

Three Essays on Oil Price and Macroeconomic Effects to United States

by

Subash Bhandari

A dissertation submitted to the Graduate Faculty of
Auburn University
in partial fulfillment of the
requirements for the Degree of
Doctor of Philosophy

Auburn, Alabama
August 8, 2026

Keywords: Oil Price, Oil Market Shock, Inflation, Shale Oil Production

Copyright 2026 by Subash Bhandari

Approved by

Hyeongwoo Kim, Chair, Patrick E. Molony Professor of Economics
Tannista Banerjee, Professor of Economics
Aditi Sengupta, Associate Professor of Economics
Gilad Sorek, Associate Professor of Economics

Abstract

This dissertation essay contains three chapters with empirical analysis on different factors affecting global crude oil price and their impact on the United States macroeconomy, with specific focus on supply side of the global oil market.

The first chapter, “How OPEC Oil Shocks Shape U.S. CPI Inflation: Evidence from an IV-SVAR Approach”, investigates the transmission of structural global oil market shocks to U.S. inflation using an IV-SVAR approach applied to highly disaggregated CPI components. We specifically utilize oil supply news shocks—market expectations of future OPEC production changes—and find that a news-driven 10% oil price increase triggers a significant 5% surge in headline inflation. Analyzing over 55 sectoral indexes reveals that these effects are heavily concentrated in energy-related goods, while other components remain muted or respond negatively. We identify consumer budget reallocation as a primary mitigating mechanism: households facing rising energy costs shift demand toward more affordable alternatives, such as used vehicles and food at home. By employing weak-instrument robust inference, this study demonstrates that headline inflation dynamics are driven by specific energy sub-components and adaptive consumer behavior rather than broad-based sectoral increases.

The second chapter, “The Effect of OPEC Shocks on Producer Prices in the United States”, examines how exogenous shocks originating from the Organization of Petroleum Exporting Countries (OPEC) influence U.S. producer prices. Using an instrumental variable structural vector autoregression (IV-SVAR) framework, I

distinguish between two types of shocks: oil supply shocks stemming from OPEC production disruptions caused by military or political events, and oil supply news shocks capturing changes in market expectations of future production following OPEC announcements. My empirical analysis suggests that both shocks significantly raise overall producer prices, primarily through higher fuel and power costs. The largest effects occur in energy-intensive industries such as chemicals and non-metallic minerals, as well as petrochemical sectors like rubber and plastics, while other sectors experience relatively muted impacts.

The third chapter, “Shale Boom and the Responsiveness of U.S. Oil Production to Global Oil Market Shocks” examines how U.S. oil production responds to oil market shocks in a structural vector autoregression (SVAR) framework. Using recursive setting, three oil market shocks are identified: flow supply shock, flow demand shock, and oil specific shock. My empirical analysis suggests that U.S. shale production is uniquely responsive, offsetting roughly one-fifth of the initial decline in non-U.S. output following a negative supply shock. Extending the analysis to aggregate production and rig counts from the seven major shale regions reveals qualitatively similar patterns, with drilling activity responding more rapidly than output. Additional evidence from drilling, completions, and drilled-but-uncompleted wells (DUCs) highlights the operational mechanisms underpinning production gains, while basin level estimates show that responses are concentrated in oil focused regions such as the Permian, Bakken, and Eagle Ford.

Artificial Intelligence (AI) Use Disclosure Statement

In the preparation of this dissertation, Artificial Intelligence (AI) tool ChatGPT was used for assistance. This tool was primarily used for providing grammatical and sentence structure corrections. The author acknowledges full responsibility for the intellectual content of this work and has ensured that all AI-assisted sections have been reviewed and revised for accuracy and appropriate academic style. All AI-generated content was reviewed and validated for relevance, appropriateness, and accuracy before incorporation into the final document to maintain the scholarly integrity of this research.

Digital Accessibility Use Disclosure Statement

In the preparation of this dissertation, the following digital accessibility tools were used to ensure this document complies with federal requirements: Adobe Acrobat Pro. The author acknowledges full responsibility for the intellectual content of this work and has made a good faith effort to comply with digital accessibility requirements in publishing, wherein the nature of the content does not significantly change in order to do so. Furthermore, all content has been reviewed and revised to meet these requirements prior to final publication.

Acknowledgments

As I reflect on my Ph.D. journey, I am deeply grateful to the many individuals whose guidance, encouragement, and unwavering support made this achievement possible. As a first-generation college graduate, this journey has been both professionally rewarding and personally transformative.

First and foremost, I would like to express my deepest gratitude to my advisor, **Dr. Hyeongwoo Kim**, for his exceptional mentorship, unwavering encouragement, and invaluable guidance throughout my doctoral studies. His support has profoundly shaped my growth as both a researcher and an educator.

I am sincerely grateful to my dissertation committee members, **Dr. Aditi Sengupta**, **Dr. Tannista Banerjee**, and **Dr. Gilad Sorek**, for their insightful comments, constructive feedback, and thoughtful guidance, all of which greatly strengthened this dissertation. I also extend my sincere thanks to **Dr. Samir Huseynov** for his careful review and valuable suggestions during the final preparation of this manuscript.

I would also like to thank the faculty, staff, and graduate students in the Department of Economics at Auburn University for fostering a supportive and intellectually stimulating environment. I am especially grateful to **Dr. Nicholas Ziebarth**, **Dr. Elahe Boskabadi**, **Dr. Dibyajyoti Sinha**, **Dr. Bibek Sapkota**, and **Mr. Pradip karki** for their friendship, encouragement, and for making my Ph.D. journey both enjoyable and memorable.

Finally, I extend my deepest gratitude to my family and friends for their unconditional love, unwavering encouragement, and constant belief in me. Their sacrifices, patience, and support sustained me throughout this journey, and this accomplishment is as much theirs as it is mine. I am especially grateful to my grandmother, **Shree Tulsa Devi Thapa**, whose constant encouragement and faith in me inspired me to pursue my dreams.

To everyone who has been a part of this journey, thank you. I will always be grateful for your kindness, generosity, and support.

Table of Contents

Abstract	2
Artificial Intelligence (AI) Use Disclosure Statement	4
Digital Accessibility Use Disclosure Statement	5
Acknowledgments	6
List of Tables	10
List of Figures	11
1 How OPEC Oil Shocks Shape U.S. CPI Inflation: Evidence from an IV-SVAR Approach	13
1.1 Introduction	13
1.2 The Empirical Model	17
1.2.1 The IV-SVAR Model	17
1.2.2 Identifying OPEC News Shocks	21
1.2.3 Instrumental Variables as Exogenous Shocks	22
1.2.4 Evaluating the Validity of the Instruments	24
1.2.5 Assessing Model Specification using Wald Statistics	26
1.3 Empirical Findings and Inferences	27
1.3.1 Baseline Model Estimations with Headline CPI Inflation	27
1.3.2 Impact on Major Expenditure Categories and Pass-through	29
1.3.3 The Substitution Effect	32

1.3.4	Choice of Alternative Oil Price Measure	34
1.3.5	Further Discussion: News Shock vs Supply Shock	35
1.4	Concluding Remarks	37
2	The Effect of OPEC Shocks on Producer Prices in the United States . .	41
2.1	Introduction	41
2.2	The Empirical Model	44
2.2.1	Econometric Framework	44
2.2.2	Empirical Model and Data Description	46
2.3	Empirical Findings and Inferences	48
2.3.1	Baseline Model Estimations with producer price index for all commodities	48
2.3.2	Impact on Major Aggregate Producer Prices	51
2.3.3	Further Evidence from Sectoral Producer Price Indexes . . .	51
2.4	Concluding Remarks	51
3	Shale Boom and the Responsiveness of U.S. Oil Production to Global Oil Market Shocks	55
3.1	Introduction	55
3.2	The Econometric Framework	60
3.2.1	Baseline Model	60
3.2.2	Impulse Response Function	63
3.2.3	Forecast Error Variance Decomposition	64
3.2.4	Data Description	65
3.3	Empirical Findings	66

3.3.1	Impact on the Components of Global Oil Production	66
3.3.2	Impact on Aggregate Production and Rig Counts in Major Shale Oil and Gas Regions	67
3.3.3	Impact on Operational Activities: Drilling, Completions, and DUCs	70
3.3.4	Further Evidence from Disaggregated Responses of Major Shale Oil and Gas Basins	74
3.4	Discussion	74
3.5	Conclusion	76
Appendices		86
A	Chapter 1	87
A.1	Disaggregated Response for Oil Supply News Shock	87
A.2	Supply vs News Shock	97
A.2.1	Assessing Model Specification using Wald Statistics	98
A.2.2	Baseline Model Estimations with Headline CPI Inflation	99
A.2.3	Impact on Inflation Rates of Major Expenditure Groups	102
A.2.4	Responses of Further Broken-Down CPI Components	106
B	Chapter 2	114
B.1	List of PPI Indexes (Source: FRED Database)	114
C	Chapter 3	115

List of Tables

1.1	Correlations between the IV Series and Structural Shocks	26
1.2	Validity of Weak-Instrument Robust Confidence Bands	27
1.3	Kernel Density Estimations (Summary Statistics)	36
3.1	Forecast Error Variance Decomposition of Components of Global Production to Oil Market Shocks	68
3.2	Oil and Natural Gas Production For Major Shale Oil and Gas Basins . .	76
A.1	Validity of Weak-Instrument Robust Confidence Bands	99
A.2	Kernel Density Estimations (Summary Statistics)	110

List of Figures

1.1	Shares of Global Oil Production	15
1.2	Instrumental Variable Series for Oil Supply and Oil News Shocks	24
1.3	Baseline Model Estimations with Headline CPI Inflation	28
1.4	Responses of Inflation Rates across Major Expenditure Groups	30
1.5	Change in Consumer Preference	33
1.6	Choice of Oil Price	39
1.7	Kernel-Based Distributions of Inflation Responses across Disaggregated CPIs	40
2.1	Baseline Model Impulse-Response Function Estimation Results	50
2.2	Responses of Major Aggregate Producer Price Indexes	52
2.3	Responses of Sectoral Producer Price Indexes	53
3.1	US Crude Oil Production	56
3.2	Response of Components of Global Oil Production to Oil Market Shocks	69

3.3	Response of Aggregate Production to Oil Market Shocks	71
3.4	Response of Different Stages of U.S. Oil Production to Oil Market Shocks	73
3.5	Response of Shale Oil Production to Supply and Oil Specific Demand Shock	75

Chapter 1

How OPEC Oil Shocks Shape U.S. CPI Inflation: Evidence from an IV-SVAR Approach

1.1 Introduction

In the post-pandemic era, the United States economy experienced unusually high inflation, peaking near 9% in June 2022—the highest level since the early 1980s. ¹This episode of rapid inflation coincided with a sharp rise in oil prices, as West Texas Intermediate crude increased by about 70% over the same period. The simultaneous surge in oil prices and inflation has renewed interest among both policymakers and academics in understanding the extent to which oil prices act as a driver of inflation.

A large body of literature examines this relationship, yielding mixed evidence on the influence of oil prices on inflation. On one hand, (Kilian and Zhou, [2022b](#)) and (Kilian and Zhou, [2022a](#)) find limited pass-through from gasoline prices to inflation expectations, with sizable short-run effects on headline inflation but much smaller effects on core inflation. On the other hand, (Aastveit et al., [2023](#)) argue

¹This chapter is coauthored with Dr. Hyeonwoo Kim.

that higher oil prices driven by global economic activity can have significant and persistent effects on both headline inflation and inflation expectations.

Much of the existing literature focuses on aggregate inflation measures, such as headline CPI, often overlooking sector-specific effects.² In contrast, (Gao et al., 2014) estimate the effects of oil price shocks on disaggregated CPI components in the United States, helping to uncover the transmission channels from structural oil price shocks to headline inflation. Building on this approach, we estimate the responses of various disaggregated inflation indices. Inspired by (Kilian, 2009), we further distinguish among the sources of oil price fluctuations, with particular attention to oil supply news shocks.

Specifically, we examine the inflationary effects of oil price movements originating from OPEC (Organization of Petroleum Exporting Countries), following studies such as (Caldara et al., 2019), (Almoguera et al., 2011), (Kilian, 2008), and (Hamilton, 2003).³ As shown in Figure 1.1, OPEC's historical share of global oil production has averaged about 38%. Despite the expansion of U.S. shale production in the 2000s, OPEC continues to exert significant influence on oil prices, accounting for roughly 35% of global output.

We employ an instrumental variable structural vector autoregression (IV-SVAR) approach, using external series as proxies for underlying structural shocks in the presence of strong endogeneity. See, among others, (Känzig, 2021), (Caldara

²Examples include (Conflitti and Luciani, 2019), (Conflitti and Cristadoro, 2018), (Binder, 2018), (Wong, 2015), (Venditti, 2013), (Clark and Terry, 2010), (Cologni and Manera, 2008), (Blanchard and Galí, 2007), (Doroodian and Boyd, 2003), (Barsky and Kilian, 2002), and (Hooker, 2002).

³Established in 1960, OPEC currently comprises 12 member nations: Algeria, Congo, Equatorial Guinea, Gabon, Iran, Iraq, Kuwait, Libya, Nigeria, Saudi Arabia, the UAE, and Venezuela.

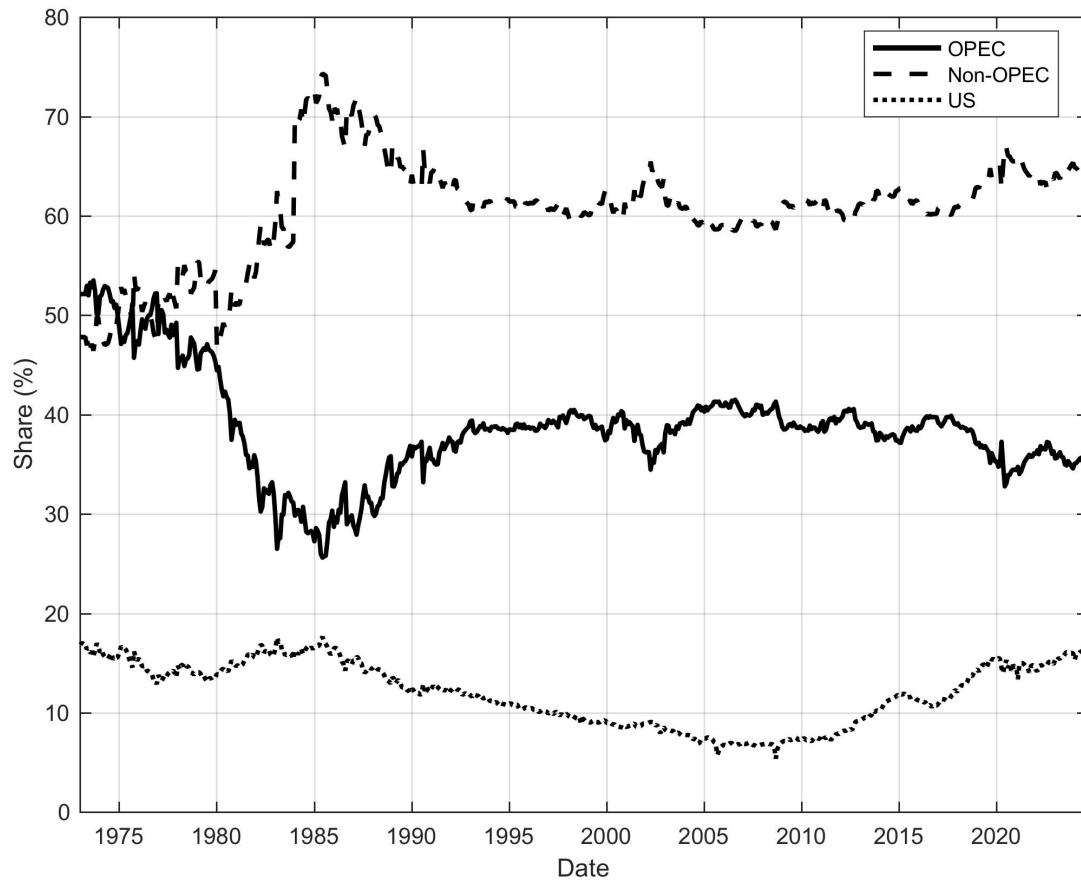


Figure 1.1: Shares of Global Oil Production

Note: Oil production data are obtained from Energy Information Agency (EIA) database, covering the period from January 1973 to September 2025.

et al., 2019), and (Arezki et al., 2017) for related approaches that rely on external instruments for causal interpretation. However, as emphasized by (Andrews et al., 2019), when instruments are weakly correlated with endogenous regressors, conventional IV estimation and inference can be unreliable. To address this concern and ensure the relevance and exogeneity of our instruments, we adopt

weak-instrument robust inference methods as recommended by (Montiel Olea et al., 2021).

Our analysis begins by examining the inflationary effects of oil supply news shocks using an instrumental variable that captures market anticipation of future production cuts, inferred from information in the oil futures market.⁴ Specifically, we use the series developed by (Känzig, 2021), which measures oil futures price movements in a narrow window around OPEC announcements and affects current prices through a supply-expectations channel. Because this series relies on high-frequency oil price fluctuations around announcement times, it helps isolate news shocks from contemporaneous supply and demand shocks.

Our empirical results indicate that news shocks raise oil prices without immediate changes in fundamentals, inducing a short-run increase in oil supply. A news shock that increases oil prices by 10% leads to an approximately 5% rise in headline inflation. The inflationary effects operate primarily through pass-through to energy-related goods—most notably gasoline and, to a lesser extent, electricity and natural gas services. Overall, news shocks generate front-loaded responses that are most pronounced at shorter horizons. We further complement our analysis by comparing these estimates with realized oil supply shocks identified using the instrumental variable series of (Kilian, 2008), based on production shortfalls among major OPEC producers and extended by (Bastianin and Manera, 2018).⁵

⁴The importance of this expectations channel for the business cycle is emphasized in (Arezki et al., 2017).

⁵This series treats actual production disruptions in OPEC countries due to political or military events as aggregate supply shocks—an approach also employed by (Hamilton, 2003), who used Middle East production shortfalls as an exogenous source of oil price fluctuations to assess their economic impact.

We also investigate why certain CPI components exhibit weak or even negative responses to OPEC-induced oil shocks. To this end, we discuss the role of consumer budget reallocation, building on (Baumeister et al., 2018). This mechanism provides an alternative explanation for the limited inflationary effects of oil price shocks, alongside the roles of monetary policy emphasized by (Blanchard and Galí, 2007) and inflation expectations highlighted by (Kilian and Zhou, 2022b) and (Kilian and Zhou, 2022a).

The remainder of the paper is organized as follows. Section 2 presents the IV-SVAR framework and discusses the validity of the instruments. Section 3 describes the data and reports the main findings with their interpretation. Section 4 concludes.

1.2 The Empirical Model

1.2.1 The IV-SVAR Model

Our main empirical model broadly follows the work of (Montiel Olea et al., 2021). Abstracting from deterministic terms, consider the following standard stationary VAR(p) process for $\mathbf{y}_t = [y_{1,t} \ y_{2,t} \ \dots \ y_{n,t}]'$.

$$\mathbf{y}_t = \sum_{i=1}^p \mathbf{A}_i \mathbf{y}_{t-i} + \mathbf{u}_t, \quad (1.1)$$

where $\mathbf{u}_t = \mathbf{0} \varepsilon_t$ is an $n \times 1$ vector of reduced-form innovations (forecast errors), ε_t is an $n \times 1$ vector of mutually orthogonal structural shocks, and $\mathbf{0}$ is an $n \times n$

non-singular contemporaneous matrix. That is,

$$\begin{aligned}\mathbb{E}[\varepsilon_t] &= \mathbf{0}_n, \quad \mathbb{E}[\varepsilon_t \varepsilon_t'] = \mathbf{D}_n = \text{diag}(\sigma_1^2, \sigma_2^2, \dots, \sigma_n^2), \\ \mathbb{E}[\mathbf{u}_t \mathbf{u}_t'] &= {}_0\mathbf{D}_{n0} =\end{aligned}$$

Assuming the covariance stationarity, $\mathbf{y}_t$ in equation (3.1) has the following infinite order vector moving average (VMA) representation based on the Wold Theorem.

$$\mathbf{y}_t = \sum_{k=0}^{\infty} \mathbf{C}_k(\mathbf{A})_0 \varepsilon_{t-k}, \quad (1.2)$$

where

$$\mathbf{C}_k(\mathbf{A}) = \begin{cases} \mathbf{I}_n & , k = 0 \\ \sum_{m=1}^k \mathbf{C}_{k-m}(\mathbf{A}) \mathbf{A}_m & , k > 0 \end{cases}$$

with $\mathbf{A}_m = \mathbf{0}_n$ when $m > p$.⁶

The k -period ahead Impulse-Response Function (IRF) of $y_{i,t}$ variable to a one-unit normalized structural shock to $\varepsilon_{j,t}$ is defined as follows.

$$\Phi_{k,i,j} = \mathbb{E}(y_{i,t+k} | \Omega_{t-1}, \varepsilon_{j,t} = 1) - \mathbb{E}(y_{i,t+k} | \Omega_{t-1}) = \mathbf{e}_i' \mathbf{C}_k(\mathbf{A})_0 \mathbf{e}_j, \quad (1.3)$$

where $\mathbf{e}_j$ denotes the selection vector that corresponds to the j^{th} column of identity matrix $\mathbf{I}_n$.

In this paper, we focus on estimating the IRFs only to the oil supply shock, denoted by $\varepsilon_{1,t}$, which is ordered first, that is, $\Phi_{k,i,1}$ from equation (1.3). Note that

⁶That is, $\mathbf{C}_0(\mathbf{A}) = \mathbf{I}_n$, $\mathbf{C}_1(\mathbf{A}) = \mathbf{A}_1$, $\mathbf{C}_2(\mathbf{A}) = \mathbf{A}_1^2 + \mathbf{A}_2$, $\mathbf{C}_3(\mathbf{A}) = \mathbf{A}_1^3 + \mathbf{A}_2 \mathbf{A}_1 + \mathbf{A}_1 \mathbf{A}_2 + \mathbf{A}_3$, and so on.

the estimates of $\Phi_{k,i,1}$ remain quantitatively identical even if the variables next to $y_{1,t}$, that is, $y_{j,t}$, for $j = 2, \dots, n$, are randomly re-ordered. See (Christiano et al., 1999a) for the proof.

Let $\mathbf{e}_{0,1}$ denote the first column of $\mathbf{e}_0$, that is, $\mathbf{e}_{0,1}$. To identify $\mathbf{e}_{0,1}$ via instrumental variable estimations, we consider a scalar random variable z_t as an instrumental variable for $\varepsilon_{1,t}$, which satisfies the following two conditions: $\mathbb{E}(z_t \varepsilon_{1,t}) = \alpha \neq 0$ (relevancy); $\mathbb{E}(z_t \varepsilon_{j,t}) = 0$ for $j \neq 1$ (exogeneity). Note that the first component of equation (3.1) can be rewritten as follows.

$$y_{1,t} = \mathbf{e}_{0,1}' \sum_{i=1}^p \mathbf{A}_i \mathbf{y}_{t-i} + \Theta_{0,1,1} \varepsilon_{1,t} + \sum_{j=2}^n \Theta_{0,1,j} \varepsilon_{j,t} \quad (1.4)$$

And we have the following $(n - 1)$ equations for the rest of the variables $y_{j,t}$,

$$y_{j,t} = \mathbf{e}_{j,1}' \sum_{i=1}^p \mathbf{A}_i \mathbf{y}_{t-i} + \Theta_{0,j,1} \varepsilon_{1,t} + \sum_{q=2}^n \Theta_{0,j,q} \varepsilon_{q,t}, \quad j = 2, 3, \dots, n \quad (1.5)$$

By solving for $\varepsilon_{1,t}$ from equation (1.4) after the scale normalization $\Theta_{0,1,1} = 1$ and substituting it into equation (1.5), we obtain the following.

$$y_{j,t} = \Theta_{0,j,1} y_{1,t} + \Xi_t, \quad (1.6)$$

where $\Xi_t = \sum_{i=1}^p \gamma_i \mathbf{y}_{t-i} + \sum_{q=2}^n \delta_{j,q} \varepsilon_{q,t}$. Note that $\{\Theta_{0,j,1}\}_{j=2}^n$ can be consistently estimated using instrumental variable regressions of $y_{j,t}$ on $y_{1,t}$, controlling for lags of $\mathbf{y}_t$, and employing z_t as an instrument under the relevancy and exogeneity assumptions, that is, $\mathbb{E}(z_t \varepsilon_{1,t}) = \alpha \neq 0$ and $\mathbb{E}(z_t \varepsilon_{j,t}) = 0$, $j = 2, \dots, n$.

From equation (1.3) for $j = 1$, the IRF $\Phi_{k,i,1}$ with $\Theta_{0,1,1} = 1$ (scale normalization) can be obtained by,

$$\Phi_{k,i,1} = \mathbf{e}_i' \mathbf{C}_k(\mathbf{A})_{0,1} = \mathbf{e}_i' \mathbf{C}_k(\mathbf{A}) / \mathbf{e}_1', \quad (1.7)$$

where $\mathbf{e}_i' = \mathbb{E}(z_t \mathbf{u}_t) = \mathbb{E}(z_{t0} \varepsilon_t) = \alpha_{0,1}$ and $\mathbf{e}_1' = \alpha$.⁷ One can obtain the IRF estimate $\hat{\Phi}_{k,i,1}$ by utilizing the least squares (LS) estimator for $\mathbf{A}$ and the sample covariance for between z_t and VAR residuals $\hat{\mathbf{u}}_t$.

In the presence of a strong instrument, confidence bands for $\hat{\Phi}_{k,i,1}$ can be obtained as usual via the δ -method or a bootstrap procedure. When z_t is a weak instrument, the normal approximation of the distribution of $\hat{\Phi}_{k,i,1}$ is known to be poor, implying poor coverage of the resulting confidence intervals. Hence, following (Montiel Olea et al., 2021), we employ the Anderson-Rubin confidence set, CS^{AR} , based on the work of (Anderson and Rubin, 1949), as a weak-instrument robust confidence set which yields asymptotically correct nominal coverage even when $\alpha_T \rightarrow \alpha = 0$.

