Revisions in Utilization-Adjusted TFP and Robust Identification of News Shocks*

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Abstract

This paper documents that the cyclical behavior of a widely-used quarterly utilization-adjusted TFP series by Fernald (2014) has significantly changed across different vintages. These changes are primarily due to revisions in the estimated utilization rate and substantially affect the conclusions about the macroeconomic effects of news shocks. The result suggests that the key identifying restriction of the news literature that utilization-adjusted TFP responds to a news shock only with a lag may not be valid. Building on the large empirical literature documenting the slow, S-shaped diffusion of new technology, we propose an alternative identification that does not rely on this zero impact restriction and instead accounts for most of the unpredictable variation in TFP at long horizons. We show that the alternative identification is robust to different measurement issues with Fernald's TFP series, including the revisions to estimated utilization, while allowing for the possibility that news about future productivity coincide with changes to current productivity. When applied to U.S. data, news about future productivity fail to generate comovement in the main macro aggregates and therefore do not constitute a main source of business cycle fluctuations. Nevertheless, news shocks account for a large part of of macroeconomic fluctuations at medium and longer horizons and generate sharp impact responses of prominent macro aggregates, including inflation and interest rates.

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1 Introduction

Dating back to Pigou (1927), economists have argued that news about future changes in fundamentals are an important source of economic fluctuations. This view has reemerged recently in large part due to a set of influential papers by Beaudry and Portier (2004) and Beaudry and Portier (2006) who report that news about future productivity are closely related to shocks driving long-run variations in productivity and constitute one of the main drivers of business cycles. While the importance of news shocks for business cycles fluctuations is hotly debated, the main identifying assumption behind news shocks is almost universally accepted: productivity reacts to a news shock only with a lag.[1]

In this paper, we critically revisit this assumption. Two conditions have to be met for the zero impact restriction on productivity to be satisfied. First, the empirical measure of productivity must be exogenous to current business cycle conditions. Second, news about future productivity do not coincide with innovations in (true) productivity. Both conditions seem questionable.

We start by documenting that the cyclical behavior of a widely used quarterly utilization-adjusted series of total factor productivity (TFP) by Fernald (2014) has changed significantly across different vintages. These changes are primarily due to revisions in the estimated utilization rate and affect the empirical results about the macroeconomic effects of news shocks in important ways. The sensitivity of adjusted-TFP to revisions in the estimate of utilization suggests – as noted by Fernald (2014) but otherwise ignored in the literature – that for all its improvements over a traditional Solow residual, utilization-adjusted TFP may not be a perfect measure of (true) productivity. But then, the key identifying restriction of the news literature that utilization-adjusted TFP responds to a news shock only with a lag may not be valid and render results sensitive to even seemingly innocuous data revisions.

As for the second condition, there is no *a priori* reason to assume that current productivity and news about future productivity are unrelated.[2] Based on Monte-Carlo simulations, we show that even if productivity is measured without error by the econometrician, incorrectly imposing the zero impact restriction can lead to very different conclusions about the importance of news shocks for business cycle fluctuations.

In light of these results, we propose an alternative identification that does not rely on news shocks having zero contemporaneous impact on TFP. Building on the large empirical literature documenting the slow, S-shaped diffusion of new technology, we instead extract innovations that account for most of unpredictable movements in TFP at long horizons. These innovations are interpreted as news because they lead to persistent and therefore predictable growth in TFP over time while accounting for only a small fraction of

[1]Beaudry and Portier (2014) and Barsky, Basu, and Lee (2015) provide excellent reviews of this literature. In particular, see Barsky and Sims (2011) who propose an alternative identification to Beaudry and Portier (2006) in a structural vector autoregression (VAR) context and find that news about future productivity do not generate comovement in macroeconomic aggregates. Also see 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; the discussion of Beuadry and Lucke (2010) by Fisher (2010) about issues with yet another VAR identification; and Schmitt-Grohe and Uribe (2012) and Kahn and Tsoukalas (2012) for identification issues in a full-information context. All of these papers impose the zero impact restriction on productivity.

[2]For example, the successful adoption of a new technology by a firm may raise current productivity and at the same time provide news that other firms will adopt the same technology in the future. To our knowledge, the only other paper that discusses this possibility is Barsky, Basu, and Lee (2015) who write: *"It is possible that news about future productivity arrives along with innovations in productivity today (page 233)."* In their empirical application, however, imposing the zero restriction or not does not significantly affect the results and thus, they impose the zero restriction.

TFP fluctuations at short forecast horizons. The identification is robust to measurement errors as long as these errors are cyclical, including the revisions to Fernald's utilization-adjusted TFP series. Moreover, the identification allows us to avoid taking a stand on whether productivity reacts only with a lag to news or not. When applied to U.S. data, we find that news about future productivity fail to generate comovement in the main real macro aggregates and therefore do not constitute a main source of business cycle fluctuations. Nevertheless, news about future productivity account for a large part of macroeconomic fluctuations at medium and longer horizons and generate sharp short-term fluctuations in prominent macroeconomic aggregates, including inflation and interest rates, that are important to understand.

Section 2 starts by reviewing the measurement of productivity in the data. Following the lead of Kydland and Prescott (1982) and Long and Plosser (1983), the modern 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 – and modeled productivity shocks as a jump process consistent with the near random walk properties of TFP in the data. Economists quickly realized, however, that TFP may be a poor measure of productivity due to imperfect input and output markets, adjustment costs, and unobserved utilization of factors of production.[3] Partly in response to these criticisms, Basu, Fernald, and Kimball (2006) apply restrictions derived from economic theory to industry-level data to construct an aggregate measure of TFP that is adjusted for compositional changes in the quality of labor and capital, sectoral heterogeneity, imperfect competition, and unobserved factor utilization. Fernald (2014) extends the analysis in Basu et al. (2006), which is carried out with annual data, to produce a quarterly measure of TFP. Because of the higher frequency, not all of the corrections in the original Basu et al. (2006) series are captured in the quarterly series, but perhaps the most important one – the correction for variable factor utilization – is. This quarterly, utilization-adjusted TFP series, which is freely available for download on Fernald's website, has proven highly influential and has become one of the most popular if not the main measure of productivity in the news literature.[4]

Fernald frequently revises his adjusted TFP series based on new data and methodological refinements.[5] In Section 3, we analyze the consequences of these revisions. We document that while most revisions have only a minor impact, the switch in March 2014 from industry-level estimates for utilization by Basu, Fernald, and Kimball (2006) to estimates by Basu, Fernald, Fisher, and Kimball (2013) affects the time series behavior of aggregate utilization and therefore adjusted TFP in important ways. For example, while pre-March 2014 vintages of adjusted TFP are positively correlated with aggregate output and uncorrelated with total hours worked, post-March 2014 vintages are uncorrelated with output and negatively correlated with total hours

[3] The idea that observed TFP fluctuations might in fact be driven by an endogenous response of factor utilization to non-productivity shocks is mentioned by Summers (1986) in his early critique of real business cycle models. Burnside, Eichenbaum, and Rebelo (1993) construct a structural model with labor hoarding (another term for labor utilization) and conclude that much of the variation in TFP is not due to exogenous productivity shocks.

[4] As of August of 2016, the working paper describing the construction of the adjusted TFP series has been cited 236 times on Google Scholar.

[5] In the text and the notes accompanying the data, Fernald describes in detail how the construction of the series has varied over time. He does not, however, analyze the extent to which the different updates change the time series properties of the TFP series across vintages.

worked.[6]

The change in time series behavior across vintages of adjusted TFP has important consequences for the identification of news shocks. We illustrate this in Section 4 by redoing the empirical analysis of Barsky and Sims (2011), who identify news shocks in a VAR context as the innovation that is orthogonal to Fernald's adjusted TFP series and accounts for the maximum share of the forecast error variance (FEV) of adjusted TFP over a ten year horizon. Based on the 2007 vintage of adjusted TFP, as originally used in Barsky and Sims (2011), we find results that are very similar to those reported in their paper. Consumption increases on impact of a positive news shock; output, investment, hours first decline slighly before increasing after a few quarters; and inflation and nominal short-term rates drop markedly on impact and return only slowly to their pre-shock levels. Furthermore, the news shock accounts for a small fraction of the FEV of real aggregates at horizons before adjusted TFP begins to change. Based on post-March 2014 vintages of adjusted TFP, in contrast, we find that a positive news shock does not lead to declines in output, investment and hours on impact (at least for certain specifications a small increase); generates a considerably less significant drop in inflation and short-term interest rates; and accounts for a larger share of the FEV at short horizons. These results are markedly different and afford a more favorable interpretation of the news-driven business cycle hypothesis laid out by Beaudry and Portier (2006) than what obtains using older, pre-March 2014 vintages.

Given the large differences in the properties of the adjusted TFP series across vintages, it might seem natural to ask which vintage of the data is "best". However, we believe that at least for the purpose of identifying news shocks, a more fruitful approach is to consider alternative identifications of news shocks that do not rely on contemporaneous orthogonality restrictions and are therefore robust to mismeasurement of the cyclical component of adjusted TFP. The identification we propose in Section 5 is based on the observation that the type of news about productivity-enhancing changes in technology, factor input quality, and efficiency in allocation that we intend to capture is a major driver of long-run growth but exhibits slow, S-shaped patterns of dissemination. See for example Griliches (1957), Mansfield (1961), Mansfield (1989), Gort and Klepper (1982), or Rogers (1995). We implement this identification by extracting the shock that accounts for the maximum FEV share of adjusted TFP at a long but finite forecast horizon without imposing a contemporaneous zero restriction. Monte-Carlo simulations with a medium-scale New Keynesian DSGE model indicate that this alternative identification is better suited to extract exogenous shocks to long-run productivity growth in the presence of cyclical measurement errors that affect adjusted TFP, independent of whether this shock has an immediate effect on productivity or not. The Monte-Carlo simulations also imply that at least in the context of our model, mismeasurement of productivity due to fixed costs in production and time-varying markups has only a negligible effect, which is a positive result for Fernald's TFP measure as it abstracts from these considerations.

