Federal Reserve Bank of Dallas

Estimating Macroeconomic News and Surprise Shocks

Lutz Kilian, Michael D. Plante and Alexander W. Richter

Working Paper 2304 **April 2023 (Revised November 2023)**

Research Department

https://doi.org/10.24149/wp2304r1

Estimating Macroeconomic News and Surprise Shocks*

Lutz Kilian†, Michael D. Plante‡ and Alexander W. Richter§

April 16, 2023
Revised: October 13, 2023

Abstract

The importance of understanding the economic effects of TFP news and surprise shocks is widely recognized in the literature. This paper examines the ability of the state-of-the-art VAR approach in Kurmann and Sims (2021) to identify responses to TFP news shocks and possibly surprise shocks in theory and practice. When applied to data generated from conventional New Keynesian DSGE models with shock processes that match key TFP moments, this estimator tends to be strongly biased, both in the presence of TFP measurement error and in its absence. This bias worsens in realistically small samples, and the estimator becomes highly variable. Incorporating a direct measure of TFP news into the VAR model (and adapting the identification strategy accordingly) substantially reduces the bias and RMSE of the impulse responses, regardless of whether there is TFP measurement error.

Keywords: Structural VAR; TFP; news; anticipated technology; measurement error; max-share

JEL Classifications: C32, C51, C61, E32

---

*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.

†Lutz Kilian, Research Department, Federal Reserve Bank of Dallas, 2200 N Pearl Street, Dallas, TX 75201, and CEPR, lkilian2019@gmail.com.

‡Michael D. Plante, Research Department, Federal Reserve Bank of Dallas, 2200 N Pearl Street, Dallas, TX 75201, michael.plante@dal.frb.org.

§Corresponding author: Alexander W. Richter, Research Department, Federal Reserve Bank of Dallas, 2200 N Pearl Street, Dallas, TX 75201, alex.richter@dal.frb.org.

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 TFP news shocks.[1]

As recently stressed by Barsky et al. (2015) and Kurmann and Sims (2021, henceforth, KS), the assumption that news shocks affect TFP only with a delay is hard to defend on *a priori* grounds. One reason is that new technologies may affect TFP immediately, 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 allow news shocks to have contemporaneous effects on TFP. Second, they construct the shock that

[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).

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 to that horizon. They interpret that shock as a news shock if it causes TFP to increase gradually, while causing TFP news indicators to jump on impact. KS show that their alternative max-share estimates are robust to revisions in the widely used measure of TFP developed by Fernald (2015), whereas the BS estimates are not. The central insight of KS is that one should not take measures of TFP at face value in empirical work. A related point has also been made by Bouakez and Kemoe (2022). The point of our paper is not to question the potential importance of TFP measurement error, but to draw attention to a separate practical issue that has not been recognized in this literature to date—the sensitivity of the KS estimator of news shocks to how much TFP is driven by surprise shocks (or other non-news shocks), not only at long horizons but also at shorter horizons.

Our first contribution is to clarify how TFP measurement error affects the identification of news and surprise shocks when using the max-share approach. KS stress that TFP measurement error prevents them from separately identifying surprise shocks to current TFP from news shocks about future TFP. We analytically show that the inability of the KS max-share estimator to identify the surprise shock is not a consequence of dropping the exclusion restriction in BS or of focusing only on longer horizons. Rather, it is the result of dropping the additional restriction underlying the BS estimator that no shock other than the news shock and surprise shock affects TFP on impact. When TFP innovations are explained by news and surprise shocks only, the impact of the surprise shock is directly implied by the impact response of the news shock without further identifying assumptions.

Even if these surprise shocks are not identified, however, their presence matters for the reliability of the KS estimator. Indeed, KS state that their approach works well "as long as news shocks account for a large part of the unpredictable variation in adjusted TFP at long horizons." Our second contribution is to show that this condition is not sufficient to ensure the accuracy of the estimator. This conclusion is based on a detailed study of the ability of the KS estimator to recover responses to news shocks from data generated by New Keynesian dynamic stochastic general equilibrium (DSGE) models, both with and without TFP measurement error.

We first examine the accuracy of the KS estimator under ideal conditions in the absence of TFP measurement error in a conventional DSGE model. We demonstrate that even when virtually all variation in TFP at the 80-quarter horizon is explained by news shocks, the KS estimator may fail to recover the responses to news shocks in the asymptotic limit. This example illustrates that the accuracy of the KS estimator not only depends on the quantitative importance of news shocks at long horizons but also at shorter horizons.

Our conclusion may seem at odds with simulation evidence reported by KS that their estimator comes somewhat close to the population responses to a news shock when $T = 10{,}000$ quarters. While we can replicate these findings under their parameterization of the TFP process, which implies that surprise shocks are not an important determinant of TFP at any horizon, our evidence suggests that this parameterization is at odds with the data. When the parameters in our DSGE model 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 $T = 240$, and in addition the estimator becomes highly variable. We trace this problem to the inability of the KS estimator to distinguish the effects of news and non-news shocks at shorter horizons.[2]

We then examine the accuracy of the KS estimator using the larger-scale DSGE model developed by KS, which allows for TFP measurement error. Setting the parameters of this model to match the TFP moments in the data reveals another potential problem with the KS estimator, in addition to the problem already encountered in the baseline model. We find that in this case the maintained assumption in KS that news shocks explain virtually all long-run variation in measured TFP no longer obviously holds. This fact further helps explain why the bias of the KS estimator in this model persists even asymptotically.

These results raise the question of what alternative methods are available to applied researchers.

[2] We also show that when TFP is measured correctly, the same model may be estimated 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. This alternative estimator is even less accurate than the original KS estimator.

Our third 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 empirical studies, will substantially reduce the asymptotic bias, assuming that the news are measured reasonably accurately.[3] We discuss two such identification strategies. One is based on maximizing the variance share of the news variable to TFP on impact and is new to the literature. The other treats news variable innovations as predetermined as in Cascaldi-Garcia and Vukotić (2022). The latter estimator may also be given an instrumental variable (IV) interpretation, and hence allows for measurement error in the TFP news variable. In practice, these estimators tend to produce similar estimates.

While we are not the first to employ direct measures of TFP news for identifying news shocks, we are the first to examine the ability of these estimators to recover the population responses from data generated by DSGE models. We first show that appropriately constructed estimators based on news variables have substantially lower bias and root mean squared error (RMSE) than the KS estimator in the absence of TFP measurement error. Our evidence suggests that estimators based on TFP news variables avoid the identification problems of the KS estimator we documented earlier. Moreover, under the maintained assumption that only news and surprise shocks affect TFP innovations, news variable based estimators of the news shock may be used to recover estimates of the surprise shock, much like the KS estimator. We then compare the news variable VAR estimators to the KS estimator in the presence of TFP measurement error. We document that these methods, while not immune from TFP measurement error, still substantially reduce the RMSE of output and TFP responses to news shocks in that case compared to the KS estimator.

Finally, we illustrate the use of TFP news for identifying news shocks using a range of alternative measures of TFP news that have been used in other studies. We find that two of these specifications generate economically plausible results in light of the underlying economic theory, suggesting that this approach may work not only in simulations but also in practice.

The remainder of the paper is organized as follows. In Section 2, we review the estimation of news shocks obtained by maximizing the contribution of the news shock to the forecast error

[3]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).

variance of TFP at long, but finite horizons, and derive the identification conditions for the surprise shock. In Section 3, we use data generated from a conventional DSGE model to examine the accuracy of the KS estimator. In Section 4, we extend the analysis to models with TFP measurement error. In Section 5, we use these DSGE models to examine the accuracy of two alternative identification strategies that accommodate TFP measurement error by including a direct measure of TFP news in the VAR model. In Section 6, we examine the plausibility of the empirical responses to news shocks from a range of models based on alternative measures of TFP news. Section 7 contains the concluding remarks.

2 IDENTIFICATION PROBLEM

KS observe that TFP mismeasurement makes it impossible to separately identify news shocks and surprise shocks. However, the basis of this conclusion is not made explicit. In this section we clarify how measurement error affects the identification of surprise shocks and formally show that, in the absence of TFP measurement error, the KS estimator identifies both news and surprise shocks. This result also applies to the alternative estimators based on directly observable news variables discussed in Section 5.

KS stress that imperfect measurement of factor utilization causes the BS estimator of the news shock to produce misleading results. Their alternative estimator is intended to be robust to TFP mismeasurement, at the cost of not being able to identify the surprise shock. KS emphasize that the key difference is that their estimator does not impose the restriction that news shocks do not affect TFP on impact and it only focuses on longer horizons. The inability of the KS estimator to identify the surprise shock, however, is not a consequence of these differences. As shown in this section, it is the result of dropping the additional restriction underlying the BS estimator that no shock other than the news shock or surprise shock can affect TFP on impact. This third key difference from the BS estimator is not discussed in KS.

Thus, the method employed by KS to estimate the news shock does not by itself prevent us from identifying the surprise shock. In fact, the estimate of the news shock in KS directly implies an estimate of the surprise shock, as long as TFP is measured correctly, given the exclusion restriction in the orthogonal matrix used in constructing the estimator. The identification of the surprise shock breaks down only when TFP is mismeasured.

While we are not questioning that TFP measurement error is likely in empirical work, this result is important for two reasons. First, it implies that these estimators will be able to deliver estimates of the surprise shock if the accuracy of TFP measures can be improved. Second, and more importantly, this result allows us to shed light on the ability of the KS estimator to recover the population responses to news and surprise shocks under ideal conditions in a model without TFP measurement error. The advantage of focusing on this ideal setting is that it clarifies that the inability of the KS estimator to identify news shocks (and therefore surprise shocks) we document in Section 3 is not related to TFP measurement error, but is more fundamental.

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 Q.

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

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

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 Q. 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. Then the orthogonal rotation matrix is given by

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

where $\gamma_{s,j}$ and $\gamma_{n,j}$ are elements associated with the impact of the surprise and news shock, respectively, on variable $j = 1, 2, 3$. $\gamma_{\ell,j}$ are the elements associated with an unnamed third shock. KS 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 Q 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.

One key difference between the BS estimator and the KS estimator is that BS restricted $\gamma_{n,1}$ and $\gamma_{\ell,1}$ to zero, which implies that $\gamma_{s,1} = 1$ given the orthogonality of Q. This follows from their assumption that TFP innovations are fully explained by the surprise shock. The KS estimator, in contrast, allows news shocks to affect TFP contemporaneously and hence leaves $\gamma_{n,1}$ unrestricted.

This leaves open the question of what to do about the additional restriction $\gamma_{\ell,1} = 0$ maintained in BS. Although KS do not directly address this question, it is readily apparent that the existence of TFP measurement error necessitates dropping the restriction that only news and surprise shocks affect TFP contemporaneously. This creates a third important difference between the BS estimator and the KS estimator in addition to the differences discussed in KS.

Whether one imposes the added restriction $\gamma_{\ell,1} = 0$ or not does not affect the estimate of the new shock proposed by KS, but determines whether the surprise shock can be identified in this model. As long as TFP innovations are fully explained by news and surprise shocks, as would be the case in DSGE models without TFP measurement error, it has to be the case that $\gamma_{\ell,1} = 0$. The latter case is of independent interest as a benchmark when studying the ability of the KS estimator to recover the population responses. If the KS estimator does not work in this ideal setting, clearly it would not be expected to work in less than ideal settings with TFP measurement error. Next, we formally show that the absence of measurement error yields an additional restriction on the KS model such that the KS estimator of the news shock implies an estimator of the surprise shock without further identifying restrictions. This result will be used in Section 3 and Section 5 in the evaluation of the KS estimator and related VAR estimators based on direct measures of TFP news.

2.3 IDENTIFICATION CONDITIONS

We now examine in more detail the identification conditions when TFP is affected only by news and surprise shocks so $\gamma_{\ell,1} = 0$. 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

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

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

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

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

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

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

Following KS, γ_n is obtained by maximizing the forecast error variance share of the news shock subject to (R1-1). Given γ_n, (R1-1)-(R1-5) 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 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 are identified. This result means it is sufficient to compare the explanatory power of both

TFP shocks without having to take a stand on the identification of the other $K-2$ structural shocks.

While our illustrative example is for $K = 3$, the following proposition shows that the KS estimator of the news shock in the absence of TFP measurement error also identifies the surprise shock more generally.

Proposition 1. *In the absence of TFP measurement error, γ_s will be uniquely identified for any given estimate of γ_n obtained using the KS estimator. 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 conditions 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 show that when solving for γ_n and γ_s, γ_ℓ can always be chosen such that Q is orthogonal.

3 Assessing the Accuracy of the KS Estimator

3.1 Data Generating Process

A useful starting point is a model in which there is no TFP measurement error. In this section, we investigate the properties of the KS max-share identification strategy given the added restriction $\gamma_{\ell,1} = 0$ using data generated from a conventional New Keynesian model (henceforth, the "baseline model"), which is a simplified version of the model used by KS. The key difference is that we abstract from time-varying factor utilization, which only matters when modeling TFP measurement error. The full KS model will be examined in Section 4.

