The Time-Varying Effects of Oil News on Inflation*

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Abstract

We investigate whether the effect of exogenous variations in oil prices on inflation has changed over time. We employ a Bayesian time-varying parameter vector autoregressive (TVP-VAR) model that identifies oil price shocks via a proxy variable. We first estimate a TVP version of Känzig (2021)'s VAR model where the proxy is constructed by summing surprise changes in daily oil futures prices around OPEC announcements. We find evidence that the dynamic response of oil production is non-negative for all points in the sample and the contemporaneous response of global economic activity is positive for some periods, casting doubt on the narrative that oil news captures expectations of future reductions in oil supply. We then compare the results with a Kilian (2024)-type TVP-VAR, which exhibits a higher reliability statistic and impulse response functions that indicate that OPEC news captures oil demand news. While this model captures a modest degree of time-variation in the inflation responses, especially in expansionary periods, its credible regions also accommodate time invariant responses.

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1 Introduction

In recent years, there has been much interest in how inflation responds to oil price and fuel price shocks.[1] Typically, in this literature, the relationship between the oil market and inflation is modeled via a linear model where the parameters are assumed to be constant over time. In this paper, we ask whether the transmission of oil price shocks has changed since 1989. A priori, there are several reasons to think that this might be the case. In recent decades, the US economy has undergone significant structural transformations, as evidenced by the expansion of the services sector and increasing knowledge/task specialization in the workforce. Oil production in the US has also evolved since 1989, with production rapidly increasing since the early 2010s and the US crude oil export ban was lifted in December 2015. In addition, possible changes in monetary policy during the Zero Lower Bound (ZLB) periods could have affected the transmission of oil price shocks to inflation. Additionally, as documented by Kilian and Zhou (2022a), the cost share of crude oil in fuel prices has evolved over time, leading to instability in the relationship between inflation and oil prices.

A major challenge in estimating the response of inflation to oil price shocks is how to identify exogenous variation in oil prices. To do so, we employ a Bayesian time-varying parameter vector autoregressive (TVP-VAR) model where we identify unexpected changes in oil price fluctuations via a proxy variable constructed from changes in daily futures prices around OPEC announcements. The Bayesian Proxy TVP-VAR framework allows us to gain valuable insights. First, the use of this framework allows us to examine the reliability of different proxies and alternative VAR specification.[2] Furthermore, by using this framework, we can assess how prior information regarding the reliability of the proxy affects impulse response estimates.

The use of instrumental variables derived from daily surprises in oil futures originally proposed by Känzig (2021) has quickly gained momentum in the empirical literature on the transmission of oil price shocks. More recently, the debate has focused on the interpretation of the type of shock captured by the OPEC news proxy. The work of Degasperi (2025) shows that in imperfectly informed markets, OPEC announcements induce agents to review their expectations about aggregate real activity. He shows that using the comovement between surprises in stock returns and oil futures can aid in disentangling oil supply and oil demand news. In related work, Kilian (2024) makes four key points regarding the estimation of the responses of macroeconomic aggregates to news derived from changes in daily oil futures prices around OPEC announcements. First, he shows that the first six years of daily oil news used in Känzig (2021) to construct the principal component

[1]See for instance, Kilian and Zhou (2022a), Kilian and Zhou (2022b), Kilian and Zhou (2023a), Kilian and Zhou (2025), Vatsa and Pino (2024), among others.

[2]The Bayesian Proxy VAR yields posterior reliability estimates of the OPEC news series used as instrumental variable. The reliability statistic measures the squared correlation between this measure of surprises around OPEC announcements and the estimated reduced-form oil price shock.

IV (PC-IV) must be discarded for several reasons (e.g., the use of maturities that were not frequently traded and the construction of the proxy). Eliminating these data from the estimation sample renders the PC-IV a weak instrument for the oil price residual in Känzig's linear reduced-form VAR model. Second, he finds that the estimated responses do not align with the narrative that the PC-IV captures oil supply news, nor are they robust across estimation periods. Third, he stresses that the proxy variable should be constructed in a way that reflects how daily OPEC surprises affect the change in the monthly average price of oil in the reduced-form VAR model. Fourth, he shows that replacing the reduced-form oil market VAR model employed by Känzig (2021) by a more conventional oil market VAR model specification as in Kilian and Murphy (2014) or Zhou (2020) removes much of the explanatory power of the proxy, produces more economically plausible response estimates and implies that OPEC news represent oil demand news.

In the current paper, we address the first of these points by restricting the estimation period to start in April 1989. As to the second point, one may wonder whether the economically implausible impulse response patterns noted by Kilian (2024) are still present when the VAR model parameters in the Känzig (2021) model are allowed to change over time. Thus, a natural starting point for our study is the estimation of a time-varying version of the Känzig (2021) proxy VAR model using data starting in April 1989. Given the computational cost of estimating TVP-VAR models, we postulate that the data can be described by a TVP-VAR(2) model, compared with the 12 lags allowed for by Känzig (2021) in his time-invariant VAR model. We find that when the Känzig specification is viewed through the lens of this time-varying VAR model, the data are only informative about the sign and magnitude of the oil price and the inflation response. The 68% credible regions for the other impulse responses are so wide that we are unable to tell what narrative, if any, is consistent with the news around OPEC announcements, making this model unsuitable for studying inflation responses.

We then examine whether addressing, in addition, the third and fourth points of Kilian (2024) about the construction of the proxy and the specification of the reduced-form VAR model produces more precisely estimated impulse responses, when modeling time-varying VAR parameters, and whether these responses are economically plausible. Our results for the Kilian (2024) TVP-VAR(2) model provide additional evidence that proxies derived from daily futures surprises around OPEC announcements capture oil demand news, as opposed to oil supply news, mirroring the results in Kilian (2024) for a time-invariant VAR(24) model. We show that the reliability statistic for the Kilian proxy is twice as high as for the Känzig proxy and there is little overlap between the posterior density of the reliability statistics for these models. These differences reflect both the reduced-form specification and the construction of the proxy. In short, unlike the Känzig-type model, the Kilian-type model appears to generate reliable and reasonably precisely estimated responses derived from a proxy that can be interpreted as oil demand news. This makes this TVP-VAR model a natural choice for assessing the evidence for time variation in the inflation responses to exogenous variation in the real price of oil. We document that such oil price shocks cause short-lived increases in inflation that are slightly larger in the years before the Great Recession and after the COVID-19 pandemic. However, the estimated posterior densities for inflation indicate that the data are also consistent with a linear specification, suggesting that the response of inflation to oil price shocks has remained relatively stable since 1989. There is no evidence at any time of a persistent response of inflation to oil price shocks.

This paper is related to several strands of literature. First, it builds on studies documenting possible time variation in inflation responses to oil price shocks. For example, Blanchard and Galí (2010), Herrera and Pesavento (2009), and Ramey and Vine (2011) allowed for time variation by imposing a deterministic structural break, while Bruns and Lütkepohl (2023), Alsalman (2021), De Michelis et al. (2024), reported evidence that response estimates may differ across subsamples. More recent work by Kilian and Zhou (2025) shows that the response of inflation to gasoline price shocks has been more stable since the early 1970s than previously argued.

More closely related to our work is Baumeister and Peersman (2013) who investigated the time-varying effect of oil supply shocks on inflation using a TVP-VAR model. However, the sign restrictions they used have been called into question by Kilian and Zhou (2023b). One advantage of the proxy VAR identification derived from Känzig (2021) and Kilian (2024) that we use in our paper is that it does not require a fully specified structural model of the oil market. The other advantage is that it avoids potentially conflating different determinants of the price of oil, as is inevitably the case in block recursively identified VAR models (e.g., Chang et al. (2023), Kilian and Zhou (2025)). To our knowledge, ours is the first application of the estimation approach proposed by Mumtaz and Petrova (2023) in the context of studying the effect of OPEC news on oil price fluctuations and inflation.

As is common in the TVP-VAR literature, the number of lags in the Proxy TVP-VARs is limited to two in order to avoid the curse of dimensionality and to reduce the computational cost of estimating the model using the Metropolis-within-Gibbs sampling method. It is important to stress that our TVP proxy VAR model does not nest the linear proxy VAR models of Känzig (2021) and Kilian (2024) based on 12 and 24 lags, respectively. Nor should our TVP model estimates be interpreted as providing statistical evidence against the linear time-invariant VAR specification. Rather we ask whether there is evidence of time variation in the inflation responses, conditional on the use of a low-order TVP-VAR model. What we find is that the conclusion in Kilian and Zhou (2025) that there is not much evidence of time variation in the inflation response over time when splitting the data into subsamples remains true even when focusing on exogenous oil price variation induced by oil demand news, restricting the data to the period since 1989, and allowing the model parameters to evolve continuously.

The paper is organized as follows. Section 2 outlines the data sources and variable construction. Section 3 discusses the econometric framework, including the identification of OPEC news, the prior distributions, and estimation strategy. Section 4 discusses the reliability of the instrumental variable used for identification. Section 5 reports the time-varying effects of OPEC news on oil market variables and U.S. inflation. Section 5 is divided into three subsections: Section 5.1 summarizes the results for the Känzig-type TVP-VAR model, Section 5.2 presents the findings from the Kilian-type TVP-VAR model, and Section 5.3 investigates the changing effects on inflation in the Kilian-type TVP-VAR model. Section 6 examines the sensitivity to alternative prior specifications. Section 7 concludes with a summary of the key findings and policy implications.

2 Data

The TVP-VAR models estimated in this paper include five monthly time series that span the period from April 1989 to December 2022, encompassing four global oil market variables, and the inflation rate, which is the annualized monthly rate of change in the US Consumer Price Index (CPI) for all urban consumers, seasonally adjusted, from FRED. Global oil production data, measured in thousands of barrels per day, are sourced from the Monthly Energy Review published by the Energy Information Administration (EIA) and are expressed in logarithmic growth rates ($\Delta prod_t$). The logarithmic change in World Industrial Production in the Känzig-type model is quantified using the OECD's + 6 industrial production (IP) index as updated by Baumeister and Hamilton (2019) and employed by Känzig (2021). In the Kilian-type model, we use the real economic activity index proposed by Kilian (2009) as revised in Kilian (2019), which captures the fact that the demand for industrial commodities tends to rise well before global industrial production, as these commodities must first be shipped to the producer. The data were obtained from FRED. In the Känzig-type model, the logarithmic change in the real price of oil (Δrpo_t) is calculated using the West Texas Intermediate (WTI) spot crude oil price deflated by the US Consumer Price Index (all items) obtained from the Federal Reserve Economic Data (FRED) database. In the Kilian-type model, we use the U.S. refiners' acquisition cost for imports, sourced from the U.S. EIA, as a measure of the global oil price. Unlike Kilian, we express the real price of oil in percent changes. In the Känzig-type model and the Kilian-type model, we follow Kilian and Murphy (2014) in employing the change in global crude oil inventories measured by total US crude oil inventories scaled by the ratio of OECD petroleum stocks to US petroleum stocks obtained from the construction of the EIA database [3].

