathrm{s}_{1,1}^2\tilde{\mathbf{s}}_{2,1} + \mathbf{S}_{2,2}\mathbf{s}'_{1,2} = \boldsymbol{\sigma}_{2,1} \tag{4}$$

$$\mathrm{s}_{1,1}^2\tilde{\mathbf{s}}_{2,1}\tilde{\mathbf{s}}'_{2,1} + \mathbf{S}_{2,2}\mathbf{S}'_{2,2} = \boldsymbol{\Sigma}_{2,2}. \tag{5}$$

From equation (3), it follows that $\mathrm{s}_{1,1} = \pm\sqrt{\sigma_{1,1} - \mathbf{s}_{1,2}\mathbf{s}'_{1,2}}$. Thus, it remains to solve for $\mathbf{s}_{1,2}\mathbf{s}'_{1,2}$. By substracting (3) multiplied by $\tilde{\mathbf{s}}_{2,1}$ from (4), one can write

$$\begin{aligned} \mathbf{S}_{2,2}\mathbf{s}'_{1,2} - \tilde{\mathbf{s}}_{2,1}\mathbf{s}_{1,2}\mathbf{s}'_{1,2} &= \boldsymbol{\sigma}_{2,1} - \tilde{\mathbf{s}}_{2,1}\sigma_{1,1} \\ (\mathbf{S}_{2,2} - \tilde{\mathbf{s}}_{2,1}\mathbf{s}_{1,2})\mathbf{s}'_{1,2} &= \boldsymbol{\sigma}_{2,1} - \tilde{\mathbf{s}}_{2,1}\sigma_{1,1} \\ \Rightarrow \mathbf{s}'_{1,2} &= (\mathbf{S}_{2,2} - \tilde{\mathbf{s}}_{2,1}\mathbf{s}_{1,2})^{-1}(\boldsymbol{\sigma}_{2,1} - \tilde{\mathbf{s}}_{2,1}\sigma_{1,1}). \end{aligned}$$

Thus,

$$\begin{aligned} \mathbf{s}_{1,2}\mathbf{s}'_{1,2} &= (\boldsymbol{\sigma}_{2,1} - \tilde{\mathbf{s}}_{2,1}\sigma_{1,1})'(\mathbf{S}_{2,2} - \tilde{\mathbf{s}}_{2,1}\mathbf{s}_{1,2})'^{-1}(\mathbf{S}_{2,2} - \tilde{\mathbf{s}}_{2,1}\mathbf{s}_{1,2})^{-1}(\boldsymbol{\sigma}_{2,1} - \tilde{\mathbf{s}}_{2,1}\sigma_{1,1}) \\ &= (\boldsymbol{\sigma}_{2,1} - \tilde{\mathbf{s}}_{2,1}\sigma_{1,1})'[\underbrace{(\mathbf{S}_{2,2} - \tilde{\mathbf{s}}_{2,1}\mathbf{s}_{1,2})(\mathbf{S}_{2,2} - \tilde{\mathbf{s}}_{2,1}\mathbf{s}_{1,2})'}_{=\boldsymbol{\Gamma}}]^{-1}(\boldsymbol{\sigma}_{2,1} - \tilde{\mathbf{s}}_{2,1}\sigma_{1,1}). \end{aligned}$$

Now, note that

$$\boldsymbol{\Gamma} = \mathbf{S}_{2,2}\mathbf{S}'_{2,2} - \mathbf{S}_{2,2}\mathbf{s}'_{1,2}\tilde{\mathbf{s}}'_{2,1} - \tilde{\mathbf{s}}_{2,1}\mathbf{s}_{1,2}\mathbf{S}'_{2,2} + \tilde{\mathbf{s}}_{2,1}\mathbf{s}_{1,2}\mathbf{s}'_{1,2}\tilde{\mathbf{s}}'_{2,1}$$

