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Estimating Macroeconomic News and Surprise Shocks[*]

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Abstract

The importance of understanding the economic effects of TFP news and surprise shocks is widely recognized in the literature. A common VAR approach is to identify responses to TFP news shocks by maximizing the variance share of TFP over a long horizon. Under suitable conditions, this approach also implies an estimate of the surprise shock. We find that these TFP max share estimators tend to be strongly biased when applied to data generated from DSGE models with shock processes that match the TFP moments in the data, both in the presence of TFP measurement error and in its absence. Incorporating a measure of TFP news into the VAR model and adapting the identification strategy substantially reduces the bias and RMSE of the impulse response estimates, even when there is sizable measurement error in the news variable. When applying this method to the data, we find that news shocks are slower to diffuse to TFP and have a smaller effect on real activity than implied by the TFP max share method.

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

JEL Classifications: C32, C51, C61, E32

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1 INTRODUCTION

There is considerable interest in understanding the economic effects of shocks to expectations about future economic activity dating back to Pigou (1927).[1] Such news shocks have received particular attention in studies that explore the effects of shocks to total factor productivity (TFP) on macroeconomic aggregates, starting with Beaudry and Portier (2006).

A common approach to identifying anticipated shocks to TFP ("news shocks") is to use the max share estimator popularized by Uhlig (2003, 2004), Barsky and Sims (2011), and Francis et al. (2014).[2] This estimator identifies the news shock by selecting parameters for the structural impact multiplier matrix of a vector autoregressive (VAR) model to maximize the forecast error variance shares of TFP over a long horizon. Under suitable conditions, this estimator also implies an estimate of the unanticipated shock to TFP ("surprise shock"). We will refer to this estimator as the "TFP max share" estimator.

Early applications of the TFP max share estimator imposed the restriction that the news shock is orthogonal to current TFP, which can be traced to Cochrane (1994) and Beaudry and Portier (2006). A further refinement of the TFP max share estimator was introduced by Kurmann and Sims (2021, henceforth, KS), who relaxed this exclusion restriction to allow for measurement error in TFP.[3] Their estimator also accounts for the fact that new technologies may affect TFP immediately, even though their effect on TFP may take many years to build up due to the slow diffusion of new technologies.

It is widely believed that TFP max share estimators of news shocks work well as long as news shocks account for the bulk of the variation in TFP at long horizons. Our first contribution is to show that this condition is not sufficient to ensure the accuracy of the estimator. Our focus is on the TFP max share estimator proposed by KS, which represents the state of the art in this literature,

[1] See Beaudry and Portier (2014) for a review of the literature on news-driven business cycles.

[2] 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, 2023; Carriero and Volpicella, 2024; 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).

[3] Christiano et al. (2004) and Bouakez and Kemoe (2023) also discuss the ramifications of TFP measurement error.

but we also consider other variants. We begin by examining the accuracy of this estimator in the ideal setting when there is no TFP measurement error using data generated from a conventional dynamic stochastic general equilibrium (DSGE) model. Our simulation results demonstrate that, even when virtually all variation in TFP at a long horizon is explained by news shocks, the TFP max share estimator may fail to recover the responses to news shocks, regardless of the sample size. In practice, the accuracy of the estimator not only depends on the quantitative importance of news shocks at long horizons but also at shorter horizons. We then show that these results also hold when using the larger-scale DSGE model developed by KS, which allows the simulated TFP data to be contaminated by measurement error.

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 in very large samples. While we can replicate these findings, we show that TFP news shocks explain all variation in TFP at all horizons under their parameterization of the TFP process. When the parameters in the DSGE model are set to match the TFP moments in the data, in contrast, the impulse response estimates are strongly biased. We trace this problem to the inability of TFP max share estimators to distinguish the effects of news and non-news shocks at short horizons. We document that these issues extend to the other variants of the TFP max share estimator used in the literature.

These results raise the question of what alternative methods are available to applied researchers. Our second contribution is to show that adding a direct measure of TFP news to the VAR model and adapting the identification strategy, as suggested in some recent empirical studies, will substantially reduce the asymptotic bias.[4] We discuss two such identification strategies. One is based on maximizing the variance share of the news variable at a short horizon (as opposed to the variance share of TFP at a long horizon) and is new to the literature. The other treats news variable innovations as predetermined as in Alexopoulos (2011) and Cascaldi-Garcia and Vukotić (2022).

While we are not the first to employ direct measures of TFP news for identifying news shocks,

[4]Examples of studies employing measures of TFP news include Shea (1999), Christiansen (2008), Alexopoulos (2011), Baron and Schmidt (2019), Cascaldi-Garcia and Vukotić (2022), Miranda-Agrippino et al. (2022), and Fieldhouse and Mertens (2023).

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 much lower bias and root mean squared error (RMSE) than the TFP max share estimator in the absence of TFP measurement error. We then compare the news variable estimators to the TFP max share estimator in the presence of TFP measurement error and show that these methods still substantially reduce the bias and RMSE of the responses to news shocks. The superior accuracy of these estimators is robust to sizable measurement error in the news variable. This evidence indicates that estimators based on TFP news variables avoid the identification issues of the TFP max share estimator.

A fundamental concern with using the TFP max share estimator is that households are likely to account for TFP news in forming expectations about future TFP. This information typically has been omitted from the VAR information set in the literature. It is well-known that the identification of structural stocks in the VAR requires these information sets to be aligned (see, e.g., Hansen and Sargent, 1991; Leeper et al., 2013). We present evidence that this problem accounts for some, but not all of the asymptotic bias of the TFP max share estimator of the impulse responses. While applying the TFP max share method to a VAR model that includes a measure of TFP news substantially alleviates this bias, we show that the two news-based identification strategies are even less biased and have lower RMSE.

Our third contribution is to empirically illustrate the use of TFP news for identifying news shocks using a range of TFP news measures that have been used in other studies in the literature. We first show that two of these news measures generate plausible results in light of the underlying economic theory. Both yield impulse response estimates that are systematically and substantially different from the estimates generated by the TFP max share method, consistent with our simulation results.

We then reexamine the question of whether these shocks are an important driver of TFP and real activity. There are conflicting views in the literature about how quickly news shocks diffuse to TFP and about the extent to which they drive macroeconomic aggregates.[5] We find that news shocks are slow to diffuse to TFP, but have a more immediate effect on real activity, explaining 24% of the fluctuations in output at a five-year horizon. In the long-run, the share of the forecast error variance explained by news shocks is 24% for TFP and 36% for output. In contrast, the estimates based on the TFP max share approach not only imply that news shocks quickly diffuse to TFP, but also that they explain 63% of the forecast error variance of output at a one-year horizon and almost 90% at horizons beyond five years.

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 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 TFP max share estimator in the absence of TFP measurement error. In Section 4, we extend the analysis to the larger-scale model developed by KS and allow for 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 empirical importance of news shocks in a range of VAR models based on alternative measures of TFP news and compare the results to those obtained using the TFP max share estimator. Section 7 contains the concluding remarks.

2 IDENTIFICATION PROBLEM

This section describes the TFP max share estimator for identifying news shocks. It also explains the conditions under which the method simultaneously identifies surprise TFP shocks.

2.1 NOTATION Consider a VAR model with K variables. Let $\mathbf{y}_t$ be a $K \times 1$ vector of variables. The reduced-form moving average representation of the VAR model is given by $\mathbf{y}_t = \Phi(L)\mathbf{u}_t$,

[5] See, for example, Barsky et al. (2015), Barsky and Sims (2011), Beaudry and Lucke (2010), Bouakez and Kemoe (2023), Cascaldi-Garcia and Vukotić (2022), Fève and Guay (2019), Forni et al. (2014), Görtz et al. (2022b), Levchenko and Pandalai-Nayar (2020), and Miranda-Agrippino et al. (2022).

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 with variance-covariance matrix $\Sigma = E[\mathbf{u}_t \mathbf{u}_t']$.

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

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

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

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

where $\Phi_{i,\tau}$ is the ith row of the lag polynomial at lag τ and γ_j is the jth column of 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 TFP MAX SHARE ESTIMATOR

For expository purposes, consider a stylized VAR model of the effects of shocks to TFP with $K = 3$. Without loss of generality, the TFP variable is ordered first. 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.

