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 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), because the VAR model becomes informationally deficient. Since TFP measurement error of this type is an important feature of the data, our evidence casts doubt of 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 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 fundamental 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 is informationally deficient. We present evidence that augmenting the VAR model to include a direct measure of TFP news substantially alleviates the large-sample bias of TFP max share estimators in the presence of TFP measurement error. However, the MS News estimator based on the same VAR model is even less biased and has even lower RMSE. Thus, the higher large-sample bias of the TFP max share estimator cannot be explained by an information deficiency alone. The other explanation is that TFP max share estimators tend to confound the news shock with non-news shocks even when the news shock is dominant, 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

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

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

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

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

where $\varepsilon_{g,t-1}$ is lagged so that the shock occurs one period before it affects TFP. 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	2.31	$SD(\tilde{\imath}_t)$	9.63	9.48
$SD(\Delta a_t)$	0.80	0.73	$AC(\tilde{a}_t)$	0.87	0.87
$SD(\tilde{y}_t)$	3.13	3.92	$AC(\Delta a_t)$	−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

	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: MEI is the marginal efficiency of investment.

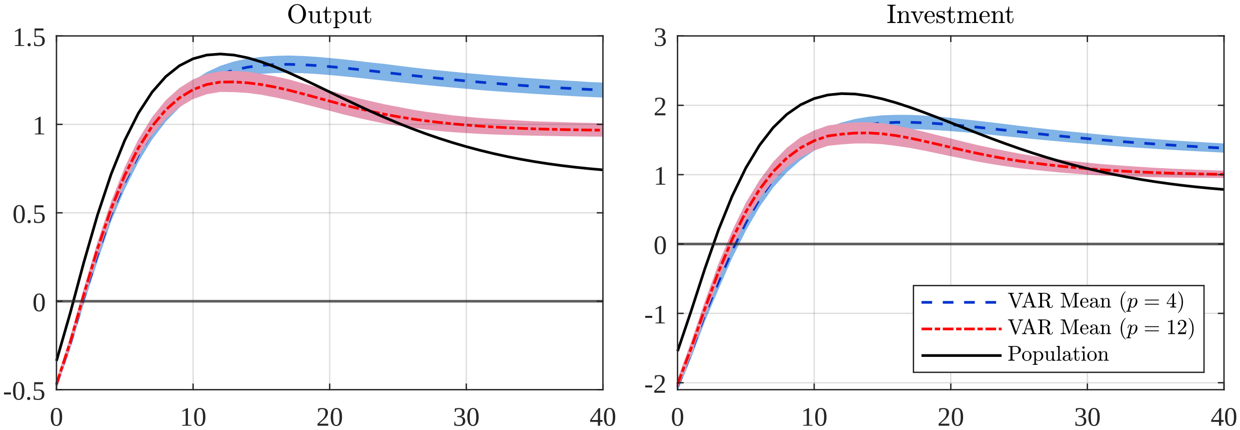
Under this calibration, news shocks are the dominant driver of the long-run variation in measured TFP. As illustrated in Table 2, news shocks explain almost all of the long-run variability of true TFP and 75% of the long-run variation in measured TFP, which is almost identical to the share Kurmann and Sims (2021) obtained when applying their estimator to actual data.

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 $\mathbf{y}_t = (\text{TFP}^u_t, y_t, i_t)'$. 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 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

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 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 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

Table 3: RMSE over 40 quarters

	$p = 4$				$p = 12$			
	TFP	Output	Invest	Total	TFP	Output	Invest	Total
	Baseline VAR Model $(\text{TFP}^u_t, y_t, i_t)$							
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 $(\text{TFP}^u_t, y_t, i_t, h_t)$							
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 $T = 10{,}000$.

there are 4 or 12 lags in the VAR model. Augmenting the VAR model to include hours worked (h_t), in recognition of the fact that with TFP measurement error there are four shocks to be considered in the VAR model, 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 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 very large samples when $p = 4$. In Appendix G, we show that this result is an artifact of their parameter choices for the TFP process. Under their parameterization, TFP growth is persistent, which is at odds with the data. Moreover, news shocks explain nearly all variation in TFP at all

[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.

horizons, which greatly enhances the accuracy of the KSMS estimator by effectively removing the identification challenge. 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. This bias arises for any specification of the TFP news process that assigns a non-trivial role to non-news shocks in driving TFP at the relevant horizons, as shown in Appendix G.