By subtracting (4) multiplied by $\tilde{\mathbf{s}}_{2,1}'$ from (5), one can write

$$\begin{aligned}\mathbf{S}_{2,2}\mathbf{S}_{2,2}' - \mathbf{S}_{2,2}\mathbf{s}_{1,2}'\tilde{\mathbf{s}}_{2,1}' &= \boldsymbol{\Sigma}_{2,2} - \boldsymbol{\sigma}_{2,1}\tilde{\mathbf{s}}_{2,1}' \\ \Rightarrow \mathbf{S}_{2,2}\mathbf{s}_{1,2}'\tilde{\mathbf{s}}_{2,1}' &= \mathbf{S}_{2,2}\mathbf{S}_{2,2}' - (\boldsymbol{\Sigma}_{2,2} - \boldsymbol{\sigma}_{2,1}\tilde{\mathbf{s}}_{2,1}').\end{aligned}$$

Substituting this and its transpose into the above equation yields

$$\boldsymbol{\Gamma} = -(\mathbf{S}_{2,2}\mathbf{S}_{2,2}' - \tilde{\mathbf{s}}_{2,1}\mathbf{s}_{1,2}\mathbf{s}_{1,2}'\tilde{\mathbf{s}}_{2,1}') + 2\boldsymbol{\Sigma}_{2,2} - \tilde{\mathbf{s}}_{2,1}\boldsymbol{\sigma}_{1,2} - \boldsymbol{\sigma}_{2,1}\tilde{\mathbf{s}}_{2,1}'.$$

Similarly, by subtracting (3) pre-multiplied by $\tilde{\mathbf{s}}_{2,1}$ and post-multiplied by $\tilde{\mathbf{s}}_{2,1}'$ from (5), one can write

$$\mathbf{S}_{2,2}\mathbf{S}_{2,2}' - \tilde{\mathbf{s}}_{2,1}\mathbf{s}_{1,2}\mathbf{s}_{1,2}'\tilde{\mathbf{s}}_{2,1}' = \boldsymbol{\Sigma}_{2,2} - \sigma_{1,1}\tilde{\mathbf{s}}_{2,1}\tilde{\mathbf{s}}_{2,1}'.$$

Using this in the equation above gives

$$\boldsymbol{\Gamma} = \boldsymbol{\Sigma}_{2,2} - (\tilde{\mathbf{s}}_{2,1}\boldsymbol{\sigma}_{1,2} + \boldsymbol{\sigma}_{2,1}\tilde{\mathbf{s}}_{2,1}') + \sigma_{1,1}\tilde{\mathbf{s}}_{2,1}\tilde{\mathbf{s}}_{2,1}'.$$

Thus,

$$\mathbf{s}_{1,2}\mathbf{s}_{1,2}' = (\boldsymbol{\sigma}_{2,1} - \tilde{\mathbf{s}}_{2,1}\sigma_{1,1})'[\boldsymbol{\Sigma}_{2,2} - (\tilde{\mathbf{s}}_{2,1}\boldsymbol{\sigma}_{1,2} + \boldsymbol{\sigma}_{2,1}\tilde{\mathbf{s}}_{2,1}') + \sigma_{1,1}\tilde{\mathbf{s}}_{2,1}\tilde{\mathbf{s}}_{2,1}']^{-1}(\boldsymbol{\sigma}_{2,1} - \tilde{\mathbf{s}}_{2,1}\sigma_{1,1}),$$

which completely characterizes the structural impact vector as a function of known quantities. Note that by choosing the positive root $\mathrm{s}_{1,1} = \sqrt{\sigma_{1,1} - \mathbf{s}_{1,2}\mathbf{s}_{1,2}'}$, one can interpret $\mathrm{s}_{1,1}$ as the standard deviation of $\varepsilon_{1,t}$, i.e. $\mathrm{s}_{1,1} = \sigma_{\varepsilon_1}$. The structural impact vector is then given by

$$\mathbf{s}_1 = \begin{pmatrix} \mathrm{s}_{1,1} \\ \tilde{\mathbf{s}}_{2,1}\mathrm{s}_{1,1} \end{pmatrix}.$$

