Jointly Estimating Macroeconomic News and Surprise Shocks

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Jointly Estimating Macroeconomic News and Surprise Shocks[*]

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Abstract

This paper clarifies the conditions under which the state-of-the-art approach to identifying TFP news shocks in Kurmann and Sims (2021, KS) identifies not only news shocks but also surprise shocks. We examine the ability of the KS procedure to recover responses to these shocks from data generated by a conventional New Keynesian DSGE model. Our analysis shows that the KS response estimator tends to be strongly biased even in the absence of measurement error. This bias worsens in realistically small samples, and the estimator becomes highly variable. Incorporating a direct measure of TFP news into the model and adapting the identification strategy accordingly removes this asymptotic bias and greatly reduces the RMSE when TFP news are correctly measured. However, the high variability of this alternative estimator in small samples suggests caution in interpreting empirical estimates. We examine to what extent empirical estimates of the responses to news and surprise shocks from a range of VAR models based on alternative measures of TFP news are economically plausible.

Keywords: Structural VAR; TFP; productivity shock; news; expectation

JEL Classifications: C32, C51, C61, E32

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[*]Thew 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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1 INTRODUCTION

The importance of distinguishing between exogenous shocks to expectations about future realizations of macroeconomic variables and exogenous shocks to current realizations of these variables not driven by expectations is widely recognized in the literature (see, e.g., Beaudry and Portier, 2014; Kilian and Murphy, 2014; Mertens and Ravn, 2012). This distinction has received particular attention in studies of the effects of shocks to total factor productivity (TFP) on economic activity.

Building on Uhlig (2004) and Francis et al. (2014), Barsky and Sims (2011, henceforth, BS) introduced the max-share approach to identifying anticipated shocks to TFP ("news shocks") and unanticipated shocks to TFP ("surprise shocks") using a structural vector autoregressive (VAR) model. Their estimator of these shocks is based on selecting parameters for the structural impact multiplier matrix of the VAR model that maximize the sum of the forecast error variance shares of TFP over a ten-year horizon subject to the restriction that the news shock is orthogonal to current TFP. The latter assumption can be traced to Cochrane (1994) and Beaudry and Portier (2006) and has been central to most identification strategies seeking to recover news shocks.[1]

However, as stressed by Barsky et al. (2015) and Kurmann and Sims (2021, henceforth, KS), the assumption that news shocks affect productivity only with a delay is difficult to defend on *a priori* grounds. One reason is that new technologies may affect TFP today, even though their main effect on TFP takes many years due to the slow diffusion of those technologies. Another reason is that changes in measured TFP are difficult to distinguish from changes in factor utilization. This fact calls into question any identification strategy involving restrictions on the short-run response of TFP.

In response to these concerns, KS proposed an alternative approach to the estimation of TFP news shocks that is conceptually similar to BS with two important differences. First, they dispense with the assumption that news shocks do not have contemporaneous effects on TFP. Second, they

[1] Variations of this max share approach have been widely used in applied work in a variety of economic contexts (e.g., Angeletos et al., 2020; Ben Zeev and Khan, 2015; Benhima and Cordonier, 2022; Bouakez and Kemoe, 2022; Carriero and Volpicella, 2022; Chen and Wemy, 2015; Fève and Guay, 2019; Forni et al., 2014; Francis and Kindberg-Hanlon, 2022; Görtz et al., 2022a,b; Levchenko and Pandalai-Nayar, 2020; Nam and Wang, 2015).

construct the shock that accounts for the maximum forecast error variance share at a given long horizon rather than maximizing the sum of the forecast error variance shares from the impact period up that horizon. They interpret that shock as a news shock if it causes TFP to increase only gradually, while causing observable measures of innovation and TFP news indicators to jump on impact. KS show that their alternative estimates are robust to revisions in the widely used measure of TFP developed by Fernald (2014), whereas the BS estimates are not. KS stress that the cost of their approach compared to the analysis in BS is that it does not allow the user to "separately identify surprise shocks to current productivity from news shocks about future productivity."

Our paper makes several contributions to this literature. Our first contribution is to clarify the conditions under which the KS approach allows the joint identification of surprise and news shocks. We first show that, under the maintained assumption that TFP innovations are explained by news and surprise shocks, the impact of the surprise shock is directly implied by the impact of the news shock, given the orthogonality assumption that KS impose on the rotation matrix. This result directly addresses the concern that one cannot identify the surprise shock when the news shock affects TFP contemporaneously. In contrast, earlier studies that identify both news and surprise shocks, such as BS, Bouakez and Kemoe (2022), and Levchenko and Pandalai-Nayar (2020), relied on the restrictive assumption that the news shock does not move TFP on impact.

Being able to construct the responses of the model variables to both news and surprise shocks is important because the interpretation of the structural model rests not only on the responses to the news shock being consistent with *a priori* reasoning, but also the responses to the surprise shock. We provide examples in which the TFP and output responses to the surprise shock appear incompatible with commonly used theoretical models of the effect of news and surprise shocks. This is true, for example, when re-estimating the empirical models in KS on updated data, calling into question the reliability of the KS estimator.

KS reported simulation evidence that shows that their estimator comes close to the population response of TFP to a news shock in a dynamic stochastic general equilibrium (DSGE) model when $T = 10{,}000$. Our second contribution is to study in more detail the ability of the KS estimator to recover responses to news and surprise shocks from data generated by a conventional New Keyesian DSGE model similar to the model used by KS. While we can replicate the findings in KS under their parameterization of the TFP process, our evidence shows that this parameterization is at odds with the data. When the parameters are set to match the TFP moments in the data, impulse responses based on the KS estimator are strongly biased, even asymptotically. This bias worsens for realistically small samples such as $T = 240$ (or 60 years of quarterly data) and the estimator is highly variable. This evidence helps explain the counterintuitive responses we documented for the KS VAR models.

Third, our analysis also implies that the estimator proposed by KS is not unique. When TFP is measured correctly, as is the case in our simulation setting, the same model may be estimated alternatively by maximizing the forecast error variance at short horizons to obtain an estimate of the surprise shock, from which the news shock may be derived. As we document, this alternative estimator is even less accurate in practice than the original KS estimator, even when TFP is measured correctly.

This result raises the question of what alternatives are available to applied researchers. Our fourth contribution is to show that adding a direct measure of TFP news to the VAR model and adapting the identification strategy accordingly, as suggested in some recent studies, will remove the asymptotic bias assuming that the news are correctly measured. We discuss two such identification strategies. Our approach differs from other recent studies that employ measures of TFP news in that we identify both the news and surprise shock, building on our analysis of the KS method.[2]

The ability of estimators based on news variables to recover responses from data generated by DSGE models has never been examined. We find that appropriately constructed estimators based on news variables have substantially lower bias and root mean-squared error (RMSE) than the KS estimator. Nevertheless, these estimators are not reliable in small samples, even when the news variable is accurately measured, because of their high variability. This suggests caution in interpreting empirical estimates.

[2]Examples of studies employing measures of TFP news include Shea (1999), Christiansen (2008), Alexopoulos (2011), Baron and Schmidt (2019), Cascaldi-Garcia and Vukotić (2022), and Miranda-Agrippino et al. (2022).

Another possible explanation of the counterintuitive response estimates we documented earlier is that the constraint that TFP innovations can be written as a linear combination of news and surprise shocks does not hold. Our fifth contribution is to discuss what features of the DSGE model and the data would cause this constraint to be violated, including the concern with TFP mismeasurement raised by KS.

Given that the degree to which the adding up constraint is violated in practice remains an open question, we recommend that applied users examine the extent to which empirical estimates of the responses to news and surprise shocks are economically plausible in light of the underlying economic theory. Our final contribution is to apply such diagnostics to a range of VAR models based on alternative measures of TFP news. We find that only one of these specifications appears economically plausible in light of the underlying theory.

The remainder of the paper is organized as follows. In Section 2, we review the estimation of news shocks by maximizing the contribution of the news shock to the forecast error variance of TFP at long, but finite horizons, and formally derive the identification conditions. In Section 3, we show that KS's empirical models do not recover economically plausible responses to surprise shocks when re-estimated on data through 2019. In Section 4, we use data generated from a conventional business cycle model to examine the accuracy of the KS estimator. In Section 5, we use the same DSGE model to examine the accuracy of two alternative identification strategies that involve a direct measure of TFP news in the VAR model. In Section 6, we discuss the conditions under which the derivation of the surprise shock breaks down. In Section 7, we examine whether news and surprise shocks are properly identified in a range of empirical models based on alternative measures of TFP news. The concluding remarks are in Section 8.

2 IDENTIFICATION PROBLEM

2.1 NOTATION Consider a VAR model with K variables, where $\mathbf{y}_t$ is a $K \times 1$ vector that collects the model variables. The reduced-form moving average representation of the VAR model is given by $\mathbf{y}_t = \Phi(L)\mathbf{u}_t$, where $\Phi(L) = I_K + \Phi_1 L + \Phi_2 L^2 + \cdots$, I_K is a K-dimensional identity matrix, L is a lag operator, and $\mathbf{u}_t$ is a $K \times 1$ vector of reduced-form shocks. The variance-covariance matrix of $\mathbf{u}_t$ is given by $\Sigma = E[\mathbf{u}_t \mathbf{u}_t']$.

Let $\mathbf{w}_t$ be a $K \times 1$ vector of structural shocks with $E[\mathbf{w}_t \mathbf{w}_t'] = I_K$. Under suitable normalizing assumptions, $\mathbf{u}_t = B_0^{-1}\mathbf{w}_t$, where the $K \times K$ structural impact multiplier matrix B_0^{-1} satisfies $B_0^{-1}(B_0^{-1})' = \Sigma$. The impact effect of shock j on variable i is given by the jth column and the ith row of B_0^{-1}. Let P denote the lower triangular Cholesky decomposition of Σ with the diagonal elements normalized to be positive and let Q be a $K \times K$ orthogonal matrix. Since $Q'Q = QQ' = I_K$ and hence $(PQ)(PQ)' = PP' = \Sigma$, we can express the set of possible solutions for B_0^{-1} as PQ. Identification involves pinning down some or all columns of the Q matrix.

One way of proceeding is to observe that the h-step ahead forecast error is given by

$$\mathbf{y}_{t+h} - E_{t-1}\mathbf{y}_{t+h} = \sum_{\tau=0}^{h} \Phi_\tau P Q \mathbf{w}_{t+h-\tau},$$

where Φ_τ is the reduced-form matrix for the moving average coefficients, which may be constructed following Kilian and Lütkepohl (2017) with $\Phi_0 = I_K$. As a result, the share of the forecast error variance of variable i that is attributed to shock j at horizon h is given by

$$\Omega_{i,j}(h) = \frac{\sum_{\tau=0}^{h} \Phi_{i,\tau} P \gamma_j \gamma_{j'} P' \Phi_{i,\tau}'}{\sum_{\tau=0}^{h} \Phi_{i,\tau} \Sigma \Phi_{i,\tau}'},$$

where $\Phi_{i,\tau}$ is the ith row of the lag polynomial at lag τ and γ_j is the jth column of the Q matrix. A unique estimate of the impact effect of structural shock j may be obtained by choosing the values of γ_j to maximize $\Omega_{i,j}(h)$ for some horizon h (or its average over selected horizons).

2.2 KURMANN-SIMS APPROACH For expository purposes, consider a stylized macroeconomic model of the effects of shocks to TFP with $K = 3$. Without loss of generality, the TFP variable is ordered first. Consistent with the DSGE model in KS, the TFP variable is assumed to be affected only by two shocks, a surprise shock and a news shock. Then the orthogonal matrix Q is given by

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

where $\gamma_{s,j}$ and $\gamma_{n,j}$ denote elements in the matrix Q associated with the impact of the surprise and the news shock, respectively, on variable $j = 1, 2, 3$. $\gamma_{\ell,j}$ are the elements of Q associated with an unnamed third shock that only affects variables $j = 2, 3$. KS propose to construct an estimate of the news shock based on

$$\gamma_n = \text{argmax } \Omega_{1,2}(H_n) = \text{argmax } \frac{\sum_{\tau=0}^{H_n} \Phi_{1,\tau} P \gamma_n \gamma_n' P' \Phi_{1,\tau}'}{\sum_{\tau=0}^{H_n} \Phi_{1,\tau} \Sigma \Phi_{1,\tau}'}, \tag{2}$$

subject to the restriction that $\gamma_n \gamma_n' = 1$, where $\gamma_n = (\gamma_{n,1}, \gamma_{n,2}, \gamma_{n,3})'$ denotes the second column in the orthogonal rotation matrix Q in (1) and H_n denotes a 20-year horizon. KS stress the importance of validating the model estimate by showing that selected news indicators respond positively to the news shock in the short run.

2.3 IDENTIFICATION CONDITIONS

We now examine in more detail the identification conditions assumed in KS. For concreteness, consider the same VAR model with three variables outlined in Section 2.2. The matrix Q 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

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

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

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

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

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

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

Following KS, 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 identify all three structural response functions up to their sign. This means that all that is required in practice 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 that the news shock has a positive effect on TFP at H_n. For $K > 3$ only the news and surprise shock are identified. This result means it is sufficient to compare the explanatory power of both TFP shocks on real GDP without having to take a stand on the identification of the remaining $K-2$ structural shocks.

While our illustrative example is for $K=3$, the fact that the KS procedure also identifies the surprise shock is general, as shown in the following proposition.

Proposition 1. *Under the identifying assumptions in KS, γ_s will be uniquely identified for any given estimate of γ_n. In particular, $\gamma_{s,1}=\pm\sqrt{1-\gamma_{n,1}^2}$ and $\gamma_{s,j}=-\gamma_{n,1}\gamma_{n,j}/\gamma_{s,1}$ for $j\in\{2,\ldots,K\}$.*

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 the orthogonality condition and some of which may not. For $K=3$, for example, there are 2^3 possible solutions. The validity of the KS estimator requires the existence of an orthogonal Q matrix. In the Appendix we show that when solving for γ_n and γ_s using the KS procedure, γ_ℓ can always be chosen such that Q is orthogonal.