The TFP max share estimator of the news shock proposed by KS, which represents the state of the art in the literature, is based on

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

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 of Q and H_n denotes a 20-year horizon. The estimates are validated by showing that selected news indicators respond positively to the news shock in the short run.

The exact form of the objective function used to solve for γ_n differs across variants of the TFP max share approach. For example, Barsky and Sims (2011) sum the variance shares over horizons up to H_n and impose $\gamma_{n,1} = 0$. The approach proposed by Dieppe et al. (2021) targets a specific horizon of the squared impulse response function. What unifies these approaches is that TFP is the target variable. We will focus on the specification in (2), but also consider these other variants.

2.3 IDENTIFICATION CONDITIONS

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

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

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

Restriction R1 implies

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

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

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

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

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

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

Restriction R2 implies

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

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

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

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

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

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

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

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

Thus, for $K = 3$ the identifying restrictions uniquely 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 example is for $K = 3$, the following proposition shows that in the absence of TFP measurement error the TFP max share estimator of the news shock always identifies the surprise shock.

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 TFP max share estimator. In particular, when TFP is ordered first in the VAR model, $\gamma_{s,1} = \pm\sqrt{1-\gamma_{n,1}^2}$ and $\gamma_{s,j} = -\gamma_{n,1}\gamma_{n,j}/\gamma_{s,1}$ for $j \in \{2,\ldots,K\}$.*

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 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. This result generalizes to $K > 3$.

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

3 Accuracy of the TFP Max Share Estimator

3.1 Data Generating Process We begin our examination of the TFP max share estimator by focusing on the ideal setting where there is no measurement error, so $\gamma_{\ell,1} = 0$. To facilitate our analysis, we generate data from a conventional New Keynesian model (henceforth, the "baseline model"). The advantage of starting with a simple model is that it allows us to highlight that our results do not depend on any nonstandard model features. In Section 4, we will consider a larger-scale model in order to examine the implications of TFP measurement error.

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

$$\ln a_t = \ln s_t + \ln z_t,$$

$$\ln z_t = \ln g_t + \ln z_{t-1},$$

$$\ln s_t = \rho_s \ln s_{t-1} + \sigma_s \varepsilon_{s,t},\ -1 < \rho_s < 1,\ \varepsilon_s \sim \mathbb{N}(0,1),$$

$$\ln g_t = (1-\rho_g)\ln \bar{g} + \rho_g \ln g_{t-1} + \sigma_g \varepsilon_{g,t-1},\ -1 < \rho_g < 1,\ \varepsilon_g \sim \mathbb{N}(0,1),$$

where $\varepsilon_{g,t-1}$ is lagged so that the shock occurs one period before it affects TFP. Households anticipate the effects of this shock when forming expectations, consistent with the interpretation of a news shock.

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

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

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

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

The final-goods firm purchases $y_t(i)$ units from each intermediate-goods firm to produce the final good, $y_t \equiv [\int_0^1 y_t(i)^{(\epsilon_p-1)/\epsilon_p} di]^{\epsilon_p/(\epsilon_p-1)}$, 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 aggregate 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 a 2% annual real interest rate. 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 log TFP growth ($SD(\Delta a)$, $AC(\Delta a)$), the standard deviation and autocorrelation of detrended TFP ($SD(\tilde{a})$,

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

Moment	Data	Baseline Model	Baseline Model KS TFP Parameterization
$SD(\tilde{a})$	2.01	2.32	1.46
$SD(\Delta a)$	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	2.92	1.88
$SD(\tilde{\imath})$	9.63	9.93	7.47

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

$AC(\tilde{a})$), and the standard deviations of detrended output and investment ($SD(\tilde{y})$, $SD(\tilde{\imath})$).[6] This yields $\rho_g = 0.6$, $\rho_s = 0.8$, $\rho_\mu = 0.9$, $\sigma_g = 0.003$, $\sigma_s = 0.007$, and $\rho_\mu = 0.007$. Table 1 shows that these parameters imply a good model fit, suggesting that this model is a useful laboratory for evaluating the TFP max share identification strategy.

3.2 Simulation Evidence

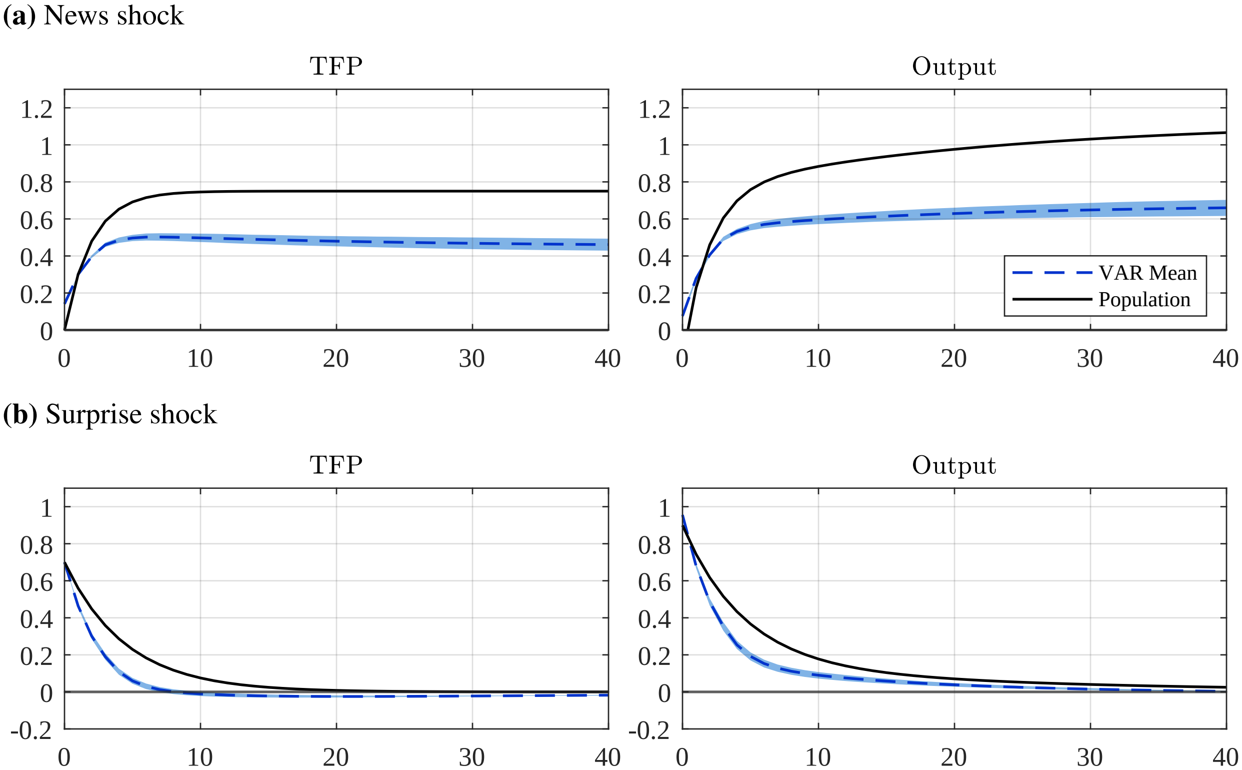
Since there are three structural shocks in the DSGE model, we fit a three-dimensional structural VAR model. We work with a VAR(4) model with intercept for $\mathbf{y}_t = (a_t, y_t, i_t)'$, given that investment has a strong connection with the MEI shock. All variables enter in logs. We generate 1,000 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. 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.[7]

We begin by presenting results for the KS version of the TFP max share estimator (henceforth, the KS estimator), since it reflects the state-of-the art in the literature. We set $T = 10{,}000$ to approximate the asymptotic properties of the estimator. The top row shows that the responses of TFP

[6] 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.

[7] 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.

