# Online Appendix: Estimating Macroeconomic News and Surprise Shocks*

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Abstract

Appendix A lists our data sources. Appendix B proves the existence of an orthogonal rotation matrix in the structural VAR model. Appendices C and D describe in more detail the baseline model and larger-scale DSGE model. Appendix E discusses the surprise shock max share estimator. Appendix F compares our analysis with the simulation evidence reported in Kurmann and Sims (2021). Appendix G provides additional simulation and estimation results.

*The views expressed in this paper are our own and do not necessarily reflect the views of the Federal Reserve Bank of Dallas or the Federal Reserve System.

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# A Data Sources

We use the following time-series provided by Haver Analytics:

1. **Civilian Noninstitutional Population: 16 Years & Over**
   Not Seasonally Adjusted, Quarterly, Thousands (LN16N@USECON)
2. **Gross Domestic Product: Implicit Price Deflator**
   Seasonally Adjusted, Quarterly, 2012=100 (DGDP@USNA)
3. **Real Gross Domestic Product**
   Seasonally Adjusted, Quarterly, Billions of Chained 2012$ (GDPH@USECON)
4. **Real Personal Consumption Expenditures**
   Seasonally Adjusted, Quarterly, Billions of Chained 2012$ (CH@USECON))
5. **Real Private Fixed Investment**
   Seasonally Adjusted, Quarterly, Billions of Chained 2012$ (FH@USECON)
6. **Hours: Private Sector, Nonfarm Payrolls**
   Seasonally Adjusted, Quarterly, Billions of Hours (LHTPRIVA@USECON)
7. **Fernald Utilization-Adjusted Total Factor Productivity**
   Quarterly, Percent, Annual Rate (TFPMQ@USECON)
8. **Capital Share of Income**, Quarterly (TFPJQ@USECON)
9. **Effective Federal Funds Rate**
   Quarterly Average, Annual Percent (FFED@USECON)
10. **S&P 500 Stock Price Index**, Quarterly Average (SP500@USECON)
11. **Real Research and Development**
    Seasonally Adjusted, Quarterly, Billions of Chained 2012$ (FNPRH@USECON)
12. **Net Stock: Private Fixed Assets**, Annual, Billions of Dollars (EPT@CAPSTOCK)
13. **Net Stock: Durable Goods**, Annual, Billions of Dollars (EDT@CAPSTOCK)
14. **Depreciation: Private Fixed Assets**, Annual, Billions of Dollars (KPT@CAPSTOCK)
15. **Depreciation: Durable Goods**, Annual, Billions of Dollars (KDT@CAPSTOCK)

We also used the following data from other sources:

1. **Information & Communication Technologies Standards Index** from Baron and Schmidt (2019). Data is available at https://www.law.northwestern.edu/research-faculty/clbe/innovationeconomics/data/technologystandards.

2. **Patent-Based Innovation Index** from Cascaldi-Garcia and Vukotić (2022). This is a quarterly version of the Kogan et al. (2017) annual index, which is based on counts of patents where each patent is weighted by its impact on the firm's stock price. Data is available at https://sites.google.com/site/cascaldigarcia/research.
3. **U.S. Patent & Trade Office Patent Count** from Marco et al. (2015). This is a quarterly count of new patent applications, excluding those classified as "missing" and "not classified". See https://www.uspto.gov/ip-policy/economic-research/research-datasets/historical-patent-data-files.
4. **Macroeconomic Forecasts** from the Survey of Professional Forecasters (SPF). We use the one and four-quarter ahead mean predictions for the unemployment rate (UNEMP), the GDP deflator (PGDP), real non-residential fixed investment (RNRESIN), and corporate profits (CPROF). These are used to construct the exogenous patent-innovation series of Miranda-Agrippino et al. (2022) that controls for SPF forecasts but not for exogenous policy shocks. Details about the construction are in Section 2.2 of Miranda-Agrippino et al. (2022). For the SPF data, see https://www.philadelphiafed.org/surveys-and-data/real-time-data-research/survey-of-professional-forecasters.

# B EXISTENCE OF AN ORTHOGONAL ROTATION MATRIX

Consider the model in Section 2. Observe that either $\gamma_{n,2}\gamma_{n,3} > 0$ and $\gamma_{\ell,2}\gamma_{\ell,3} < 0$ or $\gamma_{n,2}\gamma_{n,3} < 0$ and $\gamma_{\ell,2}\gamma_{\ell,3} > 0$. Using (R1-1) and the solution for $\gamma_s$, $\gamma_{\ell,2}$, and $\gamma_{\ell,3}$ in Proposition 1 implies

$$
\begin{aligned}
\gamma_{s,1}^2 + \gamma_{s,2}^2 + \gamma_{s,3}^2 &= 1 - \gamma_{n,1}^2 + (\gamma_{n,1}\gamma_{n,2}/\gamma_{s,1})^2 + (\gamma_{n,1}\gamma_{n,3}/\gamma_{s,1})^2 \\
&= 1 - \gamma_{n,1}^2 + (\gamma_{n,1}^2/\gamma_{s,1}^2)(\gamma_{n,2}^2 + \gamma_{n,3}^2) \\
&= 1 \\
\gamma_{\ell,2}^2 + \gamma_{\ell,3}^2 &= 1 - \gamma_{s,2}^2 - \gamma_{n,2}^2 + 1 - \gamma_{s,3}^2 - \gamma_{n,3}^2 \\
&= \gamma_{s,1}^2 + \gamma_{n,1}^2 \\
&= 1 \\
\gamma_{s,1}\gamma_{n,1} + \gamma_{s,2}\gamma_{n,2} + \gamma_{s,3}\gamma_{n,3} &= \gamma_{s,1}\gamma_{n,1} - \gamma_{n,1}\gamma_{n,2}^2/\gamma_{s,1} - \gamma_{n,1}\gamma_{n,3}^2/\gamma_{s,1} \\
&= \gamma_{s,1}\gamma_{n,1} - (\gamma_{n,2}^2 + \gamma_{n,3}^2)\gamma_{n,1}/\gamma_{s,1} \\
&= 0 \\
\gamma_{n,2}\gamma_{\ell,2} + \gamma_{n,3}\gamma_{\ell,3} &= \gamma_{n,2}(\pm\sqrt{1-\gamma_{\ell,3}^2}) + \gamma_{n,3}(\pm\sqrt{1-\gamma_{\ell,2}^2}) \\
&= \gamma_{n,2}(\pm\sqrt{\gamma_{s,3}^2 + \gamma_{n,3}^2}) + \gamma_{n,3}(\pm\sqrt{\gamma_{s,2}^2 + \gamma_{n,2}^2}) \\
&= \gamma_{n,2}(\pm\sqrt{(\gamma_{n,1}^2/\gamma_{s,1}^2 + 1)\gamma_{n,3}^2}) + \gamma_{n,3}(\pm\sqrt{(\gamma_{n,1}^2/\gamma_{s,1}^2 + 1)\gamma_{n,2}^2})
\end{aligned}
$$