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

$$r_t^k = \alpha mc_t a_t k_{t-1}^{\alpha-1} n_t^{1-\alpha},$$

$$w_t = (1-\alpha) mc_t a_t k_{t-1}^{\alpha} n_t^{-\alpha},$$

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

Following Calvo (1983), a fraction, θ_p, 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 $E_t \sum_{k=t}^{\infty} \theta_p^{k-t} x_{t,k} d_k^*$, where $x_{t,t} \equiv 1$, $x_{t,k} \equiv \prod_{j=t+1}^{k>t} x_j$, and $d_k^* = [(\bar{\pi}^{k-t} p_t^*/p_k)^{1-\epsilon_p} - mc_k(\bar{\pi}^{k-t} p_t^*/p_k)^{-\epsilon_p}] y_k$. Letting $p_{f,t} \equiv p_t^*/p_t$, optimality implies

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

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

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

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

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

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

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

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 Appendix C. We solve the log-linearized model using Sims (2002) `gensys` algorithm.

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, $\epsilon_p = 11$, the degree of price stickiness, $\theta_p = 0.75$, 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 latest vintage of TFP data produced by Fernald.

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 $\rho_g = 0.6$, $\rho_s = 0.8$, $\rho_\mu = 0.9$, $\sigma_g = 0.003$, $\sigma_s = 0.007$, 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.

3.2 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

[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.

Table 1: Data moments and model-implied moments from the baseline DSGE model

Moment	Data	Baseline Model	Baseline Model with KS TFP Parameterization
$SD(\tilde{a})$	2.01	2.31	1.45
$SD(\Delta a)$	0.80	0.83	0.30
$AC(\tilde{a})$	0.87	0.88	0.88
$AC(\Delta a)$	−0.09	0.04	0.67
$SD(\tilde{y})$	3.13	2.88	1.79
$SD(\tilde{\imath})$	9.63	9.62	7.20

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

work with a VAR(4) model with intercept for $\mathbf{y}_t = (a_t, y_t, i_t)'$, given that investment has a strong 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 1 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.[5]

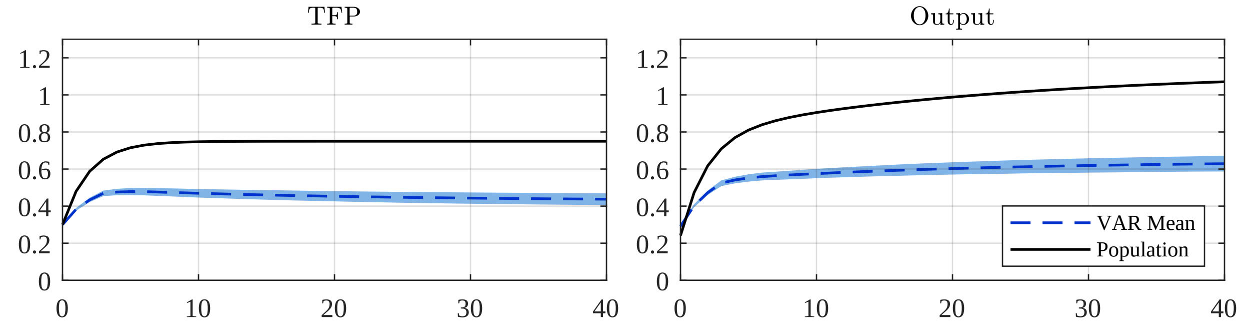
It is useful to start with results for $T = 10{,}000$. The top row shows that in this case the responses of TFP and output to a news shock are strongly biased downwards relative to the population responses. The responses to the surprise shock shown in the second row are also biased downwards with the 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, even asymptotically. The concern here is not only that the signs of the responses and the shapes of the response functions may differ systematically from the population responses, but also the magnitude, which in turn is expected to affect the quantitative importance of the news shock in explaining the variability of the model data, as reported in KS.

While our results for $T = 10{,}000$ are informative about the asymptotic properties of the es-

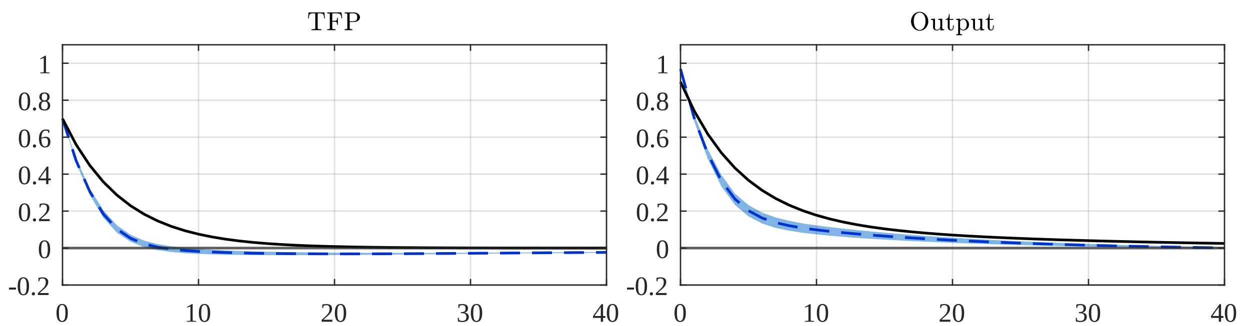
[5] It can be shown that the sufficient condition for invertibility derived in Fernández-Villaverde et al. (2007) is met in both the baseline model and in the KS DSGE model introduced in Section 4. This implies that both DSGE models have a VAR(∞) representation, as assumed by KS.

Figure 1: KS max-share identified impulse responses based on the baseline DSGE model

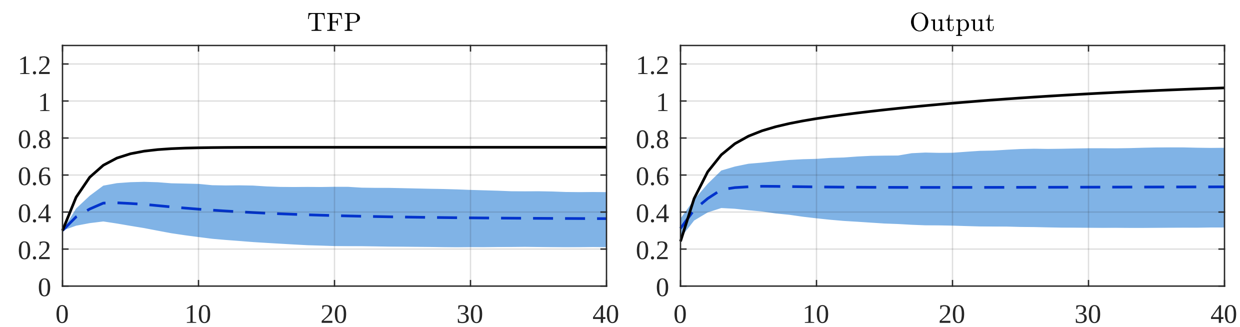
(a) News shock, $T = 10{,}000$



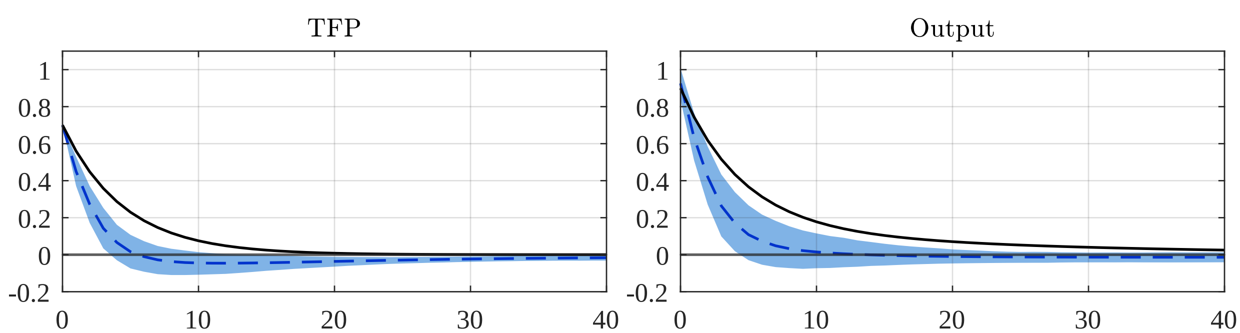
(b) Surprise shock, $T = 10{,}000$



(c) News shock, $T = 240$



(d) Surprise shock, $T = 240$



Notes: Based on a VAR(4) model for $\mathbf{y}_t = (a_t, y_t, i_t)'$. The responses have been scaled so the impact response of TFP matches the population value.

timator, 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 1 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 ideal setting without TFP measurement error. This is particularly true for the estimator of the responses to news shocks.[6]

3.3 Comparison with KS Simulation Evidence

Contrary to our findings, KS report having some success identifying the news shock in a Monte Carlo exercise with $T = 10{,}000$ based on a larger-scale DSGE model. The key difference is not the inclusion of additional DSGE model features or that KS allow for TFP measurement error, but that they use a different parameterization for the TFP process ($\rho_g = 0.7$, $\rho_s = 0.9$, $\sigma_g = 0.002125$ and $\sigma_s = 0.000425$). KS note that their TFP parameterization is based on "standard values" in the literature. However, most DSGE models feature either a stationary or a permanent TFP shock process. When a model features both processes—as is the case in their model—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. The last column of Table 1 shows the implied model moments when using 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 drives 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

[6]It can be shown that imposing additional theoretically motivated sign and magnitude restrictions, as discussed in Francis and Kindberg-Hanlon (2022), does not help address these identification problems.

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

	Baseline Model			Baseline Model with 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

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

eliminates the surprise shock and makes it easier for the KS procedure to identify the news shock. This explains the comparatively high 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 illustrated in Figure 1.

Our analysis suggests that the KS method will not work unless the role of the surprise shock is negligible at all horizons, rendering the identification of the news shock trivial. This conclusion differs materially from that in KS who state that "the max-share identification performs well as long as news shocks account for a large part of the unpredictable variation in adjusted TFP at long horizons." As Table 2 shows, even when surprise shocks only account for 3% of the variation in TFP growth at $h = 80$, the KS estimator fails to identify the response to the news shock. In other words, the success of the KS estimator hinges on the surprise shock playing a small role even at horizons much shorter than $h = 80$.

Intuitively, when surprise shocks are nontrivial in population, the estimator proposed by KS will confound surprise and news shocks. Focusing on models without TFP measurement error makes this point especially clear. Since one does not know how important surprise shocks are in applied work, this result cautions against the use of the KS estimator. After all, the objective of KS is to quantify the importance of news shocks, so a procedure that only works when news shocks are known *a priori* to explain nearly all of the variation in TFP at all horizons is of limited use in applied work. In the latter case, one could dispense with the max-share VAR approach and estimate the news shock directly from the TFP data.

These results are not specific to the DSGE model specification we employ. We show in Section 4 that the invalidity of the KS estimator also extends to the DSGE model analyzed in KS, when replacing the parameters in their TFP process with calibrated parameters set to match TFP moments.

3.4 An Alternative Estimator

It should be noted that this is not the only way to estimate this VAR model in the absence of TFP measurement error. 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 baseline DSGE model in Section 3.1.

More formally, this alternative estimator is defined as

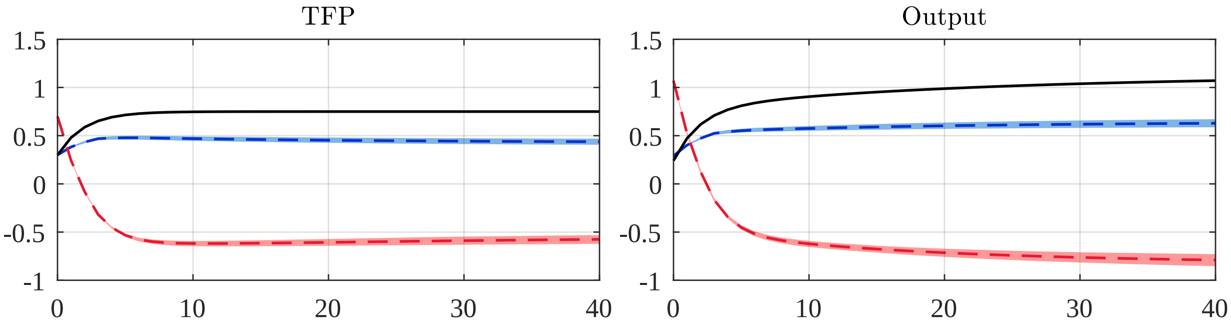
$$\gamma_s = \text{argmax } \Omega_{1,1}(H_s) = \text{argmax } \frac{\sum_{\tau=0}^{H_s} \Phi_{1,\tau} P \gamma_s \gamma_s' P' \Phi_{1,\tau}'}{\sum_{\tau=0}^{H_s} \Phi_{1,\tau} \Sigma \Phi_{1,\tau}'} \tag{3}$$

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).

