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**ESTIMATING THE
MACROECONOMIC EFFECTS OF
OIL SUPPLY NEWS**

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Estimating the Macroeconomic Effects of Oil Supply News*

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Abstract

A common approach for estimating the macroeconomic effects of oil supply news employs SVAR-IV models identified using changes in oil futures prices around OPEC quota announcements as an instrument. However, we show that the reduced-form oil price innovations, structural shocks, and the instrumental variable in these estimations are all Granger-caused by financial variables, indicating informational deficiencies in the VAR model and contamination of the instrument. To resolve these issues, we incorporate financial indicators into the econometrician's information set, yielding significantly different results. These include a sharper short-term output decline, lower and less persistent inflationary effects, and a reversal of the monetary policy response. Our results also show greater stability over time and the disappearance of puzzling responses. Finally, we identify similar issues in other prominent oil-market SVAR models, suggesting that informational deficiencies are a pervasive issue in oil-market research.

JEL classification: C32, C36, E31, E32, F31, Q43.

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1 Introduction

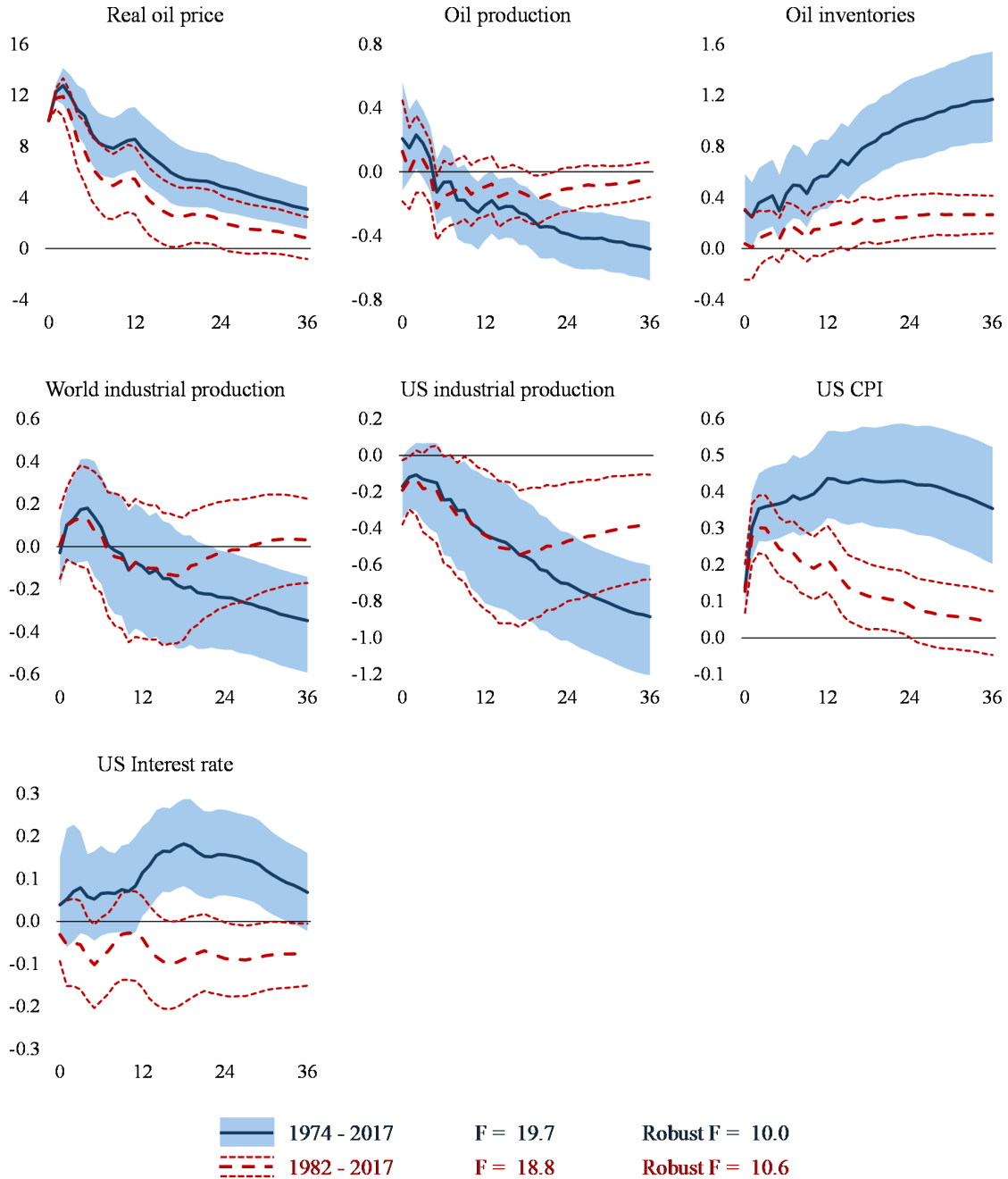
The macroeconomic implications of oil market disturbances have long been an important topic for academic research and policymakers. [Känzig \(2021\)](#) makes a major contribution by exploiting institutional features of OPEC to estimate how changes in oil supply expectations—oil supply news shocks—affect the oil market and the macroeconomy. Specifically, [Känzig \(2021\)](#) quantifies the changes in oil futures prices within a narrow (daily) window around OPEC quota announcements. Given that expectations about global economic conditions should be priced in at the time of the announcement, such high-frequency price changes can plausibly be considered as consequences of revisions in market expectations about future oil supply due to the announcement. These price changes are then used as an external instrumental variable in a monthly oil market structural vector autoregression (SVAR-IV) model to estimate the macroeconomic effects of oil supply news. Subsequently, numerous scholars have used the instrument or the structural shocks series to explore related research questions.¹

Whereas the novel instrument and empirical results based on the instrument have greatly enhanced our understanding of oil-market dynamics, some impulse responses to oil supply news shocks remain puzzling and unstable across sample periods used in the literature (e.g., [Degasperis, 2022](#); [Castelnuovo et al., 2024](#)). This is illustrated in Figure 1, where we replicate Känzig’s original VAR model, augmented with the one-year US interest rate, for the sample periods 1974-2017 and 1982-2017, respectively.² In both samples, an oil supply news shock that raises oil prices leads to a temporary increase in world industrial production, which is surprising given that most oil-exporting countries are not included in the index. While global economic activity starts to fall significantly and persistently after more than one year in the longer sample, the impact on world industrial production is never significantly negative in the shorter sample. Furthermore, we observe a less persistent impact on US output and inflation in the shorter sample period, and even an opposite monetary policy response. Finally, the responses of world oil production and oil inventories also differ markedly between both samples. Although it is plausible that the dynamics of oil market shocks shifted in the early 1980s,

¹Examples are [Bruns \(2021\)](#), [Degasperis \(2022\)](#), [Gagliardone and Gertler \(2023\)](#), [Bruns and Lütkepohl \(2023\)](#), [Forni et al. \(2023\)](#), [Nguyen et al. \(2024\)](#), [Castelnuovo et al. \(2024\)](#), [Kilian \(2024\)](#), [Degasperis et al. \(2024\)](#), [Caravello and Martinez-Bruera \(2024\)](#), [Patzelt and Reis \(2024\)](#). A key advantage of the instrumental variable is the possibility of having a longer sample period for the VAR model than the proxy. It also offers flexibility in estimating, for example, nonlinearities.

²The baseline specification in [Känzig \(2021\)](#) includes six variables: the real price of crude oil, world oil production, world oil inventories, world industrial production, US industrial production, and the US consumer price index. The VAR is estimated over the sample period 1974-2017. Due to the availability of the instrument, the contemporaneous impact matrix is estimated over a shorter period, 1983-2017. In the robustness section, Känzig reports a specification that also includes the US Federal Funds rate. We adopt this extended specification, as the instability of the monetary policy response is one of the puzzling findings. Instead of the Federal Funds rate, we use one-year government bond rates, which also capture information on unconventional monetary policy actions during the zero lower bound period, as pointed out by [Gertler and Karadi \(2015\)](#). It is important to emphasize, however, that these choices do not affect the conclusions. In the appendix (Figure A2), we show the instability in Känzig’s baseline six-variables specification. Finally, as in [Känzig \(2021\)](#), the confidence intervals are constructed using a block bootstrap with a block size of 24 and 10,000 replications.

Figure 1: Instabilities in the Känzig (2021) VAR-model



Note: Impulse responses to oil supply news shock that raise oil prices by 10 percent on impact. Känzig (2021) VAR model augmented with the US 1-year interest rate estimated over sample periods 1974-2017 and 1982-2017, respectively. Monthly horizon. 68 percent confidence intervals constructed using a moving block bootstrap.

such large differences are striking given that more than 80 percent of the observations in both samples overlap. Moreover, time variation cannot explain the instability of the contemporaneous effects because, due to the availability of the IV, the contemporaneous effects in both VARs are estimated over exactly the same period. As pointed out by [Ramey \(2016\)](#) and [Miranda-Agrippino and Ricco \(2023\)](#) in the context of monetary policy VARs identified with an external instrument, puzzling responses and sample instabilities often stem from model misspecification, such as omitted variables, or contamination of the IV by other shocks.

In this paper, we demonstrate that there are indeed distortions due to omitted variables in [Känzig \(2021\)](#) and related studies, as well as contamination of the instrument. Our analysis is based on [Forni and Gambetti \(2014\)](#), [Stock and Watson \(2018\)](#), and particularly [Miranda-Agrippino and Ricco \(2023\)](#), who derive the general conditions for identification in SVAR-IV models when only a subset of structural shocks is of interest. A first requirement is that the shock of interest is partially invertible; that is, it can be derived from a linear combination of the current and past values of the VAR variables. Non-invertibility indicates information insufficiency in the VAR model, meaning that the econometrician's information set does not span the true information of agents to recover the structural shocks. Phenomena such as anticipation and foresight can lead to non-invertible VAR representations.