Alternatively, one can set $\boldsymbol{\Omega} = \mathrm{diag}(\sigma_{\varepsilon_1}^2, \ldots, \sigma_{\varepsilon_n}^2)$ and $\mathrm{s}_{1,1} = x$, which implies that a unit positive value of $\varepsilon_{1,t}$ has a positive effect of magnitude x on $\mathrm{y}_{1,t}$. The structural impact vector is then given by

$$\mathbf{s}_1 = \begin{pmatrix} x \\ \tilde{\mathbf{s}}_{2,1}x \end{pmatrix}.$$

After having obtained the structural impact vector $\mathbf{s}_1$, it is straightforward to compute all objects of interest such as IRFs, FEVDs, the structural shock series and the historical decomposition (see e.g. Montiel-Olea, Stock, and Watson, 2016).

The above illustration of the identification strategy holds in population. In practice, identification is achieved as follows. Assume that there is a sample of size $n \times T$ available. In a first step, estimate the reduced form to get estimates of the reduced-form innovations $\hat{\mathbf{u}}_t$. In a second step, estimate (2) by regressing $\hat{\mathbf{u}}_{2:n,t}$ on $\hat{\mathrm{u}}_{1,t}$ using z_t as an instrument. Finally, using the estimated residual covariance matrix from step 1 and the IV estimates from step 2, impose the desired normalization to obtain an estimate of the structural impact vector $\hat{\mathbf{s}}_1$.

Having obtained the impact vector, it is straightforward to compute all objects of interest such as IRFs, FEVDs, and historical decompositions. In particular, as shown in Stock and Watson (2018), it is also possible to compute the structural shock series, $\varepsilon_{1,t}$. It is given by

$$\begin{aligned}
\mathbf{s}_1'\boldsymbol{\Sigma}^{-1}\mathbf{u}_t &= \mathbf{s}_1'(\mathbf{S}\mathbf{S}')^{-1}\mathbf{u}_t && \text{(assuming that } \boldsymbol{\Sigma} = \mathbf{S}\mathbf{S}'\text{)} \\
&= \mathbf{s}_1'\mathbf{S}'^{-1}\mathbf{S}^{-1}\mathbf{S}\boldsymbol{\varepsilon}_t \\
&= \mathbf{e}_1'\boldsymbol{\varepsilon}_t && \text{(because } \mathbf{S}^{-1}\mathbf{s}_1 = \mathbf{e}_1\text{)} \\
&= \varepsilon_{1,t},
\end{aligned}$$

where $\mathbf{e}_1$ is the first standard basis vector.

C.2. General case for k shocks and k instruments

In this Appendix, I provide more details on the identification strategy for the case with k shocks and k instruments.

To begin, partition the structural shocks into $\boldsymbol{\varepsilon}_t = [\boldsymbol{\varepsilon}_{1,t}', \ \boldsymbol{\varepsilon}_{2,t}']'$, where $\boldsymbol{\varepsilon}_{1,t}$ is the $k \times 1$ vector of structural shocks to be identified and $\boldsymbol{\varepsilon}_{2,t}$ is a $(n-k) \times 1$ vector containing all other shocks. The identifying restrictions are given by the moment restrictions for the instrument

$$\begin{aligned}
\mathbb{E}[\mathbf{z}_t\boldsymbol{\varepsilon}_{1,t}'] &= \boldsymbol{\alpha} \\
\mathbb{E}[\mathbf{z}_t\boldsymbol{\varepsilon}_{2,t}'] &= \mathbf{0}_{k\times(n-k)},
\end{aligned}$$

where $\boldsymbol{\alpha}$ is a $k \times k$ matrix (of full rank) and the covariance restrictions

$$\mathbf{S}\mathbf{S}' = \boldsymbol{\Sigma}.$$

In a next step, partition $\mathbf{S}$ as

$$\mathbf{S} = (\mathbf{S}_1, \ \mathbf{S}_2) = \begin{pmatrix} \mathbf{S}_{11} & \mathbf{S}_{12} \\ \mathbf{S}_{21} & \mathbf{S}_{22} \end{pmatrix},$$

where $\mathbf{S}_1$ is of dimension $n \times k$, $\mathbf{S}_2$ is of dimension $n \times (n-k)$. $\mathbf{S}_{11}$ is of dimension

$k \times k$, $\mathbf{S}_{21}$ and $\mathbf{S}_{12}$ are of dimension $(n-k) \times k$ and $k \times (n-k)$, respectively, and $\mathbf{S}_{22}$ is $(n-k) \times (n-k)$.