$$
\begin{aligned}
&= \gamma_{n,2}(\pm\sqrt{\gamma_{n,3}^2/\gamma_{s,1}^2}) + \gamma_{n,3}(\pm\sqrt{\gamma_{n,2}^2/\gamma_{s,1}^2}) \\
&= \begin{cases}
\frac{1}{\sqrt{\gamma_{s,1}^2}}\left(\gamma_{n,2}\sqrt{\gamma_{n,3}^2} + \gamma_{n,3}\sqrt{\gamma_{n,2}^2}\right) & \text{if } \gamma_{\ell,2} > 0 \text{ and } \gamma_{\ell,3} > 0 \\
\frac{1}{\sqrt{\gamma_{s,1}^2}}\left(-\gamma_{n,2}\sqrt{\gamma_{n,3}^2} - \gamma_{n,3}\sqrt{\gamma_{n,2}^2}\right) & \text{if } \gamma_{\ell,2} < 0 \text{ and } \gamma_{\ell,3} < 0 \\
\frac{1}{\sqrt{\gamma_{s,1}^2}}\left(-\gamma_{n,2}\sqrt{\gamma_{n,3}^2} + \gamma_{n,3}\sqrt{\gamma_{n,2}^2}\right) & \text{if } \gamma_{\ell,2} < 0 \text{ and } \gamma_{\ell,3} > 0 \\
\frac{1}{\sqrt{\gamma_{s,1}^2}}\left(\gamma_{n,2}\sqrt{\gamma_{n,3}^2} - \gamma_{n,3}\sqrt{\gamma_{n,2}^2}\right) & \text{if } \gamma_{\ell,2} > 0 \text{ and } \gamma_{\ell,3} < 0
\end{cases} \\
&= \begin{cases}
0 & \text{if } \gamma_{n,2}\gamma_{n,3} < 0 \\
0 & \text{if } \gamma_{n,2}\gamma_{n,3} < 0 \\
0 & \text{if } \gamma_{n,2}\gamma_{n,3} > 0 \\
0 & \text{if } \gamma_{n,2}\gamma_{n,3} > 0
\end{cases} \\
\gamma_{s,2}\gamma_{\ell,2} + \gamma_{s,3}\gamma_{\ell,3} &= (\gamma_{n,1}/\gamma_{s,1})(\gamma_{n,2}\gamma_{\ell,2} + \gamma_{n,3}\gamma_{\ell,3}) \\
&= 0 \\
\gamma_{s,2}\gamma_{s,3} + \gamma_{n,2}\gamma_{n,3} + \gamma_{\ell,2}\gamma_{\ell,3} &= (\gamma_{n,1}^2/\gamma_{s,1}^2 + 1)\gamma_{n,2}\gamma_{n,3} - (\gamma_{n,2}/\gamma_{n,3})\gamma_{\ell,2}^2 \\
&= \gamma_{n,2}\gamma_{n,3}/\gamma_{s,1}^2 - (\gamma_{n,2}/\gamma_{n,3})(\gamma_{n,3}^2/\gamma_{s,1}^2) \\
&= 0
\end{aligned}
$$

since $\gamma_{s,1}^2 = 1 - \gamma_{n,1}^2 = \gamma_{n,2}^2 + \gamma_{n,3}^2$. Thus, (R1-1)-(R1-6) and (R2-1)-(R2-6) are satisfied, and there exists a $Q$ that is orthogonal.

## C BASELINE DSGE MODEL

We detrend the model by scaling trending variables, $x_t$, as $\tilde{x}_t \equiv x_t/z_t^{1/(1-\alpha)}$, where $z_t$ is the permanent component of TFP. The equilibrium system is given by

$$r_t^k = \alpha mc_t s_t g_t(\tilde{k}_{t-1}/n_t)^{\alpha-1} \tag{C.1}$$

$$\tilde{w}_t = (1-\alpha)mc_t s_t g_t^{-\alpha/(1-\alpha)}(\tilde{k}_{t-1}/n_t)^{\alpha} \tag{C.2}$$

$$\Delta_t^p \tilde{y}_t = s_t g_t^{-\alpha/(1-\alpha)}\tilde{k}_{t-1}^{\alpha} n_t^{1-\alpha} \tag{C.3}$$

$$\tilde{w}_t = \chi n_t^{\eta}\tilde{c}_t \tag{C.4}$$

$$1 = E_t[x_{t+1}r_t/\pi_{t+1}] \tag{C.5}$$

$$\tilde{c}_t + \tilde{i}_t = \tilde{y}_t \tag{C.6}$$

$$\tilde{k}_t = (1-\delta)\tilde{k}_{t-1}/g_{y,t} + \mu_t\tilde{i}_t \tag{C.7}$$

$$1/\mu_t = E_t[x_{t+1}(r_{t+1}^k + (1-\delta)/\mu_{t+1})] \tag{C.8}$$

$$p_{f,t} = \tfrac{\epsilon_p}{\epsilon_p - 1}(\tilde{f}_{1,t}/\tilde{f}_{2,t}) \tag{C.9}$$

$$\tilde{f}_{1,t} = mc_t\tilde{y}_t + \theta_p E_t[g_{y,t+1}x_{t+1}(\pi_{t+1}/\bar{\pi})^{\epsilon_p}\tilde{f}_{1,t+1}] \tag{C.10}$$

$$\tilde{f}_{2,t} = \tilde{y}_t + \theta_p E_t[g_{y,t+1}x_{t+1}(\pi_{t+1}/\bar{\pi})^{\epsilon_p-1}\tilde{f}_{2,t+1}] \tag{C.11}$$

$$\Delta_t^p = (1-\theta_p)p_{f,t}^{-\epsilon_p} + \theta_p(\pi_t/\bar{\pi})^{\epsilon_p}\Delta_{t-1}^p \tag{C.12}$$

$$1 = (1-\theta_p)p_{f,t}^{1-\epsilon_p} + \theta_p(\pi_t/\bar{\pi})^{\epsilon_p-1} \tag{C.13}$$

$$x_t = \beta\tilde{c}_{t-1}/(\tilde{c}_t g_{y,t}) \tag{C.14}$$

$$r_t = \bar{r}(\pi_t/\bar{\pi})^{\phi_\pi} \tag{C.15}$$

$$g_{y,t} = g_t^{1/(1-\alpha)} \tag{C.16}$$

$$\ln s_t = \rho_s \ln s_{t-1} + \sigma_s\varepsilon_{s,t} \tag{C.17}$$

$$\ln g_t = (1-\rho_g)\ln\bar{g} + \rho_g \ln g_{t-1} + \sigma_g\varepsilon_{g,t} \tag{C.18}$$

$$\ln \mu_t = \rho_\mu \ln \mu_{t-1} + \sigma_\mu\varepsilon_{\mu,t} \tag{C.19}$$

**Table 1:** Baseline DSGE model calibration at quarterly frequency

| Parameter | Value | Parameter | Value |
|---|---|---|---|
| Discount Factor ($\beta$) | 0.995 | Steady-State Hours ($\bar{n}$) | 0.3333 |
| Cost Share of Capital ($\alpha$) | 0.3343 | Steady-State TFP Growth Rate ($\bar{g}$) | 1.0026 |
| Capital Depreciation Rate ($\delta$) | 0.025 | TFP News Shock Persistence ($\rho_g$) | 0.6 |
| Frisch Labor Supply Elasticity ($1/\eta$) | 0.5 | TFP Surprise Shock Persistence ($\rho_s$) | 0.8 |
| Goods Elasticity of Substitution ($\epsilon_p$) | 11 | MEI Shock Persistence ($\rho_\mu$) | 0.9 |
| Calvo Price Stickiness ($\theta_p$) | 0.75 | TFP News Shock SD ($\sigma_g$) | 0.003 |
| Taylor Rule Inflation Response ($\phi_\pi$) | 1.5 | TFP Surprise Shock SD ($\sigma_s$) | 0.007 |
| Steady-State Inflation Rate ($\bar{\pi}$) | 1.005 | MEI Shock SD ($\sigma_\mu$) | 0.007 |