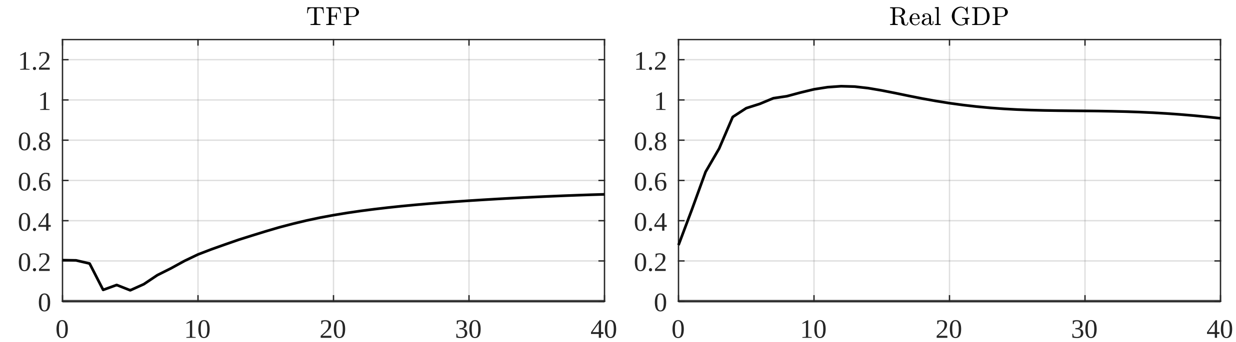
3 REVISITING THE EMPIRICAL EVIDENCE IN KS

Given that KS did not consider the implications of their VAR estimates for the surprise shock, a natural question is whether the responses to this shock are economically plausible. We examine this question by applying the KS estimator to the 8-variable VAR model in KS, which includes the utilization-adjusted TFP series of Fernald (2014), per capita real GDP, per capita real personal consumption expenditures, per capita real private fixed investment, per capita hours worked in the private sector, the real S&P 500 index computed using the GDP deflator, the federal funds rate, and the GDP deflator inflation rate. All variables enter the VAR in logs, except for the federal funds and inflation rates. We fit the model on an updated sample that runs from 1960Q1 to 2019Q4. The VAR includes four lags and a constant, in line with KS. The Appendix describes the data sources.

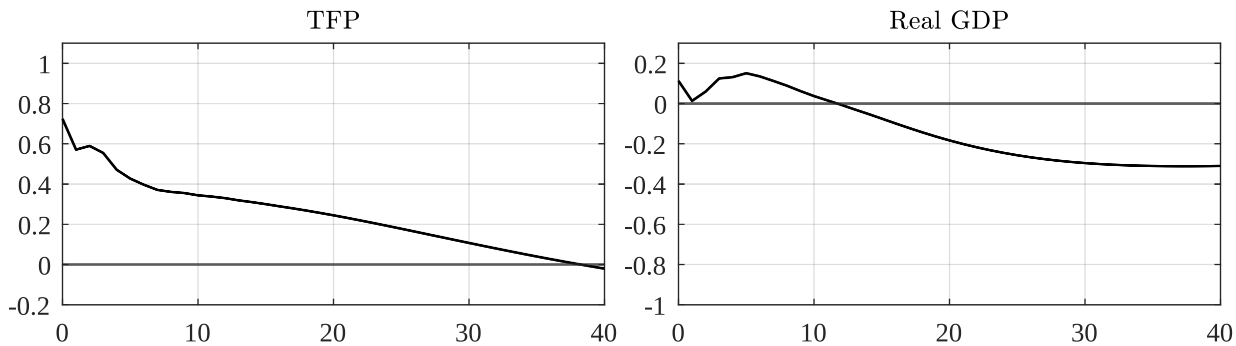
There are four natural criteria for judging whether the news and surprise shocks have been properly identified in a given VAR model. These criteria are suggested by the population responses

Figure 1: Max-share identified impulse responses based on the 8-variable VAR in KS

(a) News shock



(b) Surprise shock



in the DSGE model we discuss in Section 4 and by many other business cycle models.[3] First, while the identification does not constrain the short-run response of TFP and output to a news shock, its effect on TFP and output should weakly increase at longer horizons. Second, the news shock should have positive effects in the long run on TFP and output. Third, the surprise shock should have transient effects on TFP and output with responses approaching zero in the medium run. Fourth, the surprise shock should have positive effects on TFP and output on impact and the responses should not be far below zero in the longer run.

Figure 1 plots the responses from the 8-variable VAR model over a 40-quarter horizon, as is conventional in the literature. The top panel shows the responses of TFP and real GDP to the news shock, and the bottom panel shows the responses to the surprise shock. While the news shock raises TFP and real GDP in the long-run, the response function of real GDP is hump-shaped and

[3]It is understood that this benchmark may change depending the specification of the DSGE model. For example, Bouakez and Kemoe (2022) show that increasing returns to scale in production may cause the responses of TFP and output to a news shock to become hump shaped rather than weakly increasing.

not weakly increasing at longer horizons, as suggested by economic theory. Moreover, while the surprise TFP shock has positive short-run impacts on both variables, the response of real GDP to the surprise shock is far below zero at longer horizons, clearly invalidating the model estimate.

As shown in the Appendix, similar results also hold in the smaller VAR model considered by KS that includes TFP, real personal consumption expenditures per capita, total hours worked per capita in the nonfarm business sector, and inflation as measured by the growth rate of the GDP deflator. This evidence suggests that it is important to examine in more detail the ability of the KS estimator to recover population responses to news and surprise shocks from data generated by DSGE models.

4 Assessing the Accuracy of the KS Estimator

4.1 Data Generating Process

A useful starting point is a model in which there is no TFP measurement error. We investigate the properties of the KS max-share identification strategy using data generated from a conventional New Keynesian model similar to the model used by KS.

Households The representative household solves the Bellman equation

$$J_t = \max_{c_t, n_t, b_t, i_i, k_t} \log c_t - \chi n_t^{1+\eta}/(1+\eta) + \beta E_t J_{t+1}$$

subject to

$$c_t + i_t + b_t = w_t n_t + r_t^k k_{t-1} + r_{t-1} b_{t-1}/\pi_t + d_t,$$
$$k_t = (1-\delta)k_{t-1} + \mu_t i_t,$$

where $\beta \in (0,1)$ is the subjective discount factor, $\chi > 0$ is a preference parameter, $1/\eta$ is the Frisch elasticity of labor supply, c_t is consumption, n_t is labor hours, b_t is the real value of a privately-issued one-period nominal bond, i_t is investment, k_t is the stock of capital that depreciates at rate δ, r_t^k is the real rental rate of capital, w_t is the real wage rate, d_t is real dividends rebated from intermediate goods firms, $\pi_t = p_t/p_{t-1}$ is the gross inflation rate, r_t is the gross nominal interest rate set by the central bank, and μ_t is an investment efficiency shock that evolves according to

$$\ln \mu_t = \rho_\mu \ln \mu_{t-1} + \sigma_\mu \varepsilon_{\mu,t}, \ -1 < \rho_\mu < 1, \ \varepsilon_{\mu,t} \sim \mathbb{N}(0,1).$$

The representative household's optimality conditions imply

$$w_t = \chi n_t^\eta c_t,$$
$$1/\mu_t = E_t \left[x_{t+1} \left(r_{t+1}^k + (1-\delta)/\mu_{t+1} \right) \right],$$
$$1 = E_t[x_{t+1} r_t / \pi_{t+1}],$$

where $x_{t+1} \equiv \beta c_t / c_{t+1}$ is the pricing kernel between periods t and $t+1$.

Firms The production sector consists of a continuum of monopolistically competitive intermediate goods firms and a final goods firm. Intermediate firm $i \in [0,1]$ produces a differentiated good $y_t(i) = a_t k_{t-1}(i)^\alpha n_t(i)^{1-\alpha}$, where $k_{t-1}(i)$ and $n(i)$ are the capital and labor inputs. Following the literature, TFP (a_t) has a transitory component (s_t) and a permanent component (z_t) that evolve according to

$$\ln a_t = \ln s_t + \ln z_t,$$
$$\ln z_t = \ln g_t + \ln z_{t-1},$$
$$\ln s_t = \rho_s \ln s_{t-1} + \sigma_s \varepsilon_{s,t}, \ -1 < \rho_s < 1, \ \varepsilon_{s,t} \sim \mathbb{N}(0,1),$$
$$\ln g_t = (1-\rho_g) \ln \bar{g} + \rho_g \ln g_{t-1} + \sigma_g \varepsilon_{g,t}, \ -1 < \rho_g < 1, \ \varepsilon_{g,t} \sim \mathbb{N}(0,1).$$

Each intermediate firm chooses its inputs to minimize costs, $w_t n_t(i) + r_t^k k_{t-1}(i)$, subject to the production function. After aggregating across intermediate firms, the optimality conditions imply

$$r_t^k = \alpha m c_t a_t k_{t-1}^{\alpha-1} n_t^{1-\alpha},$$
$$w_t = (1-\alpha) m c_t a_t k_{t-1}^\alpha n_t^{-\alpha},$$

where mc_t is the real marginal cost of producing an additional unit of output.

The final-goods firm purchases $y_t(i)$ units from each intermediate-goods firm to produce the final good, $y_t \equiv [\int_0^1 y_t(i)^{(\epsilon-1)/\epsilon} di]^{\epsilon/(\epsilon-1)}$, where $\epsilon > 1$ measures the elasticity of substitution between intermediate goods. It then maximizes dividends to determine the demand function for good i, $y_t(i) = (p_t(i)/p_t)^{-\epsilon} y_t$, where $p_t = [\int_0^1 p_t(i)^{1-\epsilon} di]^{1/(1-\epsilon)}$ is the aggregate price level.

Following Calvo (1983), a fraction, θ, of intermediate firms cannot choose their price in a given period. Those firms index their price to steady-state inflation, so $p_t(i) = \bar{\pi} p_{t-1}(i)$. A firm that can set its price at t chooses p_t^* to maximize $E_t \sum_{k=t}^{\infty} \theta^{k-t} x_{t,k} d_k^*$, where $x_{t,t} \equiv 1$, $x_{t,k} \equiv \prod_{j=t+1}^{k>t} x_j$, and $d_k^* = [(\bar{\pi}^{k-t} p_t^*/p_k)^{1-\epsilon} - mc_k (\bar{\pi}^{k-t} p_t^*/p_k)^{-\epsilon}] y_k$. Letting $p_{f,t} \equiv p_t^*/p_t$, optimality implies

$$p_{f,t} = \tfrac{\epsilon}{\epsilon-1}(f_{1,t}/f_{2,t}),$$

$$f_{1,t} = mc_t y_t + \theta E_t[x_{t+1}(\pi_{t+1}/\bar{\pi})^{\epsilon} f_{1,t+1}],$$

$$f_{2,t} = y_t + \theta E_t[x_{t+1}(\pi_{t+1}/\bar{\pi})^{\epsilon-1} f_{2,t+1}].$$

The price level, price dispersion ($\Delta_t \equiv \int_0^1 (p_t(i)/p_t)^{-\epsilon} di$), and the aggregate production function are given by

$$1 = (1-\theta) p_{f,t}^{1-\epsilon} + \theta(\pi_t/\bar{\pi})^{\epsilon-1},$$

$$\Delta_t = (1-\theta) p_{f,t}^{-\epsilon} + \theta(\pi_t/\bar{\pi})^{\epsilon} \Delta_{t-1},$$

$$\Delta_t y_t = a_t k_{t-1}^{\alpha} n_t^{1-\alpha}.$$

Equilibrium The central bank sets the nominal interest rate according to a Taylor rule given by

$$r_t = \bar{r}(\pi_t/\bar{\pi})^{\phi_\pi},$$

where ϕ_π controls the response to deviations of inflation from its steady-state level.

The aggregate resource constraint is given by

$$c_t + i_t = y_t.$$

Due to the permanent component of TFP, we detrend the model by dividing trended variables by $z_t^{1/(1-\alpha)}$. The detrended equilibrium system is provided in the Appendix. We solve the log-linearized model using Sims (2002) `gensys` algorithm.

Table 1: Data moments and model-implied moments

Moment	Data	Baseline Model	Model with KS TFP
$SD(\tilde{a})$	2.01	2.31	1.52
$SD(\Delta a)$	0.80	0.83	0.31
$AC(\tilde{a})$	0.87	0.88	0.88
$AC(\Delta a)$	-0.09	0.04	0.67
$SD(\tilde{y})$	3.13	2.88	1.85
$SD(\tilde{\imath})$	9.63	9.62	7.30

Note: A tilde denotes a detrended variable and Δ is a log change.

Each period in the model is one quarter. The discount factor, $\beta = 0.995$, implies an annual real rate of interest of 2%. The Frisch elasticity of labor supply, $1/\eta = 0.5$, is set to the intensive margin estimate in Chetty et al. (2012). The steady-state inflation rate, $\bar{\pi} = 1.005$, is consistent with a 2% annual inflation target. The elasticity of substitution between goods, $\epsilon = 11$, the degree of price stickiness, $\theta = 0.75$, and the monetary response to inflation, $\phi_\pi = 1.5$, are set to the values in KS. The capital depreciation rate, $\delta = 0.025$, matches the annual average rate on private fixed assets and durable goods over 1960 to 2019. The average growth rate of TFP, $\bar{g} = 1.0026$, and the income share of capital, $\alpha = 0.3343$, are based on the updated data from Fernald (2014).

Finally, we set the parameters of the TFP and marginal efficiency of investment (MEI) processes to match six moments in the data: the standard deviation and autocorrelation of TFP growth ($SD(\Delta \ln a)$, $AC(\Delta \ln a)$), the standard deviation and autocorrelation of detrended TFP ($SD(\Delta \ln \tilde{a})$, $AC(\Delta \ln \tilde{a})$), and the standard deviations of detrended output and detrended investment ($SD(\ln \tilde{y})$, $SD(\ln \tilde{\imath})$).[4] This yields $\rho_s = 0.8$, $\rho_g = 0.6$, $\rho_\mu = 0.9$, $\sigma_s = 0.007$, $\sigma_g = 0.003$, and $\rho_\mu = 0.0075$. Table 1 shows that these parameters imply a good model fit, suggesting that this model is a useful laboratory for evaluating the KS identification strategy.

