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Subash Bhandari and Hyeongwoo Kim

Auburn University

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

Subash Bhandari* and Hyeongwoo Kim†

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Abstract

This paper 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.

Keywords: OPEC News Shock; Oil Supply Shock; Disaggregated CPI Components; Instrumental Variable Structural Vector Autoregression

JEL Classification: E3; F4; Q4

*Department of Economics, Auburn University, 101 Miller, Auburn AL 36830. Tel: (334) 591-0240. Email: szb0162@auburn.edu.

†Department of Economics, Auburn University, 138 Miller, Auburn AL 36849. Tel: (334) 844-2928. Email: hzk0001@auburn.edu

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. This 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 (2022a) and Kilian and Zhou (2022b) 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, Bjørnland, and Cross (2023) argue 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.[1] In contrast, Gao, Kim, and Saba (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.

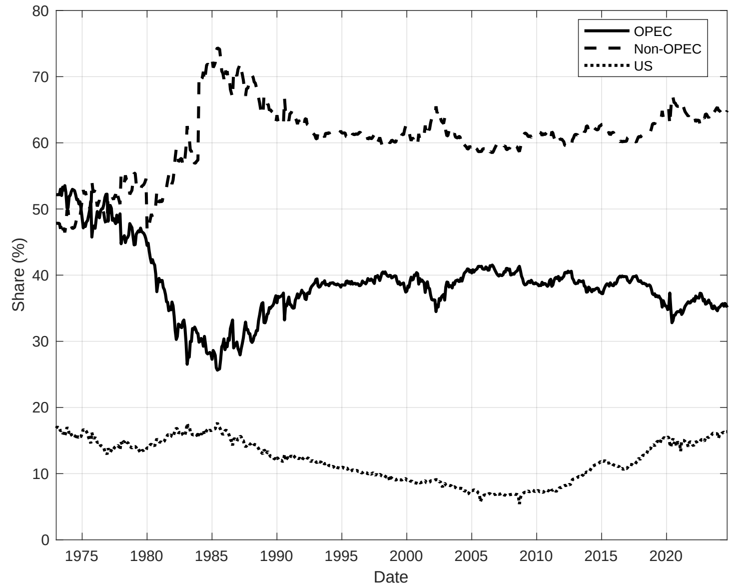
Specifically, we examine the inflationary effects of oil price movements originating from OPEC (Organization of Petroleum Exporting Countries), following studies such as Caldara, Cavallo, and Iacoviello (2019), Almoguera, Douglas, and Herrera (2011), Kilian (2008), and Hamilton (2003).[2] As shown in Figure (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, Cavallo, and Iacoviello (2019), and Arezki, Ramey, and Sheng (2017) for related approaches that rely on external instruments for causal interpretation. However, as emphasized by Andrews, Stock, and Sun (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, Stock, and Watson (2021).

[1] Examples 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).

[2] Established 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: 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 2024.

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.[3] 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).[4]

We also investigate why certain CPI components exhibit weak or even negative responses to

[3]The importance of this expectations channel for the business cycle is emphasized in Arezki, Ramey, and Sheng (2017).

[4]This 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.

OPEC-induced oil shocks. To this end, we discuss the role of consumer budget reallocation, building on Baumeister, Kilian, and Zhou (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 (2022a) and Kilian and Zhou (2022b).

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.

2 The Empirical Model

2.1 The IV-SVAR Model

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

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

where $\mathbf{u}_t = \mathbf{\Theta}_0 \varepsilon_t$ 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 $\mathbf{\Theta}_0$ is an $n \times n$ non-singular contemporaneous matrix. That is,

$$\begin{aligned} \mathbb{E}\left[\varepsilon_t\right] = \mathbf{0}_n,\ \mathbb{E}\left[\varepsilon_t \varepsilon_t^{'}\right] &= \mathbf{D}_n = \operatorname{diag}\left(\sigma_1^2, \sigma_2^2, \dots .\sigma_n^2\right), \\ \mathbb{E}\left[\mathbf{u}_t \mathbf{u}_t^{'}\right] &= \mathbf{\Theta}_0 \mathbf{D}_n \mathbf{\Theta}_0^{'} = \mathbf{\Sigma} \end{aligned}$$

Assuming the covariance stationarity, $\mathbf{y}_t$ in equation (1) has the following infinite order vector moving average (VMA) representation based on the Wold Theorem.

$$\mathbf{y}_t = \sum_{k=0}^{\infty} \mathbf{C}_k(\mathbf{A}) \mathbf{\Theta}_0 \varepsilon_{t-k}, \tag{2}$$

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 $m > p$.[5]

The k-period ahead Impulse-Response Function (IRF) of $y_{i,t}$ variable to a one-unit normalized

[5] That 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.

structural shock to $\varepsilon_{j,t}$ is defined as follows.

$$\Phi_{k,i,j} = \mathbb{E}\left(y_{i,t+k}|\Omega_{t-1}, \varepsilon_{j,t} = 1\right) - \mathbb{E}\left(y_{i,t+k}|\Omega_{t-1}\right) = \mathbf{e}_i{}'\mathbf{C}_k(\mathbf{A})\boldsymbol{\Theta}_0\mathbf{e}_j, \tag{3}$$

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 (3). Note that 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 $j = 2, ..., n$, are randomly re-ordered. See Christiano, Eichenbaum, and Evans (1999) for the proof.

Let $\boldsymbol{\Theta}_{0,1}$ denote the first column of $\boldsymbol{\Theta}_0$, that is, $\boldsymbol{\Theta}_0\mathbf{e}_1$. To identify $\boldsymbol{\Theta}_{0,1}$ 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: $\mathbb{E}\left(z_t\varepsilon_{1,t}\right) = \alpha \neq 0$ (relevancy); $\mathbb{E}\left(z_t\varepsilon_{j,t}\right) = 0$ for $j \neq 1$ (exogeneity). Note that the first component of equation (1) can be rewritten as follows.

$$y_{1,t} = \mathbf{e}_1{}'\sum_{i=1}^{p}\mathbf{A}_i\mathbf{y}_{t-i} + \Theta_{0,1,1}\varepsilon_{1,t} + \sum_{j=2}^{n}\Theta_{0,1,j}\varepsilon_{j,t} \tag{4}$$

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

$$y_{j,t} = \mathbf{e}_j{}'\sum_{i=1}^{p}\mathbf{A}_i\mathbf{y}_{t-i} + \Theta_{0,j,1}\varepsilon_{1,t} + \sum_{q=2}^{n}\Theta_{0,j,q}\varepsilon_{q,t},\ j = 2, 3, ..., n \tag{5}$$

By solving for $\varepsilon_{1,t}$ from equation (4) after the scale normalization $\Theta_{0,1,1} = 1$ and substituting it into equation (5), we obtain the following.

$$y_{j,t} = \Theta_{0,j,1}y_{1,t} + \Xi_t, \tag{6}$$

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, $\mathbb{E}\left(z_t\varepsilon_{1,t}\right) = \alpha \neq 0$ and $\mathbb{E}\left(z_t\omega_{j,t}\right) = 0,\ j = 2, ..., n$.

From equation (3) for $j = 1$, the IRF $\Phi_{k,i,1}$ with $\Theta_{0,1,1} = 1$ (scale normalization) can be obtained by,

$$\Phi_{k,i,1} = \mathbf{e}_i{}'\mathbf{C}_k(\mathbf{A})\boldsymbol{\Theta}_{0,1} = \mathbf{e}_i{}'\mathbf{C}_k(\mathbf{A})\boldsymbol{\Gamma}/\mathbf{e}_1^{'}\boldsymbol{\Gamma}, \tag{7}$$

where $\boldsymbol{\Gamma} = \mathbb{E}\left(z_t\mathbf{u}_t\right) = \mathbb{E}\left(z_t\boldsymbol{\Theta}_0\varepsilon_t\right) = \alpha\boldsymbol{\Theta}_{0,1}$ and $\mathbf{e}_1^{'}\boldsymbol{\Gamma} = \alpha$.[6] 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 $\boldsymbol{\Gamma}$ 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

[6] See Stock and Watson (2016) for more discussion on this normalization.

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, Stock, and Watson (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 $\alpha_T \to \alpha = 0$.

Let $\hat{\mathbf{A}}$ and $\hat{\mathbf{\Gamma}}_T$ be the estimates for $\mathbf{A}$ and $\mathbf{\Gamma}$. 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 (7) as follows.

$$\hat{\mathbf{H}}_T = \begin{bmatrix} \mathbf{e}_i{}'\mathbf{C}_k(\hat{\mathbf{A}})\hat{\mathbf{\Gamma}}_T \\ \mathbf{e}_1'\hat{\mathbf{\Gamma}}_T \end{bmatrix}, \tag{8}$$

that is, $\hat{\Phi}_{k,i,1} = \hat{H}_{T,1}/\hat{H}_{T,2}$. Note that large sample approximation holds for $\hat{\mathbf{H}}_T$, $\hat{\mathbf{H}}_T \overset{a}{\sim} \mathcal{N}\left(\mathbf{H}_T, T^{-1}\mathbf{\Omega}\right)$. The null hypothesis $\hat{\Phi}_{k,i,1} = \Phi_{k,i,1}$ imposes a linear restriction: $H_{T,1} - \Phi_{k,i,1}H_{T,2} = 0$, yielding the following Wald statistic,

$$q_T(\Phi_{k,i,1}) = \frac{T(\hat{H}_{T,1} - \Phi_{k,i,1}\hat{H}_{T,2})}{\hat{\omega}_{T,1,1} - 2\Phi_{k,i,1}\hat{\omega}_{T,1,2} + \Phi^2_{k,i,1}\hat{\omega}_{T,2,2}}, \tag{9}$$

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

$$CS^{AR}(\Phi_{k,i,1}) = \left(\Phi_{k,i,1} | q_T(\Phi_{k,i,1}) \leq \chi^2_{1,1-a}\right), \tag{10}$$

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

2.2 Identifying OPEC News Shocks

Our baseline empirical models employ the structural vector autoregressive (SVAR) framework of equation (1) with the following.

$$\mathbf{y}_t = \begin{pmatrix} \mathbf{x}_t \\ inf_t \end{pmatrix}, \tag{11}$$

where we employ $\mathbf{x}_t = (\Delta rpo_t,\ \Delta prod_t,\ \Delta rea_t)'$ following Känzig (2021).[7] 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.[8] The variables in $\mathbf{x}_t$ is motivated by Kilian (2009),

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

[8]Data 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)

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, Stock, and Watson (2021), we employ a weak-instrument robust Anderson-Rubin one-standard-deviation confidence interval.

2.2.1 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.

The top two panels of Figure (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 shortfalls 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.