A necessary condition for partial invertibility is that no other variables Granger-cause the residuals of the relevant VAR equation (i.e., the oil price equation), and that the structural shocks are orthogonal to past information ([Forni and Gambetti, 2014](#); [Miranda-Agrippino and Ricco, 2023](#)). We show, however, that the common factors identified in [McCracken and Ng \(2016\)](#) jointly Granger-cause the oil price residuals and the structural shocks in [Känzig \(2021\)](#). Further investigation reveals that this result is driven by the factor with a strong loading on financial variables. This observation is corroborated when considering a set of financial variables: equity prices (S&P 500 and MSCI world), stock price volatility (VXO), and interest rate spreads (excess bond premium) all Granger-cause the innovations and/or shocks. Hence, the condition of partial invertibility is not fulfilled, indicating informational deficiencies of the VAR model and non-fundamental shocks. Omitted variables may also imply that the VAR does not correctly capture the dynamic responses at longer horizons after the shocks.

[Miranda-Agrippino and Ricco \(2023\)](#) show that, under partial invertibility, in addition to the standard relevance and contemporaneous exogeneity conditions, the IV must also satisfy a "limited lead-lag exogeneity condition". This condition ensures that the instrument correlates with the VAR residuals only via the invertible shock of interest. Conversely, the IV must be uncorrelated at any leads and lags with non-invertible shocks. Otherwise, the instrument is contaminated by other shocks, inducing bias in the results. It requires that the component of the instrument that is orthogonal to the VAR information set must be unpredictable by variables not included in the VAR model. We show that the changes in oil future prices induced by the OPEC announcements are also Granger-caused by finan-

cial variables, particularly the VXO, implying contamination of the IV by other shocks.³ Note that this condition must also be satisfied for methods that do not require invertibility, such as SVARs that include the IV as an internal instrument or local projections with controls (see [Plagborg-Møller and Wolf, 2021](#)), indicating that such estimates are also distorted. Intuitively, when the internal instrument is correlated with past shocks that are not included in the VAR, its innovations will also capture these shocks. The same applies to local projections using the lags of the VAR variables as controls.

In general, partial invertibility can be restored by including additional variables in the VAR model to align the econometrician's information set with the agents' information set. Similarly, the "limited lead-lag exogeneity condition" can be fulfilled by finding a "core information set" that renders the IV conditionally exogenous. We show that both requirements can be met by incorporating the US one-year interest rate, the S&P 500, and the VXO into the VAR model. By doing this, the reduced-form oil price residuals, the oil supply news shocks, and the IV are not Granger-caused anymore by external variables. The financial variables and the monetary policy response to the oil shocks should also enrich the dynamics of the VAR system at longer horizons.

The VAR model augmented with the financial variables yields results that differ significantly from the original estimates, both statistically and quantitatively. Specifically, the rise in oil prices is less persistent, there is a much sharper short-term decline in world and US industrial production, the inflationary effects in the US are lower and less persistent, and there is a reversal in the monetary policy response. For example, world (US) industrial production decreases by -0.60 (-0.81) percent after one year, compared to -0.09 (-0.43) percent in the original VAR, while the peak response of US consumer prices is only half. The results also exhibit greater stability over time, while the puzzling responses disappear. Thus, while the informational deficiencies and contamination of the instrument are quantitatively important, they can be relatively easily resolved by incorporating financial variables into the econometrician's information set. Doing so also renders the instrumental variable less susceptible to critiques related to sample period instability and output puzzles. For instance, [Degasperis \(2022\)](#) interprets the output puzzle as evidence that the instrument also captures revisions in expectations about oil demand, but this puzzle vanishes in the augmented VAR model.

The importance of financial variables in identifying oil supply news shocks is not surprising, as these variables capture expectations about future economic activity and uncertainty. Accordingly, they are crucial for distinguishing between oil price increases due to expected supply shortfalls and those driven by anticipated future demand surges. Broadly, our approach aligns with studies that

³In the appendix, we document a negative relationship between lagged changes in the VXO and the IV. The stability of the coefficients across subsamples, along with a symmetry between increases and decreases in the VXO, suggests that this relationship is not merely a result of sample correlation. Identifying the precise reasons and mechanisms underlying this relationship is, however, beyond the scope of this paper.

augment SVAR models with financial variables to identify, for example, technology shocks (Beaudry and Portier, 2006) or monetary policy shocks (Caldara and Herbst, 2018).

Finally, because most oil-market SVAR models in the literature—including those not identified with an external instrument—rely on similar information sets, our findings suggest that informational deficiencies may be a widespread issue in oil-market research. We explore this for two prominent oil-market SVAR models: Baumeister and Hamilton (2019) and Kilian (2009). Our analysis reveals that the structural shocks in both models are indeed Granger-caused by omitted variables, although it remains unclear whether the distortions are substantial. Unlike oil supply news shocks, the shocks in these studies are not solely predictable by financial variables, while expanding these VAR models introduces complexity into the identification strategy. We leave this extension for future research. A possible avenue is the use of FAVAR models, as in Juvenal and Petrella (2015), Aastveit et al. (2015) and Stock and Watson (2018).

Section 2 discusses the conditions for identification in SVAR models with an external instrument. Section 3 reports the predictability of the VAR residuals, structural shocks, and IV. Section 4 presents the results of the VAR model incorporating financial variables, while section 5 documents the predictability of the shocks in other popular oil-market VARs. Finally, section 6 concludes.

2 Identification with External Instruments in Structural VARs

In the SVAR literature, the dynamics of an $n \times 1$ vector of observed endogenous variables Y_t are described by the following reduced-form VAR(p) model:

$$Y_t = b + B_1 Y_{t-1} + \dots + B_p Y_{t-p} + \mu_t \quad (1)$$

where p is the lag order, μ_t is an $n \times 1$ vector of reduced-form innovations, b is an $n \times 1$ vector of constants, and B_1, \dots, B_p are $n \times n$ coefficient matrices. Furthermore, it is assumed that the reduced-form innovations are related to the structural shocks via a linear mapping:

$$\mu_t = S \varepsilon_t \quad (2)$$

where S is an $n \times n$ structural impact matrix and ε_t is an $n \times 1$ vector of structural shocks. Although the structural shocks are not directly observable, they can be recovered from the reduced-form innovations if S is invertible (non-singular): $\varepsilon_t = S^{-1} \mu_t$. Obtaining the elements of S also requires identifying restrictions. Stock and Watson (2012) and Mertens and Ravn (2013) demonstrate that the coefficients of a single column i of S , which is sufficient for retrieving the corresponding structural shock i , can

be estimated with an external instrument Z_t if the standard instrument relevance and exogeneity conditions are fulfilled; that is, the instrumental variable must be correlated with the shock of interest and uncorrelated with all other structural shocks on impact.

The assumption of invertibility is crucial but non-trivial. It implies that all structural shocks in the economy can be derived from linear combinations of the VAR residuals; that is, based on current and lagged values of Y_t .⁴ This is unlikely the case in small VAR models due to omitted variables and insufficient lag length. The presence of anticipation and foresight can also lead to non-invertible VAR models. Non-invertibility indicates that the VAR model suffers from information insufficiency and has non-fundamental shocks. However, even if the VAR does not contain enough information or variables to retrieve all structural shocks, it can be sufficient to identify a specific shock or a subset of shocks; that is, only the invertibility of the shock(s) of interest—or partial invertibility—is required (Forni and Gambetti, 2014; Miranda-Agrippino and Ricco, 2023). Partial invertibility holds if the structural shock(s) of interest can be accurately recovered as a linear combination of the VAR residuals.

While Stock and Watson (2012) and Mertens and Ravn (2013) assume full invertibility, Miranda-Agrippino and Ricco (2023) formalize the conditions that an instrumental variable must satisfy to achieve correct identification in SVAR-IV models ε_t under partial invertibility. Specifically, let $\varepsilon_t^{1:m}$ be the m invertible structural shocks from a VAR in Y_t , and $\varepsilon_t^{m+1:n}$ the remaining $n - m$ non-invertible shocks. Define $Z_t^\perp = Z_t - Proj(Z_t | \mathcal{H}_{t-1}^Y)$, where Z_t is a candidate IV for the shock of interest ε_t^1 and \mathcal{H}_{t-1}^Y is the Hilbert space generated by all the observations of Y_t up to time t . The impact effects of ε_t^1 on Y_t are identified if Z_t satisfies:

$$E \left[\varepsilon_t^1 Z_t^\perp \right] \neq 0 \quad (3)$$

$$E \left[\varepsilon_t^{2:n} Z_t^\perp \right] = 0 \quad (4)$$

$$E \left[\varepsilon_{t-j}^{m+1:n} Z_t^\perp \right] = 0 \text{ for } j \neq 0 \quad (5)$$

In addition to the standard instrument relevance and exogeneity conditions (i.e., equations 3 and 4), the instrumental variable must also fulfill a limited lead-lag exogeneity condition (equation 5). This condition ensures that the instrument correlates with the VAR residuals only through the invertible shock of interest. In particular, while the instrument may correlate with leads or lags (but not contemporaneously) of other invertible shocks in the system, it must be uncorrelated at any leads and lags with all non-invertible shocks. This condition arises because of the VAR model's dynamics: if non-invertible shocks correlate at any leads or lags with the instrument, the effects of these shocks will also be captured by the instrument, leading to biased estimates (Miranda-Agrippino and Ricco,

⁴Note that all the structural shocks should not explicitly be identified; they should be captured by the VAR model.

2023). Conversely, leads and lags of other partial invertible shocks can affect the instrument without distorting the identification because they do not enter the VAR residuals.