# D LARGER-SCALE DSGE MODEL

We detrend the same way as in the baseline model except $\tilde{\lambda}_t \equiv \lambda_t z_t^{1/(1-\alpha)}$, $\tilde{f}_{1,t}^w \equiv f_{1,t}^w/z_t^{(1+\epsilon_w)/(1-\alpha)}$, and $\tilde{f}_{2,t}^w \equiv f_{2,t}^w/z_t^{\epsilon_w/(1-\alpha)}$. The labor share $\omega_{\ell,t} = w_{\ell,t}l_{s,t}/y_t$. The equilibrium system is given by

$$r_{k,t} = \alpha mc_t s_t(\tilde{k}_{s,t}/l_{s,t})^{\alpha-1} \tag{D.1}$$

$$\tilde{w}_{\ell,t} = (1-\alpha)mc_t s_t(\tilde{k}_{s,t}/l_{s,t})^{\alpha} \tag{D.2}$$

$$\Delta_t^p\tilde{y}_t = s_t\tilde{k}_{s,t}^{\alpha}l_{s,t}^{1-\alpha} - \bar{F} \tag{D.3}$$

$$\tilde{\lambda}_t = (\tilde{c}_t - b\tilde{c}_{t-1}/g_{y,t})^{-1} - \beta b E_t[(\tilde{c}_{t+1}g_{y,t+1} - b\tilde{c}_t)^{-1}] \tag{D.4}$$

$$1 = E_t[x_{t+1}r_t/\pi_{t+1}] \tag{D.5}$$

$$r_{k,t} = \gamma_1 + \gamma_2(u_t - 1) \tag{D.6}$$

$$\theta\kappa_3 e_t^{\kappa_4-1} = \tilde{\lambda}_t\tilde{w}_t h_t \tag{D.7}$$

$$\theta\kappa_1 h_t^{\kappa_2-1} = \tilde{\lambda}_t \tilde{w}_t e_t \tag{D.8}$$

$$\begin{gathered}\theta(\kappa_0 + (\kappa_1/\kappa_2)h_t^{\kappa_2} + (\kappa_3/\kappa_4)e_t^{\kappa_4}) \\ = \tilde{\lambda}_t \tilde{w}_t \left[e_t h_t - \tfrac{\psi}{2}(n_t/n_{t-1}-1)^2 - \psi(n_t/n_{t-1}-1)(n_t/n_{t-1})\right] \\ +\beta\psi E_t[\tilde{\lambda}_{t+1}\tilde{w}_{t+1}(n_{t+1}/n_t-1)(n_{t+1}/n_t)^2]\end{gathered} \tag{D.9}$$

$$\tilde{k}_t = (1-\delta)\tilde{k}_{t-1}/g_{y,t} + \mu_t \tilde{\imath}_t \tag{D.10}$$

$$\mu_t q_t = 1 + \varphi(\Phi_t - \tilde{\delta}) \tag{D.11}$$

$$\begin{gathered}q_t = E_t[x_{t+1}(r_{k,t+1}u_{t+1} - \gamma_1(u_{t+1}-1) - \tfrac{\gamma_2}{2}(u_{t+1}-1)^2 \\ -\tfrac{\varphi}{2}(\Phi_{t+1}-\tilde{\delta})^2 + \varphi(\Phi_{t+1}-\tilde{\delta})\Phi_{t+1} + (1-\delta)q_{t+1})]\end{gathered} \tag{D.12}$$

$$\Phi_t = \tilde{\imath}_t g_{y,t}/\tilde{k}_{t-1} \tag{D.13}$$

$$l_t = e_t h_t n_t \tag{D.14}$$

$$l_t = \Delta_t^w l_{s,t} \tag{D.15}$$

$$\tilde{k}_{s,t} = u_t \tilde{k}_{t-1}/g_{y,t} \tag{D.16}$$

$$x_t = \beta\tilde{\lambda}_t/(\tilde{\lambda}_{t-1}g_{y,t}) \tag{D.17}$$

$$\tilde{p}_t = \tfrac{\epsilon_p}{\epsilon_p-1}(\tilde{f}_{1,t}^p/\tilde{f}_{2,t}^p) \tag{D.18}$$

$$\tilde{f}_{1,t}^p = mc_t\tilde{y}_t + \theta_p E_t[x_{t+1}\pi_t^{-\epsilon_p\gamma_p}\bar{\pi}^{-\epsilon_p(1-\gamma_p)}\pi_{t+1}^{\epsilon_p}\tilde{f}_{1,t+1}^p g_{y,t+1}] \tag{D.19}$$

$$\tilde{f}_{2,t}^p = \tilde{y}_t + \theta_p E_t[x_{t+1}\pi_t^{(1-\epsilon_p)\gamma_p}\bar{\pi}^{(1-\epsilon_p)(1-\gamma_p)}\pi_{t+1}^{\epsilon_p-1}\tilde{f}_{2,t+1}^p g_{y,t+1}] \tag{D.20}$$

$$\Delta_t^p = (1-\theta_p)\tilde{p}_t^{-\epsilon_p} + \theta_p\pi_{t-1}^{-\epsilon_p\gamma_p}\bar{\pi}^{-\epsilon_p(1-\gamma_p)}\pi_t^{\epsilon_p}\Delta_{t-1}^p \tag{D.21}$$

$$1 = (1-\theta_p)\tilde{p}_t^{1-\epsilon_p} + \theta_p\pi_{t-1}^{(1-\epsilon_p)\gamma_p}\bar{\pi}^{(1-\epsilon_p)(1-\gamma_p)}\pi_t^{\epsilon_p-1} \tag{D.22}$$

$$\tilde{w}_{\ell,t}^* = \tfrac{\epsilon_w}{\epsilon_w-1}(\tilde{f}_{1,t}^w/\tilde{f}_{2,t}^w), \tag{D.23}$$

$$\tilde{f}_{1,t}^w = \tilde{w}_{\ell,t}^{\epsilon_w}\tilde{w}_t l_{s,t} + \theta_w\bar{g}_y E_t[x_{t+1}\pi_{t+1}^{\epsilon_w}\pi_t^{-\epsilon_w\gamma_w}\bar{\pi}^{-\epsilon_w(1-\gamma_w)}\tilde{f}_{1,t+1}^w(g_{y,t+1}/\bar{g}_y)^{1+\epsilon_w}] \tag{D.24}$$

$$\tilde{f}_{2,t}^w = \tilde{w}_{\ell,t}^{\epsilon_w} l_{s,t} + \theta_w\bar{g}_y E_t[x_{t+1}\pi_{t+1}^{\epsilon_w-1}\pi_t^{(1-\epsilon_w)\gamma_w}\bar{\pi}^{(1-\epsilon_w)(1-\gamma_w)}\tilde{f}_{2,t+1}^w(g_{y,t+1}/\bar{g}_y)^{\epsilon_w}] \tag{D.25}$$

$$\Delta_t^w = (1-\theta_w)\left(\frac{\tilde{w}_{\ell,t}^*}{\tilde{w}_{\ell,t}}\right)^{-\epsilon_w} + \theta_w\pi_{t-1}^{-\epsilon_w\gamma_w}\bar{\pi}^{-\epsilon_w(1-\gamma_w)}\pi_t^{\epsilon_w}\left(\frac{\tilde{w}_{\ell,t-1}\bar{g}_y}{\tilde{w}_{\ell,t}g_{y,t}}\right)^{-\epsilon_w}\Delta_{t-1}^w \tag{D.26}$$

$$\tilde{w}_{\ell,t}^{1-\epsilon_w} = (1-\theta_w)(\tilde{w}_{\ell,t}^*)^{1-\epsilon_w} + \theta_w\pi_{t-1}^{\gamma_w(1-\epsilon_w)}\bar{\pi}^{(1-\gamma_w)(1-\epsilon_w)}\pi_t^{\epsilon_w-1}\left(\frac{\tilde{w}_{\ell,t-1}\bar{g}_y}{g_{y,t}}\right)^{1-\epsilon_w} \tag{D.27}$$