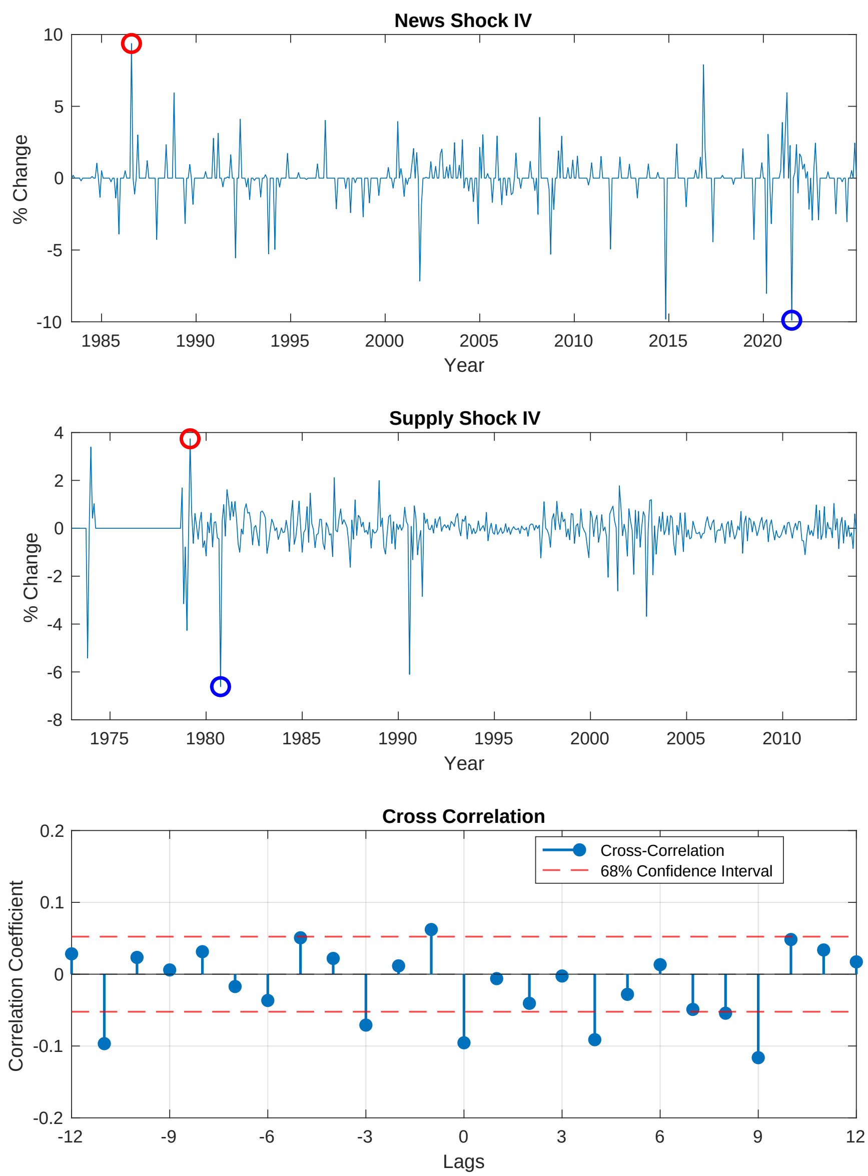
The third panel presents the estimates for the normalized cross-correlations,

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

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 ($j = 0, 1, ..., 9$), 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.

and multiplying by 100.

Figure 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.

Table 1: Correlations between the IV Series and Structural Shocks

Model	Full Sample Period $z_{N,t}$	Full Sample Period $z_{S,t}$	Common Sample Period $z_{N,t}$	Common Sample Period $z_{S,t}$
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.

2.2.2 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).

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. [9] 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.

[9] We observe similar estimates when restricting to common sample from July 1983 to December 2013.

Table 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, Stock, and Watson (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.

2.2.3 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, Stock, and Watson (2021), which implies that the $100\%(1-a)$ Anderson-Rubin (AR) confidence set $CS^{AR}(\Phi_{k,i,1})$ in equation (10) is bounded if and only if $\xi > \chi^2_{1,1-a}$.[10] The results are reported in Table (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.

3 Empirical Findings and Inferences

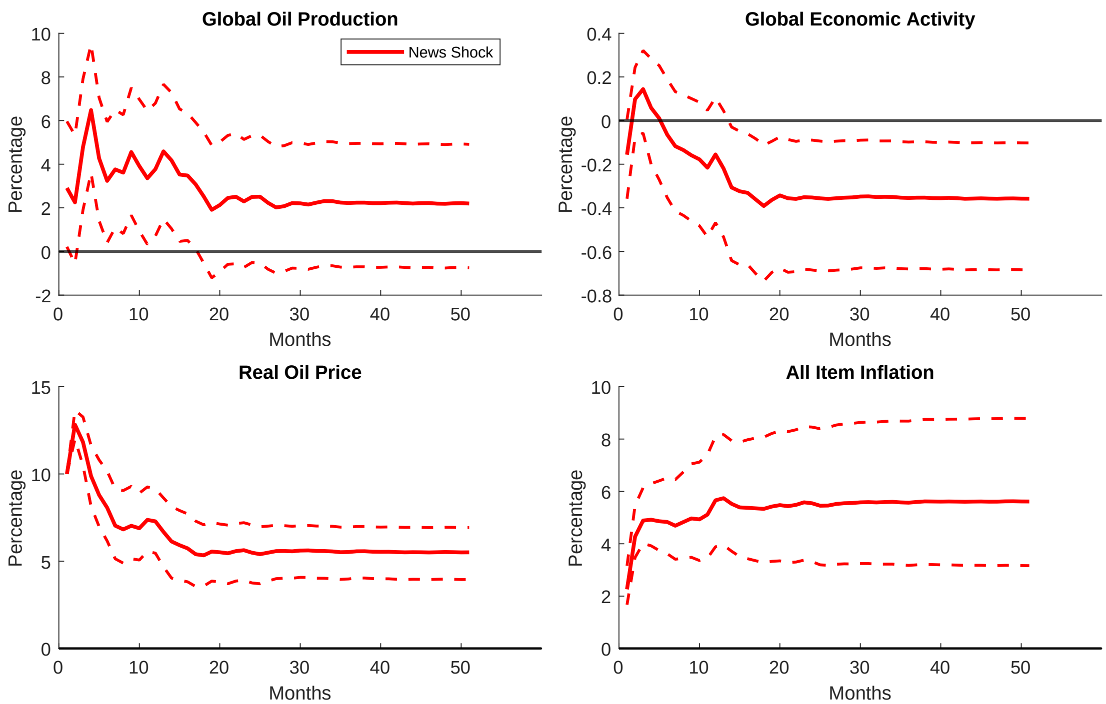
This section presents the impulse-response function (IRF) estimates from equation (7), along with the one-standard-deviation Anderson-Rubin confidence intervals in equation (10). Since all variables are expressed as month-over-month percentage changes (inflation measures annualized), the IRFs are reported 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.

3.1 Baseline Model Estimations with Headline CPI Inflation

Figure (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 (11). We use the West Texas Intermediate spot price of crude 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

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

Figure 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, Stock, and Watson (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.

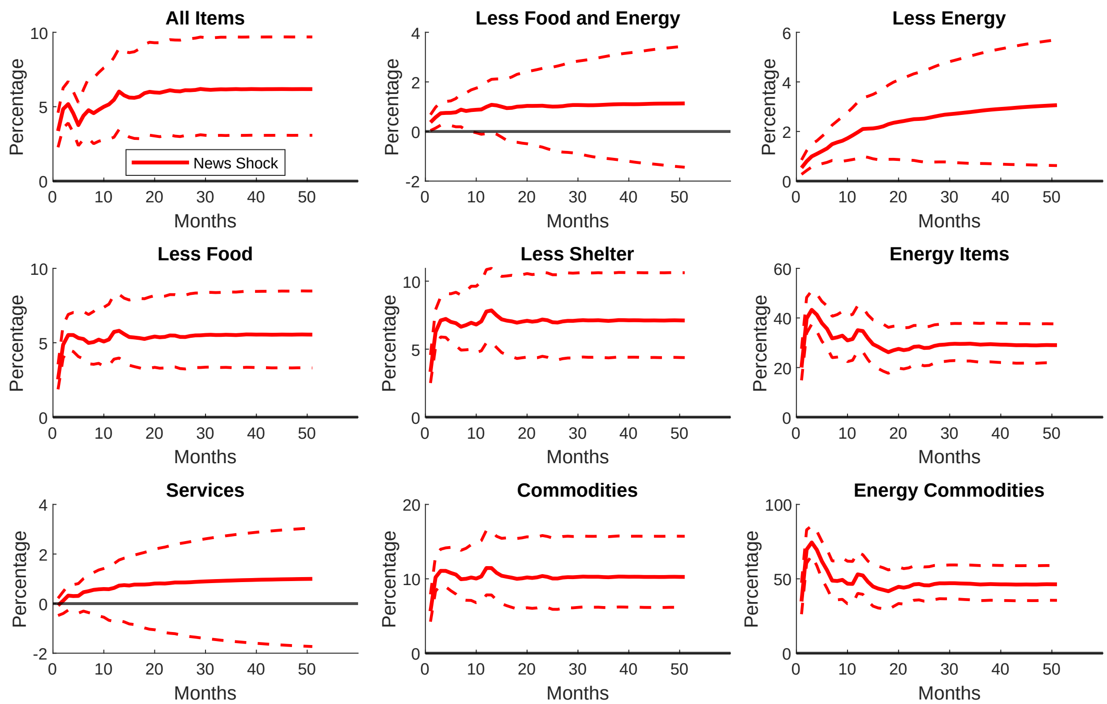
on impact, maintaining consistency with Känzig (2021), Kilian and Zhou (2022a), and Kilian and Zhou (2022b).[11]

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 looses 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

[11] For our impulse response function estimation, we use MATLAB code from the replication files of Montiel Olea, Stock, and Watson (2021), obtained from the author's GitHub repository.

Figure 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, Stock, and Watson (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.

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.

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 (4). Several notable patterns emerge. First, the increase 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 (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.