Note that the lead-lag exogeneity condition is automatically fulfilled under full invertibility because the VAR residuals are a linear combination of the contemporaneous structural shocks only. Furthermore, Miranda-Agrippino and Ricco (2023) show that this condition must also be met for methods that do not require (partial) invertibility, such as SVAR models that include the IV as an internal instrument or local projections with the lagged observables Y_t as controls. Intuitively, if the shocks contaminating the instrument are unknown, the only way to achieve identification is to control for all possible shocks. This is equivalent to including these variables in the VAR to ensure invertibility. This equivalence is the so-called "no-free lunch" result of Stock and Watson (2018).

3 Oil Supply News Shocks: Invertibility and Exogeneity of the IV

In this section, we investigate whether the partial invertibility and limited lead-lag exogeneity conditions are fulfilled in SVAR-IV models identified using changes in oil futures prices around OPEC quota announcements as an instrument. We use the original Känzig (2021) VAR model and sample period for our analysis.⁵ Känzig (2021) adheres to the standard practice in the literature by assuming full invertibility. He acknowledges the importance of this assumption, and examines how the results depend on the information in the VAR by adding other variables (one at a time) to the baseline VAR model. The robustness of the results suggests there are no informational deficiencies.⁶ We formally evaluate whether all conditions discussed in section 2 are indeed fulfilled.

3.1 Partial Invertibility

Forni and Gambetti (2014) provide a testing procedure for (partial) invertibility and informational sufficiency. A necessary condition is that no other variables Granger-cause the reduced-form residuals of the VAR or the identified structural shocks. For Känzig (2021), these are the oil price innovations and the oil supply news shocks, respectively. The underlying idea is that if these "omitted variables" do not help to predict the VAR variables (innovations), the VAR model must contain the same information;

⁵Note that the results are similar for the SVAR model augmented with the one-year interest rate shown in Figure 1, as well as for other modifications to Känzig's baseline specification used in the literature. An exception is Castelnovo et al. (2024), who have followed our recommendations.

⁶The instrument relevance condition is evaluated based on the standard (robust) F-test in the first-stage regression of the oil price residuals from the VAR on the instrument. The F-statistic for the baseline VAR turns out to be 22.7, which is safely above the threshold for possible weak instrument problems. The contemporaneous exogeneity condition of the instrument is also extensively discussed and evaluated in the paper. These arguments are plausible.

that is, the variables in the VAR convey all relevant information, and there is no gain from including these other variables. Conversely, if forecasts improve by adding the variables to the regressions, the VAR is missing this information, indicating a failure of the invertibility condition. Furthermore, a necessary condition for a shock to be "structural" is orthogonality to the past of all variables that drive the economy. Hence, once a shock has been identified and estimated, its "structuralness" can be evaluated by testing for orthogonality with respect to the lags of variables omitted from the VAR model.

Because it is not possible to test all macroeconomic variables simultaneously, and testing each of them separately would lead to rejection of informational sufficiency due to Type I error, [Forni and Gambetti \(2014\)](#) propose to use the principal components of a large dataset capturing all relevant macroeconomic information as a starting point. Following [Miranda-Agrippino and Ricco \(2023\)](#), we use the common factors extracted from the large monthly database of [McCracken and Ng \(2016\)](#), which is systematically updated for economic research.⁷ Based on the [Bai and Ng \(2002\)](#) criterion, [McCracken and Ng \(2016\)](#) identify eight relevant common factors in the macroeconomic series, which we use for the Granger-causality tests.

The left part of Table 1 summarizes the results of the partial invertibility tests for the baseline specification in [Känzig \(2021\)](#).⁸ We report the p-values of the (robust) F-statistic for the null hypothesis that the lagged variables do not Granger-cause the oil price residuals and oil supply news shocks, respectively. Given the sensitivity of such tests for the number of lags (L), we report the results for $L = 6$ and $L = 12$, the latter being the number of lags in [Känzig \(2021\)](#). The first row reveals that the common factors identified in [McCracken and Ng \(2016\)](#) jointly Granger-cause the oil price residuals and the structural shocks, suggesting that there is informational insufficiency in the VAR to retrieve the shocks, and that the estimated shocks are not orthogonal to past macroeconomic data.

A closer inspection of the individual factors, also shown in Table 1, reveals that the joint significance is driven by the factor F7. Notably, according to [McCracken and Ng \(2016\)](#), this factor (as well as F6) explains much of the variation in stock market variables. Specifically, the top 4 series that load most on F7 are S&P 500, S&P Industrials, S&P dividend yields, and the VXO. This indicates that financial variables are the source of the informational insufficiency in the VAR. This observation is corroborated when we perform the Granger-causality tests for several financial indicators used in macroeconomic research. As can be observed in the table, the "Global Financial Cycle", a common factor identified in [Miranda-Agrippino and Rey \(2020\)](#) that explains an important share of the variation of financial aggregates around the world, also Granger-causes the oil price innovations and oil

⁷We have used the "2023-10" vintage (downloaded in November 2023). Note that the time series in the database are mainly for the US. We are not aware of comparable monthly databases at the global level. However, considering the hegemonic role of the US in international markets, particularly in the oil and financial markets, this database should contain the bulk of relevant information.

⁸The oil price innovations and structural shocks series are obtained from the online replication package of the paper.

Table 1: P-values Granger causality tests - Känzig (2021) VAR-model

	Oil price residuals		Oil supply news shocks		Z_t		Z_t^\perp	
	$L = 6$	$L = 12$	$L = 6$	$L = 12$	$L = 6$	$L = 12$	$L = 6$	$L = 12$
Common factors (all)	0.40	0.03	0.04	0.00	0.34	0.51	0.28	0.00
<i>F1</i>	0.99	1.00	0.99	0.98	0.32	0.27	0.68	0.86
<i>F2</i>	0.99	1.00	0.99	1.00	0.14	0.17	0.87	1.00
<i>F3</i>	0.99	1.00	0.98	1.00	0.64	0.73	0.98	1.00
<i>F4</i>	0.31	0.41	0.22	0.43	0.13	0.13	0.40	0.12
<i>F5</i>	0.87	0.49	0.49	0.18	0.89	0.56	0.87	0.61
<i>F6</i>	0.19	0.28	0.08	0.18	0.07	0.14	0.16	0.09
<i>F7</i>	0.01	0.01	0.02	0.03	0.43	0.14	0.41	0.55
<i>F8</i>	0.74	0.81	0.74	0.81	0.40	0.53	0.53	0.22
Global Financial Cycle	0.02	0.01	0.06	0.01	0.36	0.56	0.68	0.75
OECD Global CLI	0.52	0.78	0.49	0.89	0.17	0.26	0.55	0.70
S&P 500	0.04	0.03	0.05	0.04	0.44	0.05	0.37	0.10
MSCI World	0.01	0.02	0.05	0.08	0.72	0.49	0.90	0.65
VXO	0.06	0.05	0.04	0.02	0.00	0.04	0.05	0.24
Financial uncertainty	0.65	0.93	0.91	0.99	0.00	0.00	0.01	0.02
Macro uncertainty	0.33	0.13	0.36	0.22	0.04	0.09	0.33	0.68
Excess bond premium	0.26	0.16	0.09	0.03	0.04	0.24	0.41	0.85
BAA-AAA spread	0.81	0.96	0.68	0.74	0.05	0.26	0.50	0.76
US 1-year interest rate	0.33	0.35	0.22	0.35	0.26	0.32	0.43	0.56
USD nominal effective exchange rate	0.62	0.94	0.51	0.85	0.77	0.92	0.89	0.70

Note: P-values of (robust) F-statistic for the null hypothesis that the lagged variables do not Granger-cause the oil price residuals, oil supply news shocks, the IV, and the IV orthogonalized to the impact of the lagged VAR variables. L is the number of lags used in the test. For S&P 500 and MSCI, we consider log differences. The common factors are obtained from McCracken and Ng (2016). Financial and macro uncertainty are collected from Ludvigson et al. (2021). The Global Financial Cycle are obtained from Miranda-Agrippino and Rey (2020), the S&P 500 from Robert Schiller's webpage, and the Excess bond premium from Gilchrist and Zakrajsek (2012). Numbers are in bold when $p < 0.05$.

supply news shocks. In contrast, the OECD Global Composite Leading Indicator, reflecting expectations about global real economic conditions, cannot predict the residuals and shocks. Furthermore, the S&P 500, the MSCI World, and the VXO all Granger-cause the oil price innovations and structural shocks in [Känzig \(2021\)](#). Finally, there is some weak evidence that the excess bond premium of [Gilchrist and Zakrajšek \(2012\)](#), a popular variable in VAR models estimating the effects of US monetary policy shocks, can also predict the shocks. In sum, the condition of partial invertibility is not fulfilled, indicating informational deficiencies of the VAR model and non-fundamental shocks.

3.2 Exogeneity of OPEC announcements

As discussed in section [2](#), the instrument must be uncorrelated with all non-invertible shocks at any leads and lags. Conversely, leads and lags of partially invertible shocks in the VAR can be correlated with the instrument, as they do not enter the VAR residuals. This is why the lead-lag condition in equation [5](#) applies to the orthogonalized instrumental variable Z_t^\perp . [Miranda-Agrippino and Ricco \(2023\)](#) further show that leads, lags, or even contemporaneous realizations of the non-invertible shocks can contaminate the instrument only via their projectable component in the space spanned by past realizations of the VAR variables Y_t . Granger-causality tests for "omitted variables" can thus also be used to evaluate the limited lead-lag exogeneity condition of the external instrument.