Let $\hat{\mathbf{A}}$ and $\hat{\boldsymbol{\Lambda}}_T$ be the estimates for $\mathbf{A}$ and $\boldsymbol{\Lambda}$. Then $\hat{\mathbf{H}}_T$ is defined as the 2×1 vector of the numerator and denominator of the IRF estimator $\hat{\Phi}_{k,i,1}$ in equation (1.7) as follows.

$$\hat{\mathbf{H}}_T = \begin{bmatrix} \mathbf{e}_i' \mathbf{C}_k(\hat{\mathbf{A}}) \hat{\boldsymbol{\Lambda}}_T \\ \mathbf{e}_1' \hat{\boldsymbol{\Lambda}}_T \end{bmatrix}, \quad (1.8)$$

that is, $\hat{\Phi}_{k,i,1} = \hat{H}_{T,1} / \hat{H}_{T,2}$. Note that large sample approximation holds for $\hat{\mathbf{H}}_T$, $\hat{\mathbf{H}}_T \overset{a}{\sim} \mathcal{N}(\mathbf{H}_T, T^{-1})$. The null hypothesis $\hat{\Phi}_{k,i,1} = \Phi_{k,i,1}$ imposes a linear restriction:

⁷See (Stock and Watson, 2016) for more discussion on this normalization.

$H_{T,1} - \Phi_{k,i,1}H_{T,2} = 0$, yielding the following Wald statistic,

$$q_T(\Phi_{k,i,1}) = \frac{T(\hat{H}_{T,1} - \Phi_{k,i,1}\hat{H}_{T,2})}{\hat{\omega}_{T,1,1} - 2\Phi_{k,i,1}\hat{\omega}_{T,1,2} + \Phi_{k,i,1}^2\hat{\omega}_{T,2,2}}, \quad (1.9)$$

where $\hat{\omega}_{T,i,j}$ are the elements of the covariance matrix . Then, the Anderson-Rubin confidence set is defined as follows.

$$CS^{AR}(\Phi_{k,i,1}) = (\Phi_{k,i,1} | q_T(\Phi_{k,i,1}) \leq \chi_{1,1-a}^2), \quad (1.10)$$

where $\chi_{1,1-a}^2$ denotes the chi-square value with 1 degree of freedom for $(1 - a)$ level of significance.

1.2.2 Identifying OPEC News Shocks

Our baseline empirical models employ the structural vector autoregressive (SVAR) framework of equation (3.1) with the following.

$$\mathbf{y}_t = \begin{pmatrix} \mathbf{x}_t \\ inf_t \end{pmatrix}, \quad (1.11)$$

where we employ $\mathbf{x}_t = (\Delta rpo_t, \Delta prod_t, \Delta rea_t)'$ following (Känzig, 2021).⁸ Here, $\Delta prod_t$ denotes the percentage change in monthly global crude oil production, Δrea_t denotes percentage change in a measure of global economic activity, Δrpo_t represents percentage change in the real price of crude oil, and inf_t is a measure

⁸We conducted all estimations using 12 lags and an intercept. Results with alternative lags (6 and 24) are qualitatively similar and available upon request.

of inflation.⁹ The variables in $\mathbf{x}_t$ is motivated by (Kilian, 2009), which identifies three structural shocks in the oil market, including the oil supply shock and the aggregate demand shock.

The inclusion of inf_t allows us to estimate the responses of sectoral inflation measures to OPEC shocks. Our approach aligns with that of (Kilian and Park, 2009), which included U.S. stock market variables alongside $\mathbf{x}_t$ to investigate the impact of different oil market shocks on the U.S. stock market. We substitute it with over 55 different inflation indexes, both at aggregated and disaggregate levels, to trace the sources driving headline inflation movements. Following the recommendation of (Montiel Olea et al., 2021), we employ a weak-instrument robust Anderson-Rubin one-standard-deviation confidence interval.

1.2.3 Instrumental Variables as Exogenous Shocks

Our study employs an IV-SVAR framework to investigate the transmission channels of structural oil supply news shocks to U.S. headline CPI inflation, utilizing disaggregated sectoral CPI inflation responses. As a reference, this section also introduces the oil supply shock instrumental variable (IV) series and discusses their stochastic properties relevant to the qualifications of a valid instrumental variables.

⁹Data on global crude oil production, including lease condensate, is obtained from the EIA (U.S. Energy Information Administration) database. Global economic activity is measured using the extended industrial production index series for OECD (Organization for Economic Co-operation and Development) countries plus six other major economies, as provided in (Baumeister and Hamilton, 2019), and obtained from the author's webpage. West Texas Intermediate (WTI) crude oil price data and various inflation measures are obtained from the FRED (Federal Reserve Economic Data) database. Our baseline model specification follows (Baumeister and Hamilton, 2019), with all four variables log differenced and converted in percentage terms. Inflation measures are annualized. WTI spot price is converted into real terms by dividing monthly observations by the U.S. all-city average CPI (Consumer Price Index) and multiplying by 100.

The top two panels of Figure (1.2) illustrate the dynamics of the two IV series that identify the oil supply news shock and the oil supply shock originating from the OPEC. The news shock IV series, $z_{N,t}$, is obtained from (Känzig, 2021), covering July 1983 to December 2024. $z_{N,t}$ captures oil futures price variations in short windows after OPEC news conferences, leveraging immediate market reactions to identify exogenous news shocks.

The IV series for the oil supply shock, $z_{S,t}$, is obtained from (Bastianin and Manera, 2018), an extension of the original series by (Kilian, 2008), spanning from January 1973 to December 2013. This series reflects OPEC production short-falls from major geopolitical events that disrupted global oil output. It isolates exogenous supply shocks by identifying periods when production changes are uncorrelated with global demand, ensuring a valid external instrument for structural analysis.

The third panel presents the estimates for the normalized cross-correlations,

$$\rho_{SN}(j) = \frac{E(\tilde{z}_{S,t}\tilde{z}_{N,t+j})}{\sigma_{z_S}\sigma_{z_N}}, \quad j = -12, \dots, 0, \dots, 12,$$

where $\tilde{z}_{S,t}$ and $\tilde{z}_{N,t}$ are demeaned IV series, and σ_{z_S} and σ_{z_N} are their respective standard deviations. Although statistically insignificant, the cross-correlations between $z_{S,t}$ and $z_{N,t+j}$ turn out to be negative for the first 9 months ($j = 0, 1, \dots, 9$), suggesting that production quotas are enforced after the initial announcement of production cuts. Naturally, no particular pattern was observed in the correlation between the current supply shock and the lagged ($j < 0$) news shock.

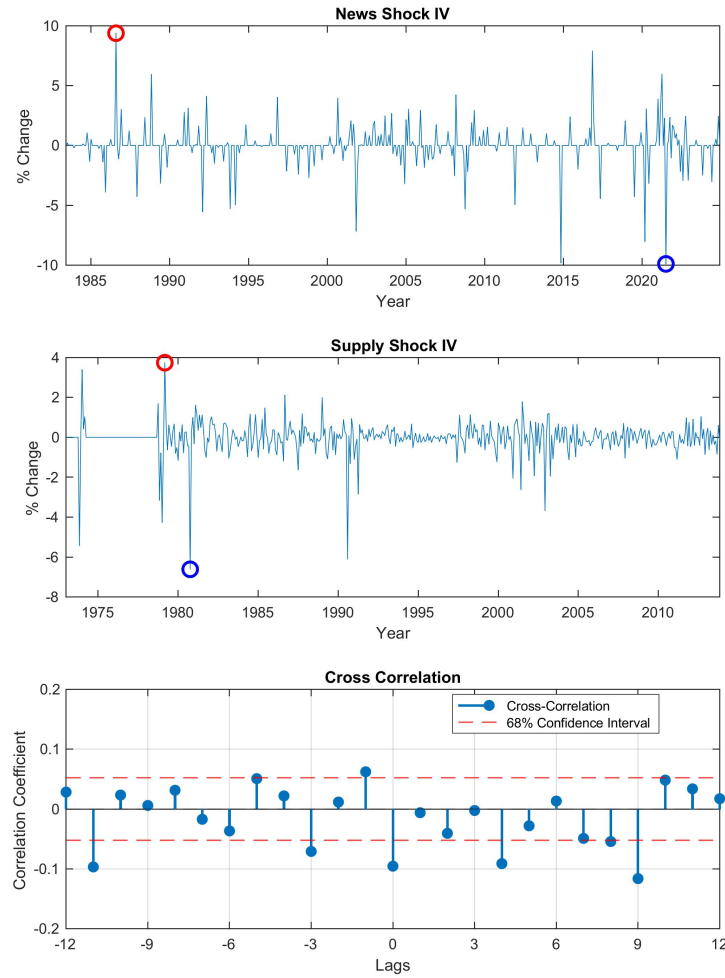


Figure 1.2: Instrumental Variable Series for Oil Supply and Oil News Shocks

Note: The top panel plots the extended version of IV series for the oil news shock of (Känzig, 2021), spanning from July 1983 to December 2024 taken from author's website. Second panel plots oil supply shock based on (Kilian, 2008), updated by (Bastianin and Manera, 2018), covering the period from January 1973 to December 2013 is obtained from the replication materials of (Känzig, 2021). The red bubble marks the highest value in the series, while the blue bubble marks the lowest value. The third panel shows the correlation between the two series over their common sample period, July 1983 to December 2013. Cross-correlations are computed relative to the news shock series; for example, positive lag values indicate correlations between the supply shock series and future values of the news shock series.

1.2.4 Evaluating the Validity of the Instruments

This section assesses the validity of the two instruments, $z_{S,t}$ and $z_{N,t}$, introduced in the previous section, following the recommendation in (Ramey, 2016) and (Stock and Watson, 2018).

We first investigate the relevancy and exogeneity assumptions via the contemporaneous correlations between each of the IV series, $z_{S,t}$ and $z_{N,t}$, and the estimated structural shocks obtained from (Kilian, 2009) and (Baumeister and Hamilton, 2019) as references. Specifically, we follow the specifications of (Kilian, 2009) to recursively estimate the oil supply shock, aggregate demand shock, and oil-specific demand shock, while using the updated series of the oil supply shock and aggregate demand shock from (Baumeister and Hamilton, 2019), which are obtained through a Bayesian approach. Results are reported in Table (1.1).

We note that the news shock IV series, $z_{N,t}$, shows a statistically significant positive correlation (0.13) with the oil-specific demand shock identified by (Kilian, 2009), while its correlations with oil supply shocks from (Kilian, 2009) and (Baumeister and Hamilton, 2019) are much weaker, at 0.04 and -0.06 , respectively and are not statistically significant.

On the other hand, the supply shock IV series, $z_{S,t}$, exhibits statistically significant correlations with the oil supply shock identified by (Kilian, 2009) and (Baumeister and Hamilton, 2019), at 0.12 and 0.17, respectively, whereas showing negligible, near-zero correlations with economic activity (demand) shocks.¹⁰ These results support the interpretation that $z_{N,t}$ primarily reflects oil futures price movements immediately following OPEC news conferences, thereby serving as a proxy for oil news shocks rather than contemporaneous supply shocks.

¹⁰We observe similar estimates when restricting to common sample from July 1983 to December 2013.

Table 1.1: Correlations between the IV Series and Structural Shocks

Model	Full Sample Period		Common Sample Period	
	$z_{N,t}$	$z_{S,t}$	$z_{N,t}$	$z_{S,t}$
(Kilian, 2009)				
Oil Supply Shock	0.04(0.43)	0.12*** (0.01)	0.05(0.35)	0.10* (0.06)
Economic Activity Shock	0.06(0.17)	−0.01(0.79)	0.14*** (0.01)	−0.10(0.86)
Oil Specific Shock	0.13*** (0.00)	−0.07(0.16)	0.15*** (0.00)	−0.09(0.11)
(Baumeister and Hamilton, 2019)				
Oil Supply Shock	−0.06(0.16)	0.17*** (0.00)	−0.08(0.11)	0.18*** (0.00)
Economic Activity Shock	−0.06(0.15)	0.02(0.71)	0.04(0.42)	−0.02(0.67)

Note: This table reports the contemporaneous Pearson correlation coefficient between the IV series and the structural oil market shocks identified by Kilian, 2009 and Baumeister and Hamilton, 2019. P-values are presented in parentheses for the null hypothesis of zero correlation. The full sample for news IV spans from July 1987 to December 2024. The full sample for supply IV spans from January 1976 to December 2013. The common sample period includes data from July 1983 to December 2013 for both series.

1.2.5 Assessing Model Specification using Wald Statistics

We next assess the validity of the weak-instrument robust confidence bands using the Wald statistics, ξ , suggested by (Montiel Olea et al., 2021), which implies that the $100\%(1 - \alpha)$ Anderson-Rubin (AR) confidence set $CS^{AR}(\Phi_{k,i,1})$ in equation (1.10) is bounded if and only if $\xi > \chi^2_{1,1-\alpha}$.¹¹ The results are reported in Table (1.2).

The news shock IV demonstrates very strong evidence in favor of well contained confidence bands. The Wald statistic for $z_{N,t}$ exceeds all conventional asymptotic critical values, with p -values below 1% regardless of the number of lags employed. In a nutshell, the Wald test indicates compact AR confidence bands at all conventional levels when the news shock IV is employed.

¹¹ $\xi = T\hat{\Gamma}_{T,1}^2/\hat{W}_{F,1,1}$ from $\sqrt{T}(\hat{\Gamma}_T - \Gamma_T) \xrightarrow{d} N(0, W_\Gamma)$

Table 1.2: Validity of Weak-Instrument Robust Confidence Bands

#Lags	$z_{N,t}$
6 lags	9.1 (0.00)
12 lags	9.5 (0.00)
24 lags	11.0 (0.00)

Note: We report Wald statistics, with p -values shown in brackets. The test statistics and corresponding critical values were computed following (Montiel Olea et al., 2021). The Wald statistics obey a chi-square distribution with one degree of freedom. The asymptotic critical values are 3.84, 2.71, and 0.99 for the 95%, 90%, and 68% confidence levels, respectively.

1.3 Empirical Findings and Inferences

This section presents the impulse-response function (IRF) estimates from equation (1.7), along with the one-standard-deviation Anderson-Rubin confidence intervals in equation (1.10). Since all variables are expressed as month-over-month percentage changes (inflation measures annualized), the IRFs are reported in cumulative form. We begin with the baseline model estimates, focusing on the response of headline CPI inflation to news shock IV ($z_{N,t}$). We then explore the propagation channels of these shocks by analyzing the responses of over 50 disaggregated CPI indexes.

1.3.1 Baseline Model Estimations with Headline CPI Inflation

Figure (1.3) presents the impulse response function estimates for the baseline IV-SVAR model with 12 lags, where headline CPI inflation (annualized) is ordered last as in equation (A.1). We use the West Texas Intermediate spot price of crude

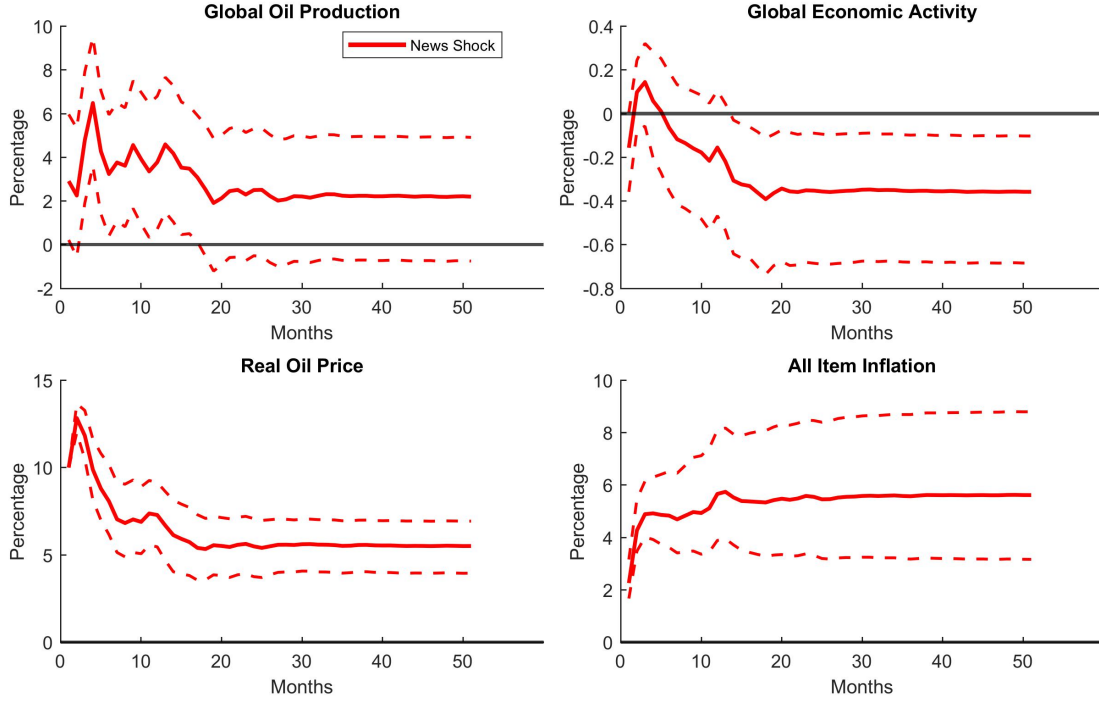


Figure 1.3: Baseline Model Estimations with Headline CPI Inflation

Note: We report the impulse-response function estimates from the IV-SVAR with 12 lags to the oil supply news shock $z_{N,t}$. Shocks are normalized to generate a 10% increase in the oil price on impact. The dashed lines are the 68% Anderson–Rubin confidence bands based on (Montiel Olea et al., 2021). The West Texas Intermediate price is used as the measure of crude oil price, and the Global Industrial Production Index of (Baumeister and Hamilton, 2019), obtained from the author’s website, is used as the measure of real economic activity. Oil price and inflation data are obtained from the FRED database, while global oil production data are taken from the EIA database. All four variables are expressed in log differences and converted to percentage terms, with inflation measures annualized (monthly percentage changes multiplied by 12). The updated IV series for the oil supply news shock is based on (Känzig, 2021) and obtained from the author’s GitHub repository. The sample period spans from July 1983 to December 2024.

oil, converted into real terms, as the measure of oil price. In a later section, we discuss the implications of other measures of oil price. The responses to the oil supply news shock $z_{N,t}$ is normalized to generate a 10% increase in the oil price

on impact, maintaining consistency with (Känzig, 2021), (Kilian and Zhou, 2022b), and (Kilian and Zhou, 2022a).¹²

The impulse response function of global oil production shows that when OPEC announces a production cut, interpreted as a news shock ($z_{N,t}$), oil production initially increases (positive growth rates). This response is driven by increased output from non-OPEC producers, who expand production in reaction to higher oil prices triggered by immediate adjustments in the oil futures market. However, over time, global oil production gradually slows and loses statistical significance.

In response to the oil news shock, oil prices increased by 13% after one month before subsequently declining. This estimated effect is consistent with the findings of (Känzig, 2021). The headline inflation rate rises in response to news shocks ($z_{N,t}$) produces a clearly significant positive pass-through to headline inflation. Moreover, oil supply news shocks exhibit recessionary effects, as shown by the responses of global industrial production which is statistically significant around 1 year later. Such recessionary dynamics likely influence the extent of pass-through to headline CPI inflation. Oil supply news shocks ($z_{N,t}$) shifts the supply curve of goods and services leftward due to rising oil prices.

1.3.2 Impact on Major Expenditure Categories and Pass-through

To identify the channels through which headline inflation responds, we examine the impulse responses of inflation across major expenditure categories, as shown in Figure (1.4). Several notable patterns emerge. First, the increase

¹²For our impulse response function estimation, we use MATLAB code from the replication files of (Montiel Olea et al., 2021), obtained from the author's GitHub repository.

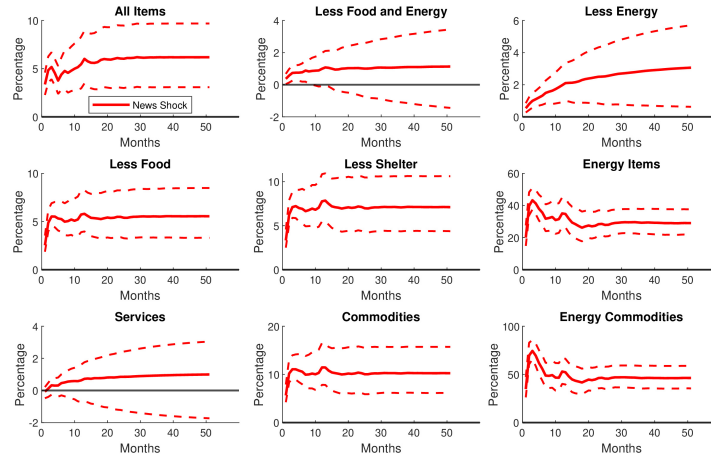


Figure 1.4: Responses of Inflation Rates across Major Expenditure Groups

Note: We report the impulse-response function estimates from the IV-SVAR with 12 lags to the oil supply news shock $z_{N,t}$. Shock is normalized to generate a 10% increase in the oil price on impact. The dashed lines are the 68% Anderson–Rubin confidence bands based on (Montiel Olea et al., 2021). The West Texas Intermediate price is used as the measure of crude oil price, and the Global Industrial Production Index of (Baumeister and Hamilton, 2019), obtained from the author's website, is used as the measure of real economic activity. Oil price and inflation data are obtained from the FRED database, while global oil production data are taken from the EIA database. All four variables are expressed in log differences and converted to percentage terms, with inflation measures annualized. The updated IV series for the oil supply news shock is based on (Känzig, 2021) and obtained from the author's GitHub repository. The sample period spans from July 1983 to December 2024.

in headline inflation is driven mainly by higher inflation in energy-related components. The point estimates for energy commodities are roughly an order of magnitude larger than those for overall inflation. In contrast, the inflationary effects become much smaller and statistically insignificant (or only marginally significant) once energy items are excluded from the consumer price index basket. For example, the impact on core inflation, which excludes food and energy, is approximately one percent, or about one-fifth of the effect on headline inflation. Similarly, the response of all items excluding energy is roughly half that of headline inflation, whereas indexes that continue to include energy, such as all items excluding food and all items excluding shelter, show responses that are similar in magnitude to headline inflation.

The third panel of Figure (1.4) further distinguishes the pass-through of shocks between services and commodities. Services display only minimal effects, consistent with their labor-intensive cost structure, whereas commodities show substantial responses driven by higher prices for energy-related items, including gasoline, electricity, and natural gas. These patterns raise the question of whether households, when confronted with oil news shocks and sharp increases in energy-related expenditures, adjust their consumption behavior by reducing spending on other categories.

1.3.3 The Substitution Effect

It is important to note that recessionary pressures may prompt consumers to adjust their spending behavior. Specifically, faced with budget constraints resulting from negative income shocks, driven by rising costs of necessities such as energy expenditures, consumers may need to reduce spending on certain items. This behavioral shift may lead to a leftward movement in the demand curve for these items. Consequently, the price impact on such goods and services may be muted. In the following sections, we present further evidence supporting these mechanisms.

Figure (1.5) provides evidence that households do, in fact, adjust their consumption behavior when confronted with higher gasoline costs. We observe a significant increase in the prices of electricity and natural gas services. Although the magnitude is smaller than the response of gasoline, it remains substantially larger than that of headline inflation. Given limited use of gasoline in electricity generation, this pattern suggests that households substitute a portion of their gasoline consumption with other energy sources that are relatively less expensive, causing significant increase in price of electricity and natural gas.

Second and third panel of Figure (1.5), provides additional evidence that consumers increase demand of relatively cheaper items. For example, the price increase of used cars and trucks is considerably larger than the increase in the price of new vehicles, indicating a shift toward more affordable transportation options. Similarly, the price of food consumed at home rises by more than the price of food

consumed away from home, consistent with households reallocating spending toward less costly forms of consumption.

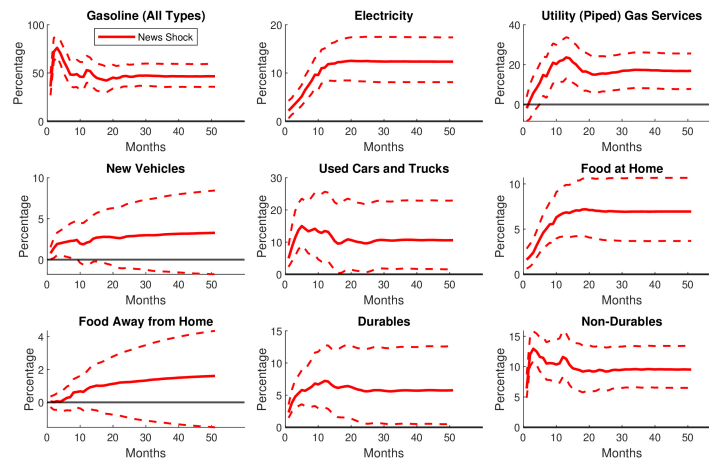


Figure 1.5: Change in Consumer Preference

While our overall findings are consistent with the conclusions of (Kilian and Zhou, 2022b) and (Känzig, 2021), that the primary transmission occurs through energy related items, we provide evidence that households reallocate spending away from more expensive items toward relatively more affordable alternatives

when budget constraints tighten due to higher gasoline prices. These findings collectively suggest that the overall effect on headline inflation is mitigated by such substitution behavior. Moreover, the results indicate that the impact of an oil supply news shock extends beyond the transportation sector. For example, increases in electricity and natural gas prices are transmitted to housing related categories and higher food prices, illustrating the broader reach of energy cost pressures within the consumption basket. Detailed results are presented in the Appendix A.

1.3.4 Choice of Alternative Oil Price Measure

In the preceding exercise, we examined the transmission mechanism using the West Texas Intermediate crude oil price. In this section, we investigate whether employing an alternative measure of oil prices materially alters the transmission mechanism. To this end, we replace the oil price variable in equation (A.1) with a gasoline price alternative, considering both measures in nominal and real terms.

Figure (1.6) highlights three key insights. First, the estimated impact is nearly twice as large when gasoline prices are used instead of West Texas Intermediate. Second, there is no discernible difference between nominal and real specifications. Third and most importantly, the overall pass-through remains similar for both gasoline and West Texas Intermediate prices. The primary transmission to headline inflation continues to operate through energy-related components, while the effects on core inflation remain limited.

1.3.5 Further Discussion: News Shock vs Supply Shock

While our main analysis uses the oil supply news shock to identify the transmission channel. This section further extends the analysis by comparing with the pass-through for the oil supply shock. To keep the comparison fair, we restrict the sample to the common period from July 1983 to December 2013. Figure (1.7) displays kernel density estimates of the inflation responses for 55 CPI components at the most disaggregated level. Complete estimations are presented in the Appendix section. We report the estimated distributions at four horizons: on impact (contemporaneous), 3 months (short run), 12 months (medium run), and 50 months (long run). The responses are shown separately for the OPEC supply shock ($z_{S,t}$) and the OPEC news shock ($z_{N,t}$). Corresponding summary statistics of these density estimates are provided in Table (1.3).

