Online Appendix: Estimating Macroeconomic News and Surprise Shocks*

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ABSTRACT

Appendix A lists our data sources and transformations. Appendix B proves the existence of an orthogonal rotation matrix in the structural VAR model. Appendix C discusses the identification conditions for the TFP max share estimator. Appendix D summarizes the DSGE model and its calibration. Appendix E compares our analysis with the simulation evidence reported in Kurmann and Sims (2021). Appendix F shows empirical MS News estimates for alternative measures of TFP news and alternative vintages of TFP. Appendix G provides additional simulation and estimation results that document the robustness of our findings.

*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.

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 γ_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}) \\
&= \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}
\end{aligned}
$$

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

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 IDENTIFICATION CONDITIONS

As long as TFP innovations are fully explained by news and surprise shocks, as would be the case in the absence of TFP measurement error, it has to be the case that $\gamma_{\ell,1} = 0$. Whether one imposes this restriction does not affect the estimate of the news shock, but it determines whether the surprise shock can also be identified. To formalize this result, assume $\gamma_{\ell,1} = 0$, and note that the Q matrix is orthogonal if and only if $Q'Q = QQ' = I_3$. This yields the restrictions

$$
\begin{pmatrix} \gamma_{s,1} & \gamma_{s,2} & \gamma_{s,3} \\ \gamma_{n,1} & \gamma_{n,2} & \gamma_{n,3} \\ 0 & \gamma_{\ell,2} & \gamma_{\ell,3} \end{pmatrix} \begin{pmatrix} \gamma_{s,1} & \gamma_{n,1} & 0 \\ \gamma_{s,2} & \gamma_{n,2} & \gamma_{\ell,2} \\ \gamma_{s,3} & \gamma_{n,3} & \gamma_{\ell,3} \end{pmatrix} = \begin{pmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{pmatrix}, \tag{R1}
$$

$$
\begin{pmatrix} \gamma_{s,1} & \gamma_{n,1} & 0 \\ \gamma_{s,2} & \gamma_{n,2} & \gamma_{\ell,2} \\ \gamma_{s,3} & \gamma_{n,3} & \gamma_{\ell,3} \end{pmatrix} \begin{pmatrix} \gamma_{s,1} & \gamma_{s,2} & \gamma_{s,3} \\ \gamma_{n,1} & \gamma_{n,2} & \gamma_{n,3} \\ 0 & \gamma_{\ell,2} & \gamma_{\ell,3} \end{pmatrix} = \begin{pmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{pmatrix}. \tag{R2}
$$

Restriction R1 implies

$$\gamma_{n,1}^2 + \gamma_{n,2}^2 + \gamma_{n,3}^2 = 1, \tag{R1-1}$$

$$\gamma_{s,2}\gamma_{\ell,2} + \gamma_{s,3}\gamma_{\ell,3} = 0, \tag{R1-2}$$

$$\gamma_{n,2}\gamma_{\ell,2} + \gamma_{n,3}\gamma_{\ell,3} = 0, \tag{R1-3}$$

$$\gamma_{s,1}^2 + \gamma_{s,2}^2 + \gamma_{s,3}^2 = 1, \tag{R1-4}$$

$$\gamma_{\ell,2}^2 + \gamma_{\ell,3}^2 = 1, \tag{R1-5}$$

$$\gamma_{s,1}\gamma_{n,1} + \gamma_{s,2}\gamma_{n,2} + \gamma_{s,3}\gamma_{n,3} = 0. \tag{R1-6}$$

Restriction R2 implies

$$\gamma_{s,1}^2 + \gamma_{n,1}^2 = 1, \tag{R2-1}$$

$$\gamma_{s,1}\gamma_{s,2} + \gamma_{n,1}\gamma_{n,2} = 0, \tag{R2-2}$$

$$\gamma_{s,1}\gamma_{s,3} + \gamma_{n,1}\gamma_{n,3} = 0, \tag{R2-3}$$

$$\gamma_{s,2}^2 + \gamma_{n,2}^2 + \gamma_{\ell,2}^2 = 1, \tag{R2-4}$$

$$\gamma_{s,3}^2 + \gamma_{n,3}^2 + \gamma_{\ell,3}^2 = 1, \tag{R2-5}$$

$$\gamma_{s,2}\gamma_{s,3} + \gamma_{n,2}\gamma_{n,3} + \gamma_{\ell,2}\gamma_{\ell,3} = 0. \tag{R2-6}$$

An estimate of γ_n is obtained by maximizing the forecast error variance share of the news shock subject to (R1-1). Given γ_n, (R2-1)-(R2-5) imply

$$\gamma_{s,1} = \pm\sqrt{1-\gamma_{n,1}^2}, \quad \gamma_{s,2} = -\frac{\gamma_{n,1}\gamma_{n,2}}{\gamma_{s,1}}, \quad \gamma_{s,3} = -\frac{\gamma_{n,1}\gamma_{n,3}}{\gamma_{s,1}},$$
$$\gamma_{\ell,2} = \pm\sqrt{1-\gamma_{s,2}^2-\gamma_{n,2}^2}, \quad \gamma_{\ell,3} = \pm\sqrt{1-\gamma_{s,3}^2-\gamma_{n,3}^2}.$$

Thus, for $K = 3$ the identifying restrictions uniquely pin down all three structural response functions up to their sign. This means that all that is required to recover the news and surprise shocks is a normalizing assumption to the effect that the surprise shock has a positive impact effect on TFP and the news shock has a positive effect on TFP at H_n. For $K > 3$ only the news and surprise shocks can be recovered. There results yield the following proposition.