3.3 The Substitution Effect

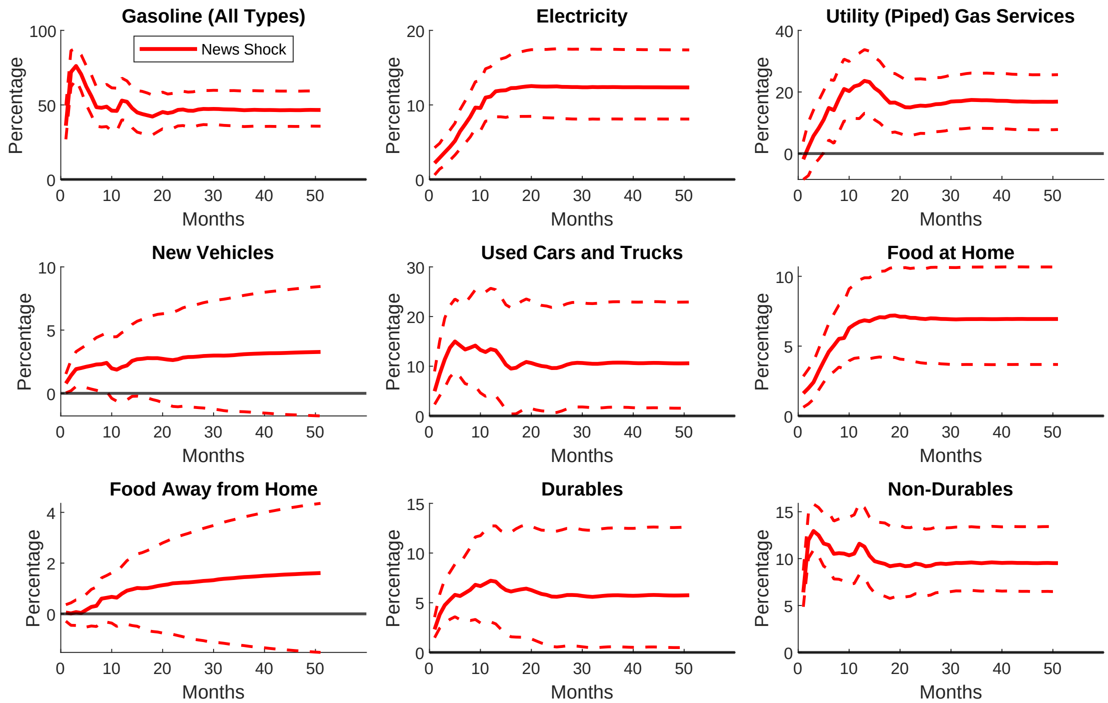
It is important to note that recessionary pressures may prompt consumers to adjust their spending behavior. Specifically, faced with budget constraints resulting from negative income shocks, driven by rising costs of necessities such as energy expenditures, consumers may need to reduce spending on certain 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 (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 (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.

While our overall findings are consistent with the conclusions of Kilian and Zhou (2022a) 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

Figure 5: Change in Consumer Preference



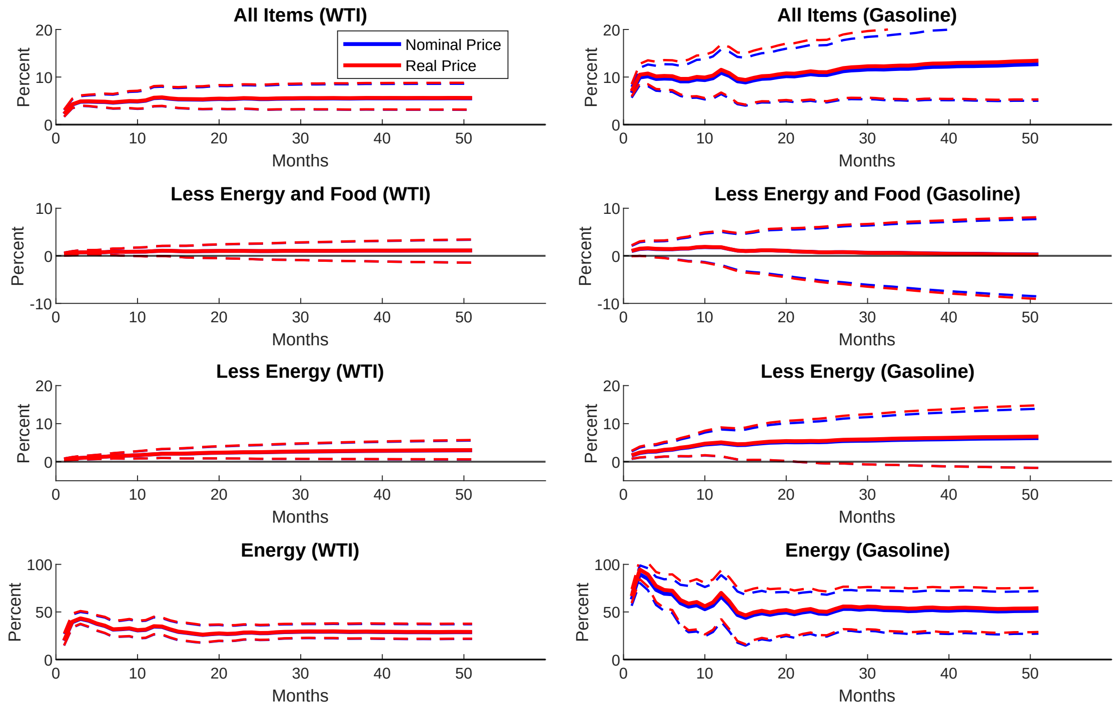
extends beyond the transportation sector. For example, increases in electricity and natural gas prices are transmitted to housing related categories and higher food prices, illustrating the broader reach of energy cost pressures within the consumption basket. Detailed results are presented in the Appendix A.

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 (11) with a gasoline price alternative, considering both measures in nominal and real terms.

Figure (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.

Figure 6: Choice of Oil Price



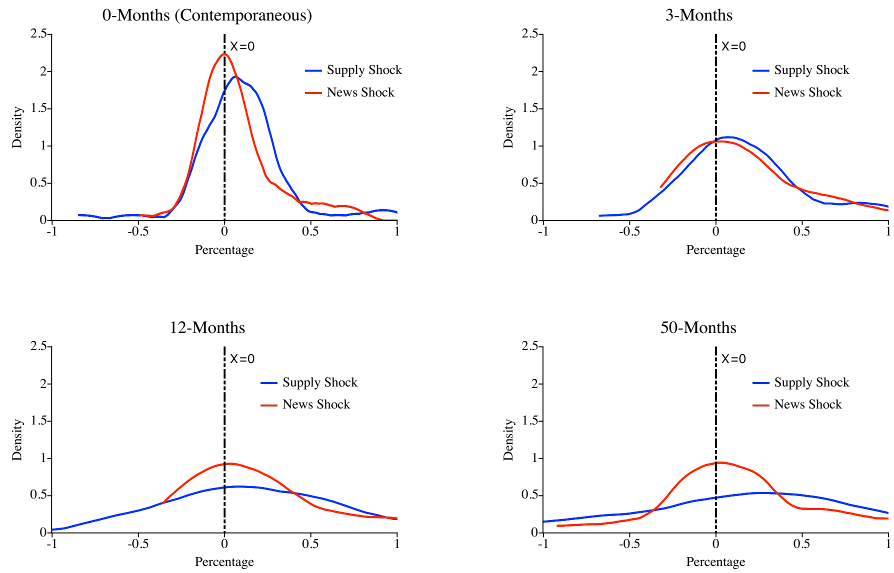
3.5 Further Discussion: News Shock vs Supply Shock

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 (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 (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,

Figure 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 ($z_{N,t}$).

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.

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

Table 3: Kernel Density Estimations (Summary Statistics)

	$z_{S,t}$				$z_{N,t}$			
k	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 $k \in 0, 3, 12, 50$.

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.

Funding: This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

Data: We obtained the data for global oil production from the Energy Information Agency. We obtained data for the world industrial production index (OECD plus 6 countries) of Baumeister and Hamilton (2019) from the author's website. We obtained data for spot price of West Texas Intermediate crude oil from FRED database. All CPI data were also taken from FRED database. 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).

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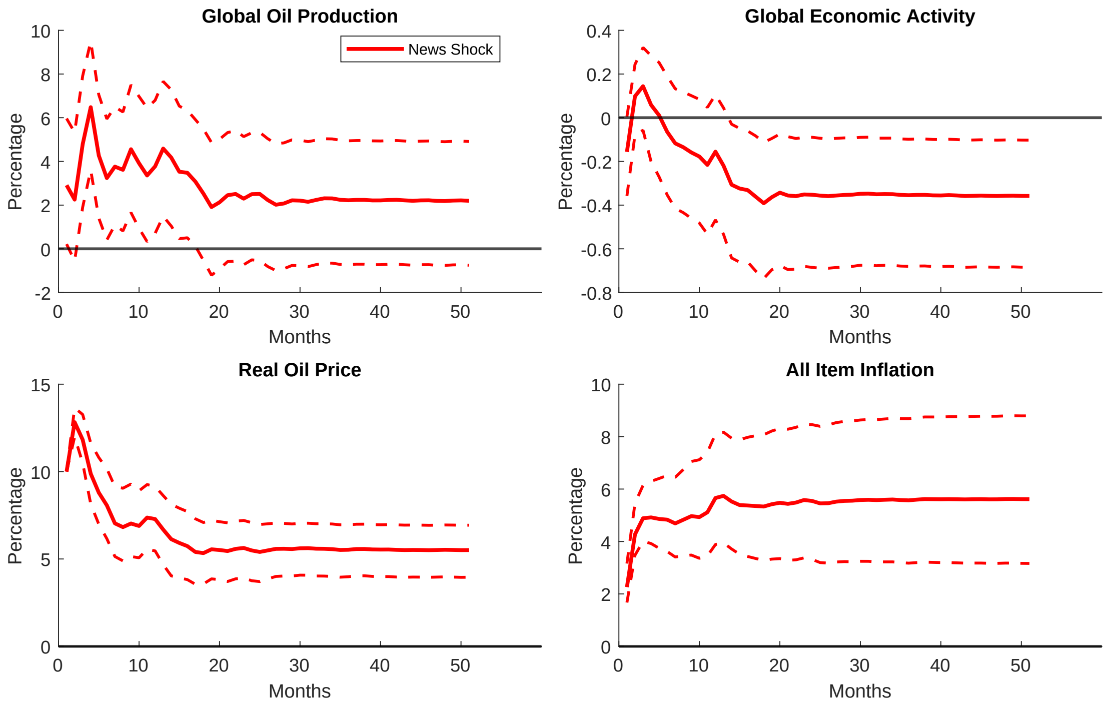
Appendix A1: Complete Estimations for News Shock

Figure 8: 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, Stock, and Watson (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 9: Special Indexes