Of course, nothing guarantees that the shock we identify captures news in the sense that that under-

[6] In contemporaneous work, Cascaldi-Garcia (2016) also points out differences in Fernald's adjusted TFP series across vintages and documents that these differences come from changes in utilization. The paper does not extensively document differences in the utilization-adjusted TFP series by vintage as we do, nor does the paper discuss why these changes may raise questions about the zero restriction employed in the literature. Instead, the paper is written purely as a comment on Kurmann and Otrok (2013) to which Kurmann and Otrok (2016) respond using the alternative identification approach proposed here.

lying changes in productivity are slowly disseminating. When applied to U.S. data, however, we find that the identified shock anticipates predictable changes in TFP growth, and accounts for almost none of the fluctuations of TFP at short horizons but more than 70 percent of longer-run fluctuations. In addition, the shock leads to large and persistent changes in measures of consumer confidence and the stock market price. The news interpretation therefore seems natural. Further, we show that the shock generates responses of macroeconomic aggregates that are indeed robust to the use of different vintages of Fernald's adjusted TFP series. In particular, in response to a positive shock, consumption jumps on impact before gradually increasing to a new permanent level; and investment and hours first decline modestly before starting to increase after a few quarters. The identified shock therefore does not generate the type of comovement that we typically associate with business cycle fluctuations. In turn, inflation and short-term interest rates drop markedly on impact of the shock before slowly returning to their initial values. Since the shock accounts for a substantial fraction of the variations in these variables, this reaction is important to understand.

The alternative identification we propose shares obvious parallels with work outside of the news literature. In particular, Blanchard and Quah (1989), Shapiro and Watson (1988) and Gali (1999) among many others identify permanent technology shocks in VAR systems based on infinite-horizon restrictions. In response to criticism that infinite-horizon restrictions imply potentially large biases in finite order VARs, Francis, Owyang, Roush, and DiCecio (2013) propose to identify permanent technology shocks at long but finite horizons. The difference to our work is that none of these papers directly target TFP and instead focus on labor productivity and other macroeconomic aggregates. As such these papers do not directly speak to the news literature and the idea that improvements in productivity disseminate slowly and in a predictable manner.[7] Our paper also relates to a recent literature on the macroeconomic effects of slowly disseminating technology due to costly adoption. The paper most closely related is Rotemberg (2003) who 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. Other papers that document the slow diffusion of technology and build models of costly adoption are Comin and Gertler (2006), Comin and Hobijn (2010), or Comin, Gertler, and Santacreu (2009).

2 Utilization-Adjusted TFP and its Use in the News Literature

This section describes the construction of the quarterly utilization-adjusted TFP series by Fernald (2014). We then review how the literature uses this series to identify news shocks, and how different measurement issues in the construction of the series raise potential challenges for this identification.

[7] Indeed, in many of these papers, labor productivity jumps immediately to essentially its new permanent level – a pattern that is very different from TFP as we document in our results.

2.1 Fernald's utilization-adjusted TFP series

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

$$Y_t = F(E_t L_t, Z_t K_t, A_t), \tag{1}$$

where Y_t denotes output, L_t labor input, K_t capital input, E_t labor effort, Z_t capital utilization, and A_t technology. As discussed for example in Acemoglu (2009), A_t should be understood simply as a shifter of the production function that captures a *"...broad notion of technology, incorporating the effects of the organization of production and of markets on the efficiency with which the factors of production are utilized (page 28)."* We call A_t technology rather than productivity because we want to distinguish it from Total Factor Productivity (TFP), which is an empirical concept discussed below, and because the news literature typically treats A_t as exogenous to current business cycle conditions.

Differentiating with respect to time and omitting time subscripts to simplify notation, the contribution of technology to output growth can be expressed as

$$\frac{\dot{A}}{A} = \frac{\dot{Y}}{Y} - \varepsilon_E \frac{\dot{E}}{E} - \varepsilon_L \frac{\dot{L}}{L} - \varepsilon_Z \frac{\dot{Z}}{Z} - \varepsilon_K \frac{\dot{K}}{K}, \tag{2}$$

where $\varepsilon_E \equiv F_E E/Y$ is defined as the elasticity of output with respect to labor effort and so forth for the other arguments of the production function, and the elasticity of output with respect to technology is normalized to one. Assuming further that input and output markets are perfectly competitive, that inputs can be instantaneously adjusted without cost, and that production is constant returns to scale, (2) can be rewritten as

$$\frac{\dot{A}}{A} = \left(\frac{\dot{Y}}{Y} - \omega_L \frac{\dot{L}}{L} - (1-\omega_L)\frac{\dot{K}}{K}\right) - \left(\omega_L \frac{\dot{E}}{E} + (1-\omega_L)\frac{\dot{Z}}{Z}\right), \tag{3}$$

where $\omega_L = \frac{WL}{PY}$ is the share of nominal labor payments, WL, in nominal output, PY. 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.

Based on (3), Fernald (2014) constructs quarterly estimates of both TFP growth and utilization-adjusted TFP growth. To construct TFP growth, he proceeds as follows. Output growth is measured as the log change in the equally weighted average of real expenditures and income in the business sector from the NIPAs. Labor input growth is measured as the sum of the log change in total hours worked in the business sector from the BLS and the log change in labor quality, which is based on worker skill estimates from wage regressions by Aaronson and Sullivan (2001) and BLS multifactor productivity data. Capital input growth is measured as the weighted log change of different capital stocks, with the weights determined by the relative income shares, and the different capital stocks computed from NIPA investment data using the perpetual inventory method. The labor share of income $\omega_{L,t}$ is constructed using interpolated annual NIPA data on payments to labor. The quarterly estimate of TFP growth is then computed as:

$$\Delta \ln TFP_t = \Delta \ln Y_t - \omega_{L,t}\Delta \ln L_t - (1 - \omega_{L,t})\Delta \ln K_t. \tag{4}$$

To construct utilization-adjusted TFP growth, Fernald (2014) follows Basu, Fernald, and Kimball (2006) and estimates an aggregate quarterly utilization series from disaggregated industry-level data. The basic idea behind this utilization series is that a cost-minimizing firm simultaneously varies inputs along all margins. This implies that variations in observed hours per worker can be used as a proxy for variations in the unobserved utilization rates, with the factor of proportionality estimated from industry-level data. The resulting industry utilization estimates are then aggregated to obtain a quarterly economy-wide utilization estimate using average industry weights, and utilization-adjusted TFP growth is computed as:

$$\Delta \ln TFP_t^U = \Delta \ln TFP_t - \Delta \ln U_t, \tag{5}$$

where $\Delta \ln U_t$ denotes the estimated change in factor utilization. Since March of 2014, Fernald (2014) computes the utilization series from updated utilization estimates by Basu, Fernald, Fisher, and Kimball (2013), which extends the Basu et al. (2006) methodology to more recent data. Since August 2014, the utilization series are based on updated industry level data of hours per worker.

2.2 Measurement issues for the news literature

Following Beaudry and Portier (2006), the news literature has generally assumed that technology is driven by two exogenous components, one capturing the slow diffusion of new technologies and the other capturing unanticipated or current shocks. In particular:

$$\ln A_t = d(L)\varepsilon_t^{news} + v(L)\varepsilon_t^{current}, \tag{6}$$

where ε_t^{news} and $\varepsilon_t^{current}$ are uncorrelated innovations, and $d(L)$ and $v(L)$ are lag polynomials governing the dynamic effects of the two innovations. Almost without exception, the key assumption that the news literature imposes on this process is $d(0) = 0$, identifying ε_t^{news} as the news shock in the sense that it affects technology only with a lag.

The assumption of $d(0) = 0$ naturally gives rise to a zero restriction that has been imposed in all empirical applications of which we are aware. For example, Beaudry and Portier (2006) identify the news shock in their VARs as the shock that is orthogonal to a conventional measure of current TFP. Beuadry and Lucke (2010) and Barsky and Sims (2011) use a similar identification in VAR models using a utilization-corrected measure of TFP. In a fully-specified DSGE model, Schmitt-Grohe and Uribe (2012) assume that the news shock affects technology (and other exogenous states variables) only with a lag.

As discussed in the Introduction, two important conditions have to be met for this zero restriction to be appropriate. First, news about future productivity must affect productivity only with a lag; and second, productivity as measured in the data must be unrelated to current business cycle conditions. There is no *a priori* reason to think that news shocks about future productivity should be completely unrelated to current productivity. Or as Barsky, Basu, and Lee (2015) put it: *"It is possible that news about future productivity arrives along with innovations in productivity today (page 233)"*. Furthermore, if the TFP series used is an imperfect measure of technology, then TFP might be systematically related to current business cycle fluctuations, including fluctuations induced by news shocks. This could arise for a number of reasons. First, the utilization series used to correct TFP series may be an inaccurate measure of actual factor utilization. Second, as emphasized by Fernald (2014) himself, *"...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...[s]imilarly,if observed factor shares do not equal output elasticities – as is the case with imperfect competition – then those effects will also show up in utilization-adjusted TFP growth (page 26)."*

This is not to say that utilization-adjusted TFP ceases to be an object of interest – it very much remains so even for this paper. Our point is simply that for a number of reasons, utilization-adjusted TFP may not be orthogonal to news shocks, which makes imposing the zero impact restriction to identify news shocks problematic. One could argue of course that these departures from orthogonality are small and do not matter quantitatively. In the next section, we show, however, that this is not generally the case. We illustrate that an otherwise unnoticed revision to Fernald (2014)'s factor utilization estimates result in large differences in both the unconditional properties of adjusted TFP and large differences in estimated impulse responses to a news shock when imposing a zero impact effect of news.