Proposition 1. *In the absence of TFP measurement error, γ_s will be uniquely determined for any given estimate of γ_n obtained using the TFP max share estimator. In particular, when TFP is ordered first in the VAR model, $\gamma_{s,1} = \pm\sqrt{1-\gamma_{n,1}^2}$ and $\gamma_{s,j} = -\gamma_{n,1}\gamma_{n,j}/\gamma_{s,1}$ for $j \in \{2,\dots,K\}$.*

The proof immediately follows from a generalization of the analysis for $K = 3$. Note that there are multiple solutions for Q, some of which will satisfy R1 and R2 and some of which may not. For $K = 3$, for example, there are 2^3 possible solutions. The validity of the estimator requires the existence of an orthogonal Q matrix. In Appendix B, we showed that when solving for γ_n and γ_s, γ_ℓ can always be chosen such that Q is orthogonal. This result generalizes to $K > 3$.

Our analysis highlights that the TFP max share estimator will be able to deliver estimates of the surprise shock even when there is no restriction on $\gamma_{n,1}$, as long as there is no TFP measurement error. This allows us to shed light on the ability of the TFP max share estimator to recover the population responses to news and surprise shocks under ideal conditions without TFP measurement error.

D KURMANN-SIMS 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 only exceptions are $\tilde{\lambda}_t \equiv \lambda_t z_t^{1/(1-\alpha)}$, $\tilde{f}_{1,t}^w \equiv f_{1,t}^w/z_t^{(1+\epsilon_w)/(1-\alpha)}$, 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

$$r_{k,t} = \alpha mc_t s_t (\tilde{k}_{s,t}/l_{s,t})^{\alpha-1} \quad \text{(R1-1)}$$

$$\tilde{w}_{\ell,t} = (1-\alpha) mc_t s_t (\tilde{k}_{s,t}/l_{s,t})^{\alpha} \quad \text{(R1-2)}$$

$$\Delta_t^p \tilde{y}_t = s_t \tilde{k}_{s,t}^{\alpha} l_{s,t}^{1-\alpha} - \bar{F} \quad \text{(R1-3)}$$

$$\tilde{\lambda}_t = (\tilde{c}_t - b\tilde{c}_{t-1}/g_{y,t})^{-1} - \beta b E_t[(\tilde{c}_{t+1} g_{y,t+1} - b\tilde{c}_t)^{-1}] \quad \text{(R1-4)}$$

$$1 = E_t[x_{t+1} r_t/\pi_{t+1}] \quad \text{(R1-5)}$$

$$r_{k,t} = \gamma_1 + \gamma_2(u_t - 1) \quad \text{(R1-6)}$$

$$\theta\kappa_3 e_t^{\kappa_4 - 1} = \tilde{\lambda}_t \tilde{w}_t h_t \quad \text{(R1-7)}$$

$$\theta\kappa_1 h_t^{\kappa_2 - 1} = \tilde{\lambda}_t \tilde{w}_t e_t \quad \text{(R1-8)}$$

$$\begin{aligned} &\theta(\kappa_0 + (\kappa_1/\kappa_2) h_t^{\kappa_2} + (\kappa_3/\kappa_4) e_t^{\kappa_4}) \\ &= \tilde{\lambda}_t \tilde{w}_t \left[e_t h_t - \tfrac{\psi}{2}(n_t/n_{t-1} - 1)^2 - \psi(n_t/n_{t-1} - 1)(n_t/n_{t-1}) \right] \\ &+\beta\psi E_t[\tilde{\lambda}_{t+1} \tilde{w}_{t+1} (n_{t+1}/n_t - 1)(n_{t+1}/n_t)^2] \end{aligned} \quad \text{(R1-9)}$$

$$\tilde{k}_t = (1-\delta)\tilde{k}_{t-1}/g_{y,t} + \mu_t \tilde{i}_t \quad \text{(R1-10)}$$

$$\mu_t q_t = 1 + \varphi(\Phi_t - \tilde{\delta}) \quad \text{(R1-11)}$$

$$\begin{aligned} q_t = E_t[&x_{t+1}(r_{k,t+1} u_{t+1} - \gamma_1(u_{t+1} - 1) - \tfrac{\gamma_2}{2}(u_{t+1} - 1)^2 \\ &-\tfrac{\varphi}{2}(\Phi_{t+1} - \tilde{\delta})^2 + \varphi(\Phi_{t+1} - \tilde{\delta})\Phi_{t+1} + (1-\delta) q_{t+1})] \end{aligned} \quad \text{(R1-12)}$$

$$\Phi_t = \tilde{i}_t g_{y,t}/\tilde{k}_{t-1} \quad \text{(R1-13)}$$

$$l_t = e_t h_t n_t \quad \text{(R1-14)}$$

$$l_t = \Delta_t^w l_{s,t} \quad \text{(R1-15)}$$

$$\tilde{k}_{s,t} = u_t \tilde{k}_{t-1}/g_{y,t} \quad \text{(R1-16)}$$

$$x_t = \beta\tilde{\lambda}_t/(\tilde{\lambda}_{t-1} g_{y,t}) \quad \text{(R1-17)}$$

$$\tilde{p}_t = \tfrac{\epsilon_p}{\epsilon_p - 1}(\tilde{f}_{1,t}^p/\tilde{f}_{2,t}^p) \quad \text{(R1-18)}$$