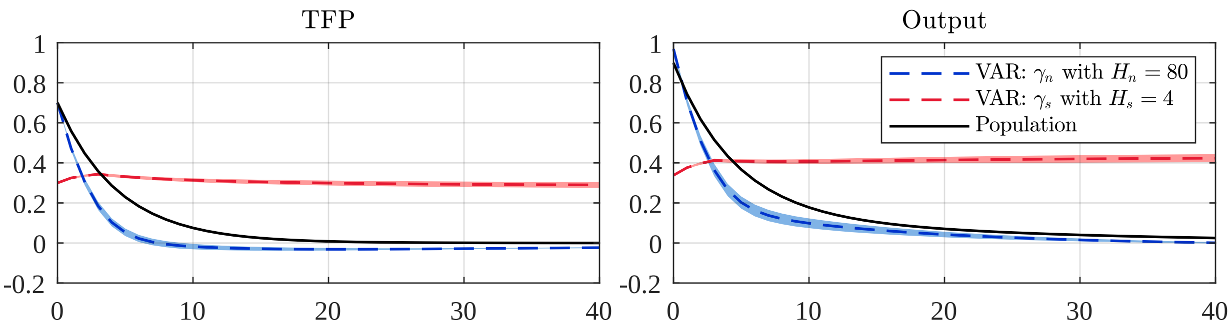
Figure 2 shows that not only is the alternative estimator much more biased than the original estimator in large samples, but it also tends to generate impulse responses that are increasing when the population response is declining and that are declining when the population response is increasing. In 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. Thus, this alternative estimator should not be used in practice.

Figure 2: Impulse responses from two max-share estimators based on the baseline DSGE model

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



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



Notes: Based on a VAR(4) model for $\mathbf{y}_t = (a_t, y_t, i_t)'$.

4 THE ROLE OF TFP MEASUREMENT ERROR

Our analysis so far has focused on DSGE models without unobserved changes in factor utilization. Of course, a key point of KS is that one needs to be concerned about measurement error driving a wedge between measured and true TFP. In this section, we consider an environment with TFP measurement error and discuss to what extent this changes our findings.

One key difference is that the adding-up constraint no longer holds in this case, so identifying surprise TFP shocks is not possible without further assumptions. However, the news shock can be identified as before. Our main finding in this section is that the presence of measurement error does not invalidate the result that the KS estimator is unable in general to recover the population responses to news shocks. The estimator works reasonably well under the KS TFP parameterization, but the impulse responses have large bias when the TFP parameters are calibrated so that measured TFP matches key moments in the data.

To illustrate this point, we evaluate the KS estimator based on data generated from the larger-scale DSGE model employed by KS, allowing for TFP measurement error.[7] There are only two differences, which are made so the results are directly comparable to the baseline model. One is that we turn off the preference and monetary policy shocks in the simulations. The other is that the shock in the TFP growth process is contemporaneous, whereas in the KS model it is lagged by one period. Our specification imposes that TFP news has a contemporaneous effect on TFP, consistent with the specification of the empirical model in KS. Appendix D shows that the timing of the shock has very little impact on the results.

We begin by briefly discussing how TFP is measured. Our approach mirrors that in KS. Their model allows for factor utilization, denoted by u, to vary over time due to changes in capital utilization and worker effort. The econometrician observes neither of these but does observe output (y), the capital stock (k), hours worked (h) and employment (n). The growth in (log) unadjusted TFP is

$$\Delta \ln \mathrm{TFP}_t = y_t - (1 - \omega_{\ell,t})\Delta \ln k_{t-1} - \omega_{\ell,t}(\Delta \ln h_t + \Delta \ln n_t),$$

where $\omega_{\ell,t}$ is the labor share. Changes in factor utilization are assumed to be proportional to changes in de-trended hours worked,

$$\Delta \ln \hat{u}_t = \hat{\beta} \Delta \ln \hat{h}_t,$$

where $\hat{\beta}$ is a proportionality factor and $\hat{h}_t$ is detrended hours worked. Following KS, we set $\hat{\beta} = 3$. Hours worked are detrended using a biweight filter, consistent with the latest vintages of the Fernald TFP measure (see Fernald, 2015). The growth in utilitzation-adjusted TFP is given by

$$\Delta \ln \mathrm{TFP}^u_t = \Delta \ln \mathrm{TFP}_t - \Delta \ln \hat{u}_t.$$

[7]The parameter choices KS used in their replication code differ slightly from those stated in the appendix of their article. We rely on the parameter values in their code. We also corrected a few errors in their derivation of the equilibrium system. The corrected equations can be found in Appendix D. These corrections do not change the main point in KS that TFP measurement error is potentially important, but they affect some of the quantitative results.

Table 3: Data moments and model-implied moments from the KS DSGE model

Moment	Data	KS Model No Measurement Error (1)	KS Model Measurement Error (2)	KS Model with Calibrated Shock Processes Measurement Error (3)
$SD(\tilde{a})$	2.01	1.44	2.60	2.31
$SD(\Delta a)$	0.80	0.30	0.55	0.73
$AC(\tilde{a})$	0.87	0.88	0.88	0.87
$AC(\Delta a)$	-0.09	0.67	0.52	0.02
$SD(\tilde{y})$	3.13	5.22	5.22	3.99
$SD(\tilde{\imath})$	9.63	11.79	11.79	9.36

Note: A tilde denotes a detrended variable and Δ is a log change. In the data, a is Fernald utilization-adjusted TFP. In the model, a is true TFP when there is no TFP measurement error and utilization-adjusted TFP (TFP^u) when there is measurement error.

In our simulations, we produce a series for the (log) level of utilitzation-adjusted TFP, $\ln \text{TFP}_t^u$, by cumulating the growth rates over time. This series represents measured TFP in the model.

In the previous section, we highlighted that the moments of the TFP process in KS are at odds with the data. This continues to be the case even when we allow for TFP measurement error and work with measured TFP rather than true TFP in the VAR model. Column (1) in Table 3 confirms that the KS model implies similar TFP moments as the baseline model in the absence of measurement error. Column (2) shows that the fit of the model does not substantially improve when incorporating measurement error. While the 0.52 autocorrelation of the growth rate of measured TFP is lower than what is reported in Column (1), it remains well above the data. Given this poor fit, we calibrate the shock processes to fit the data moments shown in Table 3. This exercise implies that $\rho_g = 0.5$, $\rho_s = 0.45$, $\rho_\mu = 0.95$, $\sigma_g = 0.0025$, $\sigma_s = 0.0065$, $\sigma_\mu = 0.004$. Column (3) shows that using the calibrated parameters improves the fit along all dimensions, particularly for the autocorrelation of TFP growth, which drops to 0.02.

As discussed in Section 3, the KS estimator may be biased even asymptotically when the variance contribution of the surprise TFP shock at shorter horizons is non-trivial. Table 4a examines whether the same problem arises in the full-fledged KS model. The left side shows the forecast error variance decomposition for measured TFP under the KS parameterization of the shock

Table 4: Forecast error variance decompositions for TFP in the KS DSGE model

(a) Measured TFP ($\ln \text{TFP}^u$)

	KS Model Measurement Error			KS Model with Calibrated Shock Processes Measurement Error		
h	News Shock	Surprise Shock	MEI Shock	News Shock	Surprise Shock	MEI Shock
1	71.5	1.7	26.7	15.5	81.7	2.8
8	83.9	0.4	15.7	50.6	41.3	8.0
20	61.4	0.3	38.3	53.2	10.4	36.4
40	86.1	0.2	13.7	64.8	2.3	32.9
80	94.8	0.1	5.1	76.0	1.0	23.0

(b) True TFP ($\ln a$)

	KS Model Measurement Error			KS Model with Calibrated Shock Processes Measurement Error		
h	News Shock	Surprise Shock	MEI Shock	News Shock	Surprise Shock	MEI Shock
1	96.2	3.8	0.0	12.9	87.1	0.0
8	99.7	0.3	0.0	75.0	25.0	0.0
20	99.9	0.1	0.0	89.6	10.4	0.0
40	99.9	0.1	0.0	94.8	5.2	0.0
80	100.0	0.0	0.0	97.4	2.6	0.0

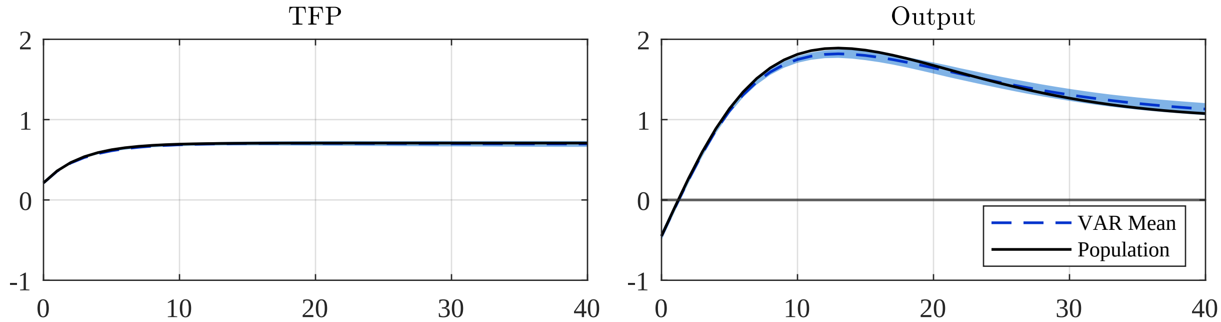
Notes: h is the horizon of the variance decomposition and MEI is the marginal efficiency of investment.

processes, while the right side shows the corresponding results when the shock processes are calibrated to the data. Under the KS parameterization, the news shock plays a substantial role at all horizons, so one would expect the KS estimator to perform well. In contrast, under the calibrated parameterization, the relative importance of news shocks is diminished at all horizons, while that of surprise and MEI shocks increases. This would lead one to expect much lower accuracy from the KS estimator than under the KS parameterization, much like in the baseline model.

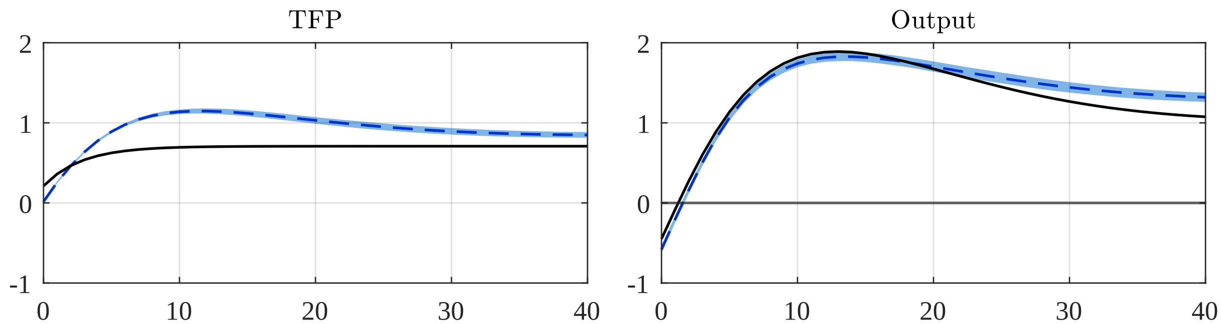
Figure 3 plots the responses of output and measured TFP under alternative parameterizations of the KS DSGE model for $T = 10{,}000$. The top panel shows the results in the absence of measurement error. As expected, the KS estimator does an excellent job at recovering the population responses when the sample size is sufficiently large. The middle panel shows the results with mea-

Figure 3: KS max-share identified responses to news shocks based on the KS DSGE model

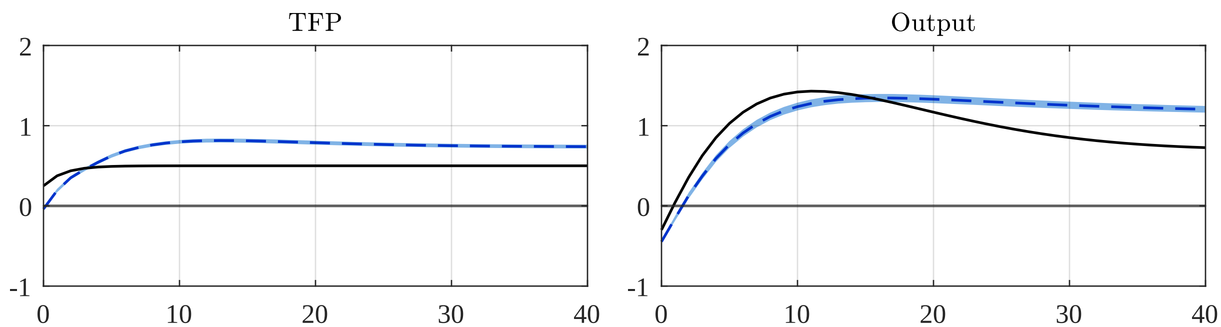
(a) KS model without measurement error, $T = 10{,}000$



(b) KS model with measurement error, $T = 10{,}000$



(c) KS model with calibrated shock processes and measurement error, $T = 10{,}000$



Notes: Based on a VAR(4) model for $\mathbf{y}_t = (a_t, y_t, i_t)'$ when there is no measurement error and $\mathbf{y}_t = (\text{TFP}^u_t, y_t, i_t)'$ where there is measurement error. The responses from models with measurement error are not scaled given that the impact responses of TFP are very close to zero.

surement error under the KS TFP parameterization. While the bias of the output response is slightly larger, the fit remains quite good. However, there is a notable discrepancy between the response of measured TFP to a news shock and the population response of true TFP, which is also apparent in the simulation evidence reported in KS. This result is not surprising, because with measurement error there is no reason to expect the VAR to recover the TFP response, since the VAR is estimated with measured TFP and the population response is based on true TFP. The bottom panel reports results for the same model after calibrating the shock processes. Not only do the discrepancies between the TFP responses remain, but there now is strong bias in the output responses, sometimes in the positive direction and sometimes in the negative direction. As expected, the variance of the estimator increases when $T = 240$, but the impulse response patterns are similar.[8]

One might argue that this result is not surprising given that KS stipulated that news shocks must account for a large part of the unpredictable variation in measured TFP at long horizons for their estimator to perform well. Of course, technically, we have no way of judging how important news shocks are for measured TFP. All we know is that news shocks are expected to explain most of the long-run variation in true TFP. As shown in Table 4b, it remains true under our calibration that news shocks explain 97% of the long-run variability of true TFP, but this does not mean that they are nearly as important a determinant of measured TFP. Table 4a shows that news shocks explain only 76% of the long-run variation in measured TFP, which is almost identical to the share KS obtained when applying their estimator to actual data. This example illustrates that DSGE models that are consistent with the data need not obviously satisfy one of the maintained assumptions required for the KS estimator to perform well, which provides another possible explanation of the bias in the KS estimator in Figure 3.

