Estimating Macroeconomic News and Surprise Shocks*

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Abstract

A common VAR approach is to identify responses to TFP news shocks by maximizing the variance share of TFP over a long horizon. We find that these TFP max share estimators tend to be biased in large sample when applied to data generated from DSGE models with shock processes that match TFP moments in the data, especially in the presence of TFP measurement error. We propose an alternative max share news estimator that reduces this bias and the RMSE of the impulse response estimates, even when there is sizable measurement error in the news variable. When applying this estimator to U.S. 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 estimator.

Keywords: Structural VAR; TFP; news; anticipated shocks; measurement error; max share; IV
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 an anticipated shock to TFP ("news shock") is to use the max share estimator popularized by Uhlig (2003, 2004), Barsky and Sims (2011) and Francis et al. (2014). 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. This class of estimators continues to be widely applied in empirical work, and studies using this estimator have given rise to theoretical work on news and surprise shocks (e.g., Bretscher et al., 2021; Chahrour and Jurado, 2018; Faccini and Melosi, 2022). Variations of this approach have also been applied in other economic contexts.[2]

Early applications of the TFP max share estimator, such as Barsky and Sims (2011), 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 refinement of the TFP max share estimator was introduced by Kurmann and Sims (2021), who relaxed this exclusion restriction to allow for measurement error in TFP due to the fact that factor utilization is unobserved in the data and has to be estimated.[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 due to the slow diffusion of

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

[2] Recent examples include Forni et al. (2014), Barsky et al. (2015), Ben Zeev and Khan (2015), Chen and Wemy (2015), Nam and Wang (2015), Ben Zeev et al. (2017), Forni et al. (2017), Fève and Guay (2019), Angeletos et al. (2020), Levchenko and Pandalai-Nayar (2020), Cascaldi-Garcia and Galvao (2021), Dieppe et al. (2021), Kurmann and Sims (2021), Benhima and Cordonier (2022), Francis and Kindberg-Hanlon (2022), Görtz et al. (2022a), Görtz et al. (2022b), Bouakez and Kemoe (2023), Chahrour et al. (2023), Miyamoto et al. (2025), and Carriero and Volpicella (2025).

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

new technologies. A further refinement of the max share estimator, known as the NAMS estimator, was introduced in Dieppe et al. (2021).

It is widely believed that the TFP max share estimator of news shocks works well as long as news shocks account for the bulk of the variation in TFP at long horizons. For example, Kurmann and Sims (2021) express confidence that, generally, the max share identification performs well as long as news shocks account for a reasonably large part of the unpredictable variation in productivity at long horizons. Our first contribution is to show that this condition is not sufficient to ensure the accuracy of this estimator. We examine the accuracy of the state-of-the-art variants of the TFP max share estimator by simulation. The data are simulated from the dynamic stochastic general equilibrium (DSGE) model discussed in Kurmann and Sims (2021). 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. One reason is the tendency of the TFP max share estimator to confound news shocks with other shocks even in large samples, causing asymptotic bias in the estimator. While this bias tends to be small in the absence of TFP measurement error, the accuracy of the TFP max share estimator substantially deteriorates when allowing the simulated TFP data to be contaminated by measurement error as in Kurmann and Sims (2021). Since TFP measurement error of this type is an important feature of the data, our evidence casts doubt on the use of the TFP max share estimator and raises 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 will substantially reduce the asymptotic bias. We propose a novel identification strategy based on maximizing the variance share of the TFP news variable at a short horizon, as opposed to the variance share of TFP at a long horizon. This MS News estimator is more appealing than the alternative identification strategy of treating TFP news as an instrument because the impact effect of TFP news on TFP may be zero in population.

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 such an estimator to recover the population responses from data generated by DSGE models.[4] We find that the MS News estimator has systematically lower root mean squared error (RMSE) than the TFP max share estimator even in the absence of TFP measurement error. In the presence of TFP measurement error, the reductions in the bias and RMSE of the responses to news shocks are substantial compared to TFP max share estimators. While TFP news is not perfectly observed in the data, the superior accuracy of the MS News estimator is robust to sizable and possibly persistent measurement error in the news variable.

These improvements in accuracy can be traced to two key differences in the construction of the estimator. One difference is the reduced-form VAR specification. Kurmann and Sims (2021) make a compelling case that even state-of-the-art measures of TFP are contaminated by measurement error. A concern with using the TFP max share estimator in the presence of such TFP measurement error is that the reduced-form VAR model underlying the estimator may be informationally deficient. We present evidence that augmenting the VAR model underlying the TFP max share estimator to include a direct measure of TFP news, while retaining the identifying assumptions, helps alleviate the large-sample bias of TFP max share estimators in the presence of TFP measurement error. The other difference in the construction of the estimator is the identification. We show that this is the primary explanation for the lower accuracy of TFP max share estimators compared to the MS News estimator. TFP max share estimators tend to confound the news shock with non-news shocks even when the news shock is dominant at long horizons, which creates asymptotic bias in the response estimators. Since the MS News estimator does not rely on longer-run restrictions, it dispenses with this concern.[5]

Our third contribution is to empirically illustrate the use of TFP news for identifying news shocks using TFP news measures that have been used 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 esti-

[4] Examples of empirical 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. (2025).

[5] Kurmann and Sims (2021) acknowledge that non-news shocks could be important at longer horizons, causing the accuracy of the TFP max share estimator to deteriorate, but consider that possibility unlikely. Dieppe et al. (2021) caution that some contamination of the news shock is inevitable. For a more in-depth analysis of the conditions required for valid TFP max share identification see Dou et al. (2025).

mates 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.[6] 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 5-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 estimator 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 a 5-year horizon.

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. In Section 3, we use data generated from a DSGE model to examine the large-sample accuracy of the TFP max share estimator in the presence of TFP measurement error. In Section 4, we use the same DSGE model to examine the accuracy of alternative identification strategies based on VAR models that include a direct measure of TFP news. We also report results for realistically small samples, and we evaluate the accuracy of these estimators when dropping the assumption of TFP measurement error. In Section 5, we discuss how to make sense of the simulation results. 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 reviews the two state-of-the-art variants of the TFP max share estimator for identifying news shocks.

[6]See, for example, Beaudry and Lucke (2010), Barsky and Sims (2011), Forni et al. (2014), Barsky et al. (2015), Fève and Guay (2019), Levchenko and Pandalai-Nayar (2020), Cascaldi-Garcia and Vukotić (2022), Görtz et al. (2022b), Miranda-Agrippino et al. (2025), and Bouakez and Kemoe (2023).

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 $\mathbf{y}_t = \Phi(L)\mathbf{u}_t$, 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

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

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 TFP MAX SHARE ESTIMATORS 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 $j \in \{1, 2, 3\}$. $\gamma_{\ell,j}$ are the elements associated with an unnamed third shock.[7]

We consider two variants of the TFP max share estimator. One variant proposed by Kurmann and Sims (2021), which we will refer to as the KS max share (KSMS) estimator, 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 the target horizon. Dieppe et al. (2021) go a step further and propose a second variant of the max share estimator, referred to as the non-accumulated max share (NAMS) estimator. When adapted to our context, this estimator maximizes the squared TFP response to the news shock at horizon H_n. The news shock estimate is based on

$$\gamma_n = \text{argmax } \frac{\Phi_{1,H_n} P \gamma_n \gamma_n' P' \Phi_{1,H_n}'}{\Phi_{1,H_n} \Sigma \Phi_{1,H_n}'}, \tag{3}$$

subject to the restriction that $\gamma_n' \gamma_n = 1$. We follow Kurmann and Sims (2021) and set $H_n = 80$.[8]

It should be noted that Kurmann and Sims (2021) and Dieppe et al. (2021) do not claim that their estimators are consistent. Rather they propose these estimators as an improvement over earlier TFP max share estimators with the understanding that in practice the estimated news shock could be contaminated by other shocks undermining their accuracy. How accurate these improved estimators are in practice must be evaluated by simulation.