$$\tilde{f}_{1,t}^p = mc_t \tilde{y}_t + \theta_p E_t[x_{t+1} \pi_t^{-\epsilon_p\gamma_p} \bar{\pi}^{-\epsilon_p(1-\gamma_p)} \pi_{t+1}^{\epsilon_p} \tilde{f}_{1,t+1}^p g_{y,t+1}] \quad \text{(R1-19)}$$

$$\tilde{f}_{2,t}^p = \tilde{y}_t + \theta_p E_t[x_{t+1} \pi_t^{(1-\epsilon_p)\gamma_p} \bar{\pi}^{(1-\epsilon_p)(1-\gamma_p)} \pi_{t+1}^{\epsilon_p - 1} \tilde{f}_{2,t+1}^p g_{y,t+1}] \quad \text{(R1-20)}$$

$$\Delta_t^p = (1-\theta_p)\tilde{p}_t^{-\epsilon_p} + \theta_p \pi_{t-1}^{-\epsilon_p\gamma_p} \bar{\pi}^{-\epsilon_p(1-\gamma_p)} \pi_t^{\epsilon_p} \Delta_{t-1}^p \quad \text{(R1-21)}$$

$$1 = (1-\theta_p)\tilde{p}_t^{1-\epsilon_p} + \theta_p \pi_{t-1}^{(1-\epsilon_p)\gamma_p} \bar{\pi}^{(1-\epsilon_p)(1-\gamma_p)} \pi_t^{\epsilon_p - 1} \quad \text{(R1-22)}$$

$$\tilde{w}_{\ell,t}^* = \tfrac{\epsilon_w}{\epsilon_w - 1}(\tilde{f}_{1,t}^w/\tilde{f}_{2,t}^w), \quad \text{(R1-23)}$$

Table 1: DSGE model parameterization at quarterly frequency

Parameter	Value	Parameter	Value
Discount Factor (β)	0.99	Taylor Rule Inflation Response (ϕ_π)	1.5
Cost Share of Capital (α)	0.3333	Taylor Rule Output Response (ϕ_y)	0.5
Capital Depreciation Rate (δ)	0.025	Taylor Rule Smoothing (ρ_r)	0.8
Utilization Function Curvature (γ_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 (φ)	2	Steady-State Labor Preference ($\bar{G}$)	$1/3$
Employment Adjustment Cost (ψ)	2	Steady-State Effort ($\bar{e}$)	5
Frisch Elasticity of Hours (η)	1	Steady-State Hours ($\bar{h}$)	$1/3$
Elasticity of Effort to Hours (ϵ_{eh})	4	Steady-State Output Growth Rate ($\bar{g}_y$)	1.0026
Goods Elasticity of Substitution (ϵ_p)	11	TFP News Shock Persistence (ρ_g)	0.5
Labor Elasticity of Substitution (ϵ_w)	11	TFP Surprise Shock Persistence (ρ_s)	0.4
Calvo Price Stickiness (θ_p)	0.75	MEI Shock Persistence (ρ_μ)	0.95
Calvo Wage Stickiness (θ_w)	0.9	TFP News Shock SD (σ_g)	0.0025
Price Indexation (γ_p)	0	TFP Surprise Shock SD (σ_s)	0.006
Wage Indexation (γ_w)	1	MEI Shock SD (σ_μ)	0.004

$$\tilde{f}^w_{1,t} = \tilde{w}^{\epsilon_w}_{\ell,t}\tilde{w}_t l_{s,t} + \theta_w \bar{g}_y E_t[x_{t+1}\pi^{\epsilon_w}_{t+1}\pi_t^{-\epsilon_w\gamma_w}\bar{\pi}^{-\epsilon_w(1-\gamma_w)}\tilde{f}^w_{1,t+1}(g_{y,t+1}/\bar{g}_y)^{1+\epsilon_w}] \tag{R1-24}$$

$$\tilde{f}^w_{2,t} = \tilde{w}^{\epsilon_w}_{\ell,t} l_{s,t} + \theta_w \bar{g}_y E_t[x_{t+1}\pi^{\epsilon_w-1}_{t+1}\pi_t^{(1-\epsilon_w)\gamma_w}\bar{\pi}^{(1-\epsilon_w)(1-\gamma_w)}\tilde{f}^w_{2,t+1}(g_{y,t+1}/\bar{g}_y)^{\epsilon_w}] \tag{R1-25}$$

$$\Delta^w_t = (1-\theta_w)\left(\frac{\tilde{w}^*_{\ell,t}}{\tilde{w}_{\ell,t}}\right)^{-\epsilon_w} + \theta_w \pi_{t-1}^{-\epsilon_w\gamma_w}\bar{\pi}^{-\epsilon_w(1-\gamma_w)}\pi_t^{\epsilon_w}\left(\frac{\tilde{w}_{\ell,t-1}\bar{g}_y}{\tilde{w}_{\ell,t}g_{y,t}}\right)^{-\epsilon_w}\Delta^w_{t-1} \tag{R1-26}$$

$$\tilde{w}^{1-\epsilon_w}_{\ell,t} = (1-\theta_w)(\tilde{w}^*_{\ell,t})^{1-\epsilon_w} + \theta_w \pi_{t-1}^{\gamma_w(1-\epsilon_w)}\bar{\pi}^{(1-\gamma_w)(1-\epsilon_w)}\pi_t^{\epsilon_w-1}\left(\frac{\tilde{w}_{\ell,t-1}\bar{g}_y}{g_{y,t}}\right)^{1-\epsilon_w} \tag{R1-27}$$

