REVISIONS IN UTILIZATION-ADJUSTED TFP AND ROBUST IDENTIFICATION OF NEWS SHOCKS

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Abstract—This paper documents large revisions in a widely used series of utilization-adjusted total factor productivity (TFP) by Fernald (2014) and shows that these revisions can materially affect empirical results about the effects of news shocks. We trace these revisions to changes in estimated factor utilization that are evocative of cyclical measurement issues with productivity. We propose an alternative identification that is robust to these measurement issues. Applied to U.S. data, the shock predicts delayed productivity growth while simultaneously generating strong responses of novel indicators of technological innovation and forward-looking variables. The shock does not lead to comovement in macroeconomic aggregates.

I. Introduction

ECONOMISTS have long argued that changes in expectations about future fundamentals are an important source of economic fluctuations. This view has reemerged recently in part due to an influential paper by Beaudry and Portier (2006), who report that news shocks about future productivity are closely related to innovations driving long-run variations in productivity and constitute one of the main drivers of business cycles. While the importance of news shocks for business cycle fluctuations continues to be debated, the main identifying restriction behind news shocks is almost universally accepted: productivity reacts to news shocks only with a delay.[1]

In this paper, we critically revisit the zero impact restriction. We argue that popular measures of productivity are likely to be confounded by business cycle fluctuations due to imperfect measurement of factor utilization. As a result, news shock identifications that rely on short-run restrictions, in particular the zero impact restriction, can produce misleading results. We then propose an alternative identification that is robust to cyclical mismeasurement of productivity and apply it to U.S. data.

The starting point of our investigation is the quarterly utilization-adjusted series of total factor productivity (TFP) constructed by Fernald (2014) that has become the main measure of productivity in the news literature. Fernald frequently updates the adjusted TFP series based on new data and, less frequently, implements methodological changes. We document that a switch in detrending methods in the estimation of utilization significantly changes the cyclical properties of this series. The sensitivity of adjusted TFP to a seemingly small change such as this suggests, as Fernald (2014) acknowledged, but otherwise mostly ignored by the literature, that measurement issues with productivity can be quantitatively important.

To assess the consequences of Fernald's revisions for news shock identification, we redo the estimation of Barsky and Sims (2011), which has emerged as one of the most popular identification approaches in the literature. Based on prerevision vintages of the adjusted TFP series, a positive news shock leads to a jump in consumption on impact but an initial decline in hours worked. As a result, the implied conditional correlation of consumption growth with hours growth is negative, leading Barsky and Sims (2011) to conclude that news shocks do not constitute a main driver of business cycles. Based on postrevision vintages constructed with the new estimate of utilization, in contrast, a positive news shock leads to a coincident increase in consumption, hours, and other real aggregates, thereby affording a news-driven interpretation of business cycles as Beaudry and Portier (2006) proposed.

To interpret these results and illustrate the consequences of productivity mismeasurement for news shock identification more generally, we consider a medium-scale New Keynesian business cycle model that allows for multiple sources of unobserved factor utilization. Under certain conditions, Fernald's estimate of utilization coincidences with factor utilization in the model and adjusted TFP provides an almost perfect measure of true productivity. But under alternative yet equally plausible conditions, Fernald's estimate of utilization and therefore productivity is confounded by substantial cyclical mismeasurement. We conduct Monte Carlo simulations to study the quantitative significance of this mismeasurement. The main insight from these simulations is that identifications relying on short-run restrictions and, in particular, the zero impact restriction can be highly sensitive to differences between factor utilization in the model and its estimation by the econometrician. Since factor utilization is not observed directly in the data and different assumptions about factor utilization are difficult to test, a more fruitful approach devises alternative identification restrictions that are robust to cyclical mismeasurement.

In the final section of the paper, we propose such an alternative identification. Building on the premise by Beaudry and Portier (2006) that news shocks capture information about slowly disseminating changes in technology and economic organization that drive long-run productivity, we extract the

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[1]See Beaudry and Portier (2014) and Barsky, Basu, and Lee (2015) for excellent reviews of this literature.

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innovation that accounts for the maximum forecast error variance (FEV) share of adjusted TFP at a long but finite horizon.[2] This max-share approach, which builds on work by Uhlig (2003), has been used previously by Francis et al. (2014) to identify long-run technology shocks. We differ in that we apply it to adjusted TFP instead of labor productivity and propose it as a possible news identification. Conceptually, the max-share identification is also similar to Barsky and Sims (2011) and many close variants in the news literature, with the crucial difference, however, that it does not impose the zero impact restriction and, more generally, does not rely on short-run fluctuations in productivity. The max-share identification should therefore be more robust to cyclical mismeasurement of productivity, and we verify this through Monte Carlo simulations with our model.[3] In these simulations, the max-share identification performs very well as long as mean-reverting surprise technology shocks do not account for a large fraction of the lower-frequency variation in true technology.

Of course, nothing guarantees that the max-share identification captures news shocks as opposed to other shocks driving future productivity. However, when applied to U.S. data, we find compelling evidence in favor of a news interpretation. The shock has no significant impact on adjusted TFP for several quarters but predicts sustained future productivity growth, accounting for 70% or more of TFP fluctuations at long forecast horizons. More important, the shock is associated with large impact responses of two novel indicators of innovation: an index of books published in the fields of technology by Alexopoulos (2011) and an index of technological standardization by Baron and Schmidt (2015), followed by a hump-shaped increase in R&D expenditures and a gradual decline in the relative price of investment goods. Third, the shock generates strong, positive immediate reactions of forward-looking information variables.

In terms of macroeconomic implications, the max-share identification implies very similar impulse responses as the ones that Barsky and Sims (2011) originally reported, with the important difference that all the results are robust to the revisions in Fernald's adjusted TFP series. Consumption increases on impact of the shock and then gradually rises to a new permanent level, while hours worked initially decline and later increase in a hump-shaped pattern before returning to the preshock level. The shock therefore implies a negative correlation between consumption growth and hours worked, which makes it an unlikely source of business cycle fluctuations. Nevertheless, the shock accounts for a large share of macroeconomic fluctuations at medium and longer horizons and generates sharp impact responses of inflation and asset prices.

The fact that the empirical findings from the max-share identification do not substantively differ from those in Barsky and Sims (2011) does not mean that mismeasurement of productivity is without consequence. In particular, there is no free lunch in the sense that because of these measurement issues, one cannot separately identify surprise shocks to current productivity from news shocks about future productivity. This is important for other research that relies on short-run fluctuations in adjusted TFP for identification.

The main lesson of the paper is that cyclical measurement issues can materially affect the identification of news shocks based on short-run restrictions. While measurement error occupies a central role in many fields of economics, it has generally taken a back seat in quantitative macroeconomics. A notable exception is Christiano, Eichenbaum, and Vigfusson (2004), who argue, as we do, that adjusted TFP may be confounded by measurement error.[4] They then apply the infinite-horizon strategy of Gali (1999) to identify long-run productivity shocks based on the assumption that measurement errors in adjusted TFP are transient. Our paper differs in important aspects from Christiano et al. (2004) and the related literature on long-run productivity shocks. First, the max-share identification proposed here does not impose that technology is the only source of long-run fluctuations in productivity and instead extracts the shock that accounts for the maximum FEV share of adjusted TFP at a long but finite horizon. The max-share approach therefore affords the possibility that other shocks (e.g., a surprise productivity shock) exert long-lasting effects on adjusted TFP and at the same time addresses the criticism that infinite-horizon restrictions imply potentially large biases in finite-order VARs.[5]

Second, the literature on long-run productivity shocks typically uses average labor productivity as the technology measure and is primarily concerned with the dynamics of hours worked in response to a shock.[6] As such, this literature does not directly relate to the news literature and the idea that improvements in technology disseminate slowly and in a predictable manner. Indeed in many cases—including the max-share implementation by Francis et al. (2014) on which our identification is based—labor productivity jumps immediately because hours fall on impact, thus resulting in capital deepening.[7] This may lead to the inadvertent conclusion, often imposed in DSGE models, that technology follows a random walk process with only one shock. While our results are consistent with the fact that empirically measured TFP is well characterized by a univariate random walk process,

[2] The idea that new technologies diffuse slowly finds ample support in a large micro-empirical literature. See Griliches (1957), Mansfield (1961, 1989), Gort and Klepper (1982), and Rogers (1995).

[3] The max-share identification is also robust to situations in which innovations to expected future productivity have an immediate impact on (true) productivity.

[4] Chang and Li (2018) is another more general investigation about the sensitivity of recent research results to measurement error in gross domestic product.

[5] Bias reduction in finite-order VARs is the main motivation of Francis et al. (2014) for the max-share identification. Also see Ereeg, Guerrieri, and Gust (2005), Christiano et al. (2006), and Chari, Kehoe, and McGrattan (2008) for important contributions in this respect. Another practical advantage of the max-share approach is that it can be implemented with either a VAR in levels that includes nonstationary variables, as we do, or a stationary VAR.

[6] Aside from Christiano et al. (2004), one other exception is Chen and Wemy (2015) who, like us, apply the max-share approach to adjusted TFP. However, they do not investigate the robustness of the approach to revisions in adjusted TFP or whether the resulting shock is a news shock.

[7] We confirm this result in our VAR specification. See the discussion in section V for details.

they nevertheless suggest that the permanent component of the series is slow diffusion, which is rather different from the oft-assumed jump process impulse response functions generated from a univariate random walk process.

Within the extensive VAR literature on news shocks, our paper is perhaps most closely related to the one by Barsky et al. (2015). They identify a news shock by imposing a longer-run restriction that is conceptually similar to the max-share approach proposed here but differs in potentially important details.[8] Using a prerevision vintage of Fernald's adjusted TFP series, they find that their news shock looks quite similar independent of whether they impose the zero impact restriction. Our results confirm their finding in the sense that the initial response of adjusted TFP to the proposed max-share shock is small and insignificantly different from 0 for several quarters. Our contribution relative to the paper by Barsky et al. (2015) and the rest of the news literature is to document the large revisions in Fernald's utilization-adjusted TFP series and show that these revisions can materially affect empirical conclusions about the effects of news shocks based on short-run restrictions.[9] We propose the max-share approach as an alternative identification of news shocks and show that it is robust to measurement issues, and we go to considerable length to establish the news content of the extracted shock by relating it to measures of technological innovation and forward-looking information variables.

The idea that the slow dissemination of technology implies predictable long-run changes in productivity relates to a recent (non-news) literature on the macroeconomic effects of persistent productivity growth processes. Rotemberg (2003) discusses extensively the available evidence on the slow dissemination of technology and proposes a model in which random technological progress leads to stochastic variations in long-run output while deviations of output from trend are mostly driven by temporary shocks. As in our empirical investigation, he finds that slowly diffusing technical progress leads to a temporary drop in hours worked and economic activity.[10] Lindé (2009) incorporates autocorrelated shocks to the growth rate of productivity into an otherwise standard RBC model. Autocorrelated shocks to productivity growth have the flavor of news, and he shows that incorporating this feature can help reconcile the RBC model with empirical results on the effects of technology shocks on hours worked.

II. Revisions in Utilization-Adjusted TFP

The business cycle literature has typically measured productivity as the residual of aggregate output not accounted for by capital and labor inputs, commonly known as TFP. Economists quickly realized, however, that TFP may be a poor proxy of technology for a variety of reasons, most notably changes in unobserved factor utilization. In response to these concerns, Basu, Fernald, and Kimball (2006) construct an aggregate measure of productivity that takes into account sectoral heterogeneity, imperfect competition, compositional changes in the quality of labor and capital, and unobserved factor utilization. Fernald (2014) extends the analysis of Basu et al. (2006), which is carried out with annual data, to construct a quarterly measure of TFP. Because of the higher frequency, not all of the corrections in the original Basu et al. (2006) series can be implemented, but perhaps the most important one—the adjustment for variable factor utilization—is.

In what follows, we briefly review the construction of Fernald's utilization-adjusted TFP series. We then document how seemingly small changes in the estimation of factor utilization lead to large revisions in utilization-adjusted TFP that materially affect its business cycle properties.