[7] Appendix B proves the existence of an orthogonal rotation matrix in the structural VAR model.

[8] As shown in Appendix C, in the absence of TFP measurement error estimates of the news shock directly imply estimates of the surprise shock without further identifying assumptions. In contrast, when TFP is subject to measurement error, only the news shock may be pinned down.

3 ACCURACY OF THE TFP MAX SHARE ESTIMATOR

A key insight in Kurmann and Sims (2021) is that, in practice, one needs to be concerned about measurement error driving a wedge between measured and true TFP, given how TFP data have been constructed in the literature (see Fernald, 2014, 2015). In practice, TFP measurement error arises from unobserved changes in factor utilization. Our main finding in this section is that the TFP max share estimator is unable, in general, to recover the population responses to news shocks in the presence of such TFP measurement error.

3.1 DATA GENERATING PROCESS

We evaluate the TFP max share estimator using data simulated from the quarterly DSGE model used by Kurmann and Sims (2021). This model includes several real and nominal frictions, such as sticky prices and wages, habit formation, and both labor and investment adjustment costs. It also includes variable factor utilization, an endogenous labor-effort choice, and monopolistic competition in product and labor markets. The full set of nonlinear equations is provided in Appendix D.

The model variables are driven by three exogenous processes. TFP (a_t) has a transitory component (s_t) and a permanent component (z_t) given by

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

where $\varepsilon_{g,t-1}$ is lagged so that the shock occurs one period before it affects TFP. Agents anticipate the effects of this shock when forming expectations, consistent with the interpretation of a news shock. Allowing news shocks to contemporaneously affect TFP has little effect on our results. The model also features an investment efficiency shock (μ_t) that evolves according to

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

3.2 MEASUREMENT ERROR Following Kurmann and Sims (2021), measured TFP is recovered from the simulated model data by mimicking how Fernald (2014) constructs the TFP variable. Factor utilization (u_t) varies over time due to changes in capital utilization and worker effort. The econometrician observes neither of these but does observe output (y_t), the capital stock (k_{t-1}), hours worked (h_t), and employment (n_t). 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 ($\Delta \ln \hat{u}_t$) are assumed to be proportional to changes in detrended hours worked ($\Delta \ln \hat{h}_t$), so $\Delta \ln \hat{u}_t = \vartheta \Delta \ln \hat{h}_t$, where ϑ is a proportionality factor. We follow Kurmann and Sims (2021) in setting $\vartheta = 3$ consistent with the data. Hours worked are detrended using a biweight filter, consistent with the latest vintages of the Fernald TFP measure (see Fernald, 2015). The growth in utilization-adjusted TFP is given by

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

In our simulations, we construct measured TFP by cumulating the growth rates of the log-level of utilization-adjusted TFP ($\ln \mathrm{TFP}^u_t$) over time. The measurement error in TFP stems from that fact that macroeconomists must rely on an imperfect estimate of u_t.

3.3 CALIBRATION We set the parameters of the TFP and marginal efficiency of investment (MEI) processes to match six moments: the standard deviation and autocorrelation of TFP growth ($SD(\Delta a_t)$, $AC(\Delta a_t)$), the standard deviation and autocorrelation of detrended TFP ($SD(\tilde{a}_t)$, $AC(\tilde{a}_t)$), and the standard deviations of detrended output and investment ($SD(\tilde{y}_t)$, $SD(\tilde{\imath}_t)$).[9] This exercise implies that $\rho_g = 0.5$, $\rho_s = 0.4$, $\rho_\mu = 0.95$, $\sigma_g = 0.0025$, $\sigma_s = 0.006$, and $\sigma_\mu = 0.004$. The other parameter values are set to those used in Kurmann and Sims (2021) and are reported in Appendix D. 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.

[9] 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 a Hodrick and Prescott (1997) filter when log series are difference stationary.

Table 1: Data and DSGE model-implied moments

Moment	Data	Model	Moment	Data	Model
$SD(\tilde{a}_t)$	2.01	2.30	$SD(\tilde{\imath}_t)$	9.63	9.38
$SD(\Delta a_t)$	0.80	0.73	$AC(\tilde{a}_t)$	0.87	0.87
$SD(\tilde{y}_t)$	3.13	3.89	$AC(\Delta a_t)$	−0.09	0.01

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

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

	Measured TFP (TFP^u)			True TFP (a)		
Horizon	News	Surprise	MEI	News	Surprise	MEI
4	33.3	55.6	11.1	47.9	52.1	0.0
8	46.3	43.3	10.4	75.7	24.3	0.0
20	47.7	9.3	43.0	91.0	9.0	0.0
40	62.3	1.8	35.9	95.6	4.4	0.0
80	75.2	0.7	24.1	97.8	2.2	0.0

Notes: The columns refer to the structural shocks. MEI is the marginal efficiency of investment.

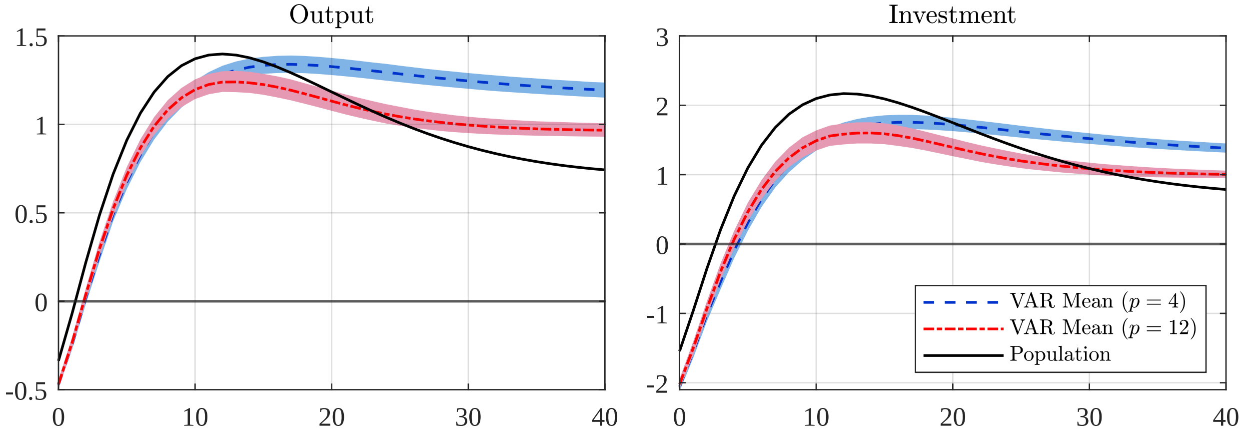
Under this calibration, news shocks are the dominant driver of the long-run variation in measured TFP. As illustrated in Table 2, news shocks explain almost all of the long-run variability of true TFP and 75% of the long-run variation in measured TFP, which is almost identical to the share Kurmann and Sims (2021) reported when applying their estimator to actual data. Thus, it is fair to conclude that Kurmann and Sims would have expected the KSMS estimator to recover the population responses in large samples in this setting.

3.4 SIMULATION EVIDENCE

Since there are three structural shocks in the DSGE model, we base the TFP max share estimator on a three-dimensional VAR model. We work with a VAR model with intercept for $\mathbf{y}_t = (\mathrm{TFP}^u_t, y_t, i_t)'$. Investment is included because of its strong connection with the MEI shock. All variables enter in logs.

We first generate $1{,}000$ realizations of log-level data of length T for measured TFP, output, and investment by simulating the DSGE model, fit the VAR model on each of these data realizations, and construct the impulse responses. We then report the expected value of these responses, the

Figure 1: KSMS estimator of the responses to a news shock



Notes: VAR(p) model with $T = 10{,}000$ and $\mathbf{y}_t = (\text{TFP}_t^u, y_t, i_t)'$. The 68% quantile bands shown as shaded areas provide a measure of the variability of the estimates.

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.