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



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

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. This evidence calls into question the ability of the TFP max share estimator to recover the population responses, even asymptotically.[8]

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

[8] 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 KS TFP Parameterization		
h	News Shock	Surprise Shock	MEI Shock	News Shock	Surprise Shock	MEI Shock
4	37.0	63.0	0.0	98.6	1.4	0.0
8	66.4	33.6	0.0	99.6	0.4	0.0
20	87.3	12.7	0.0	99.9	0.1	0.0
40	93.8	6.2	0.0	99.9	0.1	0.0
80	96.9	3.1	0.0	100.0	0.0	0.0

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

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 reports the implied model moments when using their parameterization of the TFP process in our model. This shows the KS specification is 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 TFP 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 almost all of the variance at all horizons, which effectively eliminates the surprise shock and makes it easier for the KS estimator to identify the news shock. This explains the comparatively high accuracy of the KS estimator in their simulation analysis.

Our analysis suggests that the KS estimator 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 the widespread belief that TFP max share estimators work well as long as news shocks account for the bulk of the variation in 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 responses 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 tends to confound news and surprise shocks, as illustrated in Figure 1. 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 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 TFP max share approach and estimate the news shock directly from the TFP data.

3.4 ALTERNATIVE TFP MAX SHARE ESTIMATORS

This section briefly considers three alternative versions of the TFP max share estimator. We examine whether any of them can help reduce the bias and RMSE of the KS estimator.

BS Max Share Estimator The TFP max share estimator proposed by Barsky and Sims (2011), which we will refer to as the BS estimator, differs from the KS estimator in two dimensions: (1) It imposes that news shocks do not affect TFP on impact; (2) It solves for the news shock that maximizes the sum of the forecast error variance shares of TFP over a long horizon, rather than the variance share over a particular long horizon. Specially, the news shock estimate is based on

$$\gamma_n = \operatorname{argmax} \sum_{h=0}^{H_n} \Omega_{1,2}(h), \quad \Omega_{1,2}(h) \equiv \frac{\sum_{\tau=0}^{h} \Phi_{1,\tau} P \gamma_n \gamma_n' P' \Phi_{1,\tau}'}{\sum_{\tau=0}^{h} \Phi_{1,\tau} \Sigma \Phi_{1,\tau}'}, \tag{3}$$

subject to $\gamma_{n,1} = 0$ and $\gamma_n' \gamma_n = 1$.[9] Table 3 shows the RMSE of the impulse responses. The first four columns show the sum of the RMSEs over horizons 0 through 40 for output and TFP. The last column shows the sum of these entries across the four response functions. The RMSE of the responses to a news shock are significantly reduced relative to the KS estimator. This result is

[9] We set $H_n = 80$ to align with our analysis of the KS estimator, whereas Barsky and Sims (2011) set $H_n = 40$.

Table 3: RMSE over 40 quarters based on the baseline DSGE model

	TFP Response		Output Response		
Estimator	News Shock	Surprise Shock	News Shock	Surprise Shock	Total
KS Max Share	10.2	2.3	13.1	2.4	28.0
BS Max Share	2.2	6.8	3.1	9.1	21.3
NAMS Max Share	9.9	1.9	12.8	2.0	26.7

Notes: VAR(4) model with $T = 10{,}000$ and $\mathbf{y}_t = (a_t, y_t, i_t)$.

expected given that there is no measurement error in TFP and the exclusion restriction in the VAR model aligns with the timing assumption of the news shock in the DSGE model. However, the improved accuracy of the responses to the news shock comes at the expense of a higher RMSE for the responses to the surprise shock. This result is due to the fact that the BS estimator has trouble recovering the responses of the surprise shock in the short run.

NAMS Max Share Estimator One concern with the BS estimator is that less persistent shocks could affect the estimates of the news shock. KS try to address this concern by removing the cumulative sum from the objective function. Dieppe et al. (2021) go a step further and propose a non-accumulated max share (NAMS) estimator that, when adapted to our context, maximizes the squared TFP response to the news shock at H_n. In this case, the news shock estimate is based on

$$\gamma_n = \text{argmax } \frac{\Phi_{1,H_n} P \gamma_n \gamma_n' P' \Phi_{1,H_n}'}{\Phi_{1,H_n} \Sigma \Phi_{1,H_n}'}, \tag{4}$$

subject to the restriction that $\gamma_n' \gamma_n = 1$. The belief is that this estimator can help reduce bias of the KS estimator by further reducing the influence of the surprise shock on γ_n. Table 3, however, shows that the sum of the RMSE under the KS and NAMS max share estimators are nearly identical, suggesting that there is little to choose between these estimators.

Surprise Shock Max Share Estimator A direct implication of our analysis in Section 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 when there is no TFP measurement error. A surprise shock max share estimator can be defined as

$$\gamma_s = \text{argmax } \Omega_{1,1}(H_s), \quad \Omega_{1,1}(H_s) \equiv \frac{\sum_{\tau=0}^{H_s} \Phi_{1,\tau} P \gamma_s \gamma_s' P' \Phi_{1,\tau}'}{\sum_{\tau=0}^{H_s} \Phi_{1,\tau} \Sigma \Phi_{1,\tau}'}, \tag{5}$$

subject to the restriction that $\gamma_s'\gamma_s = 1$ and that the responses of selected variables to the surprise shock match patterns that would be expected of a surprise shock, where 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.

Figure 2 shows that not only is the surprise shock max share estimator much more biased than the original estimator, but it also tends to generate impulse responses that are increasing when the population response is declining and that are declining when the population response is increasing. In fact, responses to these surprise shocks look much like one would expect responses to a news shock to look like. Moreover, the responses to the news shock are of the opposite sign of the population responses. Thus, this alternative estimator should not be used in applied work.

4 THE ROLE OF TFP MEASUREMENT ERROR

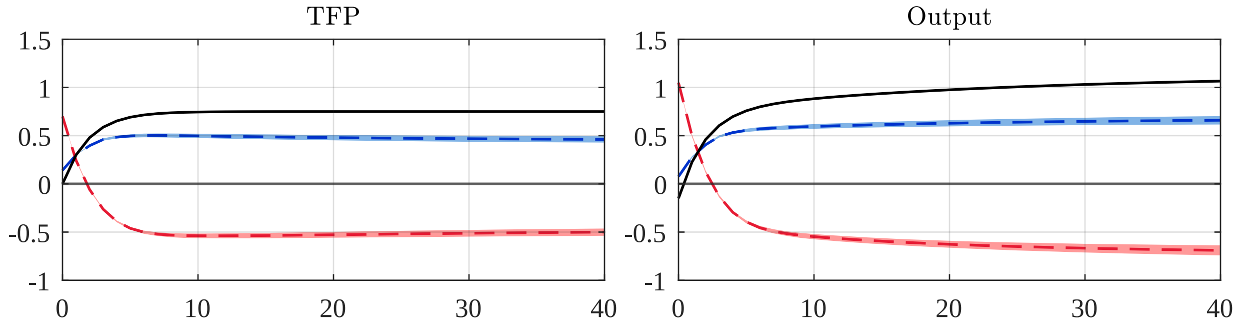
Our analysis so far has focused on DSGE models without unobserved changes in factor utilization. Of course, a key point in KS is that one needs to be concerned about measurement error driving a wedge between measured and true TFP. In this section, we consider an environment with TFP measurement error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

One key difference is that in this case the TFP innovation can no longer be written as a linear combination of news and surprise shocks, so identifying surprise TFP shocks is not possible without further identifying restrictions. 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 TFP max share 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 to match moments in the data.

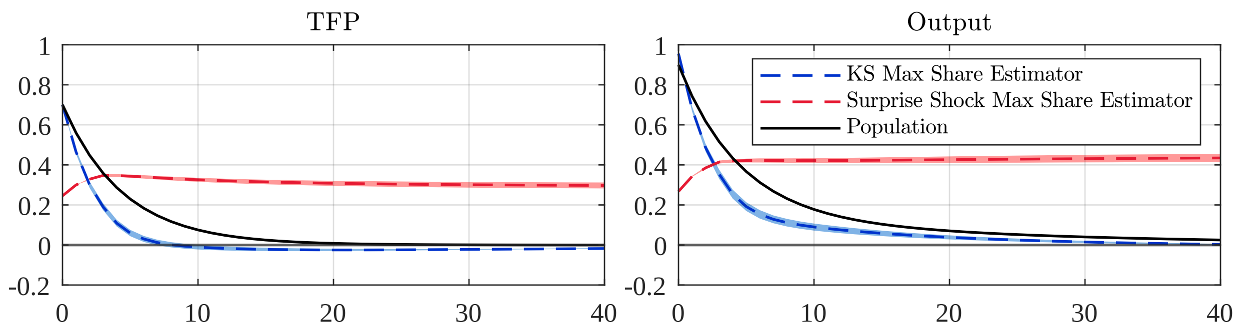
To illustrate this point, we evaluate the TFP max share estimator based on data generated from

Figure 2: Impulse responses from alternative estimators based on the baseline DSGE model

(a) News shock



(b) Surprise shock



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

the larger-scale DSGE model employed by KS, allowing for TFP measurement error.[10] The only difference is that we turn off the preference and monetary policy shocks in the simulations, so the results are directly comparable to the baseline model.