The results are also presented in Table 1. We apply Granger-causality tests to the instrument, as well as the instrument orthogonalized to the impact of the lagged variables included in the [Känzig \(2021\)](#) VAR. The orthogonalized instrument is equivalent to the structural shocks series identified by ordering the instrument first in a recursive VAR, following the approach of [Plagborg-Møller and Wolf \(2021\)](#). These tests can thus also be viewed as a direct assessment of the "structuralness" of the shocks obtained from such a VAR, as well as local projections that include the lagged VAR variables as controls. Table 1 shows that the principal components jointly Granger-cause Z_t^\perp when $L = 12$, but this result is not confirmed for Z_t and $L = 6$, nor for the individual factors. On the other hand, there is strong indication that OPEC announcements are Granger-caused by uncertainty indicators: both the VXO and the financial uncertainty indicator of [Ludvigson et al. \(2021\)](#) Granger-cause the instrument. This implies that the lead-lag exogeneity condition is also not fulfilled. In the appendix, we further explore the relationship between past VXO observations and the instrument. The analysis reveals that increases (decreases) in the VXO tend to be followed by OPEC announcements that lower (raise) oil prices. This negative relationship appears to be remarkably stable across subsamples and is symmetric for positive and negative changes in the VXO, indicating that the instrument's predictability is neither accidental nor the result of outlier observations in the sample period.

Table 2: P-values Granger causality tests - VAR-model augmented with financial variables

	Oil price residuals		Oil supply news shocks		Z_t^\perp	
	<i>L</i> = 6	<i>L</i> = 12	<i>L</i> = 6	<i>L</i> = 12	<i>L</i> = 6	<i>L</i> = 12
Principal components (all)	0.98	1.00	0.54	0.16	0.61	0.14
<i>F1</i>	1.00	1.00	0.99	0.93	0.97	0.99
<i>F2</i>	1.00	1.00	0.97	0.98	0.88	1.00
<i>F3</i>	1.00	1.00	1.00	1.00	0.99	1.00
<i>F4</i>	0.97	0.99	0.98	0.93	0.92	0.68
<i>F5</i>	0.98	0.96	0.91	0.62	0.97	0.97
<i>F6</i>	0.64	0.88	0.86	0.93	0.81	0.87
<i>F7</i>	0.96	1.00	0.97	0.96	0.97	0.99
<i>F8</i>	0.75	0.89	0.47	0.79	0.52	0.34
Global Financial Cycle	0.19	0.43	0.86	0.87	1.00	0.81
OECD Global CLI	0.96	0.87	0.85	0.92	0.84	0.85
S&P 500	1.00	1.00	1.00	0.99	1.00	0.98
MSCI World	0.07	0.26	0.45	0.85	0.98	0.74
VXO	1.00	1.00	1.00	1.00	1.00	1.00
Financial uncertainty	0.53	0.57	0.14	0.24	0.67	0.77
Macro uncertainty	0.63	0.40	0.94	0.48	0.84	0.92
Excess bond premium	0.24	0.22	0.07	0.19	0.56	0.94
BAA-AAA spread	0.96	1.00	0.92	0.98	0.55	0.77
US 1-year interest rate	1.00	1.00	1.00	1.00	1.00	1.00
USD nominal effective exchange rate	0.82	0.98	0.40	0.75	0.92	0.79

Note: P-values of (robust) F-statistic for the null hypothesis that the lagged variables do not Granger-cause the oil price residuals, oil supply news shocks, and the IV orthogonalized to the impact of the lagged VAR variables. The VAR model contains all variables of the baseline VAR in Känzig (2021), augmented with US 1-year interest rate, the S&P 500, and the VXO. *L* is the number of lags used in the test. Financial and macro uncertainty are collected from Ludvigson et al. (2021). The Global Financial Cycle are obtained from Miranda-Agrippino and Rey (2020), the S&P 500 from Robert Schiller's webpage, and the Excess bond premium from Gilchrist and Zakrajsek (2012). Numbers are in bold when $p < 0.05$.

4 Oil-Market SVAR Model Augmented with Financial Variables

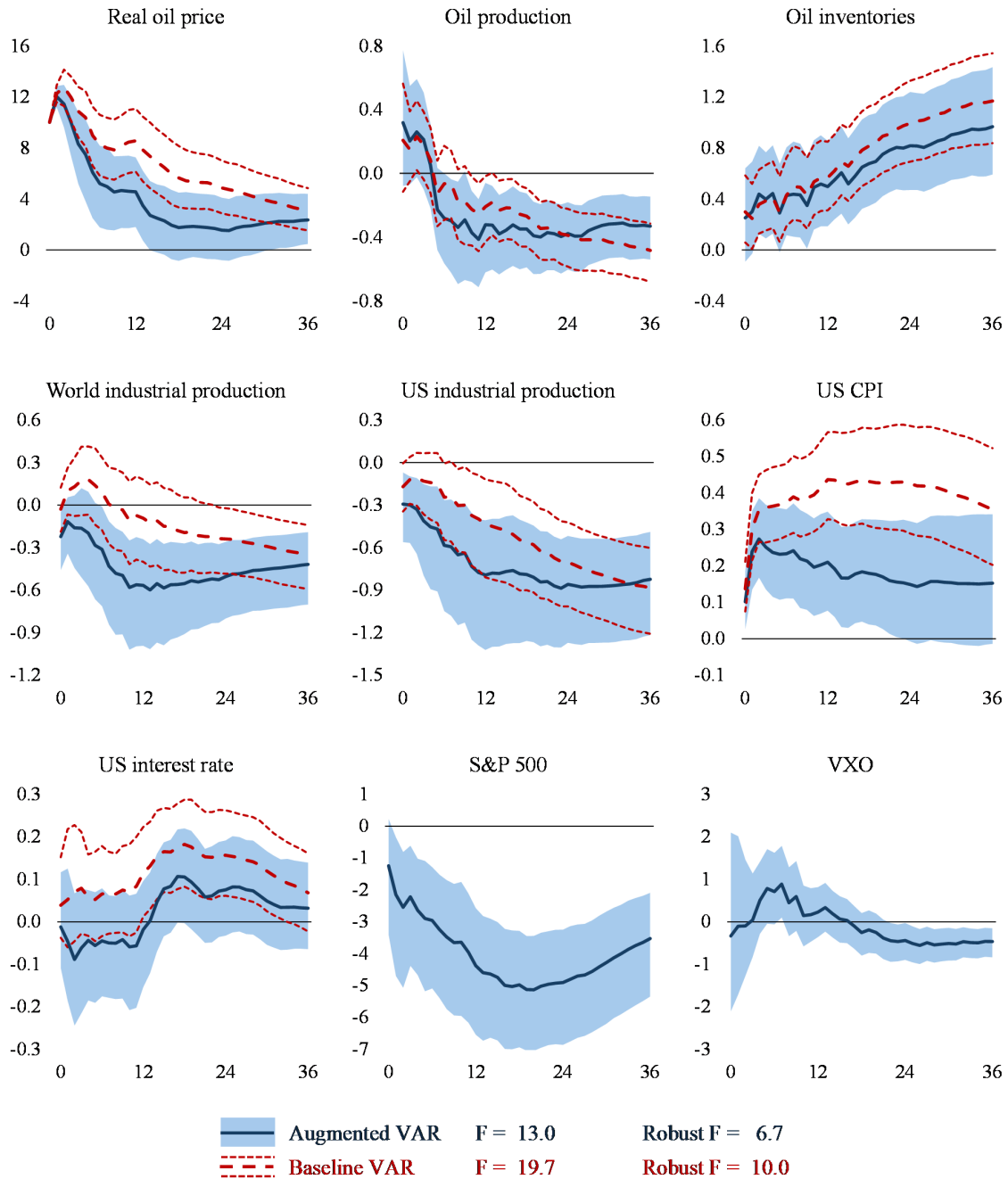
A standard solution to address informational deficiencies is to include the omitted variables in the VAR until invertibility and orthogonality of the shocks are achieved (Forni and Gambetti, 2014; Stock and Watson, 2018). Similarly, contamination of the IV can be mitigated by expanding the information set with variables that render the instrument conditionally exogenous (Miranda-Agrippino and Ricco, 2023). The analysis in section 3 suggests that financial variables are crucial for addressing both issues. We propose incorporating the S&P 500, the VXO, and the monetary policy rate into the Känzig (2021) VAR. These variables are forward looking and capture different dimensions of expectations, including those of the central bank. The financial variables and the monetary policy response could also enrich the VAR system’s dynamics. Most importantly, the invertibility and lead-lag exogeneity conditions are fulfilled by incorporating these variables.⁹ This is demonstrated in Table 2, which presents the Granger-causality tests for the augmented VAR model. Specifically, none of the common factors or other financial variables Granger-cause the oil price innovations, the identified oil supply news shocks, or the external instrument conditional on the past VAR variables.

Figure 2 shows the impulse responses of the oil-market SVAR model augmented with financial variables. To evaluate the quantitative impact of incorporating the financial variables into the VAR, the figure also displays the responses of the baseline Känzig (2021) VAR model with the interest rate. Formal statistical comparisons between the impulse responses of both VARs are shown in Figure 3. These tests are conducted by nesting the VARs within the bootstrap procedure. Specifically, for each bootstrap sample of the 9-variable VAR model with financial variables, we also estimate the 7-variable baseline VAR specification and compute the difference in responses for the common variables across both VARs. The 16-84 and 5-95 percentiles of these differences (i.e., 68% and 90% confidence intervals) are depicted in Figure 3 and used to assess the statistical significance of the omitted variable bias. In the appendix, Figure A3 and A4 display the impulse responses of both VAR models using alternative inference methods: the Bayesian approach of Miranda-Agrippino and Rey (2020) and Miranda-Agrippino and Ricco (2023), and the weak-instrument robust inference method of Monfiet Olea et al. (2021), respectively. The latter addresses possible concerns about the robust F-statistic dropping below 10 in the augmented VAR. Notably, the confidence (credible) intervals from these alternative methods are somewhat narrower compared to the block bootstrap approach that we use.