The instrument moment conditions together with $\mathbf{u}_t = \mathbf{S}\boldsymbol{\varepsilon}_t$ imply

$$\boldsymbol{\Sigma}_{\mathbf{zu}'} = \mathbb{E}[\mathbf{z}_t \mathbf{u}_t'] = \mathbb{E}[\mathbf{z}_t \boldsymbol{\varepsilon}_t'] \mathbf{S}' = \mathbb{E}[\mathbf{z}_t (\boldsymbol{\varepsilon}_{1,t}',\ \boldsymbol{\varepsilon}_{2,t}')] \begin{pmatrix} \mathbf{S}_1' \\ \mathbf{S}_2' \end{pmatrix} = (\boldsymbol{\alpha},\ \mathbf{0}) \begin{pmatrix} \mathbf{S}_1' \\ \mathbf{S}_2' \end{pmatrix} = \boldsymbol{\alpha}\mathbf{S}_1'$$

Now, partition $\boldsymbol{\Sigma}_{\mathbf{zu}'} = (\boldsymbol{\Sigma}_{\mathbf{zu}_1'},\ \boldsymbol{\Sigma}_{\mathbf{zu}_2'})$. The above restrictions can then be expressed as

$$\boldsymbol{\alpha}(\mathbf{S}_{11}',\ \mathbf{S}_{21}') = (\boldsymbol{\Sigma}_{\mathbf{zu}_1'},\ \boldsymbol{\Sigma}_{\mathbf{zu}_2'}),$$

or equivalently

$$\begin{aligned} \boldsymbol{\alpha}\mathbf{S}_{11}' &= \boldsymbol{\Sigma}_{\mathbf{zu}_1'} \\ \boldsymbol{\alpha}\mathbf{S}_{21}' &= \boldsymbol{\Sigma}_{\mathbf{zu}_2'}. \end{aligned}$$

Combining the two yields

$$\mathbf{S}_{21}\mathbf{S}_{11}^{-1} = (\boldsymbol{\Sigma}_{\mathbf{zu}_1'}^{-1} \boldsymbol{\Sigma}_{\mathbf{zu}_2'})',$$

which can be estimated from the data. In particular, $\boldsymbol{\Sigma}_{\mathbf{zu}_1'}^{-1} \boldsymbol{\Sigma}_{\mathbf{zu}_2'}$ corresponds to the 2SLS estimator in a regression of $\mathbf{u}_{2,t}$ on $\mathbf{u}_{1,t}$ using $\mathbf{z}_t$ as an instrument for $\mathbf{u}_{1,t}$.

The covariance restrictions then yield

$$\mathbf{S}\mathbf{S}' = \boldsymbol{\Sigma}$$

$$\begin{pmatrix} \mathbf{S}_{11} & \mathbf{S}_{12} \\ \mathbf{S}_{21} & \mathbf{S}_{22} \end{pmatrix} \begin{pmatrix} \mathbf{S}_{11}' & \mathbf{S}_{21}' \\ \mathbf{S}_{12}' & \mathbf{S}_{22}' \end{pmatrix} = \begin{pmatrix} \mathbf{S}_{11}\mathbf{S}_{11}' + \mathbf{S}_{12}\mathbf{S}_{12}' & \mathbf{S}_{11}\mathbf{S}_{21}' + \mathbf{S}_{12}\mathbf{S}_{22}' \\ \mathbf{S}_{21}\mathbf{S}_{11} + \mathbf{S}_{22}\mathbf{S}_{12}' & \mathbf{S}_{21}\mathbf{S}_{21}' + \mathbf{S}_{22}\mathbf{S}_{22}' \end{pmatrix} = \begin{pmatrix} \boldsymbol{\Sigma}_{11} & \boldsymbol{\Sigma}_{12} \\ \boldsymbol{\Sigma}_{21} & \boldsymbol{\Sigma}_{22} \end{pmatrix}.$$

