Monetary Policy Trade-offs Amid Global Supply Chain Disruptions

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Online Appendix

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A Identification and Transmission of GSC shocks

A.1 Proxy Structural Vector Autoregression (SVAR)

Reduced-form VAR. Consider the following Structural Vector Autoregression (SVAR) model of the form

$$\boldsymbol{A}_0 \boldsymbol{y}_t = \boldsymbol{a} + \boldsymbol{A}(p)\boldsymbol{y}_{t-1} + \boldsymbol{C}(p)\boldsymbol{x}_t + \boldsymbol{\varepsilon}_t, \tag{A.1}$$

where p is the lag order, $\boldsymbol{y}_t$ and $\boldsymbol{x}_t$ are $n \times 1$ vector of endogenous and exogenous variables, respectively, $\boldsymbol{a}$ is an $n \times 1$ vector of constants, and $\boldsymbol{A}(p)$ and $\boldsymbol{C}(p)$ denote matrix lag polynomials in the lag operator L, capturing the autoregressive dynamics. $\boldsymbol{\varepsilon}_t$ is an $n \times 1$ vector of structural shocks and $\boldsymbol{A}_0$ is a non-singular $n \times n$ structural impact matrix. Vector $\boldsymbol{x}_t$ includes COVID-related indicators to de-COVID the data following the approach of Ng (2021).

By definition, the structural shocks are mutually uncorrelated, with $\text{var}(\boldsymbol{\varepsilon}_t) = \boldsymbol{\Omega}$ diagonal. Denoting $\boldsymbol{S} = \boldsymbol{A}_0^{-1}$, the reduced-form version of the SVAR model is given by

$$\boldsymbol{y}_t = \boldsymbol{b} + \boldsymbol{B}(p)\boldsymbol{y}_{t-1} + \boldsymbol{D}(p)\boldsymbol{x}_t + \boldsymbol{u}_t, \tag{A.2}$$

where $\boldsymbol{b} = \boldsymbol{S}\boldsymbol{a}$ is an $n \times 1$ vector of constants, $\boldsymbol{B}_j = \boldsymbol{S}\boldsymbol{A}_j$ and $\boldsymbol{D}_j = \boldsymbol{S}\boldsymbol{C}_j$, $1 \leq j \leq p$, are $n \times n$ coefficient matrices. The $n \times 1$ vector of reduced-form innovations $\boldsymbol{u}_t$ is related to the structural shocks $\boldsymbol{\varepsilon}_t$ via a linear mapping

$$\boldsymbol{u}_t = \boldsymbol{S}\boldsymbol{\varepsilon}_t, \tag{A.3}$$

with covariance matrix $\text{var}(\boldsymbol{u}_t) = \boldsymbol{\Sigma} = \boldsymbol{S}\boldsymbol{\Omega}\boldsymbol{S}'$. In the literature, equation (A.3) is known as the invertibility assumption.

Identification strategy. The SVAR model in equation (A.1) faces an identification challenge as the covariance matrix $\boldsymbol{\Sigma}$ only provides $n(n+1)/2$ restrictions to identify the n^2 free parameters in $\boldsymbol{S}$. Therefore, we have to impose restrictions on the structural parameters to solve the identification problem. In this study, I resort to SVAR identification based on external instruments, commonly known as Proxy SVAR or IV SVAR (Stock and Watson, 2012; Mertens and Ravn, 2013).

Without loss of generality, let us denote the shock of interest as the first shock in the SVAR (A.1), $\varepsilon_{1,t}$. The aim is to identify the structural impact vector $\boldsymbol{s}_1$, which corresponds to the first column of matrix $\boldsymbol{S}$. The identification strategy exploits external instruments to separate exogenous variation in the innovations of the instrumented variable, $y_{1,t}$, attributed to the structural shock of interest. Suppose there is an external instrument available, z_t. For z_t to be a valid instrument, it must satisfy two conditions:

$$\text{Relevance condition:} \quad \mathbb{E}[z_t \varepsilon_{1,t}] = \alpha \neq 0, \tag{A.4a}$$

$$\text{Exogeneity condition:} \quad \mathbb{E}[z_t \boldsymbol{\varepsilon}_{2:n,t}] = \boldsymbol{0}, \tag{A.4b}$$

where $\varepsilon_{1,t}$ is the shock of interest and $\boldsymbol{\varepsilon}_{2:n,t}$ is a $(n-1) \times 1$ vector consisting of the other structural shocks. The first condition implies that the instrument is correlated with the true underlying structural shock. The second condition requires that the instrument is not correlated with any other structural shock.

Under conditions (A.4a) and (A.4b), along with the invertibility requirement (A.3), $\boldsymbol{s}_1$ is identified up to sign and scale:

$$\mathbb{E}[z_t \boldsymbol{u}_t] = \boldsymbol{s}_1 \mathbb{E}[z_t \varepsilon_{1,t}] = \boldsymbol{s}_1 \alpha. \tag{A.5}$$

It is easy to show that, this equation leads to

$$\frac{\boldsymbol{s}_{2:n,1}}{s_{1,1}} = \frac{\mathbb{E}[z_t \boldsymbol{u}_{2:n,t}]}{\mathbb{E}[z_t u_{1,t}]}, \tag{A.6}$$

provided that $\mathbb{E}[z_t u_{1,t}] \neq 0$. The scale $s_{1,1}$ is then normalised, subject to $\boldsymbol{\Sigma} = \boldsymbol{S\Omega S}'$. Setting $\boldsymbol{\Omega} = \boldsymbol{I}_n$ implies that a unit positive value of $\varepsilon_{1,t}$ induces a one standard deviation positive effect on the instrumented variable $y_{1,t}$, i.e. $s_{1,1} = 1$.

While the majority of studies employing Proxy-SVAR analysis typically use one instrument to identify one structural shock, a growing literature explores the case where multiple instruments are employed to identify multiple structural shocks (see e.g. Arias et al., 2021, and all the references therein). Achieving point identification in this case, however, may necessitate imposing additional and potentially controversial identifying restrictions (Giacomini et al., 2022). In this study, given the availability of three external instruments to identify three different shocks, I consider each of the three shocks and instruments separately, one at a time. The instruments being mutually orthogonal, there is no distinction between estimating the effects of the shocks individually versus jointly.[1]

Bayesian estimation. I estimate the reduced-form VAR(p) using Bayesian techniques. In particular, I assume a normal-inverse-Wishart prior distribution over the reduced-form parameters of the form:

$$\boldsymbol{\Sigma} \sim \mathcal{IW}(\boldsymbol{S}_0, \alpha_0) \qquad \text{and} \qquad \boldsymbol{B}|\boldsymbol{\Sigma} \sim \mathcal{N}(\boldsymbol{B}_0, \boldsymbol{\Sigma} \otimes \boldsymbol{\Omega}_0) \tag{A.7}$$

where $\boldsymbol{B} = \text{vec}([\boldsymbol{b}, \boldsymbol{B}_1, \ldots, \boldsymbol{B}_p]')$. The degrees of freedom of the inverse-Wishart distribution are set to $\alpha_0 = n + 2$, a value that guarantees the existence of the scale matrix $\boldsymbol{S}_0$ (Kadiyala and Karlsson, 1997), which is diagonal with elements σ_i^2, the residual variance of an AR(1) for variable i for $1 \leq i \leq n$. The prior mean and variance for $\boldsymbol{B}$ are characterised by a Minnesota-type prior such that

$$\mathbb{E}[(\boldsymbol{B}_\ell)_{ij}|\boldsymbol{\Sigma}] = \begin{cases} \delta_i, & i = j, \ell = 1 \\ 0, & \text{otherwise} \end{cases}, \mathbb{V}[(\boldsymbol{B}_\ell|\boldsymbol{\Sigma})_{ij}] = \begin{cases} \dfrac{\lambda^2}{\ell^2}, & i = j, \forall \ell \\ \dfrac{\lambda^2}{\ell^2}\dfrac{\sigma_i^2}{\sigma_j^2}, & \text{otherwise}, \forall \ell \end{cases}, \tag{A.8}$$

where $(\boldsymbol{B}_\ell)_{ij}$ denotes the coefficient of variable j in equation i at lag ℓ for $1 \leq \ell \leq p$. Setting $\delta_i = 1$ for all i reflects the belief that all variables are characterized by a random walk with drift as originally proposed by Litterman (1986). However, for variables believed to feature mean reversion this prior is not suitable. For those I impose a prior belief of white noise by setting $\delta_i = 0$ as in Bańbura et al. (2010). The hyperparameter λ governs the overall tightness of the priors. I follow Giannone et al. (2015) and optimally choose λ by treating it as an additional parameter in the model, in the spirit of hierarchical modelling.

[1] Arias et al. (2021) discuss individual versus joint identification with external instruments, highlighting how the results can differ across the two methods when the instruments lack orthogonality.

A.2 Data

Table A.1: Set of Variables

Variable	Description	Source	YoY	RW
E X O G E N O U S	**V A R I A B L E S**			
COVID deaths	Data are available from January 2020 onward; observations prior to this date are set to zero	CDC COVID Data Tracker		
E N D O G E N O U S	**V A R I A B L E S**			
Shortage index	Caldara et al. (2025)'s index	Matteo Iacoviello's Website		
Industrial Production	Total Index	FRED	✓	
Core PCE	PCE Excluding Food and Energy	FRED	✓	
Imported interm. prices	Import Price Index: Industrial Supplies and Materials Excluding Petroleum	FRED	✓	
Imported interm. quantities	*Real imports of goods: Industrial supplies and materials, except petroleum and products		✓	
Core PCE goods	PCE: Goods	FRED	✓	
Core PCE services	PCE: Excluding Energy and Housing	FRED	✓	
1y inflation exp.	Surveys of Consumers, University of Michigan	FRED		
5y inflation exp.	Surveys of Consumers, University of Michigan (U.M.)	U.M. Website		
Real exchange rate	Real Broad Effective Exchange Rate	FRED	✓	
Excess Bond Premium	Gilchrist and Zakrajšek (2012)'s indicator	FED Notes		
Stock Prices	S&P500 Stock Price Index	Bloomberg	✓	
Wages	Average Hourly Earnings of Production and Nonsupervisory Employees, Total Private	FRED	✓	
Employment	All Employees, Total Nonfarm	FRED	✓	
N-year yield ($N = 1, 5$)	Treasury Securities at N-Year Constant Maturity	FRED		✓
Real total government expenditures (including transfer payments)	*Government total expenditures, deflated using the CPI	FRED	✓	

Note: The series are collected from January 1991 to June 2025. The last two columns indicate the transformation of the data to year-over-year (YoY) percentage changes and whether a random walk (RW) prior was imposed on those variables, respectively. *Monthly series obtained from quarterly data through interpolation.

A.3 External Instrument

To construct the instrument, I estimate an auxiliary VAR with a selected set of variables and 12 lags to purge innovations in the Supply Bottlenecks Index (SBI) proposed by Burriel et al. (2024) of other supply-related forces—including labour market, domestic supply, and oil-related shocks—before using the resulting measure in the main Proxy VAR. Identification is achieved through sign and zero restrictions, following the procedure proposed by Arias et al. (2018). Since the SBI is available from 1990, the estimated SBI innovations are available from 1991 onwards.