$$r_t = r^{\rho_r}_{t-1}(\bar{r}(\pi_t/\bar{\pi})^{\phi_\pi}(\tilde{y}_t g_{y,t}/(\tilde{y}_{t-1}\bar{g}_y))^{\phi_y})^{1-\rho_r}\exp(\sigma_r\varepsilon_{r,t}) \tag{R1-28}$$

$$\begin{aligned}\tilde{c}_t + \tilde{i}_t + \tfrac{\psi}{2}(n_t/n_{t-1}-1)^2\tilde{w}_t n_t + \tfrac{\varphi}{2}(\Phi_t-\tilde{\delta})^2\tilde{k}_{t-1}/g_{y,t} \\ +(\gamma_1(u_t-1)+\tfrac{\gamma_2}{2}(u_t-1)^2)\tilde{k}_{t-1}/g_{y,t} = \tilde{y}_t\end{aligned} \tag{R1-29}$$

$$g_{y,t} = g_t^{1/(1-\alpha)} \tag{R1-30}$$

$$\ln s_t = \rho_s \ln s_{t-1} + \sigma_s\varepsilon_{s,t} \tag{R1-31}$$

$$\ln g_t = (1-\rho_g)\ln g + \rho_g \ln g_{t-1} + \sigma_g\varepsilon_{g,t} \tag{R1-32}$$

$$\ln \mu_t = \rho_\mu \ln \mu_{t-1} + \sigma_\mu\varepsilon_{\mu,t} \tag{R1-33}$$

All of the household, firm, and monetary policy parameters are set to the values in Kurmann and Sims (2021) and reported in Table 1. As noted in the paper, we set the persistence and standard deviations of the exogenous TFP and MEI processes to match key moments in the data.

E COMPARISON WITH KURMANN-SIMS SIMULATION EVIDENCE

Contrary to our findings, Kurmann and Sims (2021) report having some success identifying the news shock in a Monte Carlo exercise with $T = 10{,}000$ and $p = 4$. The key difference is 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 2 below reports simulated moments when using the Kurmann and Sims (2021) parameterization of the TFP process. 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. This is important for understanding their findings because it drives the forecast error variance decomposition of TFP in the DSGE model. As shown in Table 3, the news shock explains the vast majority of the variance at all horizons when using the Kurmann-Sims parameterization. Thus, their parameterization effectively eliminates the surprise shock and makes it much easier for the KSMS estimator to identify the news shock. This explains the comparatively high accuracy of the KSMS estimator in their simulation analysis.

As shown in Table 4, the RMSEs of both the KSMS and NAMS estimators are considerably lower under the Kurmann-Sims TFP parameterization than under our parameterization that matches moments in the data. However, even under the KS parameterization of TFP, the KSMS and NAMS estimators are outperformed by the Alt KSMS and Alt NAMS estimators, respectively, which in turn are less accurate than the MS News estimator.

Table 2: Data and model-implied moments under Kurmann and Sims (2021) TFP parameters

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 Δ is a log change. In the data, a_t is Fernald utilization-adjusted TFP while in the model it is measured TFP.

Table 3: Forecast error variance decompositions for TFP

	Measured TFP ($\ln \mathrm{TFP}^u$)			True TFP ($\ln a$)		
Horizon	News	Surprise	MEI	News	Surprise	MEI
4	72.1	1.0	27.0	98.6	1.4	0.0
8	79.1	0.6	20.3	99.6	0.4	0.0
20	52.6	0.4	47.0	99.9	0.1	0.0
40	84.0	0.3	15.8	99.9	0.1	0.0
80	94.5	0.1	5.4	100.0	0.0	0.0

Notes: MEI is the marginal efficiency of investment.

Table 4: RMSE over 40 quarters under the Kurmann-Sims parameterization

Estimator	TFP	Output	Invest	Total
KSMS	11.3	4.9	7.6	23.8
NAMS	10.9	4.3	5.9	21.1
MS News	8.8	2.6	5.0	16.4
Alt KSMS	9.0	3.1	6.6	18.7
Alt NAMS	8.6	3.0	6.3	17.9

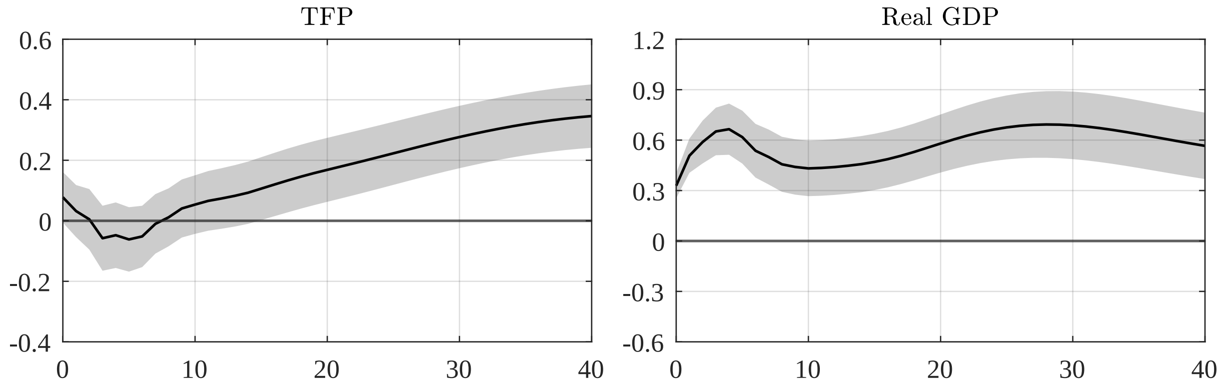
Notes: VAR(4) model with $T = 10{,}000$, where $\mathbf{y}_t = (\mathrm{TFP}_t^u, y_t, i_t)$ for the KSMS and NAMS estimators and $\mathbf{y}_t = (z_{t+1}, \mathrm{TFP}_t^u, y_t, i_t)$ for the MS News estimator. The Alt KSMS estimator uses the KS identification strategy and the MS News model variables. The Alt NAMS estimator uses the NAMS identification strategy and the MS News model variables.