To construct the instrument or proxy, z_t, we follow two alternative strategies. First, we compute the

[3] We measure oil prices, oil production, real economic activity and inventories in the Kilian-type model, similar to those in Kilian and Murphy (2014) for global oil market variables.

principal component of the change in oil futures prices across maturities around OPEC announcement dates (PC-IV), following Känzig (2021). Specifically, we gather OPEC announcements from press releases that span the period between 1989 and 2022. This results in a total of 132 announcements. Since 2002, these press releases have been available on the official OPEC website.[4] However, prior to 2002, we collect the dates of the announcements from official OPEC resolutions and press releases OPEC (1990), supplemented with information from Bloomberg's news service. To construct the oil news shock instrument, we calculate the change in the log settlement price of the WTI futures contract h months ahead for $h = 1, ..., 12$ between the day of the announcement and the previous day. Subsequently, the surprise series is computed as the first principal component of these changes. As in Känzig (2021), we assign each surprise to the month in which the corresponding OPEC meeting took place. If no meeting occurred in a month, the value of the surprise is set to zero. When more than one daily announcement occurs in a month, the monthly surprise corresponds to the sum of the daily surprises.

Second, we update the monthly average proxy proposed by Kilian (2024). We employ the 12-month futures contract. Figure 1 shows the two proxy variables from 1989:4 to 2022:12. Both series exhibit considerable volatility and notable spikes corresponding to major geopolitical and economic events, including the Gulf War (1991), the September 11 attacks (2001), the Global Financial Crisis (2008), the oil price collapse, the COVID-19 pandemic, and Russia's invasion of Ukraine in 2022. Figure 1 illustrates the evolution of the proxies and identifies notable historical episodes of oil market disruptions. Particularly relevant for our study are the large changes in oil price expectations around the OPEC meetings during the COVID-19 pandemic. In March 2020, oil futures prices plunged to levels not seen since 1991 as the COVID-19 outbreak led OPEC to revise downward its forecast of global oil demand. Of note is the greater volatility of the PC-IV proxy proposed by Känzig (red dashed line) relative to the monthly average proxy proposed by Kilian, the relatively low correlation between the two series (0.56) and, more importantly, the divergence in the timing of shocks. Note that averaging the daily surprises to compute the monthly measure leads to peaks and troughs occurring about a month later than in the PC-IV.

3 The Time-Varying Proxy SVAR

3.1 Econometric Model

We consider the joint behavior of the real price of oil (real WTI or real imported refiners' acquisition cost oil price), global oil production, an indicator of global economic activity (i.e., logarithmic change in

[4]Collected from the OPEC press release archives.

world industrial production or Kilian's real economic activity index), the change in crude oil inventories and inflation to be given by a conditionally Gaussian $VAR(p)$ model with time-varying parameters and stochastic volatility given as follows:

$$y_t = c_t + B_{1,t}y_{t-1} + B_{2,t}y_{t-2} + u_t = c_t + B_tX_t + u_t \tag{1}$$

where $X_t = \begin{bmatrix} y_{t-1} & y_{t-2} \end{bmatrix}'$, $y_t = \begin{bmatrix} \Delta rpo_t & \Delta prod_t & gea_t & \Delta INV_t & \pi_t \end{bmatrix}'$ is the 5×1 vector of endogenous variables, c_t is a 5×1 vector of time-varying intercepts. Note that, following Primiceri (2005), we set the lag length in the TVP-VAR literature to two; higher lag lengths would make the model computationally intractable.

The time-varying covariance matrix of the reduced form residuals u_t is given by:

$$\Sigma_t = (A_tq)(A_tq)'. \tag{2}$$

We define A_t as a lower triangular matrix with time-varying parameters and q as an element of orthogonal matrices of size 5 such that $q'q = I_5$. Note that the heteroskedastic reduced-form residuals, u_t, are a linear combination of the structural residuals, ε_t, given by $u_t = A_tq\varepsilon_t$ where $\varepsilon_t \sim \mathcal{N}(0, I_5)$ and u_t have variance covariance matrix Σ_t. The 5×5 matrices of time-varying autoregressive parameters are denoted by $B_{i,t}$.

As is standard in the literature (Primiceri, 2005), we assume that the autoregressive parameters $b_t = \text{vec}(B_t')$ follow a random walk process given by:

$$b_t = b_{t-1} + Q_b^{1/2}\eta_t^b,\ \eta_t^b \sim \mathcal{N}(0, I_{5(5p+1)}) \tag{3}$$

and consider the decomposition of A_t

$$A_t = \tilde{A}_tH_t^{1/2} \tag{4}$$

where $\tilde{A}_t$ is a lower triangular matrix with ones along the main diagonal and H_t is a diagonal matrix. Let α_t, be the vector stacking –by rows– the non-zero and non-one elements of $\tilde{A}_t$ and h_t be the 5×1 vector stacking the diagonal elements of H_t. Then, we assume that the data generating processes for α_t and h_t are given by:

$$\alpha_t = \alpha_{t-1} + Q_\alpha^{1/2}\eta_t^\alpha,\ \eta_t^\alpha \sim \mathcal{N}(0, I_{10}) \tag{5}$$

and

$$lnh_t = lnh_{t-1} + Q_h^{1/2}\eta_t^h,\ \eta_t^h \sim \mathcal{N}(0, I_5). \tag{6}$$

As is common in the literature, we assume that the non-zero and non-one elements of $\tilde{A}_t$ follow independent random walks, the diagonal elements of H_t evolve as geometric random walks, and all the elements are independent of each other. This specification allows for time variation in both the contemporaneous relationships among variables and the variance of structural shocks, capturing potential changes in the transmission mechanism of unexpected oil price increases over time.

3.2 Identification of Unexpected Oil Price Fluctuations

Recall that we are interested in identifying only the exogenous variation in oil prices. Let the structural shocks of the TVP-VAR model, ε_t, be given by:

$$\varepsilon_t = A_{0,t}^{-1} u_t \tag{7}$$

where $A_{0,t} = A_t q = \tilde{A}_t H_t^{1/2} q$. To identify the effect of unexpected oil price changes ε_{1t}, we employ a single external instrument that correlates with it. Let q_1 denote the first column of q, collect the remaining structural shocks in a $(n-1) \times 1$ vector $\varepsilon_{st} = [\varepsilon_{2t}, \varepsilon_{3t}, \varepsilon_{4t}, \varepsilon_{5t}]$, and let z_t denote the instrumental variable (proxy). We link the proxy to the structural shock of interest, ε_{1t}, via the following equation:

$$z_t = \beta \varepsilon_{1t} + \sigma v_t \tag{8}$$

where v_t is assumed to be distributed independently and identically over time as $\mathcal{N}(0,1)$ and $E(v_t \varepsilon_t) = 0$.

Then, identification requires that the oil surprises employed as an instrument satisfy two key conditions:

- **Relevance**: $E[z_t \varepsilon_{1t}] = \beta \neq 0$
- **Exogeneity**: $E[z_t \varepsilon_{qt}] = 0$

The above conditions imply that the proxy, z_t, carries information about the oil news shock ε_{1t}, but is not driven by any other shock, ε_{st}.

To jointly model the interaction between the TVP-VAR and the proxy, we adopt the methodology proposed by Caldara and Herbst (2019) and adapted to the time-varying setup of Mumtaz and Petrova (2023). That is, the likelihood of the TVP-VAR is augmented with a measurement equation that relates the proxy to the structural shock of interest, and the model is estimated using Bayesian techniques that involve a Metropolis-with-Gibbs sampling algorithm. The advantages of such a methodology are twofold. First, as noted in Caldara and Herbst (2019) the estimation procedure incorporates all the sources of uncertainty, and hence the proxy becomes informative about the reduced- and structural-form parameters of the model. Second, by calculating the reliability statistic, we can empirically evaluate the relevance of the prior. Specifically, we calculate the reliability statistic proposed by Mertens and Ravn (2013) as follows:

$$\rho^2 = \frac{\beta^2}{\beta^2 + \sigma^2}. \tag{9}$$

As equation (9) illustrates, the reliability of the proxy depends on the signal-to-noise ratio, β/σ. The higher the correlation between IV, z_t, and shock of interest, ε_{1t}, the more informative the proxy is to identify the shock.

We conclude this section by noting that, as evident from equation (8), we model the relationship between the proxy and the oil news shock via a constant coefficient model. We opt for this modeling choice to focus our attention on the time-varying transmission mechanism of the oil news shock, while imposing the prior that the relationship between the IV and the shock does not change over time. While we realize such an assumption is restrictive, it allows us to force the time variation to stem from the TVP-VAR parameters, while assuming that the relevance of the instruments remains unchanged. We leave the study of changes in the relevance of the prior for future work.

3.3 Prior Distributions, Starting Values and Estimation Strategy

The selection of the priors follows the standard Bayesian TVP-VAR literature and, in particular, the work by Mumtaz and Petrova (2023) for the implementation of the identification via an external instrument.[5] While we provide a detailed description of all priors in Table 1, in this section we briefly discuss the prior distribution and starting values for some key parameters.

The priors for b_t, α_t, h_t, and Q_b follow Primiceri (2005), Cogley and Sargent (2005), and Mumtaz and Petrova (2023). The priors for the initial states for the coefficients (b_t), the covariances (α_t), and $ln(h_t)$ are assumed to be normally distributed and independent of each other. The priors for b_t and Q_b are calibrated using the OLS estimates of the VAR model on a training sample of $T_0 = 120$ observations. Let the ordinary least squares(OLS) estimate of the VAR autoregressive parameters be denoted by B_{OLS} and the estimate of the variance-covariance matrix denoted by V_{OLS}. Then, the prior for Q_b is an inverse Wishart $IW(T_0 \times V_{0LS} \times 3.5 \times 10^{-4}, T_0)$. The initial states for b_t are modeled as $b_{0|0} \sim \mathcal{N}(B_{OLS}, V_{OLS})$.

As in Mumtaz and Petrova (2023) and Caldara and Herbst (2019), the prior for Σ_t is uniform and is taken from the QR decomposition of a standard normal distribution. The starting values for the parameters of Equation (8), are also calibrated using OLS on a training sample T_0. We employ the standard inverse-gamma

[5]We are grateful to Haroon Mumtaz and Katerina Petrova for making their MATLAB code for the Proxy TVP-VAR estimation publicly available at https://sites.google.com/site/hmumtaz77/research-papers.

distribution for σ^2 (i.e. $p(\sigma^2)$ is an inverse gamma density $IG(a, b)$, reparametrized in terms of the mean σ_0 and v_0). We evaluate the robustness of the results to different priors for the parameters of the IV equation in Section 6.