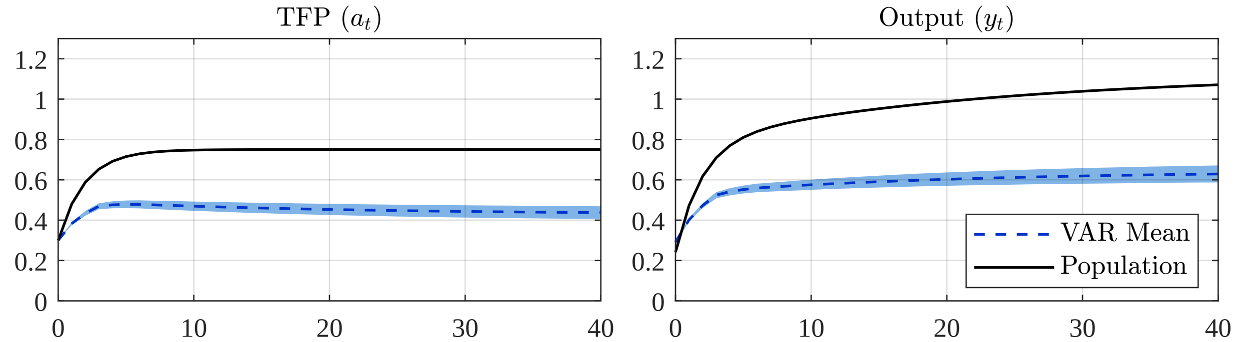
4.2 SIMULATION EVIDENCE ON THE ACCURACY OF THE KS ESTIMATOR

Since there are three structural shocks in the DSGE model, we fit a three-dimensional structural VAR model. We work with a VAR(4) model with intercept for $\mathbf{y}_t = (a_t, y_t, i_t)'$, given that investment has a strong

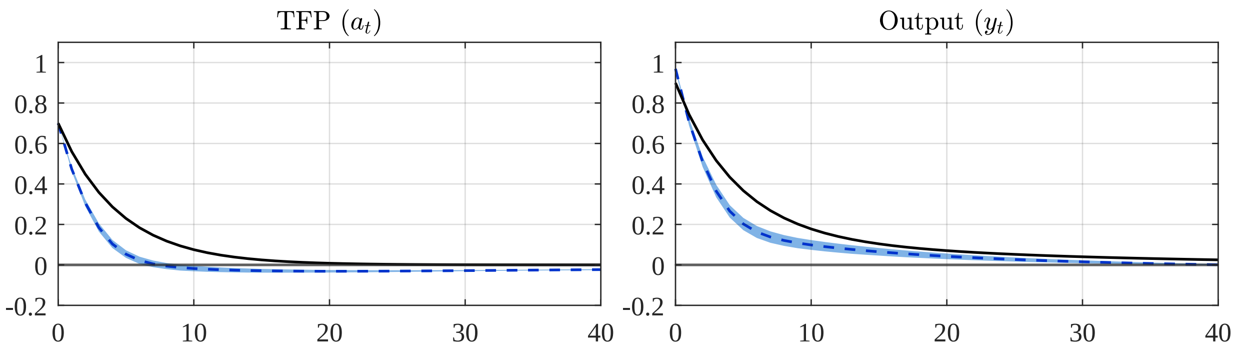
[4] We use the Hamilton (2018) filter with 4 lags and a delay of 8 quarters to detrend the data. Hodrick (2020) shows that this method is more accurate than using a Hodrick and Prescott (1997) filter when log series are difference stationary.

Figure 2: Max-share identified impulse responses based on the procedure in KS

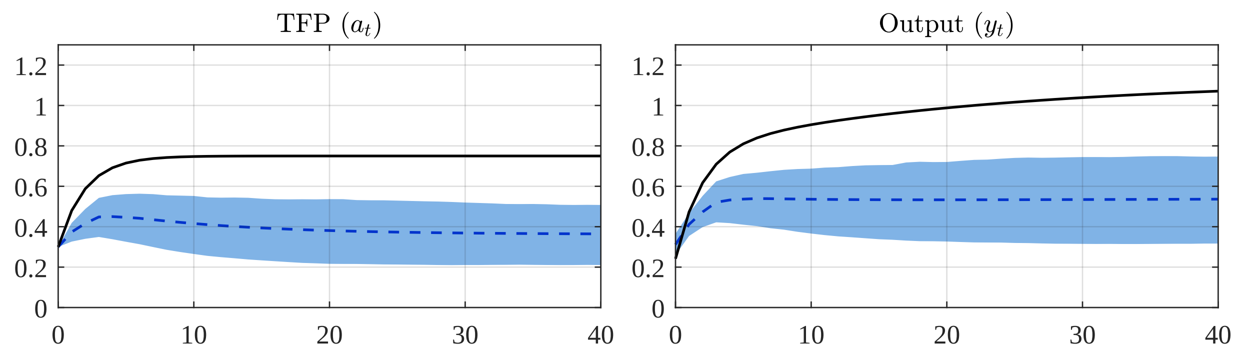
(a) News shock, $T = 10{,}000$



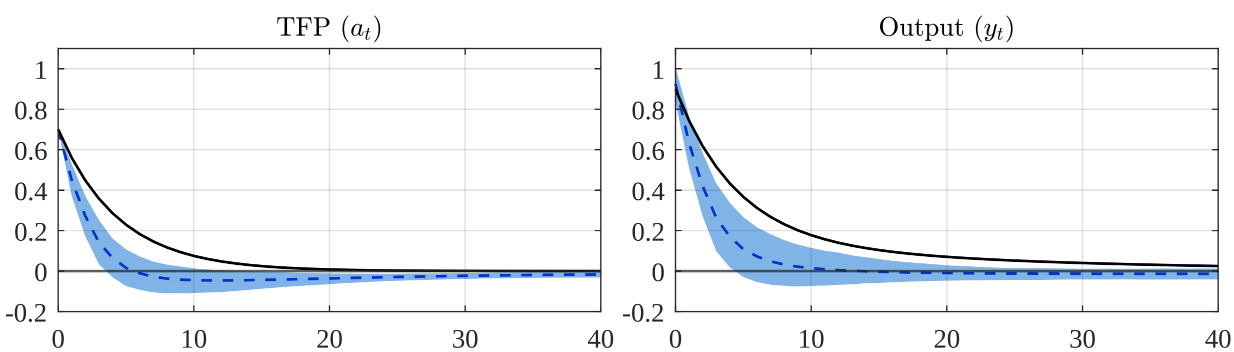
(b) Surprise shock, $T = 10{,}000$



(c) News shock, $T = 240$



(d) Surprise shock, $T = 240$



connection with the MEI shock. All variables enter in logs, and the lag order matches that used by KS. We generate $1{,}000$ realizations of log-level data of length T for TFP, output, and investment by simulating the DSGE model, fit the VAR model on each of these data realizations, and construct the impulse responses. Figure 2 reports the expected value of these responses, the underlying population response, and 68% quantiles of the distribution of the impulse response estimates, following KS. The distance between the expected value and the population value measures the bias of the estimator. The 68% quantiles provide a measure of the variability of the estimates.

It is useful to start with results for $T = 10{,}000$. The top row shows that in this case the responses of TFP and output to a news shock are strongly biased downwards relative to the population responses. In addition, the shape of the TFP response looks slightly hump-shaped rather than leveling off at longer horizons. The responses to the surprise shock shown in the second row are also biased downwards with the TFP response exhibiting the wrong sign at many horizons. This evidence calls into question the ability of the KS estimator to recover the population responses asymptotically.

While our results for $T = 10{,}000$ are informative about the asymptotic properties of the estimator, they do not speak to the properties of the KS estimator for sample sizes encountered in applied work. Therefore, we also examine the performance of the KS estimator for $T = 240$ (60 years of quarterly data), which is a reasonably long estimation period in practice. The bottom two rows of Figure 2 show that the bias of the impulse response estimator is exacerbated, while the variability of the estimator increases substantially. Thus, the KS estimator cannot be trusted to recover the population responses, even in the absence of TFP measurement error. This is particularly true for the estimator of the responses to news shocks.

4.3 Comparison with KS Simulation Evidence

Contrary to our findings, KS report having success identifying the news shock in a Monte Carlo exercise with $T = 10{,}000$ based on a similar DSGE model. The key difference is that KS use a very different parameterization for the TFP process ($\rho_g = 0.7$, $\rho_s = 0.9$, $\sigma_g = 0.002225$ and $\sigma_s = 0.000445$). In particular, the standard deviation of their surprise shock is only about 6% of our baseline value. The last column of Table 1

Table 2: Forecast error variance decompositions for TFP based on the DSGE model

	Baseline Calibration			KS TFP Parameterization		
h	News Shock	Surprise Shock	MEI Shock	News Shock	Surprise Shock	MEI Shock
1	15.5	84.5	0.0	96.2	3.8	0.0
8	70.5	29.5	0.0	99.7	0.3	0.0
20	87.9	12.1	0.0	99.9	0.1	0.0
40	93.9	6.1	0.0	99.9	0.1	0.0
80	97.0	3.0	0.0	100.0	0.0	0.0
200	98.8	1.2	0.0	100.0	0.0	0.0

Notes: h is the horizon of the variance decomposition and MEI denotes marginal efficiency of investment.

shows the implied model moments when we use their parameterization of the TFP process in our model. The table illustrates that the KS specification is clearly at odds with the data.

The unrealistically high persistence of the KS TFP growth process (0.67 compared to about zero in the data) is important for understanding their findings because it changes the forecast error variance decomposition of the TFP variable in the DSGE model, as shown in Table 2. Under our baseline calibration, the news shock plays an important role only at longer horizons. Under the KS parameterization, the news shock explains most of the variance at all horizons, which effectively eliminates the surprise shock and makes it easier for the KS procedure to identify the news shock. This explains the superior accuracy of the KS estimator in their simulation analysis. In contrast, when the surprise shock has nontrivial effects, the procedure tends to capture linear combinations of responses to surprise shocks and news shocks.

As we confirm in the Appendix, in large samples the responses to the news shock are typically close to the population response when adopting the KS parameterization of TFP growth process. The responses to the surprise shock remain biased, but the bias is much smaller than under our baseline calibration.[5] Imposing additional theoretically motivated sign and magnitude restrictions, as discussed in Francis and Kindberg-Hanlon (2022), does not help address these problems. However, this is not the only way to estimate this VAR model.

[5]Likewise, as shown in the Appendix the KS simulation results are overturned when replacing the TFP process in their medium-scale DSGE model with our parameterization.

4.4 AN ALTERNATIVE ESTIMATOR

A direct implication of our analysis in Section 2.2 is that we can either estimate γ_s given an estimate of γ_n obtained by maximizing the TFP forecast error variance share at a long horizon or, alternatively, we can estimate γ_n given an estimate of γ_s obtained by maximizing the TFP forecast error variance share at a short horizon. In other words, the estimator of γ_n is not unique. This raises the question of which estimator should be used. We already showed that the accuracy of the original KS estimator is low in practice. In this section, we show that the alternative max-share estimator focusing on short horizons is even less accurate when the data are generated from the DSGE model in Section 4. This result holds even when TFP is measured without error.

More formally, this alternative estimator is defined as

$$\gamma_s = \text{argmax } \Omega_{1,2}(H_s) = \text{argmax } \frac{\sum_{\tau=0}^{H_s} \Phi_{1,\tau} P \gamma_s \gamma_s' P' \Phi_{1,\tau}'}{\sum_{\tau=0}^{H_n} \Phi_{1,\tau} \Sigma \Phi_{1,\tau}'} \tag{3}$$

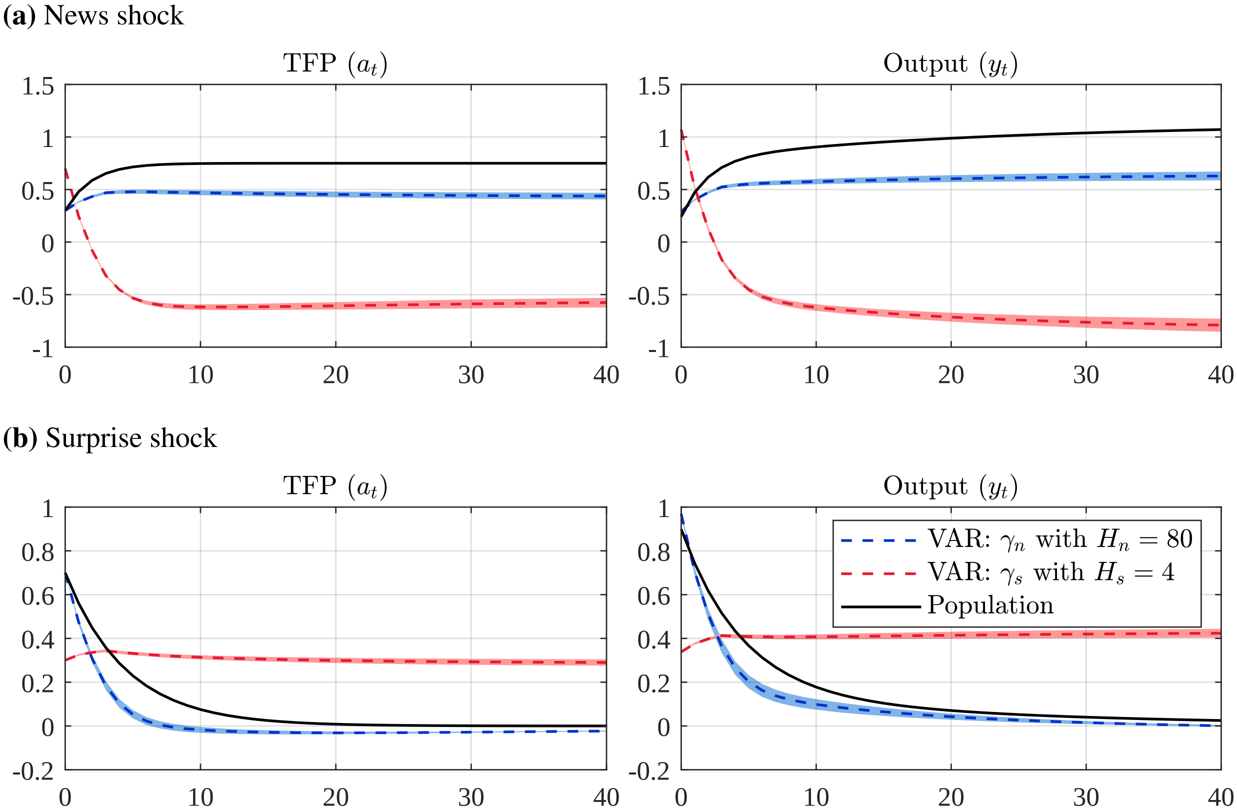
subject to the restriction that the responses of selected variables to the surprise shock match patterns that would be expected of a surprise shock and that $\gamma_s \gamma_s' = 1$, where H_s is set to a one-year horizon and $\gamma_s = (\gamma_{s,1}, \gamma_{s,2}, \gamma_{s,3})'$ denotes the first column in the orthogonal rotation matrix Q in (1).

Figure 3 shows that not only is the alternative estimator much more biased than the original estimator in large samples, 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 population responses.