Table A.2 summarises the zero and sign restrictions imposed on impact in the impulse responses of the auxiliary VAR. The identifying restrictions closely follow Banbura et al. (2023), who distinguish supply and demand forces in explaining post-pandemic core inflation dynamics in the euro area. In particular, both labour market shocks and domestic supply (technology) shocks generate opposite movements in output and prices. These two shocks are then distinguished by their implications for real wages: a negative comovement between output and real wages identifies labour market shocks, consistent with hiring frictions or labour shortages, whereas a positive comovement characterises technology shocks, reflecting productivity improvements. To separate these shocks from oil-related and global supply chain disturbances, I impose zero impact restrictions on real oil prices and the SBI.

Table A.2: Impact sign and zero restrictions in the auxiliary VAR

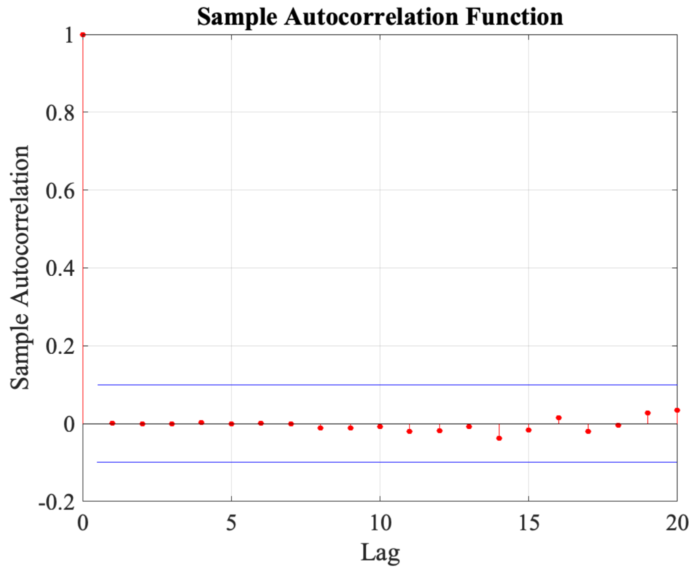
Variable / Shock	**Labour market**	**Domestic supply**	**Global supply chain**
Industrial production	−	−	
Core prices	+	+	
Real wages	+	−	
SBI	0	0	+
Real oil prices	0	0	0

Note: Entries indicate impact restrictions imposed at horizon zero. "+" ("−") denotes a positive (negative) sign restriction, "0" denotes a zero restriction, and blank cells indicate no restriction imposed.

To "identify" GSC shocks, the only restriction imposed is a positive impact response of the SBI. No additional sign restrictions are imposed on other variables, allowing the data to determine the dynamic responses within the proxy VAR. I also impose that real oil prices do not react on impact to the GSC shock, to distinguish it from oil-related shocks. Finally, the instrument corresponds to the median time series of SBI innovations drawn from the posterior distribution.

A.4 Validation Checks

Figure A.1: Autocorrelation Function of SBI innovations



Note: The estimation is based on the median time series of SBI innovations obtained from the auxiliary VAR identified with sign and zero restrictions. Estimation sample: 1991M1 to 2025M6.

Table A.3: Orthogonality of SBI innovations with U.S. monetary policy surprises

Monetary policy surprise	**Correlation (p-value)**
Jarociński (2024)'s surprises	
Conventional Monetary policy	0.08 (0.20)
Forward Guidance	0.07 (0.18)
Swanson (2024)'s surprises	
Conventional Monetary policy	0.11 (0.11)
Forward Guidance	0.05 (0.25)

Note: The entries in the table denote the pairwise correlations. The p-values are reported in parentheses. The p-values in the column of correlations correspond to a regression of the SBI innovations on the monetary policy surprise series, computed with the Newey-West HAC estimator. Estimation sample: 1991M1 to 2025M6, subject to data availability.

A.5 Robustness Checks

Alternative instrumented variables. This section briefly describes several measures of global supply chain (GSC) pressures that have been employed in the empirical literature and are used as alternative instrumented variables. Overall, most measures capture both global supply and global demand conditions, as noted by Benigno et al. (2022).

To begin with, Caldara et al. (2025) construct the Shortage Index, a text-based indicator derived from newspaper articles spanning back to 1900. The index captures shortages across goods, labour, energy, and intermediate inputs, and exhibits pronounced spikes during major disruption episodes such as wars, oil crises, and the COVID-19 pandemic. Notably, during the pandemic period, the index closely tracks global supply chain pressures associated with widespread disruptions in production networks and logistics. A closely related news-based measure is the Supply Bottlenecks Index (SBI) of Burriel et al. (2024), which captures domestic and global supply chain disruption episodes in the United States as well as in several other major economies, including the United Kingdom, Germany, France, Italy, Spain, and China.

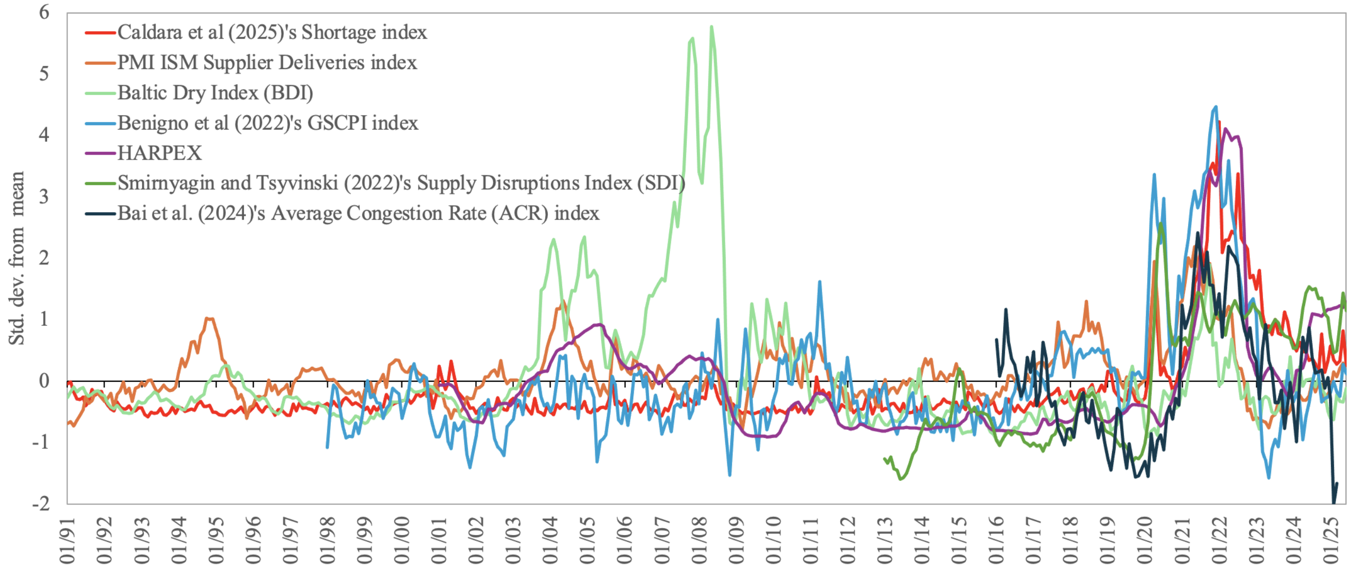
Survey-based indicators offer a complementary perspective. The PMI–ISM Supplier Deliveries Index reflects changes in suppliers' delivery times as reported by purchasing managers and is often interpreted as a proxy for supply bottlenecks. However, delivery times also respond to fluctuations in demand, as stronger demand can lengthen delivery schedules even in the absence of binding supply frictions, complicating its interpretation as a purely supply-driven measure.

By contrast, market-based indicators focus on conditions in global transportation markets. The Baltic Dry Index (BDI) measures shipping costs for bulk commodities and reflects frictions in global transport and input trade, while remaining sensitive to global demand conditions, particularly during commodity-intensive expansions. Similarly, the HARPEX index (Harper Petersen), which tracks container shipping charter rates, captures congestion in maritime transport but also responds to shifts in global trade demand.

Other approaches attempt to isolate supply-side pressures more explicitly. The Global Supply Chain Pressure Index (GSCPI) of Benigno et al. (2022) is an econometric-based composite index constructed from transportation costs and PMI indicators and explicitly purged of demand components using auxiliary demand proxies. While designed to isolate supply-side disturbances, Burriel et al. (2024) point out that even the GSCPI exhibits demand-driven movements during episodes such as the Global Financial Crisis, when collapsing demand interacted with supply rigidities. This point highlights the empirical difficulty of fully disentangling supply and demand forces in practice.

Additional insights are provided by indicators based on firm-level data and physical congestion. The Supply Disruptions Index (SDI) of Smirnyagin and Tsyvinski (2022), constructed from administrative firm-level and shipment data, captures disruptions to firms' supply chains that are relevant for both macroeconomic outcomes and asset prices. The Average Congestion Rate (ACR) of Bai et al. (2024) exploits satellite data to measure congestion at major container ports worldwide, offering an appealing indicator of physical bottlenecks in global logistics. However, its relatively short coverage starting in 2016 substantially limits its usefulness for longer-horizon analysis.

Figure A.2: Global Supply Chain Pressure Measures



Note: These indicators have been standardised for comparability. The period displayed is 1991M1–2025M6. Further details on these measures are provided in Table A.4.

Table A.4: Global Supply Chain Pressure Measures and Instrument Strength

	Instrumented variable	Source	Coverage start	Type	F-statistic	
					Pre-pandemic	Full sample
1	Shortage Index	Caldara et al. (2025)	1900	Text-based	46	34
2	PMI-ISM Supplier Deliveries Index	Bloomberg	1990	Survey-based	13	16
3	Baltic Dry Index (BDI)	Bloomberg	1985	Market-based	15	13
4	Global Supply Chain Pressure Index (GSCPI)	Benigno et al. (2022)	1998	Econometric-based	Weak	16
5	Harper Peterson Time Charter Rates Index (HARPEX)	Harper Petersen	2001	Market-based	Weak	13
6	Supply Disruptions Index (SDI)	Smirnyagin and Tsyvinski (2022)	2013	Administrative firm-level data-based	–	12
7	Average Congestion Rate (ACR)	Bai et al. (2024)	2016	Shipping/Satellite data-based	–	11

Notes: The pre-pandemic and full estimation samples cover 1991M1–2019M12 and 1991M1–2025M6, respectively. The estimation sample is shorter for indices whose coverage begins later. The instrument constructed from the SBI index of Burriel et al. (2024) spans 1991M1–2025M6 and is used for each supply chain pressure measure for which the first-stage F-statistic is reported. *Weak* indicates that the F-statistic is below 10, while "–" indicates that no estimation is performed due to limited sample availability. The reported F-statistic corresponds to the median of the posterior distribution.