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

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

[10]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 important, but they affect some of the quantitative results.

Table 4: Data and model-implied moments from the KS DSGE model

Moment	Data	KS Model No Measurement Error (1)	KS Model Measurement Error (2)	KS Model Calibrated Shock Processes Measurement Error (3)
$SD(\tilde{a})$	2.01	1.46	2.67	2.31
$SD(\Delta a)$	0.80	0.30	0.59	0.73
$AC(\tilde{a})$	0.87	0.88	0.88	0.87
$AC(\Delta a)$	−0.09	0.67	0.43	0.01
$SD(\tilde{y})$	3.13	5.15	5.15	3.92
$SD(\tilde{\imath})$	9.63	12.15	12.15	9.48

Notes: 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.

where $\omega_{\ell,t}$ is the labor share. Changes in factor utilization ($\Delta \ln \hat{u}_t$) are assumed to be proportional to changes in detrended hours worked ($\Delta \ln \hat{h}_t$), so

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

where $\hat{\beta}$ is a proportionality factor. 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

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

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. Table 4 shows that 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) 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 0.43 autocorrelation of the growth rate

Table 5: Forecast error variance decompositions for TFP in the KS DSGE model

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

	KS Model Measurement Error			KS Model Calibrated Shock Processes Measurement Error		
h	News Shock	Surprise Shock	MEI Shock	News Shock	Surprise Shock	MEI Shock
4	72.1	1.0	27.0	33.3	55.6	11.1
8	79.1	0.6	20.3	46.3	43.3	10.4
20	52.6	0.4	47.0	47.7	9.3	43.0
40	84.0	0.3	15.8	62.3	1.8	35.9
80	94.5	0.1	5.4	75.2	0.7	24.1

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

	KS Model Measurement Error			KS Model Calibrated Shock Processes Measurement Error		
h	News Shock	Surprise Shock	MEI Shock	News Shock	Surprise Shock	MEI Shock
4	98.6	1.4	0.0	47.9	52.1	0.0
8	99.6	0.4	0.0	75.7	24.3	0.0
20	99.9	0.1	0.0	91.0	9.0	0.0
40	99.9	0.1	0.0	95.6	4.4	0.0
80	100.0	0.0	0.0	97.8	2.2	0.0

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

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 4. This exercise implies that $\rho_g = 0.5$, $\rho_s = 0.4$, $\rho_\mu = 0.95$, $\sigma_g = 0.0025$, $\sigma_s = 0.006$, $\sigma_\mu = 0.004$. Column (3) shows that using the calibrated parameters improves the fit along all dimensions, particularly for the autocorrelation of TFP growth, which drops to 0.01.[11]

As discussed in Section 3, the TFP max share estimator may be biased, even asymptotically, when the variance contribution of the surprise TFP shock at short horizons is non-trivial. Table 5a

[11] Alternatively, one could have estimated the entire DSGE model, but then all of the parameters would have differed from those in KS, raising the question of whether these differences are driving our results. We instead kept the DSGE model as close as possible to the original KS model while fitting key macro moments that are central to the performance of the TFP max share estimator.

examines whether the same problem arises in the larger-scale KS model. The left side shows the forecast error variance decomposition for measured TFP under the KS parameterization of the shock 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 TFP max share estimator to perform well. In contrast, when the shock processes are calibrated, 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 lower accuracy than under the KS parameterization, much like in the baseline model.

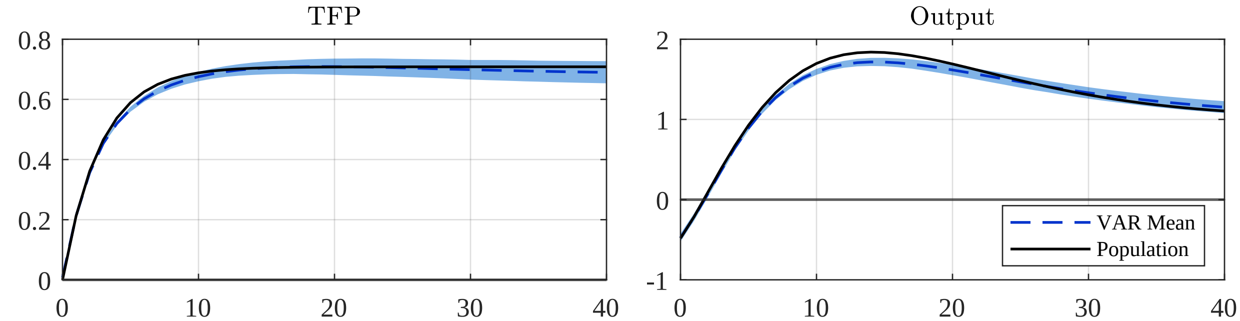
Once again, we begin by discussing the KS version of the TFP max share estimator with $T = 10{,}000$. Figure 3 plots the responses of output and measured TFP under alternative versions of the KS DSGE model. The top panel shows the results in the absence of measurement error. As expected, the KS estimator does an excellent job at recovering the population responses when the sample size is sufficiently large. The middle panel shows the results with measurement error under the KS TFP parameterization. While the bias of the output response is slightly larger, the fit remains quite good. 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. However, this result is not surprising. 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.[12]

One might argue that these results are not surprising given the belief that news shocks must account for a large part of the unpredictable variation in measured TFP at long horizons in order for a TFP max share estimator to perform well. Of course, we have no way to judge how important

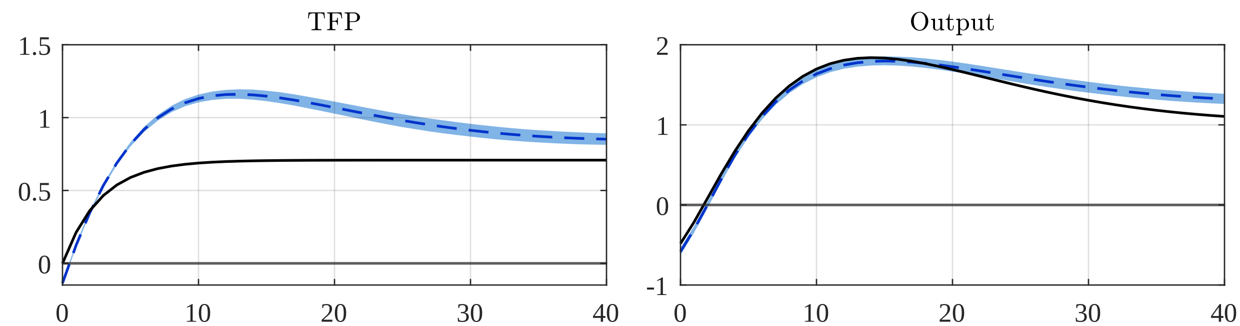
[12]Throughout the paper, we followed the literature in setting the lag order of the VAR to 4. For $T = 10{,}000$, the accuracy of the KS estimator can be improved by increasing the lag order up to a certain point. This, however, comes at the cost of substantially increasing the variability of the estimator for $T = 360$.