5 ALTERNATIVE ESTIMATORS INVOLVING DIRECT MEASURES OF TFP NEWS

KS stress that nothing guarantees that their max share identification captures news shocks as opposed to other shocks driving TFP in the long run. Given that the responses to surprise shocks are mean reverting, it seems unlikely that surprise TFP shocks would account for a large fraction of

Figure 3: Max-share identified impulse responses from two alternative estimators, $T = 10{,}000$



the lower-frequency variation in TFP, but there could conceivably be non-technology shocks that affect TFP in the long run. KS therefore validate their model estimate by showing that measures of TFP news and other forward-looking variables jump in response to news shocks. Given that the KS procedure does not properly identify the news shock, as shown in Section 4, a natural alternative approach is to base the identification of the news shock on the response of the news variables that KS use to validate their model.

In this section, we consider identifying a TFP news shock by incorporating an observed measure of TFP news into the VAR model and adapting the identification strategy accordingly. Similar approaches have been employed in a number of recent studies. For example, Shea (1999) considers models that incorporate a measure of either R&D spending or patent applications. Other examples include Christiansen (2008, patent applications), Alexopoulos (2011, new book titles in the fields of technology and computer science), Baron and Schmidt (2019, counts of new information and communication technology standards), Cascaldi-Garcia and Vukotić (2022, patent applications), and Miranda-Agrippino et al. (2022, patent applications). The premise of all these studies is that measures of TFP news should increase immediately as a positive news shock is realized, facilitating identification strategies based on short-run restrictions.

Despite the popularity of these identification strategies, there does not exist simulation evidence that quantifies the ability of these VAR models to recover news shocks (or for that matter surprise shocks) generated by DSGE models. In fact, the implications of these methods for surprise shocks have not been recognized. In this section, we focus on two identification strategies for news shocks that also allow us to recover the surprise shocks under the maintained assumption that TPF innovations are determined by news and surprise shocks alone.

5.1 IDENTIFICATION STRATEGIES BASED ON TFP NEWS

One strategy is to identify the news shock as the shock that maximizes the forecast error variance contribution of the news variable on impact (or, more generally, at short horizons). In practice, we set $H_n = 4$, but our results are robust to smaller values for H_n.

Another strategy is to treat the news measure as predetermined with respect to TFP, resulting in a partially recursive VAR model with the news variable ordered first and TFP second. This Cholesky approach is appealing when the TFP news are measured without error, as in our simulation setting. If measurement error is a concern, one could instead use the news variable as an external instrument in a VAR model excluding the news variable (e.g., Cascaldi-Garcia and Vukotić, 2022; Miranda-Agrippino et al., 2022).

One advantage of the max share and Cholesky approaches to modeling news variables that is shared with the KS approach is that we do not have to take a stand on the impact response of TFP to news shocks.

5.2 SIMULATION EVIDENCE ON THE ACCURACY OF THE NEWS VARIABLE ESTIMATORS

We use the same DSGE process as in Section 4 to compare the accuracy of estimators based on news variables to that of the original KS estimator. We fit a VAR(4) model with intercept for

Table 3: Sum of the root mean-squared errors for each estimator over a 40-quarter horizon

(a) $T = 10{,}000$

	TFP Response		Output Response		
Estimator	News Shock	Surprise Shock	News Shock	Surprise Shock	Total
KS Max Share	11.3	2.6	14.5	2.3	30.7
Max Share News	1.4	0.8	1.9	1.1	5.2
Cholesky	1.0	0.9	1.5	1.2	4.6

(b) $T = 240$

	TFP Response		Output Response		
Estimator	News Shock	Surprise Shock	News Shock	Surprise Shock	Total
KS Max Share	15.5	3.5	19.2	5.2	43.3
Max Share News	11.3	4.7	14.4	6.4	36.8
Cholesky	7.8	5.5	10.1	7.3	30.7

$\mathbf{y}_t = (z_t, a_t, y_t)'$.[6] The variables enter the VAR in logs and are directly observable in the DSGE model. Table 3 compares the RSME of these impulse response estimators to that of the KS estimator based on $\mathbf{y_t} = (a_t, y_t, i_t)'$.[7]

The first four columns show the sum of the RMSEs over horizons 0 through 40 for selected impulse response functions. The last column shows the sum of these entries across the four response functions. There is compelling evidence that the max share news estimator has substantially lower RMSE than the KS estimator not only for $T = 10{,}000$ (83% reduction in the RMSE), but in realistically small samples (15% reduction in the RMSE). The RMSE reductions obtained based on the Cholesky identification are even larger with 85% for $T = 10{,}000$ and 29% for $T = 240$. These improvements in accuracy are mainly due to RMSE reductions for the responses to news shocks.

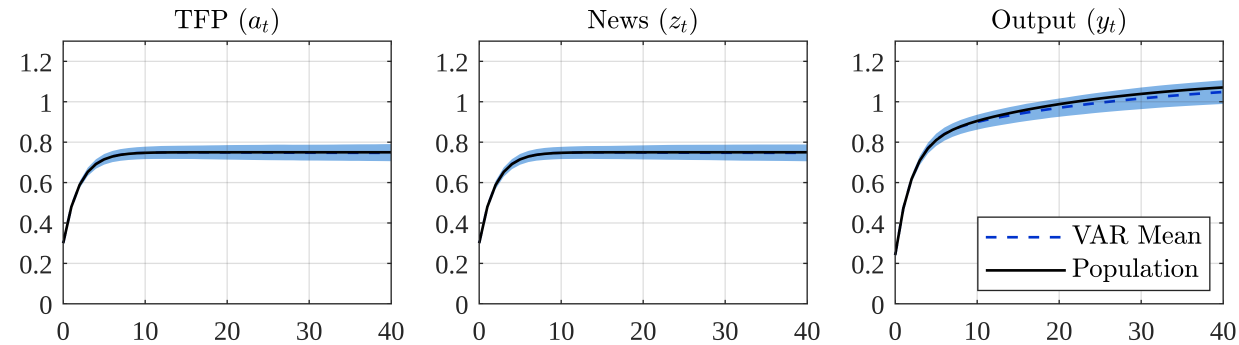
Table 3 suggests that identification strategies based on TFP news variables perform much better than strategies based on TFP data, at least when both TFP and TFP news are accurately measured.

[6]When $\mathbf{y}_t = (z_t, a_t, y_t)'$, the Q matrix is written as in (1), except that the zero restriction is in the second row of the matrix. More generally, adding z_t as an additional variable in a VAR where a_t is ordered as the jth variable requires adding a column and row to Q and placing the zero restrictions in the jth row.

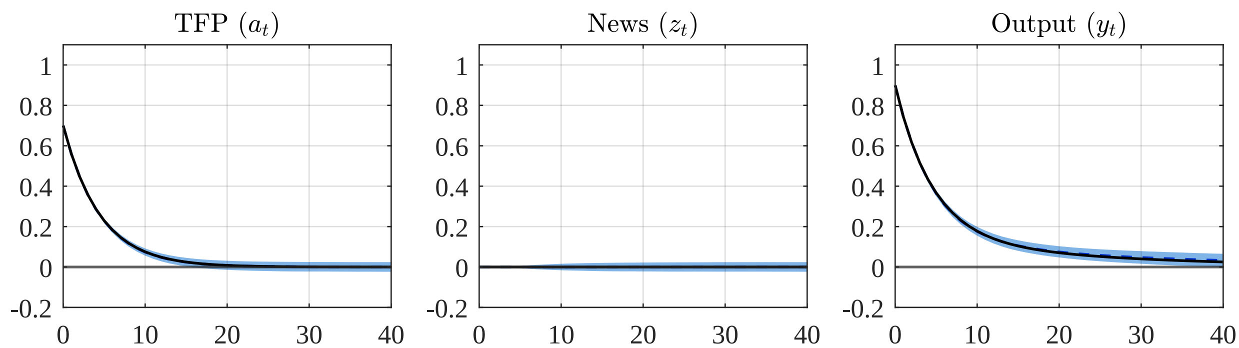
[7]It might seem more appropriate to compare the max share news and Cholesky news estimator with a two-variable VAR that includes only TFP (a_t) and output (y_t) but this would be inappropriate because the data-generating process has three unique shocks. Therefore, for the KS max share estimator, as before, we consider a three-variable VAR model that includes investment, since it has a strong connection with the MEI shock.

Figure 4: Impulse responses based on the max-share news estimator

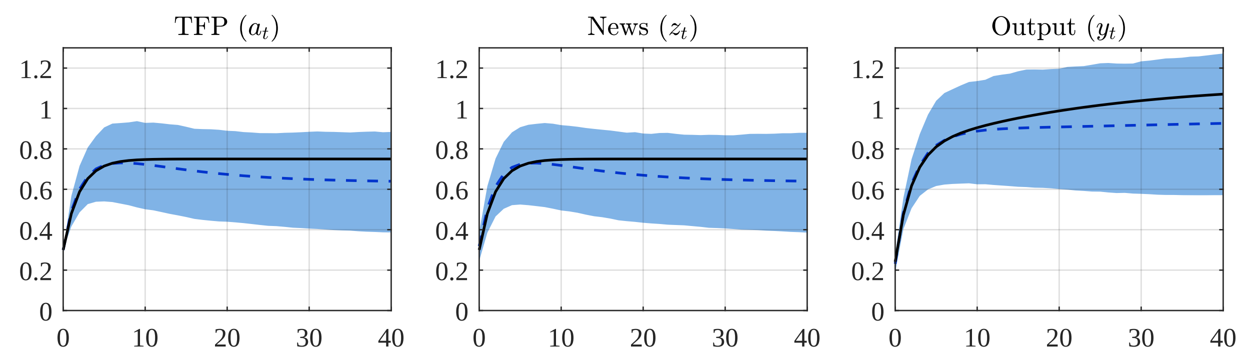
(a) News shock, $T = 10{,}000$



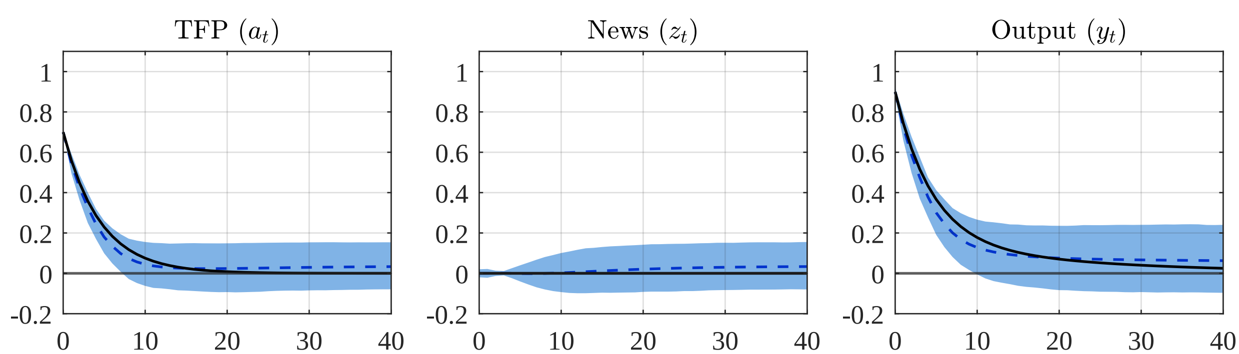
(b) Surprise Shock, $T = 10{,}000$



(c) News shock, $T = 240$



(d) Surprise Shock, $T = 240$



This does not mean that these estimates should be taken at face value, however. For illustrative purposes, Figure 4 plots the responses of TFP and output to news and surprise shocks obtained using the max share news estimator. The top two rows show the results for $T = 10{,}000$. Both shocks appear properly identified by the max share approach with very little bias in the mean estimates and small variance. The bottom two rows show the corresponding results for $T = 240$. There is some bias in the responses in this case, but more importantly there is a dramatic increase in the variability of the estimator, as measured by the 68% quantiles of the distribution of VAR estimates. Thus, one would not expect the max share news estimator to be reliable in small samples. Qualitatively similar results hold for the Cholesky approach, as shown in the Appendix.

6 THE ROLE OF THE ADDING-UP CONSTRAINT

Our analysis so far has deliberately abstracted from the possibility that measured TFP may differ from true TFP. We sidestepped this possibility by fitting VAR models to the TFP data generated by the DSGE model. This provides a useful benchmark for the performance of various estimators, but ignores some of the concerns that have arisen in applied work. In fact, a key point in KS was that one would expect the Fernald (2014) adjusted TFP series to be mismeasured in ways that are difficult to quantify. It is this measurement error that provided one motivation for their proposal to abandon the BS estimator in favor of the more robust KS estimator.

The fact that our simulation analysis in Section 4 abstracts from measurement issues does not invalidate our result that the KS procedure is unable in general to recover the population responses to news shocks even asymptotically, because allowing for measurement error in TFP cannot improve the accuracy of the estimator—it can only worsen it. Nor does allowing for TFP mismeasurement invalidate the identification of responses to news shocks based on empirical measures of TFP news, as discussed in Section 5.

However, this fact does call into question the assumption that innovations in measured TFP can be expressed as a weighted average of news and surprise shocks, which is crucial in analytically deriving surprise shocks. If measured TFP is effectively driven by a non-technology shock in addition to the news and surprise shock, the conventional decomposition breaks down. Thus, TFP measurement error may also help explain the counterintuitive responses of real GDP to the surprise shock in the empirical example in Figure 1, although it does not explain the counterintuitively hump-shaped response function of real GDP to the news shock. This concern also applies to the surprise shocks recovered from models that rely on measures of TFP news to identify news shocks.

If the adding-up constraint is violated, surprise shocks can no longer be constructed as in Sections 4 and 5. Applied researchers in that case have to restrict attention to the response to the news shocks. Given that the news and surprise shocks are constructed sequentially, abstracting from surprise shocks leaves the value of the news shock estimates unaffected.[8]

Yet another possible concern is that there may be more than one news shock in the alternative models discussed in Section 5. This situation becomes relevant, for example, when the measure of TFP news captures only some of the relevant TFP news. This would not invalidate the construction of the news shock, but it would change its interpretation, which now relates to a specific news shock only. However, the adding-up constraint would be violated in this case, invalidating the derivation of the surprise shock.

How plausible and how quantitatively important violations of the adding up constraint are in practice remains an open question. For example, KS discuss examples in which the mismeasurement of TFP is fairly benign as well as examples in which it is not. In the empirical section below, we report both the responses to news shocks and surprise shocks from selected models employing news variables for the identification. In our examples, models that produce economically plausible responses to news shocks also produce economically plausible responses to surprise shocks.