Note that $\boldsymbol{\Sigma}$ is a covariance matrix and thus symmetric, i.e. $\boldsymbol{\Sigma}_{12}' = \boldsymbol{\Sigma}_{21}$. Thus, this system yields three matrix equations (one is redundant):

$$\begin{aligned} \mathbf{S}_{11}\mathbf{S}_{11}' + \mathbf{S}_{12}\mathbf{S}_{12}' &= \boldsymbol{\Sigma}_{11} \\ \mathbf{S}_{11}\mathbf{S}_{21}' + \mathbf{S}_{12}\mathbf{S}_{22}' &= \boldsymbol{\Sigma}_{12} \\ \mathbf{S}_{21}\mathbf{S}_{21}' + \mathbf{S}_{22}\mathbf{S}_{22}' &= \boldsymbol{\Sigma}_{22}. \end{aligned}$$

Note, to identify $\mathbf{S}$ up to a rotation, it is sufficient to find $\mathbf{S}_{11}\mathbf{S}_{11}'$, $\mathbf{S}_{22}\mathbf{S}_{22}'$, $\mathbf{S}_{21}\mathbf{S}_{11}^{-1}$

and $\mathbf{S}_{12}\mathbf{S}_{22}^{-1}$. This is because one can write

$$\mathbf{S} = \begin{pmatrix} \mathbf{L}_1 & \mathbf{S}_{12}\mathbf{S}_{22}^{-1}\mathbf{L}_2 \\ \mathbf{S}_{21}\mathbf{S}_{11}^{-1}\mathbf{L}_1 & \mathbf{L}_2 \end{pmatrix},$$

where $\mathbf{L}_1 = \text{chol}(\mathbf{S}_{11}\mathbf{S}_{11}')$ and $\mathbf{L}_2 = \text{chol}(\mathbf{S}_{22}\mathbf{S}_{22}')$. This still satisfies $\mathbf{S}\mathbf{S}' = \mathbf{\Sigma}$. Thus, it proves useful to rewrite these equations in terms of $\mathbf{S}_{11}\mathbf{S}_{11}'$, $\mathbf{S}_{22}\mathbf{S}_{22}'$, $\mathbf{S}_{21}\mathbf{S}_{11}^{-1}$ and $\mathbf{S}_{12}\mathbf{S}_{22}^{-1}$:

$$\begin{aligned} \mathbf{S}_{11}\mathbf{S}_{11}' + \mathbf{S}_{12}\mathbf{S}_{22}^{-1}\mathbf{S}_{22}\mathbf{S}_{22}'(\mathbf{S}_{22}')^{-1}\mathbf{S}_{12}' &= \mathbf{\Sigma}_{11} \\ \mathbf{S}_{11}\mathbf{S}_{11}'\mathbf{S}_{11}^{-1}\mathbf{S}_{21}' + \mathbf{S}_{12}\mathbf{S}_{22}^{-1}\mathbf{S}_{12}\mathbf{S}_{22}' &= \mathbf{\Sigma}_{1,2} \\ \mathbf{S}_{21}\mathbf{S}_{11}^{-1}\mathbf{S}_{21}\mathbf{S}_{21}'\mathbf{S}_{11}^{-1}\mathbf{S}_{21}' + \mathbf{S}_{22}\mathbf{S}_{22}' &= \mathbf{\Sigma}_{2,2}. \end{aligned}$$