We note that the average inflation responses exceed the median responses across all horizons ($k = 0, 3, 12, 50$), indicating that the estimated distributions are right-skewed, a finding confirmed by the estimated skewness. In other words, positive inflation responses occur more frequently. Furthermore, all kurtosis estimates point to leptokurtic, that is, heavy-tailed distributions, implying substantial heterogeneity in the responses of disaggregated CPI components. Taken together with our earlier findings, this evidence suggests that the dynamics of headline CPI are not driven by the majority of the 55 disaggregated components, but rather are primarily attributable to energy-related sub-components.

On impact ($k = 0$), the median inflation responses to both shocks are centered around zero, although the distribution for $z_{N,t}$ is more tightly concentrated near

Table 1.3: Kernel Density Estimations (Summary Statistics)

k	$z_{S,t}$				$z_{N,t}$			
	0	3	12	50	0	3	12	50
Mean	0.20	0.83	0.74	0.62	0.27	0.79	0.66	0.49
Median	0.12	0.15	0.20	0.26	0.02	0.11	0.13	0.08
StdDev	0.55	2.09	1.80	1.60	0.72	1.85	1.38	1.16
Min	-0.84	-0.67	-1.16	-1.45	-0.49	-0.32	-0.35	-0.92
Max	2.19	8.67	6.80	5.88	2.92	7.17	6.06	4.69
Skewness	2.41	3.00	2.55	2.18	2.68	2.75	2.48	2.15
Kurtosis	9.64	11.02	8.64	7.55	9.44	9.29	8.53	7.35

Note: We employ the Epanechnikov kernel density estimator to characterize the k -month-ahead inflation responses of 55 CPI components at the most disaggregated level, where $k \in 0, 3, 12, 50$.

zero than that for $z_{S,t}$. At the same time, the news shock exhibits heavier right tails, accompanied by a larger standard deviation and higher skewness. As the horizon extends to the short run ($k = 3$), the cross-sectional dispersion widens for both shocks, with the mass of the distribution shifting modestly toward positive inflation rates, as reflected in higher means and medians. The median short-run effect rises from 0.12% to 0.15% for the supply shock and from 0.02% to 0.11% for the news shock. In the long run ($k = 50$), the median further increases from 0.20% to 0.26% for the supply shock, while the corresponding value for the news shock declines from 0.13% to 0.08%.

These results suggest that $z_{S,t}$ exerts more persistent effects, consistent with the characterization of $z_{N,t}$ as a front-loaded shock by (Känzig, 2021), whose effects are primarily observed at short horizons and dissipate relatively quickly.

1.4 Concluding Remarks

This paper examines how anticipated changes in oil supply conditions across OPEC countries affect U.S. headline CPI inflation by analyzing the responses of disaggregated CPI components using an IV-SVAR approach. We find that the substantial pass-through to overall CPI inflation is primarily driven by energy-intensive sectors, whereas contributions from other sectors—particularly non-necessities—remain relatively limited. Our findings highlight the importance of sector-specific inflation responses as a key propagation channel of oil market shocks, an aspect that has been somewhat overlooked in the existing literature.

This result raises an important question: why do not all sectors respond similarly to oil supply shocks, whether actual or anticipated? One possible explanation is that sector-specific demand conditions react differently to such shocks. Our analysis documents recessionary effects of oil supply shocks through declines in global real activity, which—by constraining consumer budgets—may reduce demand for non-essential goods and services and thereby dampen inflationary pressures in these sectors. This issue warrants further investigation in future research.

We also note that our analysis is based on a symmetric IV-SVAR model, even though our primary interest lies in the inflationary effects of negative supply shocks in the global crude oil market. Employing a nonlinear framework that distinguishes propagation channels based on the sign of the oil supply shock could yield more precise estimates. For instance, positive oil supply shocks may generate negligible inflationary responses relative to negative shocks, potentially due to downward

price rigidities. Accounting for such asymmetric dynamics could therefore produce sharper inference. We leave this promising avenue for future research.

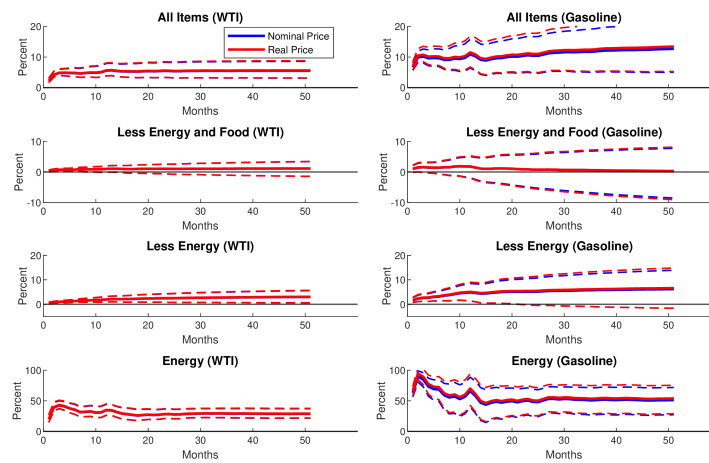


Figure 1.6: Choice of Oil Price

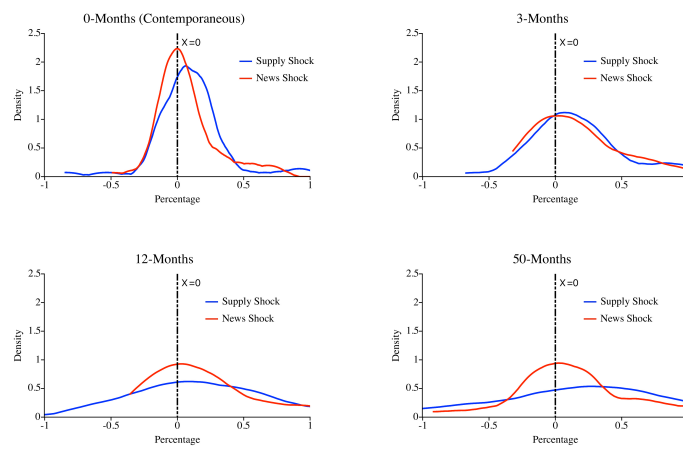


Figure 1.7: Kernel-Based Distributions of Inflation Responses across Disaggregated CPIs

Note: We employ the Epanechnikov kernel density estimator to characterize the k -month-ahead inflation responses of 55 CPI components at the most disaggregated level, where $k \in \{0, 3, 12, 50\}$. These responses are reported separately for the OPEC supply shock ($z_{S,t}$) and the OPEC news shock ($z_{N,t}$).

Chapter 2

The Effect of OPEC Shocks on Producer Prices in the United States

2.1 Introduction

Crude oil continues to play a pivotal role in international trade, serving as the primary energy source for transportation, a critical fuel for industrial and power generation activities, and an essential raw material for petrochemical production. In 2023, global crude oil trade reached approximately USD 1.28 trillion, or 5.6% of total world trade, with China as the largest importer and Saudi Arabia as the leading exporter (Observatory of Economic Complexity, OEC, 2025). Technological advancements in seismic imaging, hydraulic fracturing, and horizontal drilling have significantly boosted domestic production in the United States. According to the Energy Information Administration (EIA), the United States became a net exporter of petroleum in 2020 for the first time since 1949 and maintained this status for the third consecutive year in 2022.

There are numerous studies investigating the impact of oil market shock on producer prices. (Pradeep, [2022](#)) finds that diesel price deregulation in India in 2013 had a significant impact on oil shock propagation, asymmetry, and pass-through to wholesale diesel prices, retail diesel prices, food article prices, and

manufactured food prices. (Chen et al., [2020](#)) find that increase in oil prices driven by oil specific demand shocks is the most important cause of China's inflation at the import and production stages. (Chen and Zhu, [2021](#)) find significant inter industry differences in the effect of oil price shocks on industrial producer price index(PPI) for China as energy intensity is an important factor affecting the inter-industry differences in oil supply and oil-specific demand shocks. (Husaini et al., [2019](#)) find that oil price fluctuation have a much greater impact on producer prices compared to consumer prices for Malaysia.

In regards to the United States, there is a plethora of literature exploring the impact of oil price fluctuation on consumer price index but limited study exploring the impact of on PPI. According to Energy Information Agency, average petroleum consumption in the United States in 2023 was 20.3 million barrels per day. While transportation dominates consumption at 68%, industrial use accounts for a substantial 27%, reflecting its critical role in the economy. In particular, the petrochemical industry relies on petroleum as a feedstock to produce plastics, polyurethane, solvents, and numerous other intermediate and finished products.

(Gago and Vale, [2025](#)), which is most related to current study, analyze how oil price fluctuation influence inflation in France, Germany, Portugal, and the United States. Using an structural vector autoregression (SVAR) framework, authors find that oil supply, global demand, and oil-specific demand shocks have temporary inflationary effects, with producer prices exhibiting greater volatility compared to

consumer prices and oil specific demand shocks being the most influential. Furthermore, authors observe considerable heterogeneity in the magnitude of the responses to oil market shocks for individual countries.

This paper examines how oil price fluctuations influence U.S. producer prices with additional novelty. Firstly, I focus on OPEC (Organization of Petroleum Exporting Countries) as the source of oil price fluctuation. OPEC has been a significant player in global oil market with current market share of around 35%. Secondly, I use Instrumental variable structural vector autoregression to estimate the causal effect. I use two different instrumental variable series: the oil supply shock series of (Kilian, 2008) which is updated by (Bastianin and Manera, 2018), and oil supply news shock series of (Känzig, 2021). Supply shock series represents actual decline in oil production of OPEC countries due to military or political events whereas news shock represent fluctuation in oil price as a result of change in expectation about future production following OPEC announcement. Thirdly, I estimate the dynamic response at the disaggregated level which helps to elaborate transmission channel of oil shocks on producer prices.

The results of my empirical analysis suggests that both oil supply shock and oil supply news shock significantly raise overall producer prices, primarily through higher fuel and power costs. The largest effects occur in energy-intensive industries such as chemicals and non-metallic minerals, as well as petrochemical sectors like rubber and plastics, while other sectors experience relatively muted impacts. Additionally, the estimated effect on overall producer price index is much

higher than the corresponding effect on consumer price index reported in (Bhandari and Kim, 2025) indicating that oil price shocks have greater effect on producer side.

The remainder of the paper is organized as follows: Section 2 discusses the econometric framework, data, and model specification. Section 3 presents empirical findings and relates to existing literature. Section 4 concludes.

2.2 The Empirical Model

2.2.1 Econometric Framework

This section briefly discusses the instrumental variable structural vector autoregression (SVAR-IV) framework. I follow the econometric approach and notation in (Montiel Olea et al., 2021).¹

Abstracting from deterministic terms, let $\mathbf{y}_t = (y_{1,t}, y_{2,t}, \dots, y_{n,t})'$ denote an n -dimensional vector of endogenous variables governed by a stationary VAR(p) process:

$$\mathbf{y}_t = A_1 \mathbf{y}_{t-1} + \dots + A_p \mathbf{y}_{t-p} + u_t, \quad u_t \sim (0, \Sigma_u), \quad (2.1)$$

where u_t are reduced-form residuals with covariance matrix Σ_u .

¹A more detailed discussion on econometric framework, stochastic properties of the instrument series and their validity is available on (Bhandari and Kim, 2025) .

The structural representation links the reduced-form residuals to orthogonal structural shocks:

$$u_t = \Theta_0 \varepsilon_t, \quad \varepsilon_t \sim (0, I_n), \quad (2.2)$$

where ε_t are structural innovations and Θ_0 is the impact matrix.

Identification relies on an external instrument z_t , assumed to be correlated with the j -th structural shock of interest but orthogonal to all others. Formally, let

$$\Gamma = \mathbb{E}[z_t u_t] = \mathbb{E}[z_t \Theta_0 \varepsilon_t] \quad (2.3)$$

The instrument is assumed to satisfies two key assumptions:

1. **Relevance:** $\mathbb{E}[z_t \varepsilon_{j,t}] = \alpha \neq 0$, i.e., the instrument is correlated with the target structural shock.
2. **Exogeneity:** $\mathbb{E}[z_t \varepsilon_{k,t}] = 0$ for all $k \neq j$, i.e., the instrument is uncorrelated with non-target shocks.

The impulse-response function (IRF) of variable i at horizon h to a one-unit shock normalized on variable j is

$$\Phi_{h,i,j} = \mathbf{e}_i' C_h \Theta_0 \mathbf{e}_j = \frac{\mathbf{e}_i' C_h \Gamma}{\Gamma_j}, \quad (2.4)$$

where C_h are the reduced-form MA coefficients and $\mathbf{e}_j$ denotes the selection vector that corresponds to the j^{th} column of identity matrix $\mathbf{I}_n$.

Following (Montiel Olea et al., 2021), I employ the Anderson-Rubin confidence set, CS^{AR} , based on the work of (Anderson and Rubin, 1949), as a weak-instrument robust confidence set which yields asymptotically correct nominal coverage even when $\alpha_T \rightarrow \alpha = 0$.

The Wald statistic for testing a null $\Phi_{h,i,j} = \phi$ is

$$q_T(\phi) = \frac{T(\hat{H}_{T,1}^{(j)} - \phi \hat{H}_{T,2}^{(j)})^2}{\hat{\omega}_{T,11} - 2\phi \hat{\omega}_{T,12} + \phi^2 \hat{\omega}_{T,22}}, \quad (2.5)$$

where $\hat{\mathbf{H}}_T^{(j)} = [\mathbf{e}_i' C_h \hat{\Gamma}_T, \hat{\Gamma}_{T,j}]'$ and $\hat{\omega}_{T,ab}$ are the elements of its covariance matrix. The confidence set is

$$CS^{AR}(\Phi_{h,i,j}) = \{\phi : q_T(\phi) \leq \chi_{1,1-\alpha}^2\}. \quad (2.6)$$

2.2.2 Empirical Model and Data Description

Define the vector $\mathbf{y}_t$ as:

$$\mathbf{y}_t = \begin{pmatrix} \text{prod}_t \\ \text{rea}_t \\ \text{rpo}_t \\ \text{PPI}_{i,t} \end{pmatrix}. \quad (2.7)$$

where prod_t is monthly global crude oil production, rea_t measures global economic activity, rpo_t is the real price of crude oil, and $\text{PPI}(i, t)$ denotes a producer

price index of category “i”. The first three variables follow (Kilian, [2009](#)) and capture the global oil market, while the final variable is rotated across producer price indexes to investigate how oil market shocks propagate to wholesale prices. This approach parallels (Kilian and Park, [2009](#)), who used U.S. stock market variables instead of producer prices.

The crude oil production series, including lease condensate, comes from the EIA. Global economic activity is taken from the extended OECD+6 industrial production index of (Baumeister and Hamilton, [2019](#)), and both the WTI spot price and PPI series are drawn from the FRED database. The WTI spot price is converted into real terms by dividing monthly observations by the U.S. all-city average CPI and multiplying by 100. Following (Baumeister and Hamilton, [2019](#)), all variables are log-differenced and expressed in percentage terms, with producer price inflation reported in annualized units.

Shock identification relies on external instruments. The supply shock is normalized to reduce global oil production by 1%, whereas the news shock is normalized to raise the real oil price by 1%. For supply shocks, production is placed first in the VAR ordering, while for news shocks, oil price is placed first. Inference follows the weak-instrument robust Anderson–Rubin confidence interval approach of (Montiel Olea et al., [2021](#)), using a 68% confidence level. The baseline VAR includes 12 lags and an intercept.

2.3 Empirical Findings and Inferences

This section reports the impulse-response function (IRF) estimates from equation (2.4), together with the one-standard-deviation Anderson–Rubin confidence intervals in equation (2.6). I first present the baseline results, focusing on how the producer price index for all commodities (PPIACO) responds to the supply-shock instrument ($z_{S,t}$) and the news-shock instrument ($z_{N,t}$). I then investigate the transmission mechanisms to producer price index for all commodities by examining the responses of key production categories.

2.3.1 Baseline Model Estimations with producer price index for all commodities

The Wald statistic from equation (2.5) is estimated at 1.54 (p -value = 0.21) for the supply shock instrument, suggesting weak instrument. By contrast, the news shock instrument yields a Wald statistic of 10.42 (p -value = 0.00), indicating strong instrument. Importantly, both statistics exceed the critical value of 0.99, ensuring that the 68% Anderson–Rubin confidence intervals in equation (2.6) are bounded.

Figure (2.1) shows the impulse response functions from the baseline 12-lag IV-SVAR model, with the producer price index for all commodities (PPIACO) ordered last, as in equation (2.7). The first column displays the responses of $\mathbf{y}_t$ to the oil supply shock $z_{S,t}$, and the second column shows the responses to the oil

supply news shock $z_{N,t}$. For comparability, each shock is normalized to produce a 1% increase in the oil price on impact.²

While both supply shock $z_{S,t}$ and news shock $z_{N,t}$ cause a significant increase in oil price, they have quite different impact on global oil production. Supply shock $z_{S,t}$ which represents actual decline in OPEC production, results in partial recovery of global oil production with production level not recovering to pre-shock level. To the contrary, news shock $z_{N,t}$ which represents oil price increase without any immediate change in production, causes increase in global oil production reflecting increase in non-OPEC production responding to higher oil price. Similarly, the recessionary impact of supply shock is insignificant whereas news shock has statistically significant effect specially after 1 year.

The estimated effect of the oil supply shock $z_{S,t}$ on oil prices aligns with the findings of (Montiel Olea et al., 2021) and (Herrera and Rangaraju, 2020), while the effect of the news shock $z_{N,t}$ is consistent with (Känzig, 2021). Both shocks lead to economically and statistically significant increases in the producer price index for all commodities, exceeding the corresponding effects on the Consumer Price Index for All Urban Consumers (CPIAUCSL) reported in (Bhandari and Kim, 2025). This indicates that price increases on the production side are larger than on the consumer side, suggesting a potential reduction in demand for certain goods due to lower disposable income after higher oil prices.

²The contemporaneous impact of supply shock on oil price is 0.42. Therefore, the responses to oil supply shock are scaled by a factor of 1/0.42 to represent 1% increase in oil price.

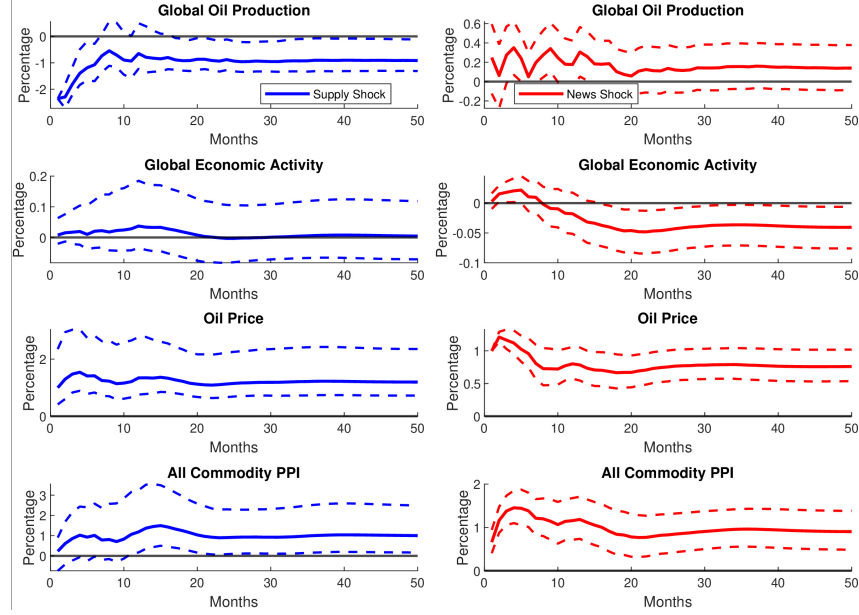


Figure 2.1: Baseline Model Impulse-Response Function Estimation Results

Note: I report the impulse-response function estimates from the IV-SVAR with 12 lags. The first column shows the responses of $\mathbf{y}_t$ to the oil supply shock $z_{S,t}$, while the second column shows the responses to the oil supply news shock $z_{N,t}$. Each shock is normalized to generate a 1% increase in the oil price on impact. The dashed lines are the 68% Anderson–Rubin confidence bands based on (Montiel Olea et al., 2021). The West Texas Intermediate price is used as the measure of crude oil price, and the Global Industrial Production Index of (Baumeister and Hamilton, 2019), obtained from the author’s website, is used as the measure of real economic activity. Oil price and producer price index for all commodities (PPIACO) data are obtained from the FRED database, while global oil production data are taken from the EIA database. All four variables are expressed in log differences and converted to percentage terms, with inflation measures annualized. The IV series for the oil supply shock is based on (Kilian, 2008), updated by (Bastianin and Manera, 2018), and the IV series for the oil supply news shock is based on (Känzig, 2021). Both IV series are obtained from the replication materials of (Känzig, 2021). The sample period spans from July 1983 to December 2013.

2.3.2 Impact on Major Aggregate Producer Prices

Figure (2.2) presents the estimated impact on major aggregate producer price indexes. The first panel of the figure shows that the impact on industrial commodities is similar to all commodities reported in the baseline model. Both supply shock $z_{S,t}$ and news shock $z_{S,t}$ causes a significant increase in industrial commodities although the confidence interval for supply shock $z_{S,t}$ are larger compared to news shock $z_{S,t}$. The second panel clearly demonstrates that the major impact of supply shock $z_{S,t}$ and news shock $z_{S,t}$ is via disproportionate increase in fuel and power cost. On the contrary, the effect on industrial commodities excluding fuel is insignificant or marginally significant (news shock $z_{S,t}$).

2.3.3 Further Evidence from Sectoral Producer Price Indexes

Figure (2.3) presents the impact of major industries. Driven by higher fuel and power costs, energy intensive items like chemical products and non metallic minerals as well as petrochemical products like rubber and plastic see the greatest increase in price whereas items like lumber and wood production, and machinery and equipment are less affected. The impact on textile and apparel items, and furniture and durable items are moderate.

2.4 Concluding Remarks

This paper examines how exogenous shocks originating from the Organization of Petroleum Exporting Countries (OPEC) influence U.S. producer prices.

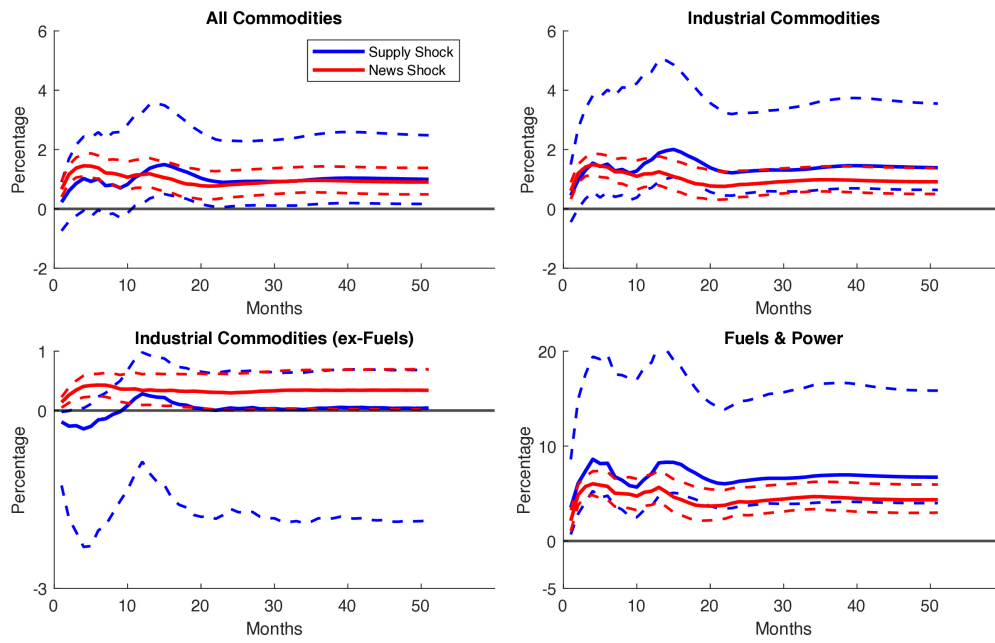


Figure 2.2: Responses of Major Aggregate Producer Price Indexes

Note: I report the responses of the major aggregate producer price indexes. The blue lines depict the responses to the oil supply shock ($z_{S,t}$), while the red lines correspond to the responses to the oil supply news shock ($z_{N,t}$). Each shock is normalized to generate a 1% increase in the oil price on impact. The dashed lines represent the 68% Anderson–Rubin confidence bands, following (Montiel Olea et al., 2021). The sample period covers July 1983 to December 2013.

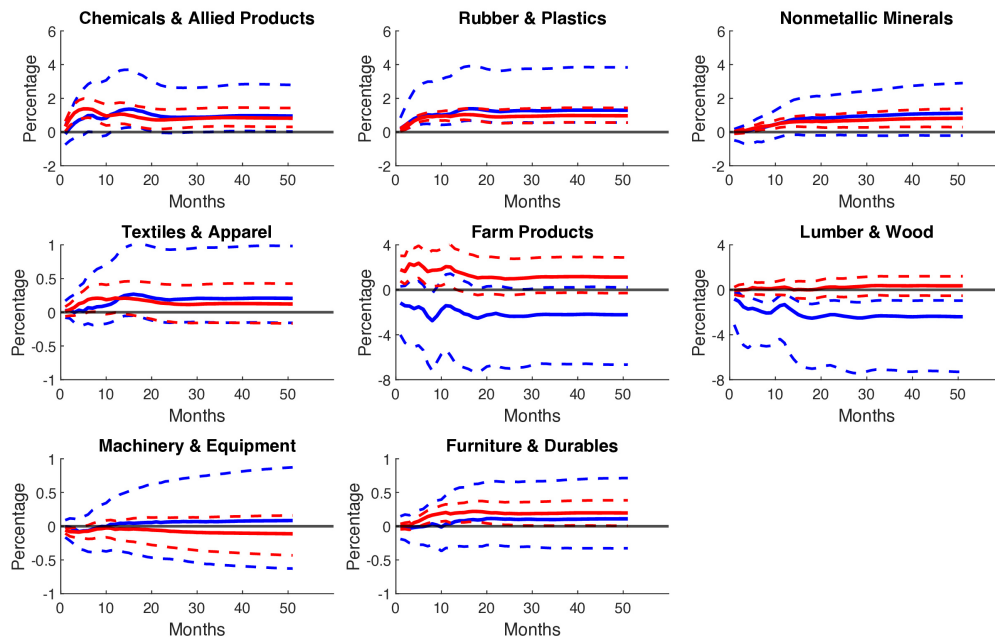


Figure 2.3: Responses of Sectoral Producer Price Indexes

Note: I report the responses of sectoral aggregate producer price indexes. The blue lines depict the responses to the oil supply shock ($z_{S,t}$), while the red lines correspond to the responses to the oil supply news shock ($z_{N,t}$). Each shock is normalized to generate a 1% increase in the oil price on impact. The dashed lines represent the 68% Anderson–Rubin confidence bands, following (Montiel Olea et al., 2021). The sample period covers July 1983 to December 2013.