A. *Fernald's Utilization-Adjusted TFP Series*

Fernald's series of utilization-adjusted TFP is based on the assumption that there exists an aggregate production function

$$Y_t = F(e_t L_t, z_t K_t, A_t), \quad (1)$$

where Y_t denotes output, L_t labor input (the product of average hours per worker, h_t, and employment, N_t, adjusted for quality of the workforce),[11] K_t capital input, e_t labor effort, z_t capital use, and A_t technology that should be understood broadly as a shifter of the production function.

Differentiating equation (1) with respect to time and further assuming constant returns to scale as well as price taking by firms in perfectly competitive input and output markets, cost minimization implies that technology growth can be expressed as

$$\frac{\dot{A}_t}{A_t} = \left(\frac{\dot{Y}_t}{Y_t} - \omega_{L,t}\frac{\dot{L}_t}{L_t} - \omega_{K,t}\frac{\dot{K}_t}{K_t}\right) - \left(\omega_{L,t}\frac{\dot{e}_t}{e_t} + \omega_{K,t}\frac{\dot{z}_t}{z_t}\right), \quad (2)$$

where $\omega_{L,t}$ denotes the cost share of labor and $\omega_{K,t}$ the cost share of capital, which under constant returns to scale equals

[8]The identification of Barsky et al. (2015) extracts the shock that accounts for all of the forecast revision of adjusted TFP at some long but finite horizon subject to the zero impact restriction, although their results would be very similar if this restriction was not imposed. We prefer the max-share approach because, as noted above, it does not impose that news shocks are the only source of predictable fluctuations at that particular horizon. Furthermore, our Monte Carlo simulations reveal that imposing the zero impact restriction can have important consequences even if without this restriction, the impact response of adjusted TFP is close to 0.

[9]In contemporaneous work, Cascaldi-Garcia (2017) also points out that revisions in Fernald's adjusted TFP series affect the macroeconomic implications of news shocks based on the Barsky and Sims (2011) identification. The paper does not document the source of these revisions in detail or discuss why these revisions raise questions about the zero impact restriction imposed by the news literature. Instead, the paper is intended as a comment on Kurmann and Otrok (2013), to which Kurmann and Otrok (2017b) respond using the alternative identification approach proposed here.

[10]Other papers that document the slow diffusion of technology and build models of costly adoption are Comin and Gertler (2006), Comin and Hobijn (2010), and Comin, Gertler, and Santacreu (2009).

[11]Fernald adjusts for changes in workforce quality using estimates of education and experience for different groups.

TABLE 1.—MOMENTS OF TFP GROWTH AND UTILIZATION FOR DIFFERENT VINTAGES

	A. Adjusted TFP Growth			
	$\Delta \ln TFP_t^{u,07}$	$\Delta \ln TFP_t^{u,13}$	$\Delta \ln TFP_t^{u,14}$	$\Delta \ln TFP_t^{u,16}$
Mean	1.49	1.41	1.42	1.42
Standard deviation	3.41	3.30	3.79	3.46
Correlation with $\Delta \ln TFP_t^{u,07}$	1.00	0.85	0.56	0.58
Correlation with $\Delta \ln Y_t$	0.53	0.38	0.18	0.07
Correlation with $\Delta \ln L_t$	−0.01	−0.06	−0.24	−0.35
	B. Unadjusted TFP Growth			
	$\Delta \ln TFP_t^{07}$	$\Delta \ln TFP_t^{13}$	$\Delta \ln TFP_t^{14}$	$\Delta \ln TFP_t^{16}$
Mean	1.42	1.37	1.37	1.39
Standard deviation	3.75	3.55	3.55	3.55
Correlation with $\Delta \ln TFP_t^{u,07}$	1.00	0.92	0.92	0.93
	C. Utilization Growth			
	$\Delta \ln \widehat{u}_t^{07}$	$\Delta \ln \widehat{u}_t^{13}$	$\Delta \ln \widehat{u}_t^{14}$	$\Delta \ln \widehat{u}_t^{16}$
Mean	−0.08	−0.04	−0.05	−0.03
Standard deviation	2.34	2.94	3.75	3.76
Correlation with $\Delta \ln \widehat{u}_t^{07}$	1.00	0.94	0.58	0.65

$\Delta \ln TFP_t^{u,j}$ is the quarterly log change expressed in annualized percentage points of Fernald's adjusted TFP series for vintages $j = 07$, 13, 14, or 16; $\Delta \ln TFP_t^j$ is unadjusted TFP growth by vintage; and $\Delta \ln \widehat{u}_t^j$ is the growth rate of Fernald's utilization series by vintage. Y_t is real GDP and H_t is total hours worked in the nonfarm business sector; these are from the NIPA tables and are expressed as quarterly log changes. The sample period for each of the statistics is 1947q3 to 2007q3.

$(1 - \omega_{L,t})$. The term in the first parenthesis is typically referred to as TFP growth and the term in the second parenthesis as the change in factor utilization.

Fernald constructs TFP growth from quarterly NIPA and BLS data as

$$\Delta \ln TFP_t = \Delta \ln Y_t - \omega_{L,t} \Delta \ln L_t - (1 - \omega_{L,t}) \Delta \ln K_t, \quad (3)$$

with output growth measured as the log change in the equally weighted average of real expenditures and income in the business sector; and labor and capital growth built up from quality-adjusted series of different labor and capital types. To adjust for variable labor effort and capital use, which are not directly observed in the data, Fernald follows Basu et al. (2006) and proxies the change in factor utilization by a weighted change in industry hours per worker, that is,

$$\Delta \ln \hat{u}_t = \sum_i \kappa_i \widehat{\beta}_i \Delta \ln h_{it}^c, \quad (4)$$

where h_{it}^c denotes a measure of hours per worker in industry i discussed further below; κ_i the industry weights; and $\widehat{\beta}_i$ the industry-specific factors of proportionality estimated using demand-side shocks as instruments.[12] The idea behind this proxy is that industry capital stocks and employment are quasi-fixed, but hours per worker, labor effort, and capital use can be adjusted costlessly. Under certain conditions, reviewed in detail in section IV, optimal firm behavior then implies that utilization is proportional to hours per worker.

[12]See Fernald (2014) for details on the data and instrumental variable estimation procedure.

Given equations (3) and (4), utilization-adjusted TFP,

$$\Delta \ln TFP_t^u = \Delta \ln TFP_t - \Delta \ln \hat{u}_t, \quad (5)$$

provides an empirical estimate of aggregate technology growth as defined in equation (1). As Fernald (2014) explicitly acknowledged, with markups, possibly heterogeneous across producers, of price above marginal cost, or with factor adjustment costs that lead the shadow cost of inputs to differ across firms . . . aggregate TFP and aggregate technology are not the same—even in the absence of variable factor utilization." Similarly, if the utilization proxy in equation (4) is incorrect, then this will also lead to mismeasurement. Despite these potential issues, adjusted TFP is an important benchmark and has become the primary measure of technology for business cycle macroeconomics.

B. *Changes across Vintages*

Fernald regularly publishes revised estimates of adjusted TFP based on new data and methodological changes.[13] Panel a of table 1 reports key statistics for the vintages of December 2007, December 2013, May 2014, and May 2016, all over the same sample period 1947:3 to 2007:3.[14] The means and standard deviations are similar across vintages. However, there is a marked change in business cycle comovement from the 2014 vintage onward. The correlation coefficient between the

[13]The different vintages of adjusted TFP, as well as the underlying components, are available on Fernald's website.

[14]The beginning and end of the sample are dictated by the availability of the December 2007 vintage. The results for other pre-2014 vintages are very similar to the 2007 and 2013 vintages, while the results for other post-2013 vintages are very similar to the 2014 and 2016 vintages.

TABLE 2.—CHANGES IN FERNALD'S UTILIZATION ESTIMATES

	$\Delta \ln \widehat{u}_t^{13}$	$\Delta \ln \widehat{u}_t^{13,BFFK}$	$\Delta \ln \widehat{u}_t^{13,BW}$	$\Delta \ln \widehat{u}_t^{13,BFFK\&BW}$	$\Delta \ln \widehat{u}_t^{14}$
Standard deviation	2.94	2.26	4.76	3.69	3.75
Correlation with $\Delta \ln \widehat{u}_t^{07}$	0.94	0.91	0.59	0.57	0.58

This table shows simulated utilization series based on the 2013 vintage data. See the text for details. The sample period for all statistics is 1947q3 to 2007q3.

2007 vintage and post-2013 vintages of adjusted TFP growth is less than 0.6. Furthermore, while the 2007 and 2013 vintages of adjusted TFP growth are positively correlated with output growth and uncorrelated with total hours growth, the 2014 and 2016 vintages of adjusted TFP growth are uncorrelated with output growth and negatively correlated with total hours growth.[15]

Panels b and c in table 1 decompose these changes in correlation into the parts coming from unadjusted TFP and utilization. The business cycle properties of unadjusted TFP growth remain essentially unchanged across vintages. Variations in utilization, by contrast, are significantly larger for the 2014 and 2016 vintages, and there is an important decline in correlation relative to the 2007 and 2013 vintages.[16]

This suggests that the large changes in business cycle properties of adjusted TFP are not due to revisions in nonadjusted TFP (i.e., due to data revisions or changes in NIPA methodology), but are instead driven primarily by revisions in utilization. We confirm this conjecture by combining the 2007 vintage of utilization with nonadjusted TFP from other vintages. Correlations for the resulting synthetic series of adjusted TFP are presented in the online appendix. The correlations of the 2007 adjusted TFP vintage with the synthetic 2014 and 2016 series are both 0.91, compared to 0.56 and 0.58 for the actual vintages. Hence, while revisions in utilization do not account for all of the changes in adjusted TFP, they explain the large majority.

C. *Revisiting Fernald's Estimation of Utilization*

What explains the changes in estimated utilization across vintages? Between December 2013 and May 2014, Fernald implemented two methodological changes. First, he switched from using estimates of industry weights and proportionality factors $\widehat{\beta}_i$ in equation (4) by Basu et al. (2006) to estimates from Basu et al. (2013), which are based on more recent data and a more detailed industry decomposition. Second, Fernald has to contend with the issue that hours per worker in many industries are trending over time. Up to the December 2013 vintage, Fernald follows Basu et al. (2006) and detrends industry hours per worker with the bandpass filter of Christiano and Fitzgerald (2003) to isolate frequencies between 8 and 32 quarters. From the May 2014 vintage onward, Fernald instead detrends industry hours per worker with the bi-weight filter used in Stock and Watson (2012), which removes a much slower-moving trend than the bandpass filter.

Using replication codes for the December 2013 and May 2014 vintages shared generously by Fernald, we assess the quantitative importance of the two changes. Table 2 reports the results. For comparison, the first and the last columns replicate the business cycle properties of the actual December 2013 and May 2014 vintages of estimated utilization growth from table 1. The second column, labeled $\Delta \ln \hat{u}_t^{13,BFFK}$, shows the effect of switching to the industry weights and proportionality factors from Basu et al. (2013). While this switch lowers the volatility of utilization somewhat, it leaves the correlation with the 2007 vintage essentially unchanged. As shown by the third column, labeled $\Delta \ln \hat{u}_t^{13,BW}$, by contrast, changing the detrending method from bandpass filtering to bi-weight filtering leads to a substantial increase in the volatility of utilization growth and a concurrent decrease in the correlation with the 2007 vintage. Finally, as shown in the fourth column, labeled $\Delta \ln \hat{u}_t^{13,BFFK\&BW}$, the two changes essentially replicate the 2014 vintage. The remaining difference is due to data revisions.

The results make clear that the change in filtering of hours per worker is the main driver of the revisions in utilization growth. We wish to emphasize, however, that it is not the bandpass or bi-weight filter per se that matters for the results, but rather the frequencies isolated by the different filters. As noted, the bandpass filter used in the earlier vintages of Fernald's series removes high-frequency fluctuations from utilization, whereas the bi-weight filter does not. It is the inclusion of the higher-frequency fluctuations with the bi-weight filter, not the relatively lower-frequency fluctuations that it captures compared to the bandpass filter, that account for the differences across vintages.[17]

For the purpose of the news identification that follows, it is not clear that either the bandpass or the bi-weight filter, or any other statistical detrending method for that matter, adequately captures the appropriate fluctuations in hours per worker to correctly infer factor utilization. This means that for either filtering choice, utilization and therefore adjusted TFP may still be confounded by cyclical mismeasurement even if the conditions underlying the proportionality assumption

[15] These changes in correlation across vintages of adjusted TFP occur for different subsamples and are not driven by a particular time period.