5 ALTERNATIVE ESTIMATORS INVOLVING DIRECT MEASURES OF TFP NEWS

KS concede 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 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

[8] Throughout the paper, we followed KS in setting the lag order of the VAR to 4. For $T = 10{,}000$, the accuracy of the KS estimator can be improved by increasing the lag order up to a certain point. This, however, comes at the cost of substantially increasing the variability of the estimator for $T = 240$.

of TFP news and other forward-looking variables jump in response to news shocks. Given that the KS estimator does not properly identify the news shock, as shown in Section 3 and 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. Moreover, the potential of these methods to recover not only news shocks, but also surprise shocks, under suitable conditions, has not been recognized. In this section, we examine two such identification strategies, first in our baseline model without TFP measurement error and then in the KS model with measurement error.

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 $H_n = 4$ (a one-year horizon), 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 block recursive VAR model with the news variable ordered first and TFP second. This approach is equivalent to using TFP news as an internal instrument, which is particularly appealing when TFP news is measured with error, as is likely to be the case in practice.

An alternative approach to dealing with TFP news measurement error would be to use the news variable as an external instrument in a VAR model excluding the TFP news variable (e.g., Montiel Olea et al., 2021; Stock and Watson, 2018). This proxy VAR approach has been used, for example, by Cascaldi-Garcia and Vukotić (2022) and Miranda-Agrippino et al. (2022). Like the methods discussed in this section and like the KS approach, the use of proxy VAR models allows the user to dispense with the assumption that news shocks do not affect TFP contemporaneously.

As shown in Plagborg-Møller and Wolf (2021), the advantage of the strategy of ordering the instrument first in a block recursive VAR model is that it yields valid impulse response estimates even if the shock of interest is non-invertible. In contrast, the proxy VAR approach that uses the instrument as an external instrument is invalid in that case.[9]

5.2 SIMULATION EVIDENCE ON THE ACCURACY OF THE NEWS VARIABLE ESTIMATORS

We start by using the baseline DSGE model from Section 3.1 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 $\mathbf{y}_t = (z_t, a_t, y_t)'$.[10] The variables enter the VAR in logs and are directly observable in the DSGE model. The choice of these variables is dictated by our interest in constructing the responses of TFP and output.

Table 5 compares the RSME of these impulse response estimators to that of the KS estimator based on $\mathbf{y_t} = (a_t, y_t, i_t)'$.[11] The first four columns show the sum of the RMSEs over horizons

[9]Invertibility here refers to the ability to recover the structural shock of interest as a function of only current and past VAR model variables. When agents anticipate future changes, as is the premise in models with TFP news shocks, the maintained assumption that the VAR prediction errors are linearly related to the contemporaneous structural shocks fails whenever agents have more information than is contained in the reduced-form VAR model (for related discussion see, e.g., Leeper et al., 2013; Mertens and Ravn, 2014). This renders the VAR model nonfundamental and distorts the impulse response estimates (see, e.g., Kilian and Lütkepohl, 2017). While this problem may be addressed by including additional variables in the reduced-form VAR model that capture the expected path of TFP, finding such variables is nontrivial. For example, stock price indices or measures of consumer sentiment, are not likely to be a good measures of expected TFP. The Cholesky approach avoids these complications.

[10]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 on $\gamma_{\ell,2}$. 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.

[11]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

Table 5: Sum of the RMSE over 40 quarters for each estimator based on the baseline DSGE model

(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

Notes: The VAR includes $\mathbf{y}_t = (a_t, y_t, i_t)$ for the KS max-share estimator and $\mathbf{y}_t = (z_t, a_t, y_t)$ for the max-share news and Cholesky estimators.

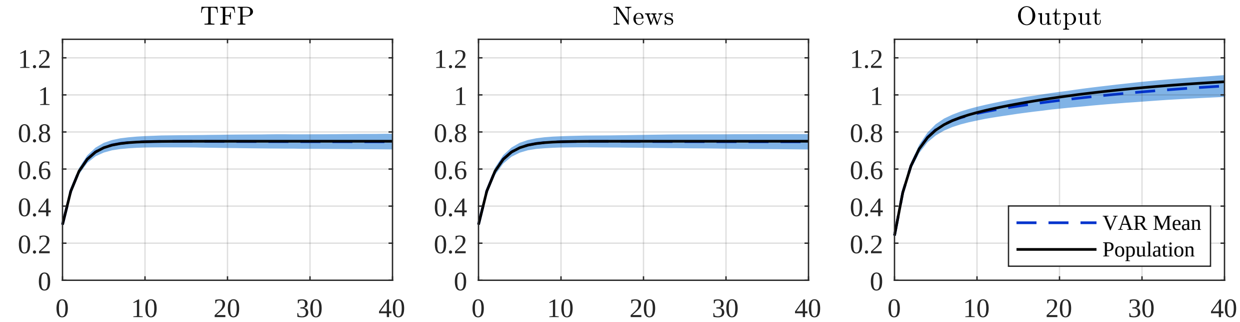
0 through 40 for selected impulse response functions. The last column shows the sum of these entries across the four response functions. There is compelling evidence that the max-share news estimator has substantially lower RMSE than the KS estimator not only for $T = 10{,}000$ (83% reduction in the 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 5 suggests that identification strategies based on TFP news variables perform much better than the KS estimator when both TFP and TFP news are accurately measured. 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.

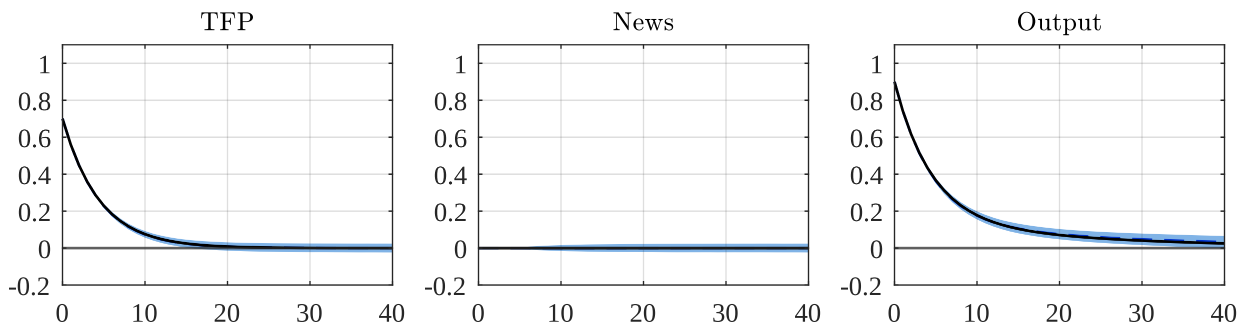
model that includes investment, since it has a strong connection with the MEI shock.

Figure 4: Max-share news identified impulse responses based on the baseline DSGE model

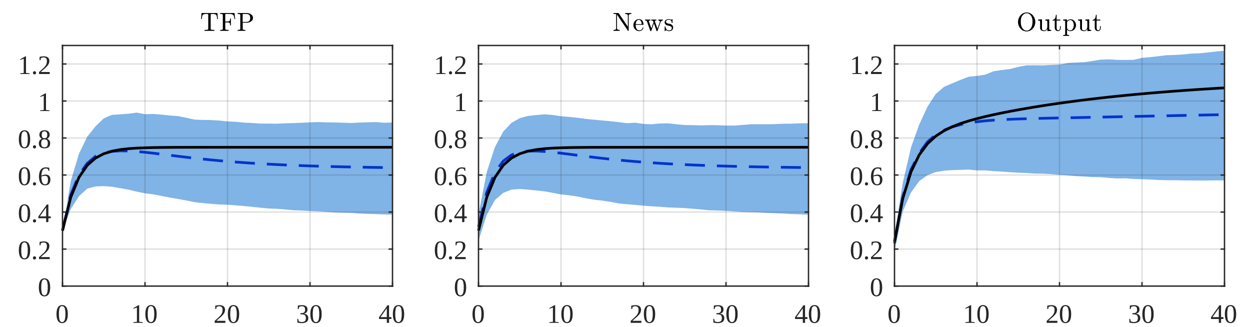
(a) News shock, $T = 10{,}000$



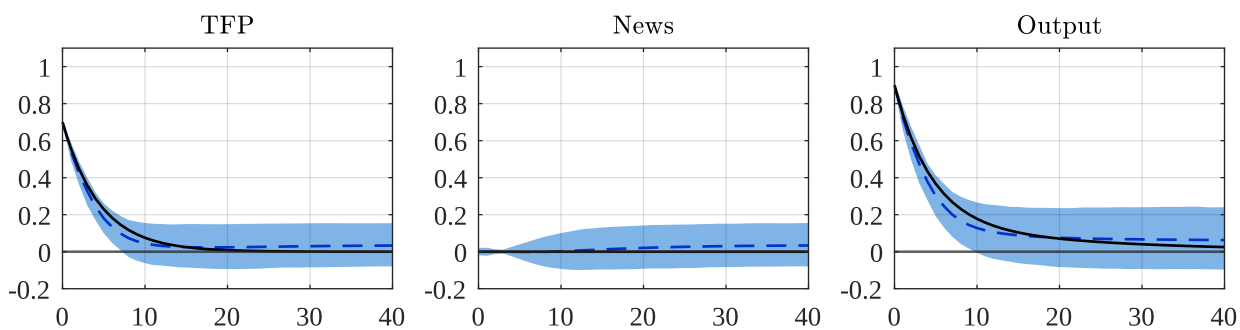
(b) Surprise Shock, $T = 10{,}000$



(c) News shock, $T = 240$



(d) Surprise Shock, $T = 240$



Notes: Based on a VAR(4) model for $\mathbf{y}_t = (z_t, a_t, y_t)'$. The responses have been scaled so the impact response of TFP matches the population value.

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 necessarily expect the max-share news estimator to be reliable in small samples. Qualitatively similar results hold for the Cholesky approach, as shown in Appendix E.

In our analysis above, we assumed that the econometrician perfectly observes the permanent component of TFP. However, the external measures of news used in empirical research are not perfectly correlated with the permanent component of TFP. To address this concern, we allow for the TFP news variable in the VAR to be an imperfect measure of the permanent component of TFP news by introducing additive Gaussian noise. Specifically, we replace z_t in the VAR model with $z_t + \sigma_n \epsilon_t^n$, where $\epsilon_{n,t} \sim \mathbb{N}(0, 1)$ is the noise. While there is no way of knowing the extent of measurement error in TFP news, Appendix D shows that our news variable results are robust to modestly large additive Gaussian measurement error in TFP news. For example, even with a 20% measurement error, expressed as a percentage of the standard deviation of the true news shock ($\sigma_n = 0.2\sigma_g$), both the Cholesky and max-share news estimators are considerably more accurate than the original KS estimator with $T = 10{,}000$, indicating substantial robustness to TFP measurement error.

5.3 THE MAX-SHARE NEWS ESTIMATOR IN THE PRESENCE OF TFP MEASUREMENT ERROR

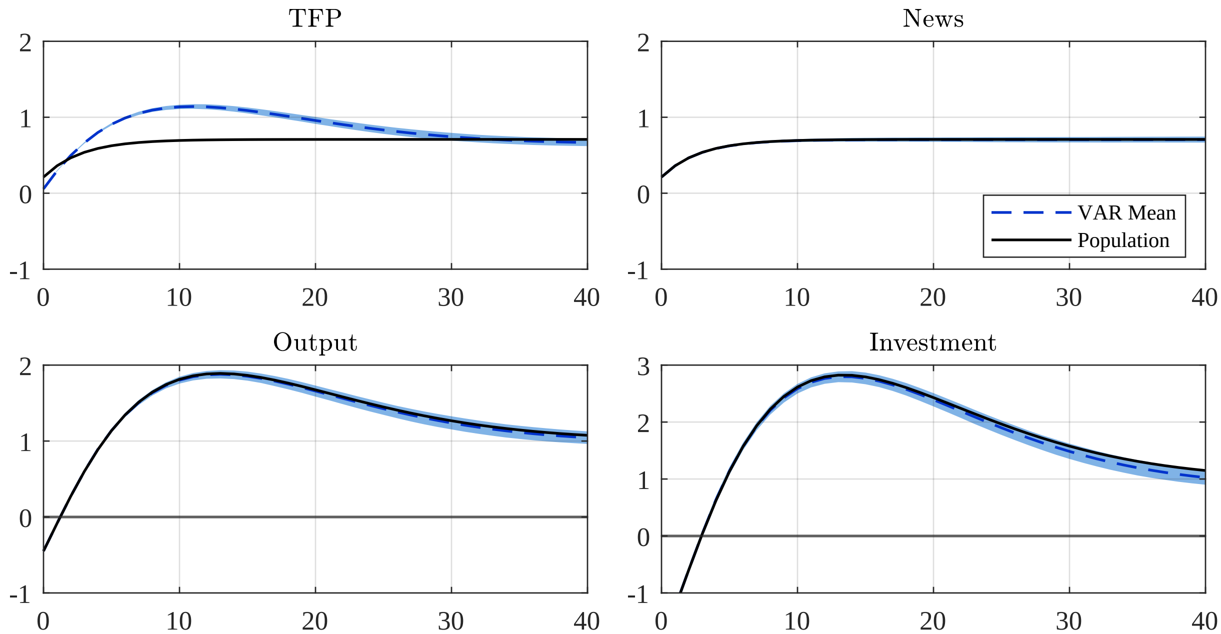
An important question is whether adding a news variable can also reduce impulse response bias in the presence of TFP measurement error. We explore this question by fitting VAR(4) models to data for $\mathbf{y}_t = (z_t, a_t, y_t, i_t)$ simulated from the KS model for $T = 10{,}000$, either under their parameterization or under our alternative parameterization discussed in Section 4.