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

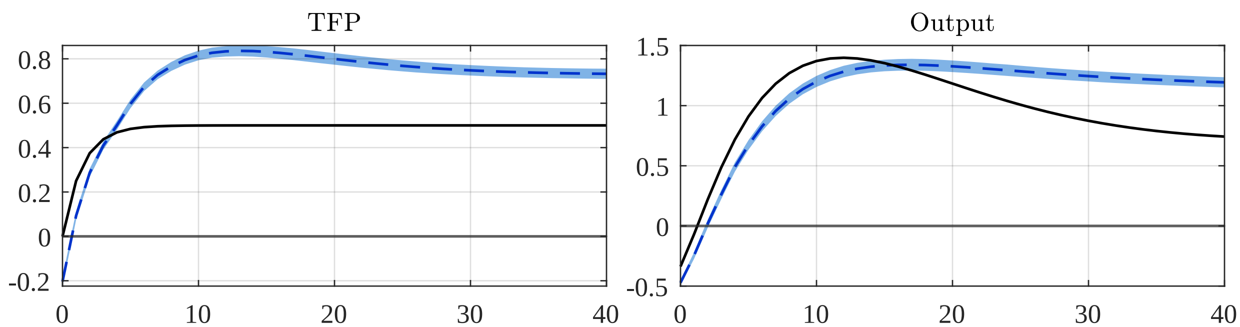
(a) KS model without measurement error



(b) KS model with measurement error



(c) KS model with calibrated shock processes and measurement error



Notes: VAR(4) model with $T = 10{,}000$, where $\mathbf{y}_t = (a_t, y_t, i_t)'$ when there is no measurement error and $\mathbf{y}_t = (\mathrm{TFP}^u_t, y_t, i_t)'$ where there is measurement error. The responses in the top row are scaled so the estimated response of TFP matches the population value when the shock first takes effect. The responses in the bottom two rows are not scaled since the estimated responses of TFP tend to be close to zero when the shock first takes effect.

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 5b, it remains true under our calibration that news shocks explain 98% of the long-run variability of true TFP, but this does not mean that

Table 6: RMSE over 40 quarters based on the KS DSGE model

Estimator	TFP Response	Output Response	Investment Response	Total
KS Max Share	10.3	10.4	19.3	40.0
BS Max Share	8.8	8.3	14.1	31.1
NAMS Max Share	10.1	10.8	21.3	42.2

Notes: VAR(4) model with $T = 10{,}000$ and $\mathbf{y}_t = (\mathrm{TFP}_t^u, y_t, i_t)$.

they are as important a determinant of measured TFP. Table 5a shows that news shocks explain only 75% 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 shows that DSGE models that are consistent with the data may not satisfy one of the maintained assumptions required for the TFP max share estimator to perform well, which provides another possible explanation of the bias.

For completeness, Table 6 shows the RMSE for the KS estimator, alongside two of the alternative TFP max share estimators that were considered in Section 3, in the presence of TFP measurement error. Once again, the performance of the KS and NAMS estimators is very similar. The BS estimator performs slightly better than the KS estimator, but the news shock estimates are not nearly as accurate as they are in the baseline model. This is because the presence of measurement error implies that the exclusion restriction in the BS estimator is no longer valid.

5 ESTIMATORS INVOLVING MEASURES OF TFP NEWS

The bias of the TFP max share estimator in large samples raises the question of whether there are alternative estimators that perform better. 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. Similar approaches have been employed in a number of studies. For example, Shea (1999) considers models that incorporate a measure of either government 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), Jinnai (2014, sector-specific productivity in the R&D sector), Baron and Schmidt (2019, counts of new information and communication technology standards), Cascaldi-Garcia and Vukotić (2022, patent applications), Miranda-Agrippino et al. (2022, patent applications), and Fieldhouse and Mertens (2023, government R&D spending). The premise of all these studies is that measures of TFP news should increase immediately as a positive news shock is realized, facilitating identification strategies based on short-run restrictions.

Despite the popularity of these identification strategies, there does not exist simulation evidence that quantifies the ability of these VAR models to recover news shocks (or for that matter surprise shocks) generated by DSGE models. In this section, we examine two such identification strategies, first in our baseline model abstracting from TFP measurement error and then in the larger-scale KS model, which allows the simulated TFP data to be contaminated by 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 at short horizons. We set $H_n = 4$, but our results are robust to smaller values for H_n. Another strategy is to treat the news measure as predetermined with respect to TFP, resulting in a 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 (see, e.g., Plagborg-Møller and Wolf, 2021). We will refer to these estimators as the "max share news" and "Cholesky news" estimators.

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, 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 news variable as an external instrument is invalid in that case.[13]

An obvious concern is that, in practice, the TFP news variable could be measured with error. The instrumental variable approach allows consistent estimation of the impulse responses in that case. In contrast, there are no results in the literature about the robustness of the max share news approach to this form of measurement error, but we present simulation evidence below that both estimators perform well with and without measurement error in the TFP news variable.

5.2 ACCURACY OF THE NEWS VARIABLE ESTIMATORS We start by using the baseline DSGE model to compare the accuracy of the news-based estimators to that of the KS estimator in the absence of TFP measurement error. The news variable reflects the permanent component of TFP, z_t. Since the news shock is lagged by one period in the DSGE model, the TFP news variable only responds with a delay of one period. We therefore fit a VAR(4) model with intercept to $\mathbf{y}_t = (z_{t+1}, a_t, y_t)'$ for the news-based estimators and to $\mathbf{y_t} = (a_t, y_t, i_t)'$ for the KS estimator. This timing mirrors the way observed TFP news has been used in applied work.[14] The choice of these variables is dictated by our interest in constructing the responses of TFP and output.[15] All variables enter the VAR in logs and are directly observable in the DSGE model.

Table 7 compares the RSME of the impulse responses to news and surprise shocks across the estimators. There is strong evidence in favor of the news-based estimators. Both the max share news and Cholesky news estimators reduce the RMSE by 82% relative to the KS estimator. These improvements in accuracy are mainly due to RMSE reductions for the responses to news shocks.

[13]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 further discussion see, e.g., Hansen and Sargent, 1991; Kilian and Lütkepohl, 2017; Leeper et al., 2013). 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.

[14]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, as before, we consider a three-variable VAR model that includes investment for the KS max share estimator, since it has a strong connection with the MEI shock.

[15]When $\mathbf{y}_t = (z_{t+1}, a_t, y_t)'$, 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+1} 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.

Table 7: RMSE over 40 quarters based on the baseline DSGE model

	TFP Response		Output Response		
Estimator	News Shock	Surprise Shock	News Shock	Surprise Shock	Total
KS Max Share	10.2	2.3	13.1	2.4	28.0
Max Share News	1.4	0.8	1.9	1.0	5.0
Cholesky News	1.3	0.9	1.8	1.2	5.1
Alt KS Max Share	2.8	1.2	3.8	1.4	9.3

Notes: VAR(4) with $T = 10{,}000$, where $\mathbf{y}_t = (a_t, y_t, i_t)$ for the KS max share estimator and $\mathbf{y}_t = (z_{t+1}, a_t, y_t)$ for the max share news and Cholesky estimators. The Alt KS max share estimator uses the KS identification strategy and the max share news model variables.

To illustrate the improvement in accuracy, Figure 4 plots the responses of TFP and output to news and surprise shocks obtained using the max share news estimator. Both shocks appear properly identified by the max share approach with little bias in the mean estimates and small variability. Qualitatively similar results hold for the Cholesky news approach, as shown in Appendix E. These results suggest that identification strategies based on TFP news variables perform much better than the TFP max share estimator when both TFP and TFP news are accurately measured.