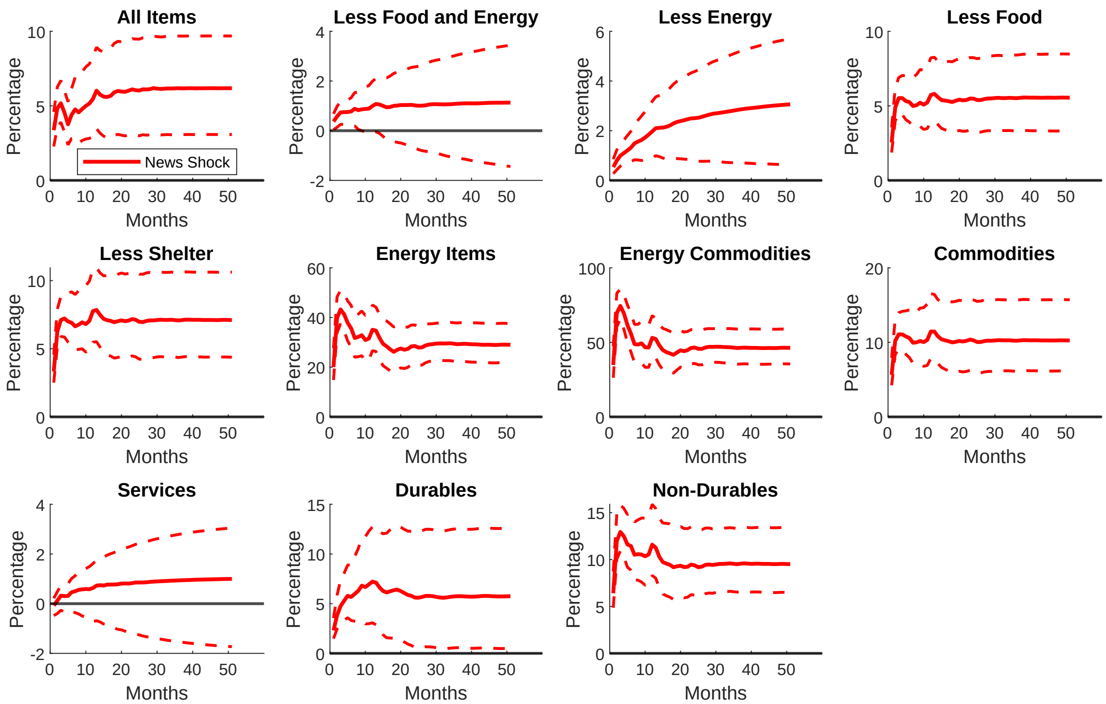


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Figure 10: Major Categories

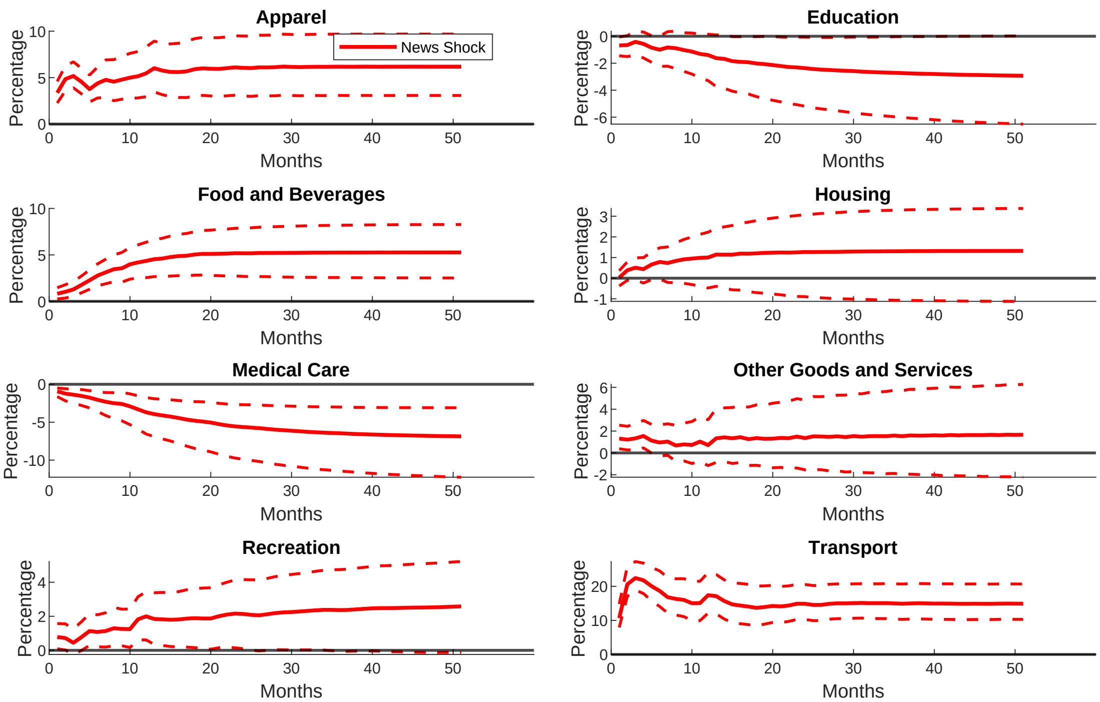

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Figure 11: Food Items

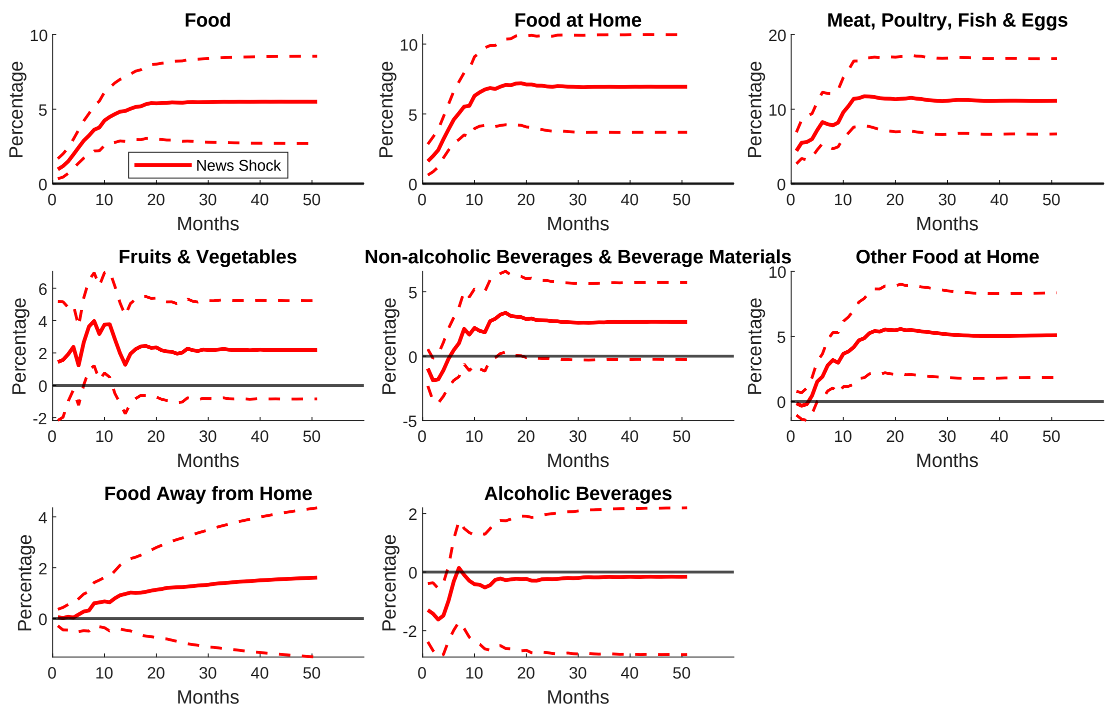

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Figure 12: Housing Items

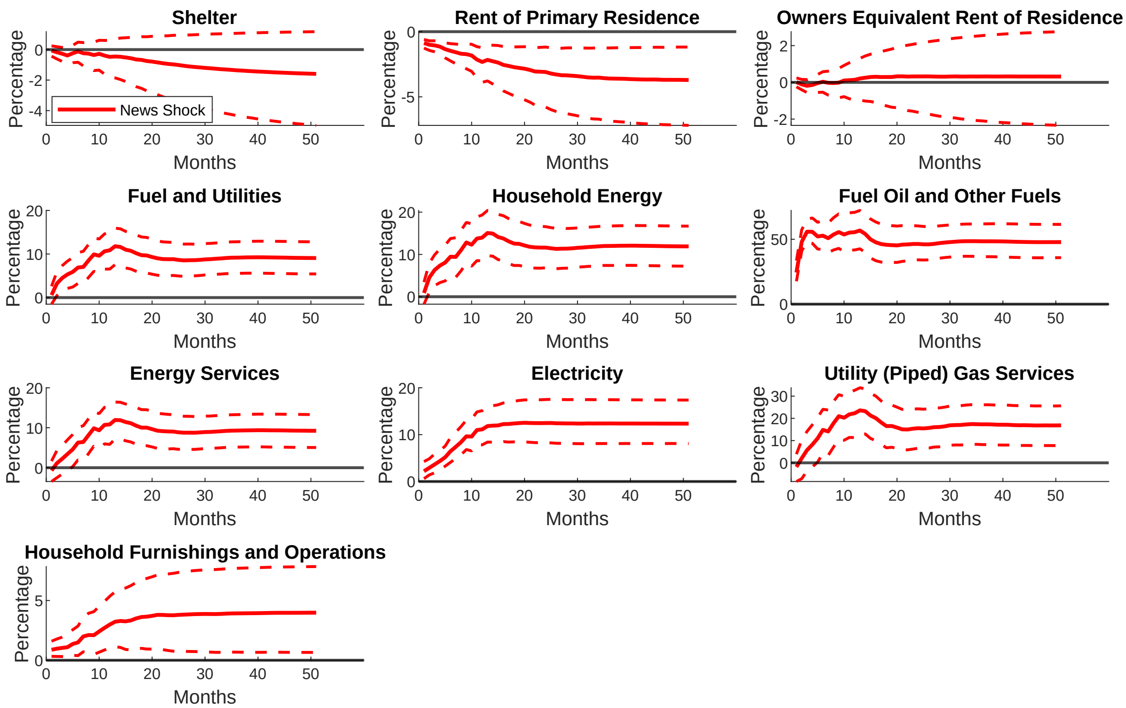

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Figure 13: Transport

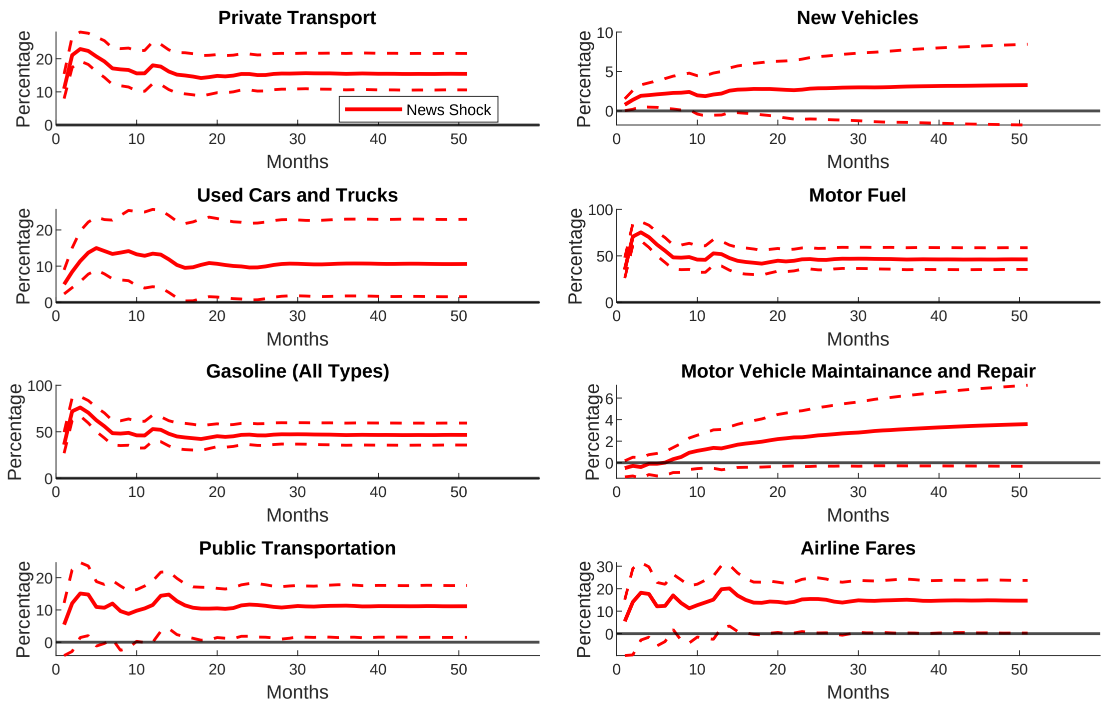

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Figure 14: Other Categories

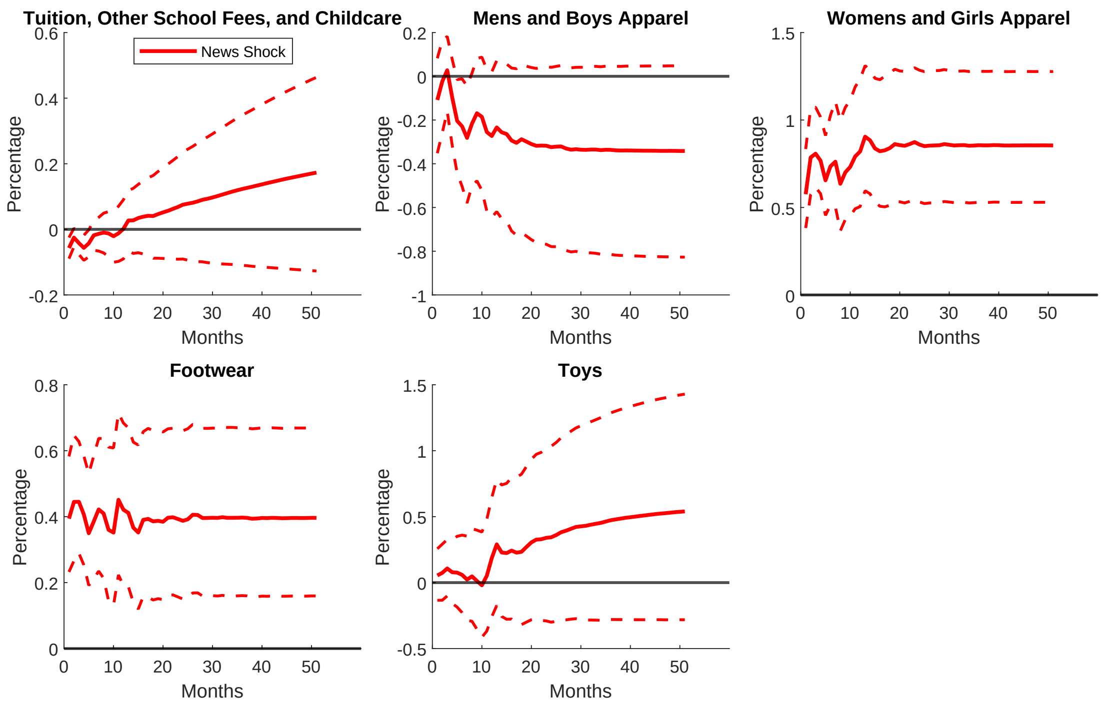

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Figure 15: Change in Consumer Preference

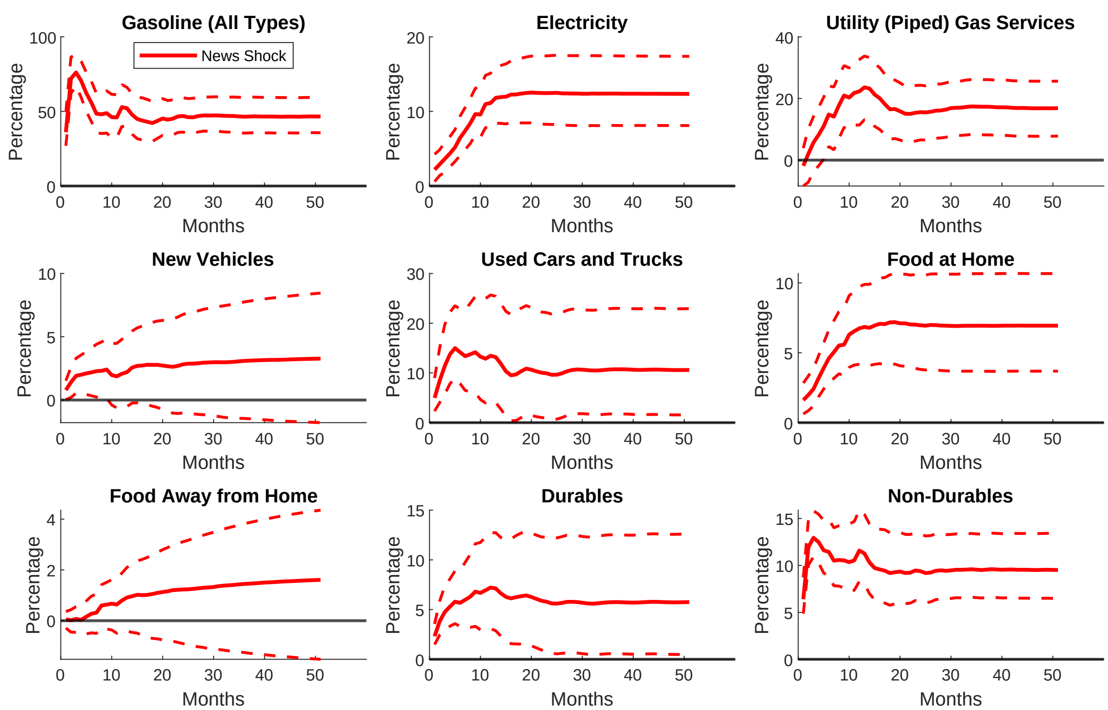

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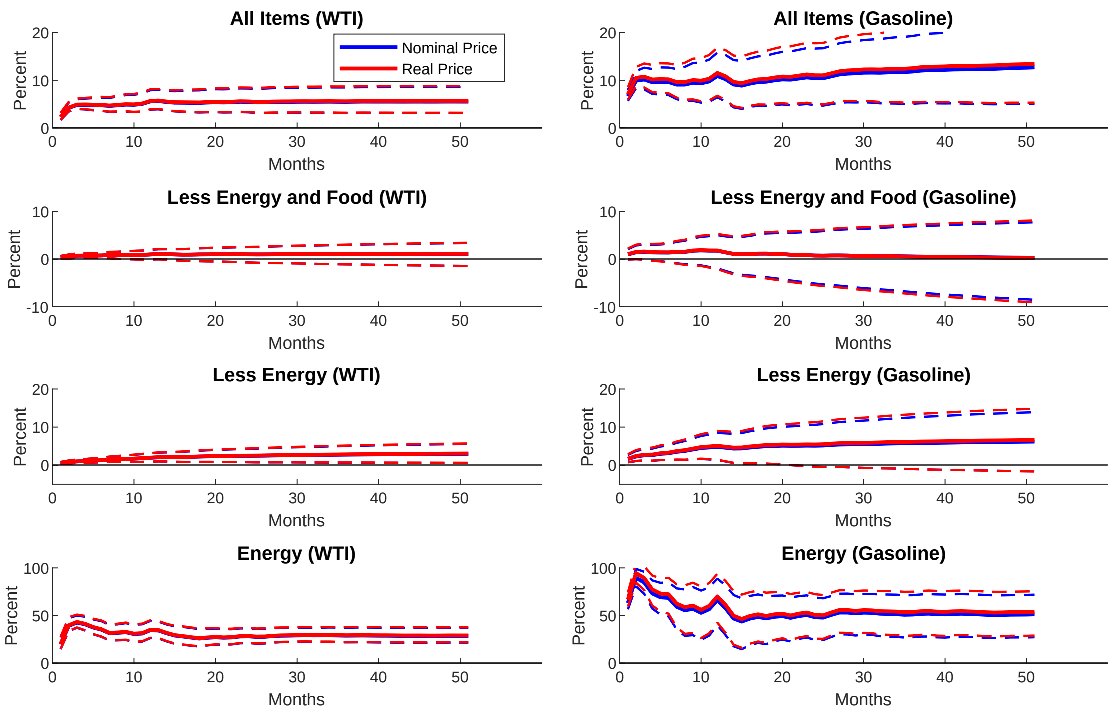
Figure 16: Choice of Oil Price



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, Stock, and Watson (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.

Appendix A2: Supply vs News Shock

Our baseline empirical models employ the structural vector autoregressive (SVAR) framework of equation (1) with the following.

$$\mathbf{y}_t = \begin{pmatrix} \mathbf{x}_t \\ inf_t \end{pmatrix}, \tag{12}$$

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, Stock, and Watson (2021).[11] 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.[12] 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).

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, Stock, and Watson (2021), we employ a weak-instrument robust Anderson-Rubin one-standard-deviation confidence interval.

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, Stock, and Watson (2021), which implies that the

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

[12] Data 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.

Table 4: Validity of Weak-Instrument Robust Confidence Bands

#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, Stock, and Watson (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.

100%$(1-a)$ Anderson-Rubin (AR) confidence set $CS^{AR}(\Phi_{k,i,1})$ in equation (10) is bounded if and only if $\xi > \chi^2_{1,1-a}$.[13] The results are reported in Table (4).

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 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.

Baseline Model Estimations with Headline CPI Inflation

Figure (3) 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 (12). 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.[14]

It should be noted that the responses of global oil production ($\Delta prod_t$) to the supply

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

[14] For our impulse response function estimation, we use MATLAB code from the replication files of Montiel Olea, Stock, and Watson (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.

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.