Recall that $\mathbf{S}_{21}\mathbf{S}_{11}^{-1}$ is identified by the instrument conditions. Thus, this is a system of 3 matrix equations in 3 unknown matrices. The solutions are given by

$$\begin{aligned} \mathbf{S}_{12}\mathbf{S}_{12}' &= (\mathbf{\Sigma}_{21} - \mathbf{S}_{21}\mathbf{S}_{11}^{-1}\mathbf{\Sigma}_{11})'\mathbf{\Gamma}^{-1}(\mathbf{\Sigma}_{21} - \mathbf{S}_{21}\mathbf{S}_{11}^{-1}\mathbf{\Sigma}_{11}) \\ \mathbf{\Gamma} &= (\mathbf{\Sigma}_{22} + \mathbf{S}_{21}\mathbf{S}_{11}^{-1}\mathbf{\Sigma}_{11}(\mathbf{S}_{11}')^{-1}\mathbf{S}_{21}' - \mathbf{S}_{21}\mathbf{S}_{11}^{-1}\mathbf{\Sigma}_{12} - \mathbf{\Sigma}_{21}(\mathbf{S}_{11}')^{-1}\mathbf{S}_{21}') \\ \mathbf{S}_{11}\mathbf{S}_{11}' &= \mathbf{\Sigma}_{11} - \mathbf{S}_{12}\mathbf{S}_{12}' \\ \mathbf{S}_{22}\mathbf{S}_{22}' &= \mathbf{\Sigma}_{22} - \mathbf{S}_{21}\mathbf{S}_{11}^{-1}\mathbf{S}_{11}\mathbf{S}_{11}'(\mathbf{S}_{11}')^{-1}\mathbf{S}_{21}' \\ \mathbf{S}_{12}\mathbf{S}_{22}^{-1} &= (\mathbf{\Sigma}_{12} - \mathbf{S}_{11}\mathbf{S}_{11}(\mathbf{S}_{11}')^{-1}\mathbf{S}_{21}')(\mathbf{S}_{22}\mathbf{S}_{22}')^{-1}. \end{aligned}$$

To show this, define $\mathbf{a} = \mathbf{S}_{21}\mathbf{S}_{11}^{-1}$ and $\mathbf{b} = \mathbf{S}_{12}\mathbf{S}_{22}^{-1}$. Then note that

$$\begin{aligned} \mathbf{\Sigma}_{12} - \mathbf{\Sigma}_{11}\mathbf{a}' =& \mathbf{b}\mathbf{S}_{22}\mathbf{S}_{22}'(\mathbf{I} - \mathbf{b}'\mathbf{a}') \\ \mathbf{\Sigma}_{22} + \mathbf{a}\mathbf{\Sigma}_{11}\mathbf{a}' - \mathbf{a}\mathbf{\Sigma}_{12} - \mathbf{\Sigma}_{21}\mathbf{a}' =& (\mathbf{I} - \mathbf{a}\mathbf{b})\mathbf{S}_{22}\mathbf{S}_{22}'(\mathbf{I} - \mathbf{b}'\mathbf{a}'). \end{aligned}$$

Thus,

$$\begin{aligned} &(\mathbf{\Sigma}_{12} - \mathbf{\Sigma}_{11}\mathbf{a}')(\mathbf{\Sigma}_{22} + \mathbf{a}\mathbf{\Sigma}_{11}\mathbf{a}' - \mathbf{a}\mathbf{\Sigma}_{12} - \mathbf{\Sigma}_{21}\mathbf{a}')^{-1}(\mathbf{\Sigma}_{21} - \mathbf{a}\mathbf{\Sigma}_{11}) \\ &= \mathbf{b}\mathbf{S}_{22}\mathbf{S}_{22}'(\mathbf{I} - \mathbf{b}'\mathbf{a}')(\mathbf{I} - \mathbf{b}'\mathbf{a}')^{-1}(\mathbf{S}_{22}\mathbf{S}_{22}')^{-1}(\mathbf{I} - \mathbf{a}\mathbf{b})^{-1}(\mathbf{I} - \mathbf{a}\mathbf{b})\mathbf{S}_{22}\mathbf{S}_{22}'\mathbf{b}' \\ &= \mathbf{b}\mathbf{S}_{22}\mathbf{S}_{22}'\mathbf{b}' = \mathbf{S}_{12}\mathbf{S}_{12}'. \end{aligned}$$

The rest of the solutions then follows immediately from the original system of matrix equations.