[16] Visual inspection of the series for unadjusted and adjusted TFP along with estimated factor utilization (see the appendix) suggests that changes in nonadjusted TFP across vintages cannot account for these large changes in the adjusted TFP series. Rather, there seem to be noticeable changes in estimated utilization across vintages, with the 2007 vintage substantially smoother than less persistent than the 2016 vintage.

[17] Indeed, experimentation with alternative values of the filtering parameters confirms that the important difference is that the bandpass filter removes higher-frequency fluctuations, whereas the bi-weight filter leaves them in.

in equation (4) are satisfied (a point to which we return in section IV).

III. Implications for News Shocks Identification

Starting with Cochrane (1994), the modern macroliterature has defined news shocks as information useful in predicting future fundamentals (often productivity) but unrelated to current and past fundamentals. As proposed by Beaudry and Portier (2006) proposed, this implies a zero impact restriction, which is that news shocks affect productivity only with a delay. This restriction is at the core of almost all news shocks identifications used to date.

In what follows, we use the news identification approach of Barsky and Sims (2011) to quantify the implications of the revisions in adjusted TFP for news shocks, although the lessons learned are relevant for other identification approaches relying on the zero impact restriction as well. We focus on the Barsky-Sims approach because it does not require taking a stand on the nature of non-news shocks.[18] Furthermore, Monte Carlo simulations show that the Barsky-Sims approach performs well provided that productivity is measured correctly. As such, the Barsky-Sims approach has emerged as one of the most commonly used identifications in the literature.

A. *Barsky-Sims Identification*

The Barsky-Sims identification consists of estimating a VAR and extracting the innovation that is orthogonal to Fernald's adjusted TFP series but maximally accounts for the FEV share of adjusted TFP over a ten-year horizon. Since our alternative identification proposed in section V is conceptually very similar, we review the details here. Let $\mathbf{Y}_t$ be a $k \times 1$ random vector process of which the first variable is a measure of productivity (e.g., Fernald's utilization-adjusted TFP), and let the reduced-form moving average representation of this process be given by $\mathbf{Y}_t = \mathbf{B}(\mathbf{L})\mathbf{u}_t$, where $\mathbf{u}_t$ is a $k \times 1$ vector of prediction errors with variance-covariance matrix $E(\mathbf{u}_t\mathbf{u}_t') = \mathbf{\Sigma}_u$, and $\mathbf{B}(L) = \mathbf{I} + \mathbf{B}_1 L + \mathbf{B}_2 L^2 + \ldots$ is a matrix lag polynomial.

Now assume that there exists a linear mapping between the prediction errors and the structural shocks, $\mathbf{u}_t = \mathbf{A}\epsilon_t$, where ϵ_t is a $k \times 1$ vector of structural shocks characterized by $E(\epsilon_t\epsilon_t') = \mathbf{I}$, and $\mathbf{A}$ is a $k \times k$ matrix satisfying $\mathbf{AA}' = \mathbf{\Sigma}_u$. Given the symmetry of $\mathbf{\Sigma}_u$, a multitude of $\mathbf{A}$ is consistent with $\mathbf{AA}' = \mathbf{\Sigma}_u$. The Choleski decomposition of $\mathbf{\Sigma}_u$ is one potential solution. Denote this by $\widetilde{\mathbf{A}}$. The entire set of permissible values of $\mathbf{A}$ consistent with $\mathbf{AA}' = \mathbf{\Sigma}_u$ is then described by $\widetilde{\mathbf{A}}\mathbf{Q}$, where $\mathbf{Q}$ is an orthonormal rotation matrix and the structural moving average representation is $\mathbf{Y}_t = \mathbf{C}(\mathbf{L})\epsilon_t$, where $\mathbf{C}(\mathbf{L}) = \mathbf{B}(\mathbf{L})\widetilde{\mathbf{A}}\mathbf{Q}$.

The h step ahead forecast error of $\mathbf{Y}_t$ can be written as

$$\mathbf{Y}_{t+h} - E_{t-1}\mathbf{Y}_{t+h} = \sum_{l=0}^{h} \mathbf{B}_l \widetilde{\mathbf{A}}\mathbf{Q}\epsilon_{t+h-l}. \tag{6}$$

The FEV share of variable i attributable to shock j at horizon h is then

$$\mathbf{\Omega}_{i,j}(h) = \frac{\sum_{l=0}^{h} \mathbf{B}_{i,l}\widetilde{\mathbf{A}}\gamma\gamma'\widetilde{\mathbf{A}}'\mathbf{B}_{i,l}'}{\sum_{l=0}^{h} \mathbf{B}_{i,l}\mathbf{\Sigma}_u\mathbf{B}_{i,l}'}, \tag{7}$$

where $\mathbf{B}_{i,l}$ is the ith row of lag polynomial evaluated at $L = l$ and γ is the jth column of Q.

The news shock identification of Barsky and Sims (2011) consists of picking γ to maximize the sum of FEV shares of productivity (the first variable in the VAR) up to some truncation horizon H subject to the restriction that the shock is orthogonal to current productivity.

Formally,

$$\max_{\gamma} \quad \sum_{h=0}^{H} \Omega_{1,2}(h) \text{ s.t. } \gamma'\gamma = 1 \text{ and } \gamma(1,1) = 0, \tag{8}$$

where without loss of generality, productivity is ordered first in $\mathbf{Y}_t$ and the news shock is defined as the second shock in ϵ_t. The first restriction ensures that γ belongs to an orthonormal matrix. The second restriction imposes that the news shock affects productivity only with a delay.

B. *Effect of Revisions on News Shock Identification*

We apply the Barsky-Sims identification to a four-variable VAR comprising either the 2007 vintage or the 2016 vintage of Fernald's utilization-adjusted TFP series, real personal consumption expenditures per capita, total hours worked per capita in the nonfarm business sector, and inflation as measured by the growth rate of the GDP price deflator.[19] Results for larger VARs that contain additional macro aggregates are similar. With the exception of the inflation rate, the variables enter the VAR in log levels. The VAR is estimated with four lags via Bayesian methods subject to a Minnesota prior.[20] Confidence bands are computed by drawing from the

[18]The zero impact restriction is sufficient to identify news shocks in bivariate VARs. In VARs with more than two variables, additional restrictions need to be imposed. Full identification approaches that do so by taking a stand on all structural shocks affecting the VAR are often subject to important robustness issues. See, for example, Kurmann and Mertens (2014), who show that the identification by Beaudry and Portier (2006) does not have a unique solution in their VAR systems with more than two variables, or Fisher (2010), who shows that the results of Beaudry and Lucke (2010) depend on the choice of cointegration restrictions imposed.

[19]VARs based on any of the pre-2014 vintages of adjusted TFP produce impulse responses that are nearly identical to those based on the 2007 vintage, while VARs based on post-2014 vintages of adjusted TFP produce impulse responses that are very similar to those based on the 2016 vintage.

[20]The Minnesota prior assumes a random walk process for adjusted TFP and consumption and a white noise process for hours worked and the inflation rate. Estimates are robust to assuming a random walk prior for all series.

resulting posterior distribution. The sample period is fixed at 1960q1 to 2007q3.[21] As in Barsky and Sims (2011), the truncation horizon is set to $H = 40$.

Figure 1a presents impulse responses to a news shock using the Barsky and Sims (2011) news identification. Here and below, the solid lines show the posterior median impulse responses implied by the posterior distribution of the VAR estimated with the 2016 vintage of adjusted TFP, and the gray bands are the corresponding 16% to 84% posterior coverage intervals. In turn, the dash-dotted lines show the posterior median impulse responses implied by the posterior distribution of the VAR estimated with the 2007 vintage of adjusted TFP, and the dashed lines are the corresponding 16% to 84% posterior coverage intervals.

Based on the 2007 vintage of adjusted TFP, the responses are very similar to those estimated by Barsky and Sims (2011). Adjusted TFP starts to increase the quarter after the shock, consumption jumps up while inflation falls on impact, and hours worked initially decline, turning significantly positive only after about twelve quarters. As shown in the appendix, these responses imply that if the economy was buffeted solely by news shocks, the correlation between consumption growth and hours growth would be negative, whereas in the data, this correlation is robustly positive.

Based on the 2016 vintage of adjusted TFP, in contrast, the impulse responses look different in economically meaningful ways. Adjusted TFP reacts to the news shock only after several quarters, while hours worked increase from the beginning (although insignificantly for the first few quarters), reaching peak response about ten quarters earlier than based on the 2007 vintage. This difference in the response of hours worked implies that the correlation of consumption growth and hours growth conditional on news shocks is now positive (see the appendix for details). Moreover, the deflationary impact of news shocks, which Barsky et al. (2015) cite as one of the most robust features of the data, is no longer statistically significant.

The difference in responses depending on the vintage of adjusted TFP used has important implications for the role of news shocks. Based on the 2007 vintage, the absence of comovement between hours and consumption leads Barsky and Sims (2011) to conclude that news shocks about future productivity are not a major source of business cycle fluctuations. Based on the 2016 vintage instead, the coincident increase in consumption and hours is consistent with the view espoused by Beaudry and Portier (2006) that news shocks have significant short-term demand effects and are a potentially important driver of business cycle fluctuations.

[21]The beginning of the sample is chosen to facilitate comparison with Barsky and Sims (2011) and because some additional variables of interest studied below are unavailable prior to 1960. Furthermore, the omission of the immediate postwar data from the sample removes some large influences due the 1951 Treasury Accord and Korean War. The end date is the last available observation for the 2007 vintage of adjusted TFP data.

IV. Interpreting the Results through a DSGE Model

The results of the preceding sections illustrate that measurement issues about productivity can have important implications for news shock identifications that rely on short-run restrictions on productivity and, in particular, on the zero impact restriction. To interpret and better understand these results, we build a medium-scale New Keynesian DSGE model and conduct different Monte Carlo simulations to address the following questions. Under what conditions does Fernald's adjusted TFP series appropriately measure technology? What are the consequences of different sources of productivity mismeasurement for news shock identification? Is Fernald's new bi-weight filtered estimate of utilization preferable to the previously used bandpass filtered estimate?

The DSGE model we use is based on Christiano, Eichenbaum, and Evans (2005), Smets and Wouters (2007), and Justiniano, Primiceri, and Tambalotti (2010) but augmented with variable labor effort and hours worked so as to analyze the conditions under which the proportionality result between utilization and hours worked set forth in Basu et al. (2006) holds. The model abstracts from heterogeneity in production across industries and imposes an aggregate production function. While potentially important, these assumptions do not invalidate the measurement issues highlighted here.

A. *Model*

To save on space, we focus on the model components that relate to the measurement of technology and utilization. A full description of the model is provided in the appendix.

The model is populated by intermediate goods producers, a representative final goods producer, a representative household, labor unions, a labor packer, and a monetary authority. Intermediate goods producers are indexed by $i \in [0\ 1]$ and produce output with

$$Y_t(i) = A_t \left(K_{s,t}(i)\right)^{\alpha} \left(L_{s,t}(i)\right)^{1-\alpha} - FX_t, \tag{9}$$

where A_t denotes exogenous technology (common across firms), $K_{s,t}(i)$ capital services, $L_{s,t}(i)$ labor services, and $FX_t \geq 0$ is a fixed cost that increases with the economy's trend X_t. Intermediate outputs are aggregated into final output via a CES technology, and intermediate producers are subject to the typical Calvo pricing friction.