3 Revisions to Utilization-Adjusted TFP

This section documents the change in time series behavior across different vintages of Fernald's (2014) utilization-adjusted TFP measure. We then analyze what drives this change. We find that the principal source of the change in business cycle properties of adjusted TFP occured in March of 2014 when Fernald switched to using new estimates for the computation of unobserved factor utilization. The working paper by Sims (2016), which serves as a supporting document for the present paper, contains additional analysis and robustness checks.

3.1 Time series properties of different vintages

We have vintages of Fernald's utilization-adjusted TFP measure from December 2007, September 2011, December 2013, May 2014, May 2015, and May 2016. Table 1 provides basic unconditional first and second moments of adjusted TFP growth for the 2007, the 2013, the 2014 and the 2016 vintage.[8] As in Fernald, TFP growth is computed as the quarterly log change, expressed in annualized percentage points. For the

[8]The results for the 2011 vintage are very similar to the results for the 2007 and the 2013 vintage while the results for the 2015 vintage are very similar to the results for the 2014 and the 2016 vintage. We therefore do not report results for these two vintages here.

unconditional second moments, similar results obtain if we apply a Hodrick-Prescott filter to the log level of adjusted TFP instead.

Table 1: Moments for the 2007, 2013, 2014 and 2016 Vintages of 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
Corr w/ $\Delta \ln TFP_t^{U,07}$	1.00	0.85	0.56	0.58

Notes: This table shows descriptive statistics for different vintages of adjusted TFP. The sample period for each of the statistics is 1947q3-2007q3. $\Delta \ln TFP_t^{U,j}$ is the log first difference of the adjusted TFP series for vintages j = 07, 13, 14 or 16, expressed in annualized percentage points.

The mean and standard deviation of adjusted TFP growth are very similar across vintages. In spite of these similarities, there is an important decline in comovement that occurs primarily from the 2014 vintage onward, with the correlation coefficient between the 2007 vintage and post-2013 vintages dropping to below 0.6. This decline in comovement across vintages of adjusted TFP holds for different subsamples and is therefore not driven by a change in business cycle behavior during a particular time period.

Table 2 documents that the decline in comovement across vintages of adjusted TFP growth matters in significant ways for business cycle correlations. As before, we report results for quarterly log changes, but similar results would obtain for Hodrick-Prescott filtered log levels.

Table 2: Business Cycle Correlations for the 2007, 2013, 2014 and 2016 Vintages of Adjusted TFP Growth

	$\Delta \ln TFP_t^{U,07}$	$\Delta \ln TFP_t^{U,13}$	$\Delta \ln TFP_t^{U,14}$	$\Delta \ln TFP_t^{U,16}$
$\Delta \ln Y_t$	0.53	0.38	0.18	0.07
$\Delta \ln C_t$	0.26	0.21	0.05	0.11
$\Delta \ln I_t$	0.20	0.13	-0.00	-0.02
$\Delta \ln H_t$	-0.01	-0.06	-0.24	-0.35

Notes: This table shows correlations of different vintages of adjusted TFP growth with growth rates of prominent macroeconomic aggregates. Y_t is headline real GDP, C_t is real personal consumption expenditures, and $I_t$is real private fixed investment; all from the NIPA tables. Both personal consumption expenditures and private fixed investment are deflated by their own deflators. H_t is total hours worked in the non-farm business sector. All data are log first differenced. The sample period for each of the statistics is 1947q3-2007q3.

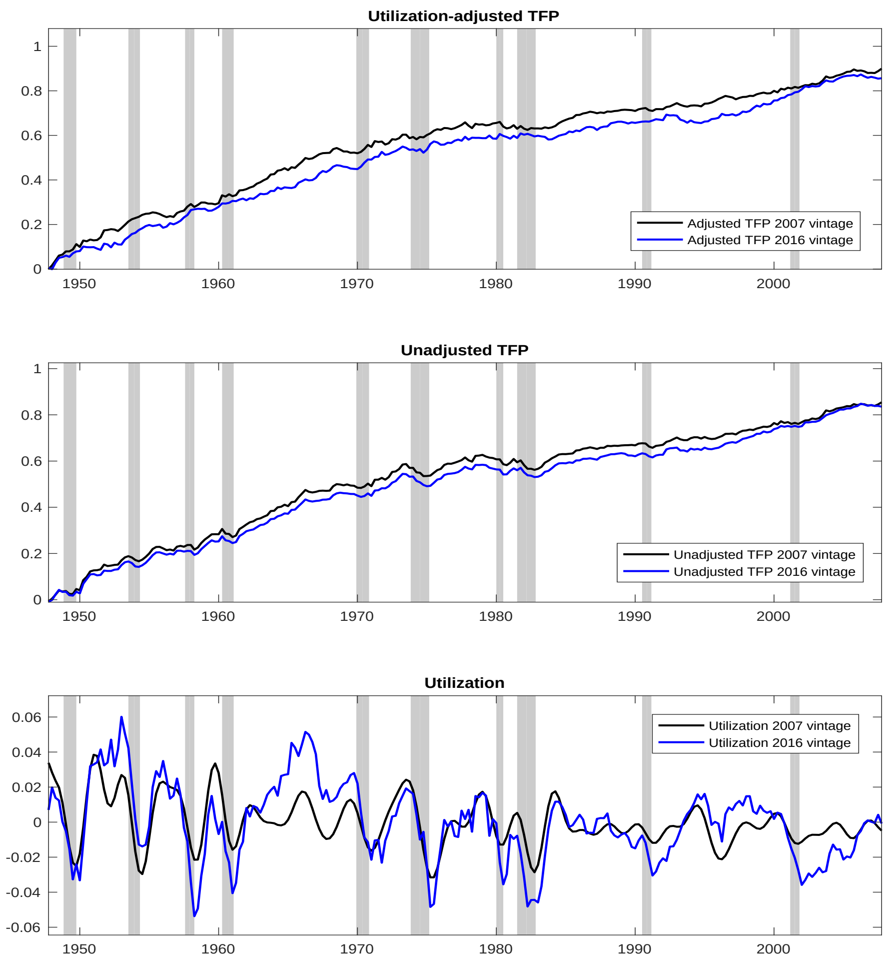
The 2007 and 2013 vintages of adjusted TFP are positively correlated with output, consumption, and investment, and essentially uncorrelated with aggregate labor hours. In contrast, the 2014 and 2016 vintage of adjusted TFP are less positively correlated with output and consumption, uncorrelated with investment, and negatively correlated with hours. As in Table 1, the decline in business cycle correlations occurs primarily from the 2014 vintage onward.

3.2 What drives the changes across vintages?

Given the large differences in business cycle correlations across vintages of adjusted TFP, it is natural to ask what drives these changes. Fernald's data by vintage contains not only the adjusted TFP series but also the different components used in calculating adjusted TFP; i.e. aggregate output Y_t, the aggregate capital stock K_t, aggregate labor hours H_t, aggregate labor quality Q_t, the labor share of income $\omega_{L,t}$, as well as aggregate utilization U_t. It is therefore straightforward to address this question.

Note from (4) and (5) that all components but the estimate for utilization enter exclusively into the computation of non-adjusted TFP. As a first step, we therefore consider the time series behavior of non-adjusted TFP and utilization across different vintages. Figure 1 plots the log *levels* of the 2007 and 2016 vintages of adjusted TFP (top panel), non-adjusted TFP (middle panel) and utilization (bottom panel). The 2007 vintages are depicted as black lines while the 2016 vintages are shown as blue lines. The grey shaded bars show NBER recessions.

Figure 1: Adjusted TFP, Non-adjusted TFP and Utilization: 2007 vs. 2016 Vintages



Notes: This figure plots the log levels of both the 2007 and 2016 vintages of the utilization-adjusted TFP series (top panel), the unadjusted TFP series (middle panel) and the utilization series (bottom panel). The 2007 vintages are depicted as black lines. The 2016 vintages are depicted as blue lines. The grey shaded bars show NBER recessions. The sample period for all graphs is 1947q3-2007q3.

As the top panel shows, the two vintages of the adjusted TFP series share roughly the same trend over the full sample but there are sizable differences over subsamples. The 2016 vintage grew more slowly during the first 25 years of the sample as well as from the mid-1980s to the mid-1990s. Concurrently, the 2016 vintage grew considerably faster from the late 1990s through the mid-2000s. Finally, whereas the 2016 vintage declined from 2005 onwards, the 2007 vintage showed an uptick near the end of the sample. As the middle panel shows, a substantial part of these differences in subsample trends are attributable to differences in non-adjusted TFP across vintages. But an equally if not more important part is driven by differences in utilization across vintages. As the bottom panel shows, while both the 2007 and the 2016 vintage of utilization are mean-reverting and procyclical, there are sizable and persistent differences.[9] In particular,

[9]By construction, Fernald's utilization series evolves around a constant mean as the different industry-specific utilization

the 2016 vintage displays substantially larger swings and is less smooth than the 2007 vintage.

To provide further insights, Table 3 reports the same summary statistics for the 2007, 2013, 2014 and 2016 vintages as in Table 1 but for non-adjusted TFP and utilization.

Table 3: Moments of the 2007, 2013, 2014 and 2016 Vintages of Non-adjusted TFP and Utilization 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
Corr w/ $\Delta \ln TFP_t^{07}$	1.00	0.92	0.92	0.93
	$\Delta \ln u_t^{07}$	$\Delta \ln u_t^{13}$	$\Delta \ln u_t^{14}$	$\Delta \ln u_t^{16}$
Mean	-0.08	-0.04	-0.05	-0.03
Standard Deviation	2.34	2.94	3.75	3.76
Corr w/ $\Delta \ln u_t^{07}$	1.00	0.94	0.58	0.65

Notes: This table shows descriptive statistics for the 2007, 2013, 2014 and 2016 vintages of the non-adjusted TFP and utilization series. The sample period for these statistics is fixed at 1947q3-2007q3.

Unadjusted TFP growth remains essentially unchanged across vintages in terms of overall mean, standard deviation and comovement. Utilization growth, in contrast, becomes significantly more volatile and there is an important decline in correlation with the 2007 vintage starting with the 2014 vintage.