5.3 WHY DOES THE TFP MAX SHARE ESTIMATOR UNDER-PERFORM?

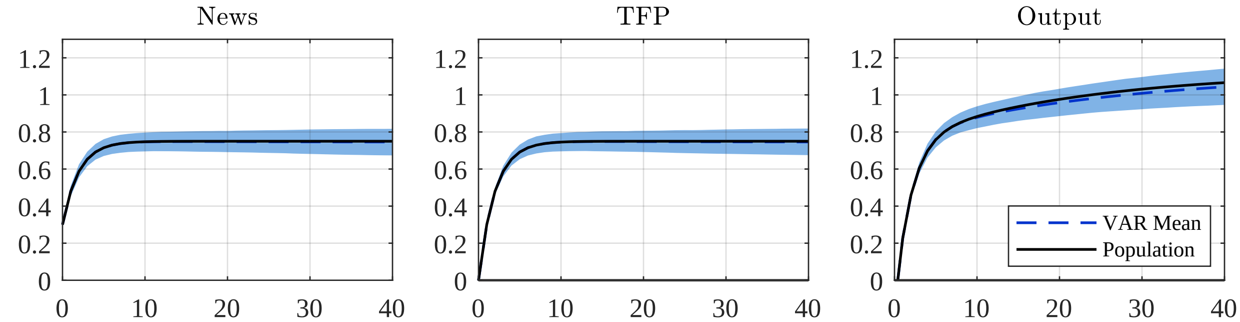
It may seem puzzling that the TFP max share estimator performs so much worse than the news-based estimators. One potential reason is that the VAR models that these methods are applied to typically do not include a direct measure of TFP news. As noted by Hansen and Sargent (1991) and Leeper et al. (2013), when economic agents form expectations based on information not contained in the information set of the VAR model, standard approaches to identifying structural shocks tend to fail.

These insights suggest that the comparatively high RMSE of the TFP max share estimator may be explained by the absence of a forward-looking variable that captures TFP news in the VAR model.[16] The last row in Table 7 explores this conjecture by applying the KS identification strategy to the max share news VAR model that includes z_{t+1}. Our simulations show that indeed the accuracy of the KS estimator substantially improves when incorporating TFP news in the VAR model, but even in that case the KS estimator is less accurate than the news-based estimators.

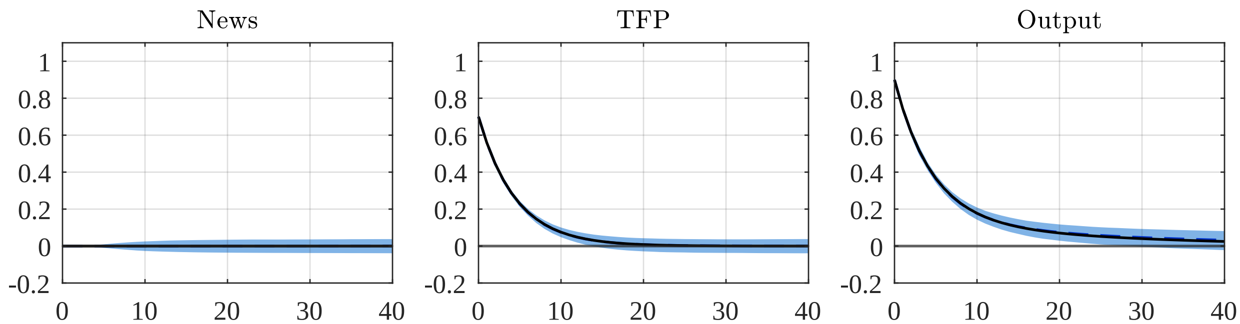
[16] KS include forward looking variables in some of their empirical work, but not in their simulation study.

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

(a) News shock



(b) Surprise Shock



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

5.4 Impact of Measurement Error in TFP News

In our analysis so far, 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 now allow the TFP news variable in the VAR model to be an imperfect measure of the permanent component of TFP news by introducing additive Gaussian measurement error, which is a standard approach in the econometrics literature (Plagborg-Møller and Wolf, 2022; Stock and Watson, 2018). Specifically, we replace z_{t+1} in the VAR model with $z^n_{t+1} = z_{t+1} + \sigma_n \epsilon^n_t$, where $\epsilon^n_t \sim \mathbb{N}(0, 1)$.

While there is no way of knowing the extent of measurement error in TFP news, Table 8 shows that our news-based estimators improve accuracy even if the news variable is measured with substantial error. For example, with 50% measurement error, expressed as a percentage of the

Table 8: RMSE over 40 quarters based on the baseline DSGE model

	TFP Response		Output Response		
Estimator	News Shock	Surprise Shock	News Shock	Surprise Shock	Total
KS Max Share	10.2	2.3	13.1	2.4	28.0
Max Share News ($\sigma_n = 0$)	1.4	0.8	1.9	1.0	5.0
Max Share News ($\sigma_n = 0.2\sigma_g$)	1.6	0.8	2.4	1.0	5.8
Max Share News ($\sigma_n = 0.5\sigma_g$)	3.6	0.8	4.9	1.0	10.2
Cholesky News ($\sigma_n = 0$)	1.3	0.9	1.8	1.2	5.1
Cholesky News ($\sigma_n = 0.2\sigma_g$)	1.7	0.9	2.4	1.2	6.3
Cholesky News ($\sigma_n = 0.5\sigma_g$)	3.8	1.0	4.7	1.2	10.6

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

standard deviation of the true news shock ($\sigma_n = 0.5\sigma_g$), both the max share news and Cholesky news estimators are still far more accurate than the KS estimator. Similarly accurate responses to news shocks are obtained even when allowing the measurement error to be serially correlated.

5.5 News-Based Estimators in the Presence of TFP Measurement Error

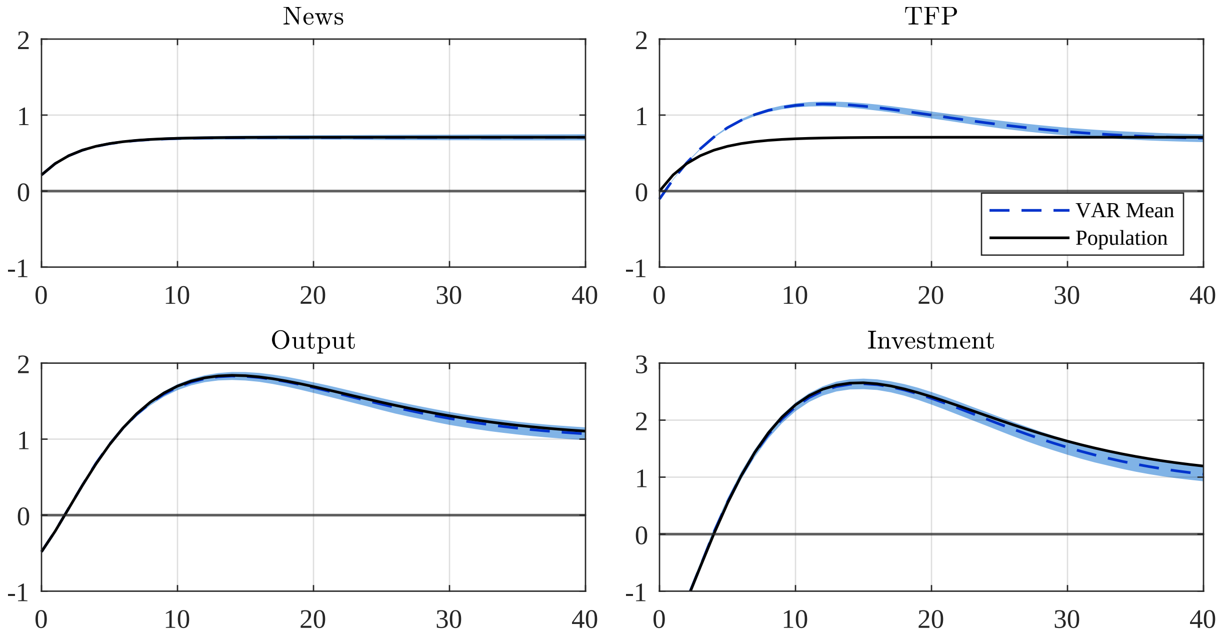
An important question is whether the max share news and Cholesky news estimators can also reduce impulse response bias in the presence of TFP measurement error. We explore this question by fitting VAR(4) models to data for $\mathbf{y}_t = (z_{t+1}, \mathrm{TFP}^u_t, y_t, i_t)$ simulated from the KS DSGE model for $T = 10{,}000$, where TFP^u_t denotes measured TFP.

The top panel of Figure 5 plots the impulse responses under the KS parameterization for the max share news estimator. The fit is very good, except for the response of measured TFP for the reasons already discussed in Section 4. The bottom panel plots the impulse responses under our calibrated shock processes. Even in that case, there is only modest bias in the responses of output and investment. The Cholesky news estimator produces similar results, as shown in Appendix E.