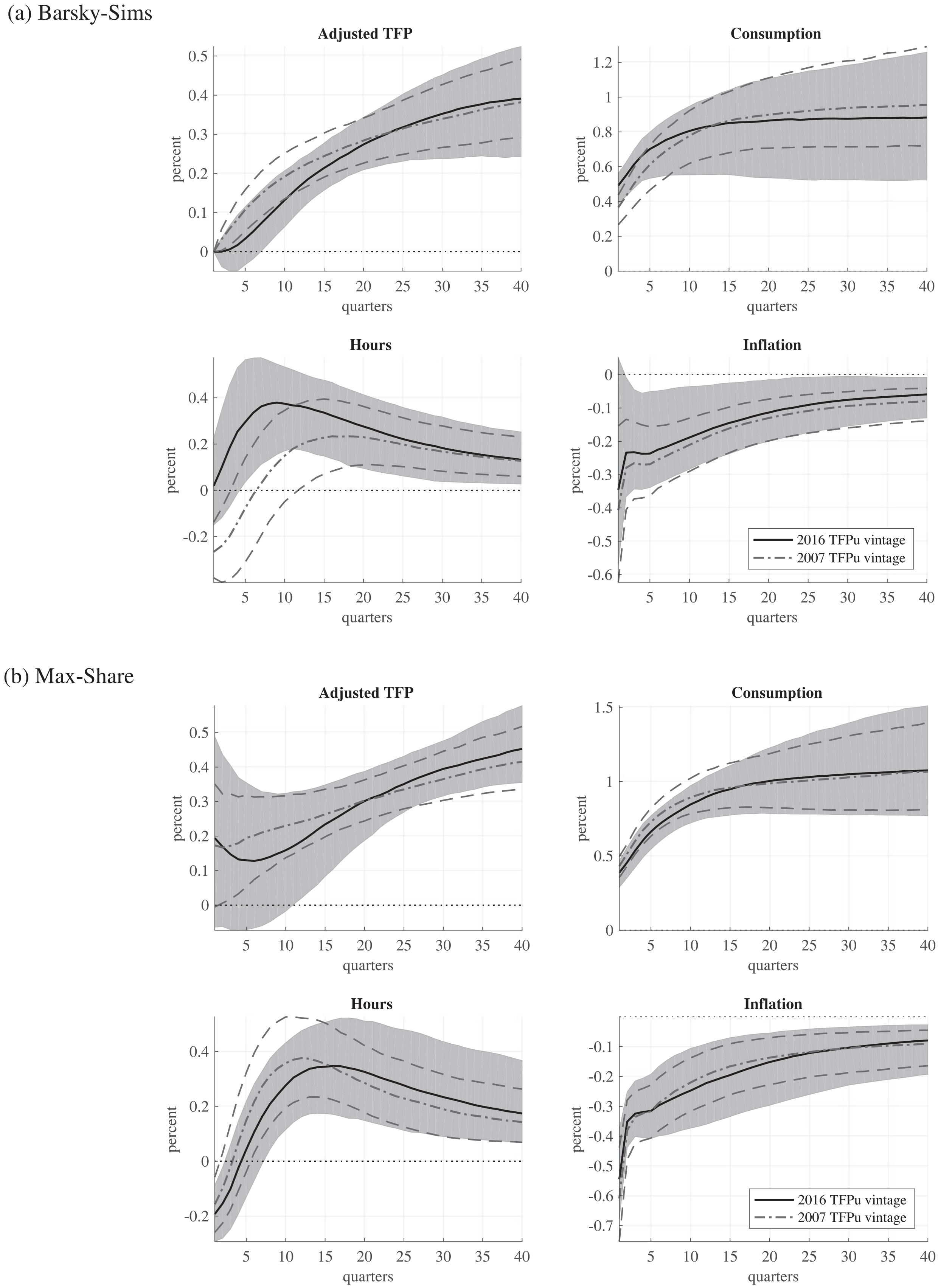
Log technology is the sum of two components, $\ln A_t = \ln S_t + \ln \Gamma_t$, where S_t follows

$$\ln S_t = \rho_S \ln S_{t-1} + \sigma_S \varepsilon_{S,t}, \tag{10}$$

with $\varepsilon_{S,t}$ i.i.d. (0,1), and Γ_t is a permanent component that evolves according to

$$\ln \Gamma_t - \ln \Gamma_{t-1} = (1 - \rho_\Gamma) \ln g + \rho_\Gamma (\ln \Gamma_{t-1} - \ln \Gamma_{t-2}) + \sigma_g \varepsilon_{g,t-1}, \tag{11}$$

FIGURE 1.—IMPULSE RESPONSES TO NEWS SHOCK, FOUR VARIABLE VAR, 2007 VERSUS 2016 VINTAGE



News shocks for different vintages of TFP via (a) Barsky-Sims and (b) the max-share. Solid lines are the posterior median estimates from the VAR system estimated with the 2016 vintage of adjusted TFP. The shaded bands correspond to the 16% to 84% posterior coverage intervals. The dash-dotted lines are the posterior median estimates for the system estimated with the 2007 vintage of adjusted TFP; the dashed lines correspond to the 16% to 84% posterior coverage intervals. The sample period is 1960q1 to 2007q3.

with $\varepsilon_{g,t-1}$ i.i.d. (0,1). This shock is assumed to occur before it starts to have an impact on technology and agents update expectations about the permanent component accordingly. Moreover, since $\rho_\Gamma > 0$, this shock portends even larger increases in the level of technology in the future.

The representative household consists of a continuum of members, a fraction N_t of whom are working and a fraction $1 - N_t$ who are not working. Employed members provide labor services $L_t = e_t h_t N_t$ to labor unions, where h_t denotes average hours worked and e_t is labor effort. Members of the household are randomly chosen to work, with the household head choosing the total fraction of workers, N_t. All workers supply the same hours and effort, and all members enjoy the same consumption regardless of whether they work or not (i.e., there is perfect intrahousehold insurance). The expected lifetime utility of the household is

$$E_t \sum_{t=0}^{\infty} \beta^t \nu_t \Big[\ln (C_t - bC_{t-1}) + \theta N_t (T - G(h_t, e_t)) + \theta(1 - N_t)T \Big], \tag{12}$$

where ν_t is a preference shock that evolves according to an AR(1) process; C_t denotes consumption; b the degree of habit formation; T the total time endowment; and $G(h_t, e_t)$ the effective time cost when working h_t hours at effort level e_t.

The household can save via investment in physical capital, I_t, or through one-period nominal bonds, B_t, that pay gross nominal interest rate R_t. It receives lump sum transfers, D_t, from ownership in production firms and labor unions, R_t^k for each unit of capital services supplied, and W_t for each unit of labor services. The flow budget constraint is

$$C_t + I_t + \frac{B_{t+1}}{P_t} \leq \frac{W_t}{P_t} L_t + (1 + R_t)\frac{B_t}{P_t} + D_t + \frac{R_t^k}{P_t} z_t K_t - a(z_t)K_t - W_t N_t \Psi\left(\frac{N_t}{N_{t-1}}\right) - K_t J\left(\frac{I_t}{K_t}\right), \tag{13}$$

where z_t is the intensity with which capital is utilized, $a(z_t)$ is a convex adjustment cost to utilizing capital, $\Psi(\cdot)$ is a convex cost of adjusting employment, and $J(\cdot)$ is a convex cost of adjusting investment.[22] Physical capital evolves according to a standard law of motion subject to an AR(1) shock to the marginal efficiency of investment (MEI).

Labor services are supplied in a competitive market to a continuum of labor unions $j \in [01]$. Unions transform these inputs into differentiated types of intermediate labor and sell them to a labor packer at nominal wage $W_t(j)$. The labor packer combines the different unions' labor into final labor service $L_{s,t}$ via a CES technology with elasticity of substitution ϵ_w and hires it out to intermediate goods producers at nominal wage rate W_t^l. Unions are subject to Calvo-style nominal wage rigidity.

Finally, the monetary authority sets the nominal interest rate according to a conventional inertial Taylor-type rule in inflation and output growth.

To assess the conditions under which Fernald's adjusted TFP series accurately measures technology, we start with unadjusted TFP as defined in equation (3). Even if utilization was constant (or variations in utilization were perfectly corrected), the model would nevertheless imply two incongruities between adjusted TFP and technology. First, with fixed cost $F > 0$, the production function is not constant returns to scale, thus invalidating the assumption that the cost shares of labor and capital sum up to 1 (i.e., $\omega_{L,t} + \omega_{K,t} = 1$). Second, if intermediate goods firms have market power and are subject to nominal price rigidities, then $\omega_{L,t}$ and $1 - \omega_{L,t}$ do not in general correspond to the true factor elasticities $1 - \alpha$ and α of the model. Specifically, cost minimization on the part of intermediate goods firms with respect to labor services implies

$$w_t^l L_{s,t} = (1 - \alpha)\psi_t \left[Y_t - F X_t \right], \tag{14}$$

where $w_t^l = W_t^l / P_t$ is the real wage of the labor service composite hired by production firms, and ψ_t denotes the inverse of the average price markup over marginal cost across intermediate firms. If the fixed cost F is chosen to ensure zero profit along the balanced growth path, a standard assumption, then equation (14) becomes

$$\omega_{L,t} = \frac{w_t^l L_{s,t}}{Y_t} = (1 - \alpha)\psi_t \psi^{-1}, \tag{15}$$

with ψ^{-1} denoting the steady-state markup. In this case, the labor share corresponds to the factor elasticity $1 - \alpha$ on average but fluctuates over time due to undesired fluctuations in the markup owing to price rigidity.[23] Hence, as foreshadowed by Fernald's quote from section II, only in the limiting case of no fixed costs and no markups is it the case that unadjusted TFP defined as in equation (3) correctly measures technology net of utilization.

Consider now factor utilization. We introduce an econometrician similar to Fernald who does not observe labor effort and capital use but instead proxies utilization with filtered hours per worker as in equation (4) except that there are no industry differences, that is, $\Delta \ln \hat{u}_t = \widehat{\beta} \Delta \ln h_t^c$. Mismeasurement can come from three sources. First, true utilization in the model, $\ln u_t = \alpha \ln z_t + (1 - \alpha) \ln e_t$, is generally not proportional to hours per worker. Optimal hours and effort supplied by workers result in

[22] Adjustment costs to employment and capital are crucial here; without them, optimal hours, effort, and capital use would be constant. See Burnside, Eichenbaum, and Rebelo (1993) or Basu et al. (2006) for details.

[23] In the absence of fixed costs, the production function is constant returns to scale, consistent with the assumption underlying the construction of TFP, while the labor share becomes $\omega_{L,t} = \frac{w_t^l L_{s,t}}{Y_t} = (1 - \alpha)\psi_t$. Hence, the labor share differs from $1 - \alpha$ even on average. All the simulations below assume a positive fixed cost, although we also experimented with zero fixed cost. The results remain very similar.

TABLE 3.—MODEL-IMPLIED MISMEASUREMENT OF UTILIZATION AND TECHNOLOGY

	No Mismeasurement of Utilization	$\sigma_z > 0, \widehat{\beta} = 3$ Hours Unfiltered	$\sigma_z > 0, \widehat{\beta} = 3$ Hours BP-Filtered	$\sigma_z > 0, \widehat{\beta} = 3$ Hours BW-Filtered
$corr(\Delta u_t, \Delta\widehat{u_t})$	1.00	0.97	0.48	0.97
$corr(\Delta A_t, \Delta TFP_t^u)$	0.95	0.82	0.59	0.82

This table shows correlations of different variables implied by the solution of the medium-scale DSGE model.

$$G_h(h_t, e_t)h_t = G_e(h_t, e_t)e_t, \tag{16}$$

which does imply proportionality between e_t and h_t, exactly as in Basu et al. (2006). For capital use, however, optimality implies

$$r_t^k = a'(z_t). \tag{17}$$

Since r_t^k is an equilibrium object determined by the capital-labor ratio, there is no time-invariant mapping between z_t and h_t. Hence, unless the elasticity of the marginal cost $a'(z_t)$ with respect to capital use is infinity so that optimal capital use is constant (the case we henceforth label as $\sigma_z = 0$), true utilization systematically differs from hours per worker.[24] The second source of utilization mismeasurement is that the proportionality factor $\widehat{\beta}$ estimated by the econometrician is biased. Basu et al. (2006), respectively Basu et al. (2013), try to address this issue by using demand-side instruments in their estimation. It remains an open question, however, to what extent these instruments truly satisfy the exogeneity conditions necessary for instrumental variable estimation. The third potential source of utilization mismeasurement, as already highlighted by the results in section II, is that the filtering of hours per worker prior to constructing the utilization proxy may be inappropriate.