Table 3 indicates that the large changes in business cycle properties of utilization-adjusted TFP across vintages are not due to data revisions in output, capital, labor, labor quality or the labor share of income but rather are a direct consequence of the changes in volatility and business cycle properties of utilization that occurred primarily between the December 2013 and the May 2014 vintage. This finding aligns with revision notes included in Fernald's dataset. Indeed, in March 2014, Fernald switched from using industry utilization estimates by Basu, Fernald, and Kimball (2006), which relied on data through 1995, to estimates from Basu, Fernald, Fisher, and Kimball (2013), which uses data through 2005.[10] We verify that this revision in utilization series is the principal source of the changes in time series behavior of adjusted TFP by constructing synthetic measures of adjusted TFP that combine post-2013 vintages of non-adjusted TFP with pre-2013 vintages of utilization. The resulting correlations with the 2007 vintage of adjusted TFP are all above 0.9. See Sims (2016) for details.

As for the differences in subsample trends of adjusted TFP highlighted in Figure 1, we compare the different vintages of the components used in constructing non-adjusted TFP. We find that the output, capital and hours series change only very little across vintages. In contrast, there are large differences in volatility and comovement of the labor quality series between the 2007 vintage and later vintages, including the 2011 vintage. These revisions to labor quality account for some of the differences in subsample trends

rates are estimated based on bandpass-filtered (and therefore demeaned) data. The aggregate utilization rate does not have an exact zero mean because it is weighted average of industry-specific rates. However, the actual means for both the 2007 and the 2016 vintages are close to zero (see Table 1). The figure reports the demeaned utilization rates to make the comparison of the two utilization vintages easier.

[10] An email exchange with Fernald confirms tha the switch to the Basu, Fernald, Fisher, and Kimball (2013) estimates is the principal source for the change in the utilization series.

of TFP across vintages. At the same time, these revisions are not an important driving force behind the differences in business cycle properties of adjusted TFP across vintages. First, as shown in Table 3, the business cycle properties of unadjusted TFP remain essentially unchanged across vintages. Second, the correlation between the 2011 vintage and the 2016 vintage of adjusted TFP growth is less than 0.6 despite the fact that the labor quality series for these two vintages is virtually identical.

4 Implications for the Identification of News Shocks

To quantify the consequences of the differences in time series behavior of adjusted TFP across vintages for the identification of new shocks, we redo the empirical analysis of Barsky and Sims (2011), who identify news shocks in a VAR context as the innovation that is orthogonal to Fernald's adjusted TFP series but maximally accounts for the forecast error variance (FEV) share of adjusted TFP over a ten year horizon. We choose to show results based on this identification rather than one of the other ones proposed in the literature because it performs well in small-sample Monte Carlo simulations (under the assumption, of course, that the zero impact restriction is satisfied in the data generating process and productivity is measured correctly) and because it is a partial identification approach that does not require us taking a stand on the nature of non-news shocks.[11] However, we suspect that results would be similar for other identification schemes used in the literature since they all impose the zero impact restriction on TFP.

4.1 Barsky-Sims identification

Since our alternative identification proposed below shares many of the elements with the identification of news shocks by Barsky and Sims (2011), we review here the details. 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

$$\mathbf{Y}_t = \mathbf{B}(\mathbf{L})\mathbf{u}_t, \tag{7}$$

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. The coefficients of $\mathbf{B}(L)$ and $\mathbf{\Sigma}_u$ can be estimated with an unrestricted VAR. Assume that there exists a linear mapping between prediction errors and structural shocks, ϵ_t

$$\mathbf{u}_t = \mathbf{A}\epsilon_t, \tag{8}$$

where $\mathbf{A}$ is a $k \times k$ matrix. The structural moving average representation then is

[11] Indeed, full identification approaches are often subject to important robustness issues with respect to non-news shocks. See for example Kurmann and Mertens (2014) who show that the news 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 by Beuadry and Lucke (2010) depend importantly on the number of cointegration restrictions imposed.

$$\mathbf{Y}_t = \mathbf{C}(\mathbf{L})\epsilon_t, \tag{9}$$

where $\mathbf{C}(\mathbf{L}) = \mathbf{B}(\mathbf{L})\mathbf{A}$ and $\epsilon_t = \mathbf{A}^{-1}\mathbf{u}_t$. Normalizing the variance-covariance matrix of structural shocks to be an identity matrix (i.e. $E(\epsilon_t\epsilon_t') = \mathbf{I}$), it must be the case that:

$$\mathbf{A}\mathbf{A}' = \mathbf{\Sigma}_u, \tag{10}$$

Given the symmetry of $\mathbf{\Sigma}_u$, there are a multitude of $\mathbf{A}$ consistent with (10). 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 (10) is given by $\widetilde{\mathbf{A}}\mathbf{D}$, where $\mathbf{D}$ is an orthonormal rotation vector.

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

$$\mathbf{Y}_{t+h} - E_{t-1}\mathbf{Y}_{t+h} = \sum_{l=0}^{h} \mathbf{B}_l \widetilde{\mathbf{A}}\mathbf{D}\epsilon_{t+h-l}. \tag{11}$$

The share of the forecast error variance of variable i attributable to shock j at horizon h is then:

$$\mathbf{\Omega}_{i,j}(h) = \frac{\sum_{l=0}^{h} \mathbf{B}_{i,l}\widetilde{\mathbf{A}}\gamma\gamma'\widetilde{\mathbf{A}}'\mathbf{B}_{i,l}'}{\sum_{l=0}^{h} \mathbf{B}_{i,l}\mathbf{\Sigma}_u\mathbf{B}_{i,l}'}, \tag{12}$$

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

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

$$\max_{\gamma} \quad \sum_{h=0}^{H} \Omega_{1,2}(h) \tag{13}$$

$$\text{s.t.}$$

$$\gamma'\gamma = 1 \tag{14}$$

$$\gamma(1,1) = 0 \tag{15}$$

As noted earlier, the measure of productivity occupies the first element of $\mathbf{Y}_t$, and the news shock is specified as the second structural shock in the system. The first restriction ensures that γ belongs to an orthonormal matrix, while the second restriction imposes that the news shock have no immediate impact on the measure of productivity.

The zero impact restriction on current productivity is the key assumption in the news literature. But as discussed above, it requires that (true) productivity is indeed unrelated to news about future productivity and that the empirical measure of productivity (e.g. adjusted TFP) accurately measure true productivity.

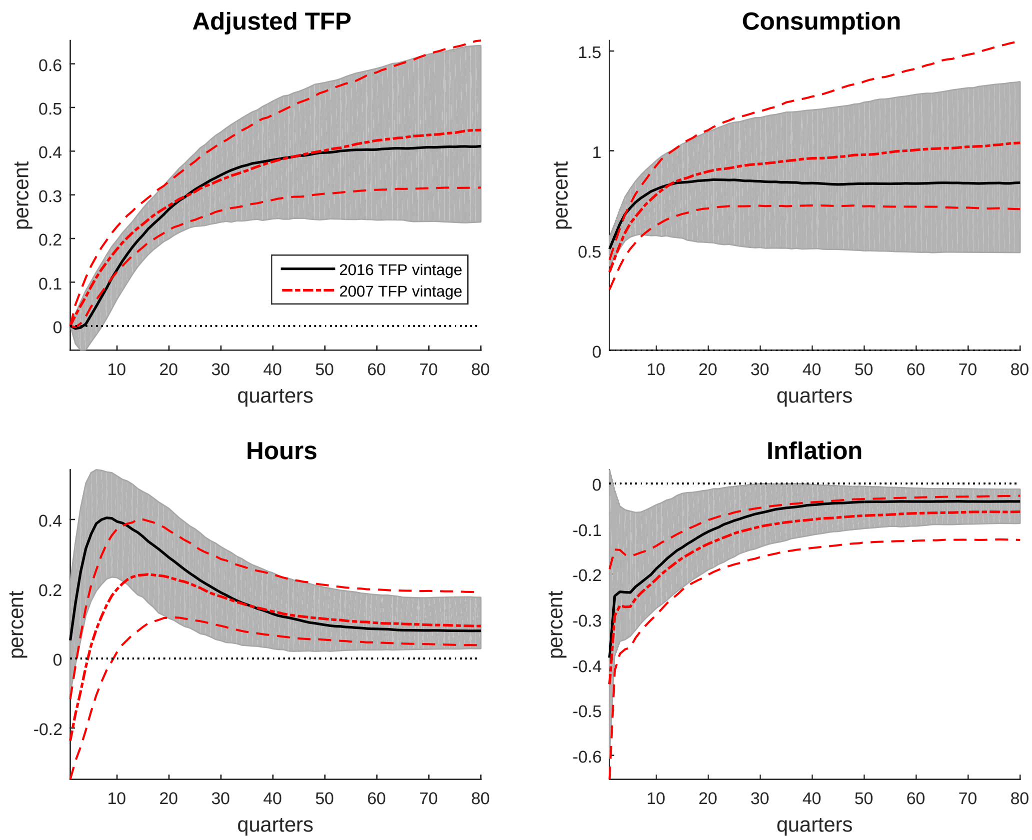
4.2 Results for a small VAR

We apply the Barsky-Sims identification strategy to a four-variable VAR. At the end of the paper, we present robustness checks with respect to larger VARs. The variables included in the VAR are Fernald's utilization-adjusted TFP series (either the 2007 or 2016 vintage), real personal consumption expenditures, total hours worked per capita in the non-farm business sector, and inflation as measured by the growth rate of the GDP price deflator. 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.[12] Confidence bands are computed by drawing from the resulting posterior distribution.The sample period is fixed at 1960q1-2007q3, which is the last period of available data for the 2007 vintage of adjusted TFP. As in Barsky and Sims (2011), the truncation horizon is set to $H = 40$.