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 alternative 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. We present simulation evidence below that the MS News

[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).

estimator performs well with and without 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, 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. 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.

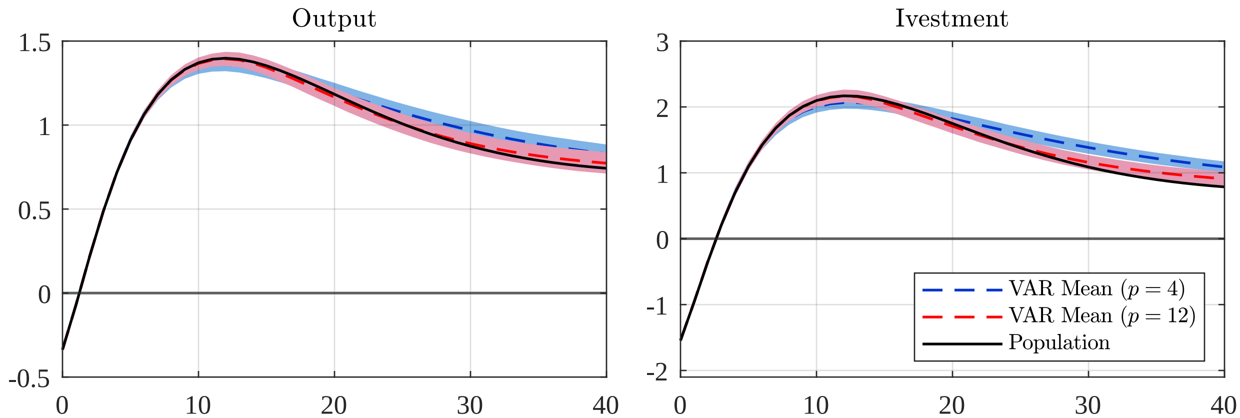
4.2 ACCURACY OF THE MS NEWS ESTIMATOR

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.[13] We therefore fit a VAR model to each draw of

[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.

[13] In Appendix G, we show 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 $\mathbf{y}_t = (z_{t+1}, \text{TFP}_t^u, y_t, i_t)'$.

$\mathbf{y}_t = (z_{t+1}, \text{TFP}_t^u, y_t, i_t)'$ of length $T = 10{,}000$. This timing mirrors the way observed TFP news has been used in applied work. For the KSMS estimator, we continue to fit a VAR model with $\mathbf{y_t} = (a_t, y_t, i_t)'$.

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 4 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 $p = 4$.[14] 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.

[14]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 4: 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 $\mathbf{y}_t = (\mathrm{TFP}^u_t, y_t, i_t)'$ for the KSMS and NAMS estimators and $\mathbf{y}_t = (z_{t+1}, \mathrm{TFP}^u_t, y_t, i_t)'$ for the MS News estimator. The Alt KSMS estimator uses the KS identification strategy and the MS News model variables. The 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.

The MS News estimator we proposed differs from the KSMS and NAMS estimators by incorporating 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 4. 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 4 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

Table 5: 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.