B. *Calibration*

The calibration of the standard model parameters is based on the estimates in Justiniano et al. (2010) except that we impose a stronger degree of nominal wage rigidity so as to generate model impulse responses for total hours and inflation to a news shock that broadly resembles the ones in the data.[25]

For the utility cost of work, we assume

$$G(h_t, e_t) = \kappa_0 + \frac{\kappa_1}{\kappa_2}h_t^{\kappa_2} + \frac{\kappa_3}{\kappa_4}e_t^{\kappa_4}. \tag{18}$$

[24] While the assumption that capital use results in a resource cost (or equivalently in higher depreciation of physical capital) is standard in the DSGE literature, an alternative view is that workers need to be compensated for undesirable shifts in order to operate capital more intensively. Specifically, assume that preferences for leisure take the form $(T - G(h_t, e_t)V(z_t))$, with the cost of capital use $V(z_t)$ interpreted as the additional disutility from working shifts at undesirable times. As long as the labor market is frictionless, optimal behavior by workers and firms then also implies proportionality between z_t and h_t, and utilization comoves perfectly with hours per worker as proposed by Basu et al. (2006). The point of our model here is not to take a stand on whether this proportionality condition holds in the data but rather to illustrate the consequences when it does not hold.

[25] See Kurmann and Otrok (2017a) for a discussion.

Given the proportionality between e_t and h_t, this time cost can be expressed in terms of hours worked only: $\tilde{G}(h_t) = G(h_t, e_t(h_t))$. We set κ_2 and κ_4 so as to target a Frisch elasticity of the intensive margin labor supply of 1 and a relative volatility of effort to hours of 4. The former is a plausible middle ground in the literature (see Keane & Rogerson, 2012); the latter is set so as to obtain a measurement error between true and observed utilization that moves inversely with hours (see equation (19) below for details). The remaining parameters of this function do not affect the linearized dynamics of the model and are set consistent with normalized steady-state values for h, e, and $G(h, e)$.

The autoregressive parameters of the exogenous processes take on standard values, and the volatilites of the shocks are chosen to generate an unconditional standard deviation of output growth of 1% (see the appendix for more details). Consistent with Justiniano et al. (2010), the preference shock and the MEI shock are main drivers of macrofluctuations in the model, accounting together for 55% of unconditional variance of output growth and about 85% of the unconditional variance of total hours growth and consumption growth.

Finally, for the proportionality factor $\widehat{\beta}$, we either set it so as to match the variance ratio of true utilization to hours per worker in the model or to $\widehat{\beta} = 3$, which is approximately the variance ratio of Fernald's aggregate utilization estimate to aggregate hours per worker in the data. This is somewhat lower than the variance ratio of true utilization to hours per worker in the model and thus leads to utilization mismeasurement.

C. *Monte-Carlo Simulations*

We simulate 10,000 periods of data from the model and assess the consequences of technology mismeasurement. Before doing so, we reemphasize that since the model abstracts from several important features of Fernald's construction of adjusted TFP in the data, the simulations are primarily an illustration of the measurement issues that can arise rather than a full explanation of how Fernald's revisions give rise to the changes in business cycle properties of adjusted TFP that we observe in the data. Nevertheless, we think that these illustrations are quite informative.

Table 3 reports the unconditional correlations between true utilization and estimated utilization and between true technology and adjusted TFP under four scenarios.

The first column shows the case when utilization is measured correctly: capital use is constant ($\sigma_z = 0$), $\widehat{\beta}$ is exactly correct so that the proportionality condition holds, and hours per worker are not filtered. The correlation between true utilization and estimated utilization is 1 by definition in this case, and adjusted TFP comoves very closely with true technology. This suggests that incongruities arising from time-varying markups and nonconstant returns to scale by themselves do not matter quantitatively. The second column shows the case of variable capital use ($\sigma_z > 0$) and the proportionality factor $\widehat{\beta}$ set to 3, but no filtering of hours. Estimated utilization still comoves closely with true utilization, and adjusted TFP remains strongly correlated with technology, albeit less so than when utilization is measured correctly.

The third and fourth columns keep variable capital use ($\sigma_z > 0$) and $\widehat{\beta} = 3$ but now also detrend hours per worker with either the bandpass filter or the bi-weight filter. Bandpass filtering clearly imparts substantial additional mismeasurement, with the correlations between true and estimated utilization and between technology and adjusted TFP dropping to around 0.5. In contrast, bi-weight filtering does not affect the comovement of measured utilization and adjusted TFP in any significant way.

It is clear from the table that at least for this particular DSGE model, bi-weight filtering leads to less mismeasurement than bandpass filtering. This is because hours per worker in the model are stationary and the bi-weight filter removes only a very slow-moving trend, which in this case is almost equivalent to no filtering. From the perspective of the model, this is preferable because hours per worker are directly related (although not perfectly proportional) to utilization. The bandpass filter, in contrast, removes high-frequency fluctuations in hours per worker and thus imparts serious mismeasurement on implied utilization. In practice, Fernald must contend with secular trends in industry hours per worker that seem unlikely to be related to utilization. As our model abstracts from secular trends, we are not able to speak to the suitability of either filter in this more general situation, although it is interesting to note that in the data, the utilization series implied by bi-weight filtered industry hours per worker turns out to be quite similar to a utilization series obtained without filtering (see the appendix).

Next, we estimate the baseline four-variable VAR from above on the simulated data to illustrate the performance of the Barsky-Sims identification of news shocks under the different scenarios.[26] First, we consider the baseline scenario in which the proportionality condition holds ($\sigma_z = 0$, and the proportionality factor is correct). Figure 2a reports the results. Here and below, the solid lines show the impulse responses to a news shock in the model; the dashed lines the VAR responses implied by the Barsky-Sims identification when hours per worker in the construction of utilization are bandpass filtered and the dotted lines the VAR responses implied by the Barsky-Sims identification when hours per worker are bi-weight filtered.

Similar to the data, consumption in the model jumps up on impact of the news shock and then gradually increases further to a new permanently higher level; total hours worked drop slightly on impact and then increase in a hump-shaped manner, and inflation falls sharply on impact and then returns to 0 over the next ten quarters. When the proportionality condition holds and hours per worker are bi-weight filtered, the Barsky-Sims identification performs well in capturing the dynamics to a news shock. The fit is somewhat less close when hours per worker are bandpass filtered, with the responses of consumption, total hours, and inflation displaying mild oscillatory behavior. This is not an issue of the Barsky-Sims identification per se but of bandpass filtering when constructing utilization, which appears to introduce artificial dynamics in the VAR.[27] Nevertheless, even with bandpass filtering, the fit with true model responses to a news shock remains good. This provides further confirmation that for reasonable markup variations as implied by our model, the difference between Fernald's construction of TFP and true TFP is quantitatively unimportant.

Second, we consider the case when the proportionality condition does not hold; that is, capital use is nonconstant ($\sigma_z > 0$) and $\widehat{\beta} = 3$. As shown in figure 2b, the VAR responses for consumption and inflation come again reasonably close to the ones implied by the model, independent of the filtering method for hours per worker in the construction of utilization. The response of total hours in the VAR, however, now depends significantly on the filtering method. Under bi-weight filtering, total hours slightly increase on impact and remain above the model-implied response for about ten quarters. In contrast, under bandpass filtering, the total hours response is, aside from the initial period, negative for several quarters before increasing in line with what the model implies.

This difference in hours response depending on the filtering method is broadly similar to what we observe in figure 1 for the 2007 (bandpass-filtered) vintage and the 2016 (bi-weight-filtered) vintage of adjusted TFP. This suggests that for the case when the proportionality condition between utilization and hours does not hold, bandpass filtering of hours per worker in the construction of utilization may actually be preferable to bi-weight filtering even though, by itself, bandpass filtering introduces substantial mismeasurement. To understand this result, it is useful to express adjusted TFP growth as

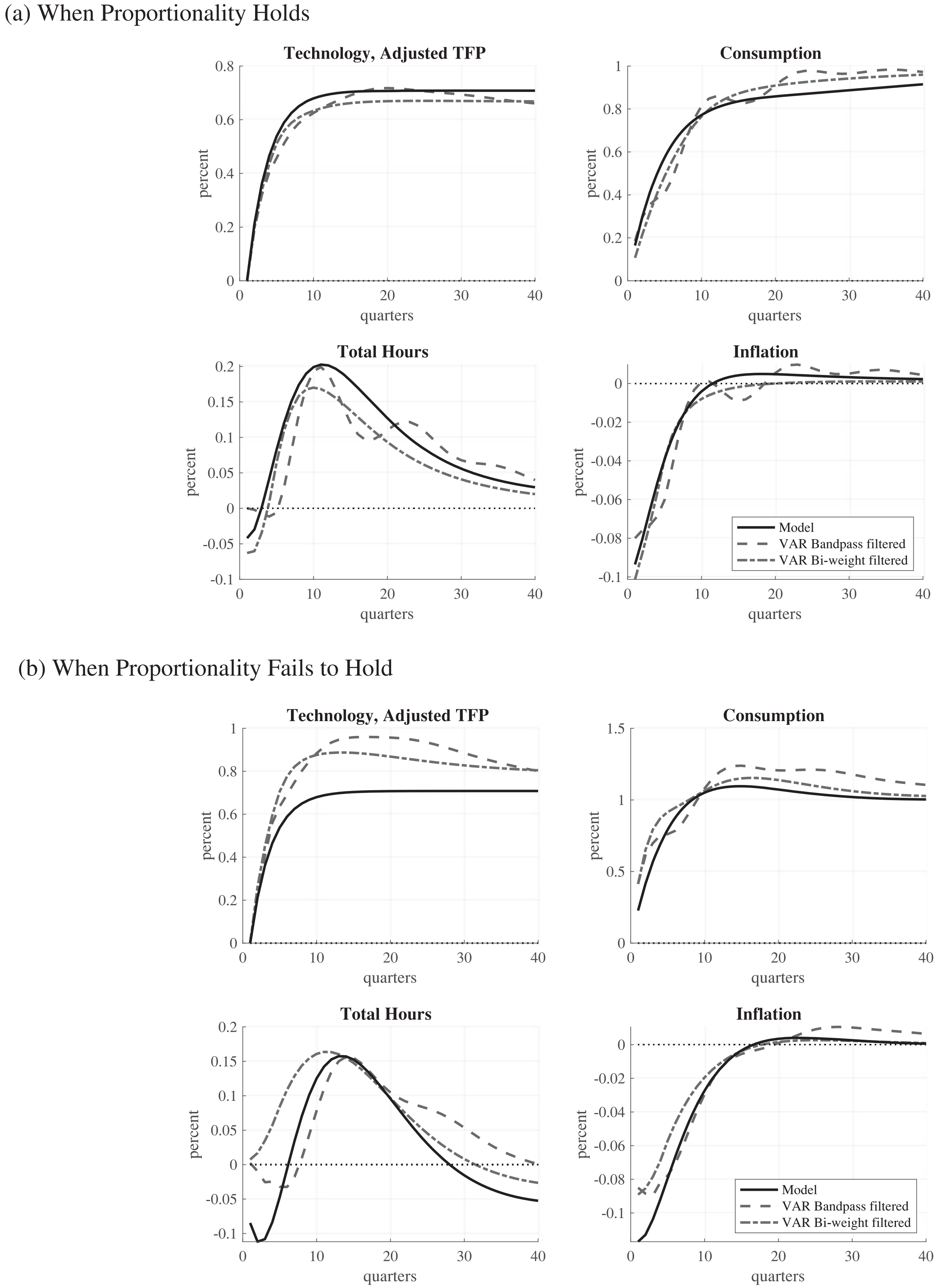
$$\triangle \ln TFP_t^u = (\triangle \ln A_t - \triangle\epsilon_t^{TFP}) + (\triangle \ln u_t - \widehat{\beta}\triangle \ln h_t^c), \quad (19)$$

where $\triangle\epsilon_t^{TFP}$ is the difference between true TFP growth as defined in the model and TFP growth as defined in equation (3). Since $\triangle\epsilon_t^{TFP} \approx 0$ in our simulations, adjusted TFP moves either because of shocks to technology or because

[26] The point of using such a long sample of simulated data is that we want to examine the asymptotic consequences of technology mismeasurement for news identification. Of course, we could also investigate the small-sample properties of our estimates. We did so and found very similar results.