Figure 2 presents impulse responses to a news shock using the Barsky and Sims (2011) identification strategy. The solid black lines are the posterior median estimates based on the VAR system with the 2016 vintage of adjusted TFP, and the gray bands are the corresponding 16 to 84 percent posterior coverage intervals. The red dash-dotted lines are the posterior median estimates for the system estimated with the 2007 vintage of adjusted TFP, and the red dashed lines are the corresponding 16 to 84 percent posterior coverage intervals.

[12] 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.

Figure 2: Empirical Responses, BS Identification, 2007 vs. 2016 Vintage of Adjusted TFP



Notes: Solid black lines are the posterior median estimates from the VAR system estimated with the 2016 vintage of adjusted TFP. The gray bands correspond to the 16 to 84 percent posterior coverage intervals. The red dash-dotted lines are the posterior median estimates for the system estimated with the 2007 vintage of adjusted TFP. The red dashed lines correspond to the 16 to 84 percent posterior coverage intervals. The impulse responses are identified using the BS identification.

Using the 2007 vintage of adjusted TFP, the responses are similar to those estimated by Barsky and Sims (2011). Adjusted TFP slowly grows, consumption jumps up on impact, inflation falls significantly, and hours worked initially declines for several periods before turning positive after several quarters. Because of the impact decline in hours, Barsky and Sims (2011) conclude that news shocks cannot be a major driving force behind the business cycle. Qualitatively, at least, the impact decline in hours worked is consistent with the predictions of a relatively frictionless real business cycle model.

While the point estimates of the responses of adjusted TFP, consumption, and inflation are fairly similar across the two different vintages, the response of hours is quite different in an economically meaningful way when the VAR is estimated with the 2016 vintage of adjusted TFP data. Hours worked now increases on impact and reaches a peak positive response only a few quarters after the shock. This difference relative to the response of hours with the 2007 vintage of adjusted TFP is economically meaningful because it (i) suggests that news shock might generate positive business cycle co-movement, and therefore could be an important contributor to business cycles, and (ii) suggests a different class of structural economic models which might be consistent with this pattern of responses. Furthermore, the impact decline in inflation is statistically insignificant when using the 2016 vintage of the adjusted TFP series. Barsky, Basu, and Lee (2015) cite the deflationary impact of a news shock as one of the most robust features of the data. This is no longer true with the 2016 vintage of the adjusted TFP series.

5 An Alternative Identification of News Shocks

An apparently innocuous change in the construction of the utilization series significantly alters the unconditional moments of the Fernald's utilization-adjusted TFP series and leads to substantial differences in the estimated response to a news shock as identified by Barsky and Sims (2011). In this section, we propose an alternative identification of news shocks that turns out to provide consistent estimates of the responses to a news shock regardless of the vintage of adjusted TFP. We first motivate the alternative identification strategy and describe its implementation. Then, we present Monte Carlo simulations based on a medium-scale DSGE model to show that the proposed identification is more more robust to a variety of misspecifications than is the Barsky and Sims (2011) identification. Finally, we present results for the same data and VAR specification as above.

5.1 Motivation and implementation of alternative identification

An extensive empirical literature documents that new technologies diffuse slowly in an S-shaped pattern. See for example Griliches (1957), Mansfield (1961), Mansfield (1989), Gort and Klepper (1982) or Rogers (1995). According to Mansfield (1989), the time until half of potential adopters actually adopt a new technology varies between 5 and 15 years, depending on technology. This strongly contrasts with most of the business cycle literature, including much of the literature on news shocks, which typically models technology as a jump process where innovations lead to an immediate change of productivity to a new level that is either permanent or highly persistent. Exceptions to this practice are Rotemberg (2003)), Comin and Gertler (2006)), Comin and Hobijn (2010) or Comin, Gertler, and Santacreu (2009) who explicitly focus on the slow adoption of new technologies.

The alternative identification we propose takes the insights from this literature one step further. We posit – and verify later in our empirical application – that the slow dissemination of productivity-enhancing changes in technology, factor input quality and efficiency in allocation constitutes news because it leads to persistent and therefore predictable changes in productivity growth. We implement the identification of this news shock using similar VAR analytics as Barsky and Sims (2011) but with two important exceptions. The first is that we identify the news shock by maximizing its contribution to the variance share of adjusted TFP at one long horizon, as opposed to maximizing the sum of variance shares from 0 onward. In practice, this difference turns out to be relatively unimportant. Second, we drop the zero restriction that the news shock has no effect on adjusted TFP on impact. Or, put differently, in contrast to the majority of work on news shocks to date, we do not impose that the news shock is orthogonal with respect to the innovation in adjusted TFP.

Formally, our identification of a news shock is given by the solution to the following optimization problem:

$$\max_{\gamma} \quad \Omega_{1,2}(H) \tag{16}$$

$$\text{s.t.}$$

$$\gamma'\gamma = 1, \tag{17}$$

Where γ is a column belonging to an orthonormal rotation matrix of the Choleski factor of the reduced form. It is restricted to have unit length, but we do not restrict it to have a zero in its first entry, meaning that we allow the news shock to impact adjusted TFP immediately. Also, we maximize the variance share at one horizon, H, instead of over many horizons.

As discussed in the Introduction, our alternative identification approach has two potentially important advantages over the existing practice of identifying news shocks based on the zero impact restriction that TFP does not contemporaneously react to news shocks. First, the identification allows us to avoid taking a stand on whether productivity reacts only with a lag to news or not. Second, if adjusted TFP is for any reason an imperfect measure of cyclical variations in technology, then imposing a zero impact restriction could induce potentially significant bias into the estimated response, as suggested by the results above based on different vintages of Fernald's utilization-adjusted TFP series.

Our identification strategy is essentially the same as the "max share" identification proposed in Francis, Owyang, Roush, and DiCecio (2013). Our work differs in that we include a measure of adjusted TFP, rather than average labor productivity, in our VAR system. One advantage of using a measure of TFP rather than labor productivity is that non-technology shocks may affect labor productivity in the long run, as argued by Uhlig (2004). Moreover, labor productivity is presumably affected in more important ways by current business cycle conditions than adjusted TFP. This can lead to important differences in the impact response to a shock. Indeed, the VAR results by Francis, Owyang, Roush, and DiCecio (2013) indicate that in response to their long-run shock, labor productivity jumps immediately to what is essentially a new permanent level. This would suggest that productivity may indeed be modeled as a jump process as discussed above. Our results below show that if instead the identification is applied to TFP, the results suggest that technology is slowly diffusing, consistent with the empirical literature.

In the next subsection, we provide some Monte Carlo results which speak to the desirable properties of our proposed identification. In particular, we show that it likely performs better than Barsky and Sims (2011). We then turn to the data. When using our identification strategy in place of Barsky and Sims (2011), we find that the differences arising from using different vintages of adjusted TFP largely disappear. While it appears that technology diffuses slowly, we consistently find that hours worked decline on impact.

5.2 Monte Carlo results

For our Monte Carlo experiments, we consider a fairly standard medium scale New Keynesian DSGE model. The model is very similar to Christiano, Eichenbaum, and Evans (2005), Smets and Wouters (2007), and Justiniano, Primiceri, and Tambalotti (2010). It features monopolistic competition in both goods and labor markets, price and wage stickiness, and a number of other real frictions. We discuss only the key features of the model in the main body of the paper. The full set of equilibrium conditions in the model is given in Appendix A.

Abstracting from trend growth and price dispersion, the aggregate production function in the model is:

$$Y_t = A_t \left(u_t K_t\right)^{\alpha} L_t^{1-\alpha} - F, \tag{18}$$

where $F \geq 0$ is a fixed cost of production, K_t is physical capital, u_t is capital utilization, L_t is labor input, and Y_t is output. Although Fernald's empirical work allows for time-varying utilization of both capital and labor, in our model there is only utilization of capital. A_t is aggregate technology. We assume that log technology is the sum of a stationary and a permanent component:

$$\ln A_t = \ln S_t + \ln \Gamma_t, \tag{19}$$

where S_t is the stationary component of technology and Γ_t is the permanent component. The stationary component obeys an AR(1) process, and the permanent component an AR(1) process in the growth rate:

$$\ln S_t = \rho_S \ln S_{t-1} + s_S \varepsilon_{S,t}, \tag{20}$$

$$\ln \Gamma_t - \ln \Gamma_{t-1} = (1 - \rho_\Gamma) \ln g + \rho_\Gamma \left(\ln \Gamma_{t-1} - \ln \Gamma_{t-2}\right) + s_g \varepsilon_{g,t-q}. \tag{21}$$

In (20)-(21), the autoregressive parameters are restricted to lie between 0 and 1. The ϵ are innovations drawn from standard normal distributions, and the s parameters are standard deviations. g is the steady state gross growth rate of technology. The innovation for the permanent component of technology is observed by agents $q \geq 0$ periods prior to impacting the level of aggregate technology. In the news literature it is typically assumed that $q > 0$. However, even with $q = 0$, the process given in (21) embodies some elements of slow diffusion if $\rho_\Gamma > 0$. In particular, if $\rho_\Gamma > 0$, then a positive shock to the permanent component of technology today portends even larger increases in the level of technology in the future. In practice, we will assume that $\rho_\Gamma > 0$, so we will refer to a shock to the permanent component of technology as a news shock regardless of whether agents observe it in advance ($q > 0$) or not ($q = 0$).