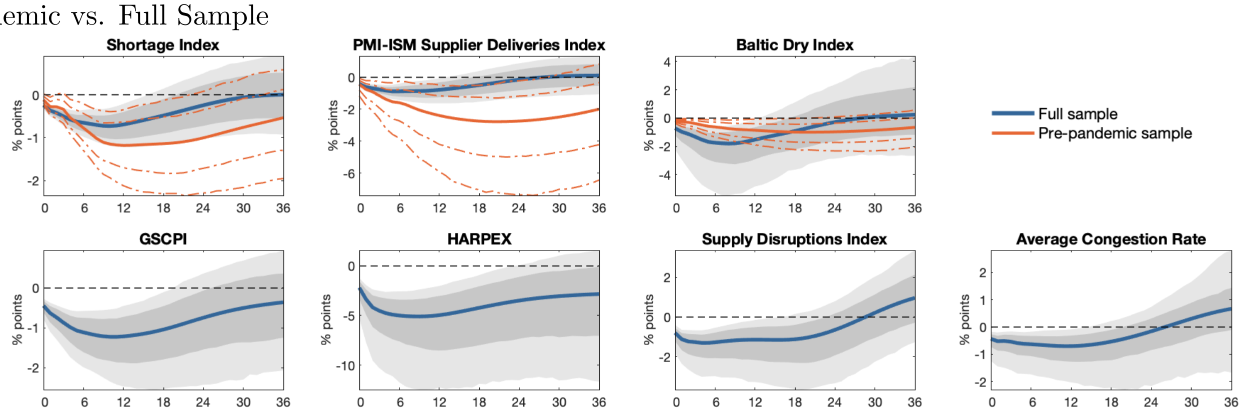
All in all, they provide a rich information set and are well suited as alternative instrumented variables. These indicators are standardised for comparability and displayed in Figure A.2, with brief descriptions provided in Table A.4. By contrast, the news-based Supply Bottlenecks Index (SBI) of Burriel et al. (2024) stands out as a particularly suitable candidate for constructing an external instrument, as it offers a coherent and historically consistent account of supply chain disruption episodes in the United States.

As can be seen from Table A.4, the first three measures—the Shortage Index of Caldara et al. (2025), the PMI–ISM Supplier Deliveries Index, and the Baltic Dry Index (BDI)—yield strong first-stage F-statistics ($F > 10$) in both the pre-pandemic and full samples. The shortage index delivers the highest F-statistic and is therefore taken as the baseline, while the remaining indices are used for robustness checks.

For measures with shorter coverage—namely, the GSCPI of Benigno et al. (2022) and the HARPEX index, which start in 1998 and 2001, respectively—the pre-pandemic estimation exhibits weak instrument relevance ($F < 10$). By contrast, the instrument is strong in the full sample. The same holds in the full sample for the Supply Disruptions Index (SDI) of Smirnyagin and Tsyvinski (2022) and the Average Congestion Rate (ACR) of Bai et al. (2024). I do not report pre-pandemic estimates for these latter indices due to limited sample availability, as they start in 2013 and 2016, respectively. Thus, the instrument appears to be strong for measures with longer coverage in pre-pandemic estimations.

Pre-pandemic evidence. As shown in the first row of Figure A.3, the monetary policy responses associated with these alternative indices indicate that, across both the pre-pandemic and full samples, the Federal Reserve has looked through GSC shocks and has even lowered the policy rate in response. Accordingly, this analysis provides strong evidence that the Fed has **historically acted in this manner.**

Figure A.3: Monetary Policy Response to a GSC shock: Alternative Instrumented Variables and Pre-pandemic vs. Full Sample

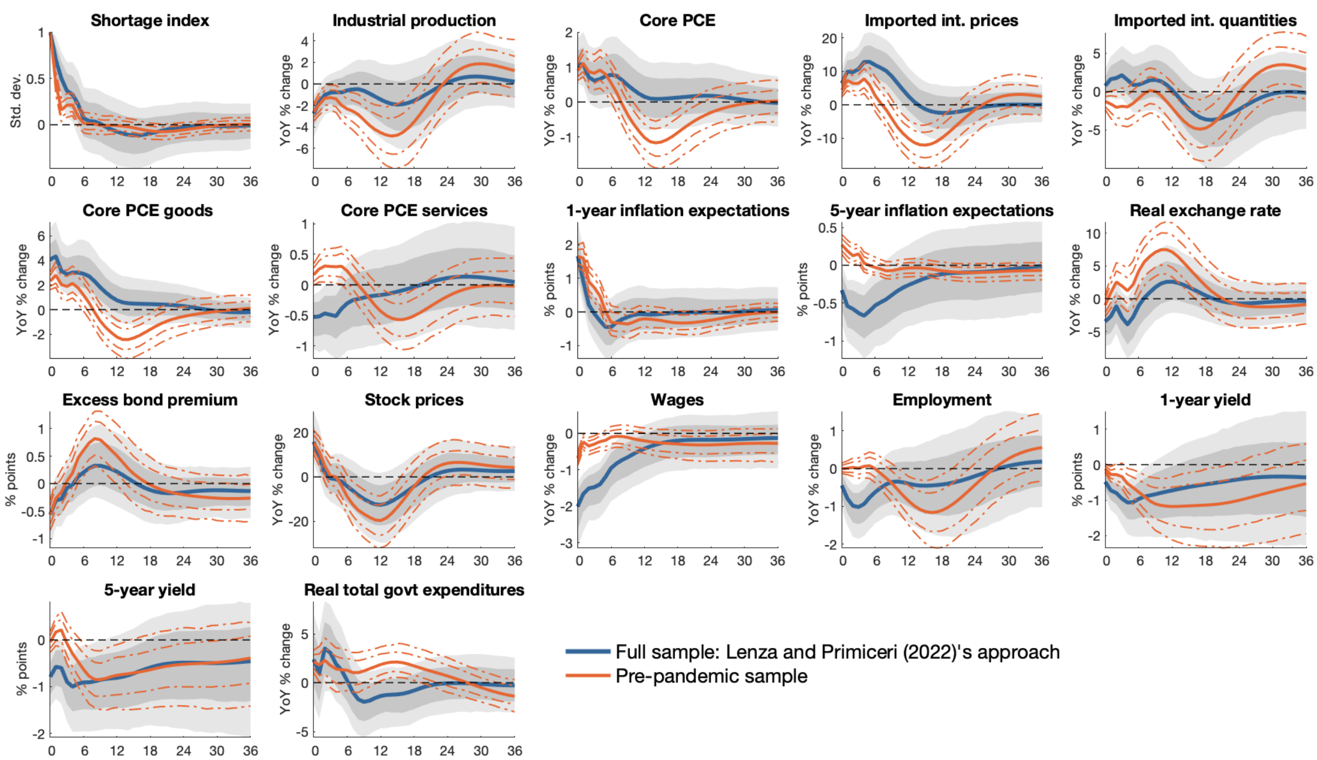


Note: The GSC shock is normalised to induce a one-standard-deviation increase in the corresponding instrumented variable. The pre-pandemic and full estimation samples cover 1991M1–2019M12 and 1991M1–2025M6, respectively. The estimation sample is shorter for indices whose coverage begins later. Solid blue and orange lines denote median responses for the full and pre-pandemic samples, respectively, while shaded areas and dotted lines indicate 68% and 90% posterior coverage bands. The horizontal axis shows months. Further details on these measures are provided in Table A.4.

Alternative Pandemic Treatment. The approach proposed by Ng (2021) is tailored to the specific features of the pandemic and *aimed at identifying structural relationships*, as noted by Carriero et al. (2024), by treating the COVID-19 episode as a distinct shock. Alternative approaches have also been proposed in the literature. In particular, I consider the strategy proposed by Lenza and Primiceri (2022), who propose downweighting extreme observations by scaling the residual covariance matrix during the pandemic. In practice, this procedure effectively excludes pandemic observations from the estimation. As a result, adopting this second approach would attenuate the role of GSC shocks during the pandemic and average the dynamics of the pre-2020 and post-2021 periods.

I re-estimate the VAR model in the full sample following the approach of Lenza and Primiceri (2022) and compare it with the pre-pandemic estimation. Overall, the key results are broadly consistent. In particular, GSC shocks act as supply shocks to which the central bank responds by easing policy. However, some differences are worth noting. The fiscal response is weaker and broadly comparable to the corresponding pre-pandemic response. Employment reacts immediately, consistent with the estimates obtained using the approach of Ng (2021). Notably, wages decline more sharply, suggesting that capacity constraints are not binding in this specification. This, in turn, may explain the earlier decline in services inflation and medium-term inflation expectations.

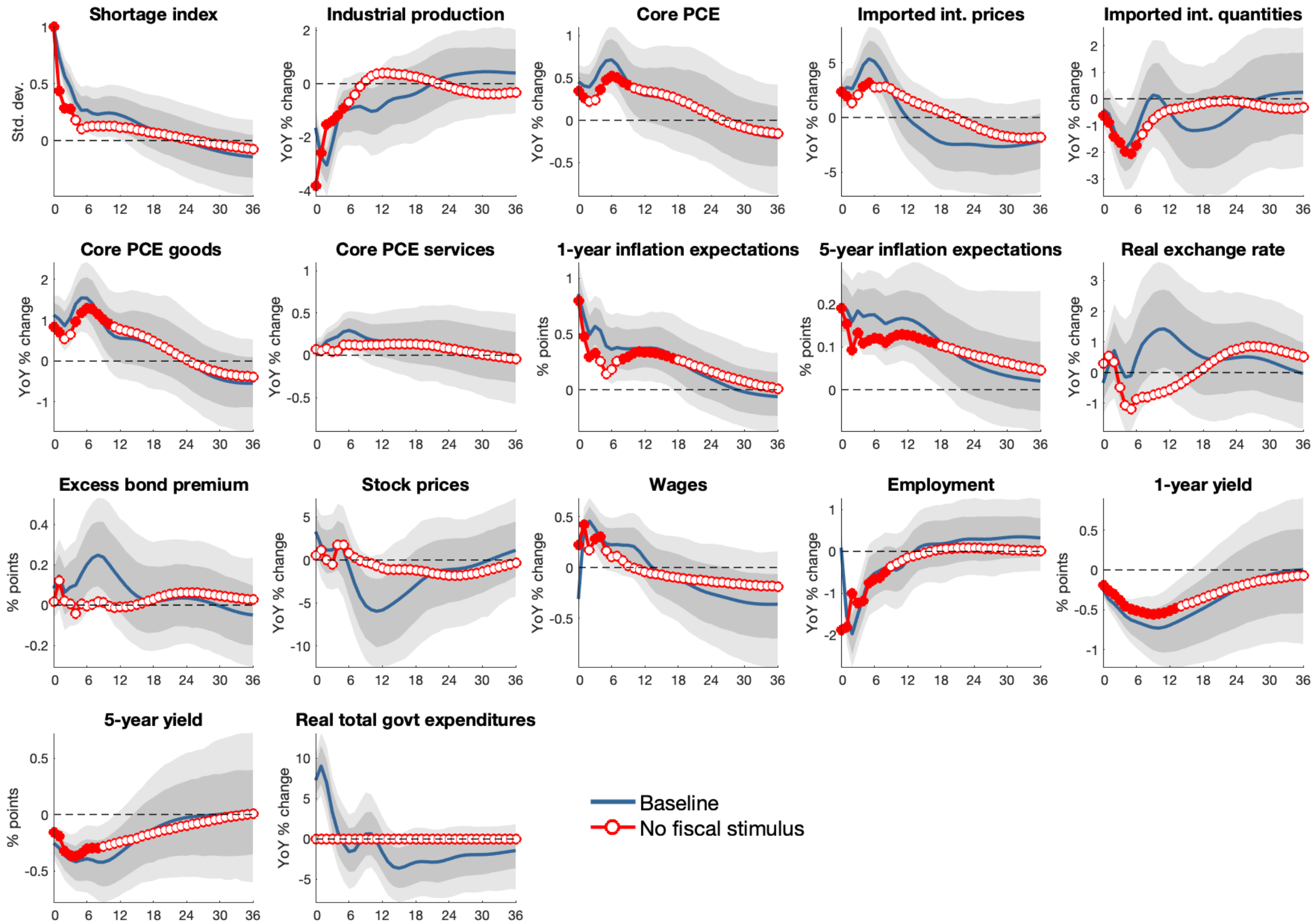
Figure A.4: IRFs to a GSC shock: Alternative Pandemic Treatment