For details regarding the estimation and specifics of the Metropolis-within-Gibbs algorithm, we refer the reader to Mumtaz and Petrova (2023) as well as to their technical appendix. We note here that, as is common in the literature, independent prior distributions are assumed to facilitate the selection of prior distributions for the different parameter blocks. Hence, the algorithm consists of six steps that iterate through five conditional posterior distributions. The first step involves using a particle-Gibbs sampler to draw α_t and $\ln h_t$ (the parameters that determine the contemporaneous response) conditional on the data and the other parameters. The second step draws the conditional posterior distribution of b, the covariance between the reduced-form error of interest and the instrument, using the algorithm developed by Carter and Kohn (1994). An independent Metropolis step is used to sample q_1 as in Caldara and Herbst (2019) in the third step. The structural shock of interest is then derived after drawing β and σ. The fourth step deals with estimating the parameters in the instrumental regression in equation (8).

The fifth step deals with drawing from the conditional posterior distributions of the volatility parameters, i.e. Q_b, Q_α, and Q_h. In this step, we estimate the variance parameters that govern the time variation in the model transition equations, i.e., equations (3), (5), and (6). Steps 4 and 5 help us to estimate the structural parameters, i.e., β and σ_v, and the volatility parameters, i.e., Q_b, Q_α, and Q_h, which govern the dynamics of the state-space model. The final step addresses missing observations in the instrumental variable (i.e., z_t) and it is executed only if there are missing observations in the instrument or proxy variable. Following Mumtaz and Petrova (2023), we run the MCMC algorithm for 100,000 iterations, discard the first 50,000 as burn-in, and use the remaining draws for inference.[6]

4 Reliability of the Instrumental Variable

Before we examine the response to the oil news shock, we provide empirical evidence on the relevance of the instrument used to identify oil shocks. To do so, in Figure 2 we report the posterior distributions of the reliability statistics, ρ, the correlation between the instrumental variable and the shock of interest β, and the variance of the instrument equation, σ^2. The posterior median for the reliability statistic in the Känzig-type TVP-VAR is $\rho = 0.226$ and the corresponding 95% credible region is [0.102, 0.340]. Given that the credible region does not contain zero, we conclude that the proxy is informative for identifying the oil news shock, albeit one may argue that it is a bit low. In contrast, the posterior median for ρ in the

[6] To assess the convergence of the MCMC algorithm we compute the joint distribution tests of Geweke (2004).

Kilian-type specification is considerably higher at 0.576 and is estimated with a high degree of precision (the 95% credible region is [0.446, 0.682]).

As Figure 2 illustrates, the posterior distribution for the correlation between the IV and the shock of interest, β, exhibits a considerably higher median for the monthly average (0.474) in the Kilian-type TVP-VAR than for the PC-IV (0.258) in the Känzig-type TVP-VAR. In contrast, the median of the posterior distribution for the variance of the IV equation is considerably higher in Känzig's model (1.112 versus 0.673). This explains why the reliability statistic for the monthly average proxy in Kilian's model is about twice as large (0.576) as the reliability statistic in Känzig's model (0.226).

In summary, the posterior densities for the reliability statistics suggest that the probability that Känzig's PC-IV and Kilian's average monthly IV are different from zero is high. Nevertheless, the two posterior distributions have minimal overlap with the reliability statistic for the Kilian-type model being centered at a larger magnitude. The degree of separation between the two posteriors suggests that both models imply different inference about the relevance of the instrument and points to the importance of the VAR specification for inference, an issue that we explore further in the following sections.

5 The Changing Effect of OPEC News

This section starts by discussing the estimation results for a Känzig-type TVP-VAR in section 5.1. Then in Section 5.2 we present the results of a Kilian-type TVP-VAR. The estimates exploring time variation in the responses of inflation to OPEC news are presented in Section 5.3.

5.1 OPEC news in a Känzig-type TVP-VAR

In Section 4, we provided evidence that PC-IV and monthly average proxies are relevant in TVP-VAR models, although the posterior median for the former is lower. While the reliability of the proxy is key for inference, its validity for identifying a particular type of shock can only be assessed by examining whether the estimated responses are consistent with economic theory. After all, the dynamic propagation of the contemporaneous responses depends on the TVP-VAR specification. If the proxy identifies oil supply news, economic theory would suggest that expectations of supply cuts would lead to an increase in real oil prices (at least on impact), and a reduction in global oil production when the surprise OPEC supply cut is implemented. In turn, on impact, anticipation of lower oil supply should result in a contemporaneous increase in oil inventories and a contemporaneous reduction in world industrial production, which depends on the use of oil (e.g., Kilian and Murphy (2014)). To inquire whether this is the case, we first examine the responses obtained from the Känzig-type TVP-VAR model.

Figures 3-7 show the estimated time-varying responses to an OPEC news shock in this model. The responses have been normalized so that the OPEC news shock increases the price of crude oil by ten percent. The top-left panel in each figure shows the median response for horizons of $h = 0, 1, 2, ..., 20$ months. In the remaining panels of each figure, the solid blue line represents the posterior median response for selected horizons of interest ($h = 0, 1, 2, 4, 6, 8$), and the shaded area denotes the 68% credible sets.[7]

Our analysis reveals that, while OPEC news causes a persistent increase in oil prices (Figure 3), the 68% posterior credible sets do not allow us to rule out the possibility that the shock has a positive effect on global oil production. This finding cast doubt on the interpretation that OPEC news captures an oil supply shock (see Figure 4). Similarly, on impact, the 68% credible sets for world industrial production include zero at all points in the sample (see Figure 5). Another piece of evidence in favor of the view that the PC-IV proxy does not capture news shocks of any kind are the credible sets for the time-varying impact responses of crude oil inventories reported in Figure 6, which again include zero. As the figure illustrates, the 68% credible regions contain zero for all dates in the sample and for all horizons. When viewed through the lens of a time-varying model, the data are uninformative about the sign of the dynamic response of crude oil inventories.

Overall, for the vast majority of the sample, the estimation results from the Känzig-type TVP-VAR raise concerns regarding the interpretation that oil news only captures the expectations of future declines in oil production. Indeed, the wide, credible intervals indicate substantial uncertainty about the sign, magnitude, and persistence of the impulse responses for all variables, but the real oil price. This could stem from the low reliability of the proxy and the model specification.

5.2 OPEC news in a Kilian-type TVP-VAR

In the previous section, we presented evidence that the identification of the oil price shock in that Känzig-type TVP-VAR model is questionable. Thus, in this subsection we turn our attention to the Kilian-type TVP-VAR model. As before the data start in April 1989. The key difference are the use of a different proxy, the monthly average proxy instead of the PC-IV, and a reduced-form VAR specification that better captures expectations in oil markets. In particular, the Kilian-type TVP-VAR specification employs Kilian's global economic activity index instead of the world industrial production, and hence, a shock to the flow demand for oil is captured by the forward component of the global real activity index. In addition, as described in Section 2, real oil prices are measured via the imported refiners' acquisition cost instead of the WTI.

Before we turn to the TVP-VAR estimates, let us recall what a flow demand shock would imply for impulse

[7] As is well known, the Bayes estimate of one or more impulse response functions cannot be obtained by stacking the pointwise medians (or means) of individual impulse responses nor are pointwise quantile error bands a valid measure of the uncertainty about the response functions (see Inoue and Kilian (2022)). In order for our results to be comparable to those reported in Känzig (2021) and Kilian (2024), we nevertheless present point-wise estimates.

responses. First, expectations of higher future demand for oil raise the price of oil, at least on impact, as storage demand increases. Second, the dynamic response of world oil production should be positive as oil producers respond to price incentives. Third, global economic activity, as defined in the model, should increase because the Kilian index is a leading indicator of world industrial production. Finally, increased storage demand raises global inventories.

Figures 8-12 plot the estimated time-varying responses to an oil news shock in a Kilian-type TVP-VAR. As before, the figures plot the responses to a news shock that increases the price of crude oil by ten percent, the top-left panel displays the median response for horizons $h = 0, 1, 2, ..., 20$. In the remaining panels, the solid blue line represents the median response for $h = 0, 1, 2, 4, 6, 8$, and the shaded area denotes the 68% credible set.

As Figure 8 illustrates, oil news leads to a persistent increase in the real price of oil. There is a noticeable, albeit minor, time variation in the response, with the effect being somewhat less persistent during the initial phase of the sample. Eight months after the shock, the real oil price is still above its pre-shock level in the earlier part of the sample, while the posterior median exceeds 10% in the years after the Great Recession.

With respect to world oil production, Figure 9 shows that the median impact response is positive for the vast majority of the sample. The only exceptions are the years after the Great Recession and the late 2000s, when the 68% credible regions include zero. For most horizons, the posterior median is positive and precisely estimated before the Great Recession, but the fact that the 68% credible regions contain zero after the Great Recession indicates that the short- and medium-run responses are not credibly different from zero during these years. Clearly, the persistent increase in oil production during the earlier years of the sample is not consistent with the narrative that oil news derived from changes in oil futures prices around OPEC announcements reflect expectations of lower future oil production (see, e.g., Degasperi (2025), Kilian (2024)). Instead, it aligns with the interpretation that OPEC announcements contain information about future oil demand.

Consider the response of world economic activity measured by Kilian's global economic activity index. Figure 10 shows that the median impact response is positive, the posterior median is slightly higher two months after shock, and slowly declines over the next eight months. However, the response is quite persistent throughout the sample; eight months after the shock, the posterior estimates rule out a return to zero. Moreover, a considerable degree of time variation is evident throughout the sample, with the posterior median exhibiting an increasing trend throughout the sample. Importantly, because this measure of real economic activity is a leading indicator, the contemporaneous positive response to oil news provides additional evidence in favor of the hypothesis that oil news captures expectations about future increases in demand. Figure 11 shows a positive response of inventories that lasts about four months in the early part of the sample, but becomes larger and more persistent in the years following the Great Recession and the COVID-19 pandemic.

To summarize, the responses estimated with a Kilian-type TVP-VAR are largely consistent with the narrative that the monthly average proxy identifies a shock to expectations about the future demand for oil; this narrative appears to be even more relevant for periods of expansion, such as the years following the Great Recession and the COVID-19 pandemic. Three insights are derived from these time-varying posterior estimates. First, the response of oil prices to oil news has become slightly more persistent over the years. Second, the estimates reveal an important degree of time variation in the response of world oil production. In particular, the posterior impact responses are positive prior to the Great Recession, suggesting that the oil news capture expectations of higher future oil demand. Third, the posterior estimates reveal that changes in world oil inventories follow a time-varying pattern similar to that observed for global economic activity. This finding is consistent with larger inventory builds that take place at times when higher oil demand is expected.