F ADDITIONAL EMPIRICAL RESULTS

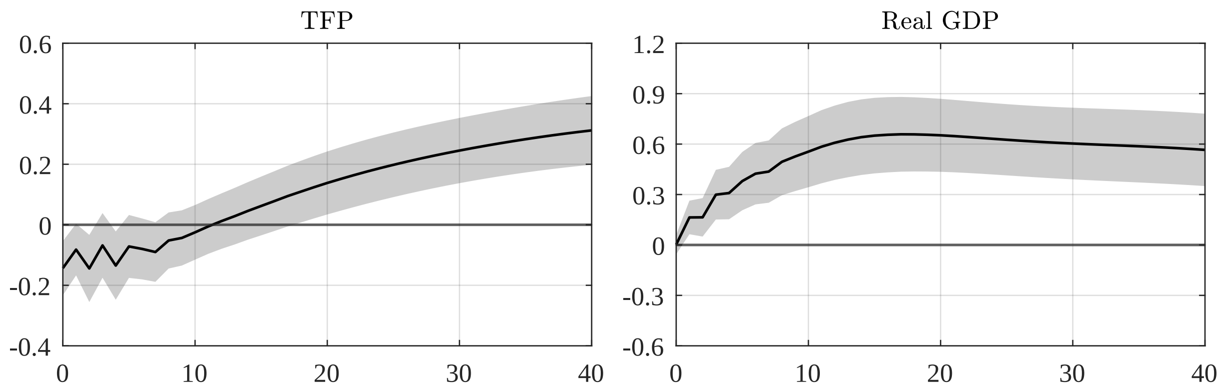
This section shows the responses from 9-variable VAR models with alternative TFP news series (Figure 1) and responses from a 4-variable VAR model with different vintages of TFP (Figure 2).