Note: The GSC shock is normalised to induce a one-standard-deviation increase in the shortage index of Caldara et al. (2025). The pre-pandemic and full estimation samples cover 1991M1–2019M12 and 1991M1–2025M6, respectively. Solid blue and orange lines denote median responses for the full and pre-pandemic samples, respectively, while shaded areas and dotted lines indicate 68% and 90% posterior coverage bands. The horizontal axis shows months.

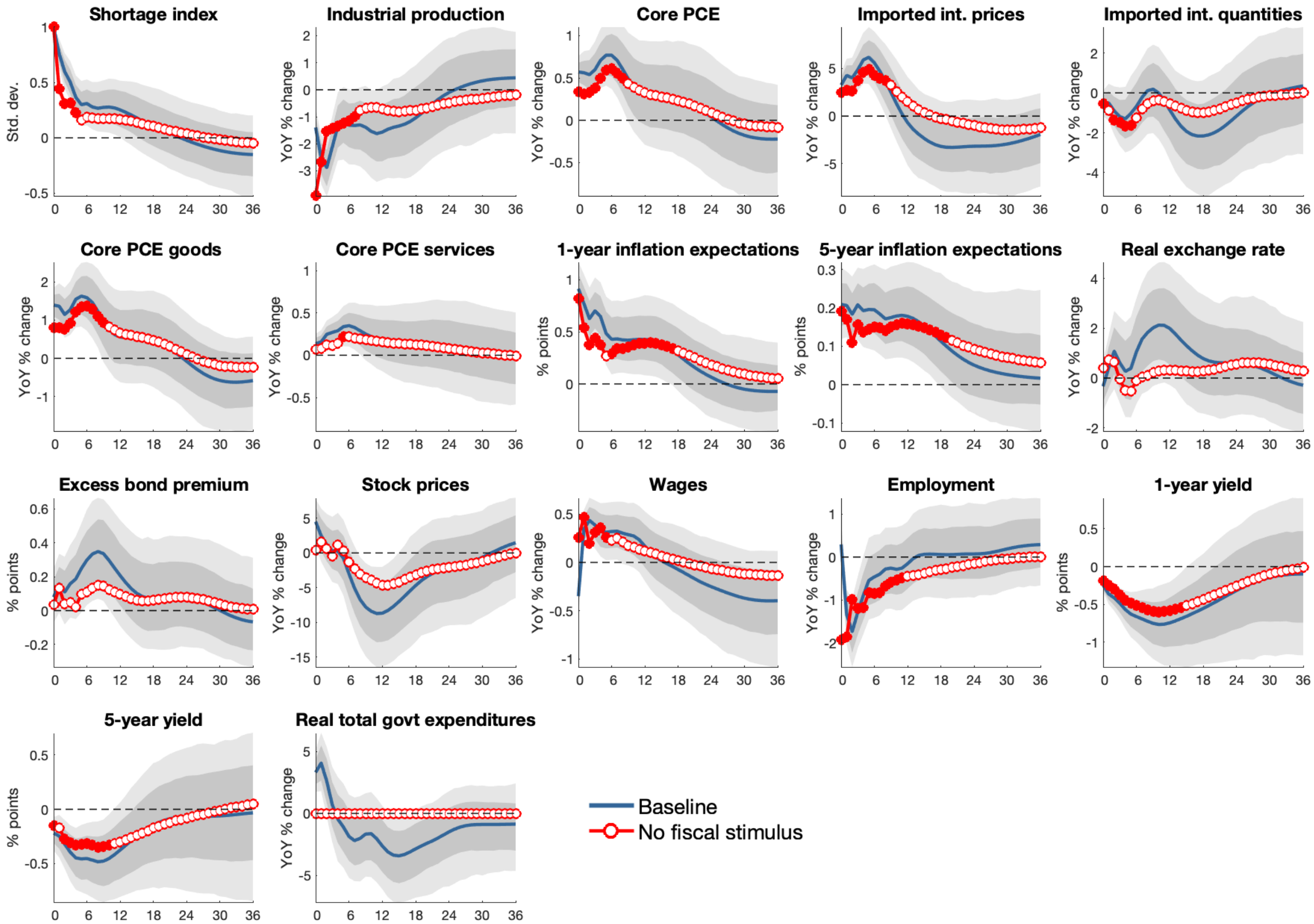
Disentangling the Role of Fiscal Stimulus. Figure A.5 reports the full set of macroeconomic responses in this counterfactual using real total government expenditures, while Figure A.6 shows the corresponding responses when using real government transfer payments instead. Finally, Figure A.7 shows the fiscal counterfactual in the pre-pandemic sample.

Figure A.5: Disentangling the Role of Fiscal Stimulus using Real Total Government Expenditures: Full Sample



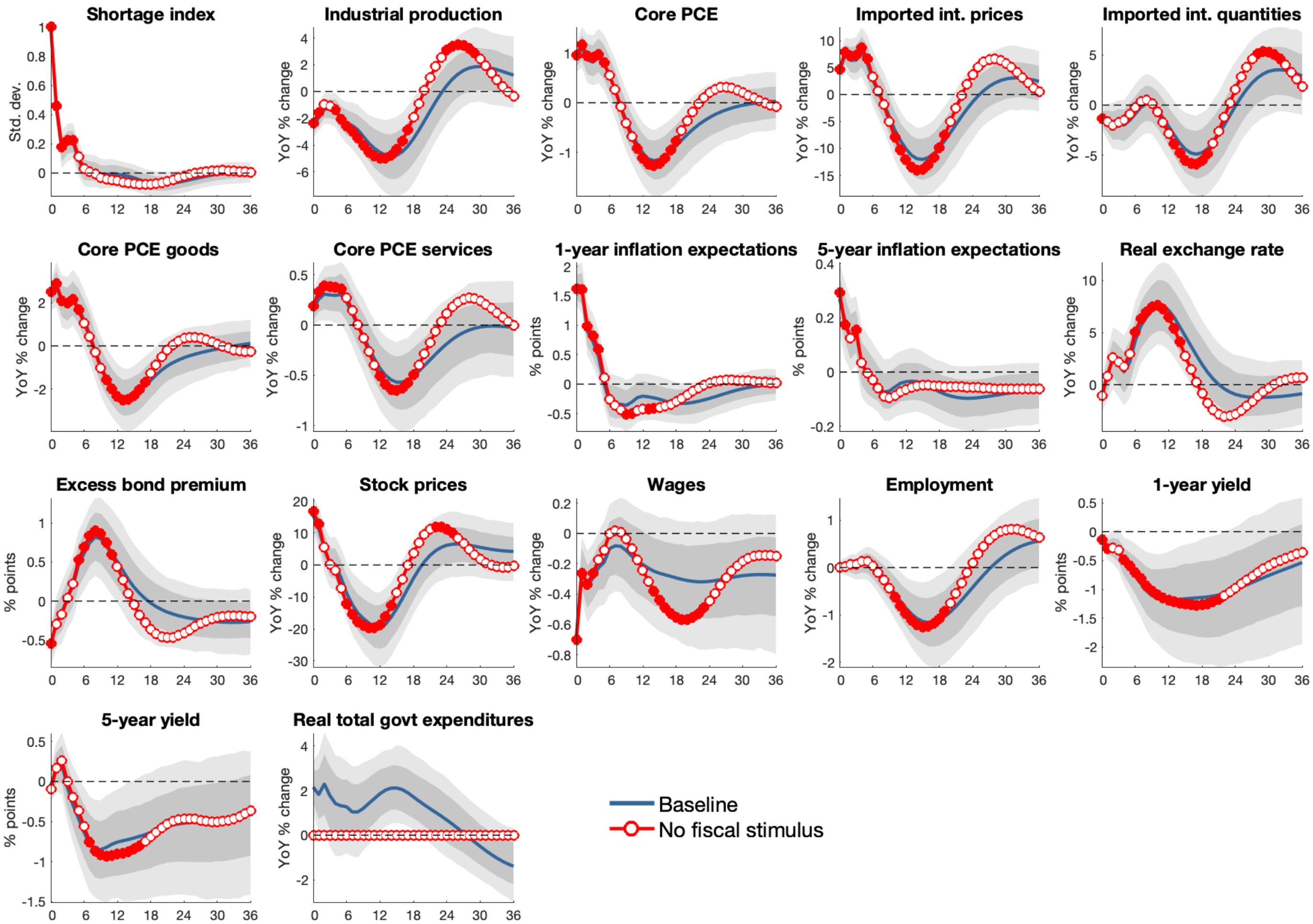
Note: The GSC shock is normalised to induce a one-standard-deviation increase in the shortage index of Caldara et al. (2025). The horizontal axis shows months. Solid lines represent median responses, while shaded areas indicate 68% and 90% posterior coverage bands. Red-circled lines show counterfactual median responses. Filled circles indicate responses within the 90% posterior coverage bands, while empty markers denote non-significant responses. Estimation sample: 1991M1–2019M12.

Figure A.6: Disentangling the Role of Fiscal Stimulus using Real Government Transfer Payments: Full Sample



Note: The GSC shock is normalised to induce a one-standard-deviation increase in the shortage index of Caldara et al. (2025). The horizontal axis shows months. Solid lines represent median responses, while shaded areas indicate 68% and 90% posterior coverage bands. Red-circled lines show counterfactual median responses. Filled circles indicate responses within the 90% posterior coverage bands, while empty markers denote non-significant responses. Estimation sample: 1991M1–2025M6.