$$r_t = r_{t-1}^{\rho_r}(\bar{r}(\pi_t/\bar{\pi})^{\phi_\pi}(\tilde{y}_t g_{y,t}/(\tilde{y}_{t-1}\bar{g}_y))^{\phi_y})^{1-\rho_r}\exp(\sigma_r\varepsilon_{r,t}) \tag{D.28}$$

$$\begin{gathered}\tilde{c}_t + \tilde{\imath}_t + \tfrac{\psi}{2}(n_t/n_{t-1}-1)^2\tilde{w}_t n_t + \tfrac{\varphi}{2}(\Phi_t-\tilde{\delta})^2\tilde{k}_{t-1}/g_{y,t} \\ +(\gamma_1(u_t-1) + \tfrac{\gamma_2}{2}(u_t-1)^2)\tilde{k}_{t-1}/g_{y,t} = \tilde{y}_t\end{gathered} \tag{D.29}$$

$$g_{y,t} = g_t^{1/(1-\alpha)} \tag{D.30}$$

$$\ln s_t = \rho_s \ln s_{t-1} + \sigma_s\varepsilon_{s,t} \tag{D.31}$$

$$\ln g_t = (1-\rho_g)\ln g + \rho_g \ln g_{t-1} + \sigma_g\varepsilon_{g,t} \tag{D.32}$$

$$\ln \mu_t = \rho_\mu \ln \mu_{t-1} + \sigma_\mu\varepsilon_{\mu,t} \tag{D.33}$$

**Table 2:** Larger-scale DSGE model parameterization at quarterly frequency

| Parameter | Value | Parameter | Value |
|---|---|---|---|
| Discount Factor ($\beta$) | 0.99 | Taylor Rule Inflation Response ($\phi_\pi$) | 1.5 |
| Cost Share of Capital ($\alpha$) | 0.3333 | Taylor Rule Output Response ($\phi_y$) | 0.5 |
| Capital Depreciation Rate ($\delta$) | 0.025 | Taylor Rule Smoothing ($\rho_r$) | 0.8 |
| Utilization Function Curvature ($\gamma_2$) | 0.01 | Steady-State Inflation Rate ($\bar{\pi}$) | 1 |
| Internal Habit Persistence ($b$) | 0.8 | Steady-State Employment Share ($\bar{n}$) | 3/5 |
| Capital Adjustment Cost ($\varphi$) | 2 | Steady-State Labor Preference ($\bar{G}$) | 1/3 |
| Employment Adjustment Cost ($\psi$) | 2 | Steady-State Effort ($\bar{e}$) | 5 |
| Frisch Elasticity of Hours ($\eta$) | 1 | Steady-State Hours ($\bar{h}$) | 1/3 |
| Elasticity of Effort to Hours ($\epsilon_{eh}$) | 4 | Steady-State Output Growth Rate ($\bar{g}_y$) | 1.0026 |
| Goods Elasticity of Substitution ($\epsilon_p$) | 11 | TFP News Shock Persistence ($\rho_g$) | 0.7 |
| Labor Elasticity of Substitution ($\epsilon_w$) | 11 | TFP Surprise Shock Persistence ($\rho_s$) | 0.9 |
| Calvo Price Stickiness ($\theta_p$) | 0.75 | MEI Shock Persistence ($\rho_\mu$) | 0.8 |
| Calvo Wage Stickiness ($\theta_w$) | 0.9 | TFP News Shock SD ($\sigma_g$) | 0.002125 |
| Price Indexation ($\gamma_p$) | 0 | TFP Surprise Shock SD ($\sigma_s$) | 0.000425 |
| Wage Indexation ($\gamma_w$) | 1 | MEI Shock SD ($\sigma_\mu$) | 0.00425 |

# E Surprise Shock Max Share Estimator

An implication of our analysis in Section 2 is that we can either estimate $\gamma_s$ given an estimate of $\gamma_n$ obtained by maximizing the TFP forecast error variance share at a long horizon or, alternatively, we can estimate $\gamma_n$ given an estimate of $\gamma_s$ obtained by maximizing the TFP forecast error variance share at a short horizon. In other words, the estimator of $\gamma_n$ is not unique. This raises the question of which estimator should be used when there is no TFP measurement error. A surprise shock max share estimator can be defined as

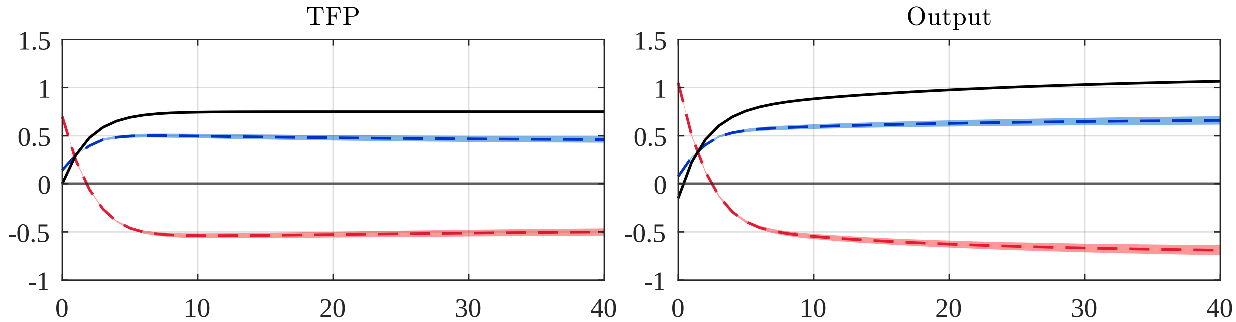
$$\gamma_s = \text{argmax } \Omega_{1,1}(H_s), \quad \Omega_{1,1}(H_s) \equiv \frac{\sum_{\tau=0}^{H_s} \Phi_{1,\tau} P \gamma_s \gamma_s' P' \Phi_{1,\tau}'}{\sum_{\tau=0}^{H_s} \Phi_{1,\tau} \Sigma \Phi_{1,\tau}'},$$

subject to the restriction that $\gamma_s' \gamma_s = 1$ and that the responses of selected variables to the surprise shock match patterns that would be expected of a surprise shock, where $\gamma_s = (\gamma_{s,1}, \gamma_{s,2}, \gamma_{s,3})'$ denotes the first column in the orthogonal rotation matrix $Q$ and the horizon $H_s$ is set to four quarters. Similarly inaccurate results are obtained for shorter horizons.

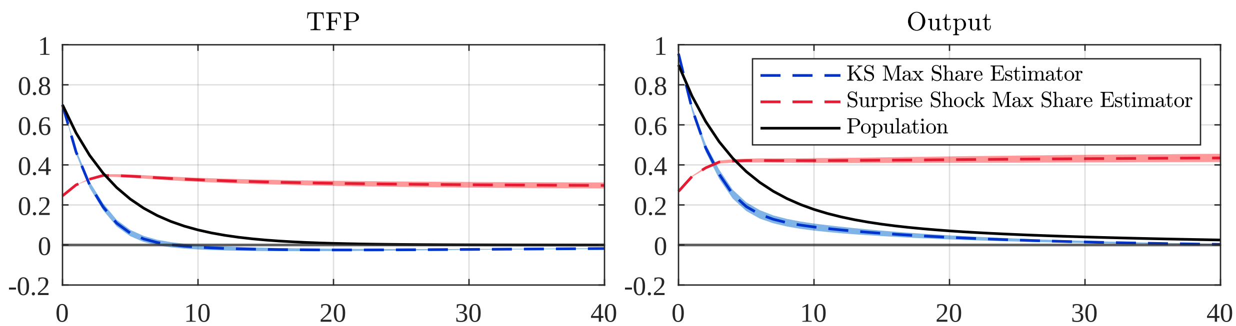
Figure 1 shows that not only is the surprise shock max share estimator much more biased than the original estimator, but it also tends to generate impulse responses that are increasing when the population response is declining and that are declining when the population response is increasing. In fact, responses to these surprise shocks look much like one would expect responses to a news shock to look like. Moreover, the responses to the news shock are of the opposite sign of the

**Figure 1:** Impulse responses from alternative estimators based on the baseline DSGE model

**(a)** News shock




**(b)** Surprise shock




*Notes:* VAR(4) model with $T = 10{,}000$ and $\mathbf{y}_t = (a_t, y_t, i_t)'$.

population responses. Thus, this alternative estimator should not be used in applied work.