7 EMPIRICAL ILLUSTRATIONS

Our simulation evidence suggest that incorporating a measure of TFP news into the VAR model may improve the identification of the news and surprise TFP shocks. In this section, we consider

[8] The alternative approach recently proposed by Bouakez and Kemoe (2022) imposes the same questionable delay restriction as BS and hence does not address the concerns of interest in this paper.

a range of VAR models that include one of four alternative news variables: (1) **R&D**: real R&D expenditures, as used in KS and Shea (1999); (2) **ICT**: the new information and communications technologies standards index introduced in Baron and Schmidt (2019); (3) **CGV**: the patent series used in Cascaldi-Garcia and Vukotić (2022); and (4) **MAHB**: the exogenous patent-innovation series in Miranda-Agrippino et al. (2022), which is based on quarterly total patent applications from the "USPTO Historical Patent Data File" in Marco et al. (2015).[9]

For each series, we estimate a 9-variable VAR(4) model that includes one of the four news variables in addition to the 8 variables from the KS VAR model. The sample for each VAR varies due to differences in the availability of the news variables. We identify the structural shocks based on the two methods introduced in Section 5. One approach utilizes a Cholesky decomposition with the news variable ordered first and the TFP series ordered second. The other approach defines the news shock as the shock that maximizes the contribution to the forecast error variance of the news variable at a 4-quarter horizon, while the surprise shock is derived analogously to Proposition 1. Both approaches generate remarkably similar results.

Table 4 summarizes the results based on a maximum horizon of 40 quarters. The full set of impulse responses is provided in the Appendix. When using the Cholesky decomposition, only the ICT model satisfies all the criteria we laid out for the TFP news and surprise shock responses in Section 3. For all four models, the surprise shock has positive short-run impacts on TFP and real GDP, but for the R&D model the effects appear too persistent to be plausible. For the news shock, only the R&D and ICT models exhibit positive long-run effects on TFP and real GDP. However, the responses to the news shock in the R&D model are not weakly increasing as predicted by

[9] Baron and Schmidt (2019) treat technological standardization as a prerequisite for new technologies to be implemented and show that shocks to the ICT series lead to increases in TFP, output, and investment over medium-run horizons. Cascaldi-Garcia and Vukotić (2022) use a quarterly version of the patent series introduced by Kogan et al. (2017). This series weights patents by their value, measured as the response of each company's stock price due to news about the patent grant. The USPTO series is monthly and provides a record of all patent applications filed at the U.S. Patents and Trademark Office (USPTO) since 1981. The exogenous patent series is the residual from regressing the quarterly growth rate of total patent applications on lags of itself and a set of control variables that can include SPF forecasts and exogeonous policy shocks. See section 2.2 of Miranda-Agrippino et al. (2022) for specific details. To provide the longest sample possible, we consider the regression where the control variables include SPF forecasts but exclude other exogenous policy shocks. Miranda-Agrippino et al. (2022) note that their identification is robust to excluding these policy shocks.

Table 4: Results from VAR models including alternative measures of TFP news.

(a) Cholesky-identified VAR with the news variable ordered first and TFP second.

Criterion	R&D	ICT	CGV	MAHB
News shock				
Responses weakly increasing at longer horizons	N	Y	N	N
Positive long-run responses	Y	Y	N	N
Surprise shock				
Responses approaching zero in medium run	N	Y	Y	Y
Positive impact responses, no large negative responses	N	Y	Y	Y

(b) Max-share identified VAR with the variance contribution of the news variable maximized at $H_n = 4$.

Criterion	R&D	ICT	CGV	MAHB
News shock				
Responses weakly increasing at longer horizons	N	Y	N	N
Positive long-run responses	Y	Y	N	N
Surprise shock				
Responses approaching zero in medium run	N	Y	Y	Y
Positive impact responses, no large negative responses	N	Y	Y	Y

theory. Using the max-share approach does not change these findings. This evidence underscores the importance of verifying that the news and surprise shocks generate economically plausible response functions.

It is understood that the use of alternative estimators may change these results. For example, Miranda-Agrippino et al. (2022) argued for using their news variable as an external instrument to allow for measurement error rather than using it as an internal instrument, as our Cholesky model does. We do not explore this question because our objective in not to argue for a specific model but to lay out criteria that help applied researchers decide whether the estimated response patterns are economically plausible. It is also understood that these impulse response estimates may be sensitive to the choice of the VAR model variables, which explains why our impulse response estimates differ from those in Cascaldi-Garcia and Vukotić (2022) and Miranda-Agrippino et al. (2022), for example.

Finally, as discussed in Section 6, it is possible that the maintained assumption that TFP on impact is determined exclusively by news and surprise shocks may be violated. In that case, only the responses to the news shock would be identified. Under this interpretation, however, once again only the model based on the ICT variable would appear to be consistent with our response criteria, reinforcing our conclusion.

8 CONCLUSION

There has been much interest in the recent literature in distinguishing news shocks from surprise shocks to TFP. The state of the art in this literature is the identification strategy recently proposed by KS. In this paper, we clarified the conditions under which the KS procedure not only identifies the impact of news shocks, but also identifies the impact of surprise shocks. Our analysis overturns the perception that this method does not to allow users to recover surprise shocks, rendering the analysis in KS incomplete compared to earlier work that identified both news and surprise shocks. Identifying surprise shocks simultaneously with news shocks is important because the interpretation of the structural model rests not only on the responses to the news shock being consistent with *a priori* reasoning, but also the responses to the surprise shock.

Simulation evidence based on data generated from DSGE models, however, suggests that the KS estimation procedure does not work well in practice. We showed that the KS impulse response estimator of the effects of surprise and news shocks tends to be heavily biased, even in very large samples, and highly variable in small samples, suggesting caution in interpreting the estimates. This is particularly true for the responses to the news shock. This conclusion is also borne out in empirical analysis, which shows responses that are implausible in light of the underlying economic theory. We show that the hump-shaped responses of TFP and output to news shocks sometimes obtained using the KS estimator are likely an artifact of the strong bias of the KS estimator, as are responses to surprise shocks that are of the wrong sign.

This evidence raises the question of how to proceed in applied work. We discussed how including direct measures of TFP news in VAR models and adapting the identification strategy helps address the bias of the KS estimator. We proposed two such approaches that allow the identification not only of news shocks, but also of surprise shocks. These estimators have at least 80%

lower RMSE for $T = 10{,}000$ and at least 15% lower RMSE for $T = 240$ than the KS estimator. However, even these alternative approaches fail to produce reliable estimates in small samples.

The approach to jointly identifying news and surprise shocks we proposed in this paper is not without limitations. We discussed under what conditions the adding-up constraint required for deriving surprise shocks may fail in practice. How quantitatively important violations of this constraint are remains an open question. While our goal is not to advocate for any one estimation approach, we recommend several diagnostics that may be used to judge whether a given VAR model estimate of news and surprise shocks is economically plausible. These diagnostics are expected to be useful more broadly as this literature evolves.

REFERENCES

ALEXOPOULOS, M. (2011): "Read All about It!! What Happens Following a Technology Shock?" *American Economic Review*, 101, 1144–1179.

ANGELETOS, G.-M., F. COLLARD, AND H. DELLAS (2020): "Business-Cycle Anatomy," *American Economic Review*, 110, 3030–3070.

BARON, J. AND J. SCHMIDT (2019): "Technological Standardization, Endogenous Productivity and Transitory Dynamics," Manuscript, Northwestern University.

BARSKY, R. B., S. BASU, AND K. LEE (2015): "Whither News Shocks?" *NBER Macroeconomics Annual*, 29, 225–264.

BARSKY, R. B. AND E. R. SIMS (2011): "News Shocks and Business Cycles," *Journal of Monetary Economics*, 58, 273–289.

BEAUDRY, P. AND F. PORTIER (2006): "Stock Prices, News, and Economic Fluctuations," *American Economic Review*, 96, 1293–1307.

——— (2014): "News-Driven Business Cycles: Insights and Challenges," *Journal of Economic Literature*, 52, 993–1074.

BEN ZEEV, N. AND H. KHAN (2015): "Investment-Specific News Shocks and U.S. Business Cycles," *Journal of Money, Credit and Banking*, 47, 1443–1464.

BENHIMA, K. AND R. CORDONIER (2022): "News, Sentiment and Capital Flows," *Journal of International Economics*, 137.

BOUAKEZ, H. AND L. KEMOE (2022): "News Shocks, Business Cycles, and the Disinflation Puzzle," *Journal of Money, Credit and Banking, forthcoming*.

CALVO, G. A. (1983): "Staggered Prices in a Utility-Maximizing Framework," *Journal of Monetary Economics*, 12, 383–398.

CARRIERO, A. AND A. VOLPICELLA (2022): "Generalizing the Max Share Identification to Multiple Shocks Identification: An Application to Uncertainty," University of Surrey Discussion Paper 03/22.

CASCALDI-GARCIA, D. AND M. VUKOTIĆ (2022): "Patent-Based News Shocks," *Review of Economics and Statistics*, 104, 51–66.

CHEN, K. AND E. WEMY (2015): "Investment-Specific Technological Changes: The Source of Long-Run TFP Fluctuations," *European Economic Review*, 80, 230–252.

CHETTY, R., A. GUREN, D. MANOLI, AND A. WEBER (2012): "Does Indivisible Labor Explain the Difference between Micro and Macro Elasticities? A Meta-Analysis of Extensive Margin Elasticities," in *NBER Macroeconomics Annual 2012, Volume 27*, ed. by D. Acemoglu, J. Parker, and M. Woodford, MIT Press, Cambridge, 1–56.

CHRISTIANSEN, L. E. (2008): "Do Technology Shocks Lead to Productivity Slowdowns? Evidence from Patent Data," IMF Working Paper 2008/024.

COCHRANE, J. H. (1994): "Shocks," *Carnegie-Rochester Conference Series on Public Policy*, 41, 295–364.

FERNALD, J. G. (2014): "A Quarterly, Utilization-Adjusted Series on Total Factor Productivity," Federal Reserve Bank of San Francisco Working Paper 2012-19.

FÈVE, P. AND A. GUAY (2019): "Sentiments in SVARs," *Economic Journal*, 129, 877–896.

FORNI, M., L. GAMBETTI, AND L. SALA (2014): "No News in Business Cycles," *Economic Journal*, 124, 1168–1191.

FRANCIS, N. AND G. KINDBERG-HANLON (2022): "Signing Out Confounding Shocks in Variance-Maximizing Identification Methods," *AEA Papers and Proceedings*, 112, 476–80.

FRANCIS, N., M. T. OWYANG, J. E. ROUSH, AND R. DICECIO (2014): "A Flexible Finite-Horizon Alternative to Long-Run Restrictions with an Application to Technology Shocks," *Review of Economics and Statistics*, 96, 638–647.

GÖRTZ, C., C. GUNN, AND T. A. LUBIK (2022a): "Is There News in Inventories?" *Journal of Monetary Economics*, 126, 87–104.

GÖRTZ, C., J. D. TSOUKALAS, AND F. ZANETTI (2022b): "News Shocks under Financial Frictions," *American Economic Journal: Macroeconomics*, 14, 210–243.

HAMILTON, J. D. (2018): "Why You Should Never Use the Hodrick-Prescott Filter," *Review of Economics and Statistics*, 100, 831–843.

HODRICK, R. J. (2020): "An Exploration of Trend-Cycle Decomposition Methodologies in Simulated Data," NBER Working Paper 26750.

HODRICK, R. J. AND E. C. PRESCOTT (1997): "Postwar U.S. Business Cycles: An Empirical Investigation," *Journal of Money, Credit and Banking*, 29, 1–16.

KILIAN, L. AND H. LÜTKEPOHL (2017): *Structural Vector Autoregressive Analysis*, Cambridge University Press, New York.

KILIAN, L. AND D. P. MURPHY (2014): "The Role Of Inventories And Speculative Trading In The Global Market For Crude Oil," *Journal of Applied Econometrics*, 29, 454–478.

KOGAN, L., D. PAPANIKOLAOU, A. SERU, AND N. STOFFMAN (2017): "Technological Innovation, Resource Allocation, and Growth," *Quarterly Journal of Economics*, 132, 665–712.

KURMANN, A. AND E. SIMS (2021): "Revisions in Utilization-Adjusted TFP and Robust Identification of News Shocks," *Review of Economics and Statistics*, 103, 216–235.

LEVCHENKO, A. A. AND N. PANDALAI-NAYAR (2020): "TFP, News, and "Sentiments": the International Transmission of Business Cycles," *Journal of the European Economic Association*, 18, 302–341.

MARCO, A., M. CARLEY, S. JACKSON, AND A. F. MYERS (2015): "The USPTO Historical Patent Data Files Two Centuries of Innovation," USPTO Economic Working Paper No. 2015-1.

MERTENS, K. AND M. O. RAVN (2012): "Empirical Evidence on the Aggregate Effects of Anticipated and Unanticipated US Tax Policy Shocks," *American Economic Journal: Economic Policy*, 4, 145–181.

MIRANDA-AGRIPPINO, S., S. H. HOKE, AND K. BLUWSTEIN (2022): "Patents, News, and Business Cycles," Manuscript, Bank of England.

NAM, D. AND J. WANG (2015): "The Effects of Surprise and Anticipated Technology Changes on International Relative Prices and Trade," *Journal of International Economics*, 97, 162–177.

SHEA, J. (1999): "What Do Technology Shocks Do?" in *NBER Macroeconomics Annual 1998, volume 13*, ed. by B. S. Bernanke and J. Rotemberg, MIT Press, 275–322.

SIMS, C. A. (2002): "Solving Linear Rational Expectations Models," *Computational Economics*, 20, 1–20.

UHLIG, H. (2004): "Do Technology Shocks Lead to a Fall in Total Hours Worked?" *Journal of the European Economic Association*, 2, 361–371.

Online Appendix: Jointly Estimating Macroeconomic Surprise and News Shocks*

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*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 from 1960Q1-2019Q4 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. **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). The series is available at https://justusbaron.org/data/.