News estimator is still 49% more accurate than the KSMS estimator with $p = 4$ and 59% more 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 5 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%, respec-

Table 6: RMSE over 40 quarters without TFP measurement error

p	TFP	Output	Total	Ratio	TFP	Output	Total	Ratio
		KSMS				NAMS		
4	4.8	6.8	11.7	–	4.5	7.4	11.9	1.02
12	1.3	2.6	4.0	–	1.3	3.1	4.4	1.10
24	0.9	2.2	3.2	–	0.9	2.5	3.5	1.09
36	0.9	2.3	3.2	–	0.9	2.5	3.5	1.09
		Alt KSMS				MS News		
4	0.6	4.7	5.3	0.45	0.6	4.5	5.1	0.43
12	0.8	2.1	2.9	0.74	0.8	2.0	2.8	0.70
24	0.9	2.2	3.1	0.97	0.8	2.0	2.9	0.90
36	0.9	2.3	3.2	1.00	0.9	2.1	2.9	0.93

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 ratios are computed with respect to KSMS.

tively. These results suggest that the benefits of the MS News estimator extend to realistic sample 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). We consider lag lengths of $p \in \{4, 12, 24, 36\}$ and for each setting calculate the RMSE for the VAR estimates of the responses of TFP and output, their combined sum, and the ratio of the combined sums relative to the KSMS estimator for the corresponding lag length.

The upper left and right panels in Table 6 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 6. 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. The next section reconciles these findings with our earlier evidence.

5 MAKING SENSE OF THE SIMULATION RESULTS

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. 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.

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, even for large T and p. The answer is related to the question of whether the reduced-form VAR model underlying the TFP max share estimator is fundamental. 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 do not apply this diagnostic because it was designed for stationary data, and the VAR model data in our application are nonstationary. Instead, we focus on the RMSEs of the response estimator relative to the population responses in the DSGE model, building on the fact that under near informational sufficiency the estimated responses should be close to the population responses in the limit, as long as the VAR identification is correct.

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%.[15] 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.

The presence of TFP measurement error undermines the accuracy of the TFP max share estimator because measurement error creates informational insufficiency, even if the structural model

[15] 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.

generating the data would imply invertibility under no measurement error. Thus, the TFP max share estimator based on $\mathbf{y}_t = (\mathrm{TFP}_t^u, y_t, i_t)'$ would be expected to fail in the empirically more relevant case of TFP measurement error, even in the absence of the contamination problem and regardless of the VAR lag order. The fact that the TFP max share estimator also confounds the TFP news shock with other shocks further undermines its accuracy.

As we showed in Table 3, the responses estimated by the TFP max share estimator tend to be far from the population responses even for large T and p, as measured by the RMSE. Given that TFP measurement error of the type modeled in Kurmann and Sims (2021) is likely to be pervasive in applied work, a strong case can be made for using the MS News estimator instead. The MS News estimator remedies the informational deficiency of the VAR model underlying the TFP max share estimator in the presence of TFP measurement by specifying a VAR for $\mathbf{y}_t = (z_{t+1}, \mathrm{TFP}_t^u, y_t, i_t)'$, and it applies an identification strategy that avoids the contamination of TFP news shocks by targeting the news variable at a short horizon. Table 4 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 large measurement error in TFP news.

The point of comparing the RMSE ratios of the Alt KSMS and Alt NAMS estimators to those of the MS News estimator is to quantify the extent to which the superior large sample accuracy of the MS News estimator is driven by the information set. Our results show that the gains in accuracy from using the MS News estimator in the presence of TFP measurement error are driven by a combination of the choice of the information set and the identification strategy.

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).[16]

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 ICT models satisfy the two criteria (see Appendix F).[17]