5.3 Has the Effect of OPEC News on Inflation Changed since 1989?

Persistent inflation, not only in the US but globally, has prompted policymakers and academics to question whether structural changes post-COVID have made the inflation process more persistent (De Michelis et al., 2024) and more volatile (Powell, 2025). Such concerns underscore the need to understand whether the dynamic effect of oil price shocks in inflation has changed. In this subsection we examine this question based on the Kilian-type TVP-VAR model, which we previously showed to be more economically plausible.

As expected, a positive oil price shock results in a contemporaneous increase in inflation (see Figure 12). The median impact ranges from about 2.0 to 12 percent. The posterior density estimates show that there is 68% probability that the oil price pass-through to inflation is immediate and short-lived. This is true across time.

There is some time variation in the median impact responses, with inflation being more sensitive during periods of expansion. The oil price pass-through tends to be higher during the expansionary period preceding the 2007-2008 financial crisis and the recovery period following the COVID-19 pandemic. The moderate degree of time variation appears to be closely linked to business cycle dynamics, with inflation exhibiting greater sensitivity to oil price shocks during expansionary periods compared to recessionary episodes, as evidenced by the lower responses during the shaded recession periods in both model specifications. However, one would not be able to rule out that the same data could be explained by a time-invariant inflation response. In particular, there is no evidence that the persistence of the inflation response has increased.

To further illustrate the relative stability of the response estimates across time, in Figure 13 we plot the responses for three specific historical episodes associated with unexpected increases in crude oil futures: (1) OPEC's agreement to reduce production in November 2016 (the first since 2008); (2) OPEC + agreement to maintain the reduced production levels established earlier in the year in April 2021; and (3) when OPEC and participating non-OPEC countries agreed to adjust production quotas upwards in light of the "well-balanced market" conditions in April 2022. Panel (b) of Figure 13 depicts the posterior median response of inflation and the 68% credible sets for the Kilian-type TVP-VAR. The message that emerges from this graph is that the posterior estimates across episodes are very similar.

To conclude this section, we investigate the importance of oil price shocks in explaining the variation of US inflation. We also ask whether the contribution of oil news to the forecast error variance decomposition (FEVD) has changed over time. To answer these questions, we take advantage of the fact that the estimation method developed by Mumtaz and Petrova (2023) allows us to identify the shock scale and therefore estimate the time-varying forecast error variance decomposition. To ensure that the contributions add up to 1, we depart from Mumtaz and Petrova (2023) and report the posterior mean estimates in panel (a) of the Figure 13 (see Inoue and Kilian (2022)).

Panel (a) of Figure 13 reveals three interesting findings. On impact, the posterior mean contribution ranges from about 30% to almost 60%. These fluctuations in part reflect changes in the cost share of oil in the price of fuel (see Kilian and Zhou (2022a)). The 68% credible regions indicate the contribution of oil price shocks to the FEVD of inflation is not negligible. Second, the surface illustrates the contribution appears elevated during recession periods (gray shaded areas), and lower during expansions, with notable increases around 2001, 2007-2009, and 2020-2021. Finally, across the horizon dimension, the posterior mean FEVD shows a decline after impact and reaches a trough around 3-6 months, then stabilizes or slightly increases at longer horizons. This pattern suggests that the effects of oil prices on inflation are most pronounced immediately but have persistent medium-term effects. Nevertheless, the fact that we could almost trace a straight line through the 68% credible sets indicates that the data could also be consistent with a FEVD that remains constant over time.

To summarize, while the TVP-VAR estimates reveal a moderate degree of time variation, the posterior estimates suggest the data are also consistent with a linear model. That the response of inflation exhibits only moderate changes since 1989 should be good news for policymakers faced with unexpected changes in oil prices.

6 Robustness Checks: The importance of the prior on the proxy variable

As mentioned above, the reliability statistic allows us to gauge the proxy's relevance for identifying the oil price shock. Recall that the priors for β and σ are set such that $\rho \approx 0.2$ in the baseline models. The posterior density for ρ has a median of 0.576 and the 95% credible sets exclude 0, indicating that the proxy is reliable. To investigate the robustness of the results to the choice of priors, we take advantage of the Bayesian setup, re-estimate the Kilian-type TVP-VAR model, and compare the posterior median ρ and the impulse responses to the baseline estimates. The various scenarios are intended to force a lower (or higher) signal-to-noise ratio β/σ. We experiment with different combinations of priors for σ, which are parametrized in terms of the mean σ_0 and varianceν_0 of the Gamma prior distribution.

The combination of priors, resulting posterior median, and credible regions for ρ are reported in Table 2. For reference, the first row reports the results for the baseline specification. The second row reports the results when we impose a looser prior on the variance of the measurement error, ν_0. As expected, a looser prior results in a lower posterior median for the reliability statistic; it decreases from 0.576 to 0.270. Similarly, if we impose a looser prior by halving the prior mean, $\sigma_0 = 0.175$ and keeping the prior variance unchanged, $\nu_0 = 0.02$, the posterior median for rho decreases relative to the baseline (see the third row). Rows 4 and 5 of Table 2 confirm the main findings derived from these exercises. When we force the TVP-VAR to take more signal from the proxy (compare the fourth row against the baseline in the first row), the reliability statistic increases.

How are these changes in the priors reflected in the impulse responses? To answer this question, we plot the baseline impulse response (solid blue line), corresponding 68% credible sets, as well as the impulse responses denoted by solid green (red) lines and corresponding credible sets denoted by the dashed green (red) lines for the looser priors where we set $\sigma_0 = 0.350$ ($\sigma_0 = 0.175$ and $\nu_0 = 0.100$ ($\nu_0 = 0.020$). For the sake of brevity, we focus our discussion on the responses for the Kilian-type TVP-VAR at horizons $h = 0, 4, 8$ in Figure 14 and relegate the figures with horizon $h = 0, 2, 4, 6, 8$ to the Online Appendix (Figures A.1-A.5).

We observe a widening of the posterior densities when we force a lower signal-to-noise ratio. Overall, while we note some changes in the time-varying pattern of the impulse responses, inference derived from the Kilian-type TVP-VAR model appears to be robust to the change in the priors. That is, (1) oil news has a positive and persistent effect on oil prices; (2) oil production responds positively to oil news, but a decreasing trend in responsiveness is observed over time; (3) global economic activity increases and its responsiveness increases during expansionary periods; (4) the response of inventories to oil news is positive and exhibits an increasing trend over time; (5) the response of inflation is positive and larger during expansions.

All in all, three messages emerge from this section. First, when the Proxy TVP-VAR is weakly identified, it is possible to increase the signal-to-noise ratio by forcing a small measurement error, and thus sharpen inference. Second, using a Kilian-type TVP-VAR we are able to recover sharp predictions on the effect of unexpected changes in oil prices when the latter are proxied by average monthly movements in oil futures. Lastly, the posterior estimates for the reliability statistic in the Känzig-type specification reported in the Online Appendix Table A.1, reveal credible regions that are rather close to zero, suggesting that the model may not be well identified when a looser prior is used.

7 Conclusions

This paper investigated how much the transmission of oil price shocks to U.S. inflation has changed over time using Bayesian proxy TVP-VAR models, where the proxy is constructed from surprises in daily oil futures around OPEC announcements. We demonstrated that the model specification and the construction of the proxy variable are key to the interpretation of the shock. We found moderate time variation in the transmission of OPEC news to inflation. While during periods of economic expansion, such as the years preceding the 2007-2008 financial crisis and the recovery following the COVID-19 pandemic, inflation appeared to be more sensitive to OPEC news, the width of the credible regions suggests that the data are also consistent with a linear time invariant model. In an era of heightened oil market volatility and structural economic transformation, the fact that the response of inflation is relatively stable and remains short-lived should be comforting news for policymakers.

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Table 1: Prior Distributions and Starting Values for the Time-Varying Proxy VAR Model

Parameter	Description	Prior Distribution	Prior Scale Matrix/Value	Degrees of Freedom/Formula
b_t	VAR coefficients	$b_t = b_{t-1} + Q_b^{1/2}\eta_t^b$	$\beta_0 = vec(b_0)'$	Initial state based on OLS
		$\eta_t^b \sim \mathcal{N}(0, I_{N(Np+1)})$	$P_{0\|0} = 10 \times V_0$	using training sample $T_0 = 120$
Q_b	Coefficient innovations	$IW(Q_0, T_0 + T)$	$Q_0 = V_0 \times T_0 \times 3.5 \times 10^{-4}$	$T_0 = 120$
			$V_0 = kron(\Sigma_0, (X_0'X_0)^{-1})$	
α_t	Non-zero, non-one elements of $\tilde{A}_t$	$\alpha_t = \alpha_{t-1} + Q_\alpha^{1/2}\eta_t^\alpha$	Initial value from C_0	$C_0 = chol(\Sigma_0)$
	(lower triangular)	$\eta_t^\alpha \sim \mathcal{N}(0, I_{N(N-1)/2})$	C_0 normalized and inverted	$C_0 = (C_0^{-1})'$
Q_α	α_t innovations	$IW(D_0, TD_0 + T)$	D_0: diagonal with 10^{-4} elements	$TD_0 = NNx + 10$
$\ln h_t$	Log volatilities	$\ln h_t = \ln h_{t-1} + Q_h^{1/2}\eta_t^h$	$MU_0 = \ln(diag(\Sigma_0))$	Prior mean for the initial log-volatilities MU_0 and
		$\eta_t^h \sim \mathcal{N}(0, I_N)$		variance $SS_0 = 10$
Q_h	$\ln h_t$ innovations	$IW(g_0 I, TG_0 + T)$	$g_0 = 10^{-4}$	$TG_0 = N + 10$
q_1	First column of q	Uniform on the unit sphere	Metropolis step	
β	Instrument relevance	$\mathcal{N}(b_{0m}, v_{0m})$	b_{0m} from OLS regression of	Estimated from regression of
			VAR residuals on instrument $v_{0m} = 0.1$	residuals on oil surprises
σ^2	Instrument noise	$\frac{1}{\sigma^2} \sim \mathcal{G}(a, b)$	$\sigma_0 = b_{0m}$(OLS estimate=0.350)	$a = \frac{\nu_1}{2}$, $b = \frac{2}{s_1}$
	variance		$\nu_0 = 2(2 + \frac{\sigma_0^2}{v_0^2})$	$\nu_1 = \nu_0 + T$
			$s_0 = 2\sigma_0(1 + \frac{\sigma_0^2}{v_0^2})$	$s_1 = s_0 + \hat{v}_t'\hat{v}_t$
			$v_0^2 = 0.02$	where $\hat{v}_t = m_t - \hat{\beta}\varepsilon_{1t}$