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. The series 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 ORTHOGONALITY CONDITIONS

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 Section 2.2 of the main text 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 by dividing trending variables by $\tilde{x}_t \equiv z_t^{1/(1-\alpha)}$. The equilibrium system is given by

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

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

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

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

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

$$\tilde{c}_t + \tilde{\imath}_t = \tilde{y}_t \tag{6}$$

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

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

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

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

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

$$\Delta_t = (1-\theta) p_{f,t}^{-\epsilon} + \theta(\pi_t/\bar{\pi})^{\epsilon} \Delta_{t-1} \tag{12}$$

$$1 = (1-\theta) p_{f,t}^{1-\epsilon} + \theta(\pi_t/\bar{\pi})^{\epsilon-1} \tag{13}$$

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

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

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

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

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

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

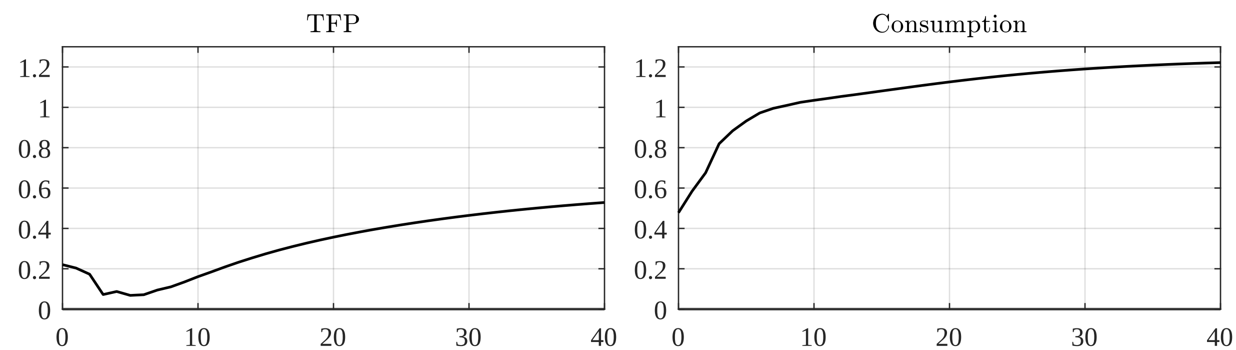
D ADDITIONAL RESULTS

This section presents several additional results:

- Empirical impulse response estimates based on the KS max share estimator of the 4-variable VAR model in KS, 1960Q1-2019Q4 (Figure 1).
- Impulse response estimates based on the KS max share estimator and $\mathbf{y}_t = (a_t, y_t, i_t)'$ using data simulated from our DSGE model under the KS TFP process (Figure 2).
- Impulse response estimates based on the Cholesky identification and $\mathbf{y}_t = (z_t, a_t, y_t)'$ using simulated data from our baseline DSGE model (Figure 3).
- Empirical impulse response estimates from 9-variable VAR models with alternative TFP news series of different lengths:
  - Cholesky identification: Figures 4-7
  - Max-share news identification: Figures 8-11
- Impulse response estimates based on the KS max share estimator using data simulated from the medium-scale DSGE model in KS under the KS TFP parameterization and our TFP calibration (Figure 12).

Figure 1: Max-share identified impulse responses based on the 4-variable VAR in KS

(a) News shock



(b) Surprise shock

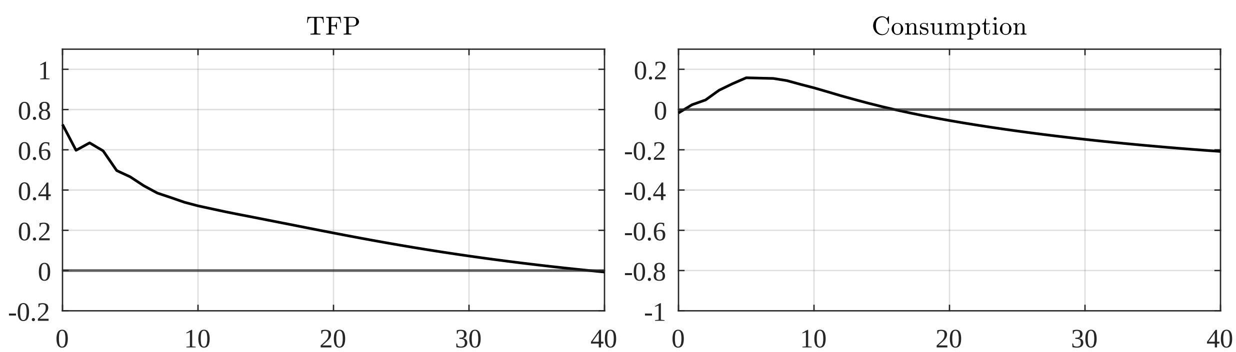
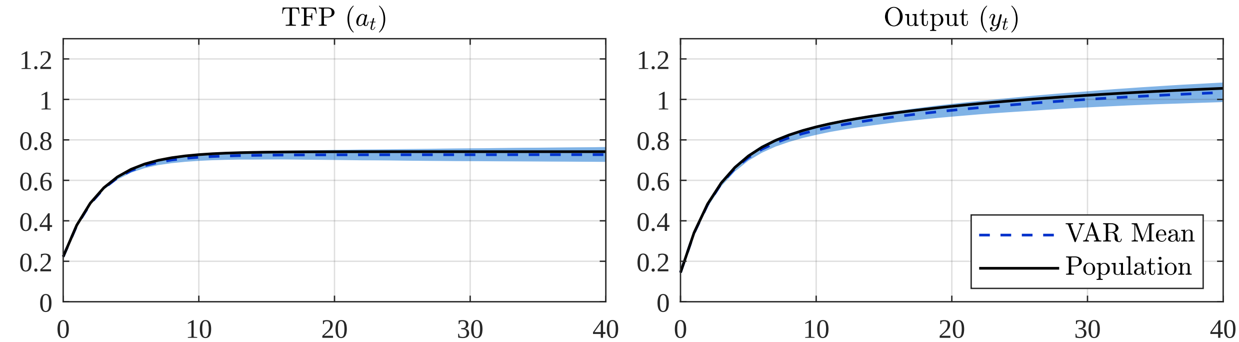
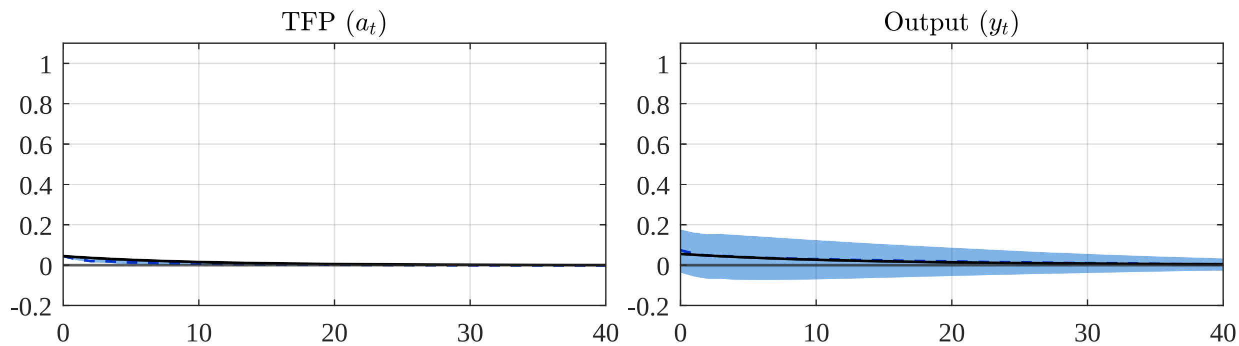


Figure 2: KS max-share identified impulse responses under the KS TFP process, $\mathbf{y}_t = (a_t, y_t, i_t)'$

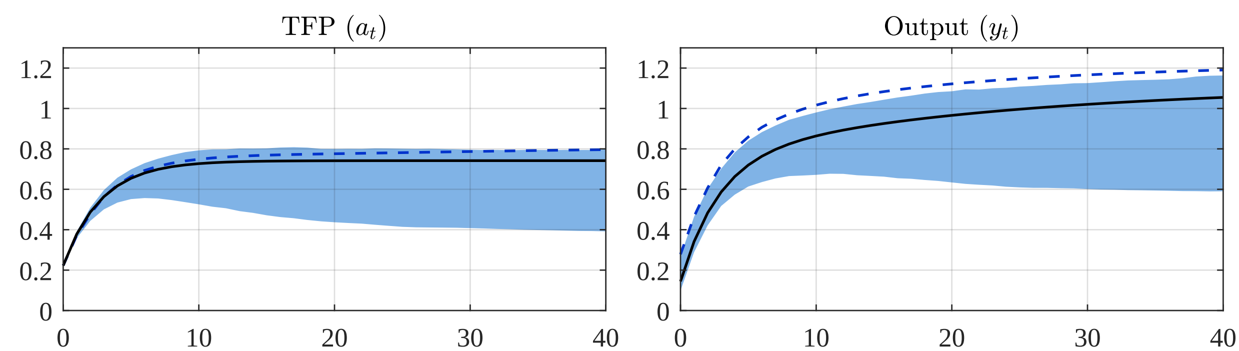
(a) News shock, $T = 10{,}000$



(b) Surprise shock, $T = 10{,}000$



(c) News shock, $T = 240$



(d) Surprise shock, $T = 240$

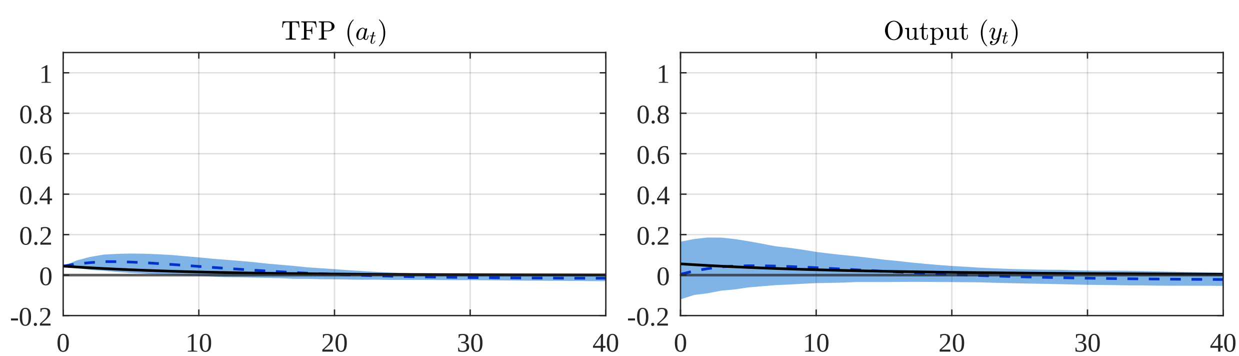
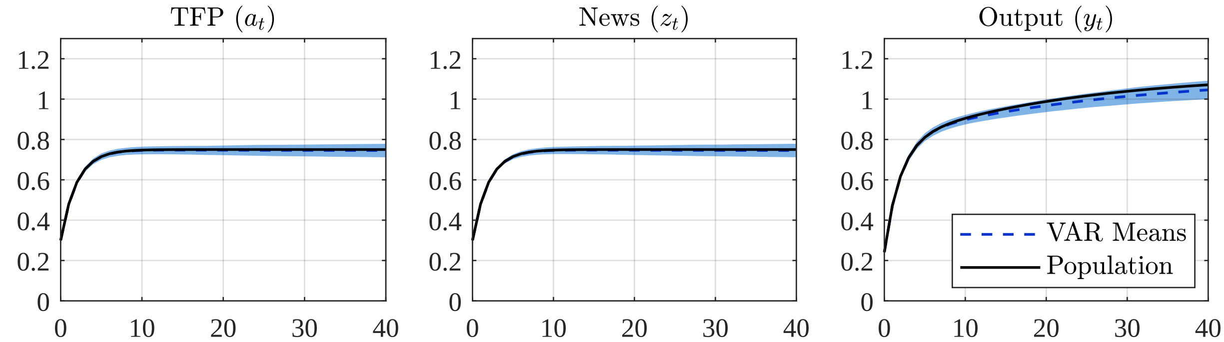
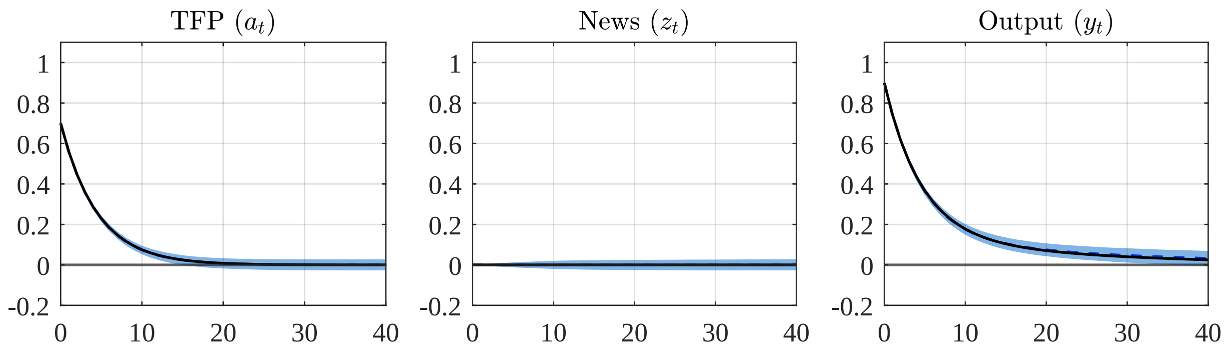


Figure 3: Cholesky identified impulse responses, $\mathbf{y}_t = (z_t, a_t, y_t)'$