Figure 2 and 3 demonstrate that the results differ significantly from the original estimates, both statistically and quantitatively. First, the rise in real oil prices is less persistent following unfavorable

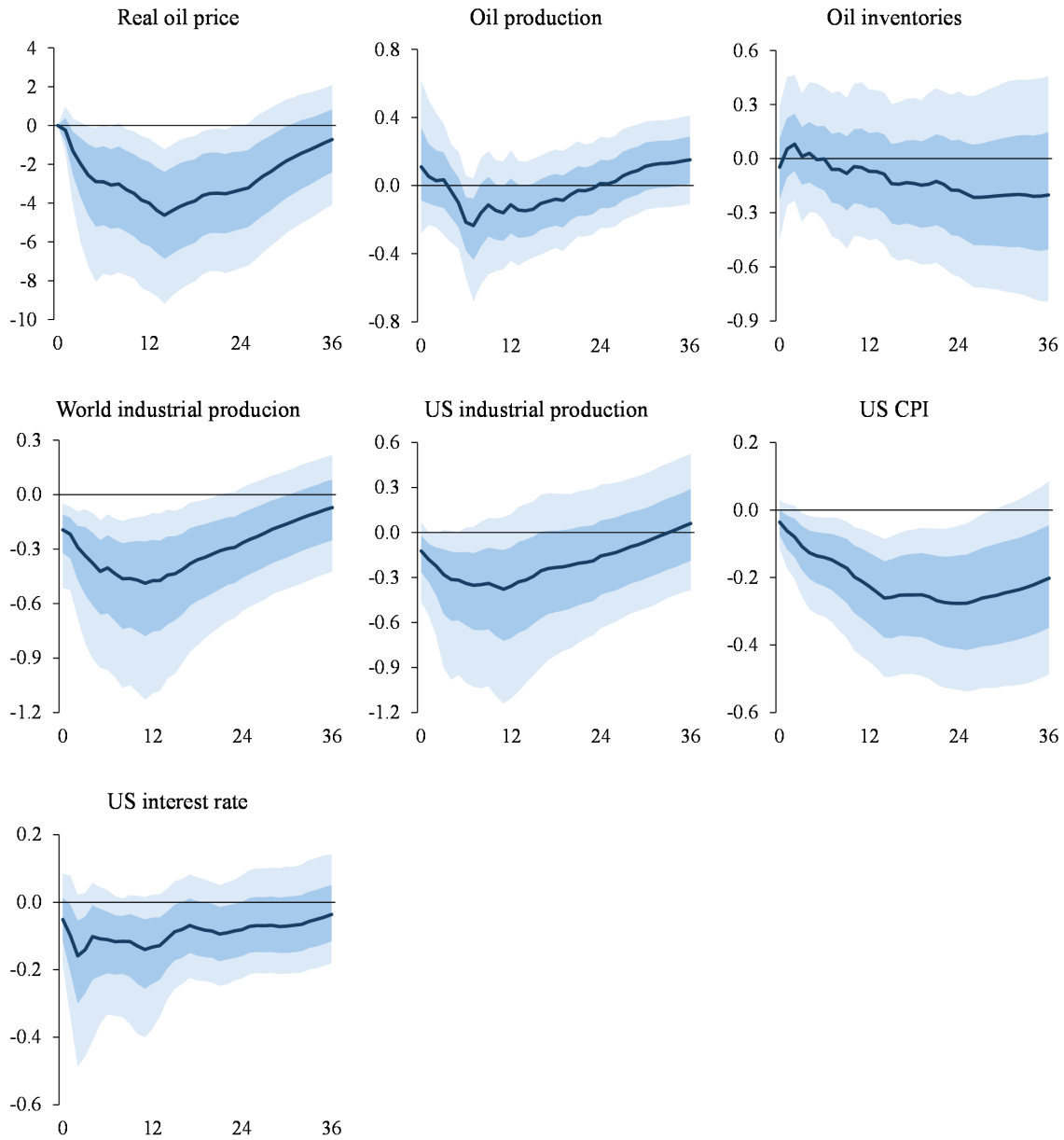
⁹The results are very similar when we incorporate more or alternative combinations of financial variables into the VAR model. Due to their ready accessibility, unlike for example the Global Financial Cycle or the financial uncertainty index of Ludvigson et al. (2021), the S&P 500, the VXO and the interest rate form the most obvious combination.

Figure 2: Impact of oil supply news shocks in an SVAR augmented with financial variables



Note: Impulse responses to oil supply news shock that raise oil prices by 10 percent on impact. Känzig VAR with interest rate (red dotted responses) versus VAR augmented with financial variables (blue full responses). Monthly horizon, 1974-2017. 68 percent confidence intervals constructed using moving block bootstrap.

Figure 3: Differences between augmented and baseline VAR impulse responses



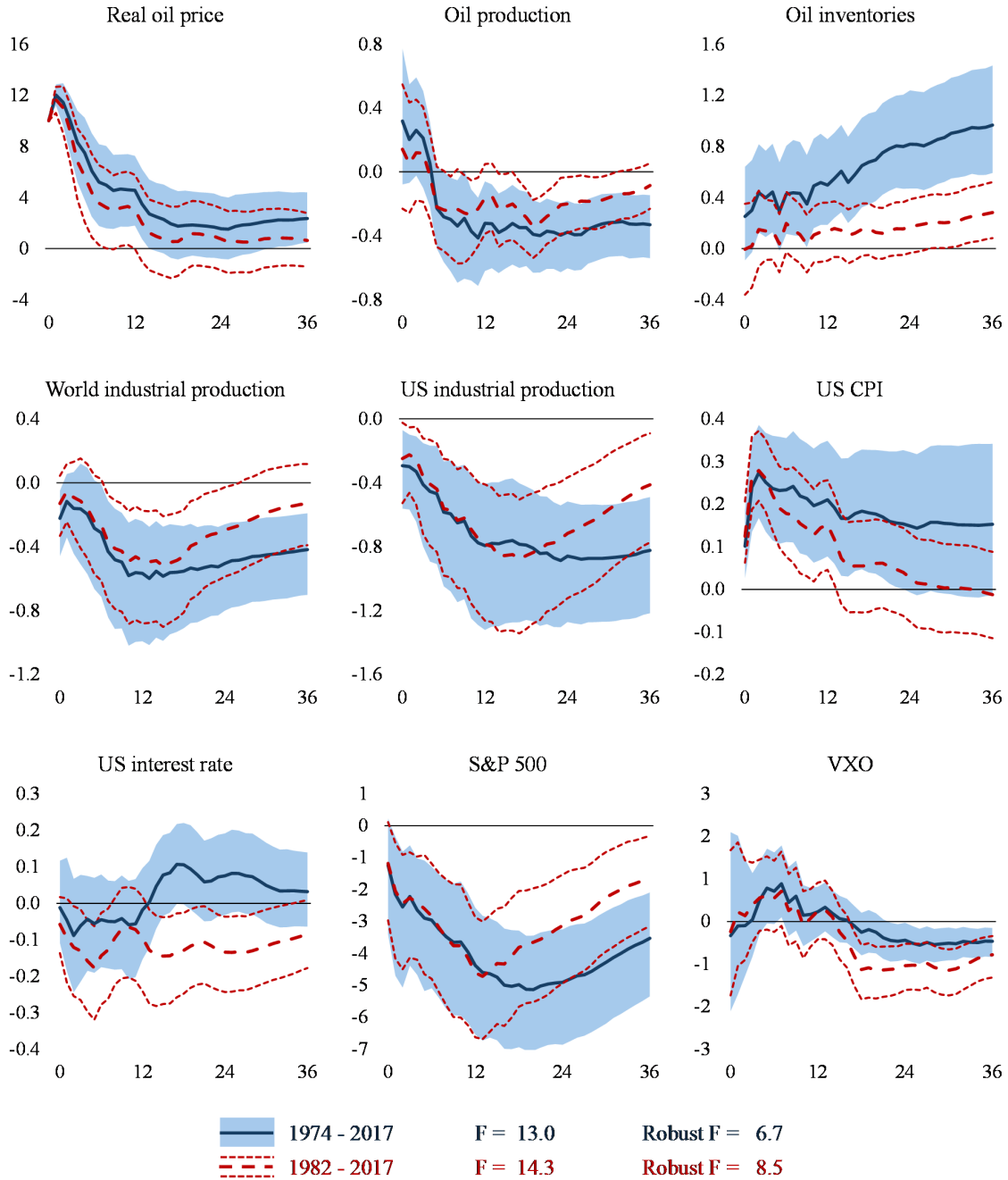
Note: Estimated differences between impulse responses of the VAR model augmented with financial variables and the Känzig VAR with interest rate for oil supply news shocks that raise oil prices by 10 percent on impact. Monthly horizon, 1974-2017. 68 and 90 percent confidence intervals constructed using moving block bootstrap.

news about future oil supply. In the original VAR, oil prices remain 8.6 percent above the baseline after one year, whereas this is only 4.6 percent in the augmented VAR. Additionally, the "output puzzle", with world industrial production rising in the first year following an oil supply news shock, is resolved. Instead, we observe an immediate sharp decline in world production, reaching its peak after one year. A similar divergence occurs for US industrial production. In particular, world (US) industrial production decreases by -0.60 (-0.81) percent after one year, compared to -0.09 (-0.43) percent in the original VAR. For policymakers, such differences at the one-year horizon are substantial. The impact on inflation also differs markedly between the two specifications: the peak response of US consumer prices in the VAR with financial variables is nearly half compared to the original VAR and exhibits much less persistence. As can be observed in Figure 3, the difference in the inflationary effects is statistically highly significant. Finally, there appears to be a reversal in the monetary policy response. Although the magnitude is moderate and statistically not significant, the VAR model with the richer information set shows a monetary policy easing, whereas the original VAR indicated a tightening¹⁰. In summary, incorporating financial variables is crucial for accurately measuring the dynamic effects of oil supply news shocks, as the omitted variables substantially affect the results.