The top panel of Figure 5 plots the impulse responses under the KS parameterization for the max-share identification method. It can be seen that this produces a very good fit, except for the response of measured TFP, for the reasons discussed in Section 4.[12] The bottom panel plots

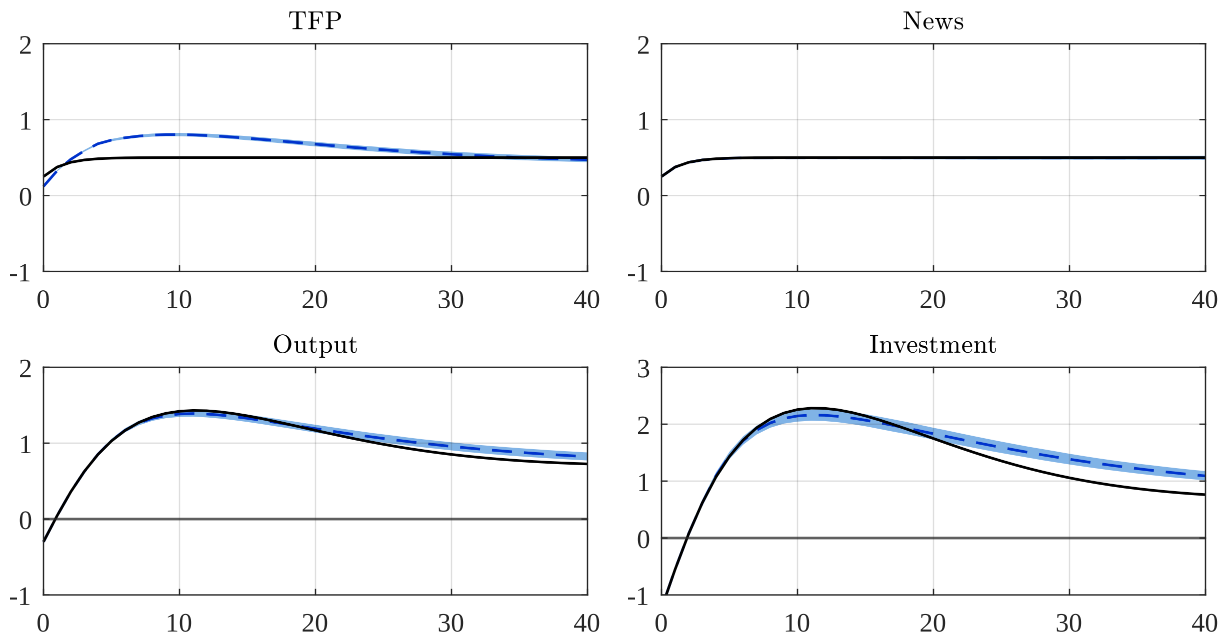
[12]It can be shown that when TFP is observed without measurement error the VAR can identify the response of TFP to the news shock almost perfectly.

Figure 5: Max-share news identified responses to news shocks based on the KS DSGE model

(a) KS model with measurement error, $T = 10{,}000$



(b) KS model with measurement error and our calibrated shock processes, $T = 10{,}000$



Notes: Based on a VAR(4) model for $\mathbf{y}_t = (z_t, \mathrm{TFP}_t^u, y_t, i_t)'$. The responses are not scaled given that the impact responses of TFP are very close to zero.

Table 6: Sum of the RMSE over 40 quarters for each estimator based on the KS DSGE model

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

	KS Model Measurement Error				KS Model with Calibrated Shock Processes Measurement Error			
Estimator	TFP	Output	Investment	Total	TFP	Output	Investment	Total
KS Max Share	10.9	5.4	8.7	25.0	10.2	11.3	20.9	42.4
Max Share News	8.4	2.6	5.0	16.0	6.1	3.0	8.3	17.4
Cholesky	8.4	2.6	4.9	15.9	6.1	3.0	8.2	17.3

(b) $T = 240$

	KS Model Measurement Error				KS Model with Calibrated Shock Processes Measurement Error			
Estimator	TFP	Output	Investment	Total	TFP	Output	Investment	Total
KS Max Share	10.7	15.0	27.6	53.4	10.4	16.3	34.1	60.9
Max Share News	12.6	22.8	36.5	71.9	9.0	14.0	23.8	46.9
Cholesky	12.6	23.2	36.7	72.5	8.6	13.5	22.7	44.9

Notes: The VAR includes $\mathbf{y}_t = (\text{TFP}^u_t, y_t, i_t)$ for the KS max-share estimator and $\mathbf{y}_t = (z_t, \text{TFP}^u_t, y_t, i_t)$ for the max-share news and Cholesky estimators.

the impulse responses under the alternative calibration. In that case, there is modest bias in the responses of output and investment. The Cholesky news estimator produces very similar results, as shown in Appendix E. This raises the question of how the Cholesky and max-share news estimators compare to the KS estimator.

Table 6 shows the RMSE of the impulse response estimator associated with each method. The left side of the table shows the RMSE under the KS parameterization and the right side the RMSE under the alternative calibration. As in the case of no measurement error, adding the TFP news variable and adapting the identification produces substantial improvements in the accuracy of the impulse response estimator relative to the KS approach. For example, based on the calibrated KS DSGE model, the RMSE is reduced by 59% for $T = 10{,}000$ and by between 23% and 26%, depending on the method, for $T = 240$.

6 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 practice, however, this approach will only be as good as the underlying measure of TFP news. In this section, we therefore consider 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).[13]

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 empirical VAR model used by KS.[14] 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. Both approaches generate remarkably similar results.

There are two natural criteria for judging whether the news shocks have been properly identified in a given VAR model. These criteria are suggested by the population responses in the DSGE models used in Section 3 and Section 4, and by many other business cycle models. First, while the identification does not constrain the short-run response of TFP and output to a news shock, its

[13]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 exclude exogenous policy shocks. Miranda-Agrippino et al. (2022) note that their identification is robust to excluding these policy shocks.

[14]Cascaldi-Garcia and Vukotić (2022) use the same variables in their VAR model, except they also include a measure of consumer sentiment. Our results are robust to including this additional variable. There are also some differences in the data sources. Most notably, they use output from the nonfarm business sector, instead of real GDP. When we use this alternative definition of output, the impulse responses to a news shock are closer to what they report.

Table 7: Empirical results from VAR models including alternative measures of TFP news.

Criterion	R&D	ICT	CGV	MAHB
Cholesky-identified VAR model				
Max response at longer horizons	Y	Y	N	N
Positive long-run responses	Y	Y	N	N
Max-share identified VAR model				
Max response at longer horizons	Y	Y	N	N
Positive long-run responses	Y	Y	N	N

Notes: The Cholesky model is identified with the news variable ordered first and TFP second. The max-share model maximizes the variance contribution of the news variable at $H_n = 4$.

effect on TFP and output should peak at horizons longer than 12 quarters. This criterion allows for weakly increasing as well as hump-shaped response functions. A peak at horizons shorter than 12 quarters would clearly be incompatible with the notion that the impact of news is largest at long horizons. This criterion is satisfied in all DSGE models we considered, even in the presence of TFP measurement error. Second, the news shock should have positive effects in the long run on TFP and output.

It is understood that sampling error and small-sample biases may cause slight violations of these criteria. For example, a response may turn marginally negative a longer horizons. Our concern in this section are strong violations of these criteria. Table 7 summarizes the results based on a maximum horizon of 40 quarters. The full set of impulse responses is provided in Appendix E. We find that only the R&D and ICT models satisfy the two criteria. This is true regardless of whether we use the Cholesky or the max-share new approach.[15]

The responses of other key variables also look reasonable, particularly for the ICT model, as shown in Appendix E. The news shock increases both consumption and investment in the long run, and the peak effects occur after 12 quarters. Hours increase over the first 12 quarters, so there is positive comovement between real GDP, consumption, and investment. This finding is

[15]The estimates for the MAHB specification differ somewhat from those reported in Miranda-Agrippino et al. (2022). One likely reason is that they combine their estimate of the impact of news with a longer sample for the reduced-form model than the instrument is available for. One key difference between the MAHB instrument and the other measures of TFP news is that Miranda-Agrippino et al. (2022) purge their instrument of all dynamics. We also produced results based on an instrument that does not control for lags of the patent series. This does not affect the results reported in Table 7.

consistent with the results in Beaudry and Portier (2006, 2014). Inflation declines in the short-run, consistent with the interpretation of the news shock as a positive supply shock. Finally, the real S&P 500 index increases on impact and over the long-run, reflecting positive expectations of future economic conditions. While our empirical results are necessarily tentative because they may change with the choice of VAR variables and estimation period, this evidence suggests that VAR models based on TFP news may work well not only in simulations but also in practice.

7 CONCLUSION

There has been much interest in the literature in distinguishing news shocks from surprise shocks to TFP. Most of these studies rely on variations of the max-share approach pioneered by Uhlig (2004) and Francis et al. (2014). The state of the art in this literature is an identification strategy recently proposed by KS, designed to generalize earlier approaches such as BS that postulated that only surprise shocks affect TFP contemporaneously. KS suggest that TFP mismeasurement makes it impossible for their estimator to separately identify news shocks and surprise shocks, but are not explicit about their reasoning.

In this paper, we started by clarifying the conditions under which the KS procedure not only identifies the impact of news shocks, but also identifies the impact of surprise shocks. We show that these conditions are not related to the two differences between the BS and KS estimators emphasized by KS, but relate to an adding up constraint imposed by BS. This constraint fails when TFP innovations depend on shocks other than news and surprise shocks, as would be the case when TFP is subject to measurement error. In the latter case, the surprise shock cannot be identified.

We used these results to examine the accuracy of the KS estimator of the responses to news and surprise shocks in an ideal setting that abstracts from TFP measurement error. Simulation evidence based on data generated from a DSGE model suggests that the KS estimator may not work well in practice, even in the absence of TFP measurement error. 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.

We reconciled our findings with the large-sample simulation evidence reported in KS that paints a more favorable picture. A key difference between our analysis and that in KS is that we calibrate the TFP growth process in the DSGE model to actual data, whereas KS use an ad hoc specification. While the responses to the news shock in large samples tend to be closer to the population responses when adopting the KS parameterization of the TFP growth process, we show that this result is not driven by the fact that their DSGE model allows for TFP measurement error. Rather it is driven by the fact that news shocks are the dominant driver of TFP at all horizons in their DSGE model, which renders the identification of the news shock trivial. In contrast, in our baseline DSGE model surprise shocks explain a sizable share of the variation in TFP at short horizons, which causes the KS estimator to fail. We showed that the inability of the KS estimator to recover the population responses to news shocks also extends to alternative DSGE models that allow for unobserved changes in factor utilization to cause TFP measurement error.

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 reduce the bias and RMSE of the impulse response estimator. We examined two such approaches to identifying news shocks, one of which is new to the literature, that avoid the identification issues with the KS estimator. In our simulations, in the absence of TFP measurement error, both of these estimators have between 83% and 85% lower RMSE than the KS estimator for $T = 10{,}000$ and between 15% and 29% lower RMSE for $T = 240$. They also perform much better than the KS estimator when applied to data generated from DSGE models with TFP measurement error with RMSE reductions of 59% for $T = 10{,}000$ and between 23% and 26% for $T = 240$.

Of course, how accurate commonly used measures of TFP news are in practice is an open question. We therefore reported empirical estimates of the responses to news shocks for a range of alternative TFP news measures and found that two of these specifications appear economically plausible in light of the underlying theory. While necessarily tentative, our evidence suggests that VAR models based on TFP news may work well not only in simulations but also in practice.

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. (2015): "Productivity and Potential Output before, during, and after the Great Recession," in *NBER Macroeconomics Annual 2014*, ed. by J. A. Parker and M. Woodford, University of Chicago Press, vol. 29, 1–51.

FERNÁNDEZ-VILLAVERDE, J., J. F. RUBIO-RAMÍREZ, T. J. SARGENT, AND M. W. WATSON (2007): "ABCs (and Ds) of Understanding VARs," *American Economic Review*, 97, 1021–1026.

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.