Using an instrumental variable structural vector autoregression (IV-SVAR) framework, I distinguish between two types of shocks: oil supply shocks stemming from OPEC production disruptions caused by military or political events, and oil supply news shocks capturing changes in market expectations of future production following OPEC announcements. I employ weak instrument robust confidence interval of (Montiel Olea et al., [2021](#)).

My empirical analysis suggests that both shocks significantly raise overall producer prices, primarily through higher fuel and power costs. The largest effects occur in energy-intensive industries such as chemicals and non-metallic minerals, as well as petrochemical sectors like rubber and plastics, while other sectors experience relatively muted impacts. Additionally, I observe a significant increase the producer price index for all commodities (PPIACO), exceeding the corresponding effects on the Consumer Price Index for All Urban Consumers (CPIAUCSL) reported in (Bhandari and Kim, [2025](#)), indicating that the overall price increase in production side is greater than consumer side. Different factors like mark up in domestic market, the volume of international trade, and decline in demand of non-essential items from domestic consumers could help explain these findings. I leave these interesting discussions for future work.

Chapter 3

Shale Boom and the Responsiveness of U.S. Oil Production to Global Oil Market Shocks

3.1 Introduction

U.S. oil production has expanded sharply in recent decades, driven by technological advances in seismic imaging, horizontal drilling and hydraulic fracturing, which enable the extraction of oil from low-permeability rock formations, commonly referred to as shale or tight oil. Unlike conventional oil, which flows easily through vertical wells in permeable reservoirs, shale oil is produced by injecting a high-pressure mixture of water, sand, and chemicals into shale rock to create fissures that release trapped hydrocarbons. These innovations have propelled the United States to become one of the world's largest oil producers, leading to the repeal of the decades-long petroleum export ban in 2015 and transforming the U.S. into a net oil exporter by 2020. As shown in Figure (3.1), crude oil output rose from about 5 million barrels per day in the mid-2000s to approximately 13 million in 2023, with tight oil accounting for 8.32 million barrels per day, roughly 64% of the total production according to the Energy Information Administration (EIA).

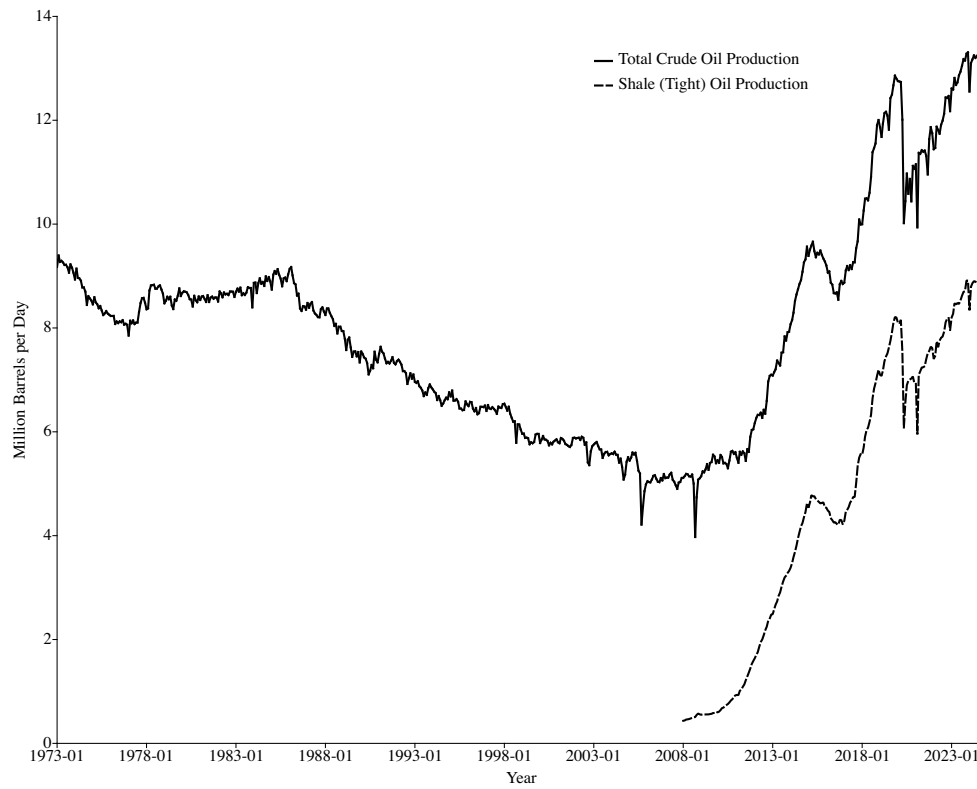


Figure 3.1: US Crude Oil Production

*Note:*Source: Energy Information Administration (EIA), 2025

A growing literature examines both the impact of the shale oil boom on global oil prices and the responsiveness of shale production to price fluctuations. (Bornstein et al., [2023](#)), using microdata from roughly 14,000 oil fields in 109 countries, find that shale production is highly responsive to oil price due to its relatively low extraction costs, about one-fifth that of conventional production. Their structural model, embedded in a general equilibrium framework, suggests that fracking has

weakened the market power of the Organization of Petroleum Exporting Countries (OPEC), contributing to lower oil prices and reduced price volatility in the long run.¹

Another strand of research considers the macroeconomic effects of the shale boom. (Bjørnland and Skretting, 2024), using a time varying parameter factor augmented vector autoregressive (FAVAR) model with state-level and industry-level U.S. data, show that oil-specific shocks increase investment, income, industrial production, and non-oil employment in many oil producing and manufacturing intensive states, effects absent before the shale boom. Similarly, (Kang et al., 2016) distinguish between U.S. and non-U.S. oil production and find that U.S. real stock returns respond positively to increases in domestic production.

(Kellogg, 2011) characterizes oil production by relating oil producers, usually large oil companies with extraction license, and drilling firms operating on contractual agreements with the oil companies. (Kellogg, 2014) investigates how oil companies make decision to drill new wells with respect to uncertainty in oil price. Drilling new wells represents a significant sunk cost and potential risk as not all wells drilled leads to production, and furthermore, not all productions are economically feasible specially when oil prices are low. (Shakya et al., 2022) focus on the information spillover between oil price and drilling activities. Using connectedness indices based on VARs, they find that since the shale boom in the U.S., drilling activities have become more responsive to oil price variations.

¹See also (Anderson et al., 2018), (Bjørnland et al., 2021), (Foroni and Stracca, 2023), (Kilian, 2016), (Newell and Prest, 2019), and (Storrøsten, 2024) for further discussion.

The broader literature on oil market dynamics builds on (Kilian, 2009), who identified three distinct sources of oil price fluctuations: flow supply shocks, aggregate demand shocks, and oil specific shocks. While some studies ((Kilian and Murphy, 2014), (Aastveit, 2014)) emphasize the dominance of demand shocks, others ((Baumeister and Hamilton, 2019), (Caldara et al., 2019)) attribute a larger role to supply shocks. Various approaches have been employed to identify structural shocks, including recursive identification ((Kilian, 2009)), sign restrictions ((Kilian and Murphy, 2014), (Baumeister and Hamilton, 2015)), Bayesian methods ((Baumeister and Hamilton, 2019)), and instrumental variable techniques ((Arezki et al., 2017), (Känzig, 2021)).

This paper examines how U.S. oil production responds to oil market shocks in a structural vector autoregression (SVAR) framework. I employ short-run restrictions, following (Kilian, 2009) recursive setting, and identify three oil market shocks: flow supply shock, flow demand shock, and oil specific shock.² My novelty is to distinguish global oil production into three separate components: U.S. shale, U.S. conventional, and the rest of global production. (Anderson et al., 2018) highlight that oil production by conventional method is less responsive because oil extraction from vertical wells is limited by reservoir pressure which declines over time whereas (Bornstein et al., 2023) find that non-conventional oil production is much for responsive to oil price fluctuations.

I identify three different oil market shocks: flow supply shock, flow demand shock, and oil specific shock. Flow supply shocks represent unanticipated change

²See (Kilian et al., 2025) and (Kilian, 2022b) for recent discussions on the merits of recursive identification of global oil market shocks.

in global oil production excluding domestic production in the United States. Unanticipated change on the current demand for crude oil driven by fluctuations in the global business cycle is defined as flow demand shock. And unexpected fluctuation in oil price that is not attributable to either flow supply shock or flow demand shock is identified as oil specific demand shock. The analysis extends the framework to examine aggregate production and drilling activity in major U.S. shale regions as well as operational measures such as drilling and completions, and disaggregated basin level responses, providing a comprehensive view of U.S. production dynamics in the global oil market.

My empirical analysis show that U.S. shale production is the most responsive component of global output, offsetting roughly one-fifth of the initial decline in non-U.S. production following a negative flow supply shock. In contrast, U.S. conventional and non-U.S. production display muted and statistically insignificant adjustments. Drilling activity reacts more strongly and immediately than production, indicating that future supply expansion is initiated quickly after flow supply shocks. Basin level analysis reveals that these effects are concentrated in oil dominant regions such as the Permian, Bakken, and Eagle Ford, while gas focused basins exhibit little to no response. Moreover, the buildup of drilled-but-uncompleted wells (DUCs) following flow supply shocks highlights the role of operational flexibility in smoothing production over time.

The remainder of the paper is organized as follows: Section 2 describes the econometric framework and data. Section 3 presents the empirical findings, Section 4 discusses the results and policy implications, and Section 5 concludes.

3.2 The Econometric Framework

3.2.1 Baseline Model

I extend (Kilian, 2009) framework by differentiating global oil production into three components: U.S. conventional production, U.S. shale production, and rest of global production.

Let, $Y_t = (\Delta prod_{RoW,t}, rea_t, rpo_t, \Delta prod_{U.S.}, \Delta prod_{U.S.Shale,t})'$, where $\Delta prod_{RoW,t}$ is percentage change in global oil production excluding U.S., $\Delta prod_{Conv,t}$ is percentage change in conventional oil production in U.S., and $\Delta prod_{U.S.Shale,t}$ is percentage change in U.S. shale oil production. Similarly, rea_t denotes a measure of global aggregate demand for all industrial commodities including oil and rpo_t represents real price of crude oil. First three variables represent global oil market while last two represent domestic production.

Assuming standard stationary finite order SVAR and omitting constant term without the loss of generality, the reduced-form VAR(p) representation is,

$$Y_t = A_1 Y_{t-1} + A_2 Y_{t-2} + \dots + A_p Y_{t-p} + \eta_t \quad (3.1)$$

where, Y_t and η_t are $n \times 1$ vectors of VAR variables and reduced-form VAR innovations respectively. A_i 's are coefficient matrix for lag components.

The structural VAR representation is,

$$B_0 Y_t = B_1 Y_{t-1} + B_2 Y_{t-2} + \dots + B_p Y_{t-p} + \epsilon_t, \quad (3.2)$$

where, B_0 is contemporaneous coefficient matrix, B_i 's are coefficient matrix for the lag terms and ϵ_t are mutually uncorrelated structural shocks.

Assuming invertibility of structural model, the reduced-form VAR innovations are related to the vector of structural shocks, ϵ_t as: $\eta_t = \Theta_0 \epsilon_t$, where structural impact multiplier matrix Θ_0 is a nxn non-singular matrix. Structural shocks are further assumed to be serially and mutually uncorrelated, with $E(\epsilon_t) = 0$ and $E[\epsilon_t \epsilon_t'] = D = \text{diag}(\sigma_1^2, \sigma_2^2, \dots, \sigma_n^2)$. Then covariance matrix for the reduced form innovation is, $E[\eta_t \eta_t'] = \Sigma = \Theta_0 D \Theta_0'$.

Cholesky factor decomposition postulates structural Vector autoregression of B_0^{-1} according to $\eta_t = B_0^{-1} \epsilon_t$. Note that $B_0^{-1} = \theta_0$ in this case.

$$\eta_t \equiv \begin{pmatrix} \Delta \text{prod}_{RoW,t} \\ \eta_t^{rea} \\ \eta_t^{rpo} \\ \eta_t^{\Delta \text{prod}_{U.S. Conv}} \\ \eta_t^{\Delta \text{prod}_{U.S. Shale}} \end{pmatrix} = \begin{bmatrix} b_{11} & 0 & 0 & 0 & 0 \\ b_{21} & b_{22} & 0 & 0 & 0 \\ b_{31} & b_{32} & b_{33} & 0 & 0 \\ b_{41} & b_{42} & b_{43} & b_{44} & 0 \\ b_{51} & b_{52} & b_{53} & b_{54} & b_{55} \end{bmatrix} \begin{pmatrix} \epsilon_t^{\text{Flow Supply Shock}} \\ \epsilon_t^{\text{Flow Demand Shock}} \\ \epsilon_t^{\text{Oil Specific Shock}} \\ \epsilon_t^{\text{Residual Shock 1}} \\ \epsilon_t^{\text{Residual Shock 2}} \end{pmatrix}. \quad (3.3)$$

As global oil production excluding U.S. is ordered first, this model postulates a vertical short-run supply curve which means that global oil production excluding U.S. does not respond to other shocks within a month i.e., ($b_{12} = b_{13} = 0$). This assumption is supported by (Anderson et al., 2018), (Bjørnland et al., 2021), (Foroni and Stracca, 2023), (Kumar and Mallick, 2024), (Newell and Prest, 2019). (Anderson et al., 2018) highlight that oil production by conventional method is less

responsive because oil extraction from vertical wells is limited by reservoir pressure which declines over time. Similarly, (Foroni and Stracca, 2023) find that while U.S. oil supply has been more responsive to price, it has minimal impact on global oil supply which is almost vertical.

Similar to (Kilian, 2009), (Hamilton, 2009), and (Bjørnland and Skretting, 2024), I assume that global economic activity does not respond to oil specific shock within a month. i.e., ($b_{23} = 0$). Furthermore, I assume that oil price is predetermined with respect to U.S. economic variables following (Kilian and Vega, 2011). (Bjørnland and Skretting, 2024), (Kilian and Park, 2009) among others use similar assumption when investigating the impact of oil market shocks on U.S. economy. Finally, I order U.S. shale production last in the VAR framework to represent that it is more responsive than U.S. conventional oil production.

Equation 3.3 follows recursive ordering to identify three different shocks: flow supply shocks, flow demand shocks, and oil-specific shocks. Flow supply shocks represent unanticipated change in global oil production excluding U.S. Unanticipated change on the current demand for crude oil driven by fluctuations in the global business cycle is defined as flow demand shock. And unexpected fluctuation in oil price that is not attributable to either flow supply shock or flow demand shock is identified as oil specific demand shock.

In order to explore the impact of above discussed shocks on regional production in the U.S., I extend to the baseline model by replacing last two variables in vector auto regression (VAR) framework. It is important to note that the econometric inferences from recursively identified VAR model may be susceptible to

alternative ordering of the variables. However, (Christiano et al., 1999b) show that impulse response functions can be invariant when the location of shocking variable is fixed. Therefore, the ordering of first three variables are fixed which is supported by (Kilian et al., 2025) and (Kilian, 2022a).

3.2.2 Impulse Response Function

Structural moving average (MA) representation for Y_t is given by,

$$Y_t = \sum_{k=0}^{\infty} C_k(A) \theta_0 \epsilon_{t-k}, \quad (3.4)$$

where moving average coefficient $C_k(A)$ is related to autoregressive coefficient $A = (A_1, A_2, \dots, A_p)$ as $C_k(A) = \sum_{m=1}^k C_{k-m}(A) A_m$, $k=1,2,\dots$ with $C_0(A) = I_n$ and $A_m = 0$ for $m > p$.

The k -step ahead structural impulse response coefficient is the response of $Y_{i,t+k}$ to one unit-change in $\epsilon_{j,t}$ at time t .

$$\frac{\partial Y_{i,t+k}}{\partial \epsilon_{j,t}} = e_i' C_k(A) \Theta_0 e_j \quad (3.5)$$

where e_j denotes the j th column of Identity matrix I_n .

Equation (5) represents impulse response coefficient as a function of MA coefficients, structural impact multiplier matrix with indicators that assigns relevant shock and VAR variables.

3.2.3 Forecast Error Variance Decomposition

While IRFs provide insight about the causal impact of a shock, another practically important question is the degree of forecast error variance or prediction mean squared error (MSPE) of Y_{t+h} at horizon $h = 0, 1, \dots, H$ accounted for by each structural shock $\epsilon_{j,t}$, $j = 1, \dots, n$.

The h -step ahead forecast error is given by:

$$Y_{t+h} - \mathbb{E}_t[Y_{t+h}] = \sum_{i=0}^{h-1} C_i(A)\Theta_0\epsilon_{t+h-i} = \sum_{i=0}^{h-1} \Theta_i\epsilon_{t+h-i}, \quad (3.6)$$

where $\Theta_i = C_i(A)\Theta_0$.

Then, the total MSPE of the k -th variable in Y_t at horizon h is:

$$\text{MSPE}_k(h) = \sum_{j=1}^n \text{MSPE}_{kj}(h) = \sum_{j=1}^n (\theta_{kj,0}^2 + \dots + \theta_{kj,h-1}^2), \quad (3.7)$$

where $\theta_{kj,i}$ is the (k, j) -th element of Θ_i .

The relative contribution of the j -th structural shock to the forecast error variance of the k -th variable at horizon h is given by:

$$\frac{\text{MSPE}_{kj}(h)}{\text{MSPE}_k(h)}. \quad (3.8)$$

Summing across all shocks,

$$1 = \sum_{j=1}^n \frac{\text{MSPE}_{kj}(h)}{\text{MSPE}_k(h)}. \quad (3.9)$$

By multiplying each ratio by 100, percentage contribution of each structural shock to the forecast error variance of each variable in Y_t at a given horizon h is obtained. This decomposition provides insight into the relative importance of each identified shock in driving forecast uncertainty over different horizons.

3.2.4 Data Description

Monthly oil production data (in Million Barrels a day) is taken from the Energy Information Administration (EIA) database. Similarly, refinery Acquisition Cost for crude oil is taken from EIA database. Nominal oil price is converted into real terms using Consumer Price Index for All Urban Consumers: All Items (CPIAUCSL) also taken from FRED database. As a proxy for aggregate demand in global industrial commodity markets including oil, I use (Kilian, [2009](#)) index from FRED database which is derived from a panel of dollar-denominated global bulk dry cargo shipping rates and is expressed in percent deviations from long-term trend. Additional data on regional production is based on Drilling Productivity Report from EIA.

All variables except for aggregate demand are log differentiated. I use VAR(24) models and an intercept for all my estimations. Error bars are for 68% confidence interval. The confidence intervals were constructed using wild bootstrap. Calculations are based on 5,000 iterations. Monthly data spans 2008M01:2024M12.

3.3 Empirical Findings

This section presents the key empirical results. I begin by analyzing impulse response functions (IRF's) of global oil production to three different shocks recursively identified from Equation 3.5. Flow supply shocks represent unanticipated change in global oil production excluding U.S.. Flow demand shock represents unanticipated change on the current flow demand for crude oil driven by fluctuations in the global business cycle. Unexpected fluctuation in oil price that is not attributable to either flow supply shock or flow demand shock is identified as oil specific demand shock. I complement with forecast error variance decomposition (FEVD) from Equation 3.9. I then extend the analysis to regional production in U.S..

All shocks are normalized to increase oil price. Flow supply shock is normalized to decrease global oil production excluding U.S. by 1%. Flow demand shock is normalized to increase global economic activity by 1%. Oil specific shock is normalized to increases oil price by 1%.

3.3.1 Impact on the Components of Global Oil Production

Figure (3.2) displays the dynamic responses of U.S. shale production, U.S. conventional production, and the rest of global oil production to oil market shocks discussed earlier. U.S. shale production responds most strongly, increasing by approximately 4 percent two years after a flow supply shock. Given shale's average share of global output is slightly over 5% for the sample period, this rise

compensates for about one-fifth of the initial decline in non-U.S. production. By contrast, neither conventional U.S. production nor global output outside the U.S. show statistically significant increases, highlighting shale's key role as a stabilizing force. Oil specific shocks also elicit the largest growth in shale production with slightly front heavy response, whereas conventional and global non-U.S. production exhibit more modest but qualitatively similar responses.

The forecast error variance decomposition in Table (3.1) further corroborates these findings. Flow supply shocks dominate short-run variation in shale production (around 33% at horizon 1 and 25% at long run) while other two shocks become increasingly influential over longer horizons (14% for flow demand shock and 18% for oil specific shock). For non-U.S. production, supply shocks account for nearly all short-term fluctuations but give way to flow demand shocks and oil specific shock over time. U.S. Conventional production is comparatively less affected by supply shocks and more sensitive to flow demand shocks and oil specific shock throughout the horizon.

3.3.2 Impact on Aggregate Production and Rig Counts in Major Shale Oil and Gas Regions

I next explore the joint dynamics of production and drilling activity. I estimate a five-variable structural VAR model in which the last two variables (U.S. shale and conventional production) in the baseline model are replaced by aggregate oil production and total rig counts summed across the seven major shale oil and gas production regions identified in the Energy Information Administration's

Table 3.1: Forecast Error Variance Decomposition of Components of Global Production to Oil Market Shocks

Horizon (Months)	Percent of h-Step Ahead Forecast Error Variance Explained by:			
	Flow Supply Shock	Flow Demand Shock	Oil Specific Shock	Residual Shock
Rest of Global Oil Production				
1	100	0.0	0.0	0.0
2	88.7	2.0	3.5	5.8
3	73.8	3.2	14.2	8.8
6	60.6	13.7	14.0	11.8
12	48.4	14.3	15.0	22.2
∞	28.5	19.4	19.7	32.3
U.S. Conventional Oil Production				
1	5.9	2.3	0.6	91.2
2	6.6	5.4	2.9	85.0
3	6.5	5.6	4.5	83.4
6	9.7	11.1	4.3	75.0
12	12.8	8.5	10.4	68.3
∞	14.2	18.8	15.2	51.7
U.S. Shale Oil Production				
1	32.5	0.0	0.8	66.7
2	44.2	3.7	5.5	46.6
3	41.6	3.8	7.8	46.8
6	37.6	6.5	9.0	47.0
12	39.7	10.6	10.7	39.0
∞	25.3	13.8	18.4	42.5

Note: Entries show forecast error variance decomposition (percent) across horizons from a 5-variable SVAR model. Monthly data from 2008M01 to 2024M04.

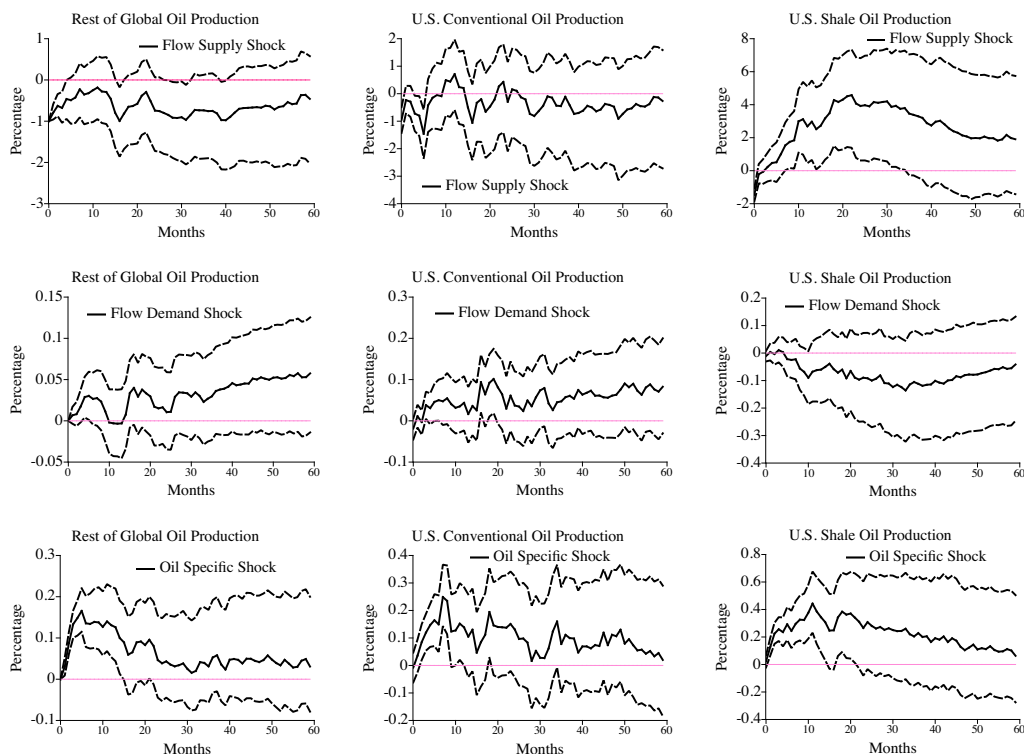


Figure 3.2: Response of Components of Global Oil Production to Oil Market Shocks

Note: Results are for SVAR(24) with intercept for three structural shocks identified by Equation 3.3. First panel shows the responses to flow supply shock normalized to decrease rest of global oil production excluding U.S. by 1%. Second panel shows the responses to flow demand shock normalized to increase global economic activity by 1%. Third panel shows the response to oil specific shock that increases oil price by 1%. First column shows the response of rest of global oil production. Second column shows the response of U.S. conventional oil production. Third column shows the response of U.S. shale oil production. Errors are for 68% confidence interval. The confidence intervals were constructed using wild bootstrap. Calculations are based on 5,000 iteration. Monthly data spans 2008M01:2024M04.

Drilling Productivity Report.³ While this combined production measure does not distinguish between shale and conventional output, the model captures the joint dynamics of aggregate regional production and drilling activity. Since rigs count

³The seven shale regions are Anadarko, Appalachia, Bakken, Eagle Ford, Haynesville, Niobrara, and Permian.

represents the machinery to start the drilling process, it therefore represents future production expansion possibility.

First panel in Figure (3.3) shows that the response of total oil production is qualitatively similar to U.S. shale oil production in the baseline model. There is a significant increase in oil production for flow supply shock and oil specific shock. Oil specific shock elicit more immediate response whereas flow supply shock causes gradual increase in production. Naturally, as this production measure includes both conventional oil as well as shale oil, the magnitude of the response are numerically smaller compared to baseline model.