[27] Total hours in the VAR are not filtered, only hours per worker in the construction of utilization.

FIGURE 2.—SIMULATED RESPONSES TO BARSKY-SIMS NEWS SHOCK



Responses when proportionality between utilization and hours (a) holds in the model and (b) fails to hold. Solid lines are the true impulse responses to a news shock in the model. The dashed lines are the estimated responses using the Barsky-Sims identification based on the simulated data with bandpass filtered hours per worker in the construction of utilization. The dash-dotted lines are the estimated responses using the Barsky-Sims identification based on the simulated data with bi-weight filtered hours per worker in the construction of utilization.

of nontechnology shocks that imply $\triangle \ln u_t - \widehat{\beta}\triangle \ln h_t^c \neq 0$. According to our model calibration, preference shocks and MEI shocks both lead to sizable short-term fluctuations in $\triangle \ln u_t - \widehat{\beta}\triangle \ln h_t^c$ and thus adjusted TFP that comove with total hours; that is, the short-run change in true utilization $\triangle \ln u_t$ in response to these shocks is larger than the short-run change in measured utilization $\widehat{\beta}\triangle \ln h_t^c$. Since bi-weight filtering is close to no filtering in our model, the Barsky-Sims identification, by relying on short-term restrictions and in particular the zero impact restriction, picks up a combination of these shocks and confounds them with news shocks to technology. This explains the positive VAR response of total hours in figure 2. In comparison, bandpass filtering of hours per worker substantially alters the dynamic characteristics of $\triangle \ln u_t - \widehat{\beta}\triangle \ln h_t^c$, which in our case results in the Barsky-Sims identification picking up less of the combination of nontechnology shocks and resulting in a more negative response of hours to the news shock, similar to what is implied by the model.

The bottom line of this discussion is that bandpass filtering hours per worker, despite inducing substantial mismeasurement of utilization, can in some cases help smooth out departures from the proportionality assumption in Fernald's proxy of utilization. Bi-weight filtering, in contrast, does not attenuate such departures from proportionality and therefore leaves news shock identifications such as the Barsky-Sims approach that focus on short-run restrictions in adjusted TFP more sensitive to utilization mismeasurement. At the same time, it should be clear that none of our simulation results are general. Indeed, for alternative model calibrations, bandpass filtering of utilization does not attenuate the effects of departures from proportionality and, to the contrary, may in fact exacerbate it.[28] Hence, we conclude from these simulations that news shock identifications relying on short-run restrictions and, in particular, the zero impact assumption can be highly sensitive to cyclical mismeasurement of true technology. A more fruitful approach is instead to devise alternative identification restrictions that are robust to cyclical measurement issues. This is what we propose in the next section.

V. An Alternative Identification of News Shocks

The central idea behind our proposed alternative identification is that new productivity-enhancing technologies disseminate slowly and, if known to agents, constitute news about future productivity growth. As long as productivity in the long run is driven primarily by new technologies, an identification that accounts for most of productivity variations in the long run should therefore capture news. At the same time, as long as this identification does not rely on short-run restrictions and in particular the zero impact restriction, it should be robust to cyclical measurement issues with productivity.

The idea that new technologies diffuse slowly finds ample support in a large microempirical literature: Griliches (1957), Mansfield (1961, 1989), Gort and Klepper (1982), and Rogers (1995). According to Mansfield (1989), for example, the time until half of potential adopters actually adopt a new technology varies between five and fifteen years, depending on technology. While the slow dissemination of new technologies and its implications for the modeling of productivity is discussed extensively by Rotemberg (2003) as well as Comin and Gertler (2006) and Lindé (2009), among others, much of the business cycle literature has modeled productivity as a jump process where innovations lead to an immediate change of productivity to a new level that is either permanent or highly persistent. Yet the assumption of slow dissemination is consistent with the basic insight of Beaudry and Portier (2006) from a bivariate VAR that news shocks identified through the zero impact restriction are closely related to the shocks driving long-run movements in productivity. Our contribution here consists of exploring this insight further by extracting a long-run productivity shock in larger VAR systems, assessing its robustness to the documented revisions in adjusted TFP, and using additional information to interpret the extracted shock as a news shock.

A. *Implementation and Discussion*

We implement our alternative news shock identification by estimating a VAR containing adjusted TFP and extracting the shock that accounts for the maximum FEV share of adjusted TFP at a long but finite horizon H,

$$\max_{\gamma} \quad \Omega_{1,2}(H) \quad \text{s.t. } \gamma'\gamma = 1, \tag{20}$$

where, as per equation (7), $\Omega_{1,2}(H)$ denotes the FEV share of adjusted TFP at horizon H accounted for by the second element in shock vector ϵ_t, and γ denotes a column vector belonging to orthonormal rotation matrix $\mathbf{Q}$ of the Choleski decomposition of the reduced-form variance covariance matrix. While conceptually similar to Barsky and Sims (2011), there are two important differences. First, we look for the shock that accounts for the maximum FEV share of adjusted TFP at a long horizon H instead of maximizing the sum of FEV shares from impact onward. Second, we drop the zero restriction (the first element of γ is not restricted to 0), which means that measured productivity is allowed to respond contemporaneously to the shock. By focusing on a long forecast horizon only, this max-share identification has the advantage that it reduces the potential bias imparted by cyclical mismeasurement of technology, especially coming from the mismeasurement of utilization. Moreover, the approach avoids taking a stand on whether (true) technology reacts to the shock only with a lag or not.[29]

[28]In particular, as discussed above, VARs with bandpass filtered hours per worker in the construction of utilization have a tendency to induce oscillatory impulse responses.

[29]There is no a priori reason to think that news about growth-enhancing advances in technology are, despite their slow diffusion, completely unrelated to current productivity. Indeed, it seems equally intuitive to assume

Mechanically, the proposed max-share identification is the same as the technology shock identification of Francis et al. (2014), which in turn builds on earlier work by Uhlig (2003), but differs in propose it as an alternative identification of news shocks and apply it to adjusted TFP instead of labor productivity as the target variable. As we will discuss, this latter difference is important. Because of variations in the ratio of capital to labor—capital deepening–labor productivity responds quite differently to the shock than adjusted TFP, thus making the news interpretation less obvious. Moreover, since capital deepening is endogenous, labor productivity is affected even in the long run by other nontechnology shocks, potentially invalidating identification of technology shocks based on long-run restrictions.[30]

Compared to other long-run identification schemes employed in the VAR literature, the max-share approach has the advantage of focusing on a long but finite horizon. As Francis et al. (2014) show, this helps to reduce small-sample bias in VARs that, as discussed in section I, can have potentially important effects for infinite-horizon identifications of long-run shocks. In addition, the max-share approach does not impose that technology is the only source of long-run fluctuations in productivity and instead affords the possibility that other shocks (e.g., a surprise productivity shock) exert at least some long-term effect on adjusted TFP.

B. Results

We apply the proposed max-share identification to the same four-variable VAR as in section III. The horizon at which the FEV share of adjusted TFP is maximized is set to $H = 80$ quarters, although similar results would obtain for other long horizons. The estimated impulses responses are reported in figure 1b.

In contrast with the results based on the Barsky and Sims (2011) approach, there is very little difference in the impulse responses between the VAR estimated with the 2007 vintage of adjusted TFP and the VAR estimated with the 2016 vintage. In both cases, consumption jumps on impact and then gradually increases further to a permanently higher level; hours worked decline significantly on impact before turning positive after about five quarters, and inflation drops sharply and significantly on impact of the shock before gradually returning toward its initial level. The only discernible difference is the short-run response of adjusted TFP, which should not be surprising given their difference in cyclical properties. For both vintages, adjusted TFP jumps on impact, although insignificantly so. The 2007 vintage then increases gradually, whereas the 2016 vintage temporarily declines and remains insignificant for more than ten quarters. Both vintages, however, increase gradually at longer horizons and end up two to three times higher than their impact responses. In other words, the max-share shock predicts delayed but sustained future productivity growth. Aside from the adjusted TFP response, these results look close to the original results reported in Barsky and Sims (2011) based on the 2007 vintage of adjusted TFP. Indeed, as shown in the appendix, the median correlation between consumption growth and hours growth implied by the max-share shock is robustly negative, contrary to what we observe unconditionally in the data.

As also shown in the appendix, the responses for consumption, hours, and inflation are robust to replacing adjusted TFP with either unadjusted TFP or labor productivity. There is, however, a sizable difference in the response of these alternative productivity measures to the max-share shock. In particular, consistent with Francis et al. (2014), labor productivity jumps considerably more on impact. This is due to a short-run capital deepening effect: a fall in hours generates an increase in the capital-to-labor ratio, which boosts labor productivity on impact relative to the more gradual increase in adjusted TFP. Failure to take this effect into account may lead to the inadvertent conclusion that technology should be modeled as a random walk process, as is quite frequently assumed in the business cycle literature, which is very different from our finding that the response of adjusted TFP to the max-share shock is insignificant on impact before gradually increasing to a new permanent level that is substantially higher, consistent with the empirical literature cited above that technology is slowly diffusing.

C. Does the Max-Share Identification Capture News Shocks?

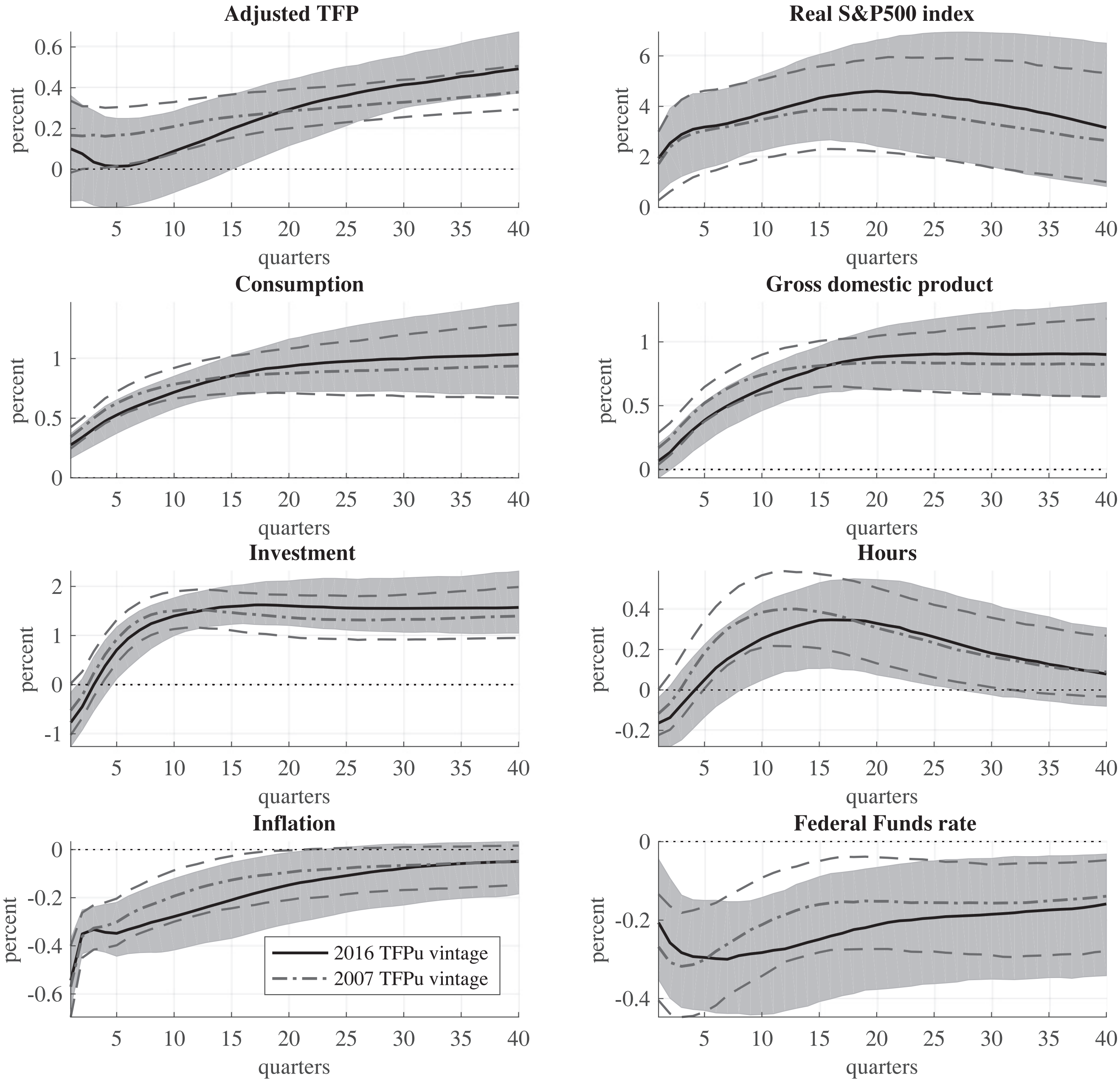
As discussed above, the news shock interpretation of the proposed alternative identification rests on several important questions, in particular: (a) Does the max-share shock lead to delayed predictable changes in future TFP? (b) Is the max-share shock correlated with measures of technological innovation?, and (c) Does the max-share shock generate sizable responses in forward-looking news indicators?