We begin by focusing on the KSMS estimator and set $T = 10{,}000$ to approximate its large-sample properties. We consider two lag orders, $p = 4$, as in Kurmann and Sims (2021), and $p = 12$. It is worth mentioning that—in the presence of TFP measurement error—there is a notable discrepancy between the response of measured TFP to a news shock in the VAR model and the population response of true TFP, regardless of the lag order. This result is not surprising. With measurement error there is no reason to expect the VAR to recover this response, since the VAR is estimated with the (mis)measured TFP variable and the population response is based on true TFP. What is more concerning is that there is also strong large-sample bias in the output and investment responses regardless of p, sometimes in the positive direction and sometimes in the negative direction (see Figure 1).

Table 3 shows the RMSEs of the impulse responses for the KSMS and NAMS estimators. For a given lag order (p), the first three columns show the sum of the RMSEs over horizons 0 to 40 for TFP, output and investment, respectively. The last column shows the sum of these entries across the three response functions. If the TFP max share estimators were able to recover the population

Table 3: RMSE over 40 quarters

	$p = 4$				$p = 12$			
	TFP	Output	Invest	Total	TFP	Output	Invest	Total
	Baseline VAR Model $(\text{TFP}_t^u, y_t, i_t)$							
KSMS	10.3	10.4	19.3	40.0	7.4	6.1	15.3	28.8
NAMS	10.1	10.8	21.3	42.2	7.3	5.7	13.6	26.6
	Augmented VAR Model $(\text{TFP}_t^u, y_t, i_t, h_t)$							
KSMS	9.0	8.1	17.6	34.7	7.2	5.3	13.5	25.9
NAMS	8.6	7.7	17.1	33.4	6.6	4.2	10.1	20.9

Notes: VAR(p) model with $T = 10{,}000$.

responses, one would expect the RMSEs to be close to zero for large T and p. However, we find that the RMSEs of both estimators are elevated for the baseline VAR model, regardless of whether there are 4 or 12 lags in the VAR model. Augmenting the VAR model to include hours worked (h_t) lowers the RMSE somewhat, but in all cases the RMSE remains far from zero.

These results raise significant concerns about the ability of the TFP max share estimator to recover the population responses, even asymptotically.[10] They call into question the conventional wisdom that a sufficient condition for the validity of TFP max share estimators is that the news shock explains a large share of the long-run variation in measured TFP. Our evidence illustrates that both the KSMS and NAMS estimators have difficulty identifying news shocks in the presence of TFP measurement error.

This conclusion may seem at odds with simulation evidence reported in Kurmann and Sims (2021) that their estimator comes somewhat close to the population responses to a news shock in large samples when $p = 4$. This result is an artifact of their parameter choices for the TFP process. Kurmann and Sims note that their TFP parameterization is based on standard values in

[10]Similar conclusions also apply to max share estimators targeting output. In contrast, the accuracy of max share estimators targeting labor productivity, which is not affected by measurement error in TFP, mirrors that of the TFP max share estimator in the absence of TFP measurement error, as discussed in Section 4.5. Of course, estimates of the effect of news about labor productivity do not tell us how the economy responds to TFP news (see Appendix G). It should also be noted that imposing additional theoretically motivated sign and magnitude restrictions, as discussed in Francis and Kindberg-Hanlon (2022), does not address the identification problems of the TFP max share estimator.

Table 4: Moments under Kurmann-Sims TFP parameterization

Moment	Data	Model	Moment	Data	Model
$SD(\tilde{a}_t)$	2.01	2.65	$SD(\tilde{\imath}_t)$	9.63	11.99
$SD(\Delta a_t)$	0.80	0.59	$AC(\tilde{a}_t)$	0.87	0.88
$SD(\tilde{y}_t)$	3.13	5.11	$AC(\Delta a_t)$	−0.09	0.43

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

Table 5: FEVD under Kurmann-Sims TFP parameterization

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

Notes: The columns refer to the structural shocks. MEI is the marginal efficiency of investment.

the literature. However, most DSGE models feature either a stationary or permanent TFP shock process. When a model features both processes, standard values from models with only one process can lead to TFP moments that are at odds with actual data. Under their parameterization, TFP growth is highly persistent, which is at odds with the data (see Table 4).

The most notable difference from our calibration is that the standard deviation of their surprise shock is only about 6% of our baseline value. As a result, as shown in Table 5, news shocks explain the vast majority of the variation in TFP at all horizons, which greatly enhances the accuracy of the KSMS estimator by effectively removing the identification challenge. It is no surprise that the KSMS estimator performs comparatively well in this special case (see Appendix E). When setting the parameters in the DSGE model to match the TFP moments in the data, in contrast, their impulse response estimator is strongly biased. These results are not unique to our parameterization. As shown in Appendix G, this bias arises for any specification of the TFP process that assigns a non-trivial role to non-news shocks in driving TFP at short and intermediate horizons.

4 ESTIMATORS INVOLVING MEASURES OF TFP NEWS

The large-sample bias of the TFP max share estimator we documented raises the question of whether there are other estimators that perform better. In this section, we consider the alternative strategy of identifying TFP news shocks by incorporating an observed measure of TFP news into the VAR model and adapting the identification strategy. TFP news data have been employed in a number of studies.[11] The premise of all these studies is that measures of TFP news should increase quickly when 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 their ability to recover news shocks generated by DSGE models. In this section, we examine the merits of TFP news-based identification strategies in the presence of TFP measurement error.

4.1 IDENTIFICATION STRATEGIES BASED ON TFP NEWS Our strategy is to identify the news shock as the shock that maximizes the forecast error variance contribution to the news variable at short horizons. We set $H_n = 4$. Our results are robust to smaller values for H_n. We refer to this estimator as the MS News estimator. An obvious concern is that, in practice, the TFP news variable could be measured with error. While our baseline analysis abstracts from measurement error in TFP news, later we present additional simulation evidence that the MS News estimator continues to perform well even in the presence of substantial measurement error in the TFP news variable.[12]

An alternative approach to dealing with TFP news measurement error would have been 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,

[11] Shea (1999) considers models that incorporate a measure of government R&D spending or patent applications. Other examples include Christiansen (2008, patent applications), Alexopoulos (2011, new book titles in 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 grants), Miranda-Agrippino et al. (2025, patent applications), and Fieldhouse and Mertens (2023, government R&D spending).

[12] When ordering the news variable first and setting $H_n = 0$, the MS News estimator reduces to a block-recursive estimator as employed in Cascaldi-Garcia and Vukotić (2022), for example. The latter specification is similarly accurate.

for example, by Cascaldi-Garcia and Vukotić (2022) and Miranda-Agrippino et al. (2025). 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. However, as shown in Plagborg-Møller and Wolf (2021), the proxy VAR approach that uses the news variable as an external instrument is not valid when the shock of interest is non-invertible.

Yet another approach would have been to treat the TFP news as an internal instrument, which requires treating the news variable in the VAR as predetermined with respect to TFP (see, e.g., Plagborg-Møller and Wolf, 2021). While this helps address concerns about the shock of interest being noninvertible, neither the external instrument nor the internal instrument approach is appealing when estimating responses to news shocks. As discussed in Montiel Olea et al. (2021) and Plagborg-Møller and Wolf (2021), when constructing the IV estimator one needs to normalize the responses by scaling the response of interest by the impact response of the variable being instrumented. In our case, one would instrument the TFP residual by the TFP news instrument.[13] However, in many DSGE models of TFP news including our model, one cannot rule out that the impact response of TFP to news is zero in population, resulting in responses that are infinite. This means that the IV estimator of the VAR responses is not well defined in general.