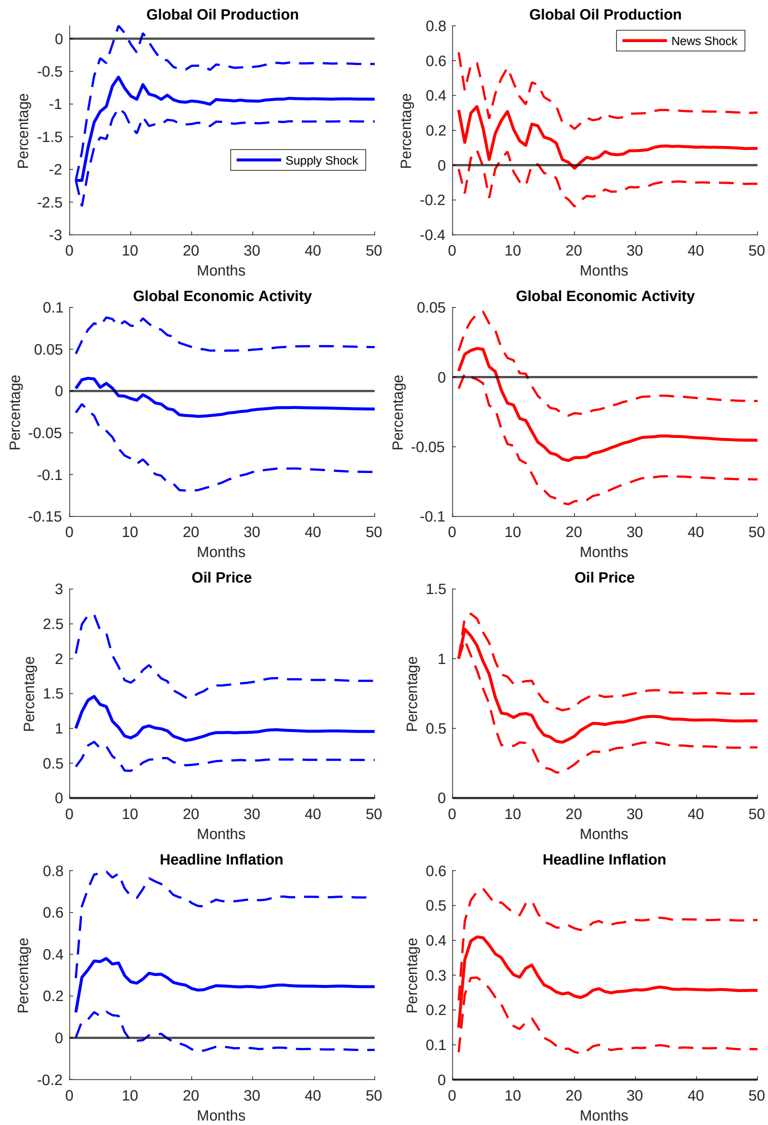
Notwithstanding the contrasting responses of global oil production, both IV shocks, $z_{S,t}$ and $z_{N,t}$, lead to statistically significant increases in oil prices. The headline inflation rate also rises in response to both shocks, although the inflation response to the supply IV shock ($z_{S,t}$) 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, Stock, and Watson (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 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.

Figure 17: 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, Stock, and Watson (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.

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 (18). 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 (17). 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.

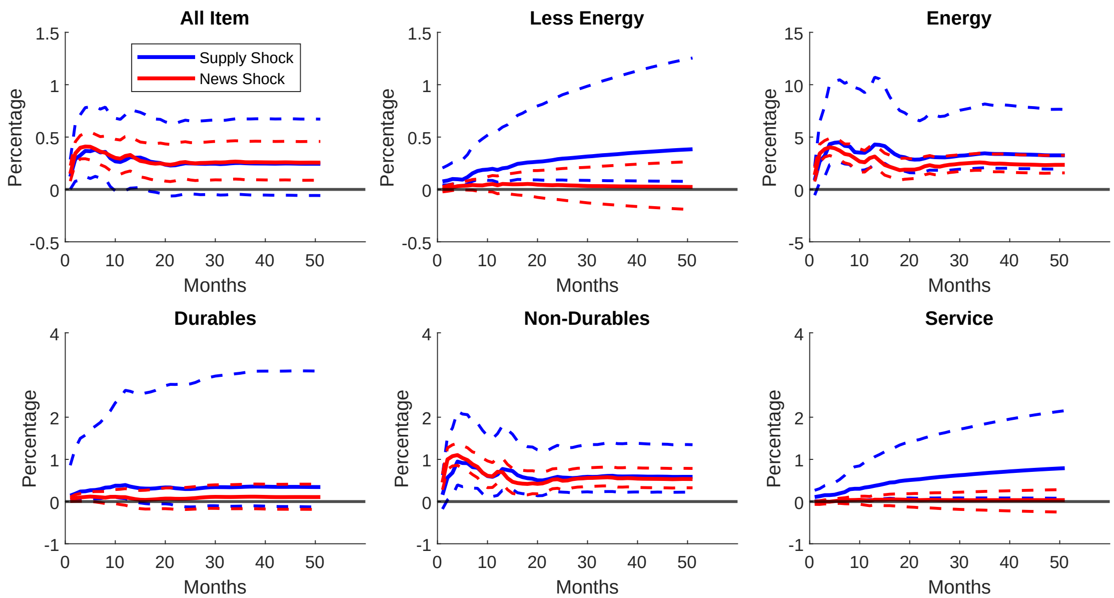
Figure (19) provides additional evidence at the disaggregated level. Inflation responses of energy commodities, such as motor fuel and gasoline (not reported), are highly significant and quantitatively large. In contrast, energy services, including electricity and natural gas, display weaker but still statistically significant 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, 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 (2022a) 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.[15] These higher

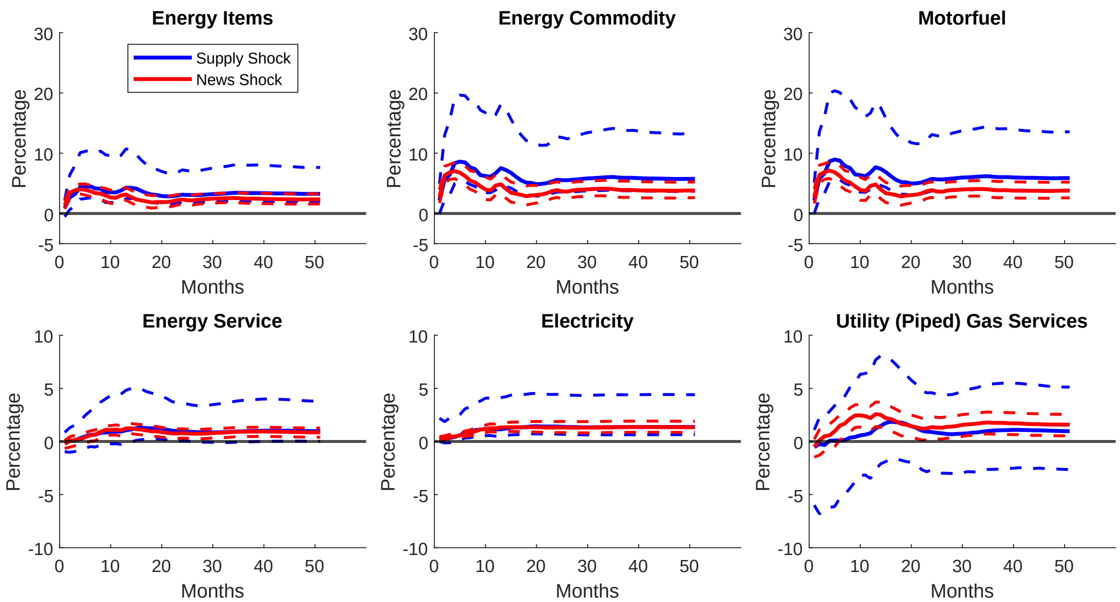
[15] Detailed results are available upon request.

Figure 18: 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, Stock, and Watson (2021). The sample period covers July 1983 to December 2013.

Figure 19: 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, Stock, and Watson (2021). The sample period covers July 1983 through December 2013.

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.

Responses of Further Broken-Down CPI Components

This subsection presents the inflation responses of highly disaggregated CPI components. Figure (20) highlights several noteworthy comparisons.

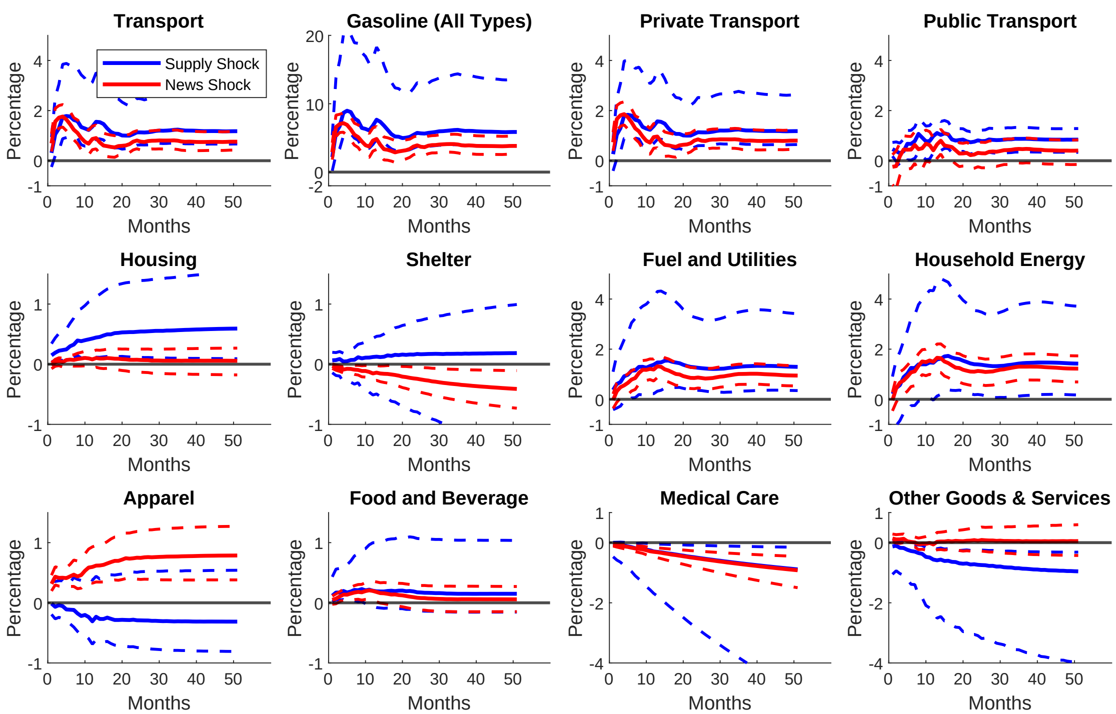
Consistent with earlier results, energy-related CPI components such as Transport and Gasoline increase substantially and significantly in response to OPEC IV shocks. Notably, Private Transportation CPI responds significantly to both supply and news shocks, whereas the response of Public Transportation 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 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 (21) 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

Figure 20: 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, Stock, and Watson (2021). The sample period spans July 1983 to December 2013, except for Public Transport CPI, for which observations begin in February 1989.

Table 5: Kernel Density Estimations (Summary Statistics)

	$z_{S,t}$				$z_{N,t}$			
k	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 $k \in 0, 3, 12, 50$.