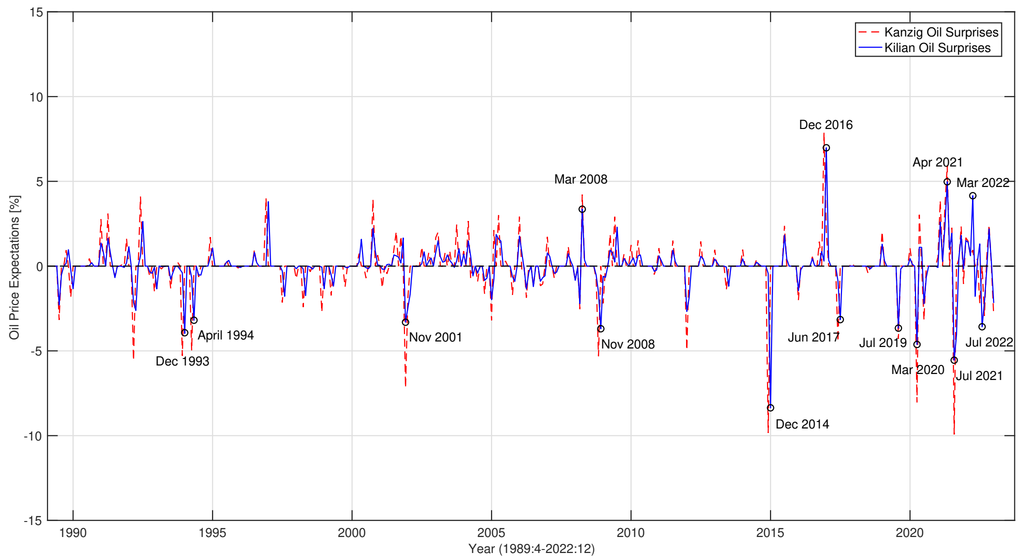
Notes: The VAR model includes real oil price, oil production, world industrial production (or global economic activity), inventories, and inflation. Key model parameters: $N = 5$ (number of variables), $p = 2$ (number of lags), $T_0 = 120$ (training sample size), T (remaining sample size), $NNx = N(N-1)/2 = 10$ (number of free elements in the impact matrix). Σ_0 is the variance-covariance matrix of reduced-form residuals from the training sample, $V_0 = kron(\Sigma_0, (X_0'X_0)^{-1})$ is the Kronecker product used for coefficient priors, and $\beta_0 = vec(b_0)'$ is the vectorized OLS coefficients. The external instrument is related to structural shocks through $m_t = \beta\varepsilon_{1t} + \sigma v_t$. MCMC uses 100,000 replications with 50,000 burn-in and every 10th draw is retained.

Table 2: Robustness of Reliability Measure (ρ) to Alternative Priors - Posterior Median and Credible Regions

Prior for σ_0	**Prior for v_0**	**Posterior Median ρ**	**68% CR**	**95% CR**
0.350	0.020	**0.576**	[0.512 0.633]	[0.446 0.682]
0.350	0.100	**0.270**	[0.208 0.332]	[0.149 0.397]
0.175	0.020	**0.395**	[0.337 0.454]	[0.276 0.509]
0.175	0.015	**0.484**	[0.423 0.542]	[0.360 0.594]
0.175	0.025	**0.347**	[0.285 0.412]	[0.227 0.474]

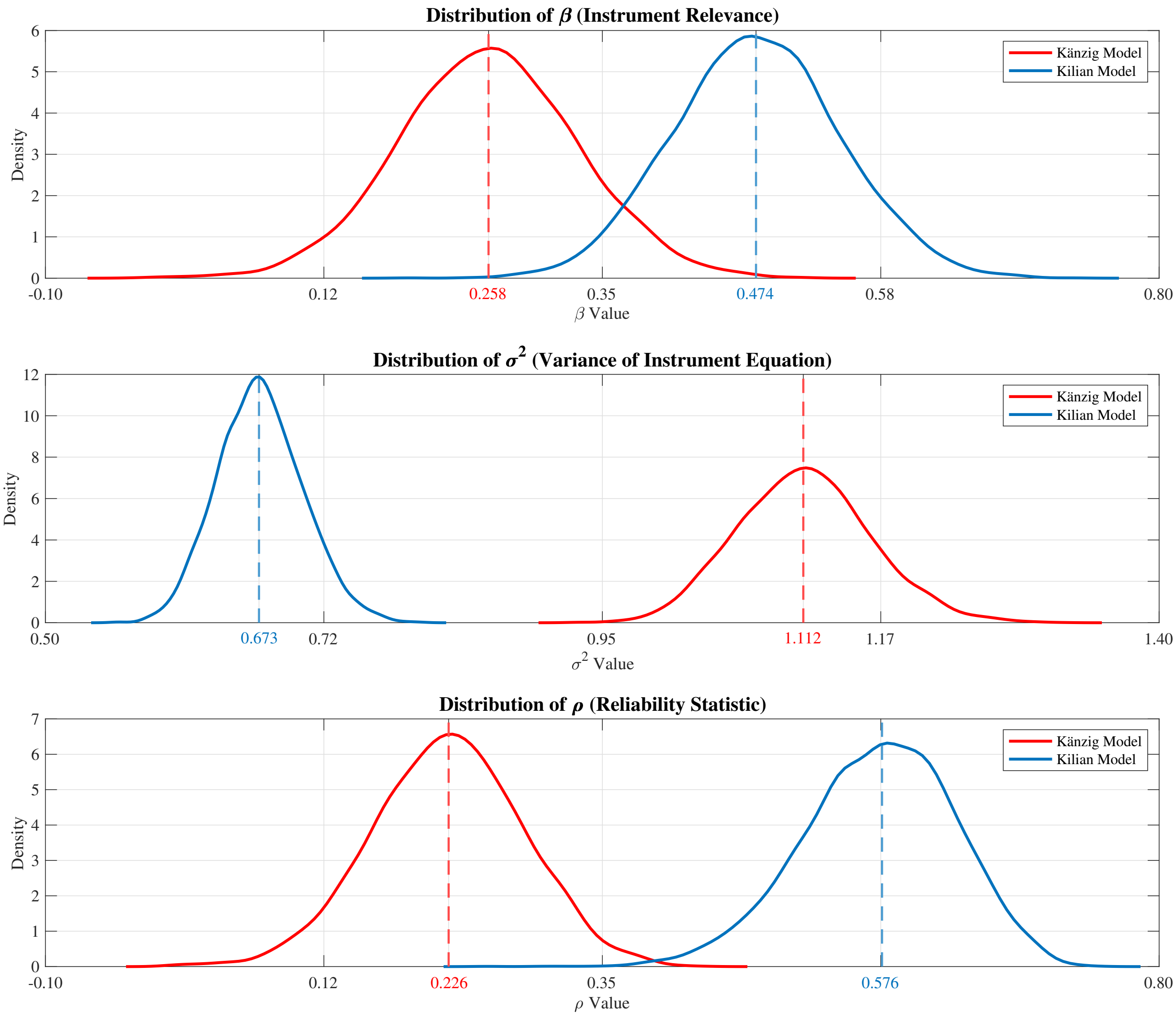
Note: The priors for σ are parameterized in terms of the mean σ_0 and the variance v_0. Note that $\frac{1}{\sigma^2} \sim \mathcal{G}(a,b)$ where $a = \frac{\nu_1}{2}$, $b = \frac{2}{s_1}$. The parameters of this Gamma density are given by $\nu_1 = \nu_0 + T$ and $s_1 = s_0 + \hat{v}_t' \hat{v}_t$ $\hat{v}_t = m_t - \hat{\beta}\varepsilon_{1t}$. $s_0 = 2\sigma_0 \left(1 + \frac{\sigma_0^2}{v_0^2}\right)$ while $\nu_0 = 2\left(2 + \frac{\sigma_0^2}{v_0^2}\right)$. CR denotes 68% and 95% credible regions.

Figure 1: Oil Surprise Series



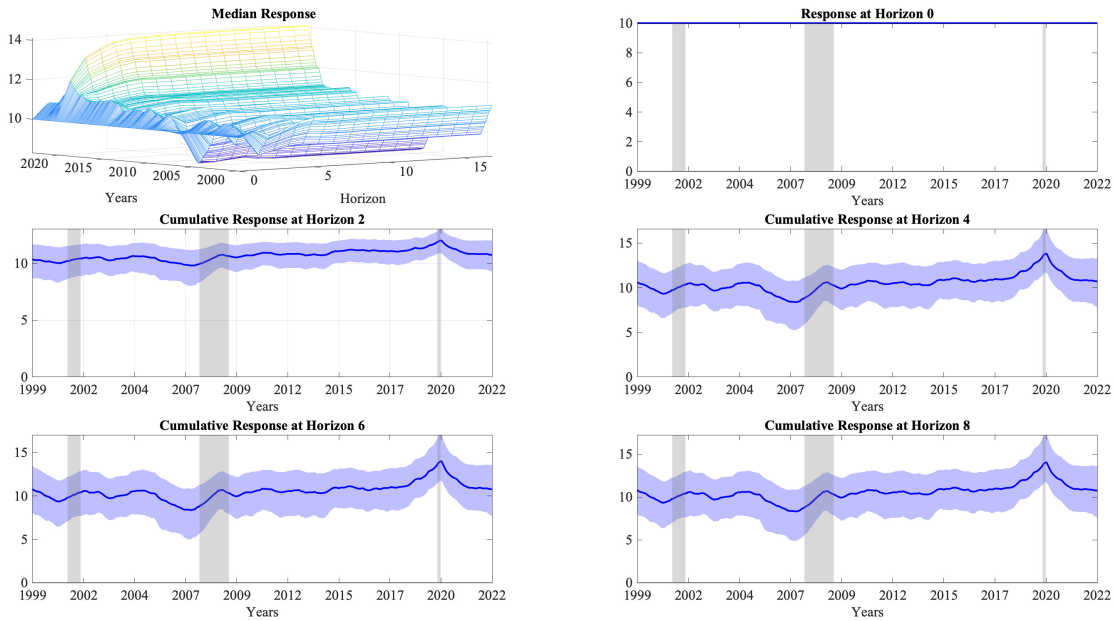
Note: This figure displays two oil surprise monthly series from 1989:4 to 2022:12. The red dashed line represents oil surprises based on Känzig's (2021) identification method, while the blue line shows oil surprises using Kilian's (2024) approach. Key episodes of large oil price surprises are labeled with corresponding dates (marked with circles).