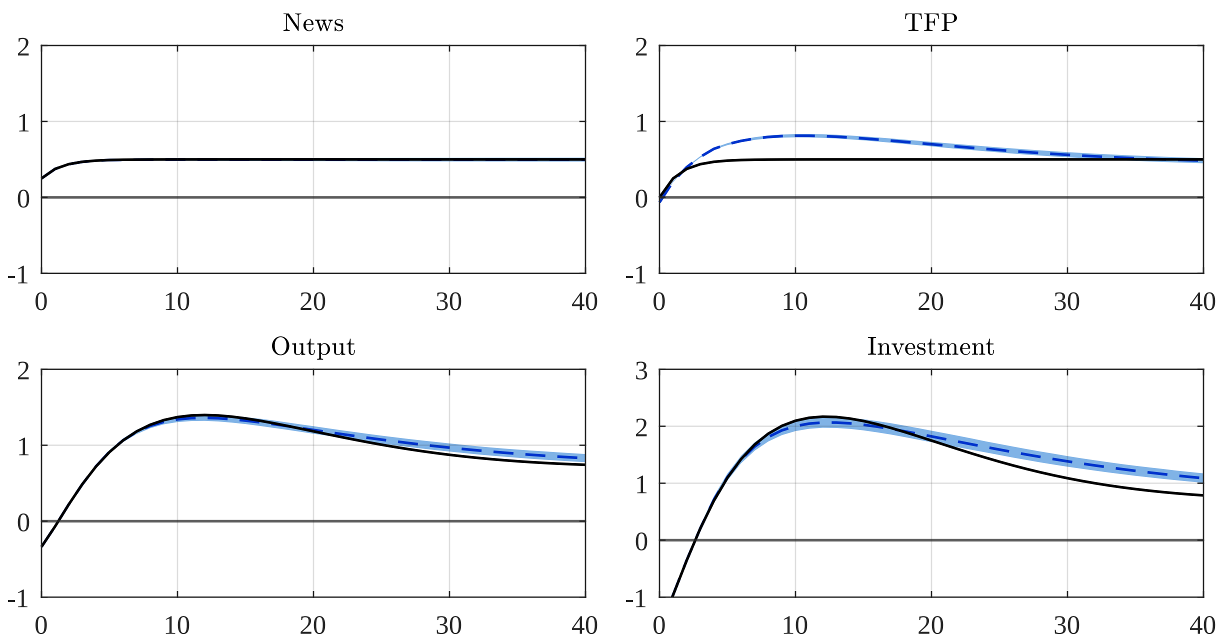
Table 9a quantifies the improvement in accuracy. It reports the RMSE of the impulse response estimator associated with each method under our calibration of the shock processes in the KS model. Adding the TFP news variable and adapting the identification procedure reduces the RMSE by 58% relative to the KS estimator. A similar reduction in accuracy also occurs when compared

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

(**a**) KS model with measurement error



(**b**) KS model with calibrated shock processes and measurement error



Notes: VAR(4) model with $T = 10{,}000$ and $\mathbf{y}_t = (z_{t+1}, \text{TFP}_t^u, y_t, i_t)'$. The responses are not scaled since the estimated responses of TFP tend to be close to zero when the shock first takes effect.

Table 9: RMSE over 40 quarters based on the KS DSGE model with calibrated shock processes

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

Estimator	TFP Response	Output Response	Investment Response	Total
KS Max Share	10.3	10.4	19.3	40.0
Max Share News	6.4	2.8	7.6	16.8
Cholesky News	6.4	2.7	7.5	16.6
Alt KS Max Share	7.0	4.9	13.9	25.7

(b) $T = 320$

Estimator	TFP Response	Output Response	Investment Response	Total
KS Max Share	10.3	14.3	29.7	54.3
Max Share News	8.1	10.8	19.0	37.9
Cholesky News	8.0	10.8	18.6	37.4
Alt KS Max Share	8.1	13.2	28.2	49.4

Notes: VAR(4) model, where $\mathbf{y}_t = (\mathrm{TFP}_t^u, y_t, i_t)$ for the KS max share estimator and $\mathbf{y}_t = (z_{t+1}, \mathrm{TFP}_t^u, y_t, i_t)$ for the max share news and Cholesky news estimators. The Alt KS max share estimator uses the KS identification strategy and the max share news model variables.

against the Alt KS max share estimator that includes the TFP news variable in the VAR model. Thus, the max share news and Cholesky news estimators improve accuracy, both in the presence of TFP measurement error and in its absence.

5.6 ACCURACY IN SMALL SAMPLES While our results for $T = 10{,}000$ indicate that the news-based estimators are much more accurate than the TFP max share estimator in long samples, they do not speak to the properties of the news-based estimators in sample sizes encountered in applied work. Therefore, we also examine the performance of the news-based estimators with $T = 320$ (80 years of quarterly data), which reflects the data available in the post-World War II period.

Table 9b shows the RMSE for the various estimators. Both the max share news and Cholesky news estimators lead to a 30% improvement in accuracy over the KS estimator and a 25% improvement over the Alt KS estimator. These results suggest that the benefits of the news-based estimators extend to realistic sample sizes and go beyond just aligning information sets.

6 EMPIRICAL FINDINGS

Our simulation evidence suggests that incorporating a measure of TFP news into the VAR model and adapting the identification strategy may improve the identification of the news shock. In practice, however, this approach will only be as good as the underlying measure of TFP news. Thus, we consider a range of VAR models that include one of four news variables: (1) **R&D**: real R&D expenditures, building on related work by Shea (1999) and Christiansen (2008); (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).[17]

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.[18] Specifically, the model includes a measure of TFP news, utilization-adjusted TFP, per capita output, consumption, investment, and hours worked, the inflation rate, the real S&P 500 index, and the federal funds rate. The data sources are provided in Appendix A. The sample for each VAR varies due to differences in the availability of the news variables. We identify the structural shocks based on the max share news and Cholesky news models introduced in Section 5.

There are two natural criteria for judging whether the news shocks have been properly identified. These criteria are suggested by the population responses in the DSGE models used in

[17]Baron and Schmidt (2019) treat technological standardization as a prerequisite for new technologies to be implemented and show that shocks to the ICT series cause 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 in Miranda-Agrippino et al. (2022) is the residual from regressing the quarterly growth rate of the USPTO series on lags of itself and a set of control variables that can include SPF forecasts and exogenous policy shocks. 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.

[18]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 10: Empirical results from VAR models including alternative measures of TFP news.

	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 $H_n = 4$.

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 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. Second, the news shock should have positive effects in the long run on TFP and output.