Figure A.7: Disentangling the Role of Fiscal Stimulus using Real Total Government Expenditures: Pre-pandemic Sample

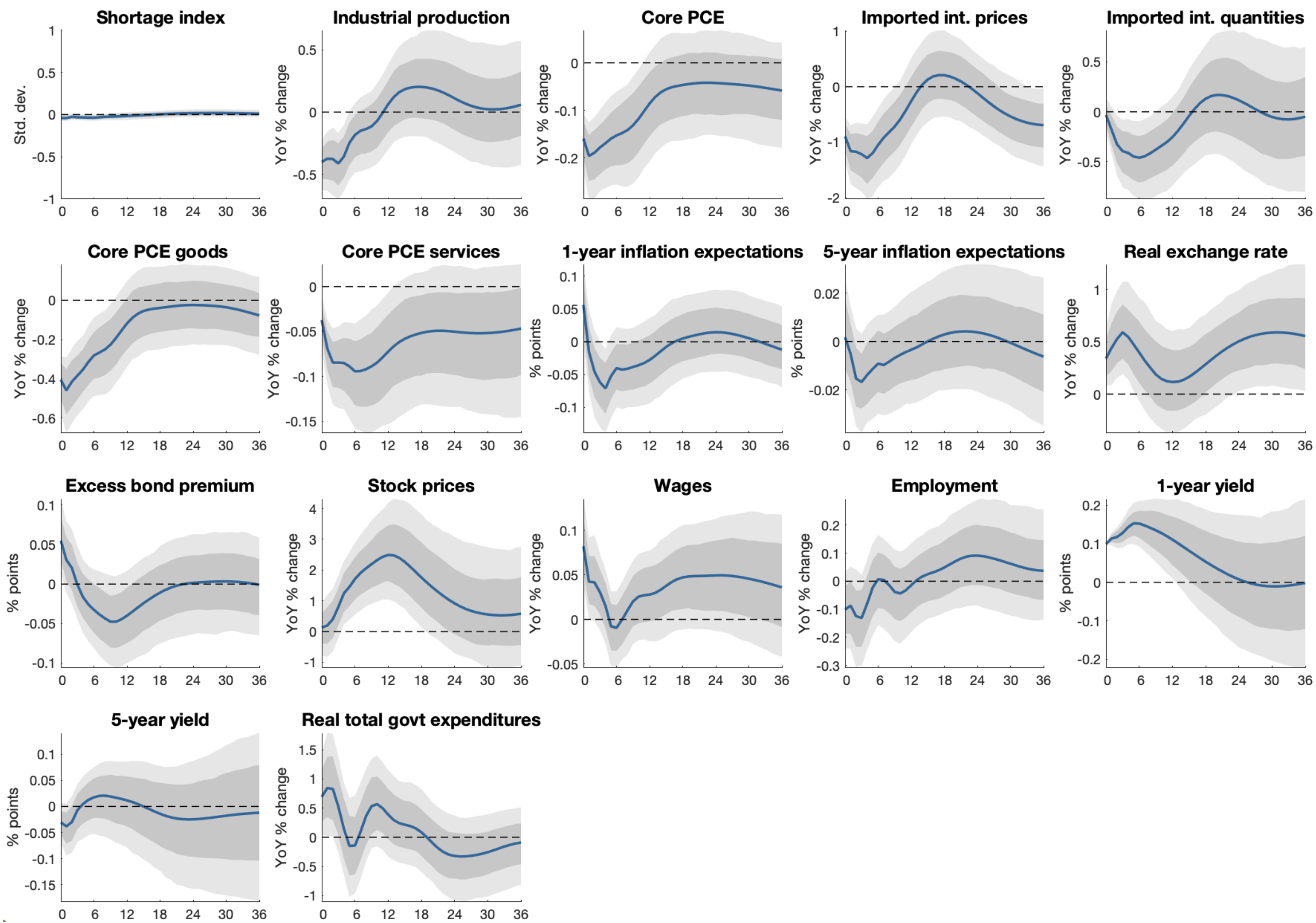


Note: The GSC shock is normalised to induce a one-standard-deviation increase in the shortage index of Caldara et al. (2025). The horizontal axis shows months. Solid lines represent median responses, while shaded areas indicate 68% and 90% posterior coverage bands. Red-circled lines show counterfactual median responses. Filled circles indicate responses within the 90% posterior coverage bands, while empty markers denote non-significant responses. Estimation sample: 1991M1–2025M6.

B U.S. monetary policy shocks

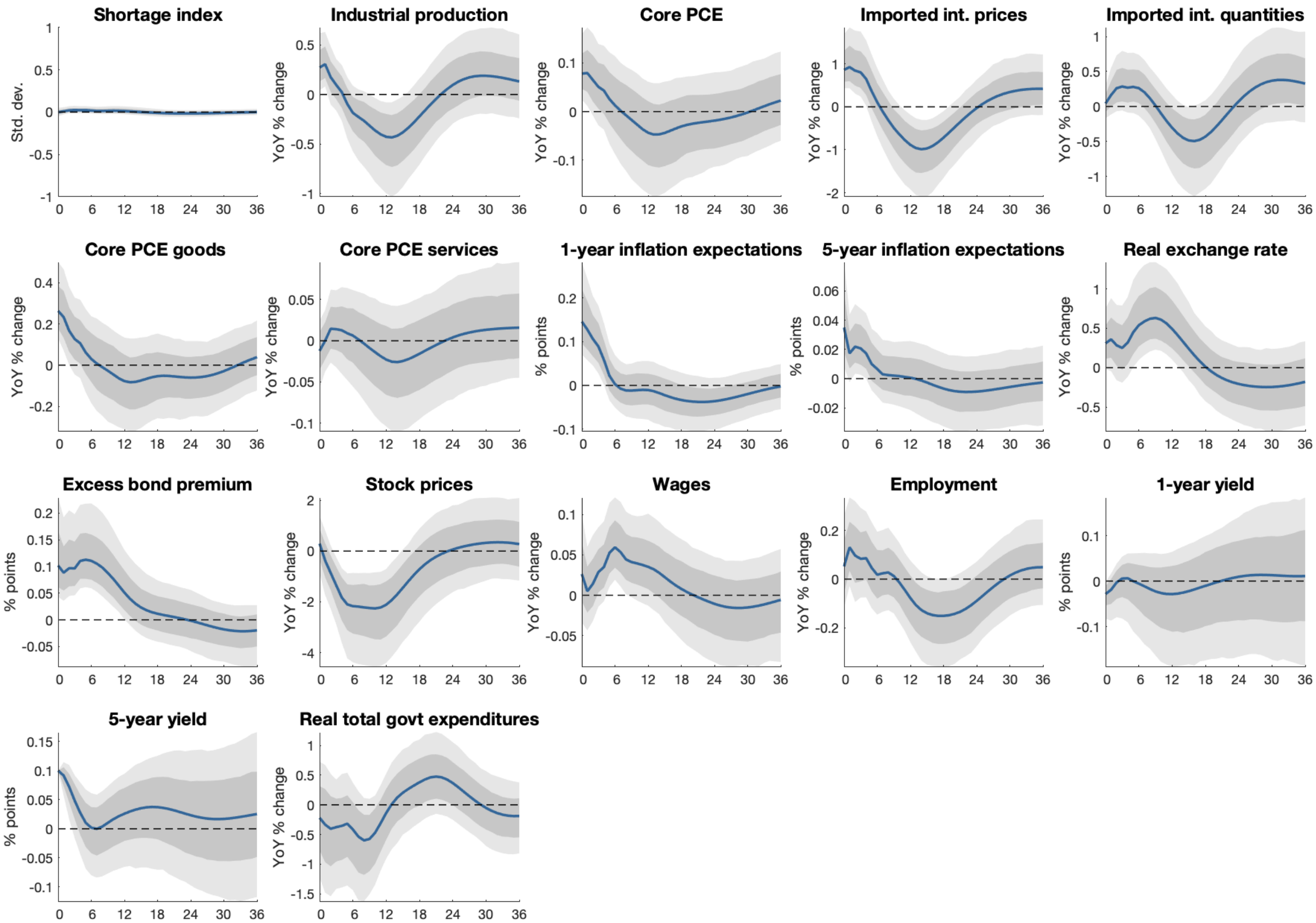
Figures B.1 and B.2 report the IRFs to conventional monetary policy (CMP) and forward guidance (FG) shocks using the surprise series of Jarociński (2024), while Figures B.3 and B.4 present the corresponding responses based on the series of Swanson (2024), respectively.

Figure B.1: IRFs to a Conventional Monetary Policy (CMP) shock using Jarociński (2024)'s surprise series



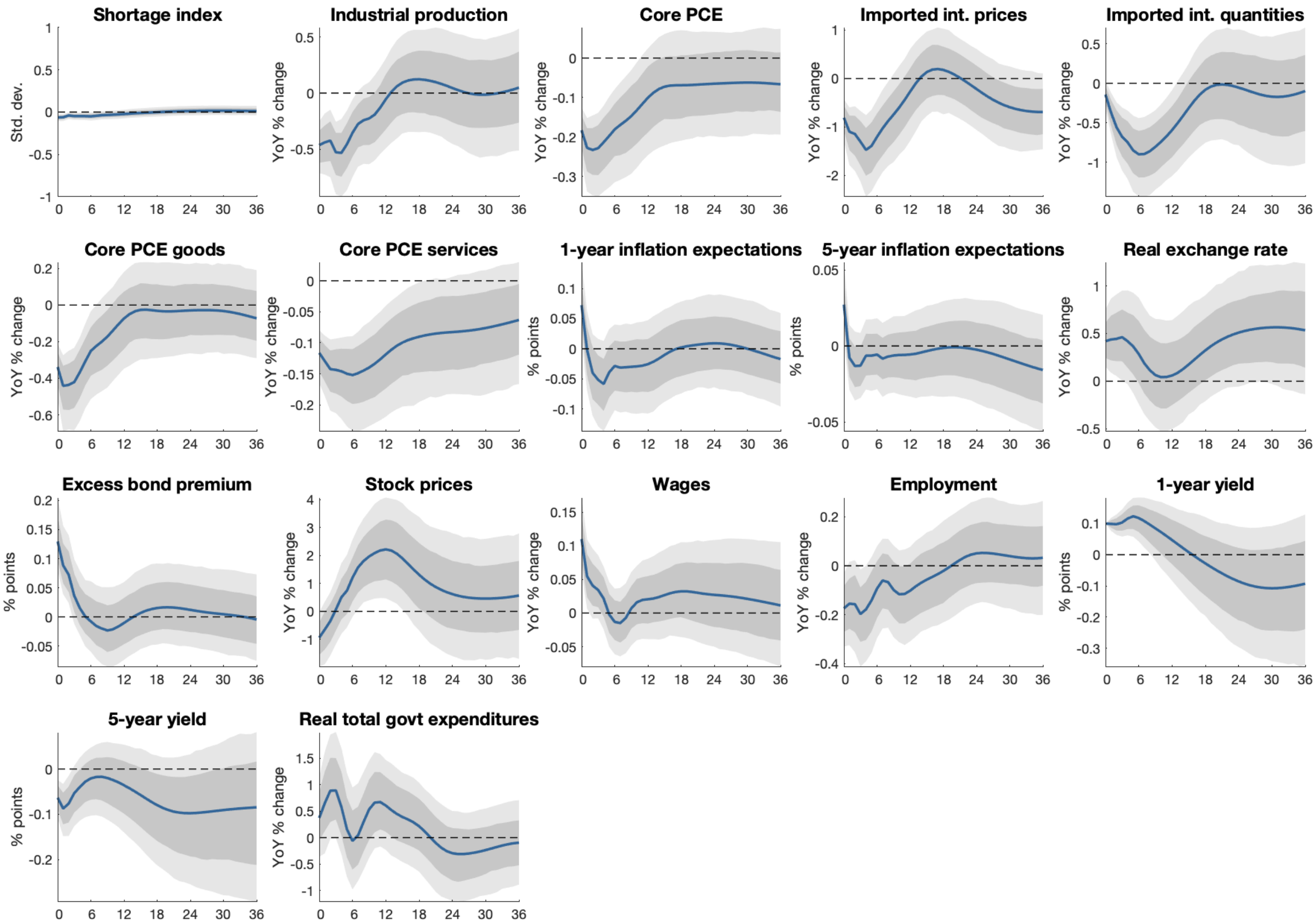
Note: IRFs of U.S. endogenous variables following a Conventional Monetary Policy (CMP) shock using Jarociński (2024)'s surprise series as an instrument, normalised to induce a 10 basis point increase in the 1-year yield. The horizontal axis shows months. Solid lines represent median responses, while shaded areas indicate 68% and 90% posterior coverage bands. Estimation sample: 1991M1–2025M6.