We measure adjusted TFP in the model exactly as Fernald does in the data. In particular, the growth rate of model TFP is defined as:

$$\Delta \ln TFP_t^M = \Delta \ln Y_t - \omega_{L,t} \Delta \ln L_t - (1 - \omega_{L,t}) \Delta \ln K_t. \tag{22}$$

The growth rate of model adjusted TFP is then:

$$\Delta \ln TFP_t^{M,U} = \Delta \ln TFP_t^M - (1 - \omega_{L,t}) \Delta \ln u_t \tag{23}$$

Even if Y_t, L_t, K_t, and u_t are perfectly observed, there are nevertheless two potential incongruities between (23) and true technology in the model, (19). First, if the production function features a fixed cost then the construction of TFP is mis-specified. Second, $\omega_{L,t}$ and $1-\omega_{L,t}$ will in general not correspond to the true factor elasticities in the model. Firms have market-power in setting their prices, though they are not freely able to adjust price each period due to a Calvo friction. Nevertheless, each period firms will choose inputs to minimize cost. Cost-minimization implies the following:

$$w_t L_t = (1-\alpha)\mu_t^{-1} \left[Y_t - F \right]. \tag{24}$$

In (24), μ_t^{-1} is the inverse price markup over marginal cost. Because of monopoly power in price-setting, the average markup, μ^*, will be greater than 1. Though firms desire a constant markup, due to price stickiness the markup will be time-varying. Suppose that there is no fixed cost, i.e. $F = 0$. Then (24) can be written:

$$\omega_{L,t} = \frac{w_t L_t}{Y_t} = (1-\alpha)\mu_t^{-1}. \tag{25}$$

While the the construction of TFP is not mis-specified with respect to the true production function when there is no fixed cost, average labor share will not correspond to $1 - \alpha$ due to the markup of price over marginal cost. Furthermore, measured labor share will vary across time due to undesired fluctuations in the markup owing to price rigidity. Suppose instead that the model features a fixed cost, and that the size of this fixed cost is chosen to ensure zero profit in steady state, which is a standard assumption used in the literature. This requires that $F = Y^*(\mu^* - 1)$. In this case, (25) can be written:

$$\omega_{L,t} = \frac{w_t L_t}{Y_t} = (1-\alpha)\mu_t^{-1}\mu^*. \tag{26}$$

In this case, the average measured labor share will correspond to the factor elasticity $1-\alpha$. But measured labor share will still fluctuate over time due to undesired fluctuations in the markup owing to price rigidity. Furthermore, while on average the measured labor share will be correct, with the fixed cost the construction of TFP is now mis-specified with respect to the true production function.

Before turning to Monte Carlo experiments to assess the adequacy of our VAR identification procedure, we first investigate the extent to which these mis-specifications matter for Fernald's adjusted TFP series. The parameterization of the model is given in Table 1 of the Appendix. In addition to the two technology shocks, the model features two other shocks. The first is a shock to the marginal efficiency of investment. This demand shock is parameterized to account for the majority of short run fluctuations in output, as in Justiniano et al. (2010). The second is a shock to the disutility from labor, and is isomorphic to the wage markup shock in Smets and Wouters (2007).

Table 4 presents correlations of the log first differences of true productivity in the model, $\Delta \ln A_t$, with Fernald's adjusted TFP series, $\Delta \ln TFP_t^{M,U}$, and a conventional measure of TFP, $\Delta \ln TFP_t^{M}$. The upper panel considers our baseline parameterization. In spite of the obvious measurement issues in the model related to Fernald's approach, the adjusted TFP series is almost perfectly correlated with true technology whether a fixed cost is included in the model or not. Measured TFP is less positively correlated with true technology. This is primarily due to fluctuations in utilization. Conventional TFP and adjusted TFP are positively correlated with one another, with a correlation coefficient of about 0.9. This is close to the correlation between the 2007 vintages of adjusted and conventional TFP in Fernald's data, which is 0.8. The correlation between the adjusted and conventional TFP series in the 2016 vintage is much lower, however, at 0.4.

Table 4: Correlations Between True and Empirical Productivity Measures

	Baseline		
	Corr $\Delta \ln A_t$, $\Delta \ln TFP_t^{M,U}$	Corr $\Delta \ln A_t$, $\Delta \ln TFP_t^{M}$	Corr $\Delta \ln TFP_t^{M,U}$, $\Delta \ln TFP_t^{M}$
No fixed cost	0.9996	0.8959	0.9022
Fixed cost	0.9947	0.9114	0.9422
	Low utilization cost, $\delta_2 = 0.00025$		
	Corr $\Delta \ln A_t$, $\Delta \ln TFP_t^{M,U}$	Corr $\Delta \ln A_t$, $\Delta \ln TFP_t^{M}$	Corr $\Delta \ln TFP_t^{M,U}$, $\Delta \ln TFP_t^{M}$
No fixed cost	0.9991	0.7688	0.7485
Fixed cost	0.9935	0.8031	0.8536
	Very sticky prices, $\theta_p = 0.90$		
	Corr $\Delta \ln A_t$, $\Delta \ln TFP_t^{M,U}$	Corr $\Delta \ln A_t$, $\Delta \ln TFP_t^{M}$	Corr $\Delta \ln TFP_t^{M,U}$, $\Delta \ln TFP_t^{M}$
No fixed cost	0.9996	0.8710	0.8774
Fixed cost	0.9933	0.8863	0.9255
	Very sticky wages, $\theta_w = 0.90$		
	Corr $\Delta \ln A_t$, $\Delta \ln TFP_t^{M,U}$	Corr $\Delta \ln A_t$, $\Delta \ln TFP_t^{M}$	Corr $\Delta \ln TFP_t^{M,U}$, $\Delta \ln TFP_t^{M}$
No fixed cost	0.9997	0.8792	0.8874
Fixed cost	0.9929	0.8968	0.9363
	Higher steady state markups, $\epsilon_p = \epsilon_w = 6$		
	Corr $\Delta \ln A_t$, $\Delta \ln TFP_t^{M,U}$	Corr $\Delta \ln A_t$, $\Delta \ln TFP_t^{M}$	Corr $\Delta \ln TFP_t^{M,U}$, $\Delta \ln TFP_t^{M}$
No fixed cost	0.9976	0.8601	0.8771
Fixed cost	0.9808	0.8844	0.9479

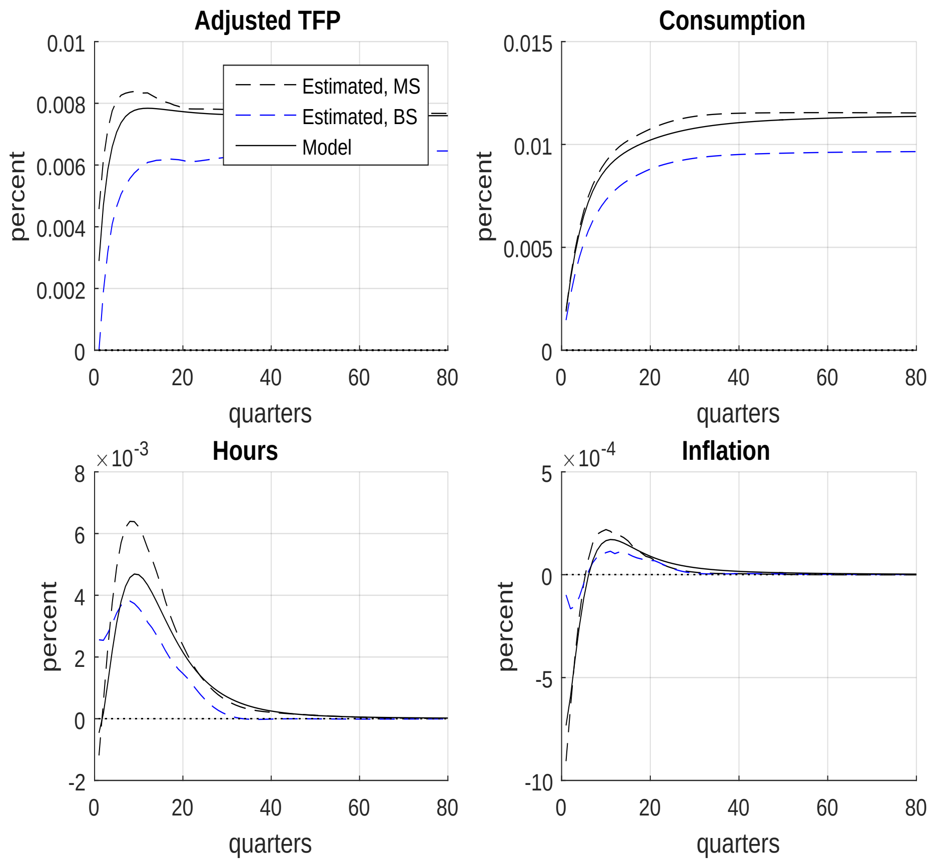
Notes: This table shows correlations of different measures of productivity from the solution of the medium scale DSGE model laid out in the text. $\Delta \ln A_t$ refers to the log first difference of true technology in the model, $\Delta \ln TFP_t^{M,U}$ refers to the log first difference of utilization-adjusted TFP as measured in the model, and $\Delta \ln TFP_t^{M}$ refers to the log first difference of TFP as measured in the model.

Our results hold qualitatively in several alternative parameterizations of the model – adjusted TFP is close to perfectly correlated with true technology regardless of parameter values and regardless of whether the model features a fixed cost of production or not. When utilization is less costly, the correlation between conventional TFP and true technology is lower. This is also true when prices or wages are stickier, which arises because factor utilization reacts more to non-technology shocks, driving a larger wedge between true and measured TFP. Nevertheless, our Monte Carlo experiments suggest that, in spite of the fact the assumptions underlying its construction are violated in a canonical macro model, Fernald's adjusted TFP series ought to be very close to true technology in the model, provided utilization and other factors are measured appropriately.