LEEPER, E. M., T. B. WALKER, AND S.-C. S. YANG (2013): "Fiscal Foresight and Information Flows," *Econometrica*, 81, 1115–1145.

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.

——— (2014): "A Reconciliation of SVAR and Narrative Estimates of Tax Multipliers," *Journal of Monetary Economics*, 68, 1–19.

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

MONTIEL OLEA, J. L., J. H. STOCK, AND M. W. WATSON (2021): "Inference in Structural Vector Autoregressions identified with an external instrument," *Journal of Econometrics*, 225, 74–87.

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.

PLAGBORG-MØLLER, M. AND C. K. WOLF (2021): "Local Projections and VARs Estimate the Same Impulse Responses," *Econometrica*, 89, 955–980.

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.

STOCK, J. H. AND M. W. WATSON (2018): "Identification and Estimation of Dynamic Causal Effects in Macroeconomics Using External Instruments," *Economic Journal*, 128, 917–948.

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: Estimating Macroeconomic News and Surprise Shocks[*]

Lutz Kilian[†] Michael D. Plante[‡] Alexander W. Richter[§]

October 13, 2023

[*]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.

[†]Research Department, Federal Reserve Bank of Dallas, 2200 N Pearl Street, Dallas, TX 75201, and CEPR (lkilian2019@gmail.com).

[‡]Research Department, Federal Reserve Bank of Dallas, 2200 N Pearl Street, Dallas, TX 75201 (michael.plante@dal.frb.org).

[§]Corresponding author: Research Department, Federal Reserve Bank of Dallas, 2200 N Pearl Street, Dallas, TX 75201 (alex.richter@dal.frb.org).

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 the model by writing trending variables in terms of TFP, $\tilde{x}_t \equiv x_t/z_t^{1/(1-\alpha)}$. The equilibrium system is given by

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

Table 1: Baseline DSGE model calibration at quarterly frequency.

Parameter	Value	Parameter	Value
Discount Factor (β)	0.995	Steady-State Hours ($\bar{n}$)	0.3333
Cost Share of Capital (α)	0.3343	Steady-State TFP Growth Rate ($\bar{g}$)	1.0026
Capital Depreciation Rate (δ)	0.025	TFP News Shock Persistence (ρ_g)	0.6
Frisch Labor Supply Elasticity ($1/\eta$)	0.5	TFP Surprise Shock Persistence (ρ_s)	0.8
Goods Elasticity of Substitution (ϵ_p)	11	MEI Shock Persistence (ρ_μ)	0.9
Calvo Price Stickiness (θ_p)	0.75	TFP News Shock SD (σ_g)	0.003
Taylor Rule Inflation Response (ϕ_π)	1.5	TFP Surprise Shock SD (σ_s)	0.007
Steady-State Inflation Rate ($\bar{\pi}$)	1.005	MEI Shock SD (σ_μ)	0.0075

D KS DSGE MODEL

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

where the labor share $\omega_{\ell,t} = w_{\ell,t} l_{s,t}/y_t$.

Table 2: KS 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)	0.7
Labor Elasticity of Substitution (ϵ_w)	11	TFP Surprise Shock Persistence (ρ_s)	0.9
Calvo Price Stickiness (θ_p)	0.75	MEI Shock Persistence (ρ_μ)	0.8
Calvo Wage Stickiness (θ_w)	0.9	TFP News Shock SD (σ_g)	0.002125
Price Indexation (γ_p)	0	TFP Surprise Shock SD (σ_s)	0.000425
Wage Indexation (γ_w)	1	MEI Shock SD (σ_μ)	0.00425

E ADDITIONAL RESULTS

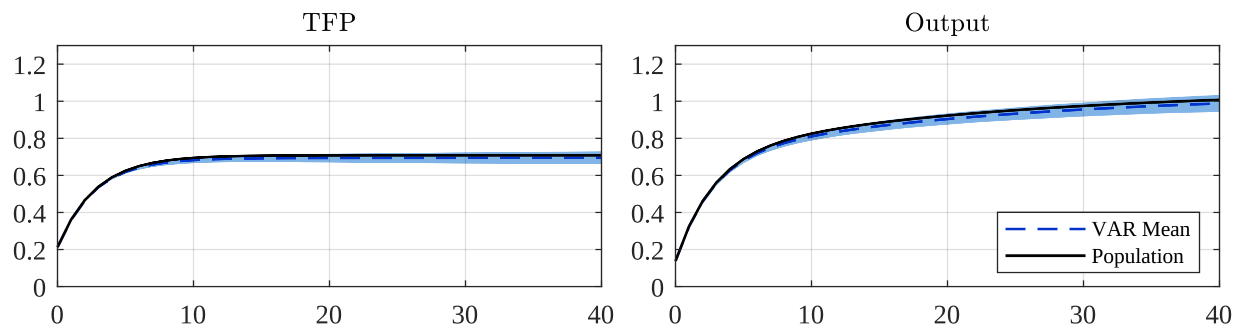
This section presents several additional results:

- Impulse responses based on the KS max share estimator and $\mathbf{y}_t = (a_t, y_t, i_t)'$ using data simulated from our baseline DSGE model with the KS TFP process and $T = 10{,}000$ (Figure 1).
- Root mean squared errors based on the KS max share estimator and $\mathbf{y}_t = (a_t, y_t, i_t)'$ using data simulated from the KS DSGE model with contemporaneous or lagged growth shocks in the TFP news process (Table 3).
- Impulse responses based on the KS max share estimator and $\mathbf{y}_t = (a_t, y_t, i_t)'$ using data simulated from the KS DSGE model with $T = 240$ (Figure 2).
- Impulse responses based on the Cholesky news estimator and $\mathbf{y}_t = (z_t, a_t, y_t)'$ using simulated data from our baseline DSGE model with $T = 10{,}000$ and $T = 240$ (Figure 3).
- Impulse responses based on the Cholesky news estimator and $\mathbf{y}_t = (z_t, a_t, y_t, i_t)'$ using simulated data from the KS DSGE model with $T = 10{,}000$ (Figure 4).

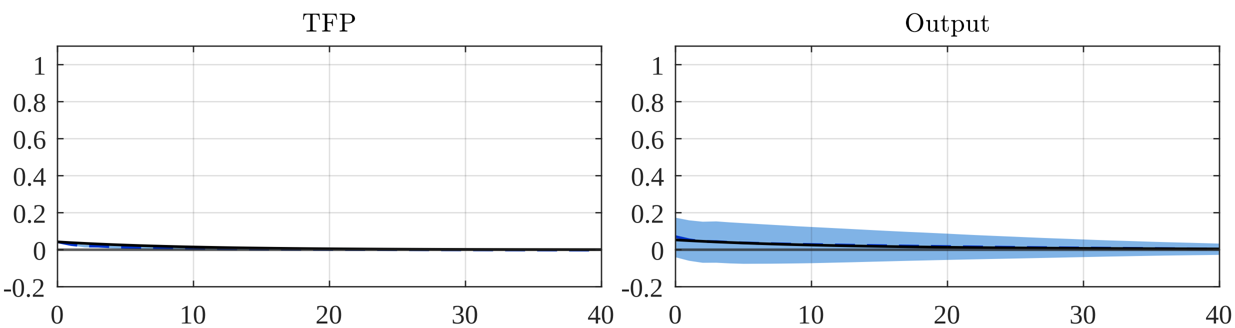
- Empirical impulse responses from 9-variable VAR models with alternative TFP news series of different lengths (Figure 5-Figure 8).
- Full set of empirical max-share identified impulse responses from the 9-variable VAR model with the ICT index (Figure 9)

Figure 1: KS max-share identified responses based on the baseline DSGE model with KS TFP

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



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



Notes: Based on a VAR(4) model for $\mathbf{y}_t = (a_t, y_t, i_t)'$. The responses have been scaled so the impact response of TFP matches the population value.

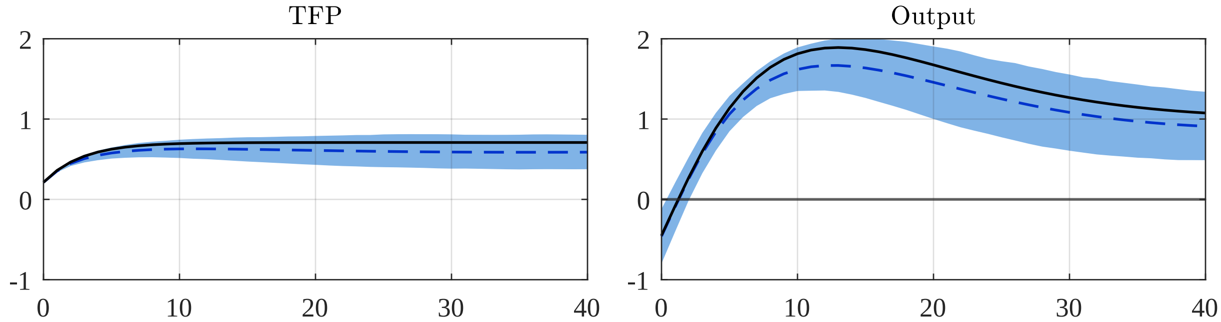
Table 3: Sum of the RMSE over 40 quarters for the KS estimator based on the KS DSGE model

	KS Model Measurement Error				KS Model with Calibrated Shock Processes Measurement Error			
Shock	TFP	Output	Investment	Total	TFP	Output	Investment	Total
$\varepsilon_{g,t}$	10.9	5.4	8.7	25.0	10.2	11.3	20.9	42.4
$\varepsilon_{g,t-1}$	11.3	4.9	7.6	23.8	10.3	10.5	19.5	40.4

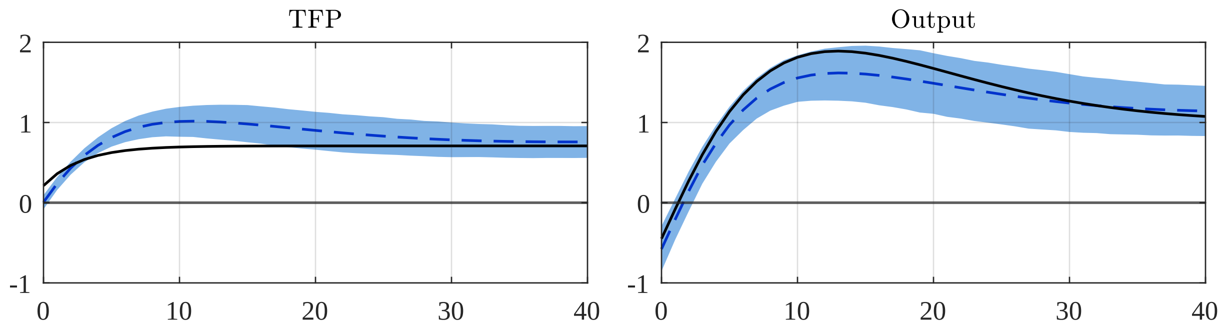
Notes: Results based on $T = 10{,}000$. The VAR includes $\mathbf{y}_t = (\text{TFP}_t^u, y_t, i_t)$. All of the results in the paper use a contemporaneous new shock, $\varepsilon_{g,t}$, while KS use a lagged news shock, $\varepsilon_{g,t-1}$.

Figure 2: KS max-share identified responses to news shocks based on the KS DSGE model

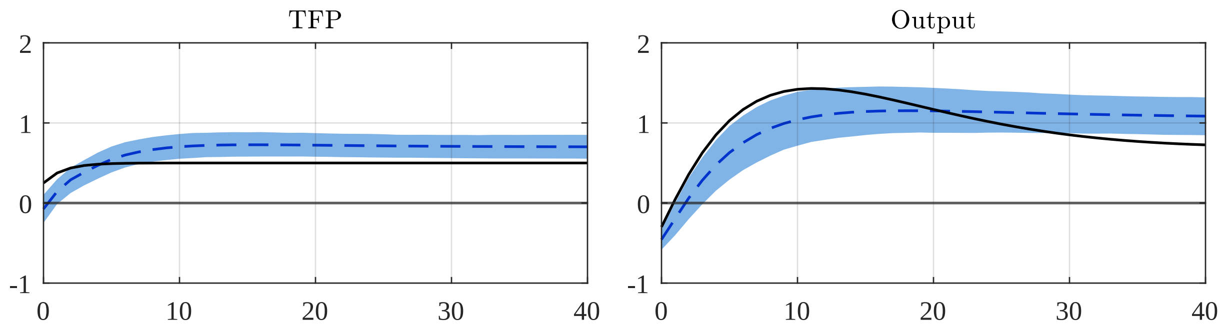
(a) KS model without measurement error, $T = 240$



(b) KS model with measurement error, $T = 240$



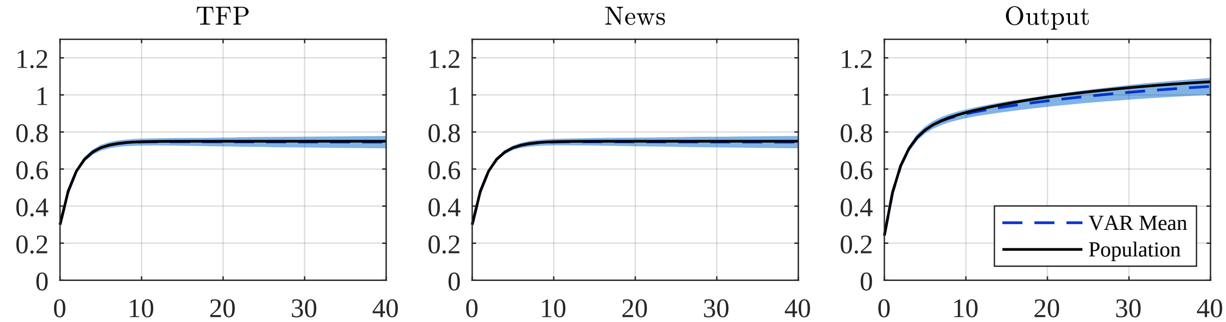
(c) KS model with calibrated shock processes and measurement error, $T = 240$