Figure B.2: IRFs to a U.S. Forward Guidance (FG) shock using Jarociński (2024)'s surprise series



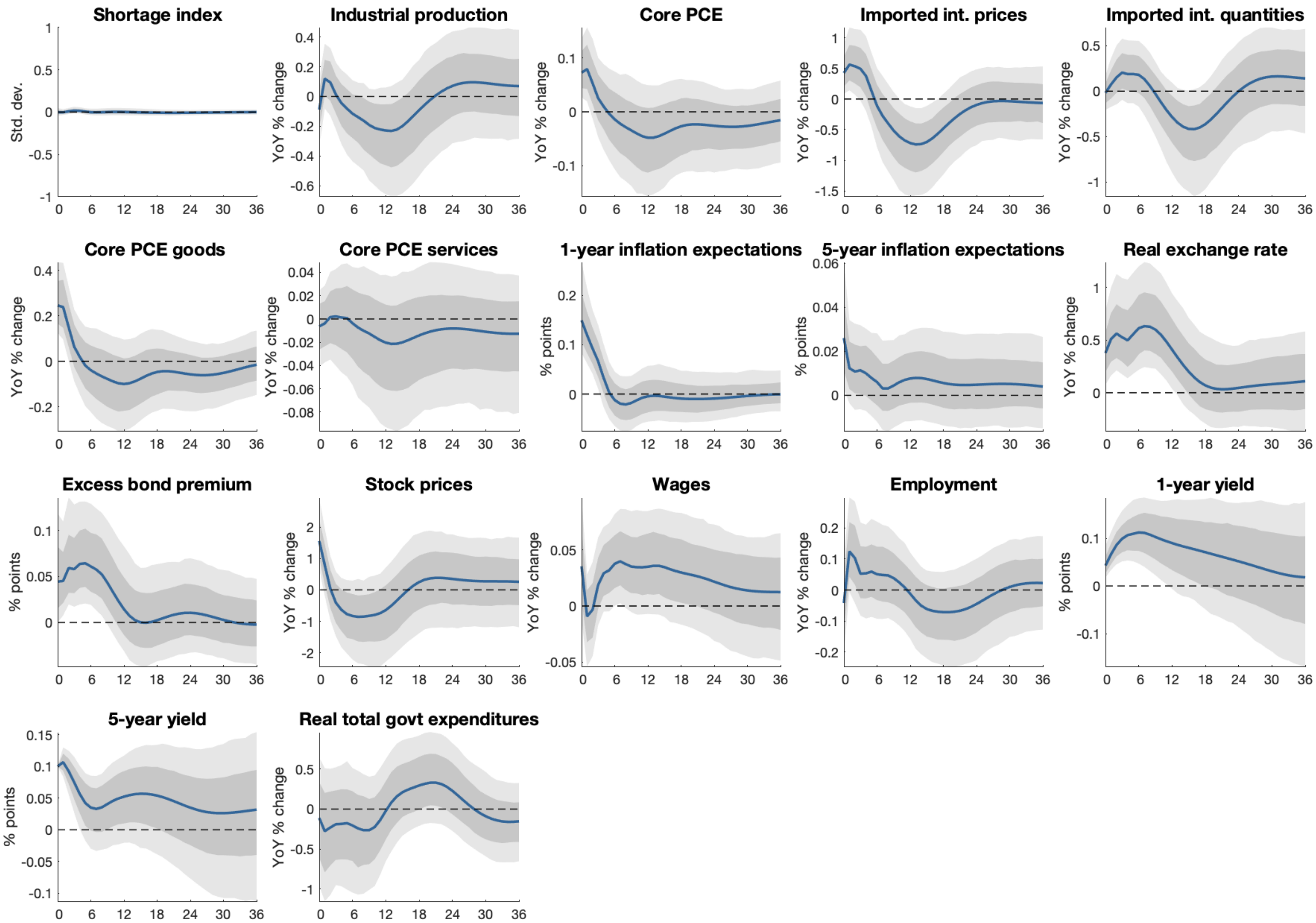
Note: IRFs of U.S. endogenous variables following a Forward Guidance (FG) shock using Jarociński (2024)'s surprise series as an instrument, normalised to induce a 10 basis point increase in the 5-year yield. The horizontal axis shows months. Solid lines represent median responses, while shaded areas indicate 68% and 90% posterior coverage bands. Estimation sample: 1991M1–2025M6.

Figure B.3: IRFs to a Conventional Monetary Policy (CMP) shock using Swanson (2024)'s surprise series



Note: IRFs of U.S. endogenous variables following a Conventional Monetary Policy (CMP) shock using Swanson (2024)'s surprise series as an instrument, normalised to induce a 10 basis point increase in the 1-year yield. The horizontal axis shows months. Solid lines represent median responses, while shaded areas indicate 68% and 90% posterior coverage bands. Estimation sample: 1991M1–2025M6.

Figure B.4: IRFs to a U.S. Forward Guidance (FG) shock using Swanson (2024)'s surprise series

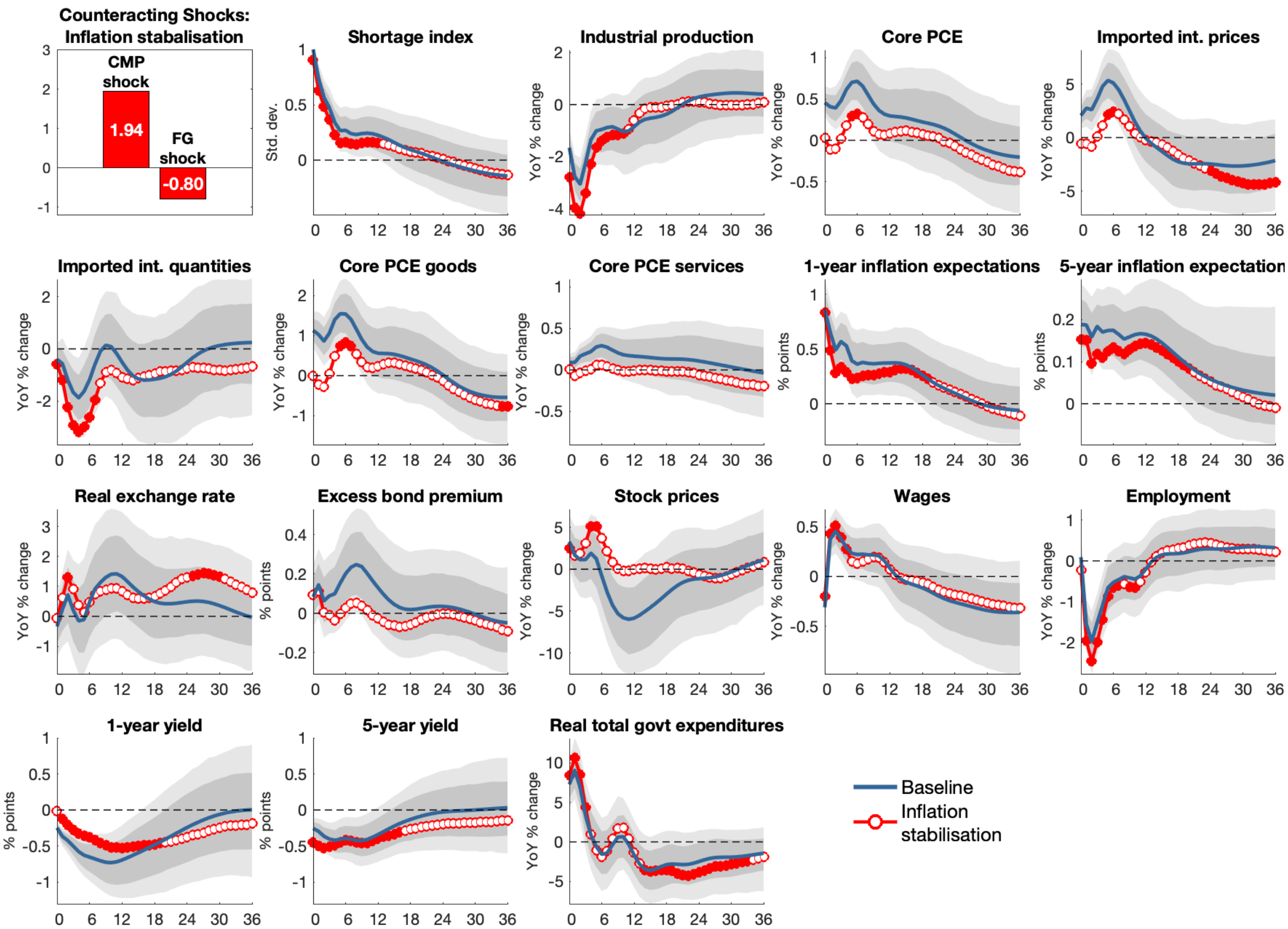


Note: IRFs of U.S. endogenous variables following a Forward Guidance (FG) shock using Swanson (2024)'s surprise series as an instrument, normalised to induce a 10 basis point increase in the 5-year yield. The horizontal axis shows months. Solid lines represent median responses, while shaded areas indicate 68% and 90% posterior coverage bands. Estimation sample: 1991M1–2025M6.