Figure 2: Proxy-VAR Posterior Parameter Distributions



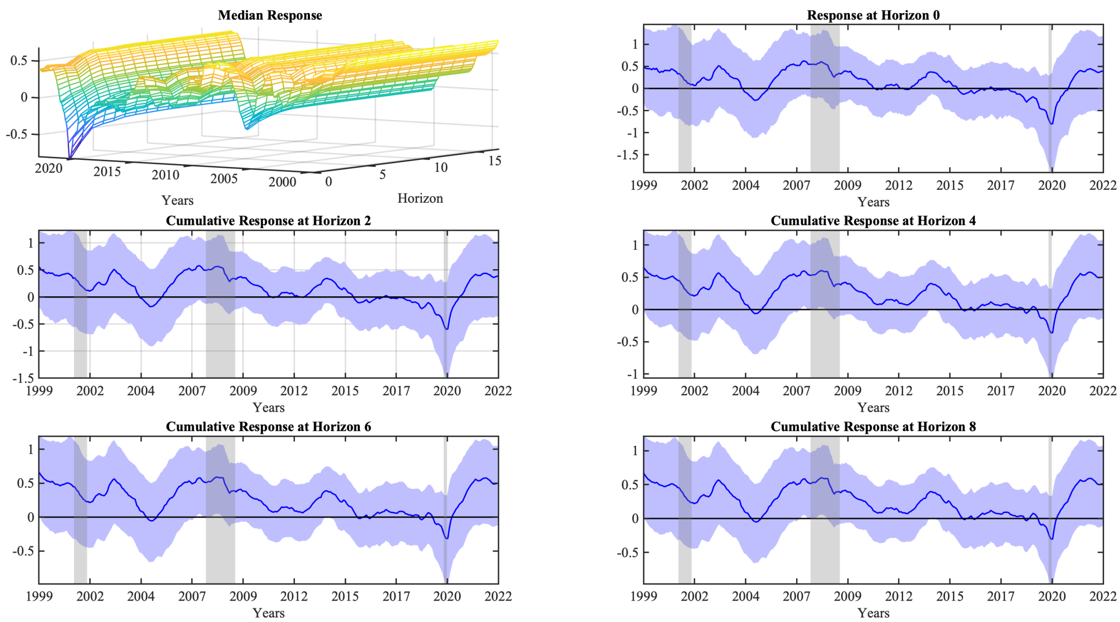
Notes: The figure shows the posterior distributions (Känzig and Kilian-type TVP-VAR) of three key parameters. Top panel: Distribution of β (instrument relevance) with median = 0.258 and 0.474. Middle panel: Distribution of σ^2 (variance of instrument equation) with median = 1.112 and 0.673. Bottom panel: Distribution of ρ (reliability statistic) with median = 0.226 and 0.576.

Figure 3: Posterior Median Response of the Real Oil Price to the Oil News Shock - Känzig-type TVP-VAR Model



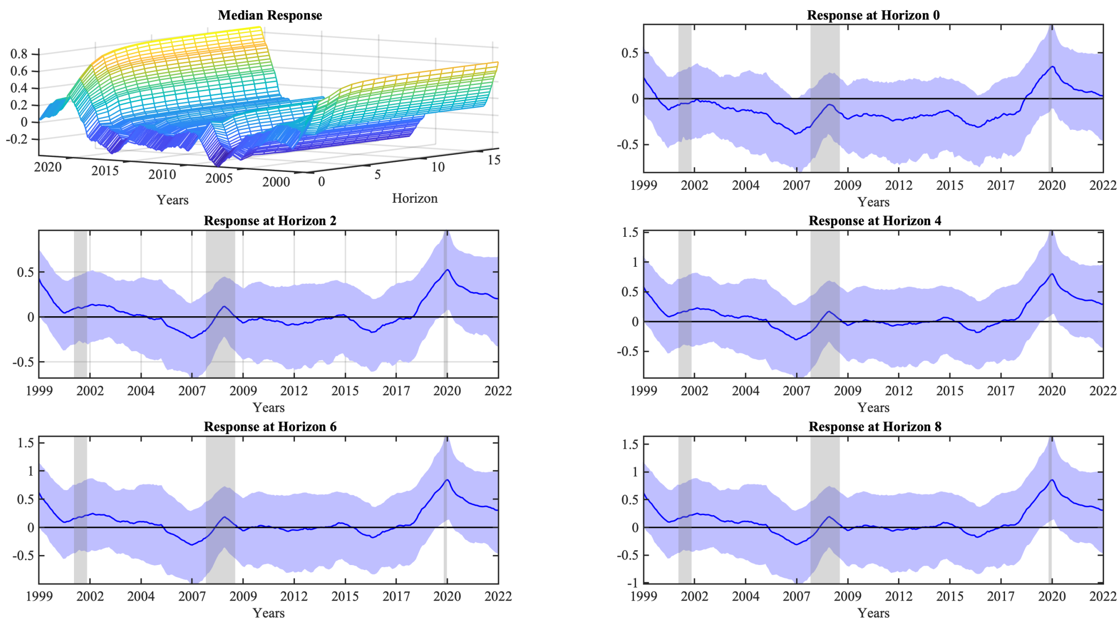
Note: The oil supply news shock normalized to a 10 percent increase in the real price of crude oil. The shaded area indicates the 68 percent posterior credible set. The vertical bars represent the recession periods for the United States as identified by the NBER.

Figure 4: Posterior Median Response of World Oil Production to Oil News Shock - Känzig-type TVP-VAR Model



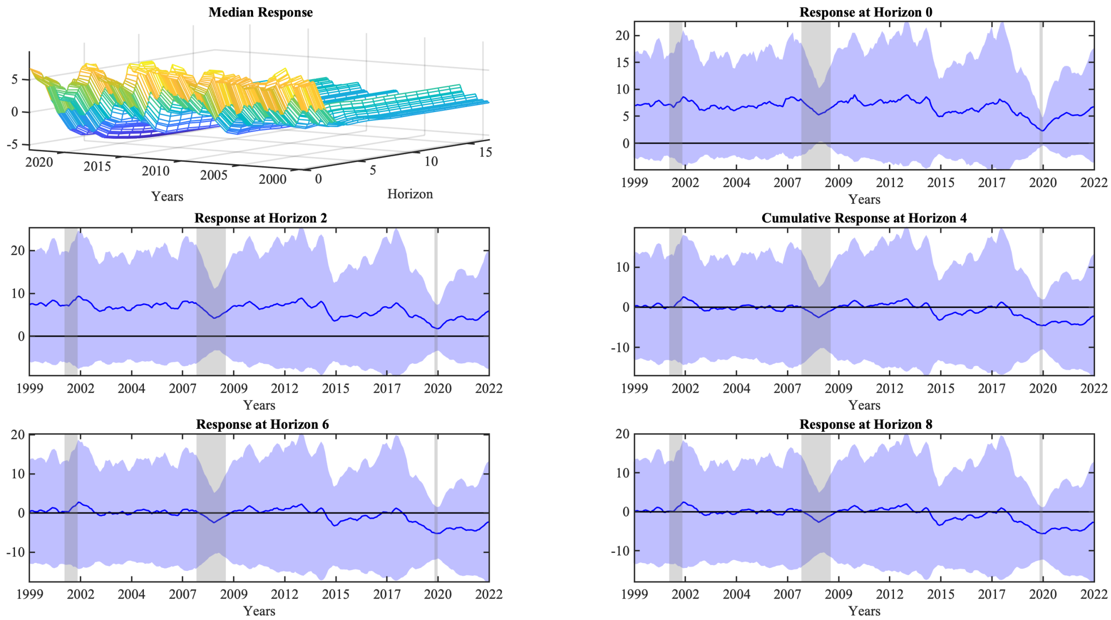
Note: The oil supply news shock normalized to a 10 percent increase in the real price of crude oil. The shaded area indicates the 68 percent posterior credible set. The vertical bars represent the recession periods for the United States as identified by the NBER.

Figure 5: Posterior Median Response of World Industrial Production to Oil News Shock - Känzig-type TVP-VAR Model



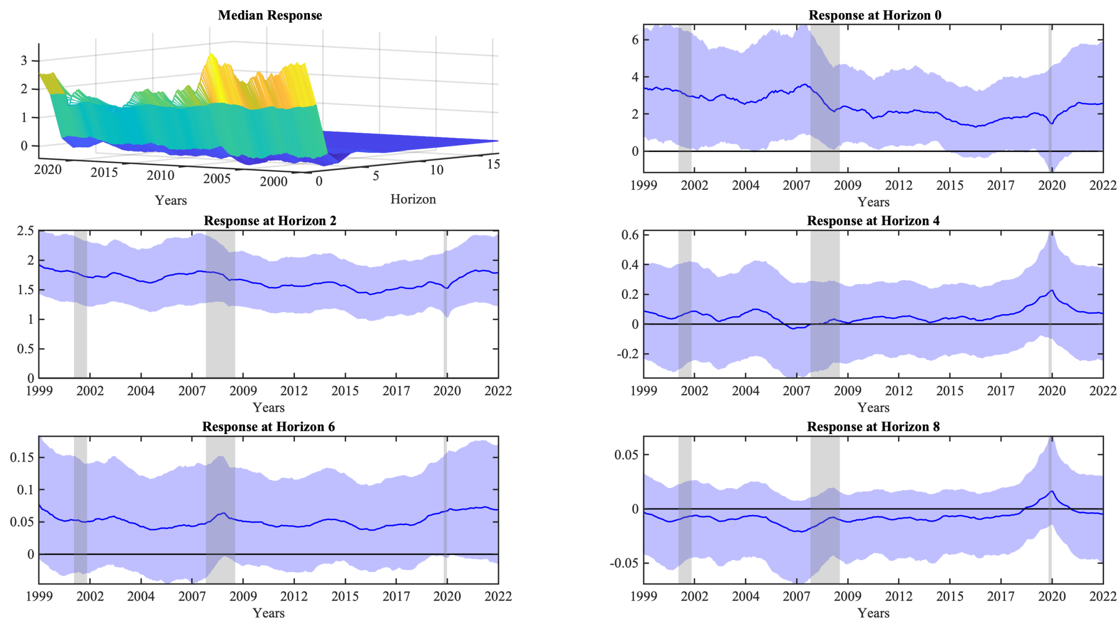
Note: The oil supply news shock normalized to a 10 percent increase in the real price of crude oil. The shaded area indicates the 68 percent posterior credible set. The vertical bars represent recession periods for the United States as identified by the NBER.