We have now all the ingredients to evaluate

$$\mathbf{S} = \begin{pmatrix} \mathbf{L}_1 & \mathbf{S}_{12}\mathbf{S}_{22}^{-1}L_2 \\ \mathbf{S}_{21}\mathbf{S}_{11}^{-1}\mathbf{L}_1 & \mathbf{L}_2 \end{pmatrix}.$$

Recall, however, that this does only identify $\mathbf{S}$ up to a rotation. The parameter space of the proxy VAR can be characterized by

$$\mathbf{SR} = \begin{pmatrix} \mathbf{L}_1 & \mathbf{S}_{12}\mathbf{S}_{22}^{-1}\mathbf{L}_2 \\ \mathbf{S}_{21}\mathbf{S}_{11}^{-1}\mathbf{L}_1 & \mathbf{L}_2 \end{pmatrix} \begin{pmatrix} \mathbf{R}_k & \mathbf{0} \\ \mathbf{0} & \mathbf{R}_{n+k} \end{pmatrix} = \begin{pmatrix} \mathbf{L}_1\mathbf{R}_k & \mathbf{S}_{12}\mathbf{S}_{22}^{-1}L_2\mathbf{R}_{n+k} \\ \mathbf{S}_{21}\mathbf{S}_{11}^{-1}\mathbf{L}_1\mathbf{R}_k & \mathbf{L}_2\mathbf{R}_{n+k} \end{pmatrix},$$

where $\mathbf{R}$ is an orthonormal rotation matrix. As I am only interested in identifying the first k shocks, identification of $\mathbf{S}_1$ amounts to choose an appropriate rotation submatrix $\mathbf{R}_k$. In the application at hand, $\mathbf{R}_k = \mathbf{I}$ is a reasonable choice provided that world oil production is ordered first and the real price of oil is ordered second in the VAR. Because $\mathbf{L}_1$ is a lower triangular matrix, this amounts to assume that the oil supply news shock does not affect world oil production on impact. This additional assumption identifies the two structural shocks.

D. Identification via heteroskedasticity

This Appendix provides more detail on the heteroskedasticity-based identification strategy. In the following, I derive the formula for the structural impact vector.

As discussed in the main text, we assume that movements in the oil futures z_t we observe in the data are governed by both oil supply news and other shocks:

$$z_t = \varepsilon_{1,t} + \sum_{j \neq 1} \varepsilon_{j,t} + v_t,$$

where $\varepsilon_{j,t}$ are other shocks affecting oil futures and v_t captures measurement error such as microstructure noise, satisfying $v_t \sim iidN(0, \sigma_v^2)$.

Recall, the identifying assumption is that the variance of oil supply news shocks increases at the time of OPEC announcements while the variance of all other shocks is unchanged. We can write the identifying assumptions as

$$\begin{aligned} \sigma^2_{\varepsilon_1,R1} &> \sigma^2_{\varepsilon_1,R2} \\ \sigma^2_{\varepsilon_j,R1} &= \sigma^2_{\varepsilon_j,R2}, \quad \text{for } j = 2, \ldots, n. \\ \sigma^2_{v,R1} &= \sigma^2_{v,R2}, \end{aligned}$$

where $R1$ is the treatment sample of OPEC announcements and $R2$ is the control sample.