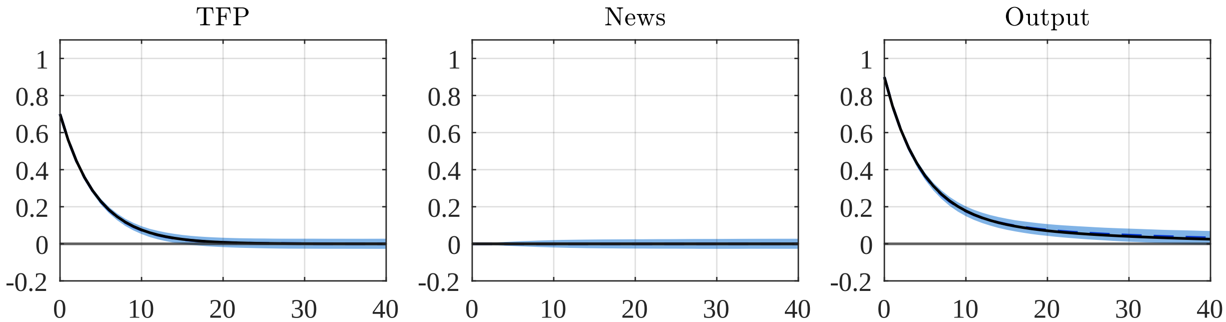
Notes: Based on a VAR(4) model for $\mathbf{y}_t = (a_t, y_t, i_t)'$ when there is no measurement error and $\mathbf{y}_t = (\text{TFP}_t^u, y_t, i_t)'$ where there is measurement error. The responses from models with measurement error are not scaled given that the impact responses of TFP are very close to zero.

Figure 3: Cholesky news identified impulse responses based on the baseline DSGE model

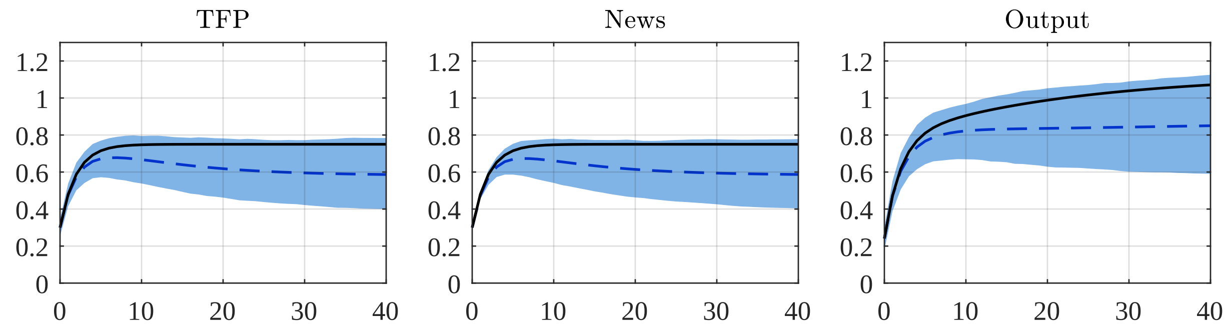
(a) News shock, $T = 10{,}000$



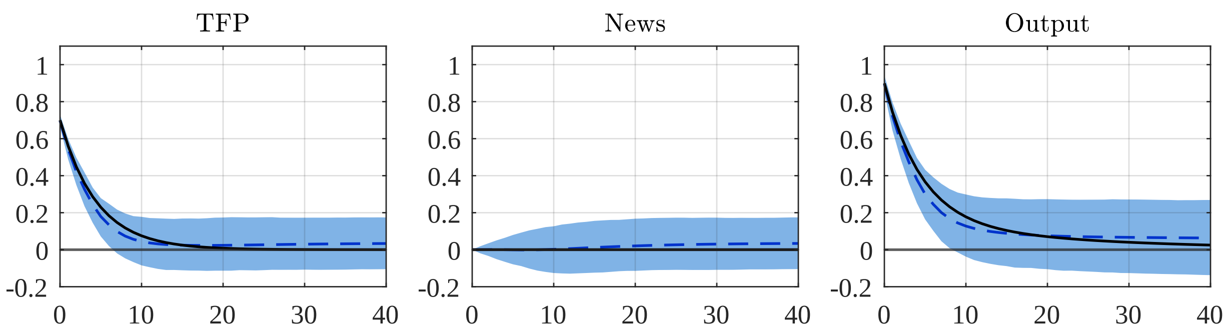
(b) Surprise shock, $T = 10{,}000$



(c) News shock, $T = 240$



(d) Surprise shock, $T = 240$



Notes: Based on a VAR(4) model for $\mathbf{y}_t = (z_t, a_t, y_t)'$. The responses have been scaled so the impact response of TFP matches the population value.

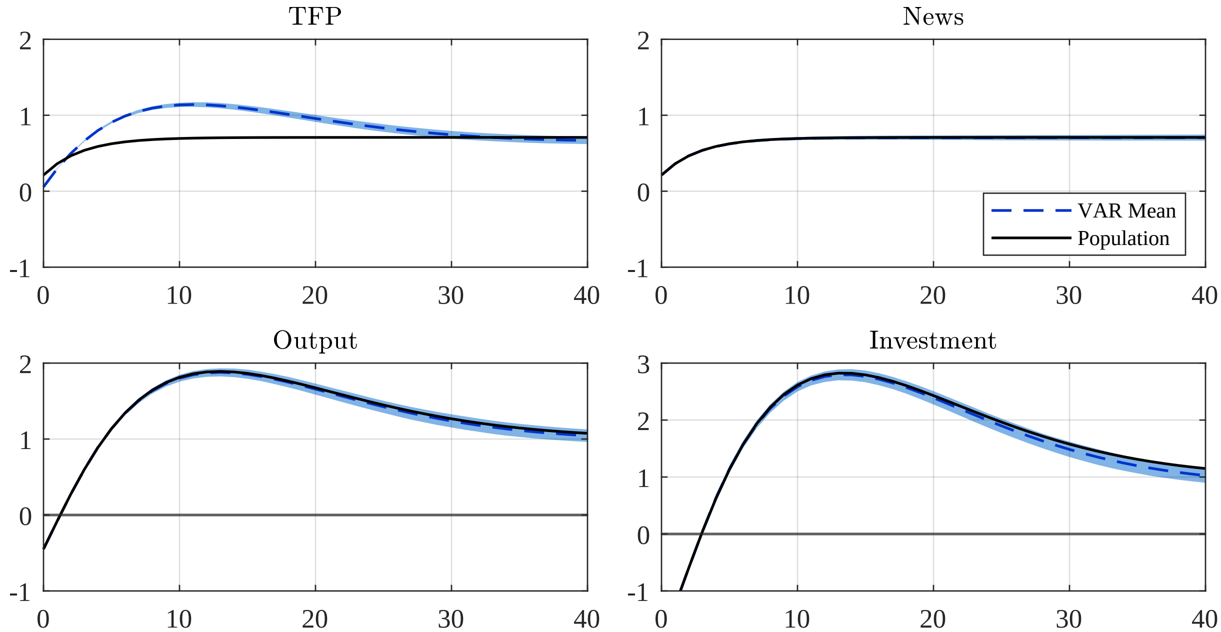
Table 4: Sum of the RMSE over 40 quarters for each estimator based on the baseline DSGE model

	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 ($\sigma_n = 0$)	1.4	0.8	1.9	1.1	5.2
Max Share News ($\sigma_n = 0.1\sigma_g$)	1.4	0.8	2.0	1.1	10.4
Max Share News ($\sigma_n = 0.2\sigma_g$)	1.6	0.8	2.4	1.1	16.4
Cholesky ($\sigma_n = 0$)	1.0	0.9	1.5	1.2	4.6
Cholesky ($\sigma_n = 0.1\sigma_g$)	1.2	0.9	1.8	1.3	9.8
Cholesky ($\sigma_n = 0.2\sigma_g$)	2.3	1.1	3.2	1.5	18.0

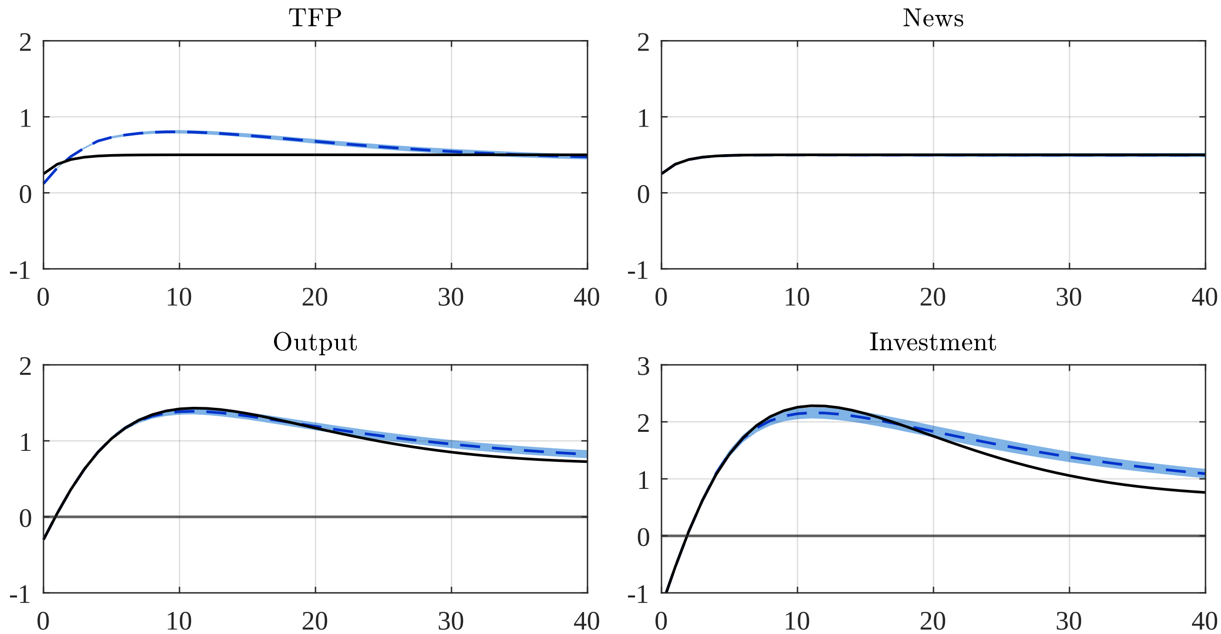
Notes: Results based on $T = 10{,}000$. The VAR includes $\mathbf{y}_t = (a_t, y_t, i_t)$ for the KS max-share estimator and $\mathbf{y}_t = (z_t, a_t, y_t)$ for the max-share news and Cholesky estimators.

Figure 4: Cholesky news identified responses to news shocks based on the KS DSGE model

(a) KS model with measurement error, $T = 10{,}000$



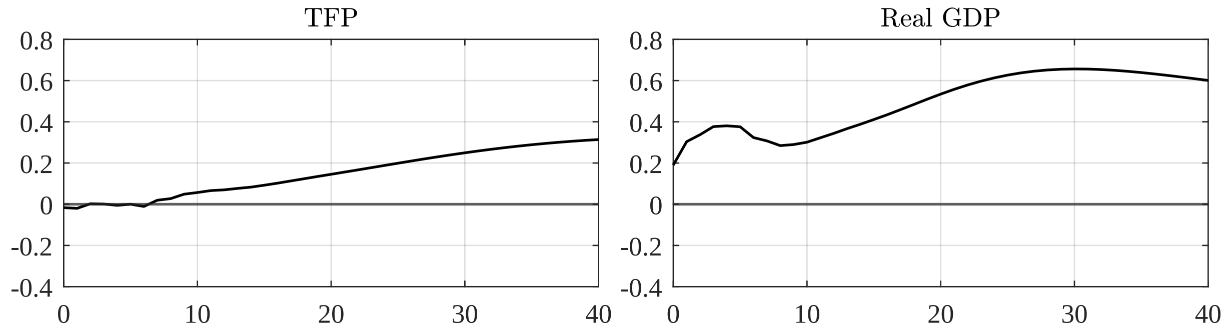
(b) KS model with measurement error and our calibrated shock processes, $T = 10{,}000$



Notes: Based on a VAR(4) model for $\mathbf{y}_t = (z_t, \mathrm{TFP}_t^u, y_t, i_t)'$. The responses are not scaled given that the impact responses of TFP are very close to zero.