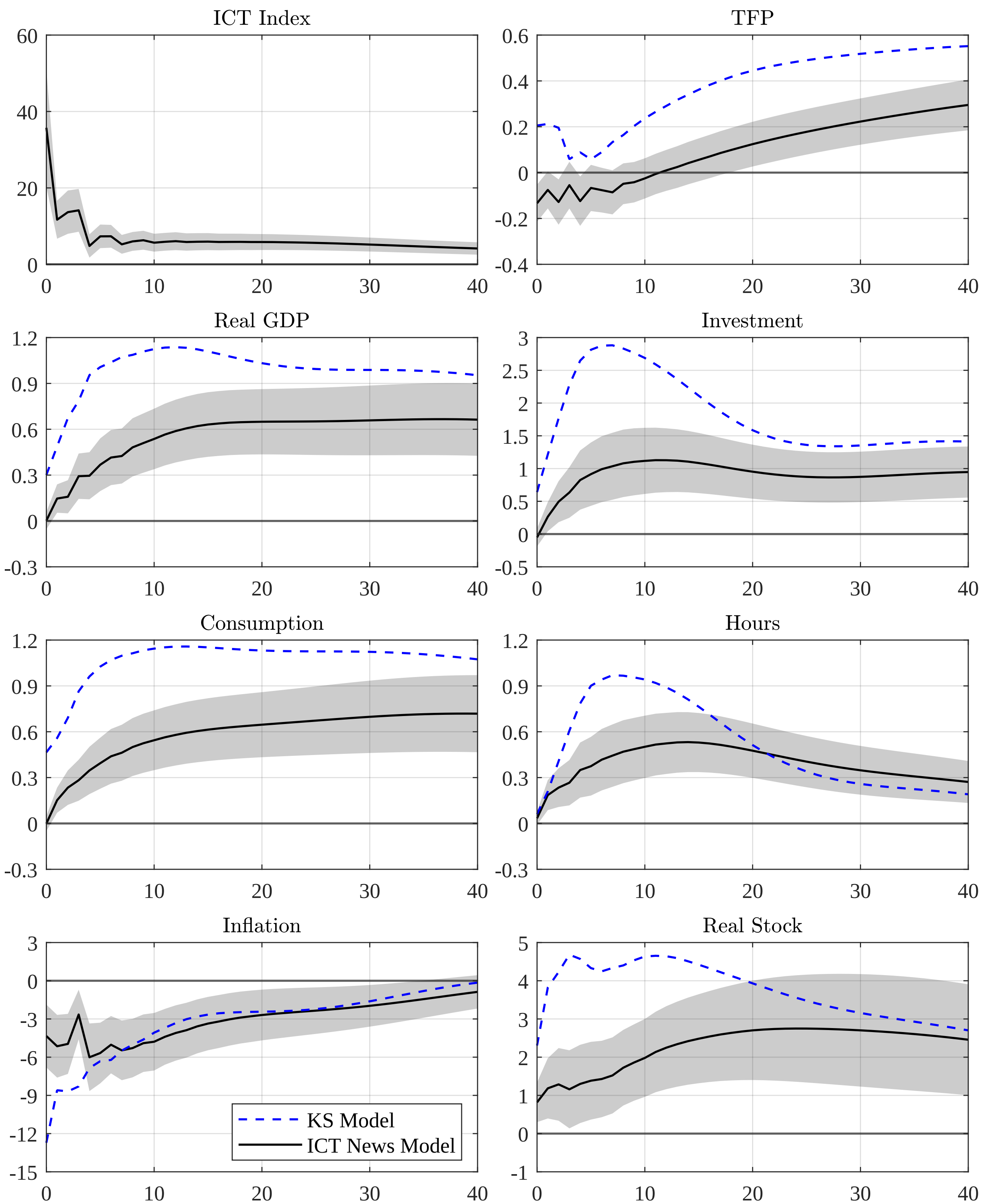
It is understood that sampling error and small-sample biases may cause slight violations of these criteria. Our focus in this section is on strong violations of these criteria. Table 10 summarizes the results based on a maximum horizon of 40 quarters. The full set of impulse responses is provided in 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 max share news or Cholesky news identification method.[19]

Figure 6 shows that the responses of other key variables also look reasonable for the ICT model. Similar results hold when using the R&D model.[20] The news shock increases both consumption

[19]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 10.

[20]We also explored the orthogonalized nondefense R&D shock series of Fieldhouse and Mertens (2023) that was designed to mitigate the potential endogeneity of the R&D series provided by the Bureau of Economic Analysis. When we replace the federal funds and inflation rates in the VAR model with their government R&D capital and cumulated nondefense R&D appropriations series, the identified shock satisfies our criteria for a news shock and yields estimates similar to the ICT and R&D specifications.

Figure 6: Comparison of max share news and TFP max share identified impulse responses



Notes: VAR(4) models estimated on identical samples from 1960-2014. Shaded regions represent 1-standard deviation error bands computed by bootstrap for the ICT news model.

and investment in the long run, and the peak effects occur after 12 quarters. Hours increase in the first 12 quarters, so there is positive comovement between real GDP, consumption, and investment. Inflation declines in the short-run, consistent with the interpretation of the news shock as a positive supply shock and declining real marginal costs in a New Keynesian model. Finally, the real S&P 500 index increases on impact and over the long-run, reflecting positive expectations of future economic conditions. The latter finding is consistent with the results in Beaudry and Portier (2006). We plot these response estimates next to the estimates from the original 8-variable KS VAR model using the same estimation period, providing an apples-to-apples comparison between the two estimators. There are systematic and substantial differences between the two sets of response estimates, consistent with the bias documented in our simulation study.

The differences in the impulse responses translate to large differences in the forecast error variance decompositions for most variables. A forecast error variance decomposition helps assess whether news shocks are an important driver of TFP and real activity. There is no consensus on this question in the literature. Some studies find that news shocks diffuse to TFP quickly (e.g., Barsky et al., 2015; Barsky and Sims, 2011), while others find that it can take many years (e.g., Beaudry and Lucke, 2010; Cascaldi-Garcia and Vukotić, 2022; Fève and Guay, 2019; Forni et al., 2014; Levchenko and Pandalai-Nayar, 2020; Miranda-Agrippino et al., 2022). Similarly, some studies find that news shocks are the dominant driver of real activity in the medium run (e.g., Beaudry and Lucke, 2010; Fève and Guay, 2019; Forni et al., 2014), while others find that news shock play a smaller role (e.g., Cascaldi-Garcia and Vukotić, 2022; Levchenko and Pandalai-Nayar, 2020; Miranda-Agrippino et al., 2022).

Table 11 shows that under the KS identification method news shocks diffuse relatively quickly, explaining 56% of the fluctuations in TFP after just ten years. News shocks also explain the vast majority of the forecast error variance in real activity, even at relatively short horizons, leaving little room for other shocks. In contrast, the news shocks recovered by the max share news estimator are much slower to diffuse to TFP and explain a much smaller share of the fluctuations in real activity. These estimates suggest that news shocks play an important role, but one that is much smaller than

Table 11: Forecast error variance decompositions based on actual data

	Max Share News				KS Max Share			
	4	20	40	80	4	20	40	80
TFP	2.6	2.1	9.9	24.3	6.1	25.5	55.7	71.8
Output	6.1	24.1	31.7	35.9	62.5	87.9	87.0	86.1
Consumption	9.1	24.4	31.4	35.9	81.9	94.0	93.3	90.2
Investment	4.0	12.9	18.4	24.3	48.8	71.1	74.8	76.8
Hours	6.9	21.2	25.4	24.8	29.0	59.8	52.1	49.2
Real Stock	2.9	10.5	14.3	15.4	34.7	49.2	38.3	34.0
Fed Funds	0.2	0.3	2.2	3.0	3.8	2.2	6.3	7.0
Inflation	10.4	14.8	14.5	14.0	38.8	26.5	23.3	22.0

Notes: Max share news estimates based on the ICT news variable. Qualitatively similar results hold for the R&D news variable. Columns denote the horizon of the forecast error variance decomposition. Results based on estimates from 1960-2014.

suggested by the state-of-the-art TFP max share estimator.

One potential explanation for the lower explanatory power of news shocks in the ICT model is that, in practice, any one proxy for TFP news is likely to capture only a subset of all such news. This concern, however, is alleviated by additional simulation evidence that the max share news estimator tends to be a nearly unbiased estimator of the forecast error variance decomposition, even when the observed TFP news variable fails to capture all of the variation in TFP news. This is true, for example, when measured TFP news explains only half of the variability of the latent TFP news variable. Qualitatively similar results also hold for the Cholesky news estimator.

7 CONCLUSION

The importance of understanding the economic effects of TFP news and surprise shocks is widely recognized in the literature, but the empirical evidence obtained from alternative identification strategies tends to be conflicting. A common VAR approach is to identify responses to TFP news shocks by maximizing the variance share of TFP over a long horizon. Under suitable conditions, this approach also implies an estimate of the surprise shock. We find that these TFP max share estimators tend to be strongly biased when applied to data generated from DSGE models with shock processes that match the TFP moments in the data, both in the presence of TFP measurement error and in its absence. This occurs even in settings when news shocks explain almost all of the long-run variation in TFP.

This evidence raises the question of how to proceed in applied work. We showed that including measures of TFP news in VAR models and adapting the identification strategy substantially reduces the bias and RMSE of the impulse responses, regardless of whether TFP is measured with error, and even when there is substantial measurement error in the TFP news variable. We then reported empirical estimates of the responses to news shocks for a range of TFP news measures. Two of these specifications appeared economically plausible in light of the underlying theory. Our estimates suggest that news shocks are slower to diffuse to TFP and have a smaller effect on real activity than implied by the state-of-the-art TFP max share method.

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