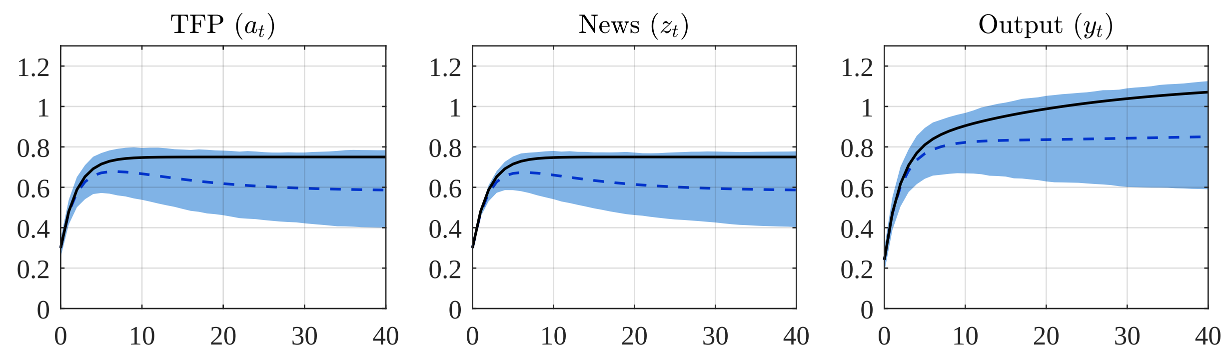
(a) News shock, $T = 10{,}000$



(b) Surprise shock, $T = 10{,}000$



(c) News shock, $T = 240$



(d) Surprise shock, $T = 240$

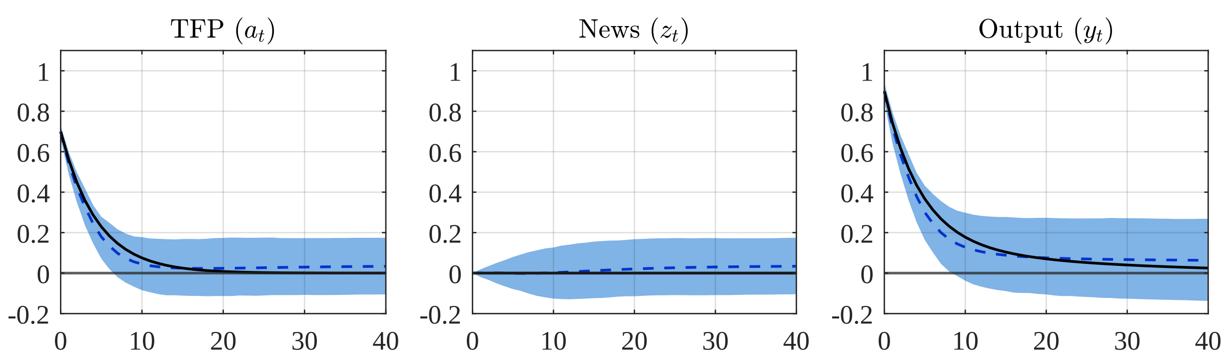
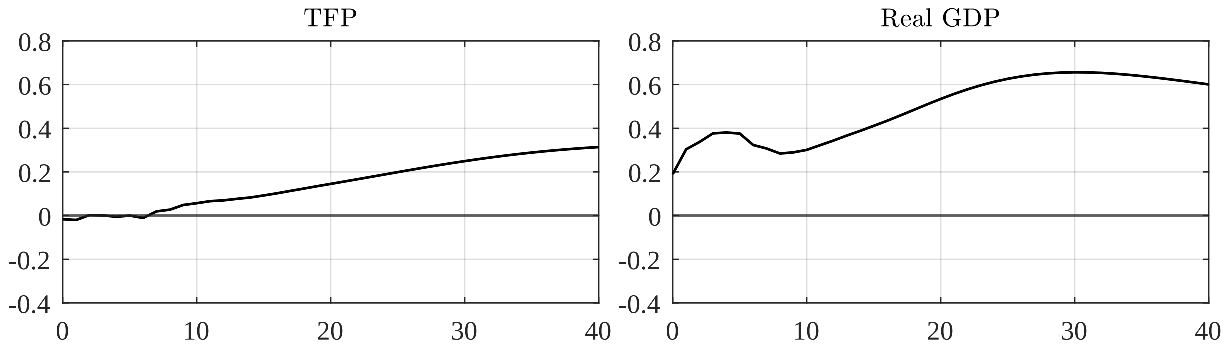


Figure 4: Cholesky identified impulse responses with real R&D expenditures

(a) News shock



(b) Surprise shock

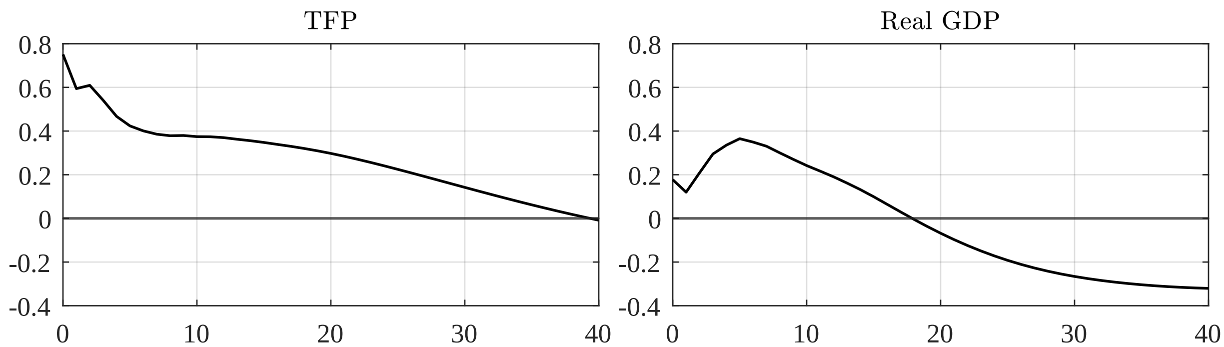
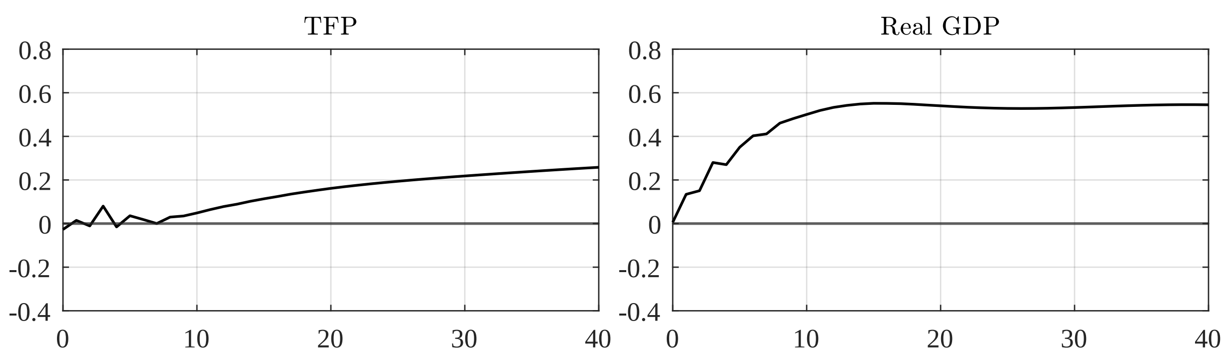


Figure 5: Cholesky identified impulse responses with the ICT index

(a) News shock



(b) Surprise shock

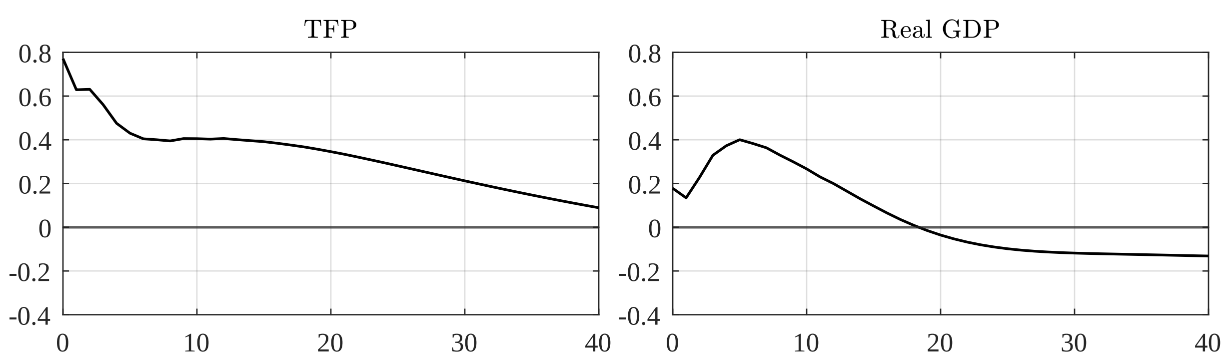
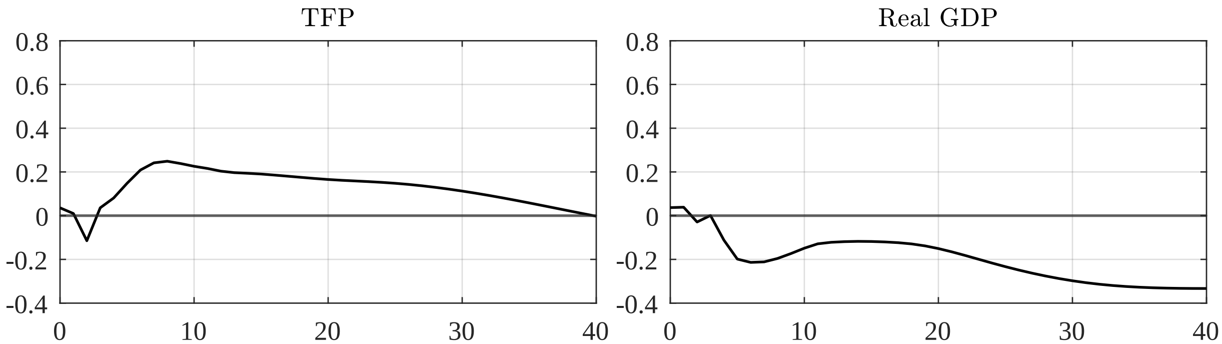


Figure 6: Cholesky identified impulse responses with the CGV series

(a) News shock



(b) Surprise shock

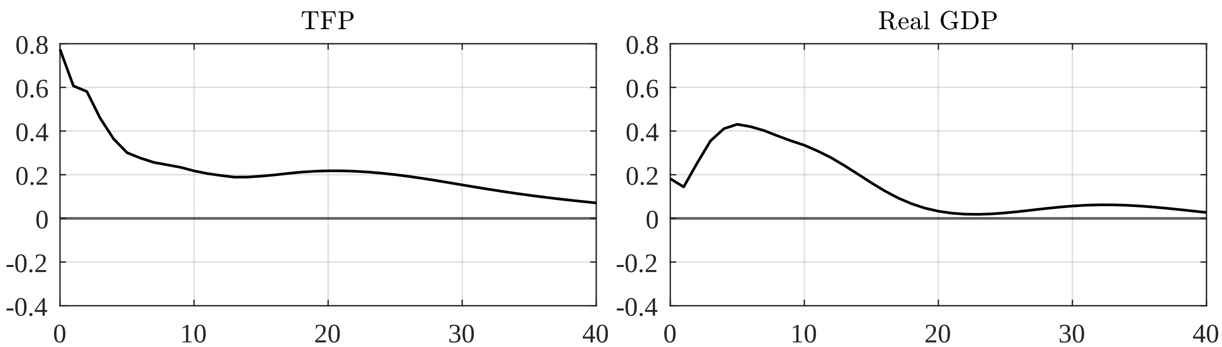
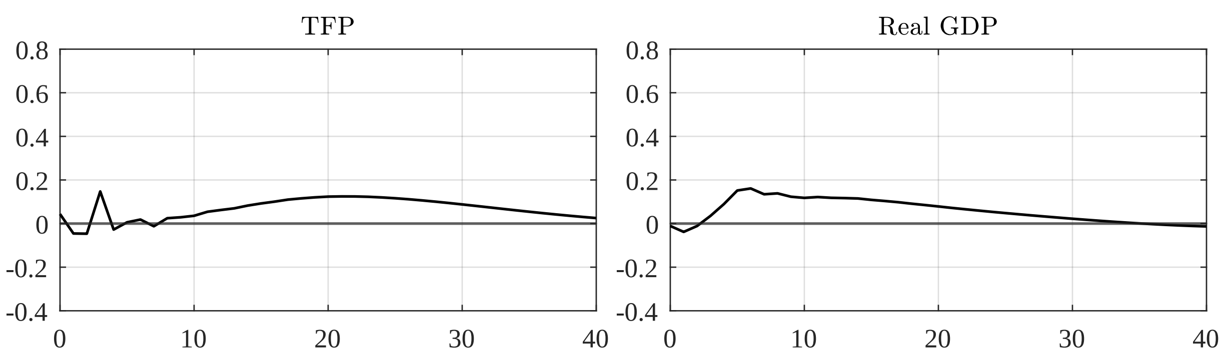


Figure 7: Cholesky identified impulse responses with the MAHB series

(a) News shock



(b) Surprise shock

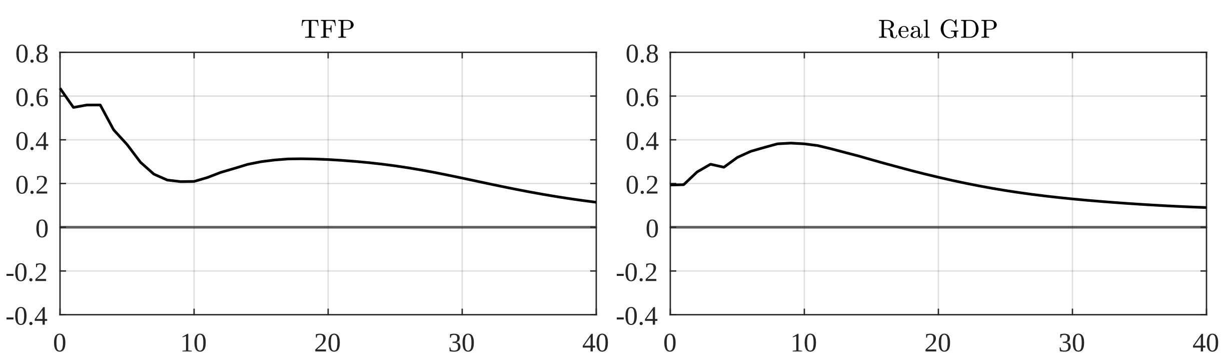
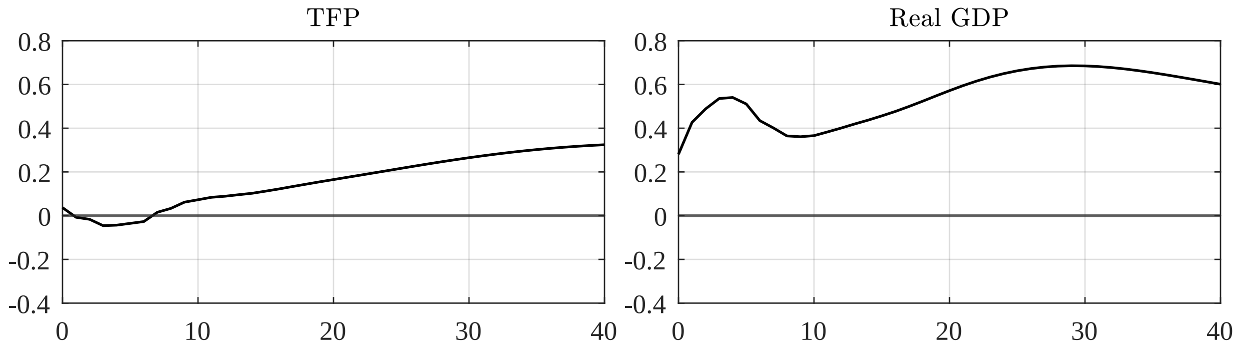