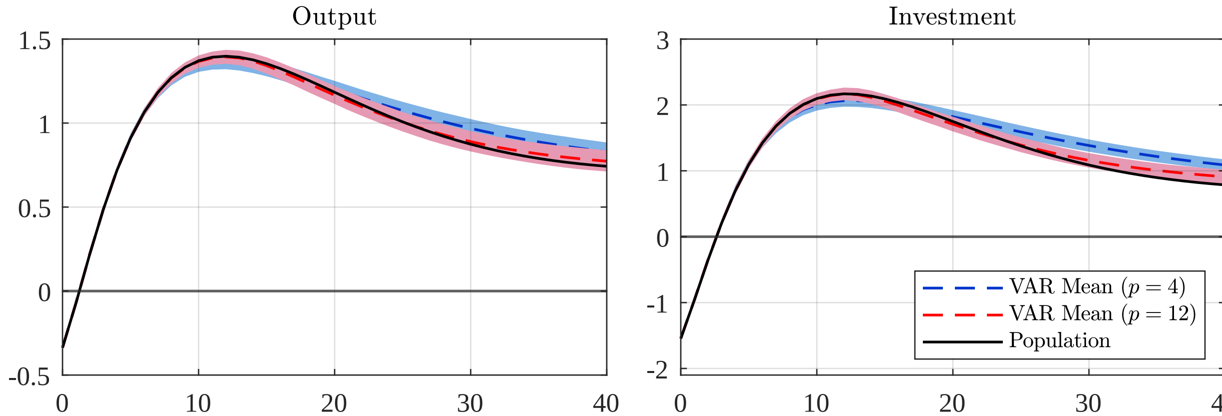
4.2 ACCURACY OF THE MS NEWS ESTIMATOR

We examine by simulation whether the MS News estimator can reduce the impulse response bias and RMSE in the presence of TFP measurement error. In the DSGE model, the TFP 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.[14] We therefore fit a VAR model to each draw of $\mathbf{y}_t = (z_{t+1}, \mathrm{TFP}_t^u, y_t, i_t)'$ of length $T = 10{,}000$. This timing mirrors the way observed TFP news

[13] In principle, other normalizations could be implemented, but the point of the normalization is to express the shock in units that are readily interpretable in practice. For example, as noted in Stock and Watson (2016), a monetary policymaker would naturally want to express a monetary policy shock as a basis point increase in the policy rate. No policymaker would be interested in normalizing this shock to imply a unit increase in real GDP. Likewise, in our context, it would not make sense to normalize an exogenous TFP shock to imply a unit increase in, say, real GDP or investment (or a unit increase in TFP two years later). Nor would it make sense to normalize on the horizon 1 response of TFP because that response estimate often is negative, given that the population response is close to zero. Such a normalization would flip the sign of the other response functions.

[14] Appendix G shows that our substantive findings are unaffected by the timing of the news shocks.

Figure 2: MS News estimator of the responses to a news shock



Notes: VAR(p) model with $T = 10{,}000$ and $\mathbf{y}_t = (z_{t+1}, \text{TFP}^u_t, y_t, i_t)'$. The 68% quantile bands shown as shaded areas provide a measure of the variability of the estimates.

has been used in applied work. For the KSMS estimator, we continue to fit a VAR model with $\mathbf{y_t} = (\text{TFP}^u_t, y_t, i_t)'$.

Figure 2 shows that the MS News estimates of the output and investment responses come much closer to recovering the population responses than the TFP max share estimates in Figure 1. The bias of the impulse responses is substantially reduced. Turning to the RMSE, our first comparison is between the MS News estimator and the KSMS and NAMS estimators. Table 6 reports the RMSE for the responses of TFP, output, and investment to a news shock and the total RMSE across the three responses. The first two rows reproduce our baseline results for the KSMS and NAMS estimators shown in Table 3. The first row of Panel A quantifies the improvement in accuracy from using the MS News estimator. This estimator reduces the total RMSE by 58% relative to the KSMS estimator and 60% relative to the NAMS estimator for $p = 4$.[15] There are similar improvements for $p = 12$. The MS News estimator is also substantially more accurate than the TFP max share estimators based on VAR models augmented to include hours worked, as shown in the lower panel of Table 3.

The MS News estimator we proposed differs from the KSMS and NAMS estimators by incor-

[15] As shown in Appendix G, similar results are obtained when adding two more structural shocks to the DSGE model and augmenting the dimension of the approximating VAR model accordingly. We also investigated whether one could replace z_{t+1} in the VAR model with a_{t+1}, but it can be shown that the latter specification does not improve on the accuracy of the KSMS or NAMS estimators.

Table 6: RMSE over 40 quarters

	$p = 4$				$p = 12$			
Estimator	TFP	Output	Invest	Total	TFP	Output	Invest	Total
KSMS	10.3	10.4	19.3	40.0	7.4	6.1	15.3	28.8
NAMS	10.1	10.8	21.3	42.2	7.3	5.7	13.6	26.6
	A. No ME ($\rho_n = 0$, $\sigma_n = 0$)							
MS News	6.4	2.8	7.6	16.8	5.9	2.0	4.5	12.4
Alt KSMS	7.0	4.9	13.9	25.7	6.3	4.6	13.9	24.8
Alt NAMS	6.9	4.5	12.9	24.3	6.1	4.1	12.1	22.3
	B. 50% iid ME ($\rho_n = 0$, $\sigma_n = 0.5\sigma_g$, FEVD: 3.8%)							
MS News	6.4	3.6	9.1	19.1	5.8	1.9	4.1	11.8
Alt KSMS	7.4	5.3	13.8	26.5	6.2	4.6	14.5	25.4
Alt NAMS	7.1	5.1	13.2	25.4	6.2	3.8	11.2	21.1
	C. 100% iid ME ($\rho_n = 0$, $\sigma_n = \sigma_g$, FEVD: 13.7%)							
MS News	6.1	4.3	10.1	20.5	5.8	2.0	4.1	11.8
Alt KSMS	7.7	5.9	14.4	28.0	6.3	4.6	14.3	25.1
Alt NAMS	7.3	5.8	13.9	27.0	6.2	3.7	11.0	20.9
	D. 50% Persistent ME ($\rho_n = 0.5$, $\sigma_n = 0.5\sigma_g$, FEVD: 5.0%)							
MS News	6.3	3.7	9.3	19.3	5.8	2.0	4.1	11.8
Alt KSMS	7.4	5.4	14.0	26.8	6.3	4.6	14.4	25.3
Alt NAMS	7.1	5.2	13.4	25.8	6.2	3.7	11.1	21.0
	E. 100% Persistent ME ($\rho_n = 0.5$, $\sigma_n = \sigma_g$, FEVD: 17.4%)							
MS News	5.8	4.6	10.4	20.8	5.4	2.1	4.3	11.8
Alt KSMS	7.8	6.2	14.7	28.8	6.3	4.6	14.1	25.1
Alt NAMS	7.4	6.2	14.5	28.1	6.2	3.8	11.0	21.0
	F. 50% Highly Persistent ME ($\rho_n = 0.9$, $\sigma_n = 0.5\sigma_g$, FEVD: 10.6%)							
MS News	6.3	3.9	9.5	19.6	5.4	2.2	4.3	12.0
Alt KSMS	7.5	5.6	14.2	27.3	6.4	4.6	14.3	25.3
Alt NAMS	7.2	5.5	14.0	26.7	6.2	3.9	11.2	21.3
	G. 100% Highly Persistent ME ($\rho_n = 0.9$, $\sigma_n = \sigma_g$, FEVD: 32.2%)							
MS News	5.4	5.2	10.9	21.5	4.3	3.5	6.2	13.9
Alt KSMS	8.2	6.8	15.6	30.6	6.6	4.9	14.3	25.8
Alt NAMS	7.7	7.0	15.8	30.6	6.4	4.3	11.6	22.3

Notes: VAR(p) model with $T = 10{,}000$ and $\mathbf{y}_t = (\mathrm{TFP}_t^u, y_t, i_t)'$ for the KSMS and NAMS estimators and $\mathbf{y}_t = (z_{t+1}, \mathrm{TFP}_t^u, y_t, i_t)'$ for the MS News estimator. The Alt KSMS estimator uses the KS identification strategy and the MS News model variables. The Alt NAMS estimator uses the NAMS identification strategy and the MS News model variables. FEVD is the contribution of the noise shock to the 4-quarter forecast error variance decomposition of TFP news.

porating the news variable into the VAR and by adjusting the identification procedure. One may wonder what the gains are from just incorporating the TFP news variable. We explore this conjecture by applying the KSMS estimator to the same reduced-form VAR model used by the MS News estimator, which we refer to as the Alt KSMS estimator. We also consider the corresponding Alt NAMS estimator. The results are reported in the last two rows of Panel A in Table 6. Our simulations show that indeed the accuracy of the KSMS and NAMS estimators substantially improves when incorporating TFP news into the VAR model. However, the Alt KSMS and Alt NAMS estimators are less accurate than the MS News estimator based on the same reduced-form VAR model because they remain subject to the contamination of the news shock. The MS News estimator improves upon the Alt KSMS estimator by 35% and the Alt NAMS estimator by 31% for $p = 4$ and by 50% and 44%, respectively, for $p = 12$. Thus, the MS News estimator is systematically more accurate than the other four estimators.