C The Role of Monetary Policy in the Transmission of GSC Shocks

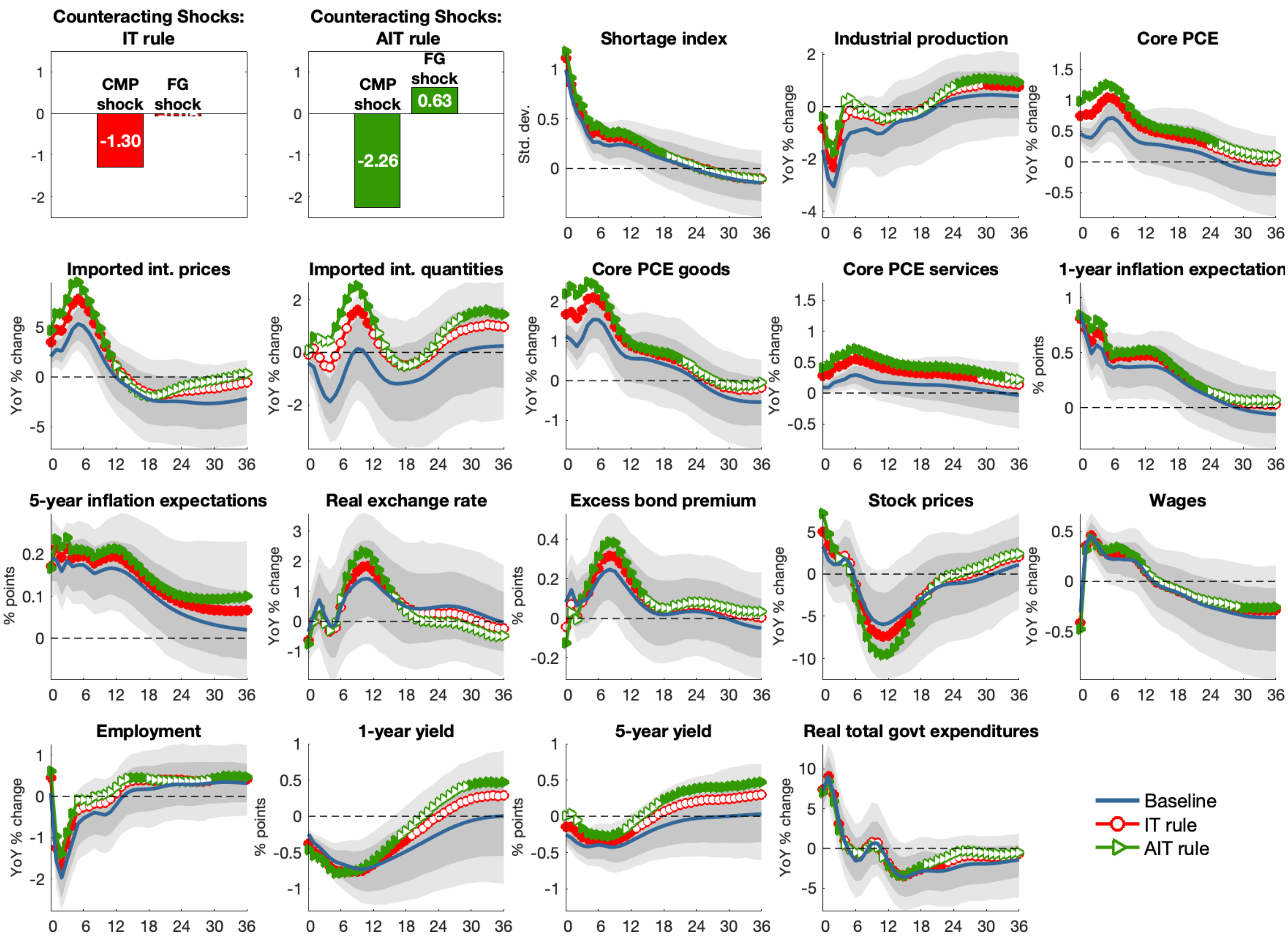
C.1 Full Set of Responses

Figure C.1: IRFs to a GSC shock under the baseline policy rule and the counterfactual policy rule that stabilises inflation using Jarociński (2024)'s surprise series



Note: The GSC shock is normalised to induce a one-standard-deviation increase in the the shortage index of Caldara et al. (2025). The figure reports the size of the counteracting policy shocks—namely, a conventional monetary policy (CMP) shock and a forward guidance (FG) shock—required to replicate the counterfactual policy rule. Contractionary CMP and FG shocks are normalised to induce a 10 bp increase in the 1-year and 5-year yields, respectively. The horizontal axis shows months. Solid lines represent median responses, while shaded areas indicate 68% and 90% posterior coverage bands. Red-circled lines show counterfactual median responses. Filled circles indicate responses within the 68% posterior coverage bands, while empty markers denote non-significant responses. Estimation sample: 1991M1–2025M6.

Figure C.2: IRFs to a GSC shock under the baseline policy rule and the counterfactual optimal inflation targeting (IT) and average inflation targeting (AIT) policy rules using Jarociński (2024)'s surprise series



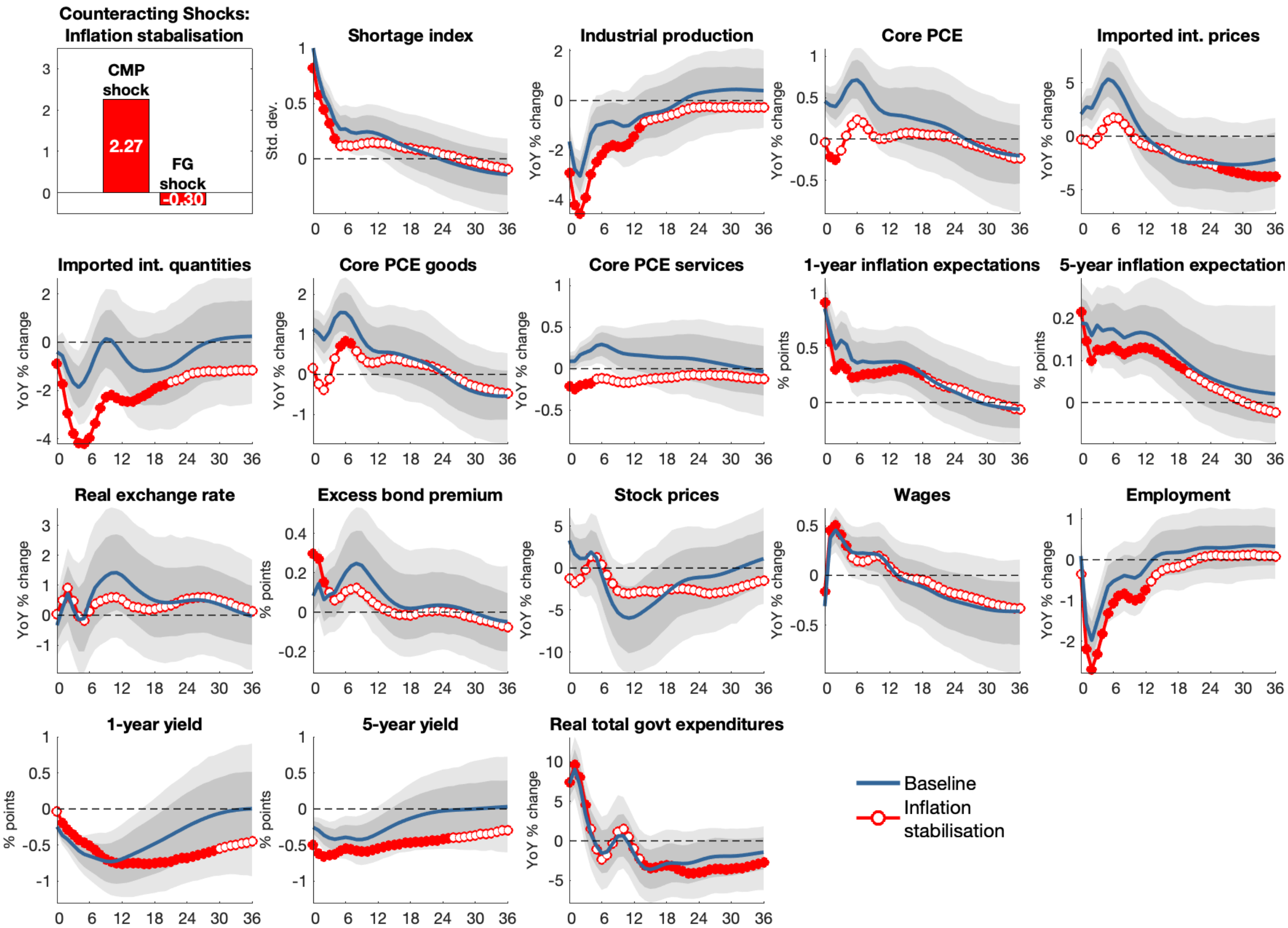
Note: The GSC shock is normalised to induce a one-standard-deviation increase in the shortage index of Caldara et al. (2025). The figure reports the size of the counteracting policy shocks—namely, a conventional monetary policy (CMP) shock and a forward guidance (FG) shock—required to replicate the counterfactual policy rule. Contractionary CMP and FG shocks are normalised to induce a 10 bp increase in the 1-year and 5-year yields, respectively. The horizontal axis shows months. Solid lines represent median responses, while shaded areas indicate 68% and 90% posterior coverage bands. Red-circled and green-triangled lines show counterfactual median responses. Filled circles indicate responses within the 68% posterior coverage bands, while empty markers denote non-significant responses. Estimation sample: 1991M1–2025M6.

C.2 Robustness Checks

Alternative monetary policy instruments. Figures C.3 and C.4 present the policy counterfactuals based on Swanson (2024).