As shown in Figure 2, there is a significant contemporaneous decline in equity prices and a rise in the VIX following negative news about oil supply, both of which align with expectations. It also indicates that the financial variables contain relevant information to recover the structural shocks from the reduced-form residuals. In general, the added value of incorporating financial variables to accurately estimate the effects of oil supply news is not surprising, as these variables capture expectations about future economic activity and macroeconomic uncertainty. In the original [Känzig \(2021\)](#) VAR, expectations about future oil market developments are implicitly formed based on past (current) oil production and economic activity. Apart from the real price of oil, the only forward looking variable in the VAR is oil inventories. This is, for example, insufficient to distinguish between oil price increases due to expected supply shortfalls and anticipated future demand surges (which both typically increase oil inventories). Financial variables provide precisely this type of forward-looking information.

¹⁰The exact reason for the monetary policy easing is out of the scope of this paper. See, for example, [Kilian and Lewis \(2011\)](#), [Barnichon and Mesters \(2023\)](#) or [Castelnuovo et al. \(2024\)](#) for possible explanations.

Figure 4: Stability of the SVAR-model augmented with financial variables



Note: Impulse responses to oil supply news shock that raises oil prices by 10 percent on impact, estimated over sample periods 1974-2017 and 1982-2017, respectively. Monthly horizon. 68 percent confidence intervals constructed using a moving block bootstrap.

Another important difference from the original VAR is that the results of the augmented VAR are more stable across sample periods. Specifically, Figure 4 shows the impulse responses when we esti-

mate the augmented SVAR over the periods 1974-2017 and 1982-2017, respectively. We consistently observe a sharp worldwide output contraction, and less persistent inflationary effects in the US. Moreover, there is no puzzling reversal in the monetary policy response, which we observed in Figure 1. Note that the results are also stable when we discard the first six years of the IV, or when we estimate the augmented SVAR over a sample starting in 1988M4.¹¹ Furthermore, when add more variables to the VAR, such as the external bond premium or principal components, the impulse responses remain very similar, indicating stability of the results. The resulting differences between the sample periods can thus be considered as time variation.

5 Other Popular Oil-Market SVAR Models

Numerous papers have utilized SVAR models to estimate the dynamic effects of structural oil-market disturbances. Two prominent contributions are [Kilian \(2009\)](#) and [Baumeister and Hamilton \(2019\)](#). [Kilian \(2009\)](#) disentangles oil supply, aggregate demand and oil-specific demand shocks in a three-variable monthly VAR model that includes real oil prices, global oil production and an index of real economic activity. [Baumeister and Hamilton \(2019\)](#) estimate a four-variable VAR that also includes oil inventories, and identify oil supply, economic activity, oil consumption demand, and oil inventory demand shocks, respectively. Various studies employ alternative identification methods, but are based on the same information set (e.g., [Peersman and Van Robays, 2009](#); [Kilian and Murphy, 2014](#)). Notably, the number of variables and structural shocks in most of these VARs are equal, which implies that the authors assume full invertibility; that is, all shocks can be obtained from linear combinations of the VAR residuals. Our findings suggest that these models may also suffer from informational deficiencies. In this section, we explore this for [Baumeister and Hamilton \(2019\)](#) and [Kilian \(2009\)](#).

Table 3 displays Granger-causality tests for the structural shocks estimated in both studies.¹² As discussed in section 3, external information is not supposed to Granger-cause the shocks. However, the table shows that the null hypothesis, which states that lagged external variables do not Granger-cause the structural shocks, is rejected for several variables not included in the VAR. Specifically, the common factors identified in [McCracken and Ng \(2016\)](#) jointly Granger-cause all the shocks in both studies. For all shocks in [Kilian \(2009\)](#), factor F7 is again the primary driver of this result. F7 also significantly predict the economic activity and oil consumption demand shocks identified in [Baumeister and Hamilton \(2019\)](#). Several financial indicators, such as the Global Financial Cycle and

¹¹[Kilian \(2024\)](#) argues that the initial six years of daily OPEC surprises rely on unsuitable data, and shows that dropping these observations renders the VAR results sensitive to the estimation period.

¹²For consistency with the above analysis, all tests are based on the sample period 1974-2017. For [Baumeister and Hamilton \(2019\)](#), we have downloaded the shocks from Christiane Baumeister's website. We have re-estimated the [Kilian \(2009\)](#) VAR model for Känzig's sample period.

Table 3: P-values Granger causality tests - Other oil-market VAR models

	Baumeister and Hamilton (2019)						Kilian (2009)							
	Oil supply		Econ. activity		Oil cons. demand		Oil inv. demand		Oil supply		Aggr. demand		Oil-spec demand	
	6L	12L	6L	12L	6L	12L	6L	12L	6L	12L	6L	12L	6L	12L
Common factors (all)	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.00
<i>F1</i>	0.43	0.57	0.01	0.02	0.10	0.36	0.11	0.33	0.15	0.08	0.67	0.42	0.90	0.44
<i>F2</i>	0.14	0.41	0.00	0.01	0.08	0.01	0.07	0.13	0.09	0.37	0.44	0.44	0.16	0.36
<i>F3</i>	0.04	0.15	0.04	0.08	0.41	0.28	0.08	0.01	0.02	0.00	0.68	0.81	0.16	0.43
<i>F4</i>	0.14	0.15	0.29	0.26	0.14	0.53	0.01	0.02	0.39	0.19	0.52	0.17	0.85	0.91
<i>F5</i>	0.15	0.01	0.01	0.01	0.45	0.22	0.09	0.04	0.02	0.00	0.67	0.49	0.52	0.33
<i>F6</i>	0.15	0.11	0.01	0.03	0.48	0.04	0.20	0.19	0.07	0.16	0.70	0.50	0.79	0.80
<i>F7</i>	0.06	0.08	0.01	0.00	0.02	0.02	0.20	0.35	0.01	0.00	0.01	0.07	0.02	0.00
<i>F8</i>	0.01	0.02	0.25	0.42	0.39	0.65	0.81	0.55	0.57	0.16	0.24	0.09	0.45	0.83
Global Financial Cycle	0.01	0.03	0.01	0.00	0.06	0.01	0.07	0.21	0.28	0.25	0.00	0.00	0.03	0.04
OECD Global CLI	0.47	0.15	0.00	0.00	0.01	0.05	0.56	0.19	0.19	0.32	0.06	0.06	0.06	0.17
S&P 500	0.03	0.06	0.03	0.09	0.29	0.09	0.01	0.10	0.02	0.02	0.16	0.49	0.37	0.10
MSCI World	0.35	0.13	0.02	0.01	0.22	0.40	0.04	0.18	0.44	0.53	0.04	0.09	0.13	0.40
VXO	0.60	0.28	0.01	0.01	0.48	0.29	0.11	0.17	0.05	0.21	0.20	0.09	0.20	0.05
Financial uncertainty	0.90	0.51	0.07	0.09	0.25	0.14	0.85	0.34	0.51	0.21	0.54	0.78	0.30	0.67
Macro uncertainty	0.92	0.49	0.00	0.01	0.03	0.00	0.34	0.02	0.05	0.00	0.04	0.01	0.18	0.19
Excess bond premium	0.05	0.08	0.02	0.00	0.06	0.20	0.57	0.65	0.42	0.34	0.33	0.41	0.01	0.02
BAA-AAA spread	0.02	0.30	0.00	0.00	0.20	0.45	0.09	0.06	0.11	0.29	0.57	0.57	0.44	0.87
US 1-year interest rate	0.22	0.00	0.18	0.09	0.06	0.16	0.00	0.00	0.03	0.01	0.50	0.03	0.45	0.84
USD nominal effective exchange rate	0.17	0.46	0.35	0.32	0.44	0.66	0.18	0.07	0.65	0.65	0.00	0.00	0.98	1.00

Note: P-values of (robust) F-statistic for the null hypothesis that the lagged variables do not Granger-cause the estimated structural shocks. Number of lags used in the test are 6 (6L) and 12 (12L). For SP500 and MSCI, we consider log differences. The common factors are obtained from McCracken and Ng (2016). Financial and macro uncertainty are collected from Ludvigson et al. (2021). The Global Financial Cycle are obtained from Miranda-Agrippino and Rey (2020), the S&P 500 from Robert Schiller's webpage, and the Excess bond premium from Gilchrist and Zakrajsek (2012). Numbers are in bold when $p < 0.05$.

financial uncertainty support this observation. However, unlike the oil supply news shocks of [Känzig \(2021\)](#), other common factors also Granger-cause the structural shocks, particularly the aggregate demand shocks in [Baumeister and Hamilton \(2019\)](#) and Kilian's [\(2009\)](#) oil supply shocks. Notably, the OECD Global Composite Leading Indicator predicts oil consumption demand shocks, while past interest rates predict oil inventory demand shocks in [Baumeister and Hamilton \(2019\)](#), and the USD nominal effective exchange rate predicts aggregate demand shocks in [Kilian \(2009\)](#).

Overall, these findings imply that the shocks in these studies are not "structural", and influenced by endogenous responses to other (non-invertible) shocks. Again, it appears that the VARs lack information on market expectations about future demand and supply conditions, potentially causing a bias in the results due to omitted variables. It remains unclear whether these distortions are substantial. Unlike [Känzig \(2021\)](#), the predictability of the shocks is not confined to financial variables, which requires other data to resolve the problem. Moreover, including additional variables in the information set necessitates assumptions for shock identification in these VARs. Addressing these challenges is beyond the scope of this paper.

6 Conclusions

[Känzig \(2021\)](#) proposes using changes in oil future prices within a narrow window around OPEC quota announcements as an instrumental variable to estimate the macroeconomic effects of oil supply news shocks with SVAR-IV methods. His empirical evidence and subsequent research based on the instrument have greatly improved our understanding of the pass-through to the macroeconomy.

In this paper, we have shown that the reduced-form oil price innovations, the oil supply news shocks, and the external instrument in these studies are Granger-caused by financial variables. The predictability of the innovations and the structural shocks indicate informational deficiencies in the VAR model and non-fundamental shocks, suggesting that the structural shocks are non-invertible. The predictability of the external instrument implies that even estimation methods not requiring invertibility, such as SVARs identified with an internal instrument or local projections using the VAR information set as control variables, are distorted.