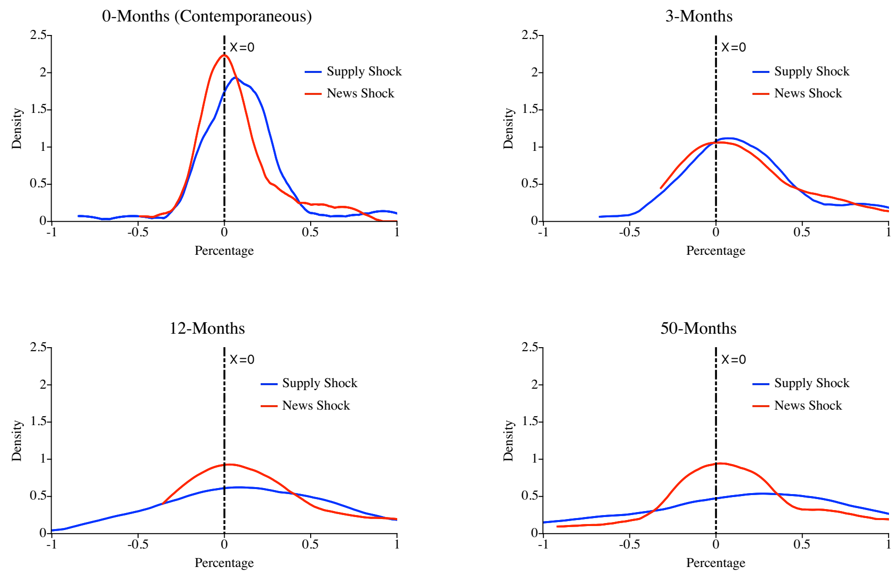
($z_{S,t}$) and the OPEC news shock ($z_{N,t}$). Corresponding summary statistics of these density estimates are provided in Table (5).

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%.

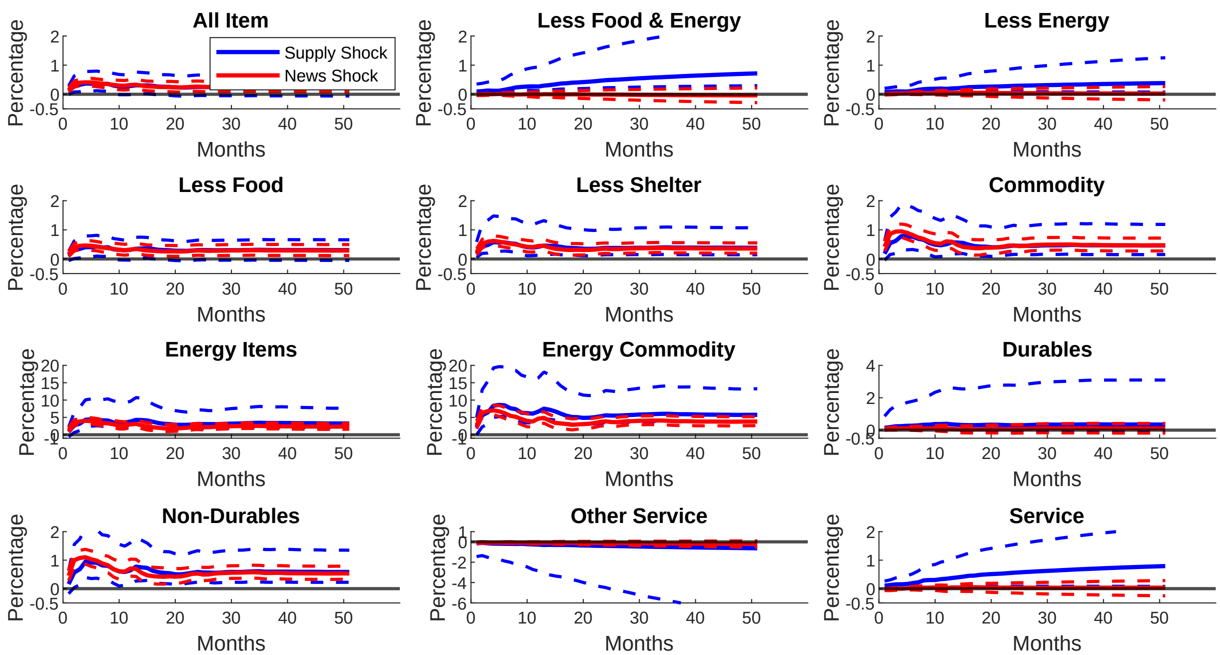
These results suggest that $z_{S,t}$ exerts more persistent effects, consistent with the characterization of $z_{N,t}$ as a front-loaded shock by Känzig (2021), whose effects are primarily observed at short horizons and dissipate relatively quickly.

Figure 21: 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 ($z_{N,t}$).

Figure 22: Effect on Special Indexes



Note: Figure shows the response based on IV-SVAR as described in the text. Blue responses are for supply shock. Red responses are for news shock. Supply shock is normalized to cause 1% decline in global oil production. News shock is normalized to cause 1% increase in oil price. Error bars are presented on 68% significance level using Anderson-Rubin Confidence Interval of Montiel Olea, Stock, and Watson (2021). Responses for supply shock is scaled by a factor of 1/0.46 for graphical representation purpose.Data spans 1983M07:2013M12.

Figure 23: Effect on Major Categories

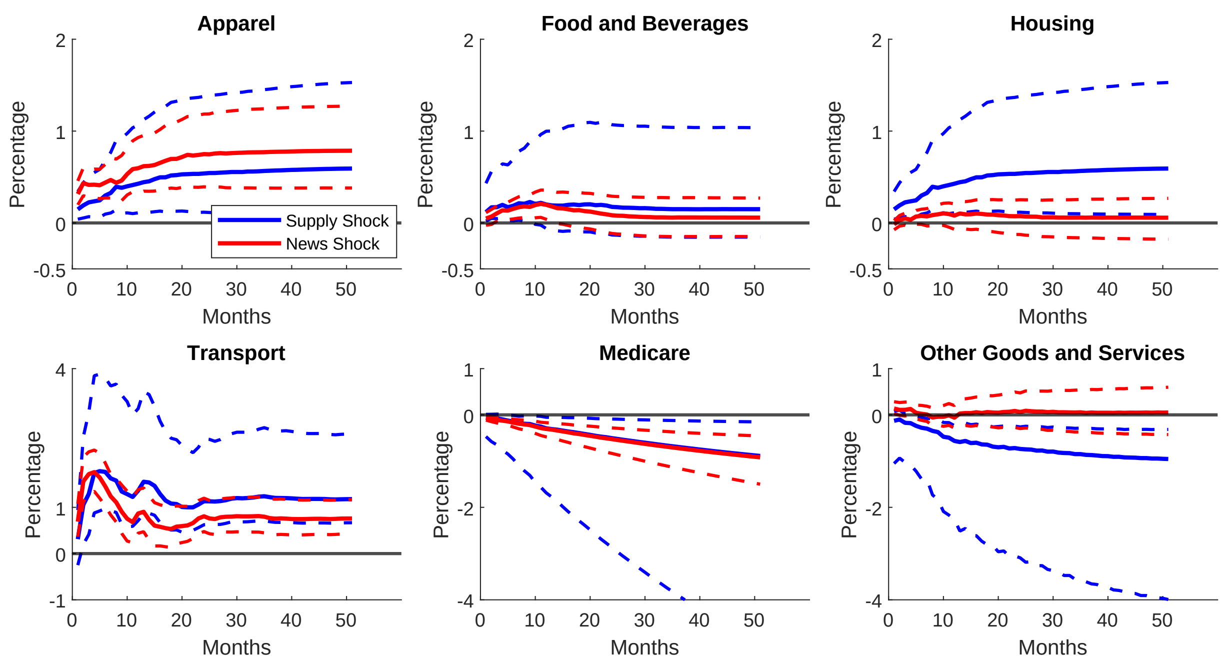
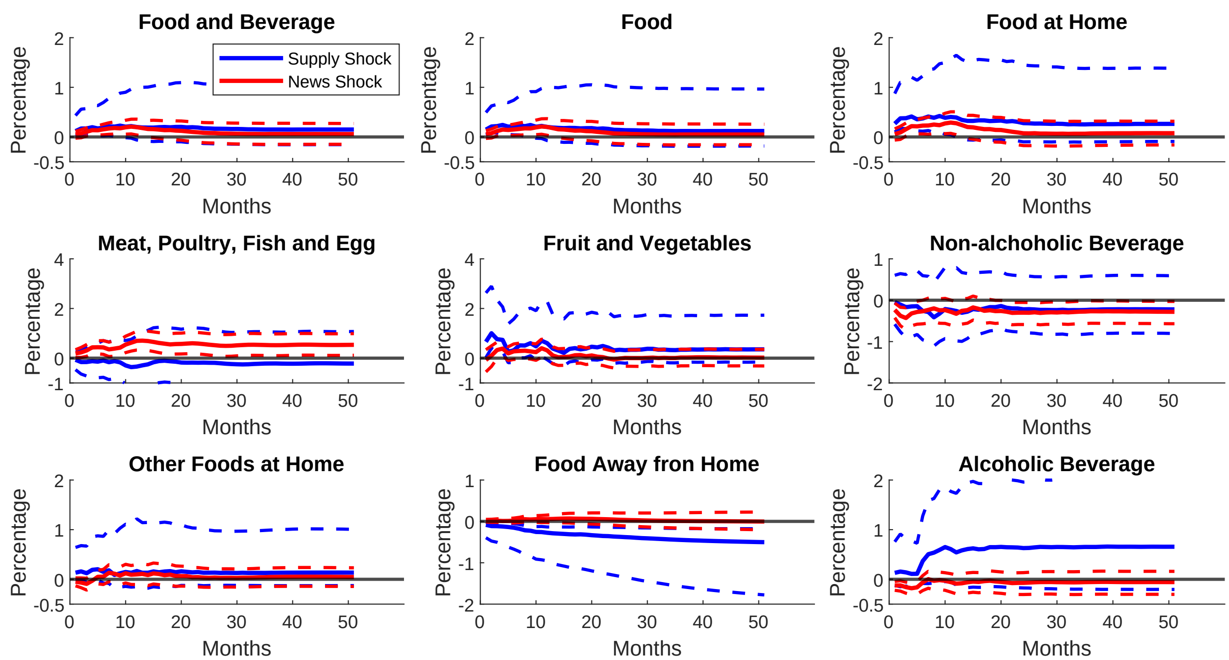
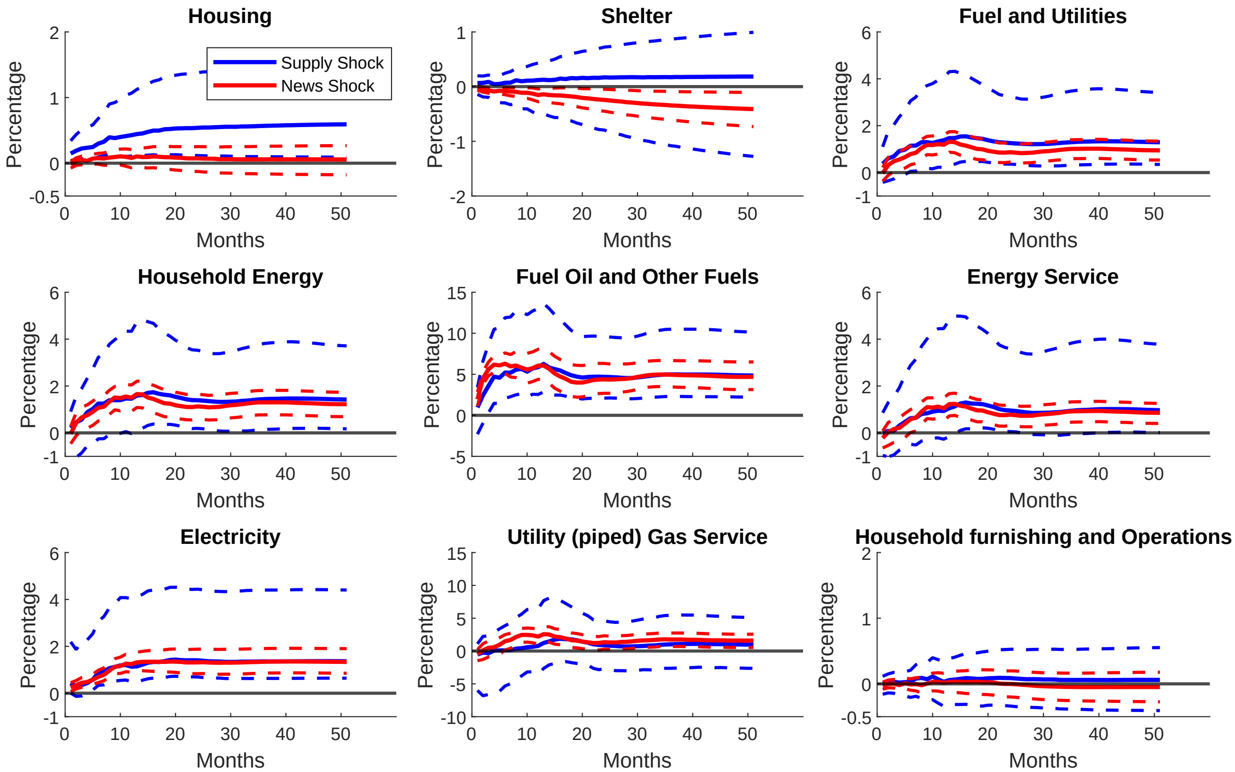