## F COMPARISON WITH OTHER SIMULATION EVIDENCE

Contrary to our findings, Kurmann and Sims (2021) report having some success identifying the news shock in a Monte Carlo exercise with $T = 10{,}000$ based on a larger-scale DSGE model. The key difference is not the structure of the model, but that they use a different parameterization for the TFP process ($\rho_g = 0.7$, $\rho_s = 0.9$, $\sigma_g = 0.002125$ and $\sigma_s = 0.000425$). They note that their TFP parameterization is based on standard values in the literature. However, most DSGE models feature either a stationary or permanent TFP shock process. When a model features both processes, standard values from models with only one process can lead to TFP moments that are at odds with actual data. The most notable difference from our calibration is that the standard deviation of their surprise shock is only about $6\%$ of our baseline value.

Table 3a reports simulated moments when using the Kurmann and Sims (2021) parameterization of the TFP process in our baseline model. These results show that their specification is at odds with the data. In particular, the autocorrelation of TFP growth is quite high in the model but close to zero in the data. Table 3b shows that this continues to be the case even when we use the larger-scale DSGE model and allow for TFP measurement error. While the $0.43$ autocorrelation of the growth rate of measured TFP is lower than what is reported in the baseline model, it remains well above the data.

The unrealistically high persistence of the TFP growth process under the Kurmann and Sims (2021) parameterization is important for understanding their findings because it drives the forecast error variance decomposition of TFP in the DSGE model. As shown in Table 4, the news shock explains the vast majority of the variance at all horizons when using the Kurmann-Sims parameterization in the baseline model and in the larger-scale DSGE model. Thus, their parameterization effectively eliminates the surprise shock and makes it much easier for the KS estimator to identify the news shock. This explains the comparatively high accuracy of the KS estimator in their simulation analysis.

# G ADDITIONAL RESULTS

This section presents several additional results:

- Impulse responses based on the Cholesky news estimator and $\mathbf{y}_t = (z_{t+1}, a_t, y_t)'$ using simulated data from our baseline DSGE model with $T = 10{,}000$ (Figure 2).
- Impulse responses based on the Cholesky news estimator and $\mathbf{y}_t = (z_{t+1}, \mathrm{TFP}^u_t, y_t, i_t)'$ using simulated data from the larger-scale DSGE model with $T = 10{,}000$ (Figure 3).
- RMSEs based on the max share news and Cholesky news estimators, where the news variable is measured with error and data is simulated from the larger-scale DSGE model (Table 5).
- Empirical impulse responses from $9$-variable VAR models with alternative TFP news series of different lengths (Figure 4-Figure 7).
- Comparison of the empirical impulse responses from the $9$-variable ICT model identified by Cholesky news to the $8$-variable and VAR model, as used in Kurmann and Sims (2021), and the $9$-variable ICT model identified by TFP max share (Figure 8).

**Table 3:** Data and model-implied moments under Kurmann and Sims (2021) TFP parameters

**(a)** Baseline model

| Moment | Data | Model | Moment | Data | Model |
|---|---|---|---|---|---|
| $SD(\tilde{a}_t)$ | 2.01 | 1.46 | $SD(\tilde{\imath}_t)$ | 9.63 | 7.47 |
| $SD(\Delta a_t)$ | 0.80 | 0.30 | $AC(\tilde{a}_t)$ | 0.87 | 0.88 |
| $SD(\tilde{y}_t)$ | 3.13 | 1.88 | $AC(\Delta a_t)$ | −0.09 | 0.67 |

**(b)** Larger-scale model

| Moment | Data | Model | Moment | Data | Model |
|---|---|---|---|---|---|
| $SD(\tilde{a}_t)$ | 2.01 | 2.67 | $SD(\tilde{\imath}_t)$ | 9.63 | 12.15 |
| $SD(\Delta a_t)$ | 0.80 | 0.59 | $AC(\tilde{a}_t)$ | 0.87 | 0.88 |
| $SD(\tilde{y}_t)$ | 3.13 | 5.15 | $AC(\Delta a_t)$ | −0.09 | 0.43 |

*Notes:* A tilde denotes a detrended variable and $\Delta$ is a log change.

**Table 4:** Forecast error variance decompositions under Kurmann and Sims (2021) TFP parameters

**(a)** Baseline model, true TFP ($\ln a_t$)

| | Horizon | | | | |
|---|---|---|---|---|---|
| Shock | 4 | 8 | 20 | 40 | 80 |
| News | 98.6 | 99.6 | 99.9 | 99.9 | 100.0 |
| Surprise | 1.4 | 0.4 | 0.1 | 0.1 | 0.0 |
| MEI | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 |

**(b)** Larger-scale model, true TFP ($\ln a_t$)

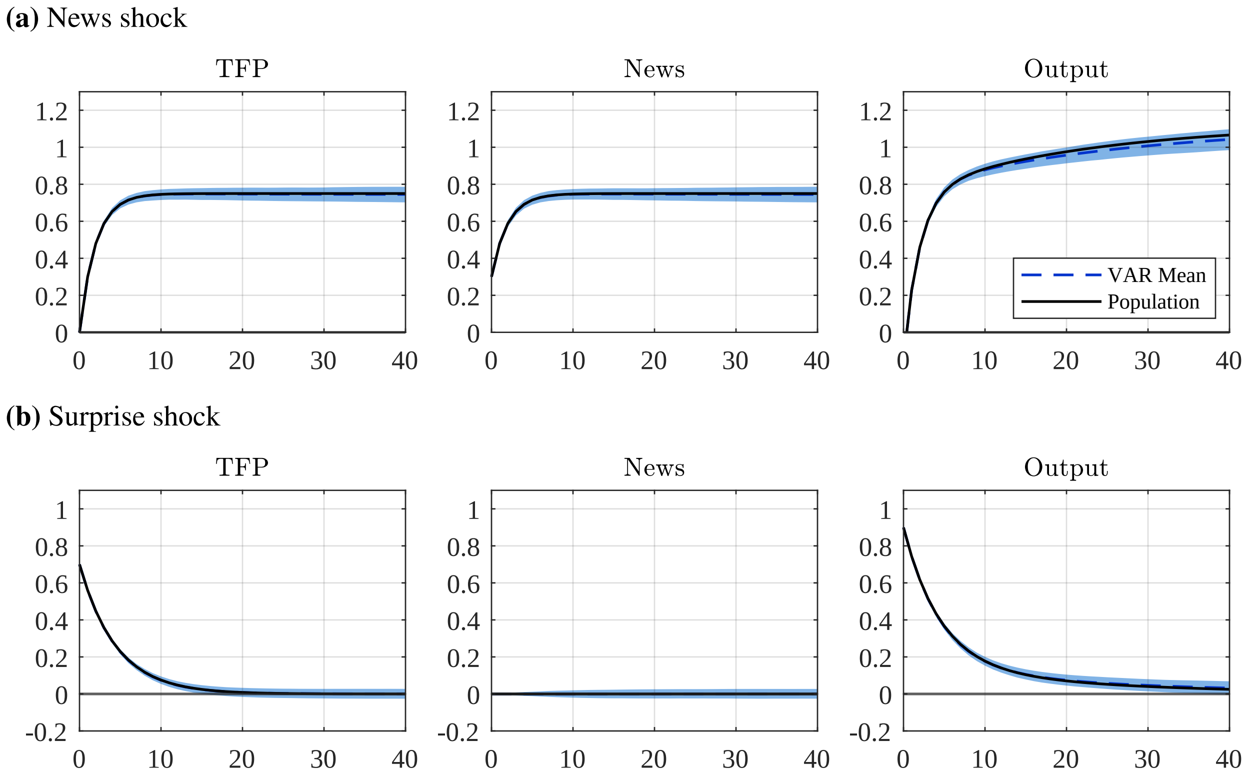
| | Horizon | | | | |
|---|---|---|---|---|---|
| Shock | 4 | 8 | 20 | 40 | 80 |
| News | 98.6 | 99.6 | 99.9 | 99.9 | 100.0 |
| Surprise | 1.4 | 0.4 | 0.1 | 0.1 | 0.0 |
| MEI | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 |