Second panel shows much greater and immediate increase in rigs count, which increases future production possibility. Similar to production, the effects are significant for flow supply shock and oil specific shock whereas flow demand shock has minimal impact.

3.3.3 Impact on Operational Activities: Drilling, Completions, and DUCs

In order to examine the mechanisms behind the aggregate production responses, I estimate a six-variable structural VAR model where first three variables of global oil market are arranged similar to baseline model with three additional variables: new wells drilled, wells completed, and drilled-but-uncompleted wells (DUCs).⁴ These measures provide a more detailed view of the supply side adjustment process and the timing between drilling activity, completions, and realized production.

⁴As the sample is restricted to observations since January 2014, I use shorter lag length of 12 months.

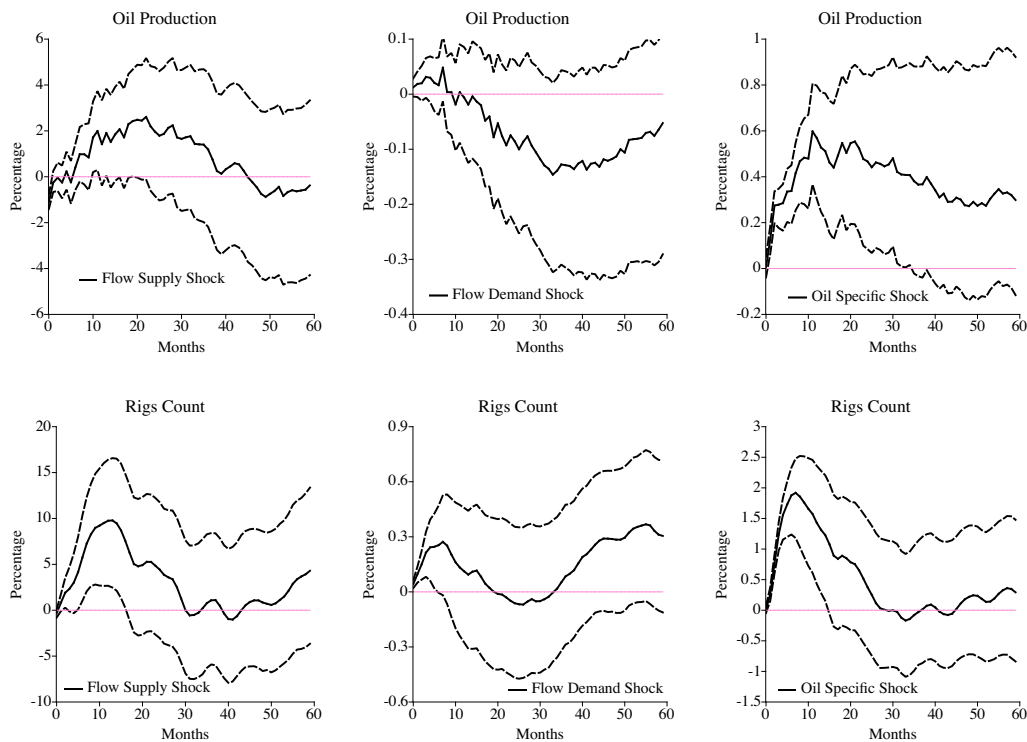


Figure 3.3: Response of Aggregate Production to Oil Market Shocks

Note: Results are for SVAR(24) with intercept for structural shocks identified by Equation 3.3. Figure shows the response of oil production and rigs count, collectively, for seven oil basins (Anadarko, Appalachia, Bakken, Eagle Ford, Haynesville, Niobrara and Permian) based on Drilling Productivity Report from Energy Information Agency (EIA). First column shows the responses to flow supply shock normalized to decrease global oil production excluding U.S. by 1%. Second column shows the responses to flow demand shock normalized to increase global economic activity by 1%. Third column shows the response to oil specific shock normalized to increase oil price by 1%. Errors are for 68% confidence interval. The confidence intervals were constructed using wild bootstrap. Calculations are based on 5,000 iteration. Monthly data spans 2008M01:2024M04.

The impulse responses in Figure (3.4) indicate that flow supply shocks produce the largest and most persistent increases in drilling and completions, both peaking roughly one year after the shock. Drilling rises more sharply than completions, leading to a buildup of DUC inventories that store productive capacity

and support gradual production gains. Oil specific shocks generate moderate increases in drilling and completions with minimal effects on DUCs, while flow demand shocks have negligible effects on all three measures. These results suggest that sustained production gains from flow supply shocks are driven by substantial expansions in drilling and completion activity, with DUCs serving as a buffer that smooths the realization of output over time.

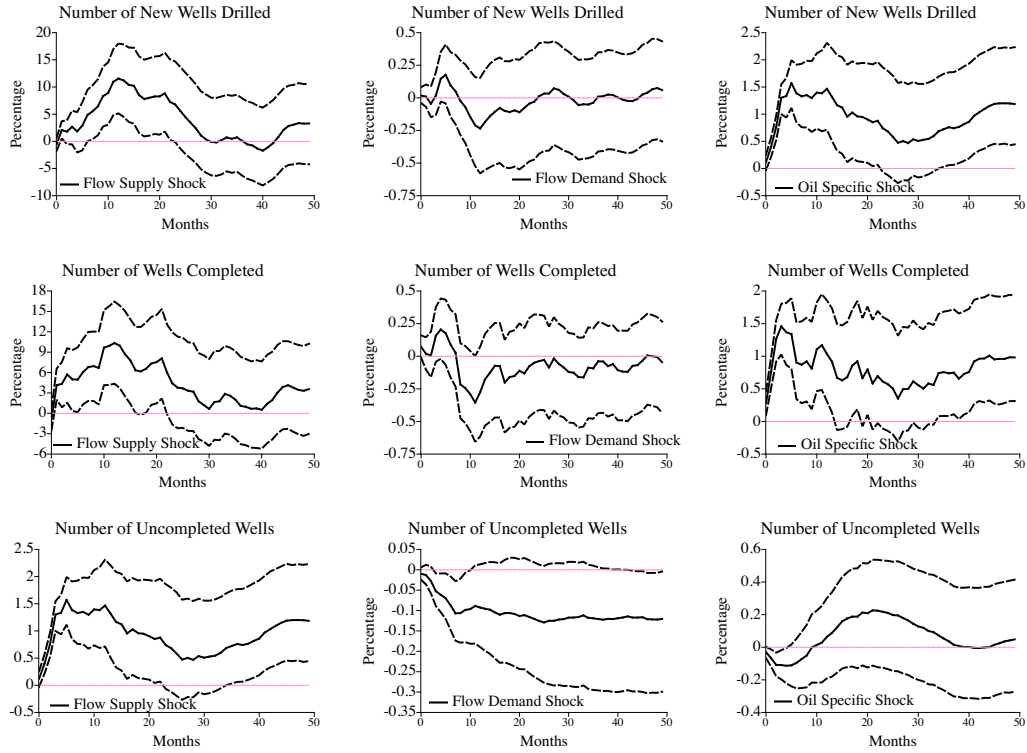


Figure 3.4: Response of Different Stages of U.S. Oil Production to Oil Market Shocks

Note: Results are for SVAR(12) with intercept for three structural shocks identified by Equation 3.3. First column shows the responses to flow supply shock normalized to decrease rest of global oil production excluding U.S. by 1%. Second column shows the responses to flow demand shock normalized to increase global economic activity by 1%. Third column shows the response to oil specific shock that increases oil price by 1%. First panel shows the response of new wells drilled. Second panel shows the response of U.S. conventional oil production. Third column shows the response of U.S. shale oil production. Errors are for 68% confidence interval. The confidence intervals were constructed using wild bootstrap. Calculations are based on 5,000 iteration. Monthly data spans 2014M01:2024M04.

3.3.4 Further Evidence from Disaggregated Responses of Major Shale Oil and Gas Basins

To assess regional heterogeneity, I analyze oil production in the seven major shale basins reported in the Drilling Productivity Report. Table (3.2) shows their distinct production profiles. The Permian Basin leads with over 6 million barrels per day of oil, alongside substantial natural gas output. Similarly, Bakken and Eagle Ford are primarily oil focused with lower gas-to-oil ratios. Appalachia and Haynesville are predominantly gas producing, as reflected in their high gas-to-oil production ratios.

Using a five-variable structural VAR specification analogous to Section 3.2, I estimate production and rig count responses separately for each basin. The impulse responses in Figure (3.5) reveal that response of aggregate production is predominantly driven by oil focused regions. Both flow supply shocks and oil specific shocks cause significant increase in production for Permian, Bakken, and Eagle Ford while the gas dominant Appalachia and Haynesville exhibit negligible changes.

3.4 Discussion

Empirical analysis consistently show that U.S. shale production is the most responsive component of global oil supply, adjusting sharply to flow supply shock

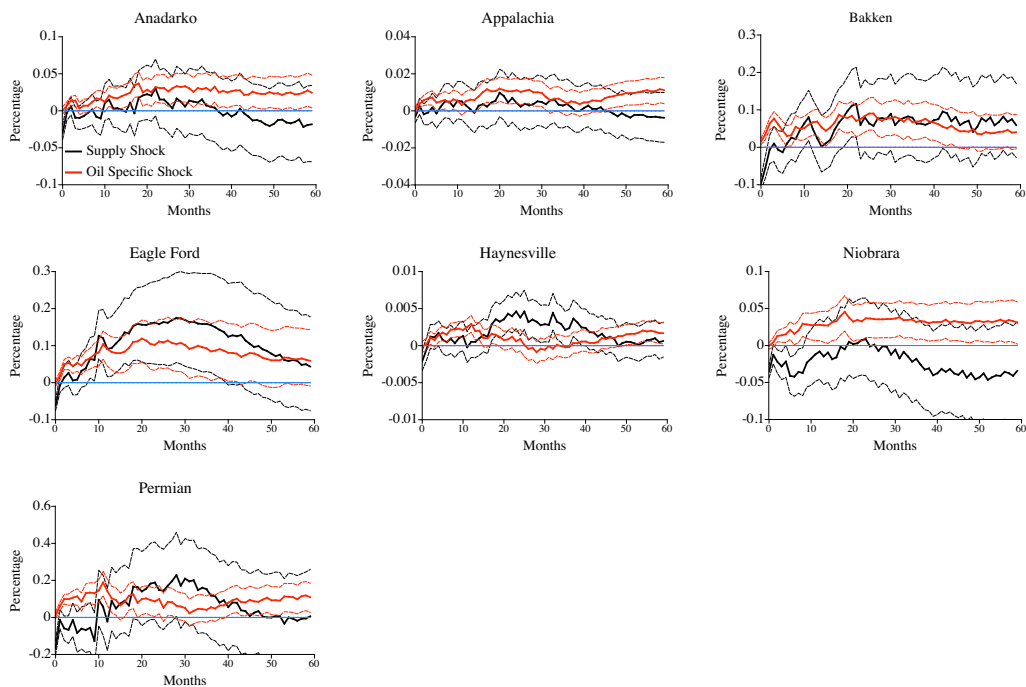


Figure 3.5: Response of Shale Oil Production to Supply and Oil Specific Demand Shock

Note: Results are for SVAR(24) with intercept for four structural shocks identified by Equation 3.3. Flow supply shock normalized to decrease global oil production excluding U.S. by 1%. Oil specific demand shock is normalized to increase oil price by 1%. Errors are for 68% confidence interval. The confidence intervals were constructed using wild bootstrap. Calculations are based on 5,000 iteration. Monthly data spans 2008M01:2024M04.

and oil specific shocks, while conventional U.S. output and the rest of global production remain relatively unresponsive. This responsiveness enables U.S. producers to offset a significant portion of non-U.S. production losses. Extending the analysis to combined production and rig counts from the seven major shale regions reveals similar qualitative patterns, with rig activity rising immediately after flow supply shock and oil specific shock. The strong and rapid drilling response highlights the forward-looking nature of investment in productive capacity.

Table 3.2: Oil and Natural Gas Production For Major Shale Oil and Gas Basins

Region	Oil Production (million bbl/d)	Natural Gas Production (million Mcf/d)	Ratio
Anadarko	0.38	6.54	17.20
Appalachia	0.14	36.10	264.80
Bakken	1.31	3.45	2.60
Eagle Ford	1.10	7.37	6.70
Haynesville	0.03	15.82	483.70
Niobrara	0.71	5.37	7.60
Permian	6.16	25.11	4.10

Note: Regional production figures are for April, 2024 based on Drilling Productivity Report from the Energy Information Agency. Oil production is represented in million barrels per day. Natural gas production is represented in billion cubic feet per day. Ratio represents the ratio of natural gas production to oil production.

Operational measures further clarify the adjustment mechanism: flow supply shocks drive sustained increases in drilling and completions, with the initial drilling surge leading to a buildup of drilled-but-uncompleted well inventories that smooths production gains over time. Basin level estimates confirm that these aggregate effects are concentrated in oil focused regions, particularly the Permian, Bakken, and Eagle Ford while gas dominant regions such as Appalachia and Haynesville contribute little to the overall response. Together, the findings underscore that both production composition and operational capacity are central to the resilience of U.S. oil output in the face of global market disruptions.

3.5 Conclusion

This paper applies a Structural Vector Autoregression (SVAR) with short-run restrictions to quantify the responsiveness of U.S. oil production to global oil market shocks. I extend (Kilian, 2009) framework by distinguishing global oil production into U.S. shale, U.S. conventional, and the rest of global output. I identify

three different shocks: flow supply shocks, flow demand shocks, and oil-specific shocks. My empirical analysis with impulse response functions (IRFs) and forecast variance decomposition (FEVD) offers a comprehensive view of U.S. supply dynamics. I also extend the framework to aggregate and basin level production and drilling activity for major shale regions. These findings highlight the strategic value of maintaining flexible and scalable U.S. production capacity. Investments in drilling technology, completion infrastructure, and transportation networks can strengthen the ability of U.S. producers to stabilize markets and enhance energy security in face of exogenous shocks from global oil market. While this study is solely based on linear estimation technique, non-linear approach including threshold VAR framework can also be reasonable given high investment nature of oil production. I defer these interesting avenues for future work.

Bibliography

- Aastveit, Knut Are (2014). “Oil price shocks in a data-rich environment”. In: *Energy Economics* 45, pp. 268–279.
- Aastveit, Knut Are, Hilde C Bjørnland, and Jamie L Cross (2023). “Inflation expectations and the pass-through of oil prices”. In: *Review of Economics and Statistics* 105.3, pp. 733–743.
- Almoguera, Pedro A, Christopher C Douglas, and Ana María Herrera (2011). “Testing for the cartel in OPEC: Non-cooperative collusion or just non-cooperative?”. In: *Oxford Review of Economic Policy* 27.1, pp. 144–168.
- Anderson, Soren T, Ryan Kellogg, and Stephen W Salant (2018). “Hotelling under pressure”. In: *Journal of Political Economy* 126.3, pp. 984–1026.
- Anderson, Theodore W and Herman Rubin (1949). “Estimation of the parameters of a single equation in a complete system of stochastic equations”. In: *Annals of Mathematical Statistics* 20.1, pp. 46–63.
- Andrews, Isaiah, James H. Stock, and Liyang Sun (2019). “Weak instruments in IV regression: Theory and practice”. In: *Annual Review of Economics*.
- Arezki, Rabah, Valerie A Ramey, and Liugang Sheng (2017). “News shocks in open economies: Evidence from giant oil discoveries”. In: *The Quarterly Journal of Economics* 132.1, pp. 103–155.

- Barsky, Robert B and Lutz Kilian (2002). “Oil and the macroeconomy since the 1970s”. In: *Journal of Economic Perspectives* 18.4, pp. 115–134.
- Bastianin, Andrea and Matteo Manera (2018). “How does stock market volatility react to oil price shocks?” In: *Macroeconomic Dynamics* 22.3, pp. 666–682.
- Baumeister, Christiane and James D Hamilton (2015). “Sign restrictions, structural vector autoregressions, and useful prior information”. In: *Econometrica* 83.5, pp. 1963–1999.
- (2019). “Structural interpretation of vector autoregressions with incomplete identification: Revisiting the role of oil supply and demand shocks”. In: *American Economic Review* 109.5, pp. 1873–1910.
- Baumeister, Christiane, Lutz Kilian, and Xiaoqing Zhou (2018). “Is the discretionary income effect of oil price shocks a hoax?” In: *The Energy Journal* 39.2_suppl, pp. 117–137.
- Bhandari, Subash and Hyeonwoo Kim (July 2025). *Identifying the Transmission Channel of OPEC Oil Shocks to U.S. Inflation through Sectoral CPI Responses*. Working Paper.
- Binder, Carola Conces (2018). “Inflation expectations and the price at the pump”. In: *Journal of Macroeconomics* 58, pp. 1–18.
- Bjørnland, Hilde C, Frode Martin Nordvik, and Maximilian Rohrer (2021). “Supply flexibility in the shale patch: Evidence from North Dakota”. In: *Journal of Applied Econometrics* 36.3, pp. 273–292.

- Bjørnland, Hilde C and Julia Skretting (2024). “The shale oil boom and the US economy: Spillovers and time-varying effects”. In: *Journal of Applied Econometrics* 39.6, pp. 1000–1020.
- Blanchard, Olivier J and Jordi Galí (2007). *The macroeconomic effects of oil shocks: Why are the 2000s so different from the 1970s?*
- Bornstein, Gideon, Per Krusell, and Sergio Rebelo (2023). “A world equilibrium model of the oil market”. In: *The Review of Economic Studies* 90.1, pp. 132–164.
- Caldara, Dario, Michele Cavallo, and Matteo Iacoviello (2019). “Oil price elasticities and oil price fluctuations”. In: *Journal of Monetary Economics* 103, pp. 1–20.
- Chen, Jinyu and Xuehong Zhu (2021). “The effects of different types of oil price shocks on industrial PPI: Evidence from 36 sub-industries in China”. In: *Emerging Markets Finance and Trade* 57.12, pp. 3411–3434.
- Chen, Jinyu, Xuehong Zhu, and Hailing Li (2020). “The pass-through effects of oil price shocks on China’s inflation: A time-varying analysis”. In: *Energy Economics* 86, p. 104695.
- Christiano, Lawrence J, Martin Eichenbaum, and Charles L Evans (1999a). “Monetary policy shocks: What have we learned and to what end?” In: *Handbook of Macroeconomics* 1, pp. 65–148.
- (1999b). “Monetary policy shocks: What have we learned and to what end?” In: *Handbook of macroeconomics* 1, pp. 65–148.

- Clark, Todd E and Stephen J Terry (2010). "Time variation in the inflation passthrough of energy prices". In: *Journal of Money, Credit and Banking* 42.7, pp. 1419–1433.
- Cologni, Alessandro and Matteo Manera (2008). "Oil prices, inflation and interest rates in a structural cointegrated VAR model for the G-7 countries". In: *Energy Economics* 30.3, pp. 856–888.
- Conflitti, Cristina and Riccardo Cristadoro (2018). "Oil prices and inflation expectations". In: *Bank of Italy Occasional Paper* 423.
- Conflitti, Cristina and Matteo Luciani (2019). "Oil price pass-through into core inflation". In: *The Energy Journal* 40.6, pp. 221–248.
- Doroodian, K and Roy Boyd (2003). "The linkage between oil price shocks and economic growth with inflation in the presence of technological advances: A CGE model". In: *Energy Policy* 31.10, pp. 989–1006.
- Foroni, Claudia and Livio Stracca (2023). "The shale oil revolution and the global oil supply curve". In: *Journal of Applied Econometrics* 38.3, pp. 370–387.
- Gago, Joana and Sofia Vale (2025). "Oil price swings and inflationary echoes: The impact of oil market shocks on consumer and producer prices in Europe and the US". In: *Resources Policy* 107, p. 105667.
- Gao, Liping, Hyeongwoo Kim, and Richard Saba (2014). "How do oil price shocks affect consumer prices?" In: *Energy Economics* 45, pp. 313–323.
- Hamilton, James D (2003). "What is an oil shock?" In: *Journal of Econometrics* 113.2, pp. 363–398.

- Hamilton, James D (2009). *Causes and consequences of the oil shock of 2007-08*. Tech. rep. National Bureau of Economic Research.
- Herrera, Ana Maria and Sandeep Kumar Rangaraju (2020). “The effect of oil supply shocks on US economic activity: What have we learned?” In: *Journal of Applied Econometrics* 35.2, pp. 141–159.
- Hooker, Mark A (2002). “Are oil shocks inflationary? Asymmetric and nonlinear specifications versus changes in regime”. In: *Journal of Money, Credit and Banking*, pp. 540–561.
- Husaini, Dzul Hadzwan, Chin-Hong Puah, and Hooi Hooi Lean (2019). “Energy subsidy and oil price fluctuation, and price behavior in Malaysia: A time series analysis”. In: *Energy* 171, pp. 1000–1008.
- Kang, Wensheng, Ronald A Ratti, and Joaquin Vespignani (2016). “The impact of oil price shocks on the US stock market: A note on the roles of US and non-US oil production”. In: *Economics Letters* 145, pp. 176–181.
- Känzig, Diego R (2021). “The macroeconomic effects of oil supply news: Evidence from OPEC announcements”. In: *American Economic Review* 111.4, pp. 1092–1125.
- Kellogg, Ryan (2011). “Learning by drilling: Interfirm learning and relationship persistence in the Texas oilpatch”. In: *The Quarterly Journal of Economics* 126.4, pp. 1961–2004.
- (2014). “The effect of uncertainty on investment: Evidence from Texas oil drilling”. In: *American Economic Review* 104.6, pp. 1698–1734.

- Kilian, Lutz (2008). “Exogenous oil supply shocks: How big are they and how much do they matter for the US economy?” In: *The Review of Economics and Statistics* 90.2, pp. 216–240.
- (2009). “Not all oil price shocks are alike: Disentangling demand and supply shocks in the crude oil market”. In: *American Economic Review* 99.3, pp. 1053–69.
- (2016). “The impact of the shale oil revolution on US oil and gasoline prices”. In: *Review of Environmental Economics and Policy*.
- (2022a). “Facts and fiction in oil market modeling”. In: *Energy Economics* 110, p. 105973.
- (2022b). “Understanding the estimation of oil demand and oil supply elasticities”. In: *Energy Economics* 107, p. 105844.
- Kilian, Lutz and Daniel P Murphy (2014). “The role of inventories and speculative trading in the global market for crude oil”. In: *Journal of Applied Econometrics* 29.3, pp. 454–478.
- Kilian, Lutz and Cheolbeom Park (2009). “The impact of oil price shocks on the US stock market”. In: *International Economic Review* 50.4, pp. 1267–1287.
- Kilian, Lutz, Michael D Plante, and Alexander W Richter (2025). “Macroeconomic responses to uncertainty shocks: the perils of recursive orderings”. In: *Journal of Applied Econometrics* 40.4, pp. 395–410.
- Kilian, Lutz and Clara Vega (2011). “Do energy prices respond to US macroeconomic news? A test of the hypothesis of predetermined energy prices”. In: *Review of Economics and Statistics* 93.2, pp. 660–671.

- Kilian, Lutz and Xiaoqing Zhou (2022a). “Oil prices, gasoline prices, and inflation expectations”. In: *Journal of Applied Econometrics* 37.5, pp. 867–881.
- (2022b). “The impact of rising oil prices on US inflation and inflation expectations in 2020–23”. In: *Energy Economics* 113, p. 106228.
- Kumar, Abhishek and Sushanta Mallick (2024). “Oil price dynamics in times of uncertainty: Revisiting the role of demand and supply shocks”. In: *Energy Economics* 129, p. 107152.
- Montiel Olea, José L, James H Stock, and Mark W Watson (2021). “Inference in structural vector autoregressions identified with an external instrument”. In: *Journal of Econometrics* 225.1, pp. 74–87.
- Newell, Richard G and Brian C Prest (2019). “The unconventional oil supply boom: Aggregate price response from microdata”. In: *The Energy Journal* 40.3.
- Pradeep, Siddhartha (2022). “Impact of diesel price reforms on asymmetry of oil price pass-through to inflation: Indian perspective”. In: *Journal of Economic Asymmetries* 26, e00249.
- Ramey, Valerie A (2016). “Macroeconomic shocks and their propagation”. In: *Handbook of Macroeconomics* 2, pp. 71–162.
- Shakya, Shishir, Bingxin Li, and Xiaoli Etienne (2022). “Shale revolution, oil and gas prices, and drilling activities in the United States”. In: *Energy Economics* 108, p. 105877.
- Stock, James H and Mark W Watson (2016). “Dynamic factor models, factor-augmented vector autoregressions, and structural vector autoregressions in macroeconomics”. In: *Handbook of Macroeconomics* 2, pp. 415–525.

- Stock, James H and Mark W Watson (2018). "Identification and estimation of dynamic causal effects in macroeconomics using external instruments". In: *The Economic Journal* 128.610, pp. 917–948.
- Storrøsten, Halvor Briseid (2024). "US light tight oil supply flexibility-A multivariate dynamic model for production and rig activity". In: *Energy Economics* 131, p. 107386.
- Venditti, Fabrizio (2013). "From oil to consumer energy prices: How much asymmetry along the way?" In: *Energy Economics* 40, pp. 468–473.
- Wong, Benjamin (2015). "Do inflation expectations propagate the inflationary impact of real oil price shocks?: Evidence from the michigan survey". In: *Journal of Money, Credit and Banking* 47.8, pp. 1673–1689.

Appendices

Appendix A

Chapter 1

A.1 Disaggregated Response for Oil Supply News Shock

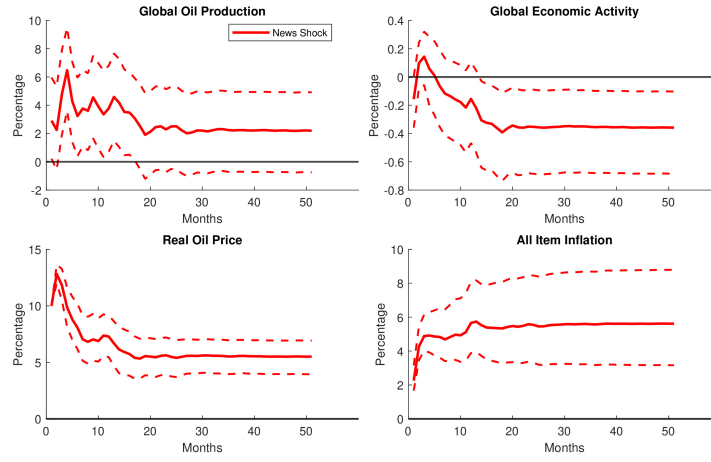


Figure A.1: Main Model

Note: We report the impulse-response function estimates from the IV-SVAR with 12 lags to the oil supply news shock $z_{N,t}$. Shock is normalized to generate a 10 % increase in the oil price on impact. The dashed lines are the 68% Anderson-Rubin confidence bands based on (Montiel Olea et al., 2021). The West Texas Intermediate price is used as the measure of crude oil price, and the Global Industrial Production Index of (Baumeister and Hamilton, 2019), obtained from the author's website, is used as the measure of real economic activity. Oil price and inflation data are obtained from the FRED database, while global oil production data are taken from the EIA database. All four variables are expressed in log differences and converted to percentage terms, with inflation measures annualized (monthly percentage changes multiplied by 12). The updated IV series for the oil supply news shock is based on (Känzig, 2021) and obtained from the author's GitHub repository. The sample period spans from July 1983 to December 2024.