4.3 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, next we 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 $z^n_{t+1} = z_{t+1} + \epsilon^n_t$, where $\epsilon^n_t = \rho^n \epsilon^n_{t-1} + \sigma^n \upsilon^n_t$ with $\upsilon^n \sim \mathbb{N}(0, 1)$. We consider values of σ^n equal to 50% and 100% of the standard deviation of the true news shock, σ_g. We also report the share of the forecast error variance of z_{t+1} due to the measurement error at a four-quarter horizon as another metric for gauging the size of the measurement error in TFP news.

While there is no way of knowing the extent of measurement error in TFP news, Panels B and C of Table 6 show that the MS News estimator remains more accurate even if the news variable is measured with substantial error. For example, with 100% measurement error ($\sigma^n = \sigma_g$), the MS News estimator is still 49% more accurate than the KSMS estimator with $p = 4$ and 59% more

Table 7: Small-sample RMSE over 40 quarters

Estimator	TFP	Output	Invest	Total
KSMS	10.4	15.4	32.0	57.7
NAMS	10.2	16.8	36.1	63.1
MS News	8.8	13.4	22.9	45.0
Alt KSMS	8.8	15.4	32.0	56.3
Alt NAMS	9.0	15.7	31.4	56.1

Notes: VAR(4) with $T = 240$, where $\mathbf{y}_t = (\text{TFP}_t^u, y_t, i_t)'$ for the KSMS and NAMS estimators and $\mathbf{y}_t = (z_{t+1}, \text{TFP}_t^u, y_t, i_t)'$ for the MS News estimator. The Alt KSMS estimator uses the KSMS identification strategy and the MS News model variables. The Alt NAMS estimator uses the NAMS identification strategy and the MS News model variables.

accurate with $p = 12$. These results are promising, but in practice one would expect TFP news to be systematically mismeasured, inducing persistent deviations between true and measured TFP news. Panels D-G show that similarly accurate responses to news shocks are obtained even when allowing the measurement error to be serially correlated, which mimics a situation in which TFP news are systematically mismeasured. The MS News estimator reduces the RMSE by between 46% and 52% relative to the KSMS estimator when $p = 4$ and between 52% and 59% when $p = 12$, depending on the specification of the measurement error. The MS News estimator also remains more accurate than both the Alt KSMS and Alt NAMS estimators.

4.4 Accuracy in Small Samples

While our results for $T = 10{,}000$ indicate that the MS News estimator is much more accurate than the TFP max share estimator in large samples, they do not speak to its properties in sample sizes encountered in applied work. Therefore, we also examine its accuracy for $T = 240$ (60 years of quarterly data), which reflects a typical length of TFP news series in practice. For this setting, we only consider the VAR model with $p = 4$ due to the small sample size. This is a lag length that is also used in other papers (e.g., Kurmann and Sims, 2021).

Table 7 shows the RMSEs for the various estimators. The MS News estimator yields a 22% improvement in accuracy over the KSMS estimator and a 20% improvement over the Alt KSMS estimator. Relative to the NAMS and Alt NAMS estimators, the gains are 29% and 20%, respectively. These results suggest that the benefits of the MS News estimator extend to realistic sample

Table 8: RMSE over 40 quarters without TFP measurement error

p	TFP	Output	Total	% Change	TFP	Output	Total	% Change
	KSMS				NAMS			
4	4.8	6.8	11.7	–	4.5	7.4	11.9	2.3
12	1.3	2.6	4.0	–	1.3	3.1	4.4	10.0
24	0.9	2.2	3.2	–	0.9	2.5	3.5	9.5
36	0.9	2.3	3.2	–	0.9	2.5	3.5	8.7
	Alt KSMS				MS News			
4	0.6	4.7	5.3	−54.9	0.6	4.5	5.1	−56.6
12	0.8	2.1	2.9	−26.0	0.8	2.0	2.8	−29.9
24	0.9	2.2	3.1	−3.1	0.8	2.0	2.9	−9.6
36	0.9	2.3	3.2	−0.2	0.9	2.1	2.9	−7.3

Notes: VAR(p) model with $T = 10{,}000$ and $\mathbf{y}_t = (a_t, y_t, i_t)'$ for the KSMS and NAMS estimators and $\mathbf{y}_t = (z_{t+1}, a_t, y_t)'$ for the MS News estimator. The Alt KSMS estimator uses the KS identification strategy and the MS News model variables. The percent change in the RMSE is computed with respect to the KSMS estimator.

sizes and go beyond just aligning information sets.

4.5 The Case Without TFP Measurement Error

For comparison, we now consider the case without TFP measurement error, even if that case is not of practical relevance for U.S. data. This involves estimating VAR models that include true TFP from the DSGE model (a_t) rather than measured TFP (TFP_t^u). For each combination of T and p, we calculate the RMSE for the VAR estimates of the responses of TFP and output, their combined sum, and the percent change of the combined sums relative to the KSMS estimator.

The upper left and right panels in Table 8 show the RMSEs for the KSMS and NAMS estimators, respectively. We find that both estimators are significantly more accurate than when TFP is measured with error. The KSMS estimator is somewhat more accurate than NAMS, although the differences in absolute terms are modest. More generally, the RMSEs are relatively low in absolute terms once enough lags have been added to the VAR model, as required for the VAR model to be a good approximation to the moving-average representation implied by the DSGE model.

Next we consider the performance of the Alt KSMS and MS News estimators in the lower panel of Table 8 with $\mathbf{y}_t = (z_{t+1}, a_t, y_t)'$. Both estimators significantly improve on the accuracy of the TFP max share estimators for low p, but these gains diminish as p increases. The MS News estimator continues to outperform the other estimators for all lag lengths considered, but the gains in absolute terms are much smaller than in the presence of TFP measurement error.[16]

5 MAKING SENSE OF THE SIMULATION RESULTS

A question of obvious interest is why the TFP max share estimator appears reasonably accurate for large T and p in the model without TFP measurement error, while its accuracy is much lower in the model with TFP measurement error. There are two potential reasons why the TFP max share estimator may fail even asymptotically. One is that the VAR model used to approximate the data generated by the DSGE model may be informationally deficient or nonfundamental. The other is that even state-of-the-art TFP max share estimators tend to confound responses to TFP news with responses to other shocks.

Nonfundamentalness means that the variables in the VAR model do not convey enough information to recover all of the structural shocks. In that case, the VAR model is informationally deficient. Fernández-Villaverde et al. (2007) provide an invertibility condition for the VAR approximation of data generated by a DSGE model to be fundamental. When this condition is met, the VAR model will be informationally sufficient, provided enough autoregressive lags are used. If a VAR model is informationally sufficient and the structural shocks are correctly identified, the response estimates will equal the population responses in the asymptotic limit.