Figure 6: Posterior Median Response of Inventories to Oil News Shock - Känzig-type TVP-VAR Model



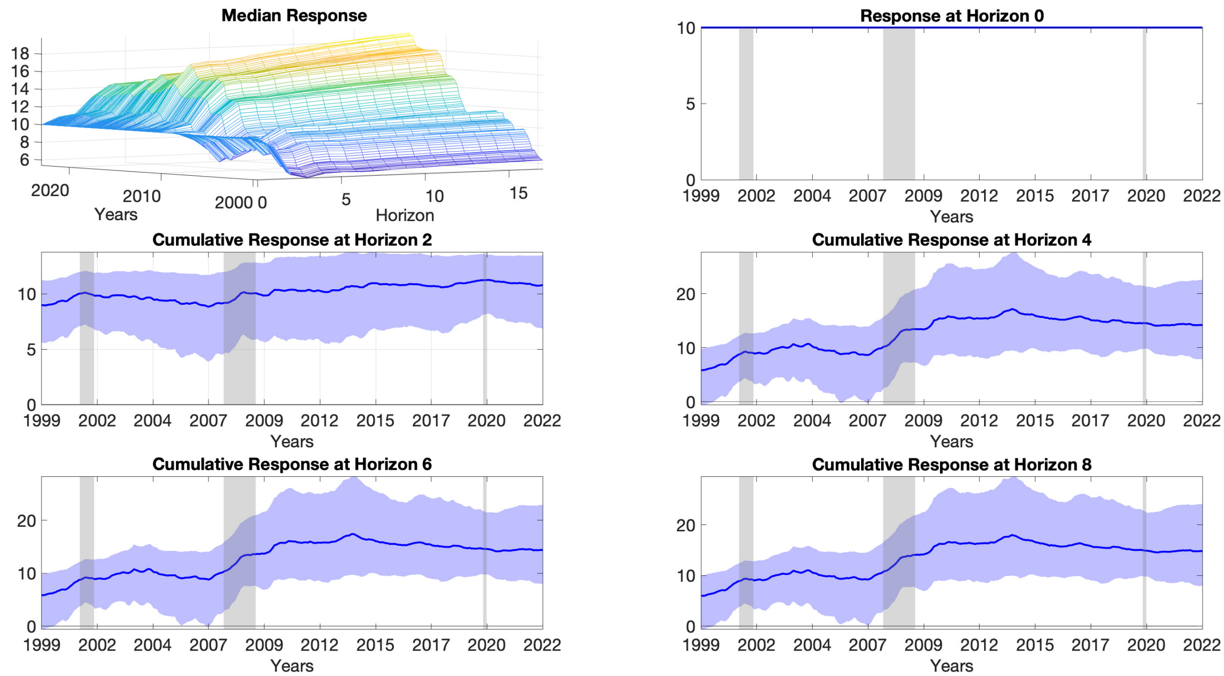
Note: The oil supply news shock normalized to a 10 percent increase in the real price of crude oil. The shaded area indicates the 68 percent posterior credible set. The vertical bars represent the recession periods for the United States as identified by the NBER.

Figure 7: Posterior Median Response of the Inflation Rate to the Oil News Shock - Känzig-type TVP-VAR Model



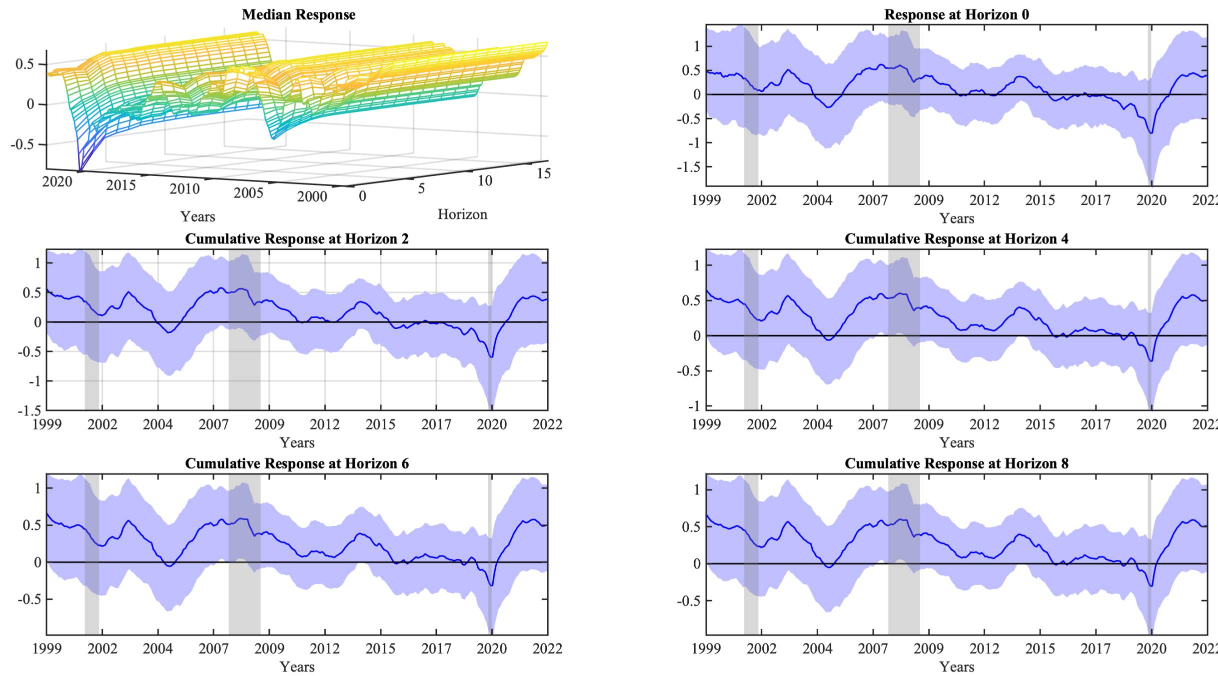
Note: The oil supply news shock normalized to a 10 percent increase in the real price of crude oil. The shaded area indicates the 68 percent posterior credible set. The vertical bars represent the recession periods for the United States as identified by the NBER.

Figure 8: Posterior Median Response of the Real Oil Price to the Oil News Shock - Kilian-type TVP-VAR Model



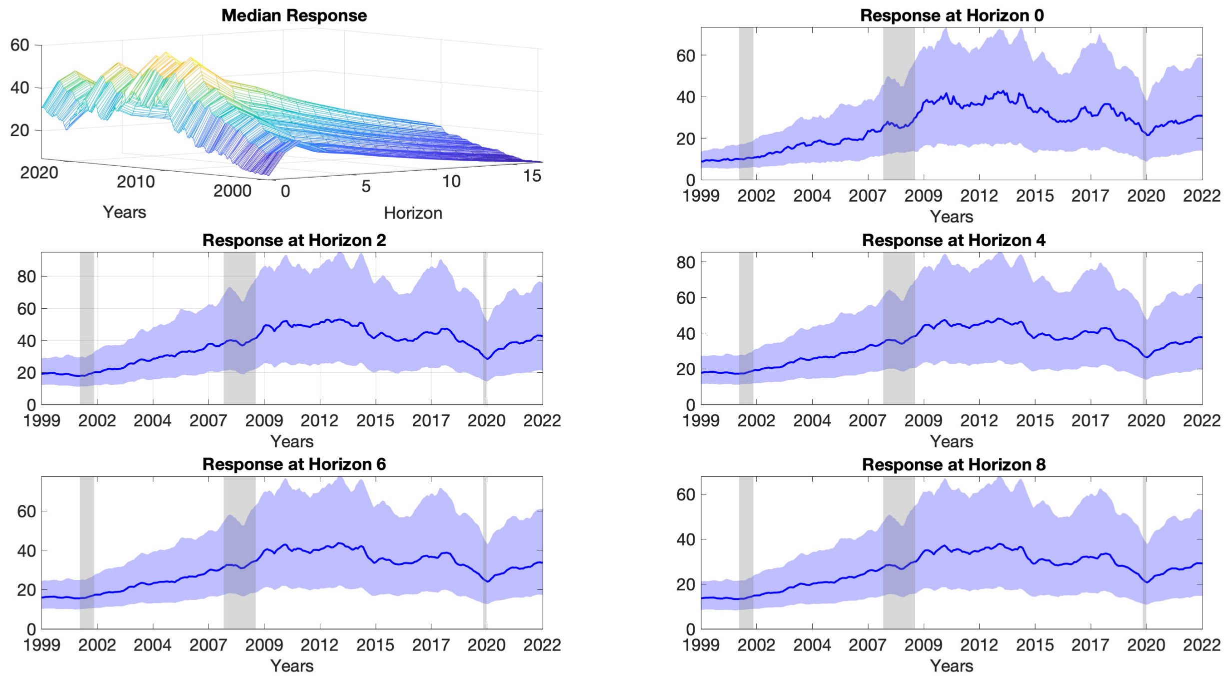
Note: The shock is normalized to a 10 percent increase in the real price of crude oil. The shaded area indicates the 68 percent posterior credible set. The vertical bars represent the recession periods for the United States as identified by the NBER.

Figure 9: Posterior Median Response of World Oil Production to Oil News Shock - Kilian-type TVP-VAR Model



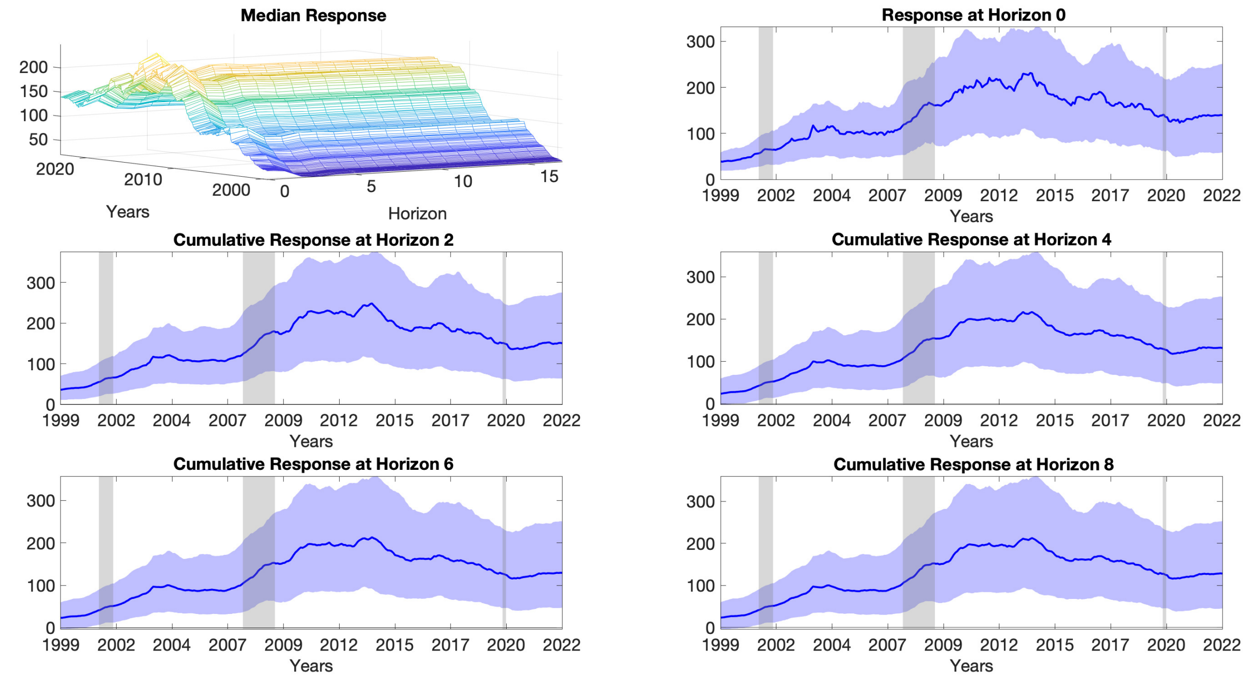
Note: The shock is normalized to a 10 percent increase in the real price of crude oil. The shaded area indicates the 68 percent posterior credible set. The vertical bars represent the recession periods for the United States as identified by the NBER.