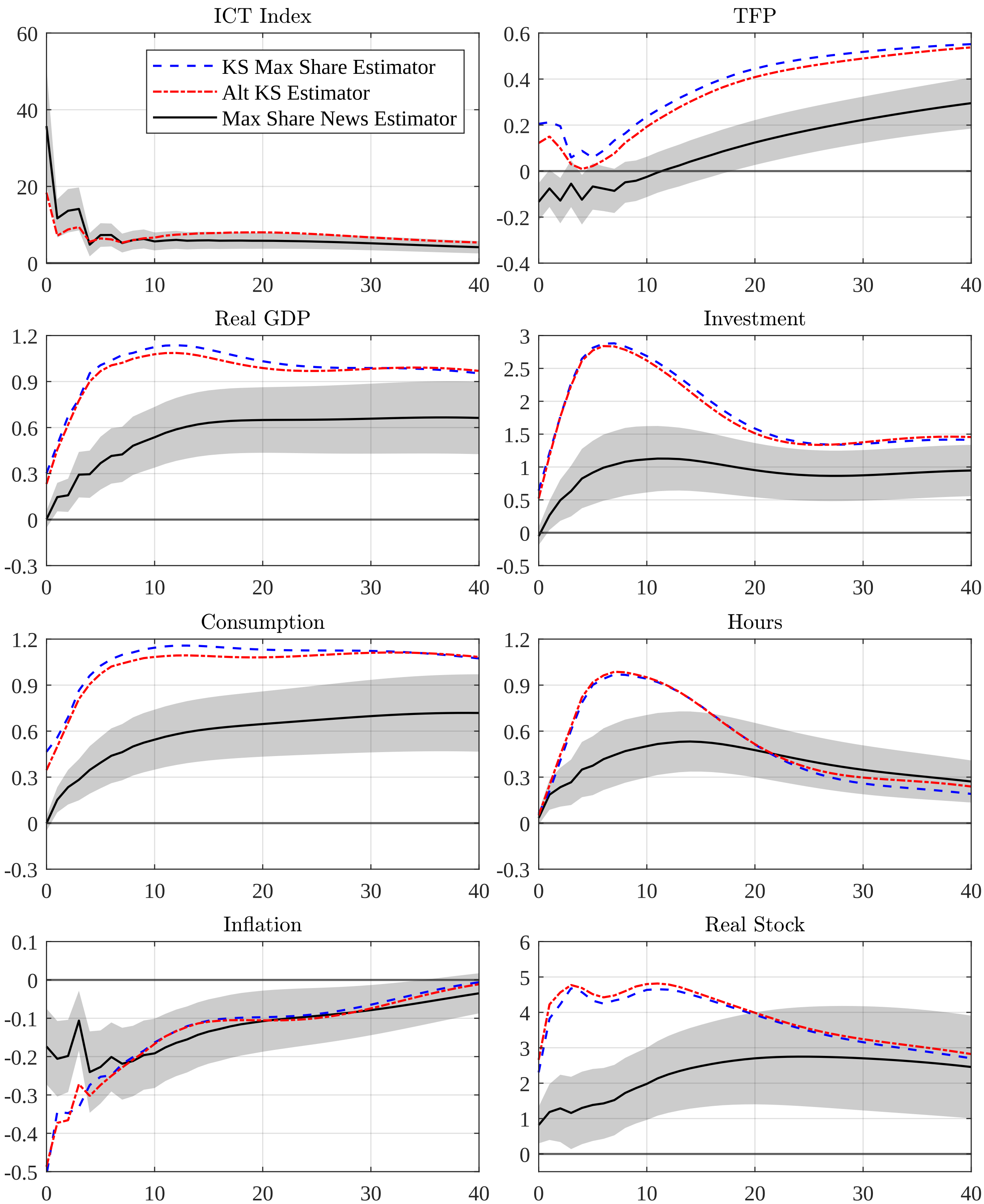
Figure 3 shows the responses in the ICT model. Similar results hold when using the R&D model.[18] The news shock increases TFP, output, consumption, and investment in the long run,

[16] 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.

[17] 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.

[18] 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 3: 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.

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, once again highlighting that the differences between the MS News estimator and the TFP max share estimator cannot be simply explained by an information deficiency of the original VAR model.

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., 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 7 shows that, according to the KSMS estimator, news shocks diffuse relatively quickly,

Table 7: 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.

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 addresses the two potential sources of asymptotic bias in the TFP max share estimator and systematically reduces the bias and RMSE 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.