Forni et al. (2019) observe that even when the VAR model is not fundamental, it may be possible for the model to identify a subset of the structural shocks. They refer to such VAR models as partially informationally sufficient. In practice, even near-sufficiency may be enough for a reasonably close approximation of the population responses to these shocks. They propose a diagnostic for detecting near sufficiency of the VAR model for the responses to a given shock of interest. We

[16]Alternatively, one could have implemented the MS News estimator using $\mathbf{y}_t = (z_{t+1}, y_t, i_t)'$. In that case, the RMSE reductions from using the MS News estimator are even larger for large p than in Table 8. However, the Alt KSMS estimator cannot be constructed for this model.

do not apply this diagnostic because it was designed for stationary data, and the VAR model data in our application are nonstationary.

5.1 VAR MODELS WITHOUT TFP MEASUREMENT ERROR It can be shown that the reduced-form VAR model for $\mathbf{y}_t = (a_t, y_t, i_t)'$ on which the KSMS and NAMS estimators are based, satisfies the invertibility condition in Fernández-Villaverde et al. (2007) when the data are generated from the DSGE model in Section 3. This implies that as long as the lag order is large enough for the VAR errors to be serially uncorrelated and as long as the identifying restrictions are correct, one would expect the structural response estimates to TFP news shocks and the corresponding population responses to coincide in the asymptotic limit.

This view is consistent with our evidence that the RMSE reductions from using the MS News estimator instead of the TFP max share estimator shrink as the lag order is increased. However, the MS News estimator remains systematically more accurate than the TFP max share estimator even for large p because the TFP max share estimator confounds responses to TFP news with responses to other shocks, as stressed by Dieppe et al. (2021) and Dou et al. (2025). In other words, the model is not correctly identified.

How severe the RMSE loss from confounding news shocks with other shocks is in general depends on the context. In our example, this contamination of the TFP news shocks explains why even for large T and p the MS News estimator reduces the RMSE by 7%.[17] While these RMSE reductions are relatively small, there is little comfort in this result for users of the TFP max share estimator, given that models without TFP measurement error are not empirically relevant. In the empirically more plausible setting of TFP measurement error, a much stronger case for the MS News estimator emerges.

5.2 VAR MODELS WITH TFP MEASUREMENT ERROR The presence of TFP measurement error complicates matters. When working with VAR models involving mismeasured TFP as in

[17] The fact that the excessive RMSE of the TFP max share estimator for large T and p is not driven by the information set is also supported by the fact that the Alt TFP max share estimator based on the same information set as the MS News estimator does not improve on the RMSE of the TFP max share estimator.

Kurmann and Sims (2021), assessing the informational sufficiency of the VAR model becomes more challenging. Not only is the Forni et al. (2019) diagnostic not designed for nonstationary data as in our model, but the invertibility condition in Fernández-Villaverde et al. (2007) cannot be applied because there is no closed-form expression for TFP_t^u. The use of this condition requires expressing the variables contained in the VAR model in state-space form. As discussed in Section 3.2, this is straightforward for unadjusted TFP, but measured TFP depends on unobserved factor utilization that is inferred by applying a nonlinear biweight filter to hours worked, mirroring the procedure in Fernald (2015). This makes it impossible to derive a closed-form expression for TFP_t^u. Thus, the question of the invertibility of the VAR model can only be addressed indirectly.

If the TFP measurement error were exogenous, it would be readily apparent that the reduced-form VAR model for $\mathbf{y}_t = (\mathrm{TFP}_t^u, y_t, i_t)'$ must be informationally deficient because there would be four shocks but only three variables in the VAR model. The TFP measurement error in our study is endogenous with respect to the model variables, however. This may seem to suggest that the VAR model for $\mathbf{y}_t = (\mathrm{TFP}_t^u, y_t, i_t)'$ remains informationally sufficient and will recover the population responses as long as we include enough autoregressive lags. The validity of this argument is not obvious, because the TFP measurement error in our analysis is computed as a nonlinear transformation of the simulated data from the DSGE model. It is not clear that a linear VAR model will be able to capture this information, no matter how many lags are included.

We therefore examine the importance of the invertibility of the model for $\mathbf{y}_t = (\mathrm{TFP}_t^u, y_t, i_t)'$ by simulation. Throughout, we set $T = 10{,}000$ and examine $p \in \{4, \ldots, 40\}$, as the VAR model approximation may improve for large p. Table 9 shows that the RMSE of the KSMS estimator stabilizes near 26 for large p. Suppose, for the sake of argument, that the TFP measurement error renders the 3-variable model informationally deficient. In that case, informational sufficiency may be restored by augmenting the VAR model to include TFP news. One would expect the inclusion of TFP news to reduce the RMSE. This is what we find. The Alt KSMS estimator improves on the accuracy of the KSMS estimator by about 9% for large p. It is hard to explain why this improvement would occur if the original VAR model were informationally sufficient.

Table 9: Decomposing the RMSE reductions from using the MS News estimator

	RMSE			RMSE Percent Change		
p	KSMS	Alt KSMS	MS News	MS News/ KSMS	MS News/ Alt KSMS	Alt KSMS/ KSMS
4	40.0	25.7	16.8	−58.1	−34.8	−35.7
8	32.8	24.9	13.0	−60.3	−47.6	−24.2
12	28.8	24.8	12.4	−56.9	−49.9	−14.0
16	26.9	24.6	12.2	−54.5	−50.3	−8.5
20	26.0	24.4	12.1	−53.4	−50.3	−6.2
24	25.7	24.3	12.1	−52.8	−50.1	−5.4
28	25.6	24.2	12.2	−52.5	−49.7	−5.5
32	25.6	24.1	12.2	−52.3	−49.3	−5.9
36	25.7	23.9	12.2	−52.3	−48.8	−7.0
40	25.7	23.3	12.2	−52.4	−47.6	−9.2

Notes: VAR(p) model with $T = 10{,}000$ and $\mathbf{y}_t = (\text{TFP}^u_t, y_t, i_t)'$ for the KSMS estimator and $\mathbf{y}_t = (z_{t+1}, \text{TFP}^u_t, y_t, i_t)'$ for the MS News estimator. The Alt KSMS estimator uses the KS identification strategy and the MS News model variables. The RMSE is defined as the sum of the RMSEs of the responses of measured TFP, output, and investment over 40 quarters.

We further observe that the MS News estimator, which additionally addresses concerns about the identification of the KSMS estimator, is 52% more accurate than the KSMS estimator for large p. This suggests that the lower accuracy of the KSMS estimator is driven in large part by a failure of the identification.[18]

Now suppose that the VAR model for $\mathbf{y}_t = (\text{TFP}^u_t, y_t, i_t)'$ is actually invertible and hence informationally sufficient. In this case, one wold expect the MS News estimator to be misspecified because there are 4 variables in the VAR model but only 3 structural shocks in the population model. This concern may be addressed by implementing the MS News estimator based on a VAR model for $\mathbf{y}_t = (z_{t+1}, y_t, i_t)'$ or for $\mathbf{y}_t = (z_{t+1}, \text{TFP}^u_t, y_t)'$. This is possible because TFP^u_t is not required for the MS News identification. Table 10 illustrates that both of these MS News estimators systematically improve on the KSMS estimator with RMSE reductions approaching 26% for large p in one case and 67% in the other. As the third and sixth columns in the table illustrate, however,

[18] If the RMSE reductions were measured in logs, the overall RMSE reduction would equal the sum of the last two columns. We did not present the results in logs because a log approximation is inaccurate for large percent changes.