**(c)** Larger-scale model, measured TFP ($\ln \mathrm{TFP}_t^u$)

| | Horizon | | | | |
|---|---|---|---|---|---|
| Shock | 4 | 8 | 20 | 40 | 80 |
| News | 72.1 | 79.1 | 52.6 | 84.0 | 94.5 |
| Surprise | 1.0 | 0.6 | 0.4 | 0.3 | 0.1 |
| MEI | 27.0 | 20.3 | 47.0 | 15.8 | 5.4 |

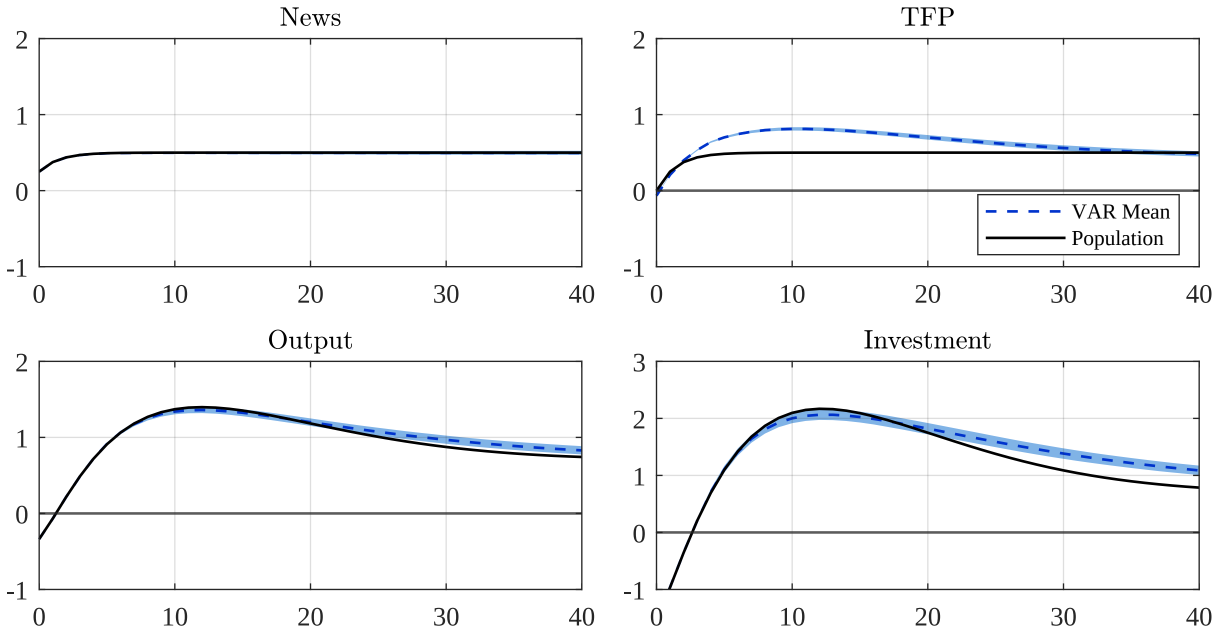
*Notes:* MEI denotes marginal efficiency of investment.

**Figure 2:** Cholesky news estimator of responses based on the baseline DSGE model




*Notes:* VAR(4) model with $T = 10{,}000$ and $\mathbf{y}_t = (z_{t+1}, a_t, y_t)'$. The responses are scaled so the estimated response of TFP matches the population value when the shock first takes effect.

**Figure 3:** Cholesky news estimator of responses based on the larger-scale DSGE model




*Notes:* VAR(4) model with $T = 10{,}000$ and $\mathbf{y}_t = (z_{t+1}, \mathrm{TFP}_t^u, y_t, i_t)'$.

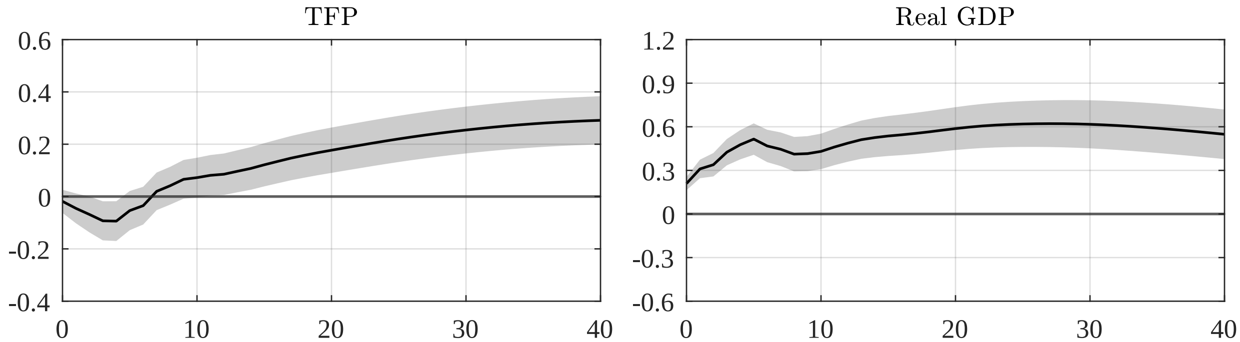
**Table 5:** RMSE over 40 quarters based on the larger-scale DSGE model

| Estimator | TFP | Output | Investment | Total |
|---|---|---|---|---|
| KS Max Share | 10.3 | 10.4 | 19.3 | 40.0 |
| Max Share News ($\sigma_n = 0$) | 6.4 | 2.8 | 7.6 | 16.8 |
| Max Share News ($\sigma_n = 0.2\sigma_g$) | 6.4 | 3.0 | 8.1 | 17.4 |
| Max Share News ($\sigma_n = 0.5\sigma_g$) | 6.4 | 3.6 | 9.1 | 19.1 |
| Cholesky News ($\sigma_n = 0$) | 6.4 | 2.7 | 7.5 | 16.6 |
| Cholesky News ($\sigma_n = 0.2\sigma_g$) | 5.9 | 2.9 | 7.8 | 16.6 |
| Cholesky News ($\sigma_n = 0.5\sigma_g$) | 4.2 | 3.8 | 8.6 | 16.6 |