Figure 1: MS News estimates for alternative measures of TFP news

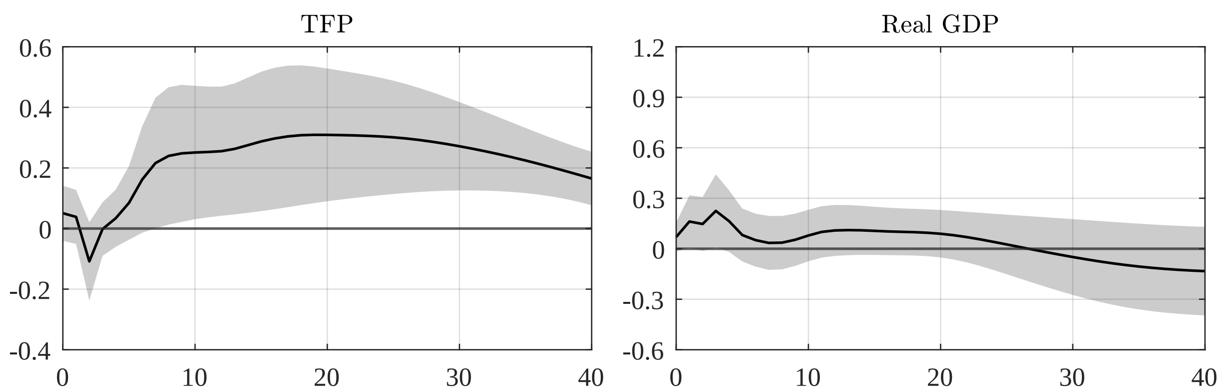
(a) R&D expenditures



(b) ICT index



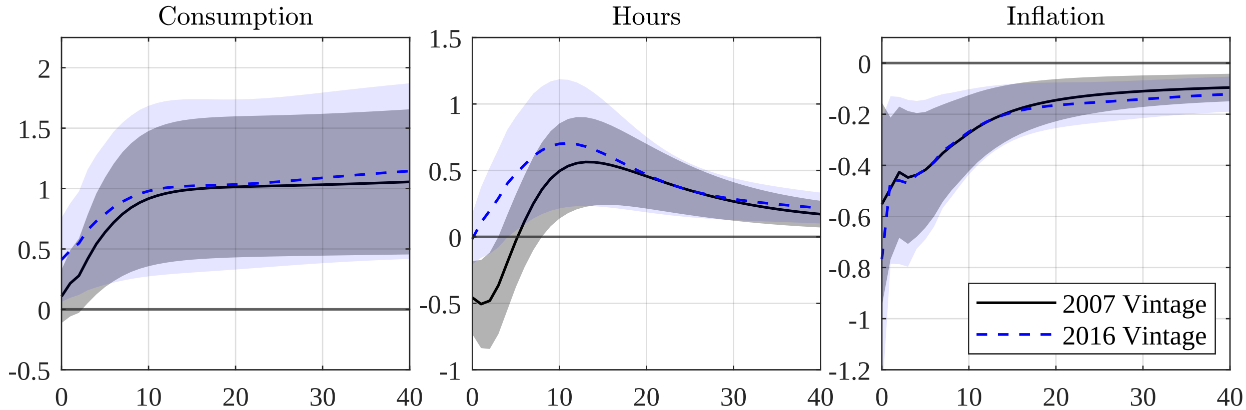
(c) CGV series



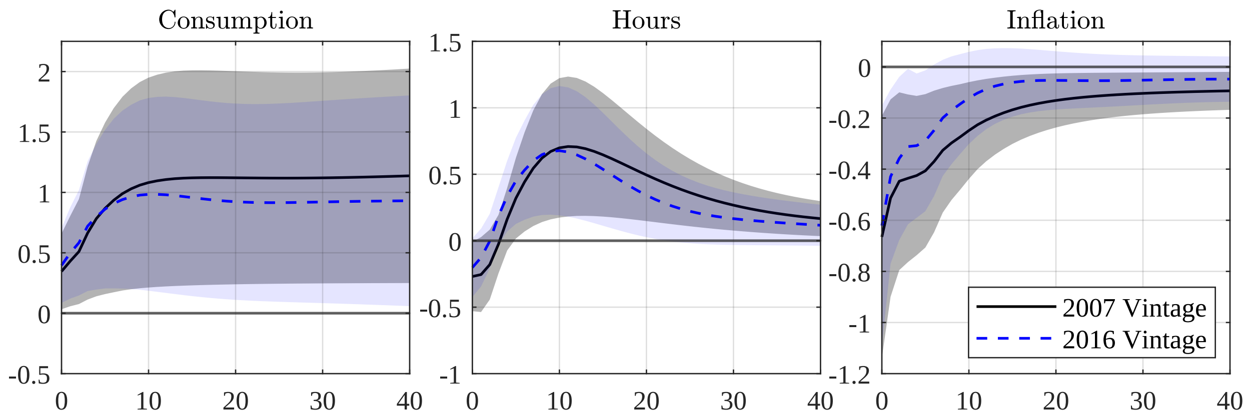
Notes: VAR(4) models estimated on identical samples from 1960-2010 using the 9-variable VAR model. Shaded regions represent 1-standard deviation error bands computed by residual-based bootstrap for the MS News estimator. Responses are in percent deviations from the baseline.

Figure 2: Impulse responses to a news shock with different vintages of TFP

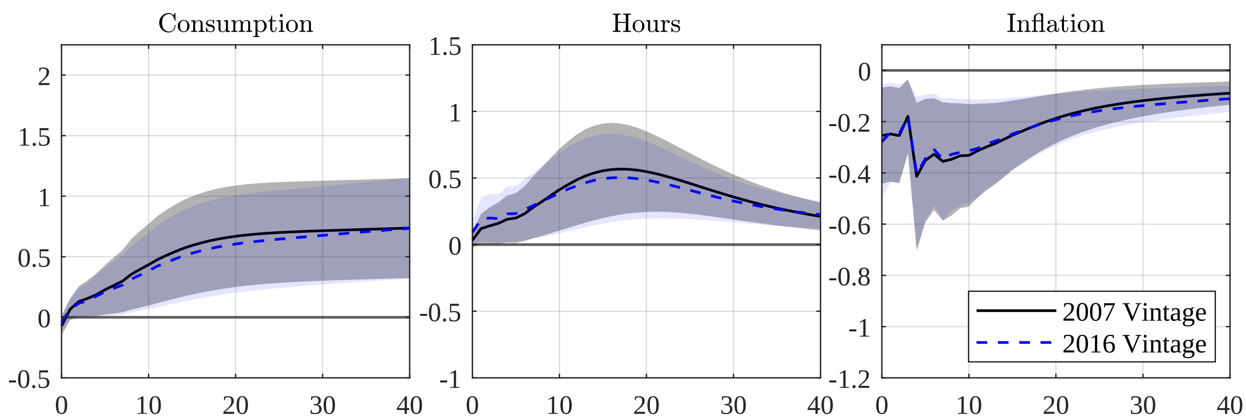
(a) BSMS estimator



(b) KSMS estimator



(c) MS News estimator



Notes: The BSMS and KSMS estimators are based on a VAR(4) model with log TFP, log consumption, log hours, and inflation. The model for the MS News estimator also includes the ICT index. The sample is 1960Q1 to 2007Q4. The vintages match those in Figure 1 of Kurmann and Sims (2021). The data for TFP, consumption, hours, and inflation come from the replication package of Kurmann and Sims (2021). Shaded regions represent 1-standard deviation error bands computed by residual-based bootstrap. Responses are in percent deviations from the baseline.

G ADDITIONAL ROBUSTNESS CHECKS

This section presents several additional results:

- RMSEs of alternative estimators based on the DSGE model with the news shock occurring with a delay of $k \in \{0, 1, 2, 4\}$ quarters (Table 5).
- RMSEs of alternative estimators with five variables in the VAR model and five shocks in the DSGE model (Table 6).
- Impulse responses based on max share estimators that target labor productivity (Figure 3).
- RMSEs of alternative max share estimators that target output (Table 7).
- Results under alternative calibrations of the DSGE model (parameters, Table 8; model fit, Table 9; FEVD, Table 10; RMSE of alternative estimators, Table 11).