Table 10: MS News estimator in the 3-variable setting

	TFP & Output Responses			Output & Investment Responses		
p	(z, TFP^u, y) RMSE	(z, TFP^u, y) % Change	(z, TFP^u, y, i) % Change	(z, y, i) RMSE	(z, y, i) % Change	(z, TFP^u, y, i) % Change
4	8.4	−59.3	−55.8	13.1	−56.0	−65.1
8	7.5	−54.1	−50.2	7.9	−67.7	−71.0
12	7.9	−41.4	−41.5	7.3	−65.8	−69.5
16	7.9	−34.0	−34.3	6.6	−67.3	−68.3
20	7.9	−29.4	−29.9	6.2	−68.2	−68.1
24	8.0	−26.5	−27.4	6.2	−68.1	−68.1
28	8.1	−25.5	−26.6	6.2	−67.8	−67.9
32	8.1	−25.7	−26.4	6.3	−67.5	−67.7
36	8.1	−26.1	−26.5	6.3	−67.3	−67.7
40	8.0	−26.3	−26.6	6.4	−67.3	−67.7

Notes: VAR(p) model with $T = 10{,}000$. The variables included in the VAR model are shown in parentheses. The RMSE is defined as the sum of the RMSEs of the responses listed in the first row over 40 quarters. The percent change in the RMSE is computed with respect to the RMSE of the KSMS estimator.

the MS News estimator based on the 4-variable model tends to be at least as accurate as that based on the 3-variable models for large p, which again is difficult to reconcile with the premise that the 4-variable model is misspecified.

In short, regardless of how the MS News estimator is implemented, it is substantially more accurate in the presence of TFP measurement error than the KSMS estimator. While we lack the tools to assess the invertibility of the VAR model for $\mathbf{y}_t = (\text{TFP}^u_t, y_t, i_t)'$ directly, our analysis suggests that informational insufficiencies play at best a modest role in undermining the accuracy of the KSMS estimator. Most of the gains in accuracy are driven by the identifying assumptions.

5.3 VAR Models with Measurement Error in TFP and TFP News

Table 6 highlights that the superior accuracy of the MS News estimator in the presence of TFP measurement error—even for large T and p—is robust to allowing for substantial measurement error in TFP news. Obviously, there has to be sufficient information in the TFP news variable for this estimator to work well. If TFP news consisted only of measurement error, the MS News estimator would fail.[19] Next, we

[19]This observation is analogous to an IV estimator correcting for measurement error in the regressor only when the regressor does not primarily or exclusively consist of noise.

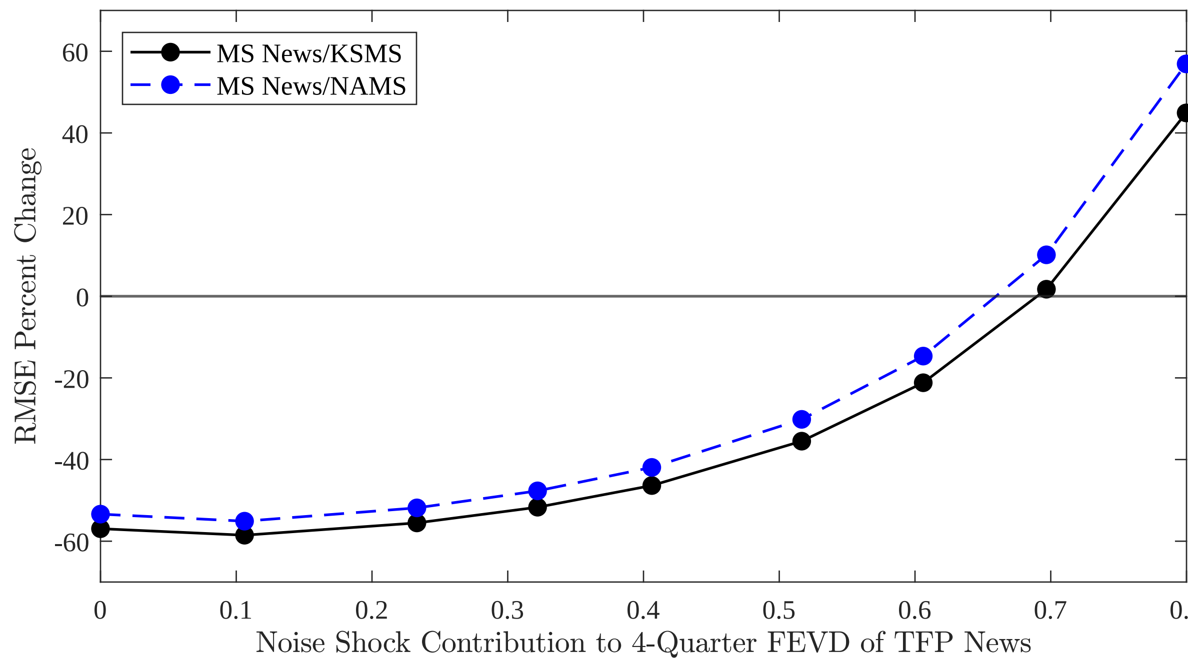
examine how much measurement error in TFP news would be required to make the MS News estimator based on $\mathbf{y}_t = (z_{t+1}, \text{TFP}_t^u, y_t, i_t)'$ no more accurate than the KSMS or NAMS estimators.

Figure 3 plots the reduction in the RMSE from using the MS News estimator rather than the KSMS or NAMS estimators as a function of the noise shock contribution to the 4-quarter FEVD of TFP news. For Panel A, the data are generated from the DSGE model with TFP measurement error specified in Section 3. All results are based on $T = 10{,}000$ and $p = 12$ for expository purposes. We focus on the case of highly persistent measurement error in Table 6. The plot shows that only when the measurement error in TFP news reaches about 70% of the FEVD of TFP news, the RMSE of the KSMS estimator drops below that of the MS News estimator. Essentially the same result holds for the NAMS estimator. Very similar results hold for the 3-variable version of the MS News estimator. This result fully supports and in fact strengthens our previous conclusion that the MS News estimator is robust to a substantial degree of measurement error in TFP news. While it is difficult to know how severe the measurement error in TFP news is in practice, one way of protecting against such situations is to check the economic plausibility of the responses to TFP news shocks, as illustrated in the next section.

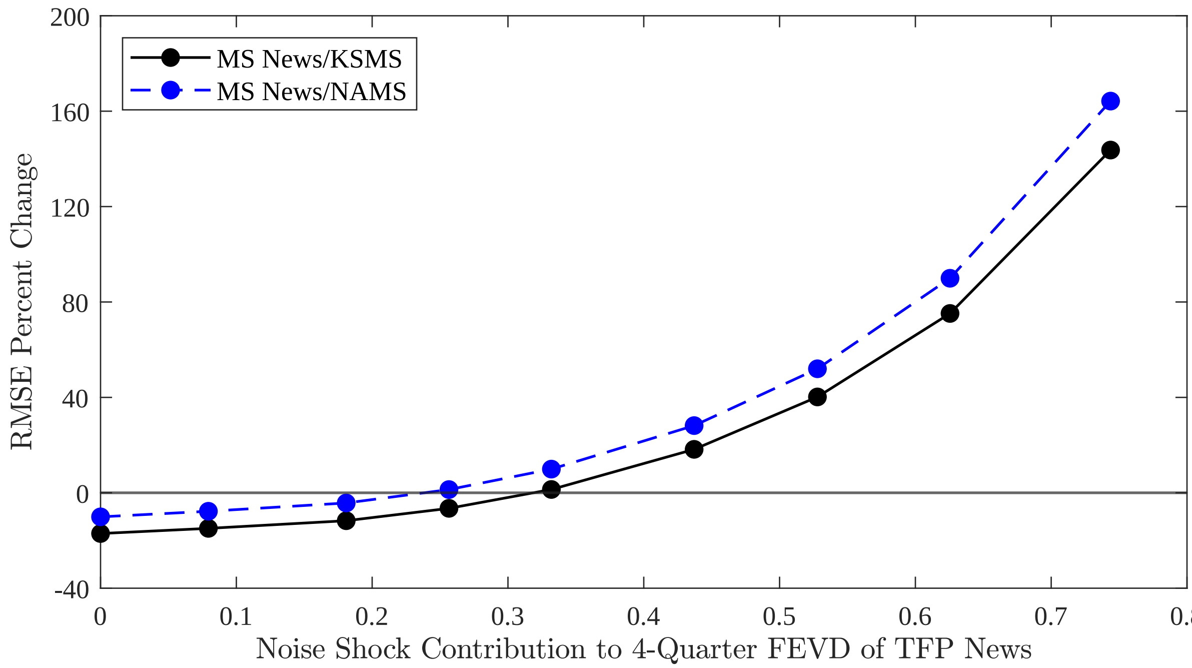
For completeness, Panel B shows the corresponding results under the parameterization of the TFP process adopted in Kurmann and Sims (2021). As discussed in Section 3.4, this parameterization is at odds with the data, making these simulation results uninformative for applied researchers. In addition, this parameterization does not provide a useful laboratory for evaluating the ability of TFP max share estimators to recover news shocks because it all but eliminates the surprise shock, not only at long horizons but at all horizons. Since the objective of the TFP max share estimator is to separate news shocks from surprise shocks, it is not clear what can be learned about the accuracy of this estimator in this setting. This simulation design overstates the accuracy of TFP max share estimators in practice. Even in this environment, the MS News estimator is more accurate than the KSMS estimator for modest amounts of TFP news measurement error, but the gains are smaller and it takes noise in TFP news in excess of about 33% for the 4-quarter ahead FEVD of TFP news for the KSMS estimator to become more accurate than the MS News estimator.