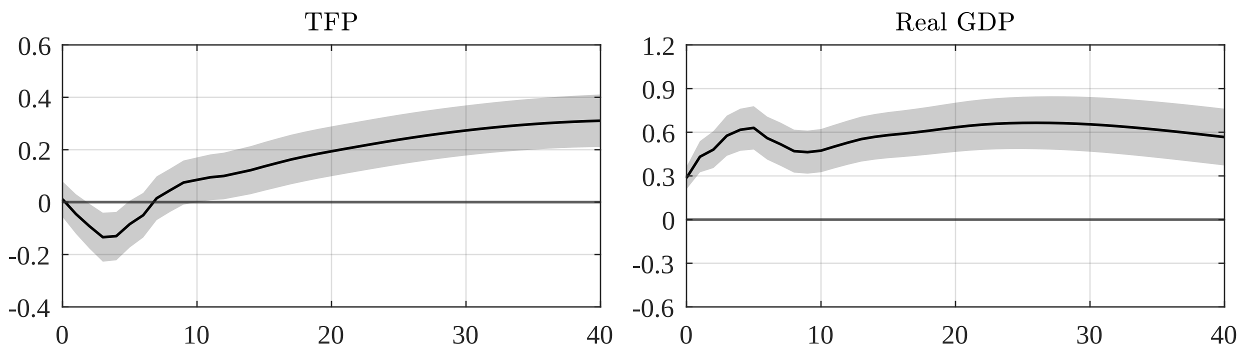
*Notes:* VAR(4) model with $T = 10{,}000$, where $\mathbf{y}_t = (\mathrm{TFP}_t^u, y_t, i_t)'$ for the KS estimator and $\mathbf{y}_t = (z_{t+1}^n, \mathrm{TFP}_t^u, y_t, i_t)'$ for the max share news and Cholesky news estimators.

**Figure 4:** Impulse responses with real R&D expenditures

**(a)** Cholesky news identified VAR model



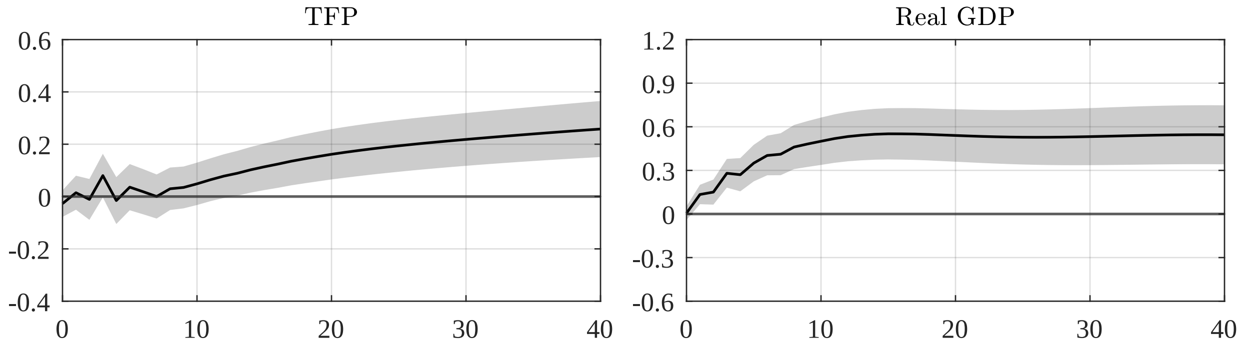

**(b)** Max share news identified VAR model



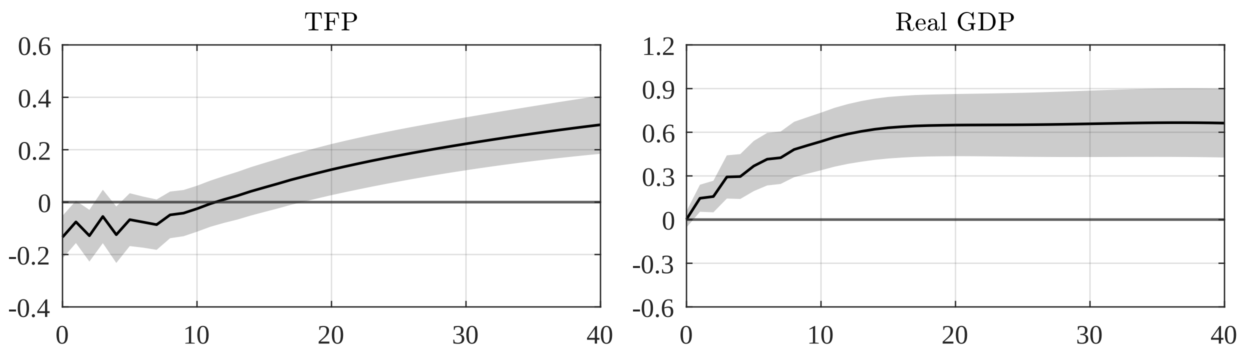

*Notes:* Shaded regions represent 1-standard deviation error bands computed by residual-based bootstrap.

**Figure 5:** Impulse responses with the ICT index

**(a)** Cholesky news identified VAR model



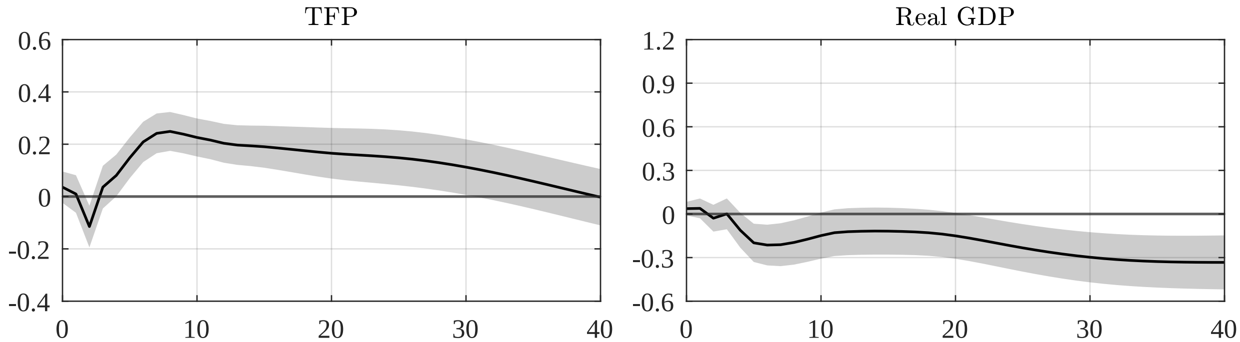

**(b)** Max share news identified VAR model



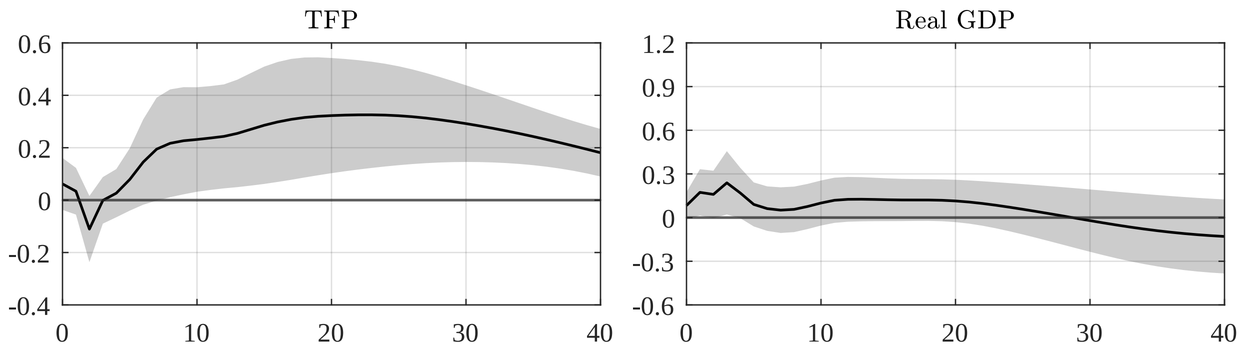

*Notes:* Shaded regions represent 1-standard deviation error bands computed by residual-based bootstrap.