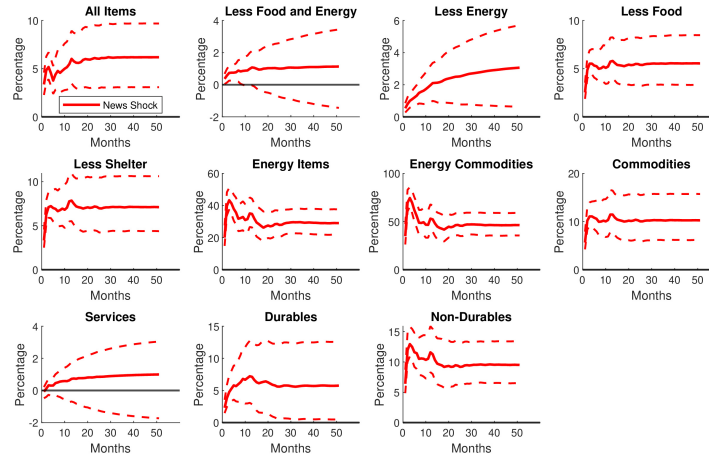


Figure A.2: Special Indexes

Note: We report the impulse-response function estimates from the IV-SVAR with 12 lags to the oil supply news shock $z_{N,t}$. Shock is normalized to generate a 10 % increase in the oil price on impact. The dashed lines are the 68% Anderson-Rubin confidence bands based on (Montiel Olea et al., 2021). The West Texas Intermediate price is used as the measure of crude oil price, and the Global Industrial Production Index of (Baumeister and Hamilton, 2019), obtained from the author's website, is used as the measure of real economic activity. Oil price and inflation data are obtained from the FRED database, while global oil production data are taken from the EIA database. All four variables are expressed in log differences and converted to percentage terms, with inflation measures annualized (monthly percentage changes multiplied by 12). The updated IV series for the oil supply news shock is based on (Känzig, 2021) and obtained from the author's GitHub repository. The sample period spans from July 1983 to December 2024.

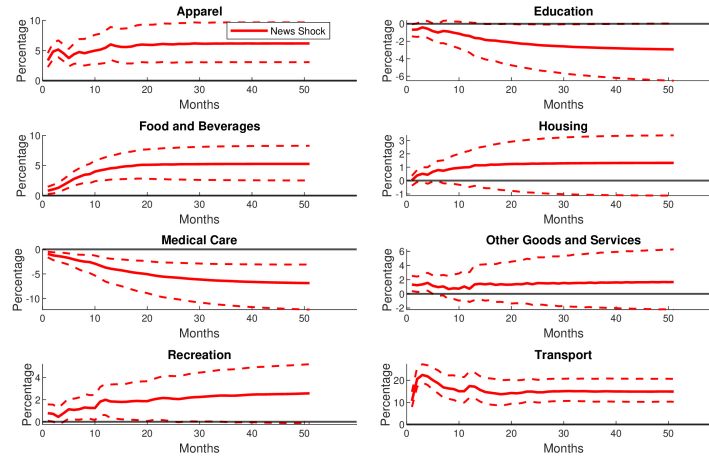


Figure A.3: Major Categories

Note: We report the impulse-response function estimates from the IV-SVAR with 12 lags to the oil supply news shock $z_{N,t}$. Shock is normalized to generate a 10% increase in the oil price on impact. The dashed lines are the 68% Anderson–Rubin confidence bands based on (Montiel Olea et al., 2021). The West Texas Intermediate price is used as the measure of crude oil price, and the Global Industrial Production Index of (Baumeister and Hamilton, 2019), obtained from the author’s website, is used as the measure of real economic activity. Oil price and inflation data are obtained from the FRED database, while global oil production data are taken from the EIA database. All four variables are expressed in log differences and converted to percentage terms, with inflation measures annualized. The updated IV series for the oil supply news shock is based on (Känzig, 2021) and obtained from the author’s GitHub repository. The sample period spans from July 1983 to December 2024.

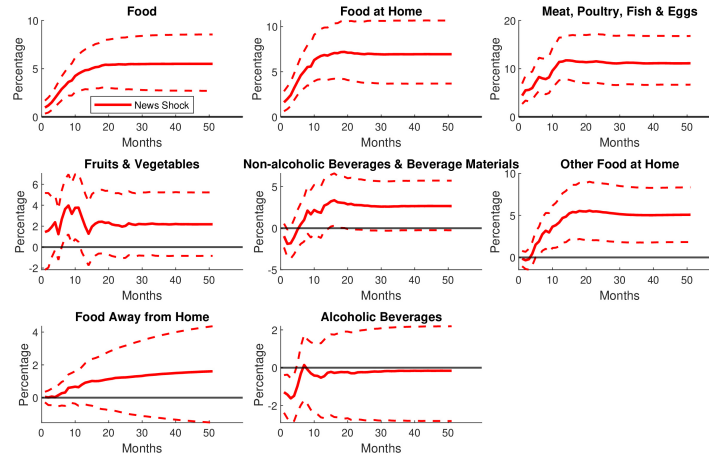


Figure A.4: Food Items

Note: We report the impulse-response function estimates from the IV-SVAR with 12 lags to the oil supply news shock $z_{N,t}$. Shock is normalized to generate a 10% increase in the oil price on impact. The dashed lines are the 68% Anderson–Rubin confidence bands based on (Montiel Olea et al., 2021). The West Texas Intermediate price is used as the measure of crude oil price, and the Global Industrial Production Index of (Baumeister and Hamilton, 2019), obtained from the author’s website, is used as the measure of real economic activity. Oil price and inflation data are obtained from the FRED database, while global oil production data are taken from the EIA database. All four variables are expressed in log differences and converted to percentage terms, with inflation measures annualized. The updated IV series for the oil supply news shock is based on (Känzig, 2021) and obtained from the author’s GitHub repository. The sample period spans from July 1983 to December 2024.

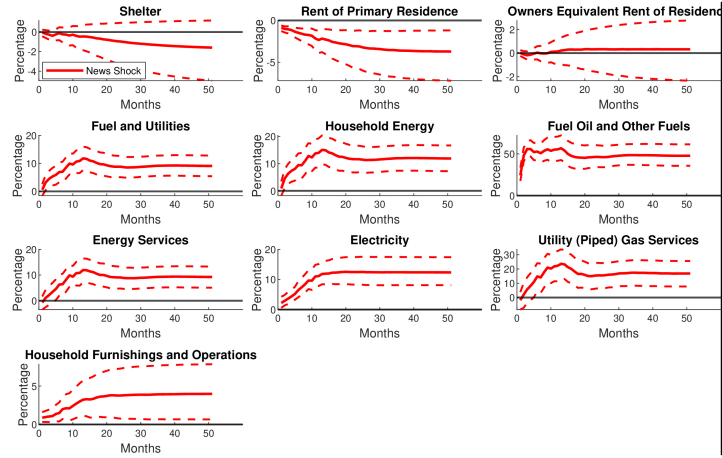


Figure A.5: Housing Items

Note: We report the impulse-response function estimates from the IV-SVAR with 12 lags to the oil supply news shock $z_{N,t}$. Shock is normalized to generate a 10% increase in the oil price on impact. The dashed lines are the 68% Anderson–Rubin confidence bands based on (Montiel Olea et al., 2021). The West Texas Intermediate price is used as the measure of crude oil price, and the Global Industrial Production Index of (Baumeister and Hamilton, 2019), obtained from the author’s website, is used as the measure of real economic activity. Oil price and inflation data are obtained from the FRED database, while global oil production data are taken from the EIA database. All four variables are expressed in log differences and converted to percentage terms, with inflation measures annualized. The updated IV series for the oil supply news shock is based on (Känzig, 2021) and obtained from the author’s GitHub repository. The sample period spans from July 1983 to December 2024.

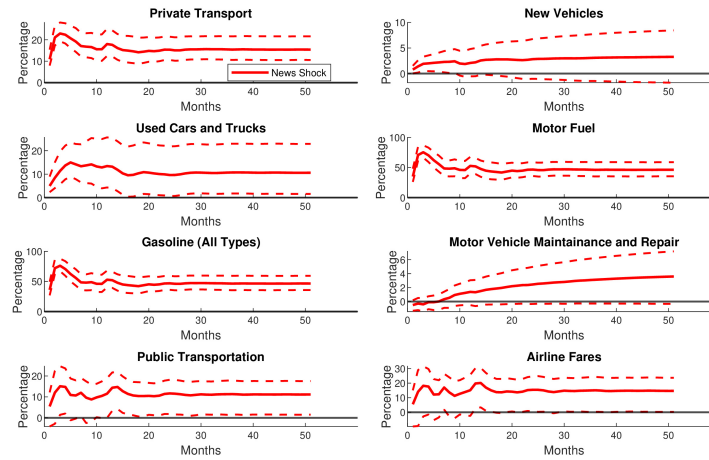


Figure A.6: Transport Items

Note: We report the impulse-response function estimates from the IV-SVAR with 12 lags to the oil supply news shock $z_{N,t}$. Shock is normalized to generate a 10% increase in the oil price on impact. The dashed lines are the 68% Anderson–Rubin confidence bands based on (Montiel Olea et al., 2021). The West Texas Intermediate price is used as the measure of crude oil price, and the Global Industrial Production Index of (Baumeister and Hamilton, 2019), obtained from the author’s website, is used as the measure of real economic activity. Oil price and inflation data are obtained from the FRED database, while global oil production data are taken from the EIA database. All four variables are expressed in log differences and converted to percentage terms, with inflation measures annualized. The updated IV series for the oil supply news shock is based on (Känzig, 2021) and obtained from the author’s GitHub repository. The sample period spans from July 1983 to December 2024.

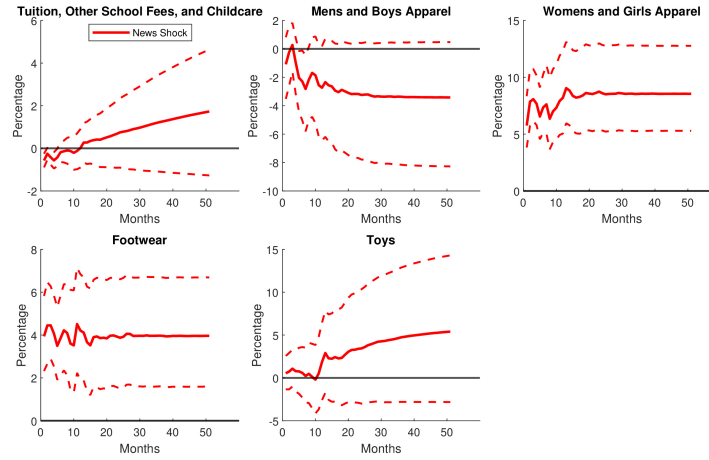


Figure A.7: ther Categories

Note: We report the impulse-response function estimates from the IV-SVAR with 12 lags to the oil supply news shock $z_{N,t}$. Shock is normalized to generate a 10% increase in the oil price on impact. The dashed lines are the 68% Anderson–Rubin confidence bands based on (Montiel Olea et al., 2021). The West Texas Intermediate price is used as the measure of crude oil price, and the Global Industrial Production Index of (Baumeister and Hamilton, 2019), obtained from the author’s website, is used as the measure of real economic activity. Oil price and inflation data are obtained from the FRED database, while global oil production data are taken from the EIA database. All four variables are expressed in log differences and converted to percentage terms, with inflation measures annualized. The updated IV series for the oil supply news shock is based on (Känzig, 2021) and obtained from the author’s GitHub repository. The sample period spans from July 1983 to December 2024.

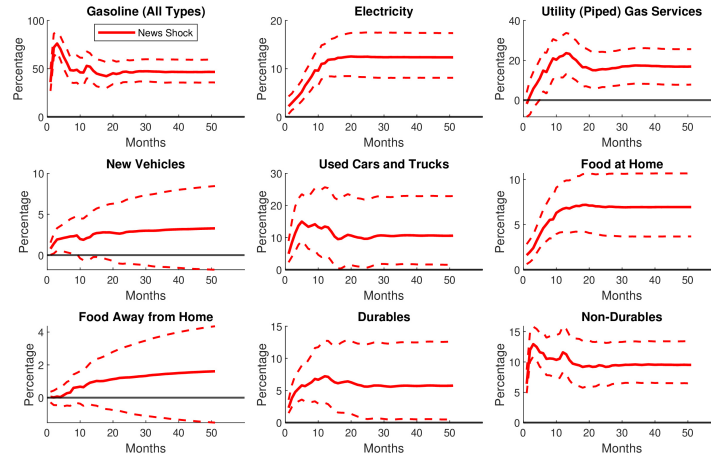


Figure A.8: Change in Consumer Preference

Note: We report the impulse-response function estimates from the IV-SVAR with 12 lags to the oil supply news shock $z_{N,t}$. Shock is normalized to generate a 10% increase in the oil price on impact. The dashed lines are the 68% Anderson–Rubin confidence bands based on (Montiel Olea et al., 2021). The West Texas Intermediate price is used as the measure of crude oil price, and the Global Industrial Production Index of (Baumeister and Hamilton, 2019), obtained from the author’s website, is used as the measure of real economic activity. Oil price and inflation data are obtained from the FRED database, while global oil production data are taken from the EIA database. All four variables are expressed in log differences and converted to percentage terms, with inflation measures annualized. The updated IV series for the oil supply news shock is based on (Känzig, 2021) and obtained from the author’s GitHub repository. The sample period spans from July 1983 to December 2024.

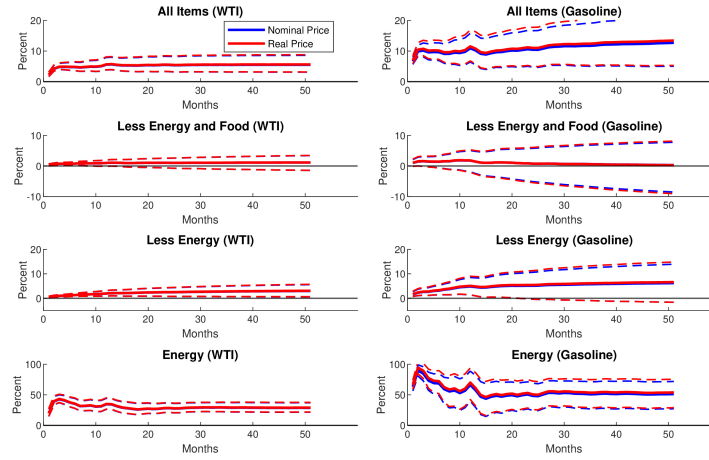


Figure A.9: Choice of Oil Price

Note: We report the impulse-response function estimates from the IV-SVAR with 12 lags to the oil supply news shock $z_{N,t}$. Shock is normalized to generate a 10% increase in the oil price on impact. The dashed lines are the 68% Anderson–Rubin confidence bands based on (Montiel Olea et al., 2021). The West Texas Intermediate price is used as the measure of crude oil price, and the Global Industrial Production Index of (Baumeister and Hamilton, 2019), obtained from the author’s website, is used as the measure of real economic activity. Oil price and inflation data are obtained from the FRED database, while global oil production data are taken from the EIA database. All four variables are expressed in log differences and converted to percentage terms, with inflation measures annualized. The updated IV series for the oil supply news shock is based on (Känzig, 2021) and obtained from the author’s GitHub repository. The sample period spans from July 1983 to December 2024.

A.2 Supply vs News Shock

Our baseline empirical models employ the structural vector autoregressive (SVAR) framework of equation (3.1) with the following.

$$\mathbf{y}_t = \begin{pmatrix} \mathbf{x}_t \\ inf_t \end{pmatrix}, \quad (\text{A.1})$$

where $\mathbf{x}_t = (\Delta prod_t, \Delta rea_t, \Delta rpo_t)'$ for the OPEC supply shock IV ($z_{S,t}$) as in (Montiel Olea et al., 2021).¹ Here, $\Delta prod_t$ denotes the percentage change in monthly global crude oil production, Δrea_t denotes percentage change in a measure of global economic activity, Δrpo_t represents percentage change in the real price of crude oil, and inf_t is a measure of inflation.² The variables in $\mathbf{x}_t$ is motivated by (Kilian, 2009), which identifies three structural shocks in the oil market, including the oil supply shock and the aggregate demand shock. On the other hand, for the OPEC news shock IV ($z_{N,t}$), we employ $\mathbf{x}_t = (\Delta rpo_t, \Delta prod_t, \Delta rea_t)'$ following (Känzig, 2021).

¹We conducted all estimations using 12 lags and an intercept. Results with alternative lags (6 and 24) are qualitatively similar and available upon request.

²Data on global crude oil production, including lease condensate, is obtained from the EIA (U.S. Energy Information Administration) database. Global economic activity is measured using the extended industrial production index series for OECD (Organization for Economic Co-operation and Development) countries plus six other major economies, as provided in (Baumeister and Hamilton, 2019), and obtained from the author's webpage. West Texas Intermediate (WTI) crude oil price data and various inflation measures are obtained from the FRED (Federal Reserve Economic Data) database. Our baseline model specification follows (Baumeister and Hamilton, 2019), with all four variables log differenced and converted in percentage terms. Inflation measures are annualized. WTI spot price is converted into real terms by dividing monthly observations by the U.S. all-city average CPI (Consumer Price Index) and multiplying by 100.

The inclusion of inf_t allows us to estimate the responses of sectoral inflation measures to OPEC shocks. Our approach aligns with that of (Kilian and Park, 2009), which included U.S. stock market variables alongside $\mathbf{x}_t$ to investigate the impact of different oil market shocks on the U.S. stock market. We substitute it with over 55 different inflation indexes, both at aggregated and disaggregate levels, to trace the sources driving headline inflation movements. Following the recommendation of (Montiel Olea et al., 2021), we employ a weak-instrument robust Anderson-Rubin one-standard-deviation confidence interval.

A.2.1 Assessing Model Specification using Wald Statistics

We next assess the validity of the weak-instrument robust confidence bands using the Wald statistics, ξ , suggested by (Montiel Olea et al., 2021), which implies that the $100\%(1 - \alpha)$ Anderson-Rubin (AR) confidence set $CS^{AR}(\Phi_{k,i,1})$ in equation (1.10) is bounded if and only if $\xi > \chi_{1,1-\alpha}^2$.³ The results are reported in Table (A.1).

The Wald statistic for $z_{S,t}$ exceeds the asymptotic critical value at the 10% significance level only when 24 lags are employed, implying a well-contained 90% AR confidence band in this case. However, with fewer lags, the AR confidence bands are valid at the one-standard-deviation level, as the Wald statistic exceeds 0.99, the critical value for 68%.

The news shock IV, on the other hand, demonstrates very strong evidence in favor of well contained confidence bands. The Wald statistic for $z_{N,t}$ exceeds

³ $\xi = T\hat{\Gamma}_{T,1}^2/\hat{W}_{F,1,1}$ from $\sqrt{T}(\hat{\Gamma}_T - \Gamma_T) \xrightarrow{d} N(0, W_\Gamma)$

Table A.1: Validity of Weak-Instrument Robust Confidence Bands

Number of Lags	$z_{S,t}$	$z_{N,t}$
6 lags	1.77 (0.18)	10.0 (0.00)
12 lags	1.77 (0.18)	11.4 (0.00)
24 lags	2.73 (0.10)	15.4 (0.00)

Note: We report Wald statistics, with p -values shown in brackets. The test statistics and corresponding critical values were computed following (Montiel Olea et al., 2021). The Wald statistics obey a chi-square distribution with one degree of freedom. The asymptotic critical values are 3.84, 2.71, and 0.99 for the 95%, 90%, and 68% confidence levels, respectively.

all conventional asymptotic critical values, with p -values below 1% regardless of the number of lags employed. In a nutshell, the Wald test indicates compact AR confidence bands at all conventional levels when the news shock IV is employed.

A.2.2 Baseline Model Estimations with Headline CPI Inflation

Figure (A.10) presents the impulse response function estimates for the baseline IV-SVAR model with 12 lags, where headline CPI inflation is ordered last as in equation (A.1). The first column shows the responses of $\mathbf{y}_t$ to the oil supply shock $z_{S,t}$, while the second column shows the responses to the oil supply news shock $z_{N,t}$. Each shock is normalized to generate a 1% increase in the oil price on impact.⁴

⁴For our impulse response function estimation, we use MATLAB code from the replication files of (Montiel Olea et al., 2021), obtained from the author's GitHub repository. The responses to supply shocks were initially estimated to correspond to a 1% decline in global oil production. We then scale these responses to the oil supply shock using the contemporaneous effect on the oil price, which is approximately a 0.46% increase. The responses to news shocks were directly estimated to correspond to a 1% increase in the oil price. That is, both IV shocks are normalized to produce the same contemporaneous effect on the oil price.

It should be noted that the responses of global oil production ($\Delta prod_t$) to the supply shock $z_{S,t}$ differ markedly from those of to the news shock $z_{N,t}$. Specifically, following a supply shock $z_{S,t}$, global oil production substantially decreases on impact and reaching to a permanent reduction in output. In contrast, when OPEC announces a production cut, interpreted as a news shock ($z_{N,t}$), oil production initially increases (positive growth rates). This reflects a rise in output from non-OPEC oil-producing countries, consistent with their typical response to higher oil prices driven by immediate reactions in the oil futures market. However, over time, global oil production gradually slows, eventually reaching an insignificant rate within approximately two years.

Notwithstanding the contrasting responses of global oil production, both IV shocks, $z_{S,t}$ and $z_{N,t}$, lead to statistically significant increases in oil prices. The headline inflation rate also rises in response to both shocks, although the inflation response to the supply IV shock ($z_{S,t}$) is only marginally significant, whereas the news IV shock ($z_{N,t}$) produces a clearly significant positive pass-through to headline inflation. Our estimate of the impact on oil prices is slightly higher than that reported by (Montiel Olea et al., 2021), but it lies at the lower end of the range presented by (Herrera and Rangaraju, 2020). In response to the oil news shock, oil prices increase by 1.25% after one month before subsequently declining. This estimated effect is consistent with the findings of (Känzig, 2021).

The above results demonstrate that supply and news shocks are distinct forces, each exerting a unique impact on the oil market. A supply shock leads to a persistent increase in oil prices through realized changes in oil production, whereas

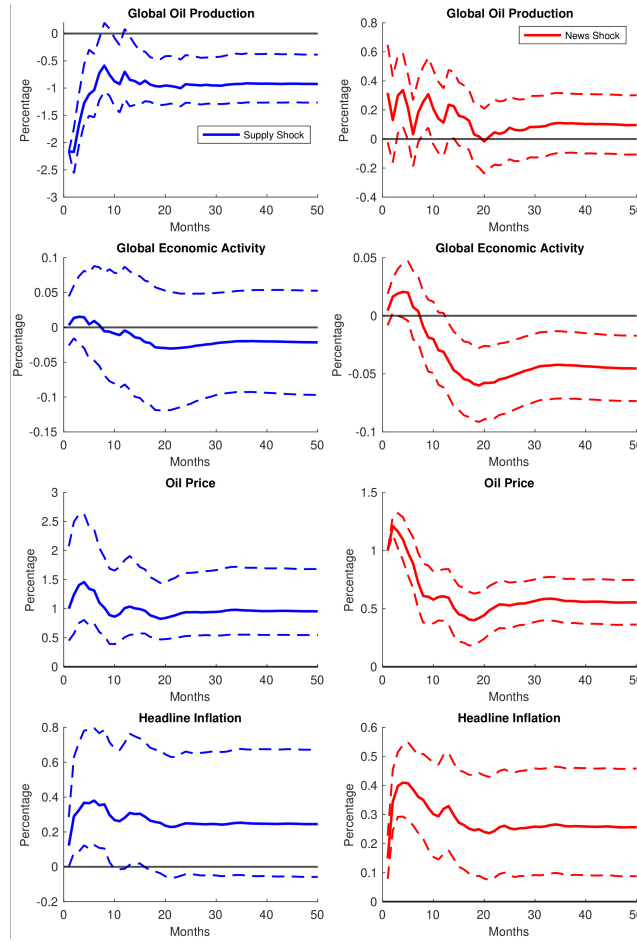


Figure A.10: Baseline Model Impulse-Response Function Estimation Results

Note: We report the impulse-response function estimates from the IV-SVAR with 12 lags. The first column shows the responses of $\mathbf{y}_t$ to the oil supply shock $z_{S,t}$, while the second column shows the responses to the oil supply news shock $z_{N,t}$. Each shock is normalized to generate a 1% increase in the oil price on impact. The dashed lines are the 68% Anderson–Rubin confidence bands based on (Montiel Olea et al., 2021). The West Texas Intermediate price is used as the measure of crude oil price, and the Global Industrial Production Index of (Baumeister and Hamilton, 2019), obtained from the author's website, is used as the measure of real economic activity. Oil price and inflation data are obtained from the FRED database, while global oil production data are taken from the EIA database. All four variables are expressed in log differences and converted to percentage terms, with inflation measures annualized. The IV series for the oil supply shock is based on (Kilian, 2008), updated by (Bastianin and Manera, 2018), and the IV series for the oil supply news shock is based on (Känzig, 2021). Both IV series are obtained from the replication materials of (Känzig, 2021). The sample period spans from July 1983 to December 2013.

the price increase associated with a news shock is highly significant but occurs without any corresponding change in market fundamentals.

Moreover, both shocks exhibit recessionary effects, as shown by the responses of global industrial production. However, the response to the supply shock is generally insignificant, in contrast to the highly significant response to the news shock. These recessionary dynamics likely influence the extent of pass-through to headline CPI inflation. Regardless of the timing of supply cuts, whether immediate ($z_{S,t}$) or anticipated ($z_{N,t}$), oil supply shocks shift the supply curve of goods and services leftward due to rising oil prices.