Figure 3: Relative accuracy as a function of the degree of measurement error in TFP news

(A) Our calibration



(B) KS Parameterization



Notes: VAR(4) model with $T = 10{,}000$ and $\mathbf{y}_t = (\text{TFP}^u_t, y_t, i_t)'$ for the KSMS estimator and $\mathbf{y}_t = (z_{t+1}, \text{TFP}^u_t, y_t, i_t)'$ for the MS News estimator. The FEVD is adjusted by varying standard deviation of the noise in TFP news σ_n, given a persistence of $\rho_n = 0.9$.

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 VAR models that include one of three 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); and (3) **CGV**: the patent grant series used in Cascaldi-Garcia and Vukotić (2022).[20]

For each series, we estimate a 9-variable VAR(4) model that includes one of the three news variables in addition to the 8 variables from the empirical VAR model used in Kurmann and Sims (2021). 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 model extends from 1960Q1 to 2010Q4. We identify the structural shocks based on the MS News estimator introduced in Section 4.

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 Section 3, 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 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. We find that only the R&D and

[20]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.

ICT models satisfy the two criteria (see Appendix F).[21]

Figure 4 shows the responses in the ICT model. Similar results hold when using the R&D model.[22] The news shock increases TFP, output, consumption, and investment in the long run, and the peak effects occur after 12 quarters. TFP initially falls, consistent with the view that new technologies are inconsistent with the incumbent technology (Baron and Schmidt, 2019). Hours respond positively, so there is positive comovement between real GDP, consumption, and investment. Inflation declines, 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).

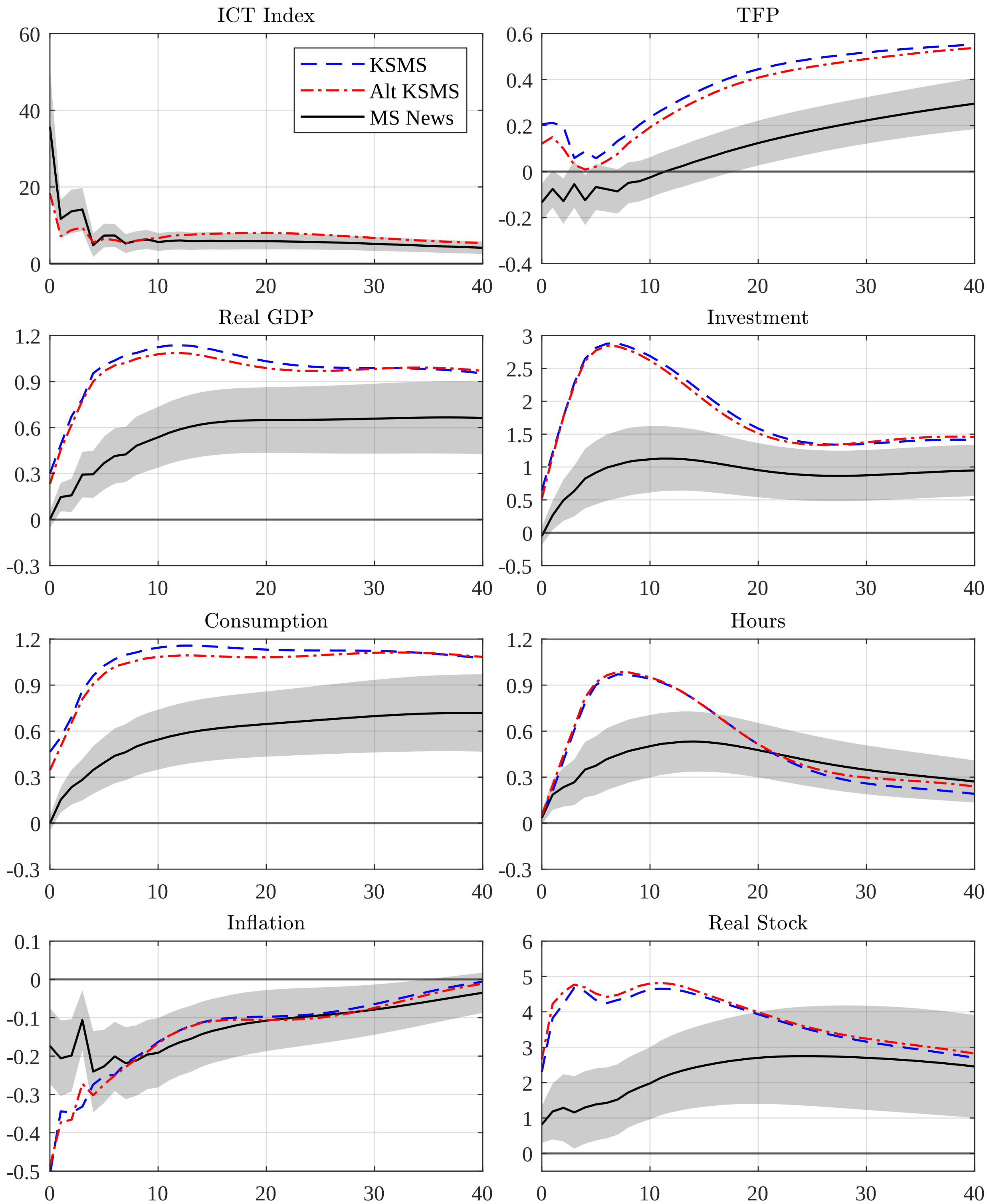
We plot these response estimates next to the estimates from the original 8-variable VAR model reported in Kurmann and Sims (2021) using the same estimation period, providing an apples-to-apples comparison between the two estimators. There are systematic and substantial differences between the two sets of response estimates, consistent with the bias documented in our simulation study. We also report the response estimates for the Alt KSMS estimator. The responses are almost identical to those for the KSMS estimator based on the 8-variable VAR model without ICT news.

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;

[21] 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.

[22] 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 4: Comparison of MS News and TFP max share identified impulse responses



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

Table 11: Forecast error variance decompositions by horizon based on actual data

	MS News Estimator				KSMS Estimator			
	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 for 1960-2014.

Levchenko and Pandalai-Nayar, 2020; Miranda-Agrippino et al., 2025). 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., 2025).

Table 11 shows that, according to the KSMS estimator, 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 MS 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 suggested by the 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 MS 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.

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 biased even in large samples 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 when news shocks explain almost all of the long-run variation in TFP. While this bias tends to be small in models without TFP measurement error, it becomes large in the presence of empirically plausible TFP measurement error of the type considered in Kurmann and Sims (2021).

Our evidence raises the question of how to proceed in applied work. We showed that adopting the novel MS News estimator systematically reduces the bias and RMSE of the TFP max share estimator of the impulse responses. The RMSE reductions are particularly large in the presence of TFP measurement error, even when there is substantial measurement error in the TFP news variable. They tend to be much smaller in the absence of TFP measurement error. We reported empirical estimates of the responses to news shocks based on this alternative estimator for three 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 in the United States than implied by the TFP max share method.

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