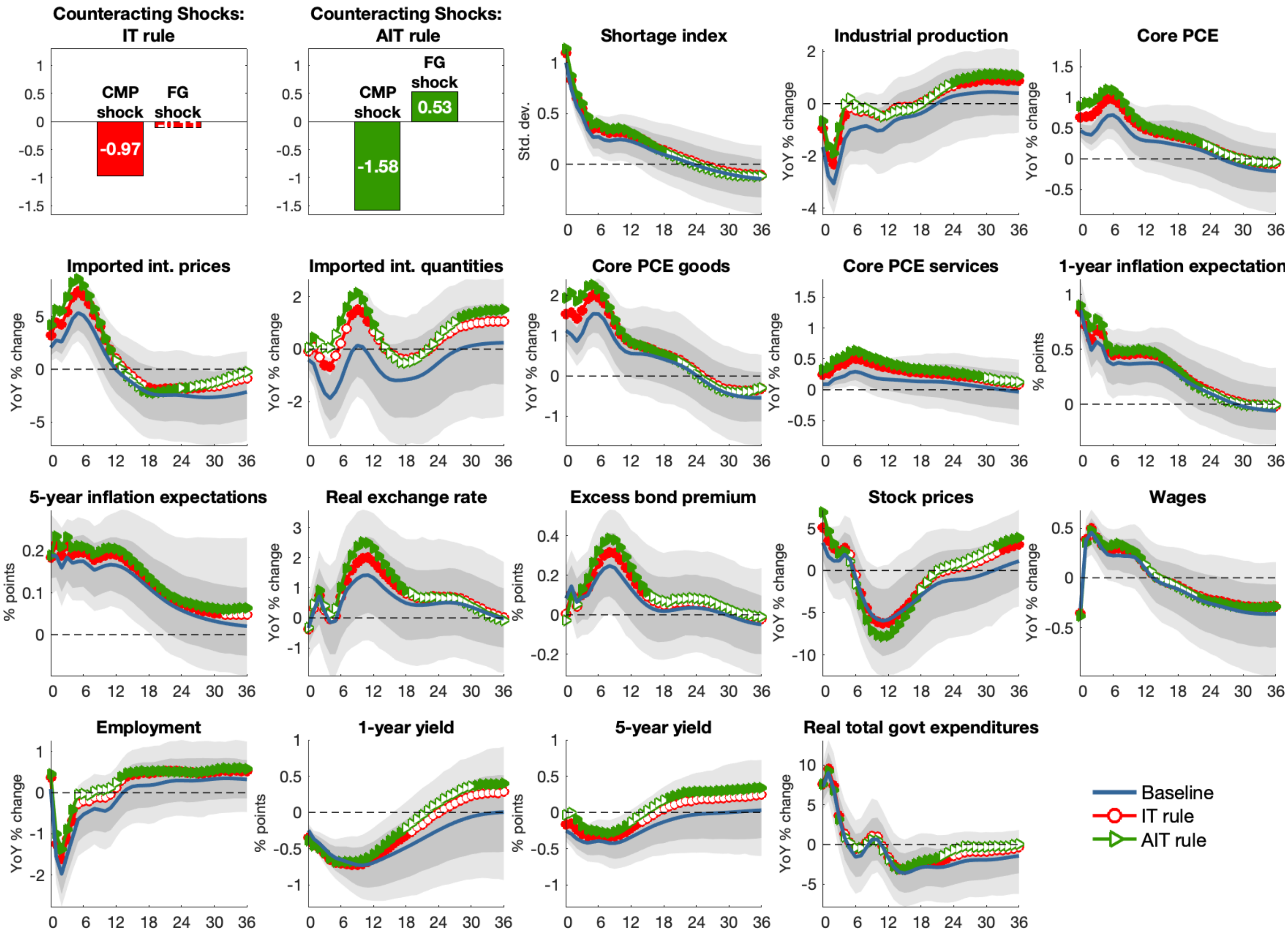
Pre-pandemic evidence. Figures C.5 and C.6 present the policy counterfactuals estimated over the pre-pandemic sample.

Figure C.3: IRFs to a GSC shock under the baseline policy rule and the counterfactual policy rule that stabilises inflation using Swanson (2024)'s surprise series



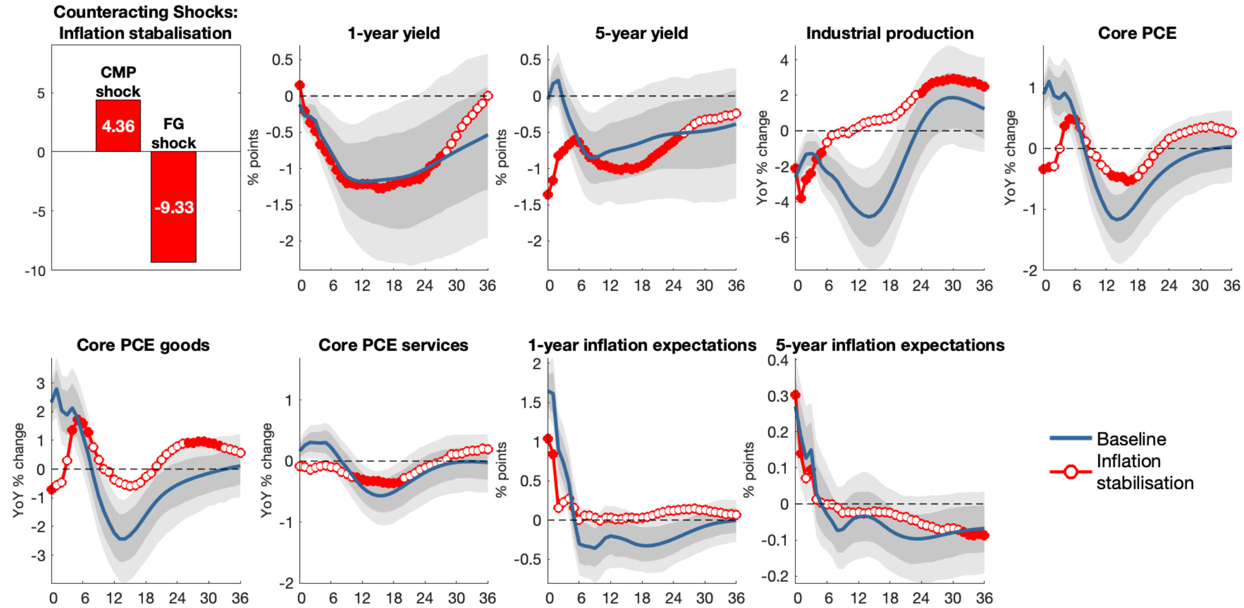
Note: The GSC shock is normalised to induce a one-standard-deviation increase in the the shortage index of Caldara et al. (2025). The figure reports the size of the counteracting policy shocks—namely, a conventional monetary policy (CMP) shock and a forward guidance (FG) shock—required to replicate the counterfactual policy rule. Contractionary CMP and FG shocks are normalised to induce a 10 bp increase in the 1-year and 5-year yields, respectively. The horizontal axis shows months. Solid lines represent median responses, while shaded areas indicate 68% and 90% posterior coverage bands. Red-circled lines show counterfactual median responses. Filled circles indicate responses within the 68% posterior coverage bands, while empty markers denote non-significant responses. Estimation sample: 1991M1–2025M6.

Figure C.4: IRFs to a GSC shock under the baseline policy rule and the counterfactual optimal inflation targeting (IT) and average inflation targeting (AIT) policy rules using Swanson (2024)'s surprise series



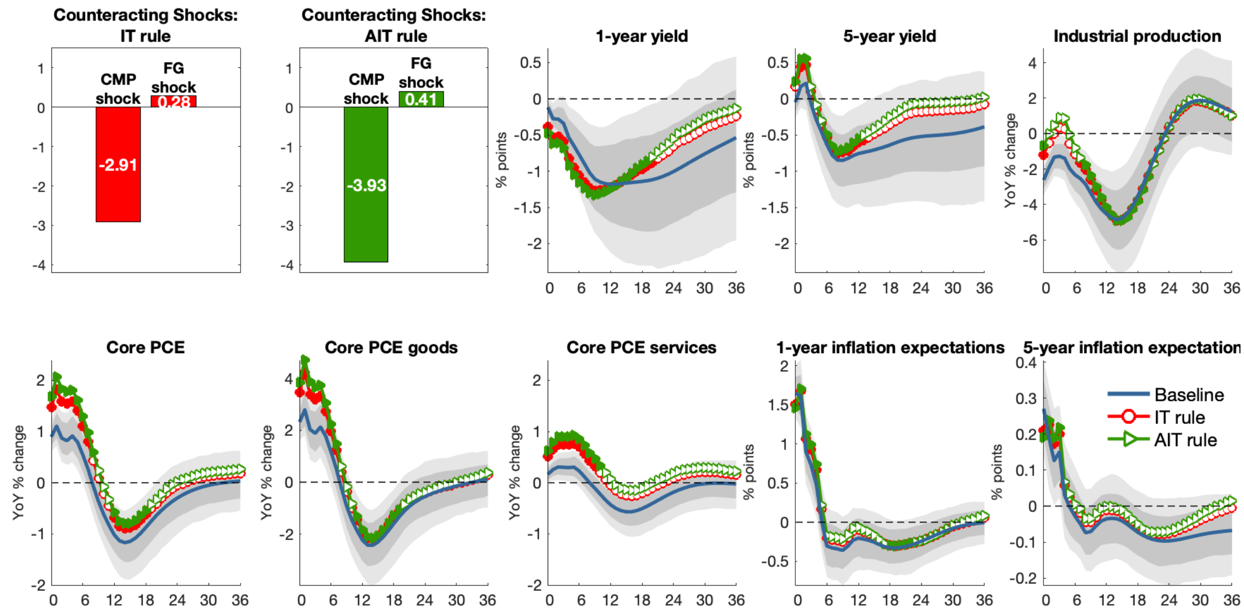
Note: The GSC shock is normalised to induce a one-standard-deviation increase in the shortage index of Caldara et al. (2025). The figure reports the size of the counteracting policy shocks—namely, a conventional monetary policy (CMP) shock and a forward guidance (FG) shock—required to replicate the counterfactual policy rule. Contractionary CMP and FG shocks are normalised to induce a 10 bp increase in the 1-year and 5-year yields, respectively. The horizontal axis shows months. Solid lines represent median responses, while shaded areas indicate 68% and 90% posterior coverage bands. Red-circled and green-triangled lines show counterfactual median responses. Filled circles indicate responses within the 68% posterior coverage bands, while empty markers denote non-significant responses. Estimation sample: 1991M1–2025M6.

Figure C.5: IRFs to a GSC shock under the baseline policy rule and the counterfactual policy rule that stabilises inflation: Pre-Pandemic Sample



Note: The GSC shock is normalised to induce a one-standard-deviation increase in the the shortage index of Caldara et al. (2025). The figure reports the median posterior magnitude of the counteracting policy shocks—namely, a conventional monetary policy (CMP) shock and a forward guidance (FG) shock—required to replicate the counterfactual policy rule. Contractionary CMP and FG shocks are normalised to induce a 10 bp increase in the 1-year and 5-year yields, respectively. The horizontal axis shows months. Solid lines represent median responses, while shaded areas indicate 68% and 90% posterior coverage bands. Red-circled lines show counterfactual median responses. Filled circles indicate responses within the 68% posterior coverage bands, while empty markers denote non-significant responses. Estimation sample: 1991M1–2019M12.

Figure C.6: IRFs to a GSC shock under the baseline policy rule and the counterfactual optimal IT and AIT policy rules: Pre-Pandemic Sample



Note: The GSC shock is normalised to induce a one-standard-deviation increase in the shortage index of Caldara et al. (2025). The figure reports the median posterior magnitude of the counteracting policy shocks—namely, a conventional monetary policy (CMP) shock and a forward guidance (FG) shock—required to replicate the counterfactual policy rule. Contractionary CMP and FG shocks are normalised to induce a 10 bp increase in the 1-year and 5-year yields, respectively. The horizontal axis shows months. Solid lines represent median responses, while shaded areas indicate 68% and 90% posterior coverage bands. Red-circled and green-triangled lines show counterfactual median responses. Filled circles indicate responses within the 68% posterior coverage bands, while empty markers denote non-significant responses. Estimation sample: 1991M1–2019M12.

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