At the same time, recessionary pressures may prompt consumers to adjust their spending behavior. Specifically, faced with budget constraints resulting from negative income shocks, driven by rising costs of necessities such as energy expenditures, consumers may need to reduce spending on non-essential goods and services. This behavioral shift leads to a leftward movement in the demand curve for these items. Consequently, the price impact on such goods and services may be muted. In the following sections, we present further evidence supporting these mechanisms.

A.2.3 Impact on Inflation Rates of Major Expenditure Groups

To identify the propagation channels to headline inflation from the two OPEC IV shocks, we examine the responses of inflation rates across major expenditure categories, as shown in Figure (A.11). For a fair comparison of the inflationary effects of the supply and news IV shocks, we scale each shock to generate an initial 1% increase in the oil price.

The notable findings are as follows. Both IV shocks generate qualitatively similar effects on the inflation rates of major expenditure groups and on the headline CPI inflation rate. However, the confidence bands for the responses to $z_{N,t}$ are considerably tighter than those for $z_{S,t}$. The increase in headline inflation appears to be primarily driven by higher energy inflation. In particular, the point estimates for energy inflation responses are roughly ten times larger than those for overall inflation under both shocks, whereas the inflationary effects become substantially smaller and statistically insignificant (or marginally significant) once energy items are excluded from the headline CPI.

The three figures in the second row reveal interesting patterns. Inflation for non-durable goods rises significantly, approximately twice as much as the headline inflation response, whereas inflation rates for durable goods and services respond only minimally or insignificantly. The weaker inflation responses for durable goods and services may reflect reduced demand caused by the recessionary effects of the OPEC shocks as shown in Figure (A.11). Confronted with oil shocks and substantial increases in energy-related expenditures, households may cut back on other spending, shifting demand away from items such as refrigerators and dining out, which in turn dampens the inflation responses for these categories.

Figure (A.12) provides additional evidence at the disaggregated level. Inflation responses of energy commodities, such as motor fuel and gasoline (not reported), are highly significant and quantitatively large. In contrast, energy services, including electricity and natural gas, display weaker but still statistically significant

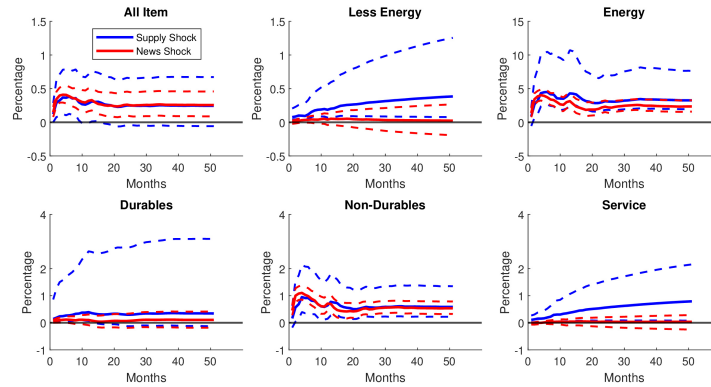


Figure A.11: Responses of Inflation Rates across Major Expenditure Groups

Note: We report the inflation responses of the major expenditure groups. The blue lines depict the responses to the oil supply shock ($z_{S,t}$), while the red lines correspond to the responses to the oil supply news shock ($z_{N,t}$). Each shock is normalized to generate a 1% increase in the oil price on impact. The dashed lines represent the 68% Anderson–Rubin confidence bands, following (Montiel Olea et al., 2021). The sample period covers July 1983 to December 2013.

responses to the OPEC news shock $z_{N,t}$, while the confidence bands remain considerably wider for the responses to the OPEC supply shocks $z_{S,t}$.

These results highlight how oil market shocks transmit into various parts of the consumer basket most strongly in the transport sector both public and private,

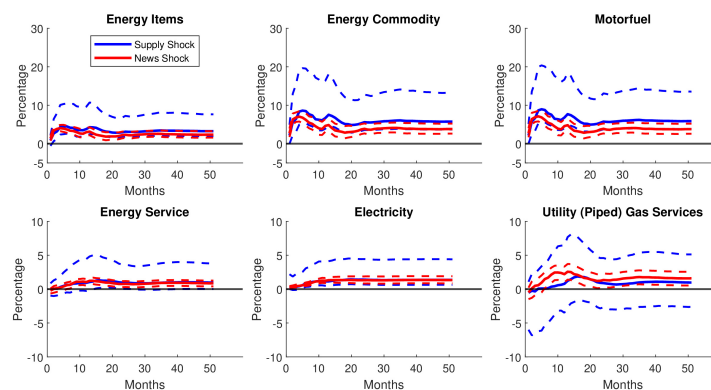


Figure A.12: Inflation Rate Responses of Disaggregated Energy Components

Note: We report the inflation responses of disaggregated energy components. The blue lines depict the responses to the oil supply shock $z_{S,t}$, while the red lines depict the responses to the oil supply news shock $z_{N,t}$. Each shock is normalized to generate a 1% increase in the oil price on impact. The dashed lines indicate the 68% Anderson–Rubin confidence bands, following (Montiel Olea et al., 2021). The sample period covers July 1983 through December 2013.

through higher fuel prices. Beyond transportation, we also find increase in household utility costs as well as higher price of food and beverage items, and apparel items.

Our overall findings are consistent with the conclusions of (Kilian and Zhou, 2022b) and (Känzig, 2021). Both shocks increase the price of gasoline as well as other fuels, such as electricity and natural gas, which are regularly used by average households.⁵ These higher fuel costs lead to price increases in specific components of the economy beyond the transport sector. For example, higher fuel and utility costs can raise inflation in the housing category. Similarly, higher electricity costs may be passed on to higher prices in communication and recreation items. Furthermore, these higher operating costs can also translate into higher food prices, particularly for food consumed at home.

A.2.4 Responses of Further Broken-Down CPI Components

This subsection presents the inflation responses of highly disaggregated CPI components. Figure (A.13) highlights several noteworthy comparisons.

Consistent with earlier results, energy-related CPI components such as Transport and Gasoline increase substantially and significantly in response to OPEC IV shocks. Notably, Private Transportation CPI responds significantly to both supply and news shocks, whereas the response of Public Transportation expenditure is quantitatively smaller and only marginally significant, likely reflecting price rigidities in public transportation systems such as buses and subways.

Fuel and Utilities CPI and Household Energy CPI also rise in response to OPEC supply and news shocks, yielding statistically significant and economically

⁵Detailed results are available upon request.

substantial inflation effects. These findings are consistent with our earlier discussion that expenditures on necessities are highly price inelastic. As a result, negative supply shifts are transmitted almost entirely into higher prices, since the limited demand response prevents offsetting downward adjustments along the demand curve. Food and Beverages CPI exhibit similar but somewhat weaker patterns, reflecting their status as necessities with slightly greater demand flexibility.

The responses of Food CPI and its two sub-components, Food at Home CPI and Food Away from Home CPI, also exhibit distinct patterns. Food inflation is primarily driven by increases in the prices of items consumed at home following unexpected oil price shocks. Confronted with OPEC supply or news shocks and constrained by their budgets, households economize by cutting back on more price-elastic expenditures such as dining out, while being unable to substantially reduce spending on necessities consumed at home. The significant inflation responses of Food at Home CPI, together with the insignificant or even negative responses of Food Away from Home CPI, are consistent with this budget reallocation, reflecting a negative shift in the demand for non-necessities.

Figure (A.14) displays kernel density estimates of the inflation responses for 55 CPI components at the most disaggregated level. We report the estimated distributions at four horizons: on impact (contemporaneous), 3 months (short run), 12 months (medium run), and 50 months (long run). The responses are shown separately for the OPEC supply shock ($z_{S,t}$) and the OPEC news shock ($z_{N,t}$). Corresponding summary statistics of these density estimates are provided in Table (A.2).

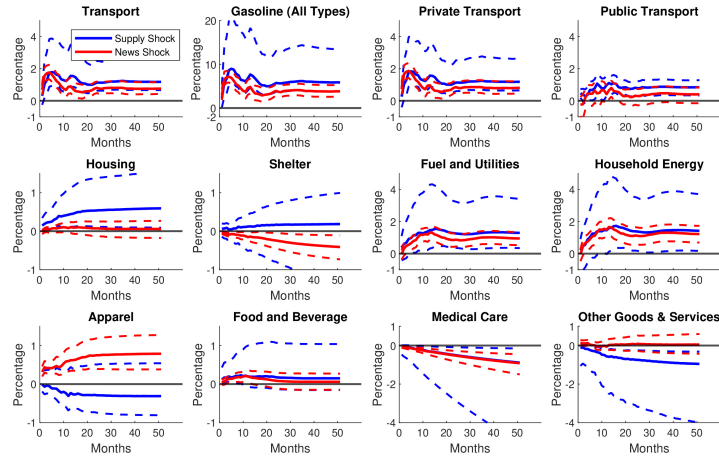


Figure A.13: Inflation Responses of Highly Disaggregated CPI Components

Note: We report the inflation responses of disaggregated energy components. The blue lines depict the responses to the oil supply shock $z_{S,t}$, while the red lines depict the responses to the oil supply news shock $z_{N,t}$. Each shock is normalized to generate a 1% increase in the oil price on impact. The dashed lines indicate the 68% Anderson–Rubin confidence bands, following (Montiel Olea et al., 2021). The sample period spans July 1983 to December 2013, except for Public Transport CPI, for which observations begin in February 1989.

We note that the average inflation responses exceed the median responses across all horizons ($k = 0, 3, 12, 50$), indicating that the estimated distributions are right-skewed, a finding confirmed by the estimated skewness. In other words, positive inflation responses occur more frequently. Furthermore, all kurtosis estimates

point to leptokurtic, that is, heavy-tailed distributions, implying substantial heterogeneity in the responses of disaggregated CPI components. Taken together with our earlier findings, this evidence suggests that the dynamics of headline CPI are not driven by the majority of the 55 disaggregated components, but rather are primarily attributable to energy-related sub-components.

On impact ($k = 0$), the median inflation responses to both shocks are centered around zero, although the distribution for $z_{N,t}$ is more tightly concentrated near zero than that for $z_{S,t}$. At the same time, the news shock exhibits heavier right tails, accompanied by a larger standard deviation and higher skewness. As the horizon extends to the short run ($k = 3$), the cross-sectional dispersion widens for both shocks, with the mass of the distribution shifting modestly toward positive inflation rates, as reflected in higher means and medians. The median short-run effect rises from 0.12% to 0.15% for the supply shock and from 0.02% to 0.11% for the news shock. In the long run ($k = 50$), the median further increases from 0.20% to 0.26% for the supply shock, while the corresponding value for the news shock declines from 0.13% to 0.08%.

These results suggest that $z_{S,t}$ exerts more persistent effects, consistent with the characterization of $z_{N,t}$ as a front-loaded shock by (Känzig, 2021), whose effects are primarily observed at short horizons and dissipate relatively quickly.

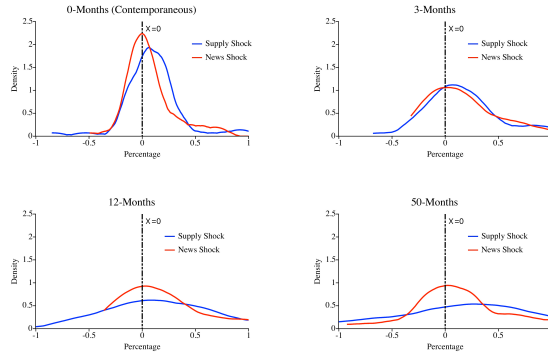


Figure A.14: Kernel-Based Distributions of Inflation Responses across Disaggregated CPIs

Note: We employ the Epanechnikov kernel density estimator to characterize the k -month-ahead inflation responses of 55 CPI components at the most disaggregated level, where $k \in 0, 3, 12, 50$. These responses are reported separately for the OPEC supply shock ($z_{S,t}$) and the OPEC news shock ($z_{N,t}$).

Table A.2: Kernel Density Estimations (Summary Statistics)

k	$z_{S,t}$				$z_{N,t}$			
	0	3	12	50	0	3	12	50
Mean	0.20	0.83	0.74	0.62	0.27	0.79	0.66	0.49
Median	0.12	0.15	0.20	0.26	0.02	0.11	0.13	0.08
StdDev	0.55	2.09	1.80	1.60	0.72	1.85	1.38	1.16
Min	-0.84	-0.67	-1.16	-1.45	-0.49	-0.32	-0.35	-0.92
Max	2.19	8.67	6.80	5.88	2.92	7.17	6.06	4.69
Skewness	2.41	3.00	2.55	2.18	2.68	2.75	2.48	2.15
Kurtosis	9.64	11.02	8.64	7.55	9.44	9.29	8.53	7.35

Note: We employ the Epanechnikov kernel density estimator to characterize the k -month-ahead inflation responses of 55 CPI components at the most disaggregated level, where $k \in 0, 3, 12, 50$.

List of CPI Indexes (Source: FRED Database)

No.	Category	Series ID
1	ALL ITEMS	CPIAUCSL
SPECIAL INDEXES		
2	All Items Less Food and Energy	CPILFESL
3	All Items Less Energy	CPILEGSL
4	All Items Less Food	CPIULFSL
5	All Items Less Shelter	CUSR0000SA0L2
6	Energy Item	CPIENGSL
7	Energy Commodities	CUSR0000SACE
8	Commodities	CUSR0000SAC
9	Services	CUSR0000SAS
10	Durables	CUSR0000SAD
11	Nondurables	CUSR0000SAN
12	FOOD AND BEVERAGES	CPIFABSL
13	Food	CPIUFDSL
14	Food at Home	CUSR0000SAF11
15	Meats, Poultry, Fish, and Eggs	CUSR0000SAF112
16	Fruits and Vegetables	CUSR0000SAF113
17	Nonalcoholic Beverages and Beverage Materials	CUSR0000SAF114
18	Other Food at Home	CUSR0000SAF115
19	Other Foods	CUSR0000SEFT
20	Food Away from Home	CUSR0000SEFV
21	Alcoholic Beverages	CUSR0000SAF116
22	Alcoholic Beverages at Home	CUSR0000SEFW
23	Alcoholic Beverages Away from Home	CUSR0000SEFX

No.	Category	Series ID
24	MEDICAL CARE	CPIMEDSL
25	Medical Care Commodities	CUSR0000SAM1
26	Medical Care Services	CUSR0000SAM2
27	Professional Services	CUSR0000SEMC
28	Hospital and Related Services	CUSR0000SEMD
29	HOUSING	CPIHOSSL
30	Shelter	CUSR0000SAH1
31	Rent of Primary Residence	CUSR0000SEHA
32	Owners' Equivalent Rent of Residences	CUSR0000SEHC
33	Fuels and Utilities	CUSR0000SAH2
34	Household Energy	CUSR0000SAH21
35	Fuel Oil and Other Fuels	CUSR0000SEHE
36	Energy Services	CUSR0000SEHF
37	Electricity	CUSR0000SEHF01
38	Utility (Piped) Gas Service	CUSR0000SEHF02
39	Household Furnishings and Operations	CUSR0000SAH3
40	APPAREL	CPIAPPSL
41	Men's and Boys' Apparel	CUSR0000SAA1
42	Women's and Girls' Apparel	CUSR0000SAA2
43	Footwear	CUSR0000SEAE

No.	Category	Series ID
44	TRANSPORTATION	CPITRNSL
45	Private Transportation	CUSR0000SAT1
46	New Vehicles	CUSR0000SETA01
47	Used Cars and Trucks	CUSR0000SETA02
48	Motor Fuel	CUSR0000SETB
49	Gasoline (All Types)	CUSR0000SETB01
50	Motor Vehicle Maintenance and Repair	CUSR0000SETD
51	Public Transportation	CUSR0000SETG
52	Airline Fares	CUSR0000SETG01
EDUCATION & COMMUNICATION		
53	Educational Books and Supplies	CUSR0000SEEA
54	Tuition, Other School Fees, and Childcare	CUSR0000SEEB
RECREATIONN		
55	Toys	CUSR0000SERE01
56	OTHER GOODS AND SERVICES	CPIOGSSL

Appendix B

Chapter 2

B.1 List of PPI Indexes (Source: FRED Database)

No.	Category	Series ID
1	All Commodities	PPIACO
2	Industrial Commodities	PPIENG
3	Industrial Commodities Less Fuels	PPIIDC
4	Fuels and Related Products and Power	WPU04
5	Chemicals and Allied Products	WPU06
6	Rubber and Plastic Products	WPU07
7	Nonmetallic Mineral Products	WPU13
8	Textile Products and Apparel	WPU03
9	Farm Products	WPU01
10	Lumber and Wood Products	WPU08
11	Furniture and Household Durables	WPU12
12	Machinery and Equipment	WPU11

Appendix C

Chapter 3

Table C.1: Forecast Error Variance Decomposition of U.S. Oil Production at Different Stages to Oil Market Shocks

Horizon (Months)	Percent of h-Step Ahead Forecast Error Variance Explained by:			
	Flow Supply Shock	Flow Demand Shock	Oil Specific Shock	Residual Shock
Number of New Well Drilled				
1	1.4	0.3	3.6	94.6
2	14.6	0.3	12.6	72.6
3	12.1	2.2	24.3	62.4
6	9.2	9.7	36.5	44.5
12	15.0	14.2	27.8	43.0
∞	16.4	12.8	25.9	44.9
Number of Completed Drills				
1	1.2	2.2	8.8	87.8
2	23.4	2.3	18.7	55.5
3	20.4	2.0	28.7	48.9
6	15.7	7.0	22.1	54.2
12	13.9	14.7	20.4	51.0
∞	14.3	15.6	21.0	49.0
Number of Uncompleted Drills				
1	0.2	1.0	2.5	96.3
2	1.5	0.9	5.9	91.8
3	3.7	2.4	8.5	85.4
6	12.3	6.6	6.5	74.5
12	9.6	8.4	13.6	68.2
∞	10.8	8.3	21.2	59.6

Note: Entries show forecast error variance decomposition (percent) across horizons from a 4-variable SVAR model. Monthly data from 2008M01 to 2024M04.

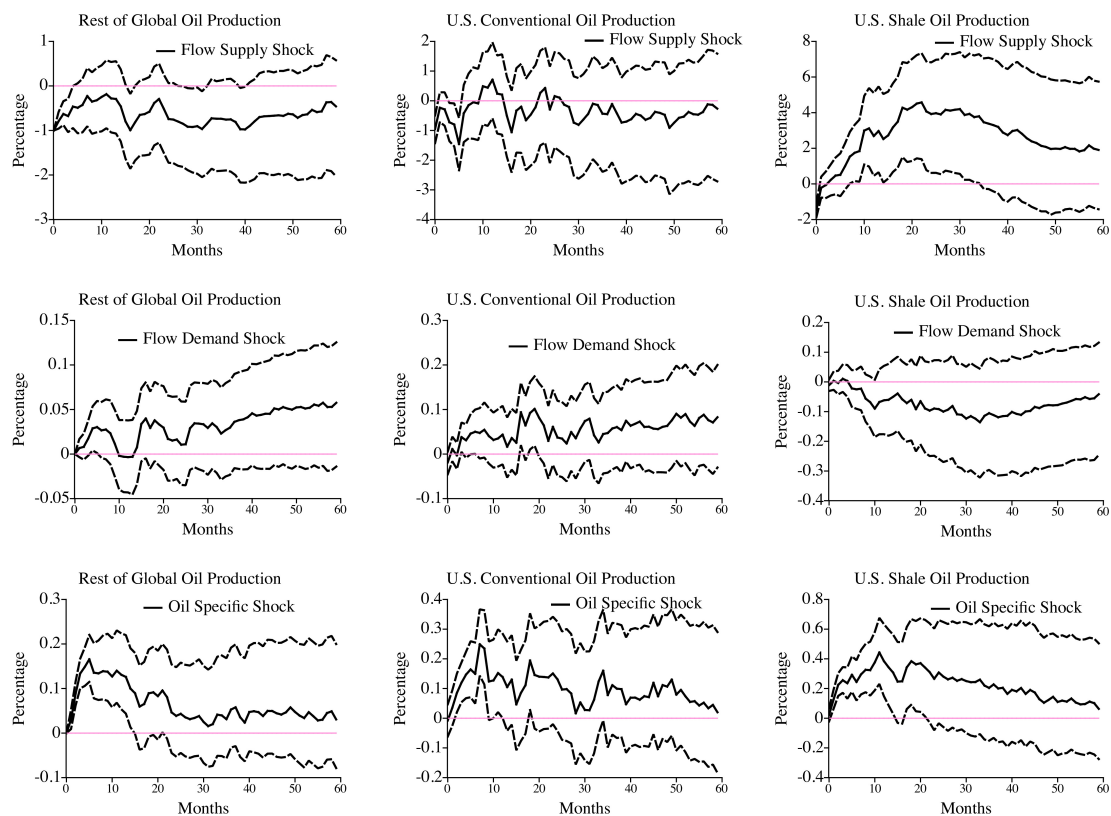


Figure C1: Response of Global Oil Production to Oil Market Shocks

Note: Results are for SVAR(24) with intercept for three structural shocks identified in the text. First panel shows the responses to flow supply shock normalized to decrease rest of global oil production excluding U.S. by 1%. Second panel shows the responses to flow demand shock normalized to increase global economic activity by 1%. Third panel shows the response to oil specific shock that increases oil price by 1%. First column shows the response of rest of global oil production. Second column shows the response of U.S. conventional oil production. Third column shows the response of U.S. shale oil production. Errors are for 68% confidence interval. The confidence intervals were constructed using wild bootstrap. Calculations are based on 5,000 iteration. Monthly data spans 2008M01:2024M12.

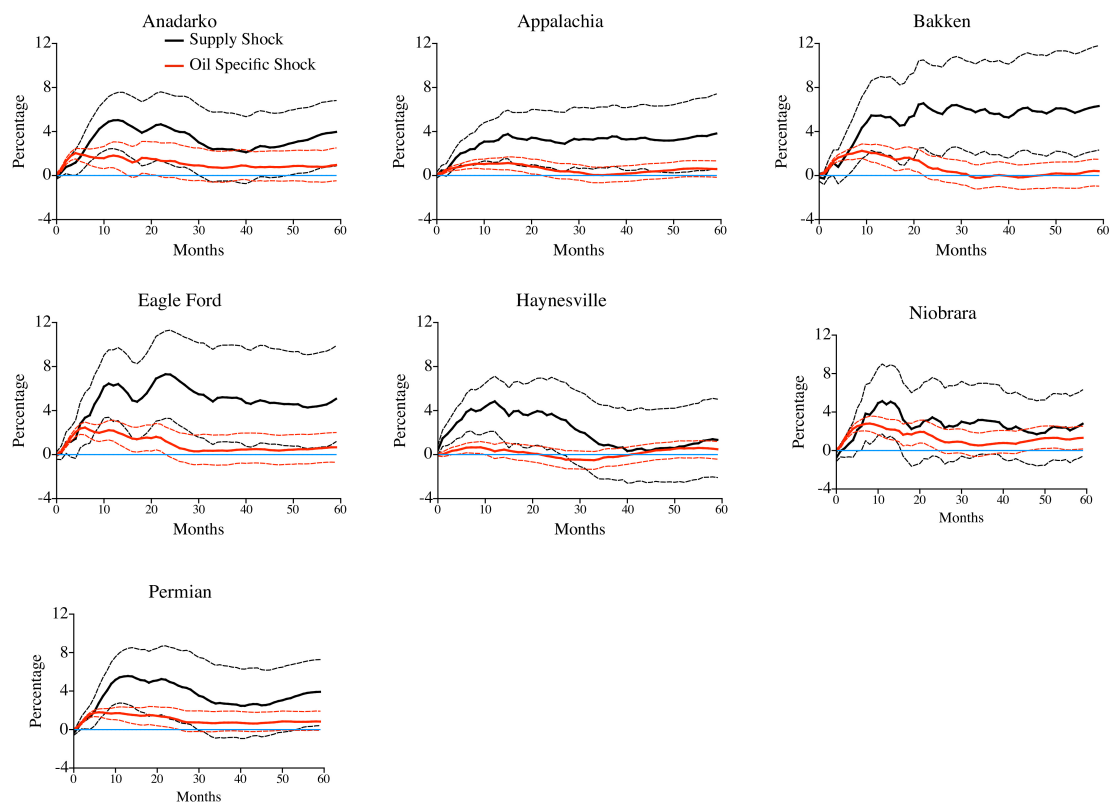


Figure C2: Response of Number of Rigs to Supply and Aggregate Demand Shock

Note: Results are for SVAR(24) with intercept for four structural shocks identified in the text. First panel shows the responses to rest of global oil production shock normalized to decrease global oil production by 1%. Second panel shows the responses to U.S. shale oil supply shock normalized to decrease global oil production by 1%. Errors are for 68% confidence interval. Data spans 2008M01:2024M12.

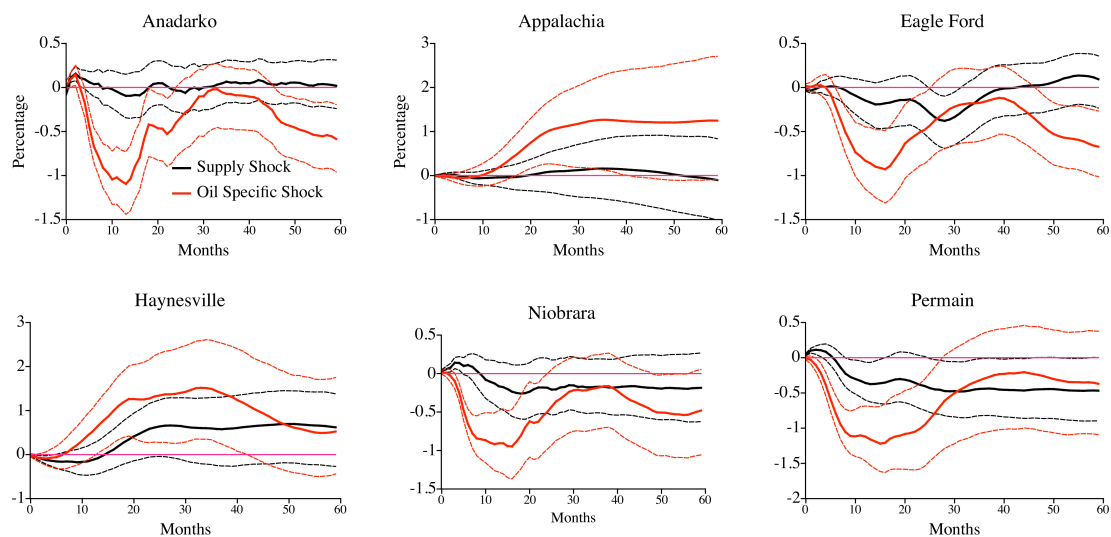


Figure C3: Response of Number of Rigs to Supply and Aggregate Demand Shock

Note: Results are for SVAR(24) with intercept for four structural shocks identified in the text.. First panel shows the responses to rest of global oil production shock normalized to decrease global oil production by 1%. Second panel shows the responses to U.S. shale oil supply shock normalized to decrease global oil production by 1%. Errors are for 68% confidence interval. Data spans 2008M01:2024M12.