For the first question, we already know from the results with the four-variable VAR that the max-share shock leads to persistent and therefore predictable changes in future TFP growth. We now extend the analysis by considering an eight-variable VAR system that contains, in addition to the four variables already included above, real gross domestic product

that market participants revise their expectations about future fundamentals only once there is evidence that at least some firms have successfully adopted the new technology. To our knowledge, the only other paper that discusses this possibility is Barsky et al. (2015) who write: "It is possible that news about future productivity arrives along with innovations in productivity today" (233).

[30]In particular, persistent changes in capital taxes and worker composition are likely to affect labor productivity even in the long run but should leave long-run TFP unaffected (provided that Fernald's aggregate production function assumption and his measures of effective labor and capital are correct). See Uhlig (2004) or Bocola, Manovskii, and Hagedorn (2014) for examples. Of course, nontechnology shocks may affect adjusted TFP (as well as labor productivity) in the long run if the discovery and adoption of new technologies arises endogenously. In this case, the proposed identification as well as the other existing identifications of technology shocks will confound news shocks with nontechnology shocks. This point remains an unresolved issue in the literature that we start to address below by examining the response of novel indicators of technological innovation to our extracted shock.

FIGURE 3.—IMPULSE RESPONSES OF EIGHT-VARIABLE VAR TO MAX-SHARE SHOCK



Solid lines are the posterior median estimates from the VAR system estimated with the 2016 vintage of adjusted TFP. The shaded bands correspond to the 16% to 84% posterior coverage intervals. The dash-dotted lines are the posterior median estimates for the system estimated with the 2007 vintage of adjusted TFP. The dashed lines correspond to the 16% to 84% posterior coverage intervals. The impulse responses are identified using the max-share identification.

(GDP) per capita, real private investment expenditures per capita, the real S&P 500 index (deflated by the consumer price index), and the Federal Funds rate.[31] This choice of variables is motivated by the desire to learn about the effects of the max-share shock for other prominent macroeconomic aggregates and by the idea that including forward-looking information variables may help sharpen the results and address issues of nonfundamentalness (Leeper, Walker, & Yang, 2013). Indeed, as Beaudry and Portier (2006) argue, a large literature suggests that stock prices reflect expectations about future economic conditions and should therefore be an important indicator of news. Similarly, the Federal Reserve may have superior forecasting abilities and thus, news could also be reflected in the Federal Funds rate, the main monetary policy instrument up until the recent financial crisis. As before, the VAR is estimated with four lags for the 1960:1–2007:3 period subject to a Minnesota prior.

Figure 3 displays the impulse responses. The estimated responses again match closely across the two vintages,

[31]The real S&P 500 index is taken directly from Robert Shiller's website http://www.econ.yale.edu/∼shiller/data.htm.

confirming the robustness of the max-share approach to the revisions in Fernald's adjusted TFP series. Compared to the four-variable VAR, the reaction of adjusted TFP to the shock is more delayed and gradual, with an impact response for the 2016 vintage that starts closer to 0. This difference in results is primarily due to the inclusion of the real S&P 500 index in the VAR, confirming the point of Beaudry and Portier (2006) that stock prices contain valuable information about market expectations of future economic conditions.

The real S&P 500 index itself reacts strongly on the impact of the shock and then displays a mild hump-shaped response that is quite persistent. Investment and total hours worked both decline initially, while output rises slightly and consumption jumps up robustly on impact. Thereafter, output, consumption, and investment gradually increase toward a permanently higher level, while total hours worked responds in a hump-shaped manner similar to its response in the four-variable VAR. Inflation and the Federal Funds rate both decline significantly on impact and then remain persistently below their original values. The initial decline of inflation substantially exceeds the decline in the Federal Funds rate, implying that real short interest rates increase on impact of the shock. Hence, the shock triggers a contractionary monetary policy response despite the deflationary effect that the shock has on the economy.

The opposite-signed impact responses of consumption relative to hours and investment imply that the max-share shock generates negative business cycle comovement between these variables. This confirms the conclusion from the four-variable VAR that the shock is unlikely to be a main driver of business cycle dynamics. This does not mean, however, that the shock is unimportant for macroeconomic fluctuations more generally. As we document in the appendix, while the shock accounts for only a small fraction of the FEV of real macroeconomic aggregates at short horizons (with consumption being the notable exception), the shock is the main driver of these variables at longer horizons with the exception of hours worked. Indeed, at the eighty-quarter horizon, the shock accounts for about three-fourths of unpredictable variations in adjusted TFP, GDP, consumption, and investment. Quite strikingly, the shock also accounts for almost half of unpredicted variations in the real S&P 500 index and inflation at forecast horizons of twenty quarters and more, and about one-third of unpredictable variations in the Federal Funds rate at horizons of forty quarters or more.

To answer the second and third questions above, we reestimate the eight-variable VAR with the Federal Funds rate replaced sequentially with different measures of technological innovation and forward-looking information variables. The rest of the VAR specification is kept unchanged except when we have to adapt the sample due to data availability, as described below. To save on space, we only report impulse responses for the variables that replace the Federal Funds rate. The seven other variables in the VAR, which are kept the same throughout the exercise, react very similarly to the max-share shock as reported in figure 3.

We first consider four measures of technological innovation: the index of information and communications technology (ICT) standards by Baron and Schmidt (2015), the index of new technology manuals by Alexopoulos (2011), real R&D expenditures per capita from the NIPAs, and the inverse of the relative price of investment price from Justiniano et al. (2010). The index by Baron and Schmidt (2015) counts the number of new ICT industry standards per quarter released by standard-setting organizations (SSOs) in the United States.[32] As Baron and Schmidt (2015) argue, standardization is an essential step in the introduction and adoption of new technologies. It precedes the implementation of new technologies but presumably provides an important signal about the commercial viability of an innovation and thus future growth opportunities. As such, standardization represents an ideal measure to assess the extent to which our max-share shock captures news. As in Baron and Schmidt (2015), we focus on ICT standards because they have constituted the dominant type of general-purpose technology, although results are robust to using broader industry standards. Alexopoulos's (2011) count of books published in the field of technology provides a complementary measure even though she develops her measure primarily to investigate the role of contemporaneous technology shocks.[33] As she explains in her paper, new book titles in this area "appear precisely when the innovation is first introduced to market, for the very good reason that the whole purpose of publications is to spread the word about the new product or process." R&D expenditures and the relative investment price are common measures of the quality and/or efficiency of newly produced investment goods. If our max-share shock captures news about future productivity growth, then we would expect both of these measures to react gradually as new technologies are being implemented and start to affect productivity.[34]

Alexopoulos's book measure is only available at an annual frequency and stops in 1997. We therefore estimate a smaller, annual VAR for this case, containing adjusted TFP, consumption, inflation, and Alexopoulos's book measure. For all the other variables, the impulse responses are estimated with the

[32]SSOs are mostly private organizations that exist in many industries to establish voluntary and regulatory standards. Prominent examples include the electricity plug, the USB key, the WiFi communications protocol, and quality standards (e.g., ISO). Also see Russell and Vinsel (2019). The standardization index by Baron and Spulber (2015) and Baron and Schmidt (2015) is based on information from the Searle Center database on technology standards and standard setting organizations. See their papers for details. We thank Justus Baron and Julia Schmidt for making their index available.

[33]As we have emphasized, the two are not necessarily distinct, as news about future productivity growth may coincide with contemporaneous innovations to productivity. Alexopoulos (2011) also constructs different new book titles for different technology categories, including new titles for computer hardware and software, and telecommunications. The results presented below are robust to using these alternative measures.

[34]Note that any standard TFP series is in fact an appropriately weighted average of neutral and investment-specific technologies. Moreover, as argued, for example, by Chen and Wemy (2015), there may be spillovers from capital-embodied technological change to neutral, general-purpose technology. See Basu et al. (2013) for separately identified consumption- and investment-specific TFP series.

above described VAR based on quarterly data for the 1960:3–2007:3 sample.

Figure 4a reports the impulse responses. Both the index of new ICT standards and the index of new technology manuals jump markedly on impact of the shock. The index of new ICT standards then declines back toward its preshock level, while the new manuals measure remains permanently higher. The response of the ICT standards index is particularly striking and matches closely with the evidence reported in Baron and Schmidt (2015), who use a recursive identification approach based on zero impact restrictions. R&D expenditures and the (inverse of the) relative price of investment goods in turn increase only gradually after the shock, although this increase occurs at a considerably faster pace than for adjusted TFP, as reported in figure 3.

Taken together, the impulse responses indicate that the max-share shock picks up the introduction of new technologies to markets instead of other shocks that endogenously lead to more R&D activity and eventually more innovation and higher productivity. Otherwise, one would expect ICT standards and new technology book titles to respond not with an initial jump but only gradually and with a delay relative to R&D expenditures.

Next, we consider forward-looking variables that have been interpreted as capturing news: the spread between long-term (five-year) Treasury bond yields and the Federal Funds rate as used in Kurmann and Otrok (2013); the Michigan Survey's five-year-ahead consumer confidence index as used in Barsky and Sims (2012); and the business confidence index from the Business Outlook Survey (BOS) conducted by the Federal Reserve Bank of Philadelphia as used in Bachmann, Elstner, and Sims (2013). Figure 4b shows the impulse responses of these series. For reference, we also include the impulse response of the real S&P 500 index, which is part of the VAR used to generate these results. All of the indicators jump up sharply on impact of the news shock and then decline gradually back to their original level. These responses are highly significant and indicate that the identified max-share shock captures news about the future that is picked up not only by financial markets but also the Fed, consumers, and businesses.[35]

The results provide compelling evidence that the max-share shock captures news about future productivity growth. The shock predicts delayed sustained future TFP growth, accounting for only a small fraction of TFP fluctuations at short forecast horizons but for 70% or more of TFP fluctuations at longer horizons. Perhaps more important, the shock is associated with large and persistent jumps in two novel measures of innovation, followed by a hump-shaped increase in R&D expenditures and a gradual decline in the relative price of investment goods, and the shock generates jumps in a wide variety of forward-looking information variables. Taken together, these responses suggest that the max-share identification picks up technological innovation as opposed to other business cycle shocks or noise that endogenously lead to changes in productivity and that market participants clearly update their forecasts about the economy. The news interpretation therefore seems natural.

[35]In previous versions of the paper, we also reported that the max-share shock leads to strong, positive impact responses of capital returns, providing further evidence that the identified shock contains important information about the future that market participants know about. Interestingly, the max-share shock also leads to strong, negative impact responses of different measures of uncertainty.