Table 5: RMSE over 40 quarters based on the DSGE model with different news lags

(a) KSMS estimator

News Shock	TFP	Output	Invest	Total
No Lags ($\varepsilon_{g,t}$)	10.1	11.2	20.7	42.1
1 Lag ($\varepsilon_{g,t-1}$)	10.3	10.4	19.3	40.0
2 Lags ($\varepsilon_{g,t-2}$)	10.4	9.4	17.5	37.2
4 Lags ($\varepsilon_{g,t-4}$)	10.8	7.4	14.3	32.5

(b) NAMS estimator

News Shock	TFP	Output	Invest	Total
No Lags ($\varepsilon_{g,t}$)	10.0	11.6	23.0	44.6
1 Lag ($\varepsilon_{g,t-1}$)	10.1	10.8	21.3	42.2
2 Lags ($\varepsilon_{g,t-2}$)	10.3	9.7	19.1	39.0
4 Lags ($\varepsilon_{g,t-4}$)	10.8	7.4	14.2	32.4

(c) MS News estimator

News Shock	TFP	Output	Invest	Total
No Lags ($\varepsilon_{g,t}$)	6.1	2.9	8.1	17.2
1 Lag ($\varepsilon_{g,t-1}$)	6.4	2.8	7.6	16.7
2 Lags ($\varepsilon_{g,t-2}$)	6.9	2.6	7.1	16.6
4 Lags ($\varepsilon_{g,t-4}$)	8.1	2.4	6.5	16.9

Notes: Results based on $T = 10{,}000$. The VAR(4) includes $\mathbf{y}_t = (\text{TFP}_t^u, y_t, i_t)'$ for the KSMS and NAMS estimators and $\mathbf{y}_t = (z_{t+k}, \text{TFP}_t^u, y_t, i_t)$ for the MS News estimator with k lags.

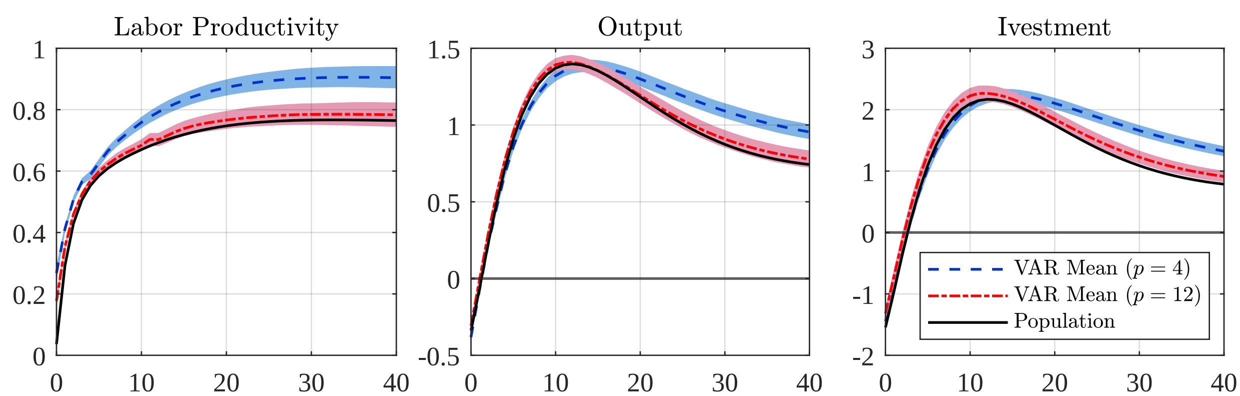
Table 6: RMSE over 40 quarters based on a DSGE model with five shocks

Estimator	TFP	Output	Invest	Cons	Labor	Total
KSMS	7.3	4.5	18.8	2.9	4.4	37.9
NAMS	6.8	4.5	16.4	2.1	3.7	33.6
MS News	6.1	2.7	8.2	1.5	2.3	20.8

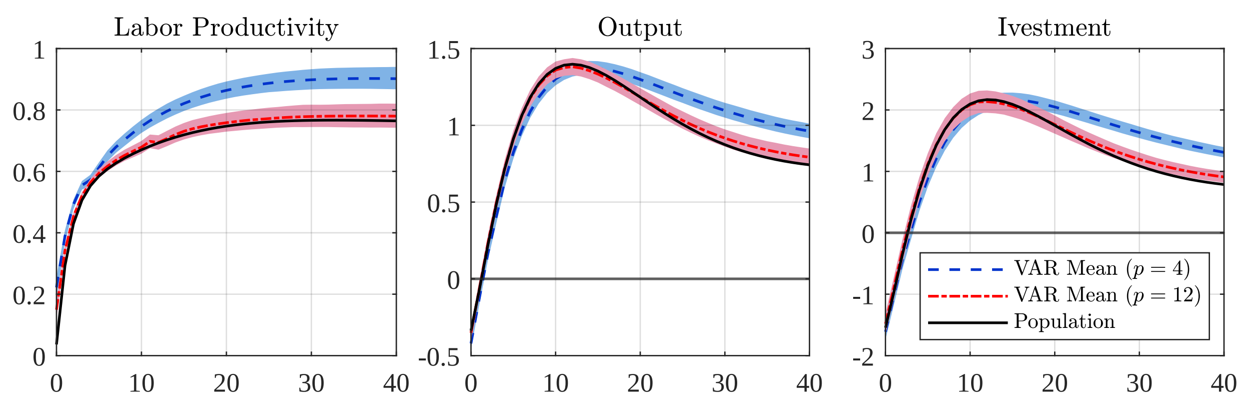
Notes: VAR(4) model with $T = 10{,}000$. $\mathbf{y}_t = (\text{TFP}^u_t, y_t, i_t, c_t, l_t)$ for the KSMS and NAMS estimators and $\mathbf{y}_t = (z^n_{t+1}, \text{TFP}^u_t, y_t, i_t, c_t, l_t)'$ for the MS News estimator.