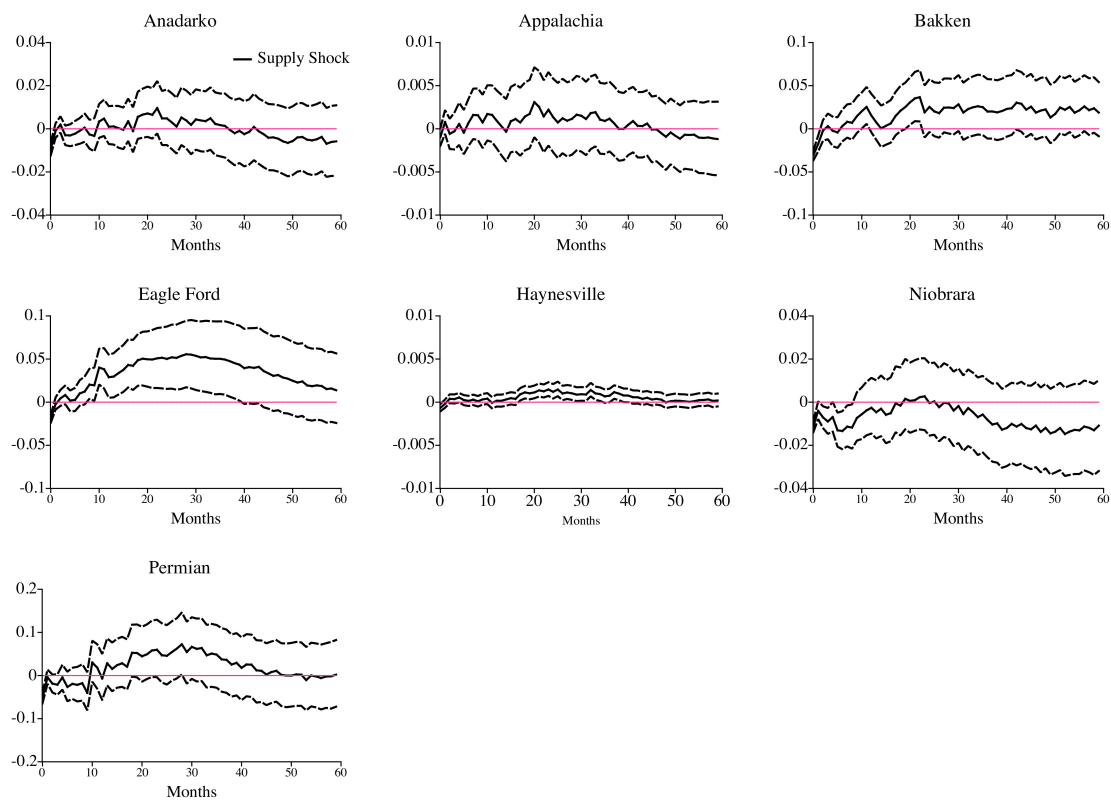


Figure C4: Response of Shale Oil Production to Supply Shock

Note: Results are for SVAR(24) with intercept for four structural shocks identified in the text.. First panel shows the responses to rest of global oil production shock normalized to decrease global oil production by 1%. Second panel shows the responses to U.S. shale oil supply shock normalized to decrease global oil production by 1%. Errors are for 68% confidence interval. Data spans 2008M01:2024M12.

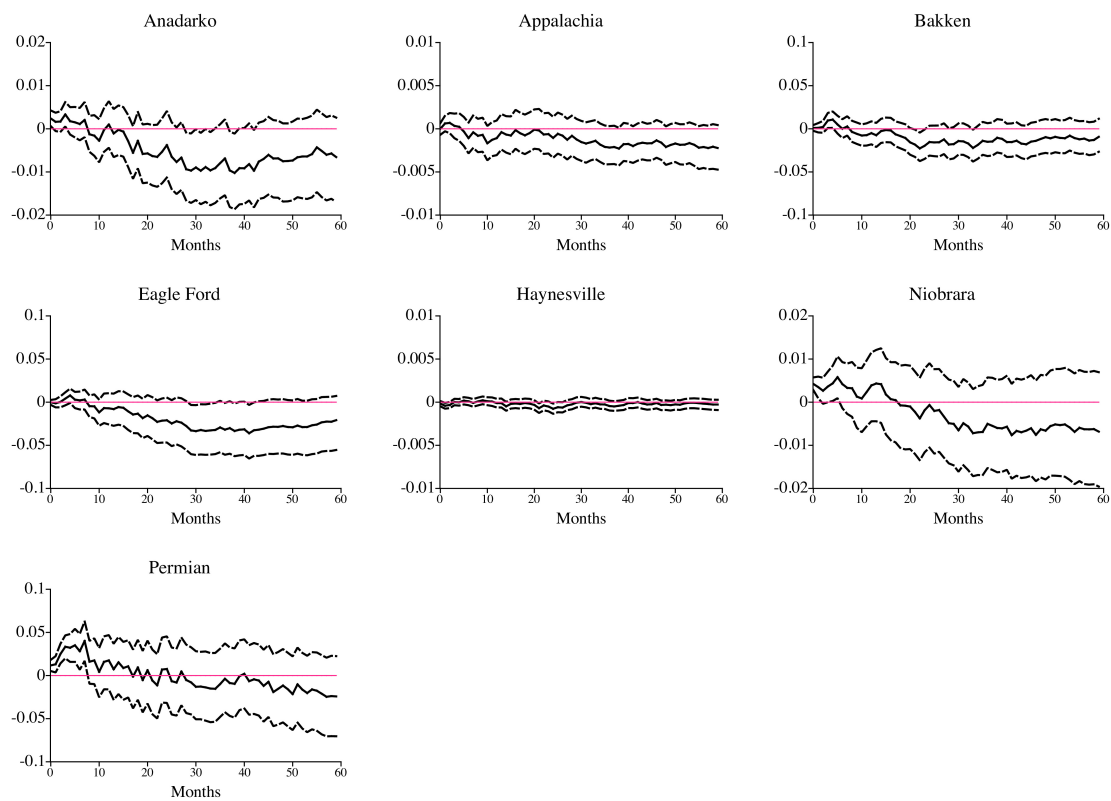


Figure C5: Response of Shale Oil Production to Demand Shock

Note: Results are for SVAR(24) with intercept for four structural shocks identified in the text.. First panel shows the responses to rest of global oil production shock normalized to decrease global oil production by 1%. Second panel shows the responses to U.S. shale oil supply shock normalized to decrease global oil production by 1%. Errors are for 68% confidence interval. Data spans 2008M01:2024M12.

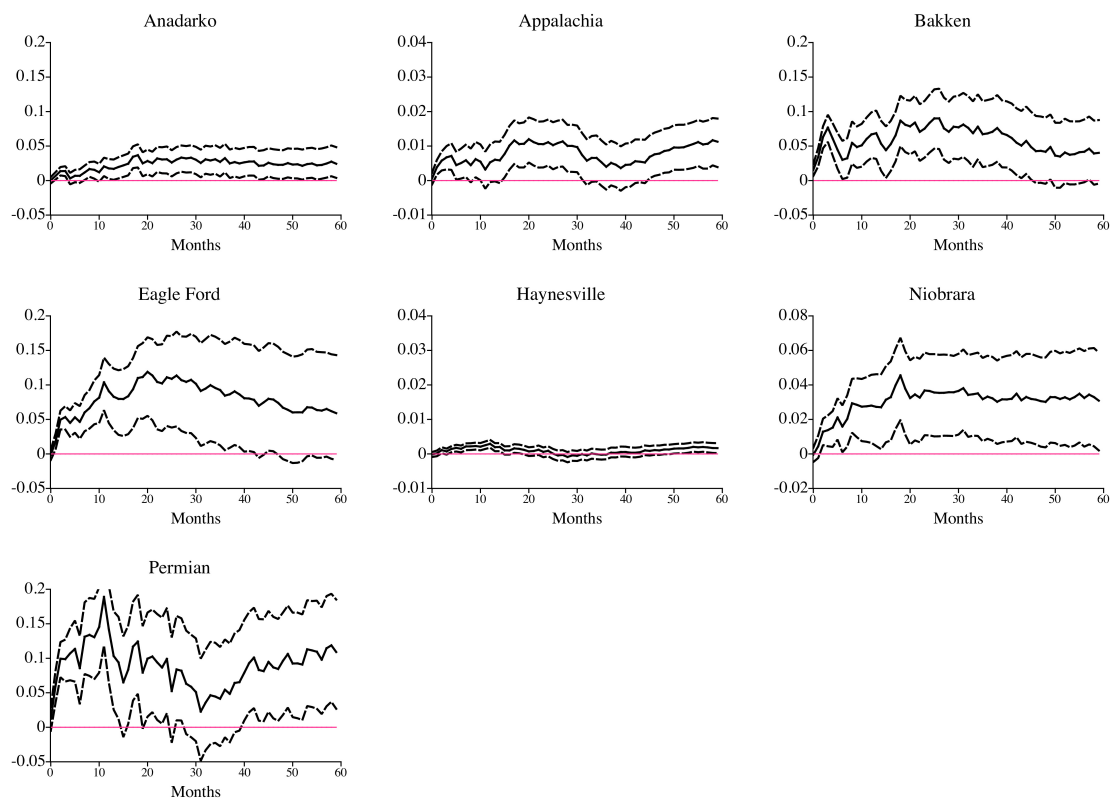


Figure C6: Response of Shale Oil Production to Oil Specific Demand Shock

Note: Results are for SVAR(24) with intercept for four structural shocks identified in the text. First panel shows the responses to rest of global oil production shock normalized to decrease global oil production by 1%. Second panel shows the responses to U.S. shale oil supply shock normalized to decrease global oil production by 1%. Errors are for 68% confidence interval. Data spans 2008M01:2024M12.

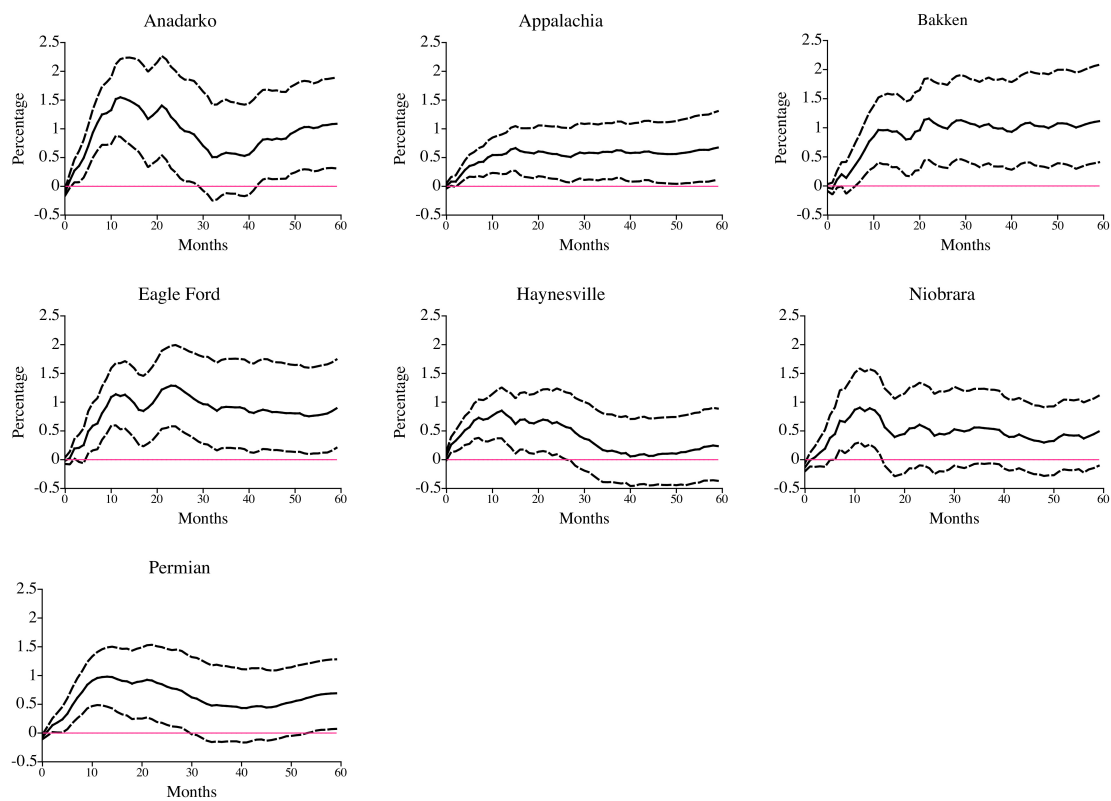


Figure C7: Response of Number of Drills to Supply Shock

Note: Results are for SVAR(24) with intercept for four structural shocks identified in the text.. First panel shows the responses to rest of global oil production shock normalized to decrease global oil production by 1%. Second panel shows the responses to U.S. shale oil supply shock normalized to decrease global oil production by 1%. Errors are for 68% confidence interval. Data spans 2008M01:2024M12.

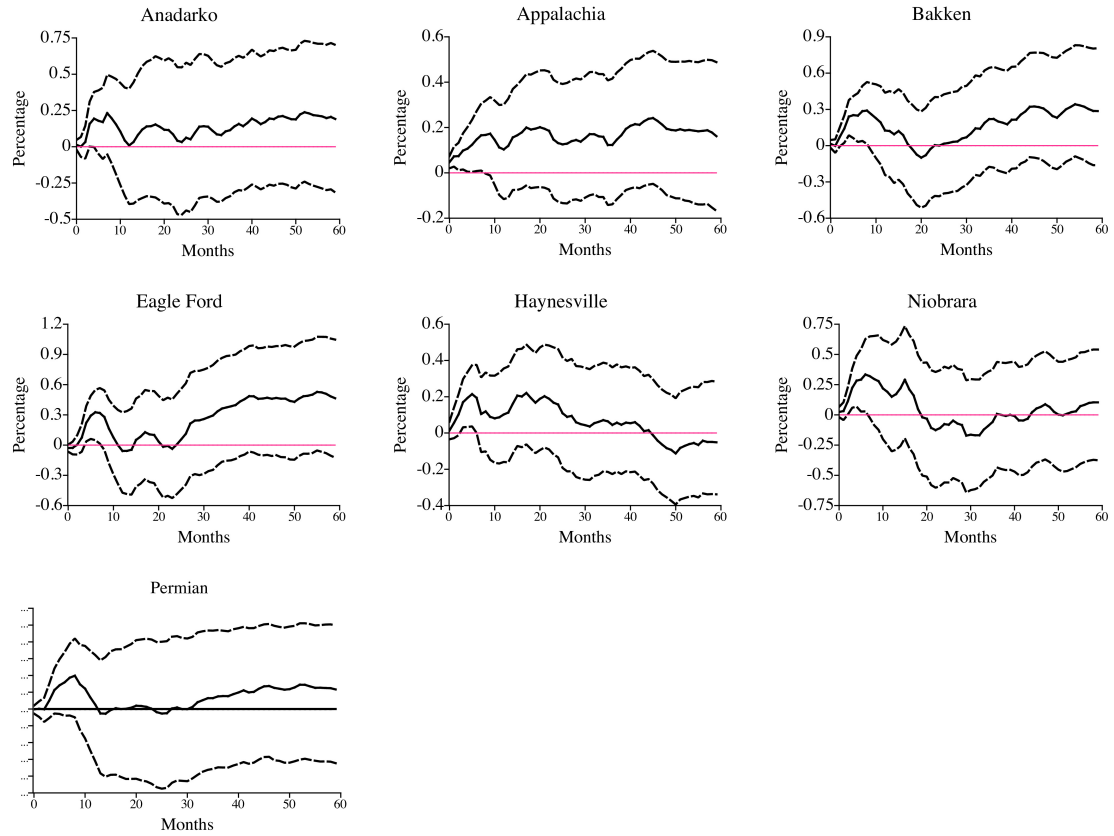


Figure C8: Response of Number of Drills to Demand Shock

Note: Results are for SVAR(24) with intercept for four structural shocks identified in the text. First panel shows the responses to rest of global oil production shock normalized to decrease global oil production by 1%. Second panel shows the responses to U.S. shale oil supply shock normalized to decrease global oil production by 1%. Errors are for 68% confidence interval. Data spans 2008M01:2024M12.

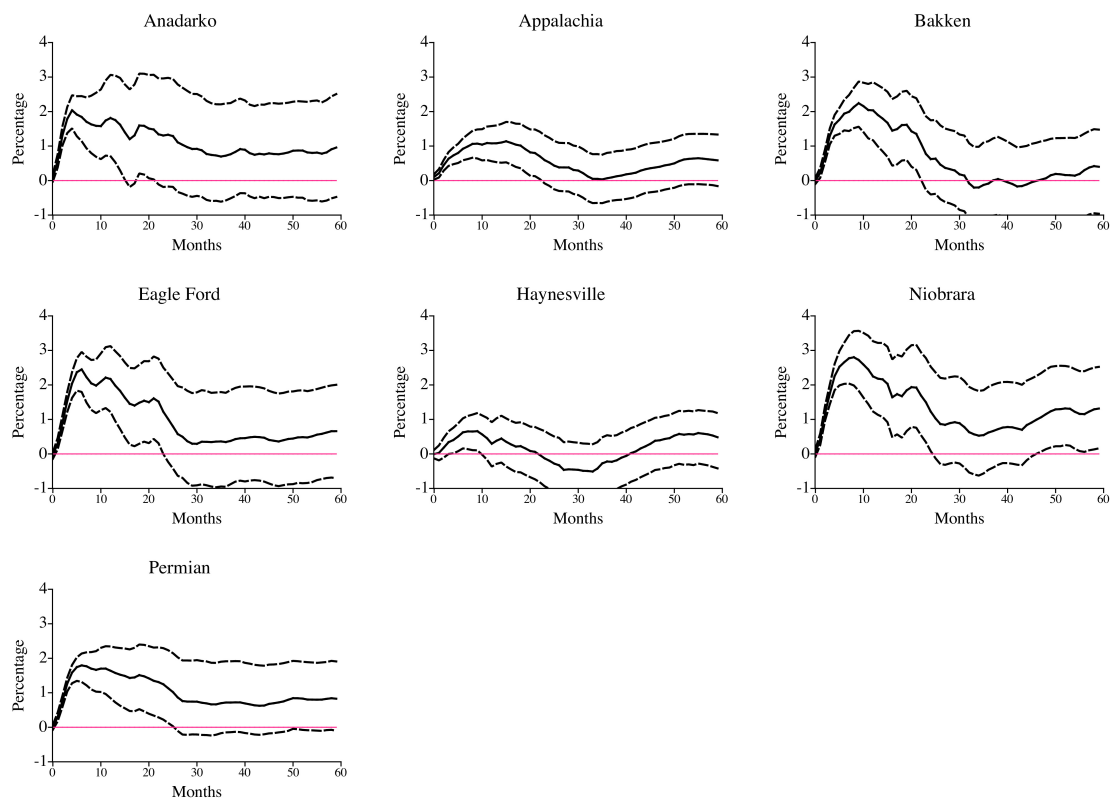


Figure C9: Response of Number of Drills to Oil Specific Demand Shock

Note: Results are for SVAR(24) with intercept for four structural shocks identified in the text.. First panel shows the responses to rest of global oil production shock normalized to decrease global oil production by 1%. Second panel shows the responses to U.S. shale oil supply shock normalized to decrease global oil production by 1%. Errors are for 68% confidence interval. Data spans 2008M01:2024M12.

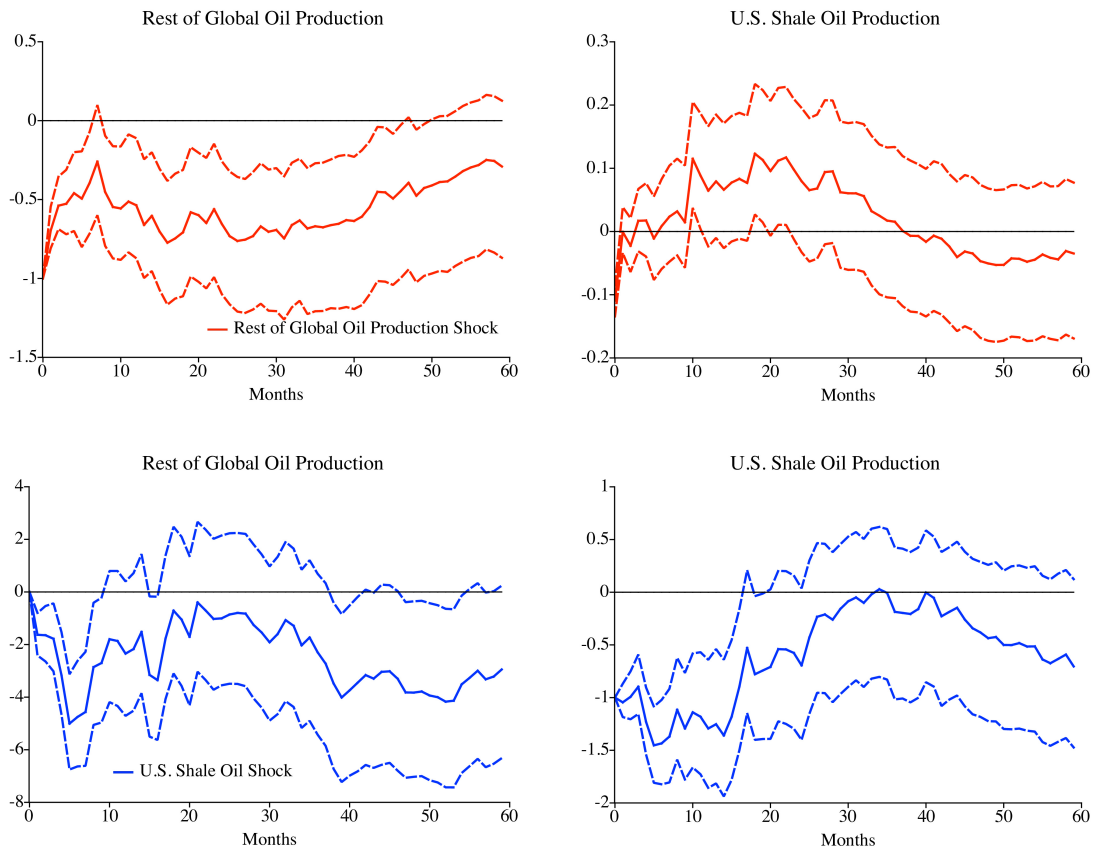


Figure C10: Response of Global Oil Production: U.S. Shale Oil Production vs Rest of Global Oil Production

Note: Results are for SVAR(24) with intercept for four structural shocks identified in the text.. First panel shows the responses to rest of global oil production shock normalized to decrease global oil production by 1%. Second panel shows the responses to U.S. shale oil supply shock normalized to decrease global oil production by 1%. Errors are for 68% confidence interval. Data spans 2008M01:2024M12.

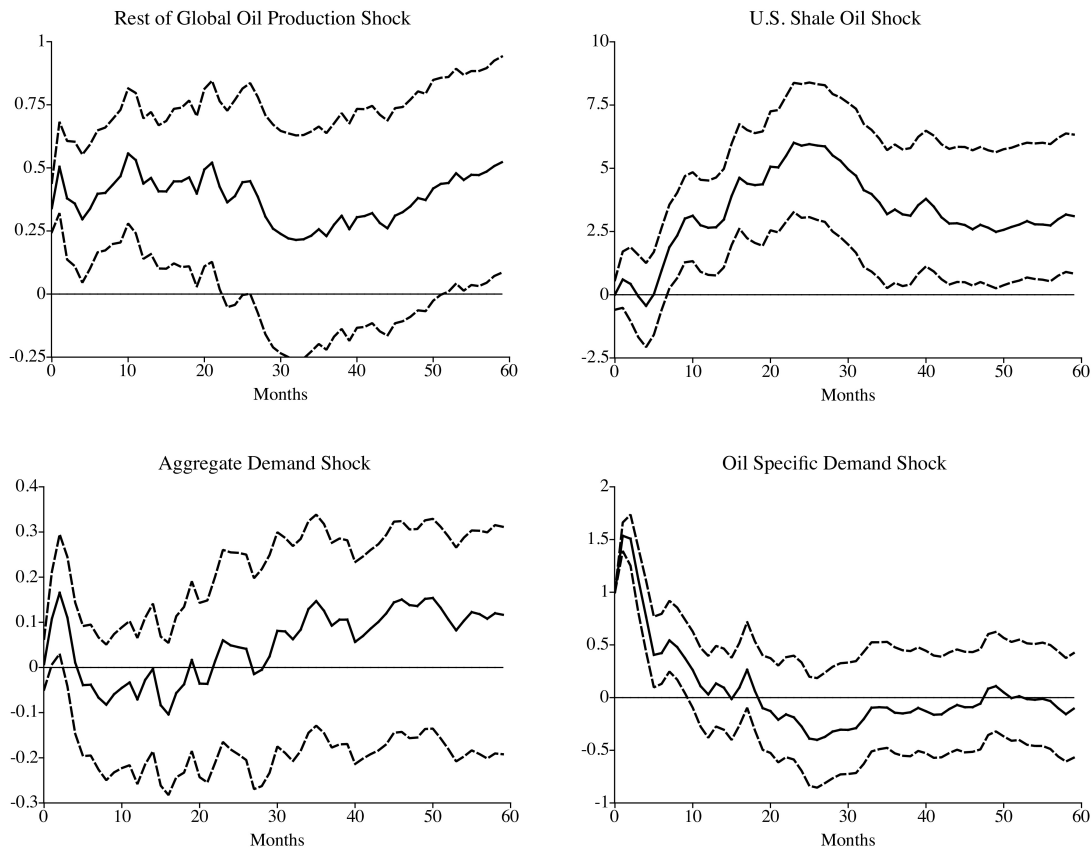


Figure C11: Response of Crude Oil Price to Global Oil Market Shocks

Note: Results are for SVAR(24) with intercept for four structural shocks identified in the text. Both U.S. Shale Supply Shock and rest of global oil supply shock are normalized to decrease global oil production 1%. Aggregate demand shock normalized to increase global economic activity by 1%. Oil specific demand shock normalized to increase oil price by 1%. Errors are for 68% confidence interval. Data spans 2008M01:2024M12.