D. Monte Carlo Simulations

As a final check, we perform the same Monte Carlo simulations as above to assess whether the max-share identification captures more robustly the model responses to a news shock than the Barsky-Sims identification. To save on space, we consider directly the situation where the proportionality condition for utilization does not hold; that is, capital use is variable ($\sigma_z > 0$) and the factor of proportionality $\widehat{\beta} = 3$ is different from the variance ratio of true utilization to hours per worker. Results for the case when the proportionality conditions hold are reported in the appendix and match the model responses as closely as the ones obtained with the Barsky-Sims identification.

Figure 5 reports the results. The max-share identification clearly outperforms the Barsky-Sims identification (compare to figure 2), closely matching the impulse responses of not only consumption but also total hours and inflation, regardless of whether utilization is estimated from bandpass-filtered or bi-weight-filtered hours per worker. In particular, for both cases, the max-share identification implies a drop in total hours on impact followed by a hump-shaped increase after about ten quarters that matches the model response. This further confirms the robustness of the max-share identification approach to different measures of utilization.

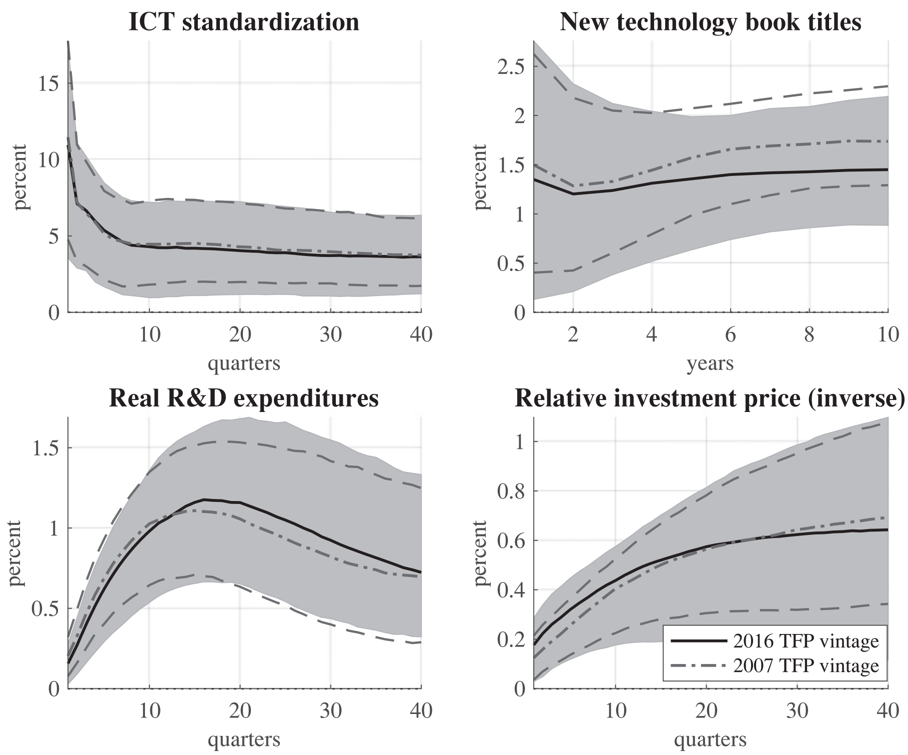
The Monte Carlo simulation also allows us to assess the robustness of the max-share identification to alternative data-generating scenarios. Generally the max-share identification performs well as long as news shocks account for a large part of the unpredictable variation in adjusted TFP at long horizons (or whatever measure of productivity that one may choose). This performance gradually deteriorates as the importance of other shocks for long-run movements in adjusted TFP is increased, either because these shocks have a direct impact on neutral technology or because of measurement issues. Nevertheless, as we have argued, since long-term changes in productivity are typically slow to diffuse, the assumption that surprise (unanticipated) changes in productivity are important at long horizons seems unlikely. With regard to other shocks that have an impact on adjusted TFP due to measurement error, this is of course a possibility, although one that is true of any identification.

VI. Conclusion

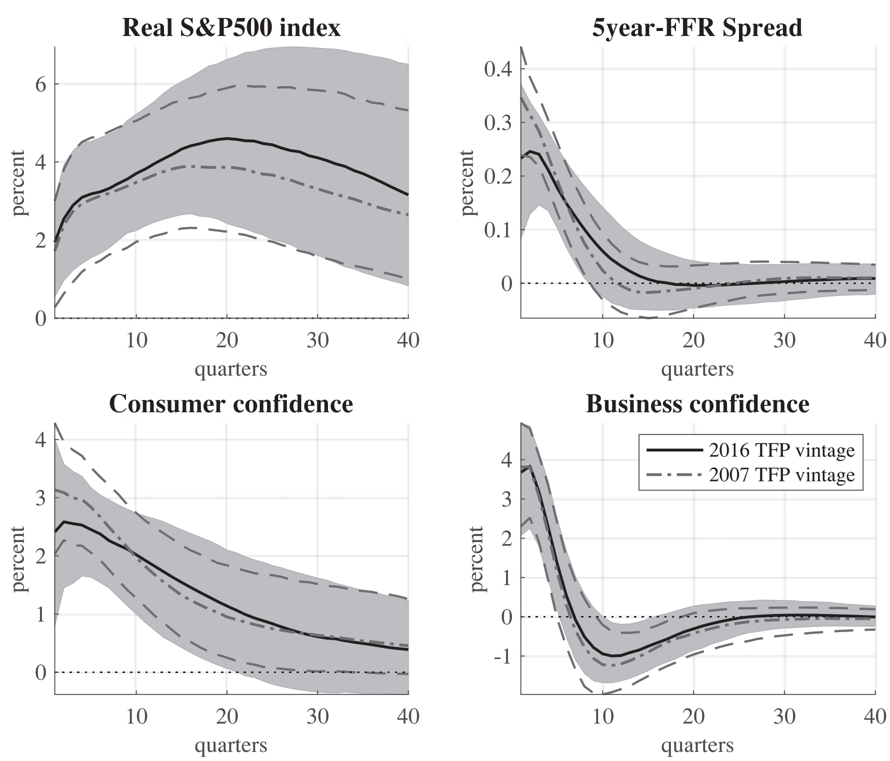
An almost universally imposed restriction in the news literature is that news shocks have an impact on productivity

FIGURE 4.—IMPULSE RESPONSES OF INNOVATION MEASURES AND NEWS INDICATORS TO MAX-SHARE SHOCK

(a) Innovation Measures

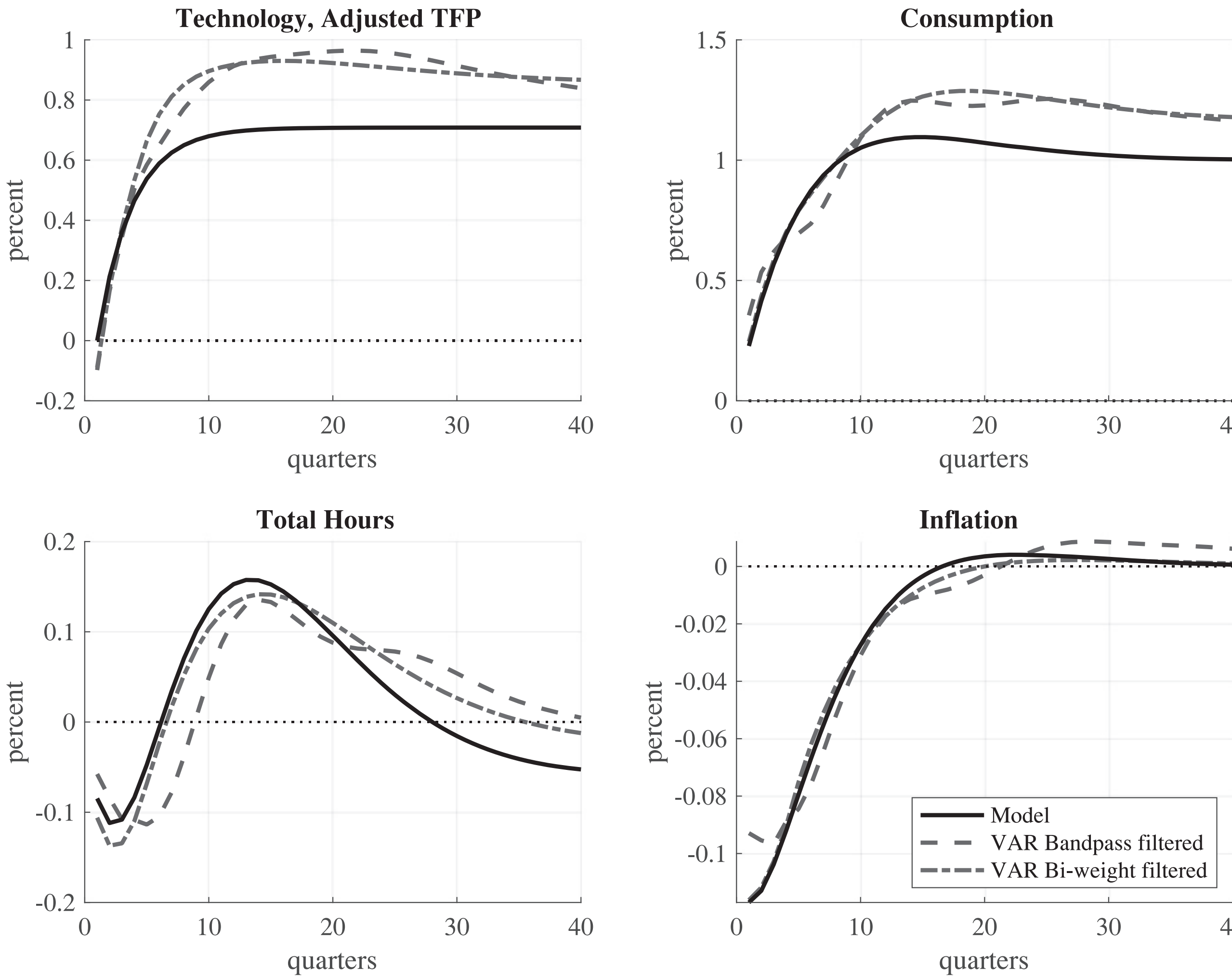


(b) News Indicators



Solid lines are the posterior median estimates from the VAR system estimated with the 2016 vintage of adjusted TFP. The shaded bands correspond to the 16% to 84% posterior coverage intervals. The dash-dotted lines are the posterior median estimates for the system estimated with the 2007 vintage of adjusted TFP. The dashed lines correspond to the 16% to 84% posterior coverage intervals. The impulse responses are identified using the max-share identification.

FIGURE 5.—SIMULATED RESPONSES TO MAX-SHARE SHOCK WHEN PROPORTIONALITY FAILS TO HOLD



Solid lines are the true impulse responses to a news shock in the model. The dashed lines are the estimated responses using the max-share identification based on the simulated data with bandpass filtered hours per worker in the construction of utilization. The dash-dotted lines are the estimated responses using the max-share identification based on the simulated data with bi-weight filtered hours per worker in the construction of utilization.

only with a delay. This restriction may be violated if empirical series of productivity systematically mismeasure true technology.

In this paper, we document large revisions in one of the most popular measures of productivity, adjusted TFP by Fernald (2014), and show that these revisions are due to a switch in filtering of hours per worker in the estimation of factor utilization. These changes are evocative of cyclical mismeasurement and materially affect empirical conclusions about the macroeconomic effects of news shock as identified by Barsky and Sims (2011). We therefore propose an alternative identification, based on the max-share approach by Francis et al. (2014), which does not rely on short-run restrictions, in particular, the zero impact restriction. We show that our identification is robust to the revisions in Fernald's series and performs well in Monte Carlo simulations under different assumptions about cyclical mismeasurement of productivity. When applied to U.S. data, we find results that are consistent with a news interpretation: adjusted TFP increases only gradually, whereas indicators of technological innovation and forward-looking information variables jump on impact. The identified shock does not generate comovement in real, and is therefore not a main driver of business cycle fluctuations. This does not imply that the shock is unimportant for macroeconomics as it accounts for the majority of unpredictable fluctuations in real aggregates at medium and long horizons and generates strong impact responses of inflation, the Federal Funds rate, and asset prices. Investigating these results further and assessing the type of models that are consistent with these dynamics are important topics of future research.

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