To address this problem and quantify the distortions, we incorporated the omitted financial variables in Känzig's baseline VAR specification. The results are markedly different: there is an immediate and more pronounced decline in economic activity in the short run, the impact on consumer prices is much lower and less persistent, and we observe a reversal in the monetary policy response to the shocks. Additionally, the results are more stable over time, and puzzling responses disappear. In summary, while the informational deficiencies and contamination of the instrument are quantitatively

important, they can be relatively easily resolved by incorporating financial indicators into the econometrician's information set. The stability across sample periods and the disappearance of the puzzles also makes Känzig's instrumental variable less susceptible to critiques raised in the literature.

Finally, we demonstrated that the structural shocks identified in other prominent global oil-market SVAR models, particularly those of [Baumeister and Hamilton \(2019\)](#) and [Kilian \(2009\)](#), are also predictable by several variables not included in the VAR information set. The shocks in these models are, however, not solely predictable by financial variables. Addressing this issue and measuring the relevance of the omitted variables bias is left for future research.

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Appendix

A.1 Relationship between the VXO and the Instrumental Variable

The predictability of changes in oil future prices around OPEC quota announcements is surprising, given that future prices are expected to follow a random walk. The rejection of the null that financial variables do not Granger-cause the instrumental variable might be coincidental, possibly driven by in-sample noise or outlier observations, and could vanish asymptotically. If this is the case, incorporating variables correlated with the instrument into the VAR model, such as the VXO (in our case), may be problematic. These variables could "absorb" part of the actual effects of oil supply news.

In this appendix, we examine the relationship between the VXO and the IV in more detail. Specifically, if the correlation is accidental, it should be unstable within the sample. We explore this by regressing the IV on lagged changes in the VXO using the following specification:

$$IV_t = constant + \sum_{i=1}^n \beta_i \Delta VXO_{t-i} + \varepsilon_t \quad (6)$$

The results of this regression are presented in Table A1. Given that higher lag orders are statistically insignificant across all results we report, we set $n = 4$. The first four lags of changes in the VXO all exhibit a negative impact on the IV. The sum of the coefficients, as reported in the lower part of the table, is -0.158 and highly significant ($p < 0.01$). When the sample is restricted to months with OPEC announcements (i.e., when $IV_t \neq 0$), as shown in the second column, the relationship becomes even stronger, with a sum of -0.613. The fact that all four lags are significant and have the same sign provides an initial indication that this predictability is not accidental.

This conclusion is further supported by the observation that the negative relationship holds for both increases and decreases in the VXO, as reported in the third column, with symmetric coefficient sums (-0.156 for increases and -0.163 for decreases). Specifically, increases in the VXO tend to be followed by announcements that lower oil futures prices, while decreases in the VXO predict announcements that raise oil prices. The right panel of Table A1 demonstrates that the predictability and significant negative relationship also holds for changes in nominal oil prices in months with OPEC announcements. In contrast, the relationship between the VXO and oil prices is much weaker in months without announcements. This suggests that the VXO can predict OPEC announcements, rather than average oil price changes.

Finally, Figure A1, which plots the sum of the coefficients over a 15-year moving window, reveals that the relationship has remained remarkably stable throughout the sample period. In conclusion, the stability and symmetry of the instrument's predictability based on lagged changes in the VXO

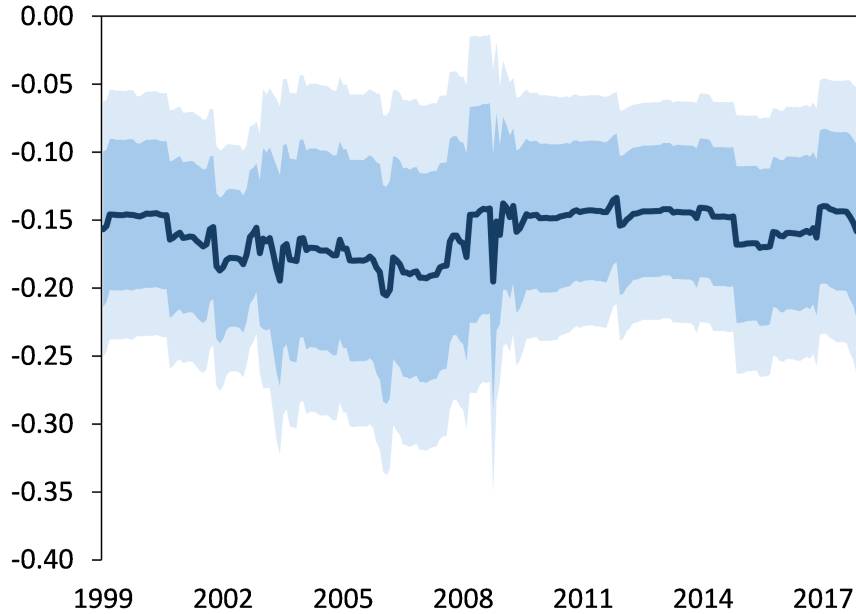
indicate that this relationship is neither coincidental nor the result of outlier observations. Identifying the reasons behind this relationship, however, is beyond the scope of this paper.

Table A1: Predictability of the Instrumental Variable and Oil Price Changes

	<i>IV</i>			Δp_{oil}	
	Full sample	Months with announcement	Full sample	Months with announcement	Months without announcement
ΔVXO_{t-1}	-0.033* (0.019)	-0.202*** (0.071)		-0.539 (0.338)	-0.217 (0.150)
ΔVXO_{t-2}	-0.046* (0.024)	-0.088** (0.045)		-0.527*** (0.161)	-0.168 (0.157)
ΔVXO_{t-3}	-0.039** (0.015)	-0.174*** (0.056)		-0.581*** (0.226)	-0.014 (0.086)
ΔVXO_{t-4}	-0.041** (0.018)	-0.148** (0.059)		-0.461* (0.252)	-0.170* (0.088)
$\sum_i \Delta VXO_{t-i}$	-0.158*** (0.041)	-0.613*** (0.121)		-2.108*** (0.612)	-0.569* (0.293)
$\sum_i \Delta VXO_{t-i}^+$			-0.156*** (0.044)		
$\sum_i \Delta VXO_{t-i}^-$			-0.163*** (0.060)		
\bar{R}^2	0.03	0.13	0.03	0.17	0.02
#obs	417	117	417	117	300

Note: The table reports the sum of the coefficients of lagged changes in the VXO (4 lags). All estimations also include a constant (not reported). Dependent variables are the IV and changes in nominal oil prices, respectively. "+" and "-" are positive and negative changes in the VXO, respectively. Robust standard errors between parentheses. Significance as * p<0.10, ** p<0.05, *** p<0.01.

Figure A1: Predictability of the IV - 15-year moving window estimation

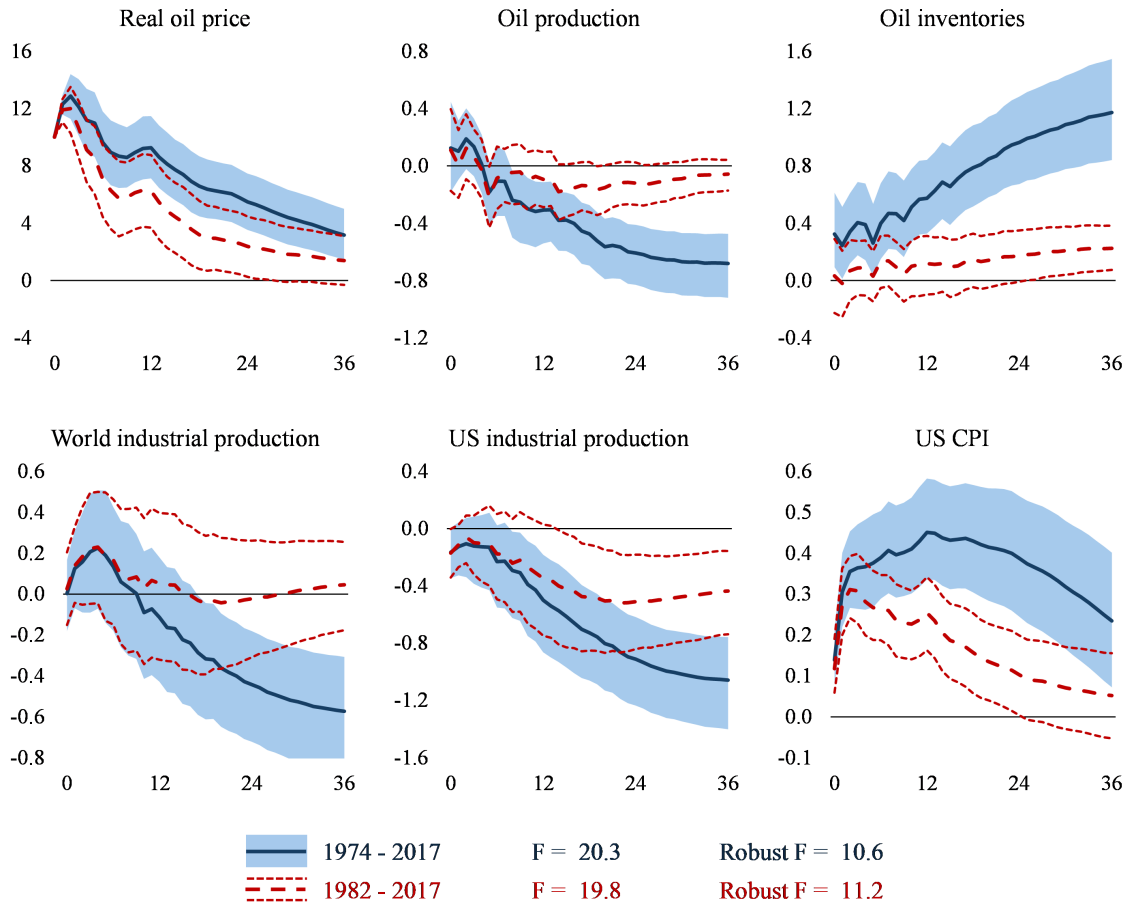


Note: The figure shows the sum of the coefficients of lagged changes in the VXO (4 lags), estimated over a moving window of 15 years (180 months). Dependent variable is the IV. The estimations also include a constant (not reported). 68 and 90 percent (robust) confidence intervals.