Figure 24: Effect on Food Categories



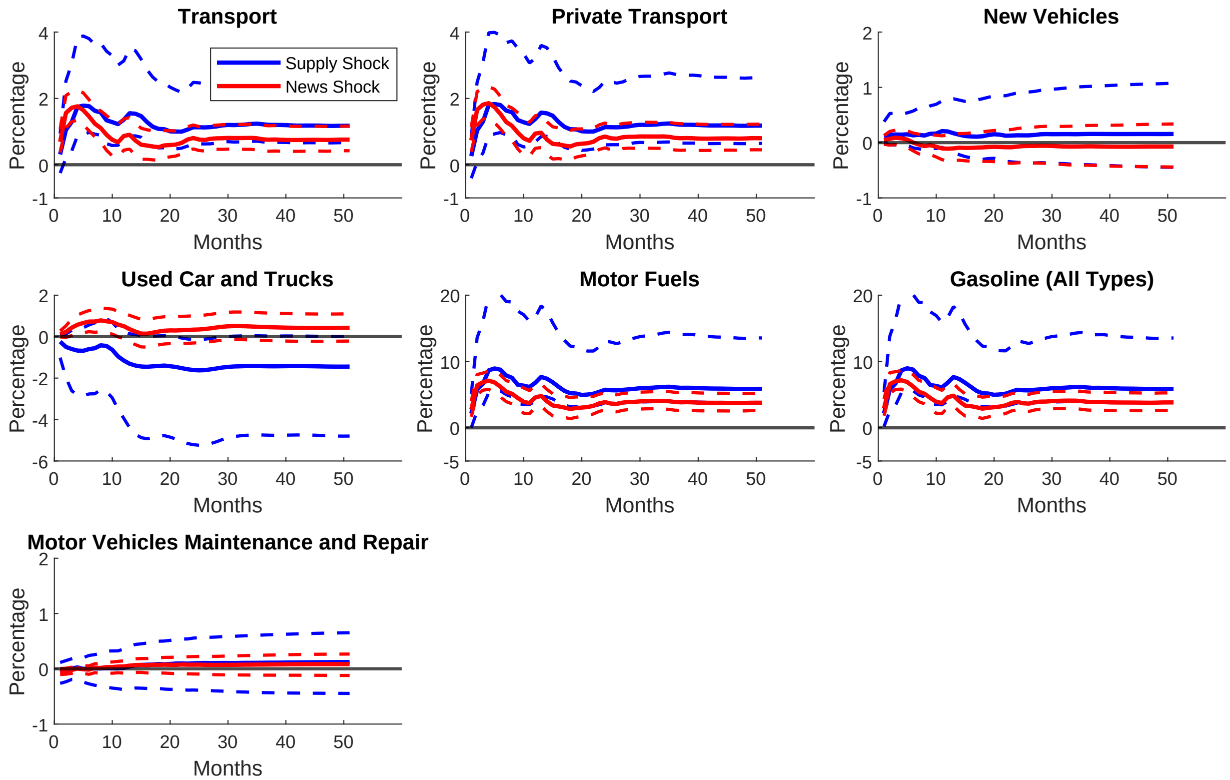
Note: Figure shows the response based on IV-SVAR as described in the text. Blue responses are for supply shock. Red responses are for news shock. Supply shock is normalized to cause 1% decline in global oil production. News shock is normalized to cause 1% increase in oil price. Error bars are presented on 68% significance level using Anderson-Rubin Confidence Interval of Montiel Olea, Stock, and Watson (2021). Responses for supply shock is scaled by a factor of 1/0.46 for graphical representation purpose.Data spans 1983M07:2013M12.

Figure 25: Effect on Housing Categories



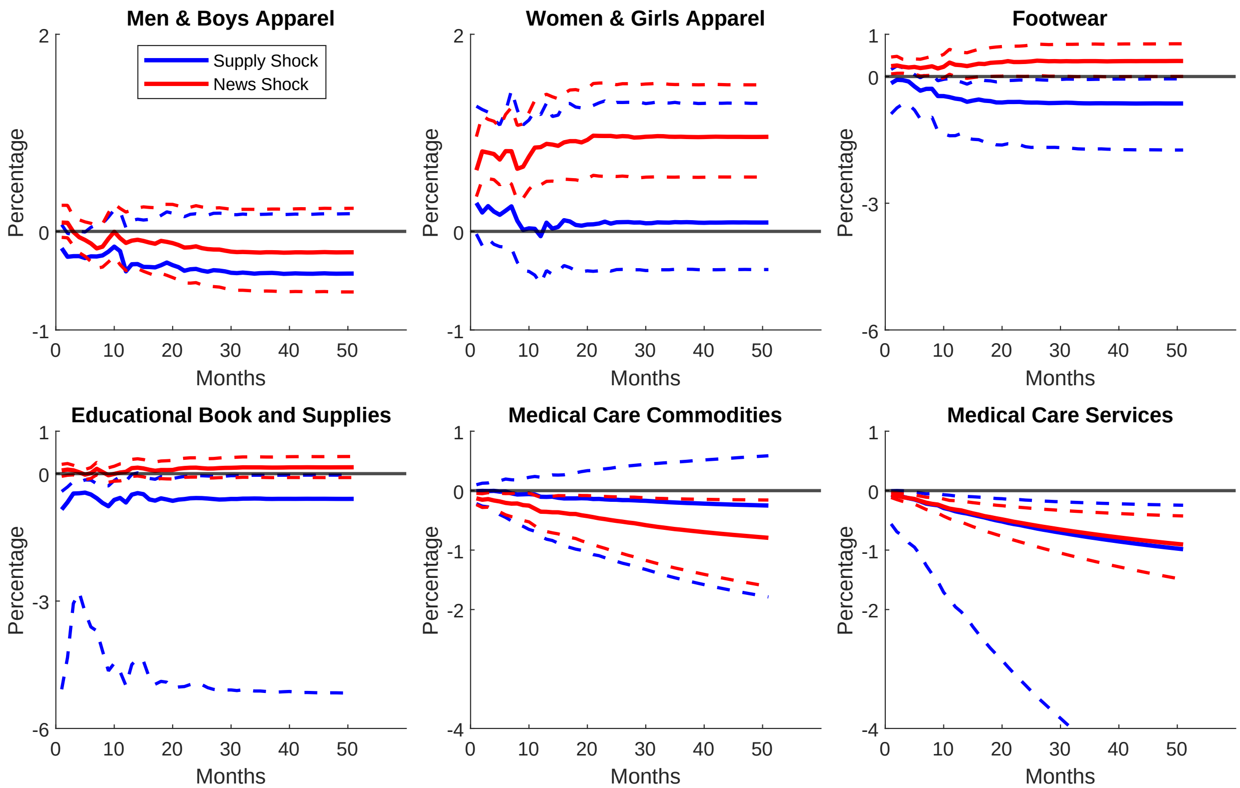
Note: Figure shows the response based on IV-SVAR as described in the text. Blue responses are for supply shock. Red responses are for news shock. Supply shock is normalized to cause 1% decline in global oil production. News shock is normalized to cause 1% increase in oil price. Error bars are presented on 68% significance level using Anderson-Rubin Confidence Interval of Montiel Olea, Stock, and Watson (2021). Responses for supply shock is scaled by a factor of 1/0.46 for graphical representation purpose.Data spans 1983M07:2013M12.

Figure 26: Effect on Transport Categories



Note: Figure shows the response based on IV-SVAR as described in the text. Blue responses are for supply shock. Red responses are for news shock. Supply shock is normalized to cause 1% decline in global oil production. News shock is normalized to cause 1% increase in oil price. Error bars are presented on 68% significance level using Anderson-Rubin Confidence Interval of Montiel Olea, Stock, and Watson (2021). Responses for supply shock is scaled by a factor of 1/0.46 for graphical representation purpose.Data spans 1983M07:2013M12.

Figure 27: Effect on Other Categories



Note: Figure shows the response based on IV-SVAR as described in the text. Blue responses are for supply shock. Red responses are for news shock. Supply shock is normalized to cause 1% decline in global oil production. News shock is normalized to cause 1% increase in oil price. Error bars are presented on 68% significance level using Anderson-Rubin Confidence Interval of Montiel Olea, Stock, and Watson (2021). Responses for supply shock is scaled by a factor of 1/0.46 for graphical representation purpose.Data spans 1983M07:2013M12.

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[16]this is more on baseline model. Montiel Olea, Stock, and Watson (2021) report immediate increase in oil price by 0.14% and a peak of 0.22%.Herrera and Rangaraju (2020) compare estimates from various models and find the impact to range from 0.05% to 4.27%.