Figure 3: Impulse responses to a news shock when targeting labor productivity

(a) KSMS estimator



(b) NAMS estimator



Notes: VAR(p) model with $T = 10{,}000$ and $\mathbf{y}_t = (lp_t, y_t, i_t)$, where lp_t is labor productivity.

Table 7: RMSE over 40 quarters when targeting output compared to the MS News estimator

	$p = 4$				$p = 12$			
	TFP	Output	Invest	Total	TFP	Output	Invest	Total
KSMS Output	9.7	9.5	15.7	35.0	6.6	3.8	6.3	16.7
NAMS Output	10.2	10.5	19.7	40.4	7.2	5.2	11.5	23.8
MS News	6.4	2.8	7.6	16.8	5.9	2.0	4.5	12.4

Notes: VAR(p) model with $T = 10{,}000$. $\mathbf{y}_t = (\text{TFP}_t^u, y_t, i_t)$ for the max share estimators that target output and $\mathbf{y}_t = (z_{t+1}, \text{TFP}_t^u, y_t, i_t)$ for the MS News estimator.

Table 8: Parameters for alternative DSGE models

Parameter	Baseline	Alternative 1	Alternative 2
TFP Growth Persistence (ρ_g)	0.50	0.30	0.25
Surprise TFP Persistence (ρ_s)	0.40	0.25	0.20
MEI Persistence (ρ_μ)	0.95	0.95	0.95
TFP Growth Shock SD (σ_g)	0.0025	0.0015	0.004
Surprise TFP Shock SD (σ_s)	0.006	0.006	0.007
MEI Shock SD (σ_μ)	0.004	0.006	0.0035

Notes: MEI is the marginal efficiency of investment.

Table 9: Data and model-implied moments from alternative DSGE models

Moment	Data	Baseline	Alternative 1	Alternative 2
$SD(\tilde{a}_t)$	2.01	2.31	1.62	2.46
$SD(\Delta a_t)$	0.80	0.73	0.70	0.88
$SD(\tilde{y}_t)$	3.13	3.92	3.24	4.08
$SD(\tilde{\imath}_t)$	9.63	9.48	9.83	9.33
$AC(\tilde{a}_t)$	0.87	0.87	0.83	0.86
$AC(\Delta a_t)$	−0.09	0.01	−0.20	−0.12

Notes: A tilde denotes a detrended variable and Δ is a log change. In the data, a_t is Fernald utilization-adjusted TFP while in the model it is measured TFP. The alternative models are described in Table 8.

Table 10: Forecast error variance decompositions for TFP in alternative DSGE models

(a) Measured TFP (TFP^u)

	Alternative 1			Alternative 2		
Horizon	News	Surprise	MEI	News	Surprise	MEI
4	10.2	59.8	30.1	43.0	50.4	6.5
8	14.4	53.4	32.1	53.4	40.3	6.2
20	9.4	6.3	84.3	62.2	8.2	29.5
40	13.4	1.3	85.3	73.4	1.4	25.3
80	20.9	0.7	78.4	82.6	0.5	16.9

(b) True TFP (a)

	Alternative 1			Alternative 2		
Horizon	News	Surprise	MEI	News	Surprise	MEI
4	21.3	78.7	0.0	57.3	42.7	0.0
8	42.7	57.3	0.0	78.1	21.9	0.0
20	68.6	31.4	0.0	91.1	8.9	0.0
40	82.1	17.9	0.0	95.5	4.5	0.0
80	90.3	9.7	0.0	97.8	2.2	0.0

Notes: MEI is the marginal efficiency of investment. The alternative models are described in Table 8.

Table 11: RMSE over 40 quarters based on alternative DSGE models

(a) Alternative 1

	$p = 4$				$p = 12$			
Estimator	TFP	Output	Invest	Total	TFP	Output	Invest	Total
KSMS	8.6	12.6	49.6	70.8	7.2	14.6	55.5	77.3
NAMS	8.2	11.0	41.4	60.6	5.6	8.2	28.8	42.6
MS News	3.2	2.2	6.4	11.9	2.6	1.6	5.2	9.3

(b) Alternative 2

	$p = 4$				$p = 12$			
	TFP	Output	Invest	Total	TFP	Output	Invest	Total
KSMS	10.2	10.7	19.4	40.3	7.3	5.8	13.2	26.3
NAMS	9.9	11.2	21.9	42.9	7.2	5.9	13.5	26.6
MS News	6.5	2.6	7.2	16.3	6.2	2.1	4.1	12.4

Notes: VAR(p) model with $T = 10{,}000$, where $\mathbf{y}_t = (\text{TFP}_t^u, y_t, i_t)$ for the KSMS and NAMS estimators and $\mathbf{y}_t = (z_{t+1}, \text{TFP}_t^u, y_t, i_t)$ for the MS News estimator. The alternative models are described in Table 8.

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