A.2 Robustness Checks

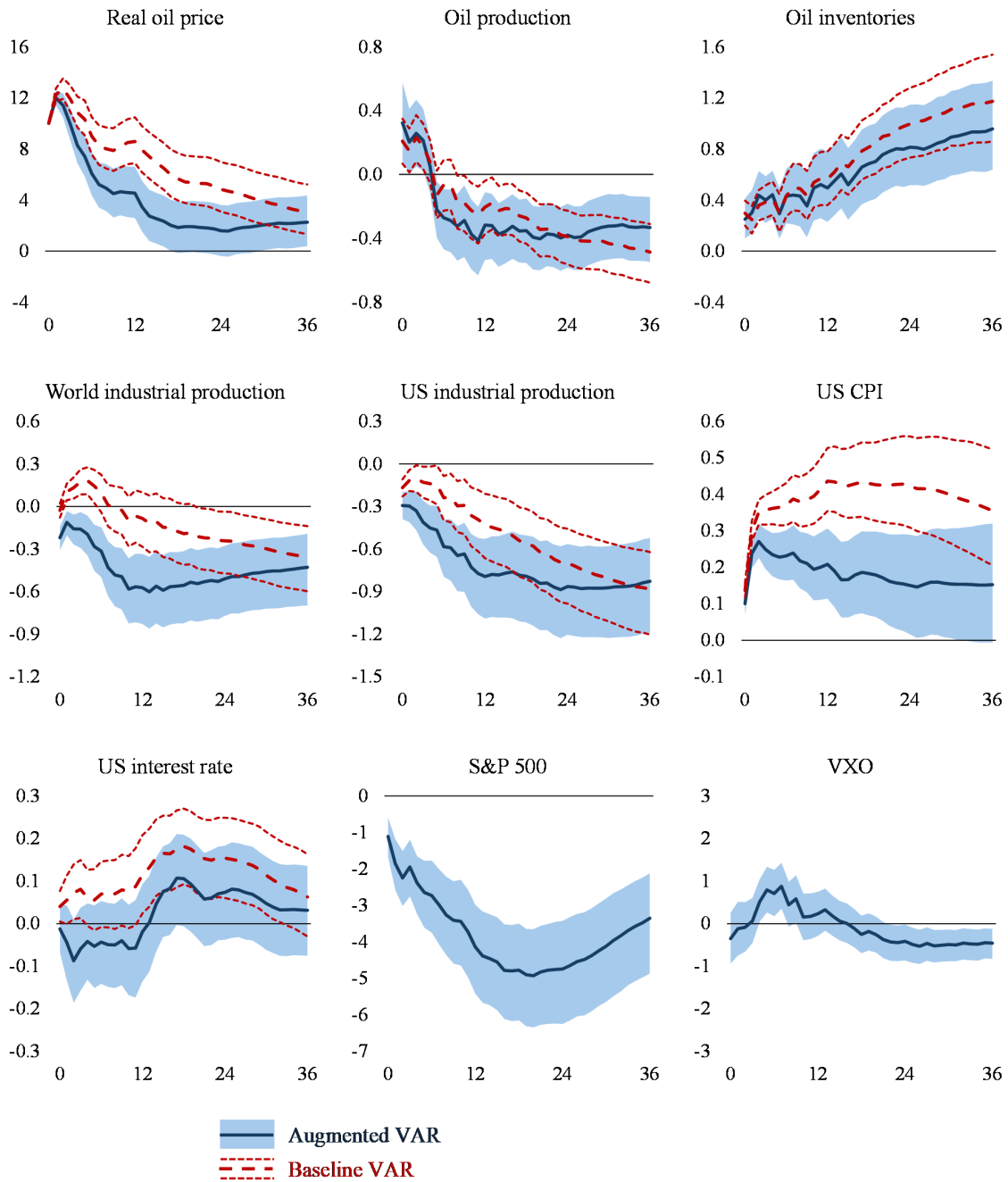
Figure A2, A3 and A4 present three robustness checks discussed in this paper. Figure A2 illustrates the instability in the original [Känzig \(2021\)](#) VAR-model (without the US interest rate). Figure A3 and A4 display the impulse responses of the augmented and original VAR models using alternative inference methods: the Bayesian approach from [Miranda-Agrippino and Rey \(2020\)](#) and [Miranda-Agrippino and Ricco \(2023\)](#), and the weak-instrument robust inference method of [Montiel Olea et al. \(2021\)](#), respectively. Consistent with the discussion in [Mertens and Ravn \(2019\)](#), the confidence (credible) intervals generated by these alternative inference methods are somewhat narrower.

Figure A2: Instabilities in the original Känzig (2021) VAR-model



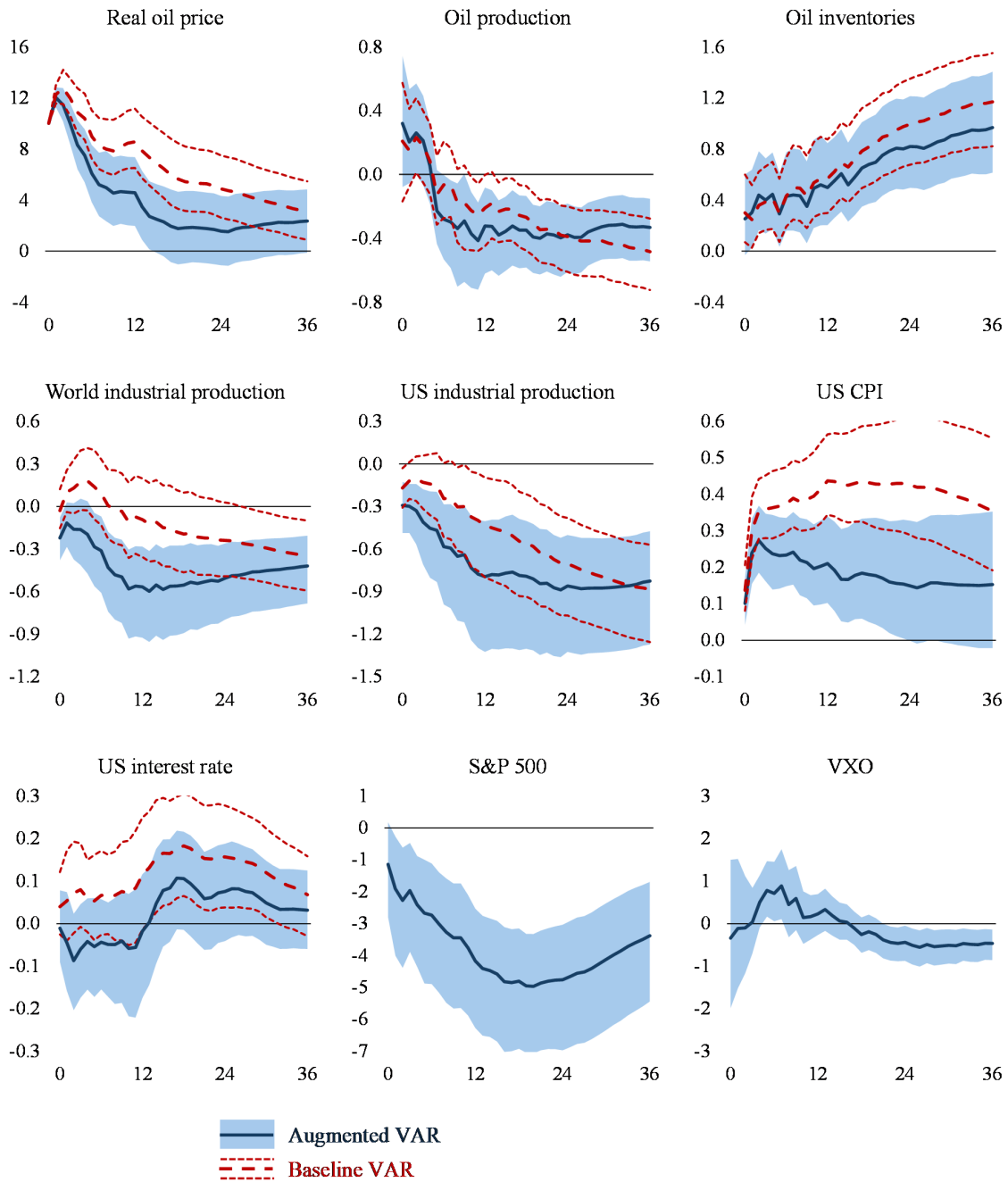
Note: Impulse responses to oil supply news shock that raise oil prices by 10 percent on impact. Original Känzig (2021) VAR model estimated over sample periods 1974-2017 and 1982-2017, respectively. Monthly horizon. 68 percent confidence intervals constructed using a moving block bootstrap.

Figure A3: Impact of oil supply news shocks - Bayesian SVAR



Note: Impulse responses to oil supply news shock that raise oil prices by 10 percent on impact. Känzig VAR with interest rate (red dotted responses) versus VAR augmented with financial variables (blue full responses). Monthly horizon, 1974-2017. 68 percent credible intervals constructed using the Bayesian approach of Miranda-Agrippino and Ricco (2023), using a flat prior.

Figure A4: Impact of oil supply news shocks - Weak instrument robust inference



Note: Impulse responses to oil supply news shock that raise oil prices by 10 percent on impact. Känzig VAR with interest rate (red dotted responses) versus VAR augmented with financial variables (blue full responses). Monthly horizon, 1974-2017. 68 percent confidence intervals constructed using the weak instrument robust inference approach of Montiel Olea et al. (2021).