We next turn to Monte Carlo experiments designed to assess the adequacy of our proposed identification procedure, particular as it relates to Barsky and Sims (2011). Our experiments are conducted as follows. We simulate 100,000 periods of data from the model using the parameter values listed in Table 1. For these simulations, we assume that the model features a fixed cost of production, but our results are similar whether there is a fixed cost or not. From the simulation, we recover simulated time series of adjusted TFP, consumption, inflation, and hours worked. These are the same series we use in the empirical VAR from the previous section. On this one long data set, we estimate a VAR with twenty lags. The high lag order is meant to diminish any role of the so-called "lag-truncation bias" arising when estimating VARs on data generated from linearized DSGE models. Our results are nevertheless qualitatively similar with a much smaller number of lags. We then identify a news shock using either our identification procedure (which we label "MS" for max-share) or Barsky and Sims (2011), which we label "BS." In the figures below, solid lines correspond to the true impulse response to a news shock in the model. Dashed black lines are the estimated response from our max-share identification, while dashed blue lines are the responses under the Barsky and Sims (2011) identification. In the panel labeled "Adjusted TFP," the solid line corresponds to the response of true technology in the model, while the dashed black and blue lines are responses of observed adjusted TFP from the Monte Carlo simulations.

We first consider a case in which $q = 0$, but $\rho_\Gamma = 0.6$. This means that the news shock portends future increases in technology which do not immediately materialize, but that the news shock does affect technology contemporaneously. Model and estimated response from model-generated data are shown in Figure 3. In the model, consumption increases, while hours and inflation decline on impact. The max-share identification captures these features well. The Barsky and Sims (2011) identification, which imposes orthogonality between the news shock and current adjusted TFP, performs considerably worse. This should not be particularly surprising, as the assumption of impact orthogonality is inconsistent with the structure of the model. The Barsky and Sims (2011) identification gets the sign of the impact response of hours incorrect and delivers little or no response of inflation. The Barsky and Sims (2011) identification also results in downward-biased estimates of the responses of adjusted TFP and consumption at long horizons. While the max-share identification is not perfect, qualitatively it generates the correct pattern of responses and performs much better than Barsky and Sims (2011).

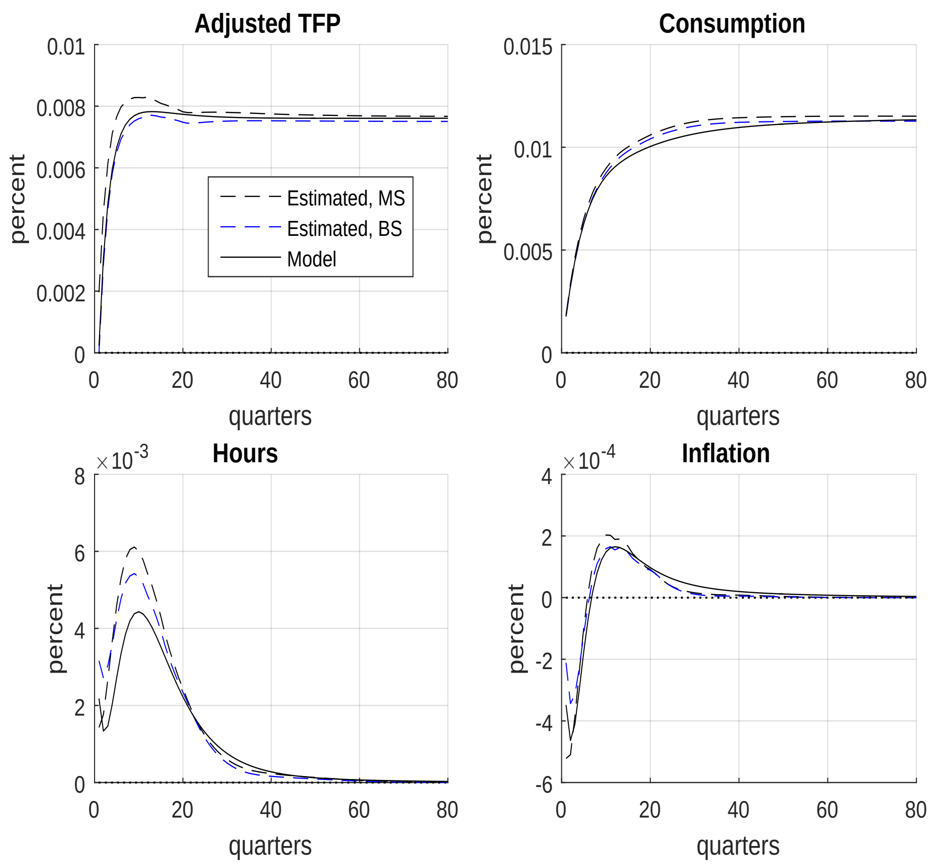
Figure 3: Model and Estimated Responses to a News Shock



Notes: Solid lines are the true impulse responses to an estimated growth shock in the model. The dashed black lines are the estimated responses using the max share identification at a 80 quarter horizon, without imposing impact orthogonality. This is labeled "MS" for "Max Share." The dashed blue lines are the estimated responses using the BS identification with a 40 quarter truncation horizon, imposing impact orthogonality between the identified shock an adjusted TFP. This is labeled "BS".

Next, we continue to assume that $\rho_\Gamma = 0.6$, but now set $q = 1$. This means that agents in the economy observe the news shock one period in advance of it impacting technology. In this situation, impact orthogonality between the news shock and technology is satisfied in the model. Figure 4 plots true model and estimated responses from both our max-share identification and the BS identification. Qualitatively, while the BS identification performs better than when $q = 0$, it is not obviously better than the max-share identification which does not impose impact orthogonality. The max-share identification does a better job at estimating the impact response of hours, and also does a better job of estimating the impact decline in inflation than does the BS identification.

Figure 4: Model and Estimated Responses to a News Shock with a One Period Lag



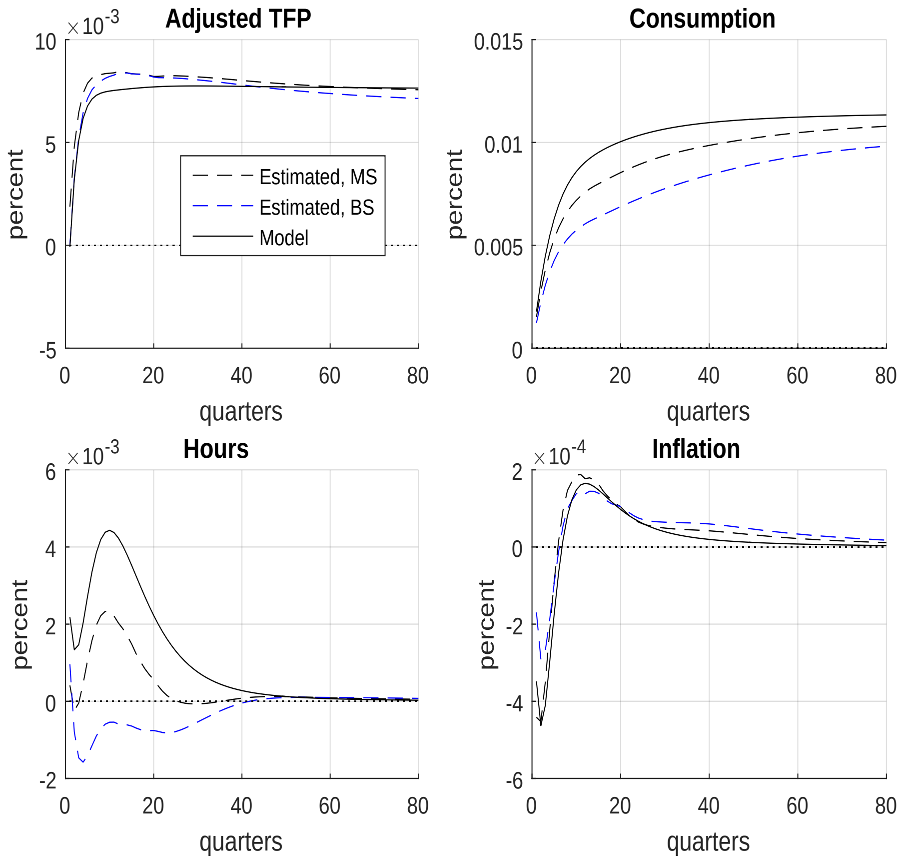
Notes: Solid lines are the true impulse responses to an estimated growth shock which affects technology with a one period lag in the model. The dashed black lines are the estimated responses using the max share identification at a 80 quarter horizon, without imposing impact orthogonality. This is labeled "MS" for "Max Share." The dashed blue lines are the estimated responses using the BS identification with a 40 quarter truncation horizon, imposing impact orthogonality between the identified shock an adjusted TFP. This is labeled "BS".

We next consider a specification in which observed utilization is measured incorrectly. This incorrect measurement of utilization therefore impacts the time series of adjusted TFP. In particular, we assume that measured utilization is simply proportional to measured hours work:

$$\ln u_t^{ob} = \varphi \left[\ln L_t - \ln L^*\right]. \tag{27}$$

We use this mis-measured utilization series to construct an adjusted TFP series in the model. For the simulation, we use a value of $\varphi = 1.5$. We continue to assume that $q = 1$, so that the impact orthogonality restriction from Barsky and Sims (2011) would be valid if one appropriately measured adjusted TFP. Impulse responses obtained in the model as well as on simulated data are shown in Figure 5.

Figure 5: Model and Estimated Responses to a News Shock with a One Period Lag, Mis-Measured Utilization



Notes: Solid lines are the true impulse responses to an estimated growth shock which affects technology with a two period lag in the model. The dashed black lines are the estimated responses using the max share identification at a 80 quarter horizon, without imposing impact orthogonality. This is labeled "MS" for "Max Share." The dashed blue lines are the estimated responses using the BS identification with a 40 quarter truncation horizon, imposing impact orthogonality between the identified shock an adjusted TFP. This is labeled "BS".