Figure 10: Posterior Median Response of Global Economic Activity to Oil News Shock - Kilian-type TVP-VAR Model



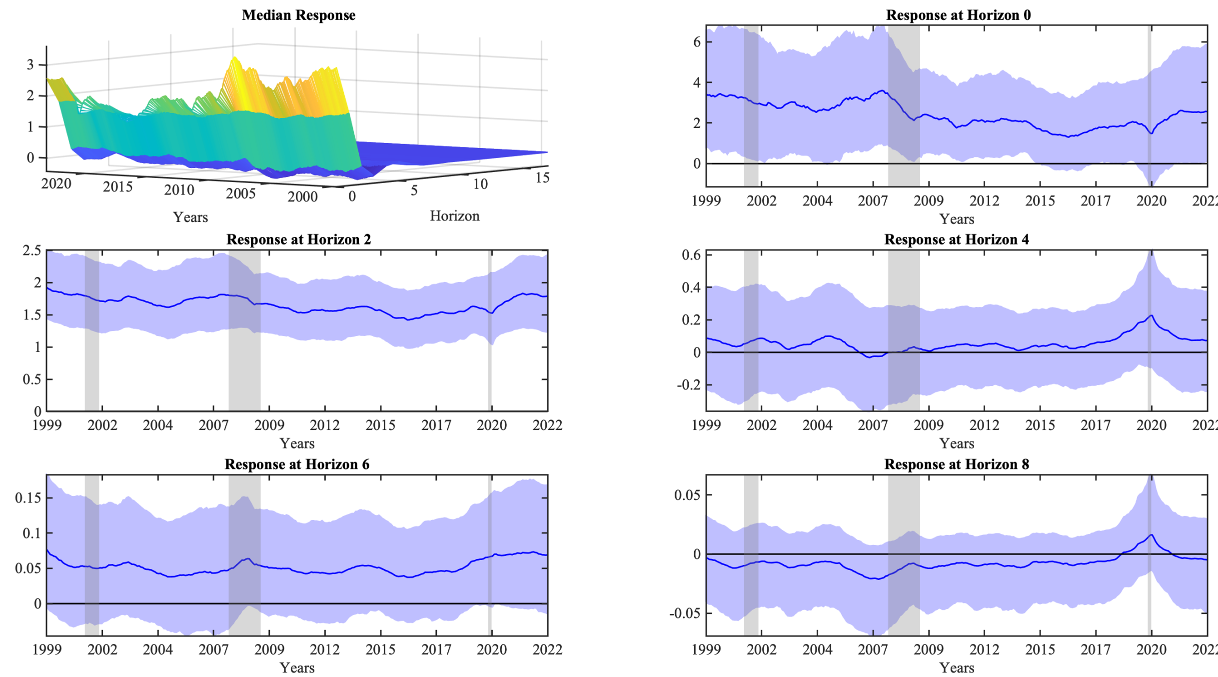
Note: The shock is normalized to a 10 percent increase in the real price of crude oil. The shaded area indicates the 68 percent posterior credible set. The vertical bars represent recession periods for the United States as identified by the NBER.

Figure 11: Posterior Median Response of Inventories to Oil News Shock - Kilian-type TVP-VAR Model



Note: The shock is normalized to a 10 percent increase in the real price of crude oil. The shaded area indicates the 68 percent posterior credible set. The vertical bars represent the recession periods for the United States as identified by the NBER.

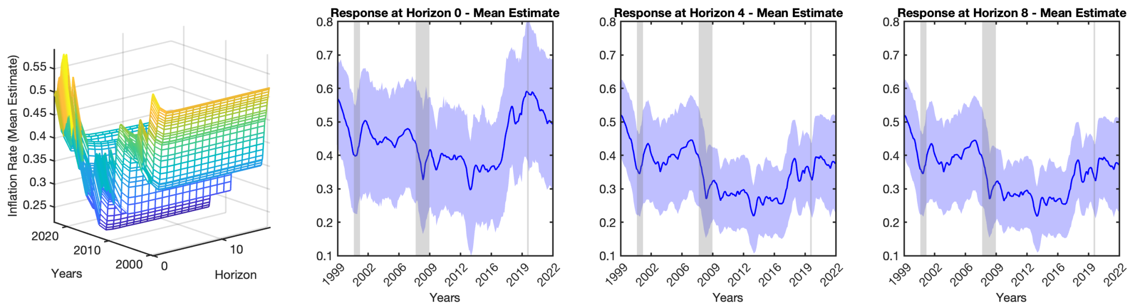
Figure 12: Posterior Median Response of the Inflation Rate to Oil News Shock - Kilian-type TVP-VAR Model



Note: The shock is normalized to a 10 percent increase in the real price of crude oil. The shaded area indicates the 68 percent posterior credible set. The vertical bars represent the recession periods for the United States as identified by the NBER.

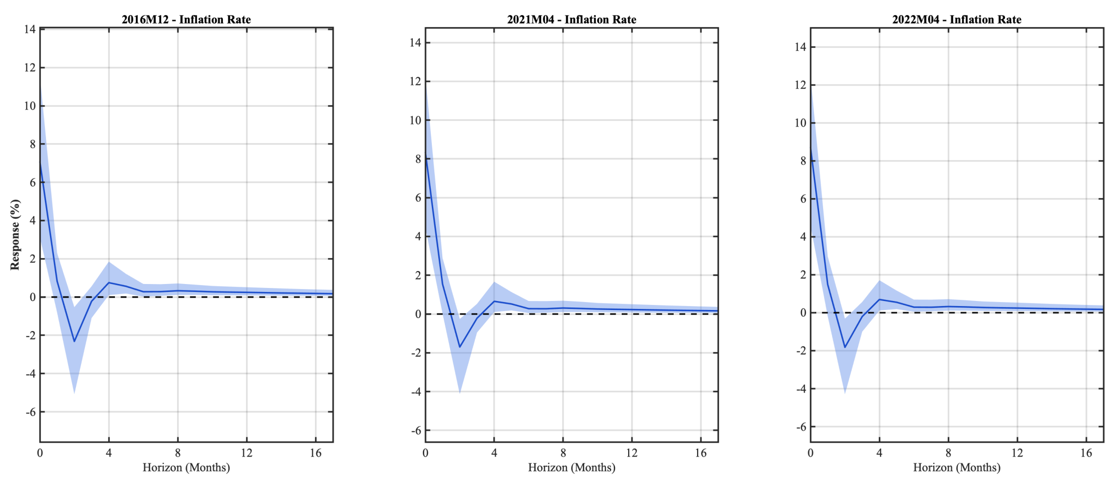
Figure 13: Response of the Inflation Rate

(a) Forecast Error Variance on Inflation Rate



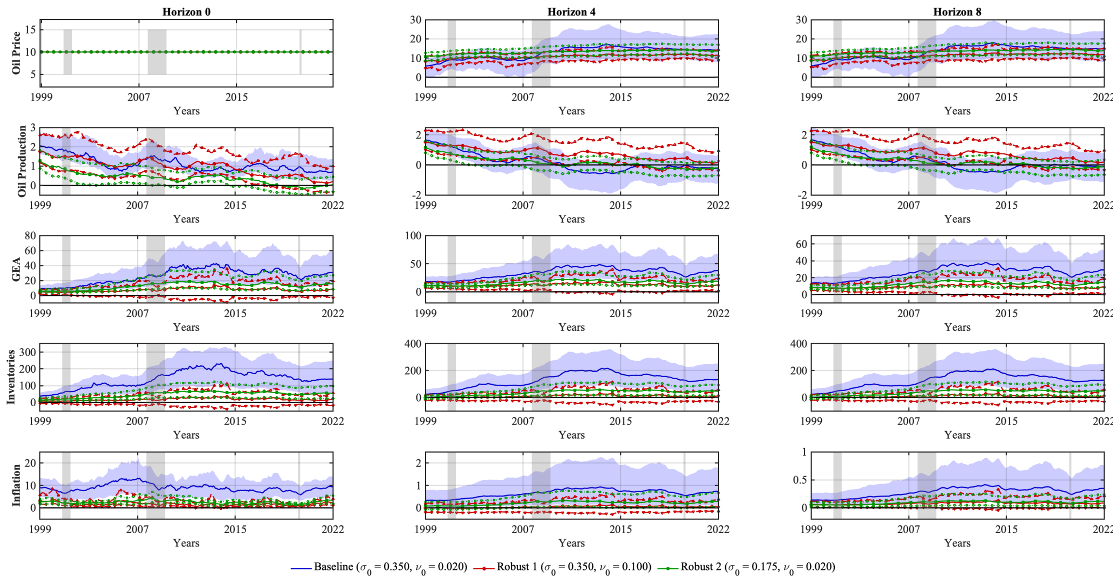
Note: The solid line indicates the mean contribution in the Kilian-type TVP-VAR model. The shaded area indicates the 68 percent posterior credible set. The vertical bars represent the recession periods for the United States as identified by the NBER.

(b) Inflation Rate- Impulse Response Function at Three Points in Time



Note: This figure shows the posterior median responses of the inflation rate for three episodes: 2016M12, 2021M04 and 2022M04. The solid blue line shows the responses for the Kilian-type TVP-VAR Model. Shaded areas indicate 68% posterior credible sets.

Figure 14: Posterior Median Response to the Oil News Shock - Kilian-type TVP-VAR Model. The Role of the Prior on the Proxy Variable.



Note: The figure shows impulse responses to a shock normalized to a 10 percent increase in crude oil prices. The baseline specification ($\sigma_0 = 0.350$, $\nu_0 = 0.020$) appears as a solid blue line with 68 percent posterior credible regions shown as shaded areas. Two robustness checks are displayed: the solid red line ($\sigma_0 = 0.350$, $\nu_0 = 0.100$) and solid green line ($\sigma_0 = 0.175$, $\nu_0 = 0.020$), both are posterior medians and dashed credible regions marked by circular and square markers, respectively. Vertical gray bars indicate NBER-identified U.S. recession periods.