**Figure 6:** Impulse responses with the CGV series

**(a)** Cholesky news identified VAR model



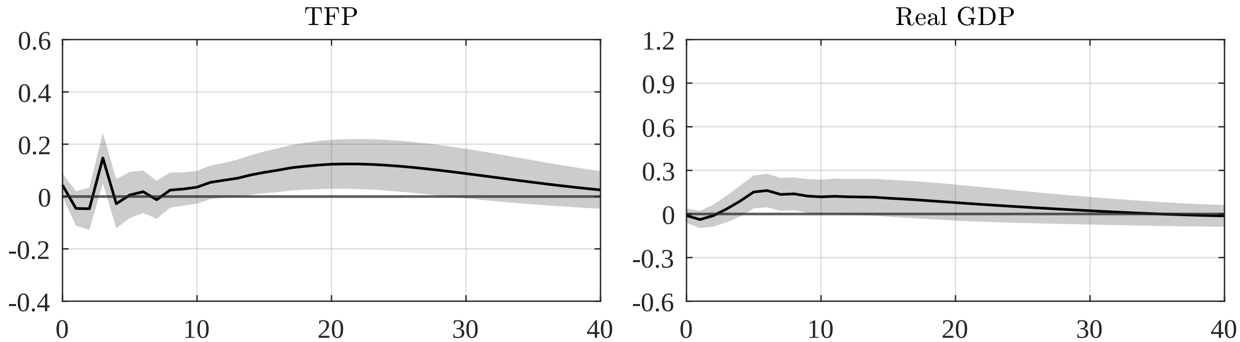

**(b)** Max share news identified VAR model



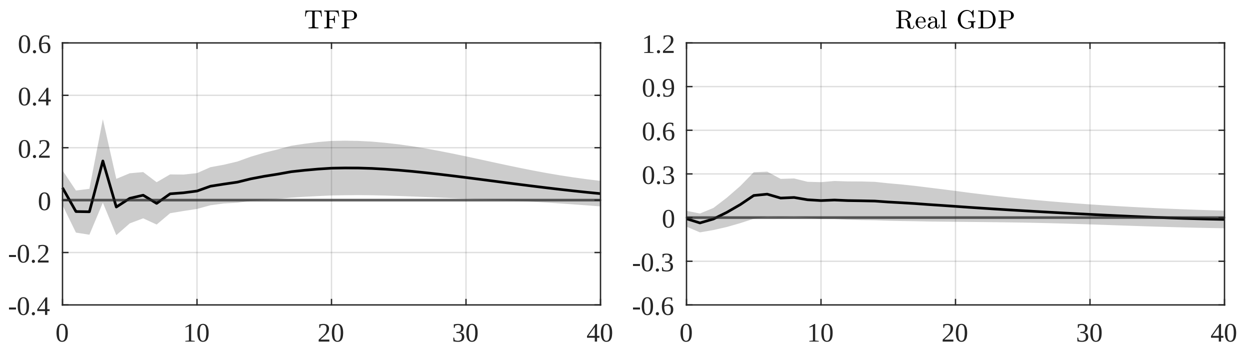

*Notes:* Shaded regions represent 1-standard deviation error bands computed by residual-based bootstrap.

**Figure 7:** Impulse responses with the MAHB series

**(a)** Cholesky news identified VAR model

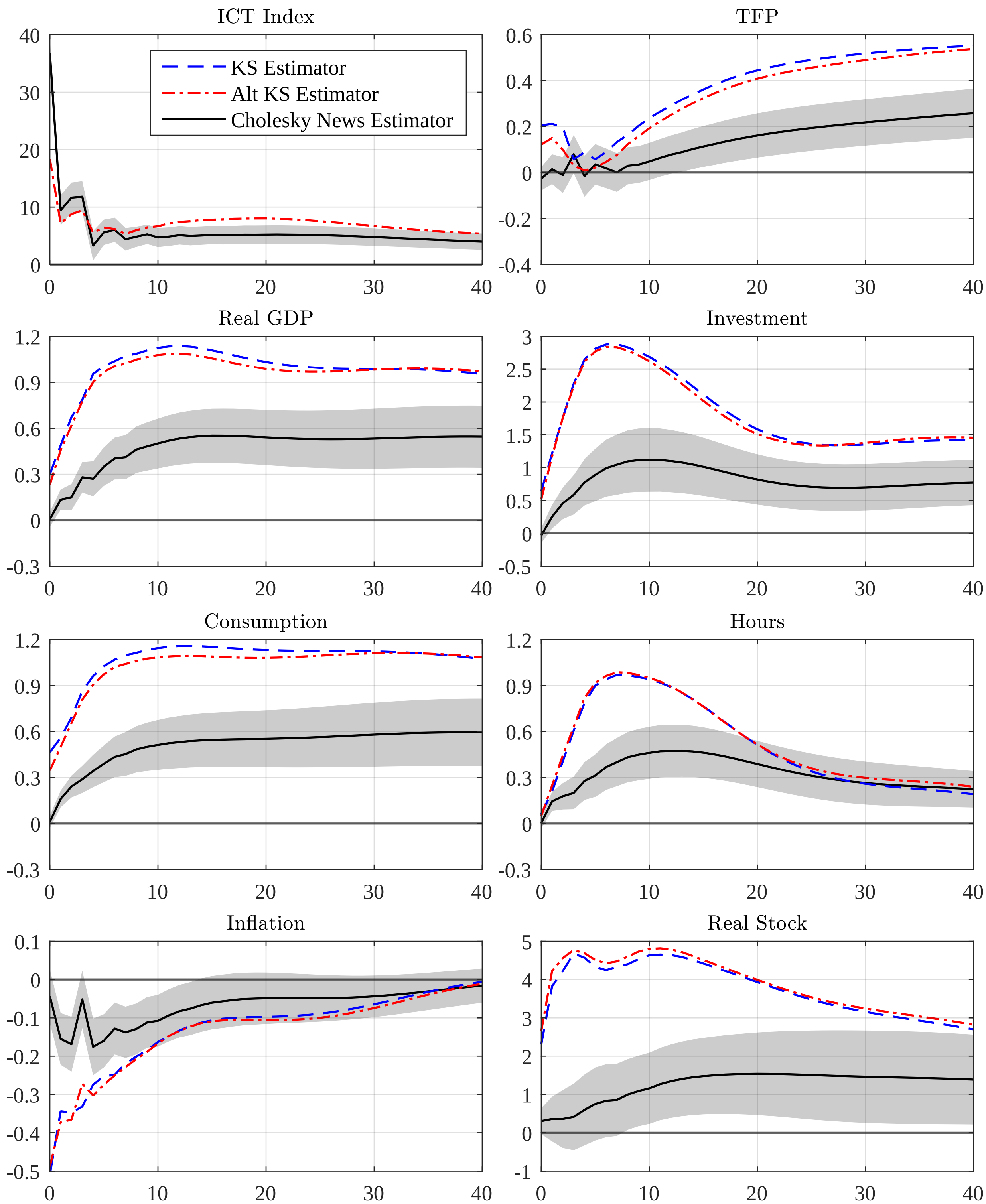



**(b)** Max share news identified VAR model




*Notes:* Shaded regions represent 1-standard deviation error bands computed by residual-based bootstrap.

**Figure 8:** Comparison of Cholesky news and TFP max share identified impulse responses




*Notes:* VAR(4) models estimated on identical samples from 1960-2014. Shaded regions represent 1-standard deviation error bands computed by residual-based bootstrap for the max share news estimator. Responses are in percent deviations from the baseline. The inflation response is annualized.

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