Under these assumptions, the structural impact vector obtains as

$$\mathbf{s}_1 = \frac{\mathbb{E}_{R1}[z_t\mathbf{u}_t] - \mathbb{E}_{R2}[z_t\mathbf{u}_t]}{\mathbb{E}_{R1}[z_t^2] - \mathbb{E}_{R2}[z_t^2]}.$$

To see why this is the case, note that

$$\frac{\mathbb{E}_{R1}[z_t\mathbf{u}_t]-\mathbb{E}_{R2}[z_t\mathbf{u}_t]}{\mathbb{E}_{R1}[z_t^2]-\mathbb{E}_{R2}[z_t^2]}=\frac{\mathbf{S}\,\mathbb{E}_{R1}[z_t\boldsymbol{\varepsilon}_t]-\mathbf{S}\,\mathbb{E}_{R2}[z_t\boldsymbol{\varepsilon}_t]}{\mathbb{E}_{R1}[z_t^2]-\mathbb{E}_{R2}[z_t^2]}=\frac{\mathbf{s}_1(\sigma^2_{\varepsilon_1,R1}-\sigma^2_{\varepsilon_1,R2})}{\sigma^2_{\varepsilon_1,R1}-\sigma^2_{\varepsilon_1,R2}}=\mathbf{s}_1,$$

where the first equality uses $\mathbf{u}_t=\mathbf{S}\boldsymbol{\varepsilon}_t$ and the second equality follows directly from $\sigma^2_{\varepsilon_j,R1}=\sigma^2_{\varepsilon_j,R2}$ and $\sigma^2_{v,R1}=\sigma^2_{v,R2}$, and the fact that the structural shocks are mutually uncorrelated.

As shown by Rigobon and Sack (2004), we can also obtain this estimator through an IV approach, using $\tilde{\mathbf{z}}=(\mathbf{z}'_{R1},\ -\mathbf{z}'_{R2})'$ as an instrument for $\mathbf{z}=(\mathbf{z}'_{R1},\ \mathbf{z}'_{R2})'$ in a regression of $\mathbf{U}=(\mathbf{U}'_{R1},\ \mathbf{U}'_{R2})'$ on $\mathbf{z}$, where $\mathbf{z}$ is an $T\times 1$ vector containing the daily changes in futures prices in the treatment and the control regime and $\mathbf{U}$ is a $T\times n$ matrix containing the reduced-form residuals in the treatment and the control regime. To see why this is the case, substitute these expressions in the IV estimator $\mathbb{E}[\tilde{\mathbf{z}}'\mathbf{z}]^{-1}\,\mathbb{E}[\tilde{\mathbf{z}}'\mathbf{U}]$, and the above estimator obtains.

Based on $\mathbf{s}_1$, it is then straightforward to compute the impulse responses to the oil supply news shock and all other objects of interest. As in the external instruments case, we can also obtain an estimate of the structural shock. From the covariance restrictions, we have that

$$\begin{aligned}\boldsymbol{\Sigma}_{R1}&=\mathbf{S}\boldsymbol{\Omega}_{R1}\mathbf{S}'\\ \boldsymbol{\Sigma}_{R2}&=\mathbf{S}\boldsymbol{\Omega}_{R2}\mathbf{S}'.\end{aligned}$$

We can then obtain the structural shock as

$$\varepsilon_{1,t}=\mathbf{s}'_1\boldsymbol{\Sigma}^{-1}_{R1}\mathbf{u}_t(\mathbf{s}'_1\boldsymbol{\Sigma}^{-1}_{R1}\mathbf{s}_1)^{-1}.$$

To see why this is the case, note that

$$\begin{aligned}\mathbf{s}'_1\boldsymbol{\Sigma}^{-1}_{R1}\mathbf{u}_t&=\mathbf{s}'_1(\mathbf{S}\boldsymbol{\Omega}_{R1}\mathbf{S}')^{-1}\mathbf{S}\boldsymbol{\varepsilon}_t\\ &=\mathbf{e}'_1\boldsymbol{\Omega}^{-1}_{R1}\boldsymbol{\varepsilon}_t\\ &=\frac{\varepsilon_{1,t}}{\sigma^2_{\varepsilon_1,R1}},\end{aligned}$$

and $(\mathbf{s}'_1\boldsymbol{\Sigma}^{-1}_{R1}\mathbf{s}_1)^{-1}=\sigma^2_{\varepsilon_1,R1}$.[8]

[8]Note that we can also estimate the shock based on the covariance matrix of the second regime. In population, the two should be the same. In my sample, the two were almost identical (correlation stands at over 99 percent).

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