REFERENCES

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

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

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

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

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

BEAUDRY, P. AND B. LUCKE (2010): "Letting Different Views about Business Cycles Compete," in *NBER Macroeconomics Annual 2009, Volume 24*, ed. by D. Acemoglu, K. Rogoff, and M. Woodford, University of Chicago Press, NBER Chapters, 413–455.

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

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

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

BEN ZEEV, N., E. PAPPA, AND A. VICONDOA (2017): "Emerging Economies Business Cycles: The Role of Commodity Terms of Trade News," *Journal of International Economics*, 108, 368–376.

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

BOUAKEZ, H. AND L. KEMOE (2023): "News Shocks, Business Cycles, and the Disinflation Puzzle," *Journal of Money, Credit and Banking*, 55, 2115–2151.

BRETSCHER, L., A. MALKHOZOV, AND A. TAMONI (2021): "Expectations and Aggregate Risk," *Journal of Monetary Economics*, 123, 91–108.

CARRIERO, A. AND A. VOLPICELLA (2025): "Max Share Identification of Multiple Shocks: An Application to Uncertainty and Financial Conditions," *Journal of Business & Economic Statistics*, 43, 1–13.

CASCALDI-GARCIA, D. AND A. B. GALVAO (2021): "News and Uncertainty Shocks," *Journal of Money, Credit and Banking*, 53, 779–811.

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

CHAHROUR, R., S. K. CHUGH, AND T. POTTER (2023): "Anticipated Productivity and the Labor Market," *Quantitative Economics*, 14, 897–934.

CHAHROUR, R. AND K. JURADO (2018): "News or Noise? The Missing Link," *American Economic Review*, 108, 1702–1736.

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

CHRISTIANO, L. J., M. EICHENBAUM, AND R. VIGFUSSON (2004): "The Response of Hours to a Technology Shock: Evidence Based on Direct Measures of Technology," *Journal of the European Economic Association*, 2, 381–395.

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

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

DIEPPE, A., N. FRANCIS, AND G. KINDBERG-HANLON (2021): "The Identification of Dominant Macroeconomic Drivers: Coping with Confounding Shocks," European Central Bank Working Paper 2534.

DOU, L., P. HO, AND T. A. LUBIK (2025): "Max-Share Misidentification," Manuscript, Federal Reserve Bank of Richmond.

FACCINI, R. AND L. MELOSI (2022): "Pigouvian Cycles," *American Economic Journal: Macroeconomics*, 14, 281–318.

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

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

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

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

FIELDHOUSE, A. J. AND K. MERTENS (2023): "The Returns to Government R&D: Evidence from U.S. Appropriations Shocks," Federal Reserve Bank of Dallas Working Paper 2305.

FORNI, M., L. GAMBETTI, M. LIPPI, AND L. SALA (2017): "Noisy News in Business Cycles," *American Economic Journal: Macroeconomics*, 9, 122–152.

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

——— (2019): "Structural VARs and Noninvertible Macroeconomic Models," *Journal of Applied Econometrics*, 34, 221–246.

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

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

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

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

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

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

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

JINNAI, R. (2014): "R&D Shocks and News Shocks," *Journal of Money, Credit and Banking*, 46, 1457–1478.

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

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

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

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

MIRANDA-AGRIPPINO, S., S. H. HOKE, AND K. BLUWSTEIN (2025): "Patents, News, and Business Cycles," *Review of Economic Studies*, forthcoming.

MIYAMOTO, W., T. L. NGUYEN, AND H. OH (2025): "In Search of Dominant Drivers of the Real Exchange Rate," *Review of Economics and Statistics*, 107, 1059–1073.

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

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

PIGOU, A. C. (1927): *Industrial Fluctuations*, London: Macmilan.

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

——— (2022): "Instrumental Variable Identification of Dynamic Variance Decompositions," *Journal of Political Economy*, 130, 2164–2202.

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

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

UHLIG, H. (2003): "What moves real GNP?" Working paper, Humboldt University.

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