Figure 8: Max-share identified impulse responses with real R&D expenditures

(a) News shock



(b) Surprise shock

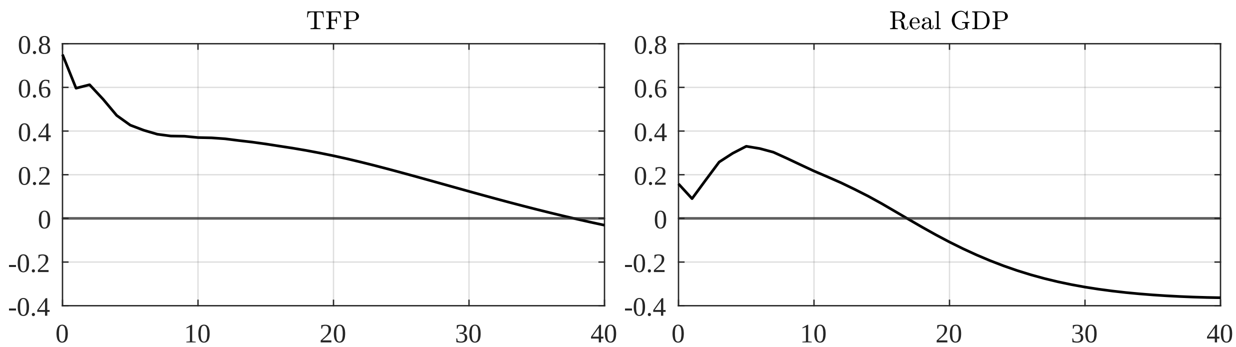
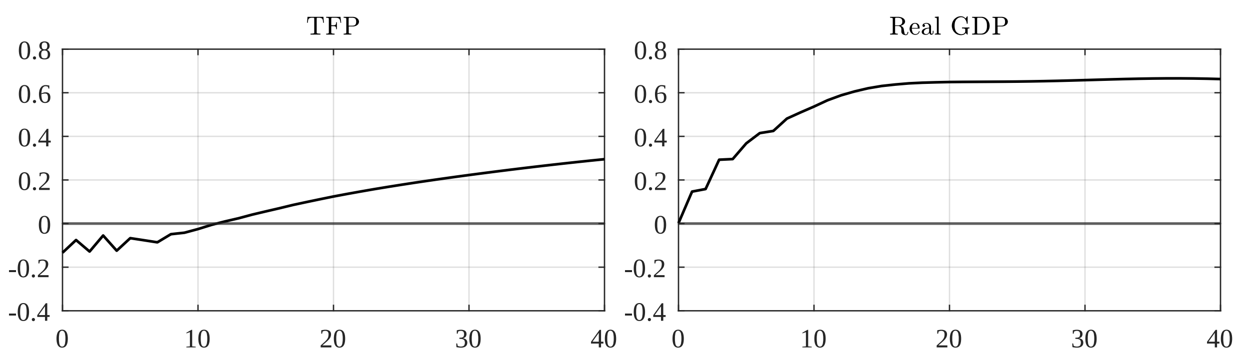


Figure 9: Max-share identified impulse responses with the ICT series

(a) News shock



(b) Surprise shock

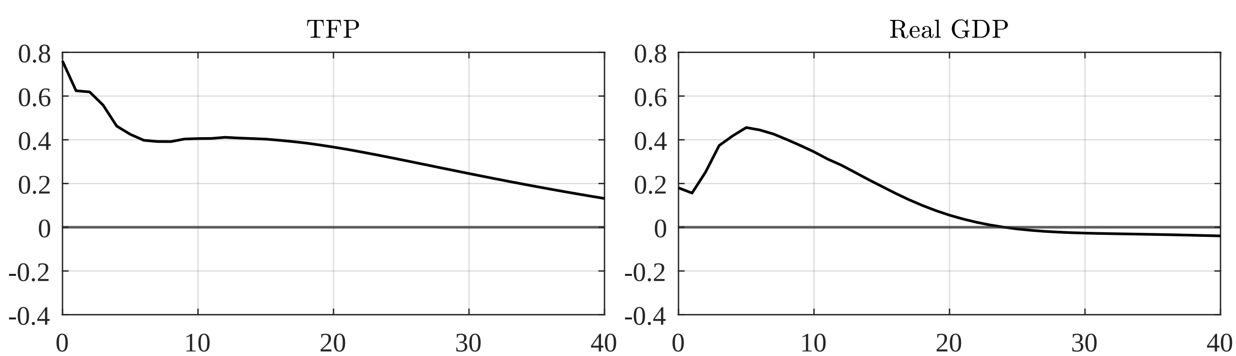
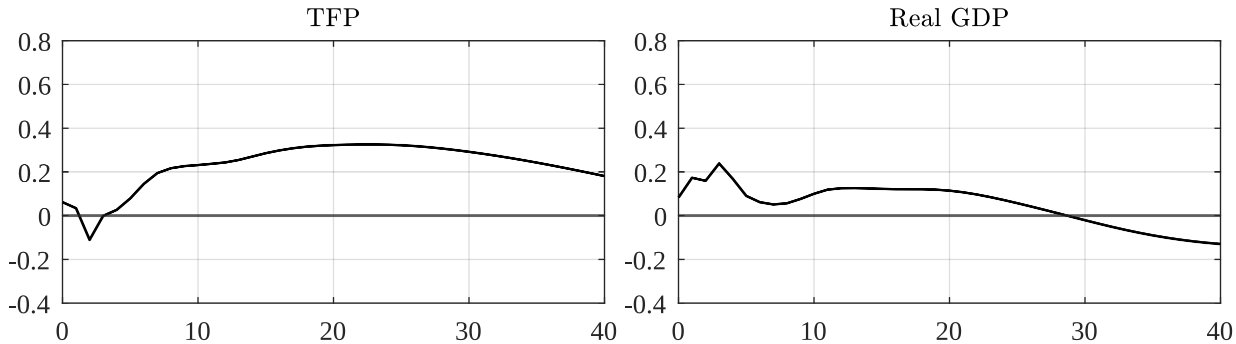


Figure 10: Max-share identified impulse responses with the CGV series

(a) News shock



(b) Surprise shock

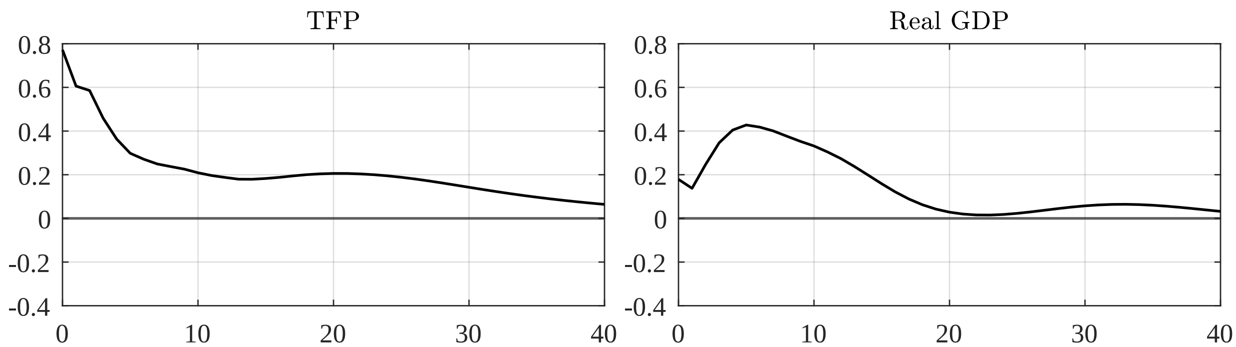
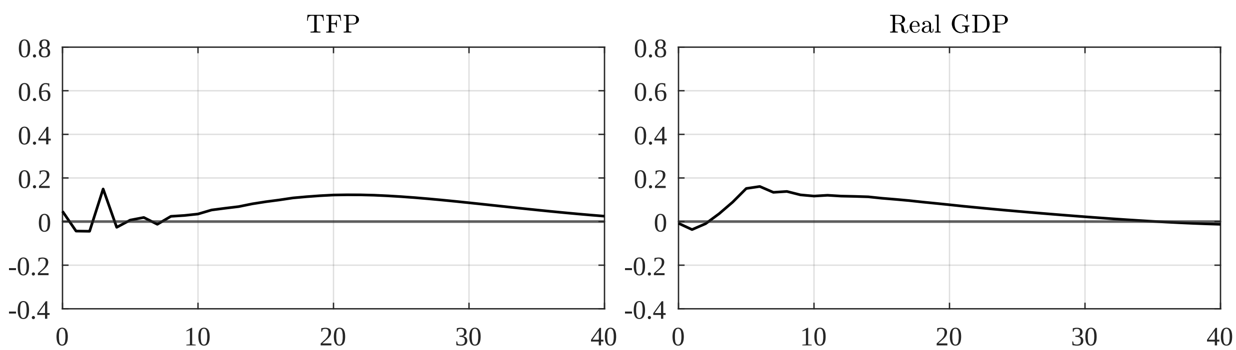


Figure 11: Max-share identified impulse responses with the MAHB series

(a) News shock



(b) Surprise shock

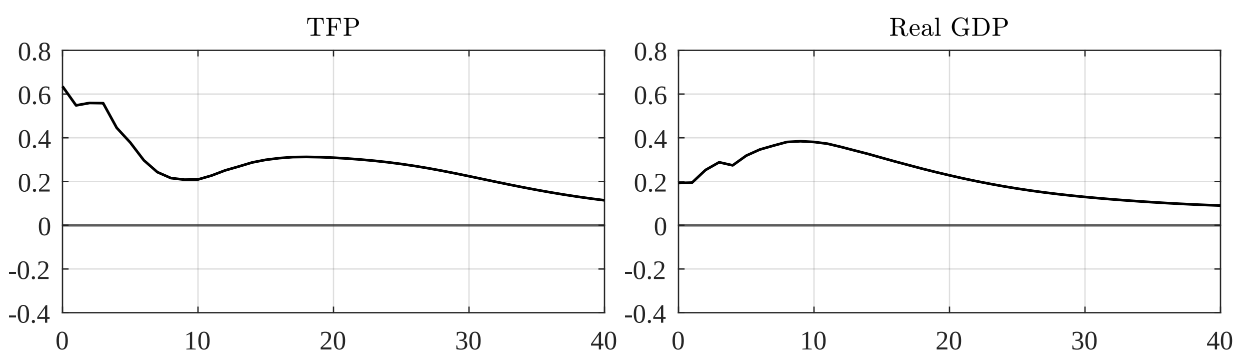
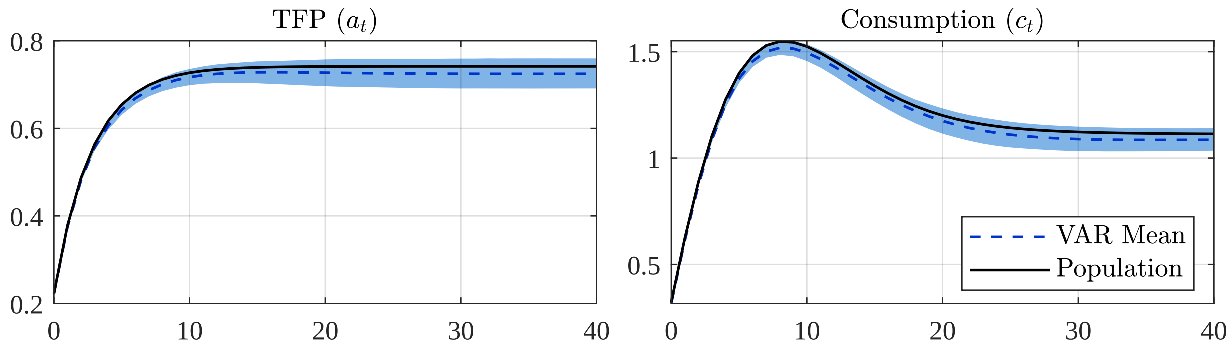
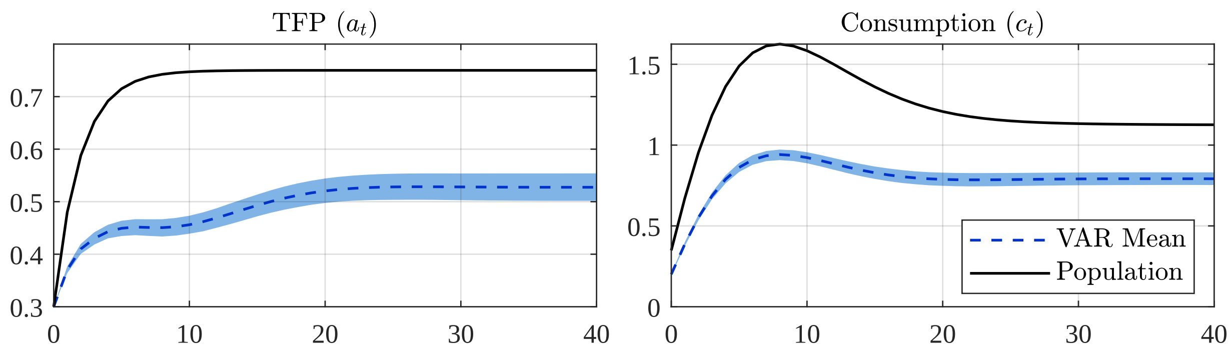


Figure 12: Max-share identified impulse responses to a news shock based on KS DSGE model

(a) KS TFP parameterization



(b) Our TFP calibration



REFERENCES

BARON, J. AND J. SCHMIDT (2019): "Technological Standardization, Endogenous Productivity and Transitory Dynamics," Manuscript, Northwestern University.

CASCALDI-GARCIA, D. AND M. VUKOTIĆ (2022): "Patent-Based News Shocks," *Review of Economics and Statistics*, 104, 51–66.

KOGAN, L., D. PAPANIKOLAOU, A. SERU, AND N. STOFFMAN (2017): "Technological Innovation, Resource Allocation, and Growth," *Quarterly Journal of Economics*, 132, 665–712.

MARCO, A., M. CARLEY, S. JACKSON, AND A. F. MYERS (2015): "The USPTO Historical Patent Data Files Two Centuries of Innovation," USPTO Economic Working Paper No. 2015-1.

MIRANDA-AGRIPPINO, S., S. H. HOKE, AND K. BLUWSTEIN (2022): "Patents, News, and Business Cycles," Manuscript, Bank of England.