Figure 5: Impulse responses with real R&D expenditures

(a) Cholesky identified VAR model



(b) Max-share identified VAR model

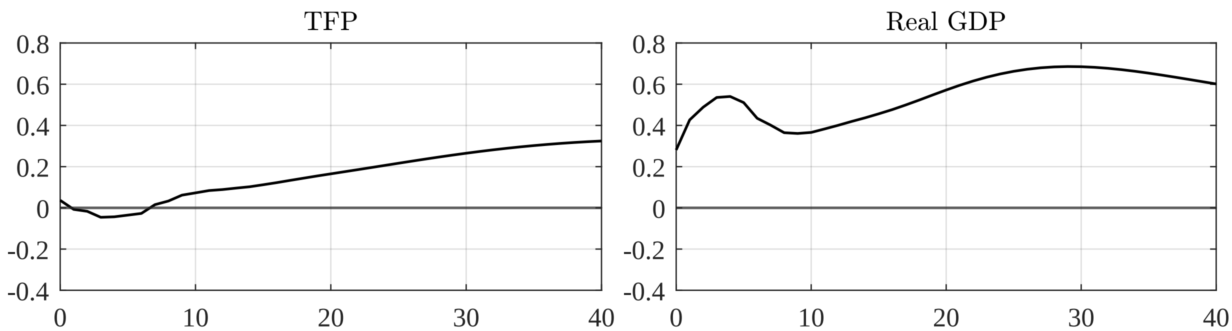
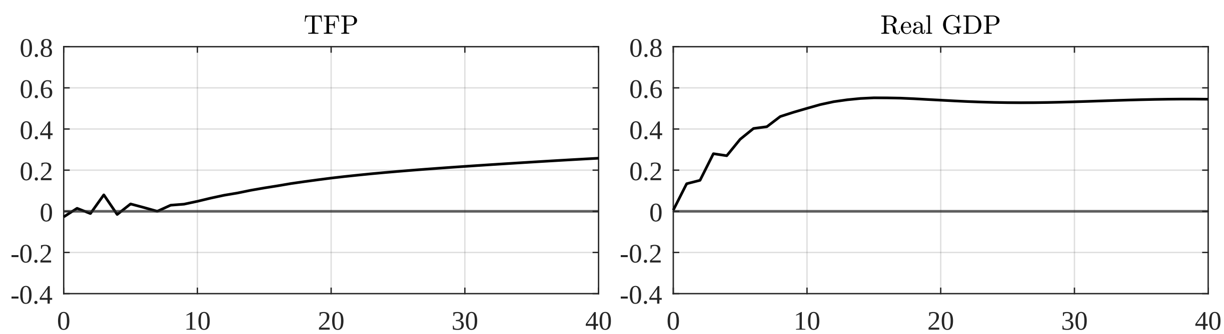


Figure 6: Impulse responses with the ICT index

(a) Cholesky identified VAR model



(b) Max-share identified VAR model

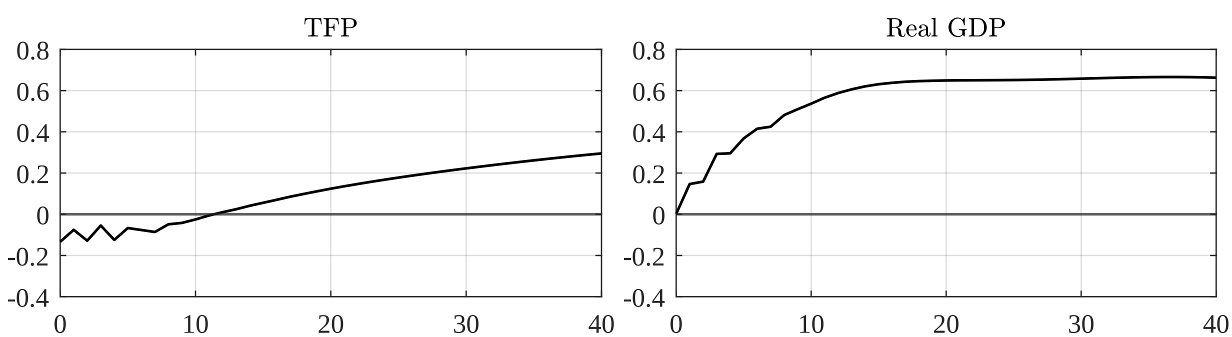
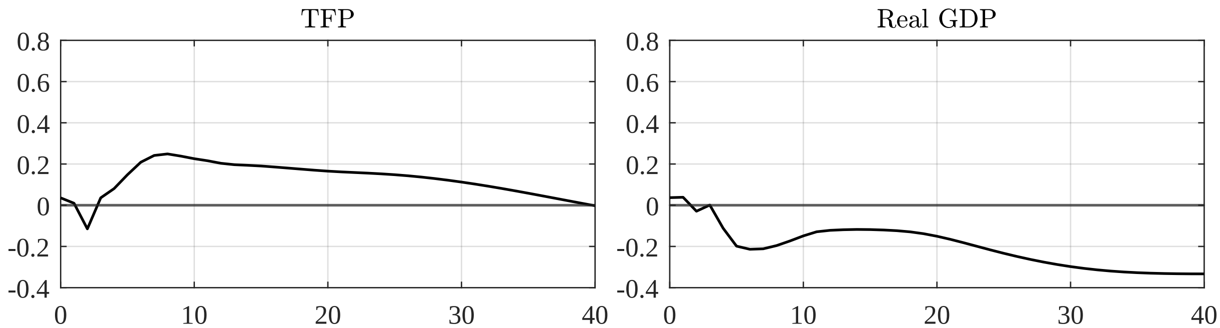


Figure 7: Impulse responses with the CGV series

(a) Cholesky identified VAR model



(b) Max-share identified VAR model

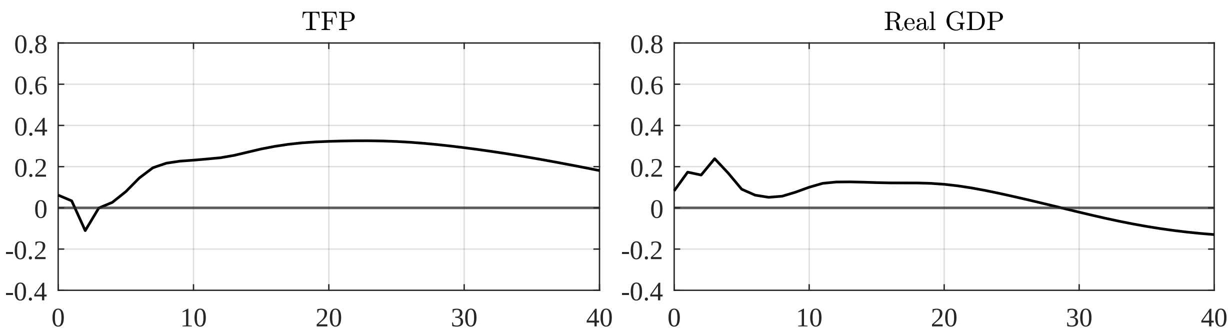
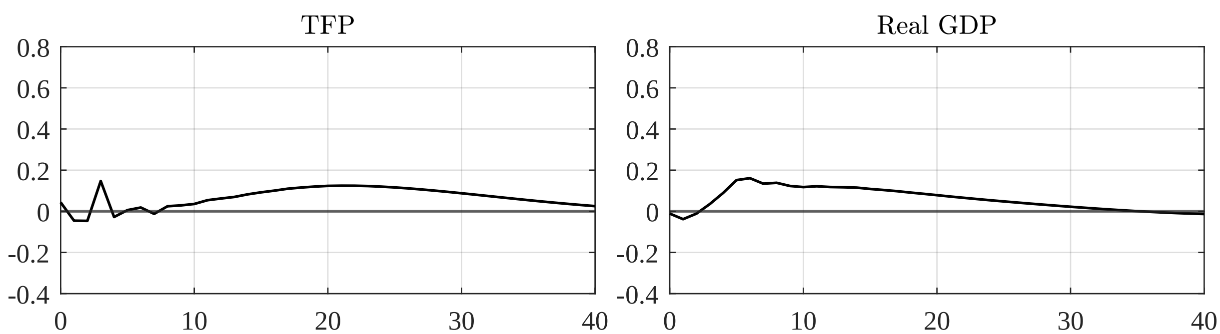


Figure 8: Impulse responses with the MAHB series

(a) Cholesky identified VAR model



(b) Max-share identified VAR model

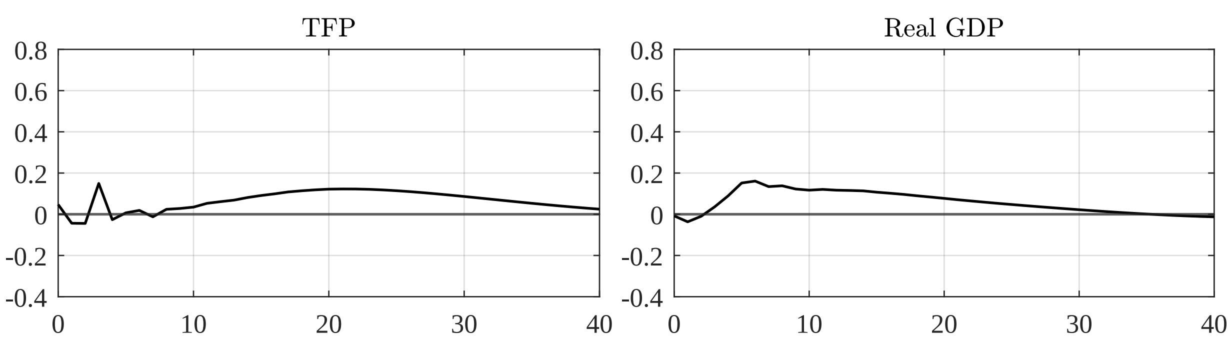
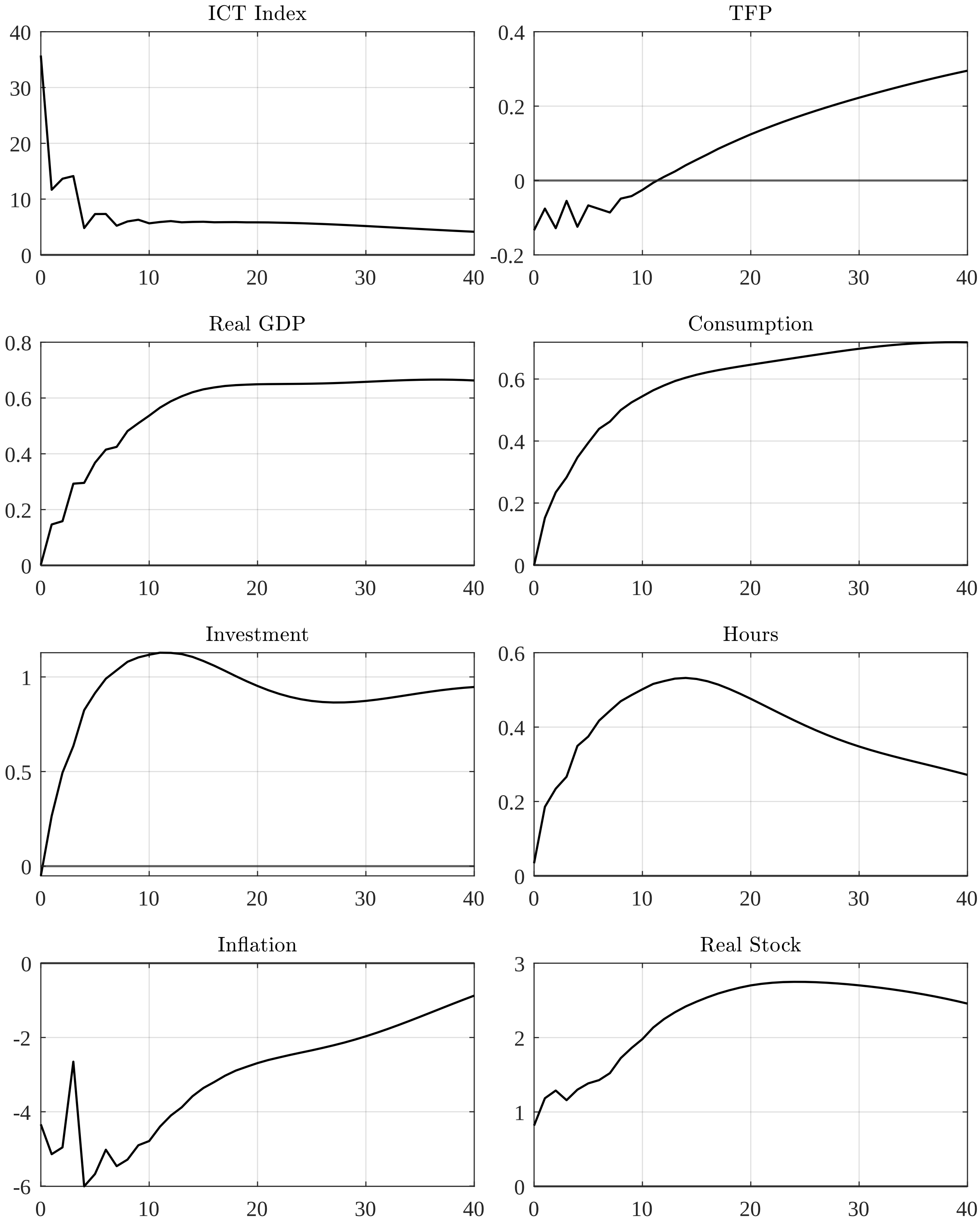


Figure 9: Max-share identified impulse responses with the ICT index



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.