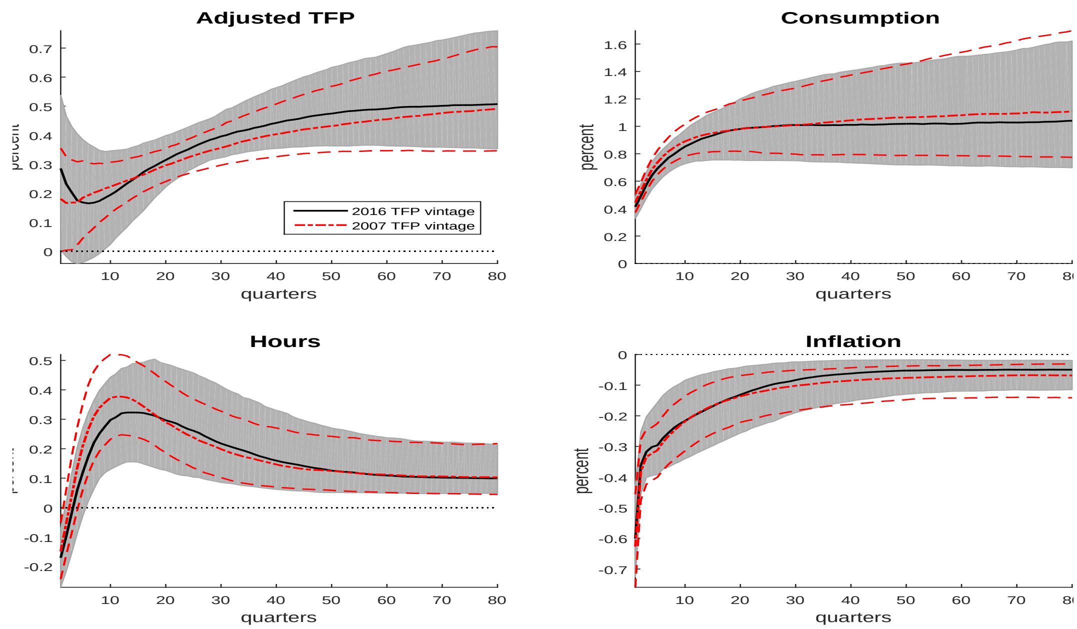
The mis-measurement of utilization does not impact the impulse responses of variables in the model, but it does impact the responses obtained from estimating a VAR on data simulated from the model. Relative to the case where utilization is observed perfectly, both the MS and BS identification perform worse. However, the BS identification seems to perform significantly worse than the MS identification, even though the impact orthogonality restriction which differentiates the two approaches is theoretically satisfied in the model. In particular, the BS identification generates a persistent decline in hours worked and underestimates the impact decline in inflation. The MS identification, in contrast, generates the correct sign and shape of the hours response, and almost perfectly matches the inflation response, both on impact and at longer forecast horizons. Furthermore, while both identifications underestimate the response of consumption at most forecast horizons, the bias is substantially larger for the BS approach.

We conclude from these Monte Carlo exercises that our proposed identification performs well at qualitatively recovering the impulse responses to a news shock. It performs significantly better than the BS identification if impact orthogonality between news and technology is not satisfied in the model. Even if this restriction is satisfied in the model, our identification continues to perform well. When utilization is perfectly observed and the news shock is orthogonal to technology on impact, both approaches perform well at capturing the dynamic responses of hours, inflation, and consumption. It utilization is measured incorrectly, in contrast, the MS approach may perform significantly better than the BS approach, even when impact orthogonality is consistent with the underlying model. This is because, if utilization is measured incorrectly, a news shock may not be orthogonal to measured adjusted TFP, even if it is with respect to true technology. Imposing this orthogonality on imperfectly measured adjusted TFP can therefore create more problems than it solves. We conclude from these Monte Carlo exercises that there is little to gain from imposing impact orthogonality in the identification of the news shock, while the costs of doing so could be large.

5.3 Results for small VAR

Having established the good properties of our proposed empirical identification, we next implement this identification on actual data. The data used in this empirical exercise are the same as in Section 3. The estimated responses for VAR systems estimate with both the 2007 and 2016 vintages of the adjusted TFP series are shown in Figure 6. Solid lines are responses when the 2016 vintage of adjusted TFP is included in the VAR, while dash-dotted red lines are responses when using the 2007 vintage of adjusted TFP.

Figure 6: Empirical Responses, Alternative Identification, 2007 vs. 2016 Vintage of Adjusted TFP



Notes: Solid black lines are the posterior median estimates from the VAR system estimated with the 2016 vintage of adjusted TFP. The gray bands correspond to the 16 to 84 percent posterior coverage intervals. The red dash-dotted lines are the posterior median estimates for the system estimated with the 2007 vintage of adjusted TFP. The red dashed lines correspond to the 16 to 84 percent posterior coverage intervals. The shock is identified using our alternative identification, which does not impose impact orthogonality between the news shock and adjusted TFP. The shock is identified as the structural shock which maximizes the variance share of adjusted TFP at a 80 quarter horizon.

There are several notable features evident in Figure 6. First, although our identification does not impose impact orthogonality, the estimated response of adjusted TFP to a news shock is slow and protracted, with the the estimated long run response of adjusted TFP two to three times larger than the impact response. This is true regardless of the vintage of adjusted TFP. Thus, a "news" interpretation of the response to the identified shock seems natural.

Second, there is very little difference in the responses when estimating the VAR using the 2007 vintage compared to the 2016 vintage of the adjusted TFP series, which is very different than when using the Barsky and Sims (2011) identification. Hours worked declines on impact before turning positive after several quarters. Inflation falls on impact. The impact decline in inflation is statistically significant when estimate the VAR on either vintage of adjusted TFP data, unlike the Barsky and Sims (2011) identification.

Third, the estimated responses are quite similar to the theoretical response to a news shock (when $q = 0$)

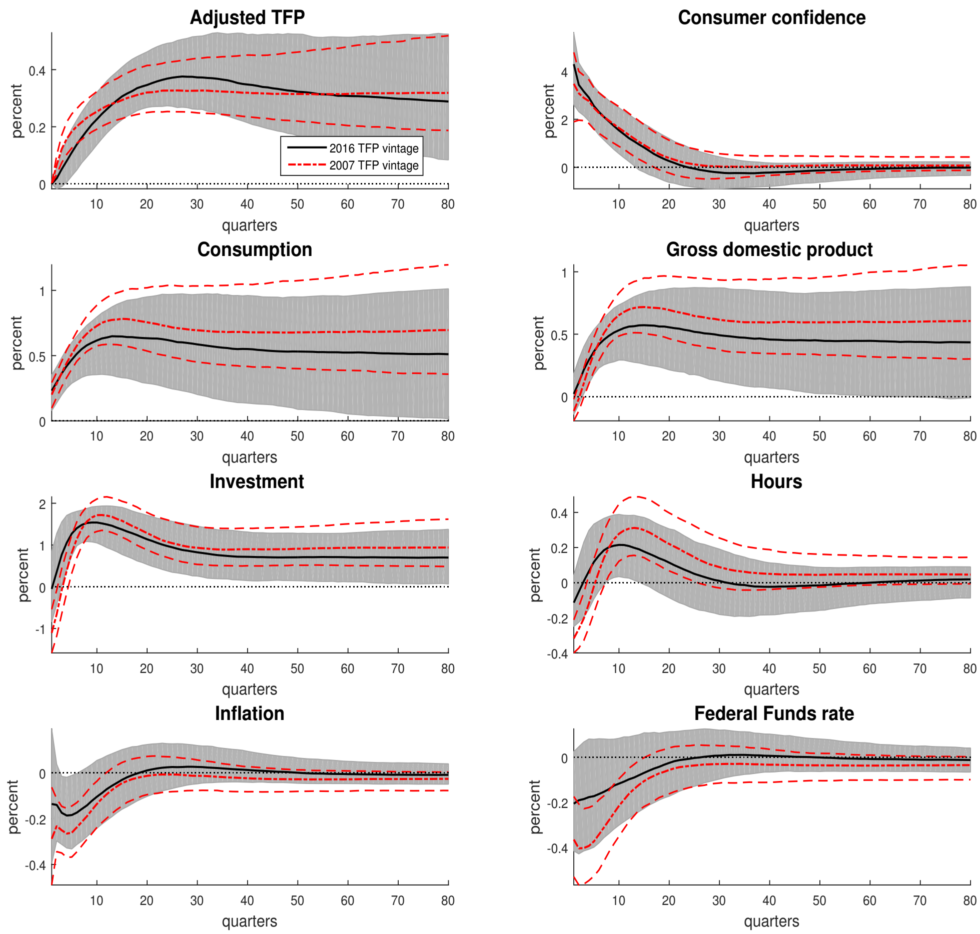
in our medium scale model, which can be seen by comparing Figure 6 to the solid lines in Figure 3. This in spite of the fact that the parameterization of the model is taken from the literature, rather than being chosen to force the model produce impulse responses similar to what we observe in the data. In both model and data, adjusted TFP jumps up slightly on impact and continues to grow for several quarters thereafter. Consumption follows a similar path. Hours worked declines on impact before turning positive, and inflation falls significantly. Qualitatively, these responses are similar to those estimated in Barsky and Sims (2011), even with the most recent vintage of the adjusted TFP data.

6 Results in Larger VARs

A natural extension is to examine how robust these results are to higher dimensional VAR systems. To that end, we estimate a larger VAR system with eight variables. In addition to the four variables in our baseline VAR, we include real GDP, real investment, the Federal Funds Rate, and a survey measure of consumer confidence. This is similar to the larger dimensional system in Barsky and Sims (2011).

To illustrate how the different vintage of adjusted TFP might matter, we first consider the BS identification, choosing the news shock to the be shock orthogonal to adjusted TFP on impact which maximizes the sum of variance shares to adjusted TFP from impact to 40 quarters. Like in the four variable VAR, there are important differences between the estimated response depending on which vintage of adjusted TFP data one uses. With the 2007 vintage of data, output, investment, and hours all decline on impact in response to a favorable news shock. Inflation falls significantly, as does the Federal Funds Rate. With the 2016 vintage of data, output and investment increase on impact, and the impact decline in hours is significantly smaller than with the 2007 vintage of adjusted TFP. The impact declines in inflation and the Federal Funds Rate are smaller with the 2016 vintage of data compared to the 2007 vintage, and cease to be statistically significant.

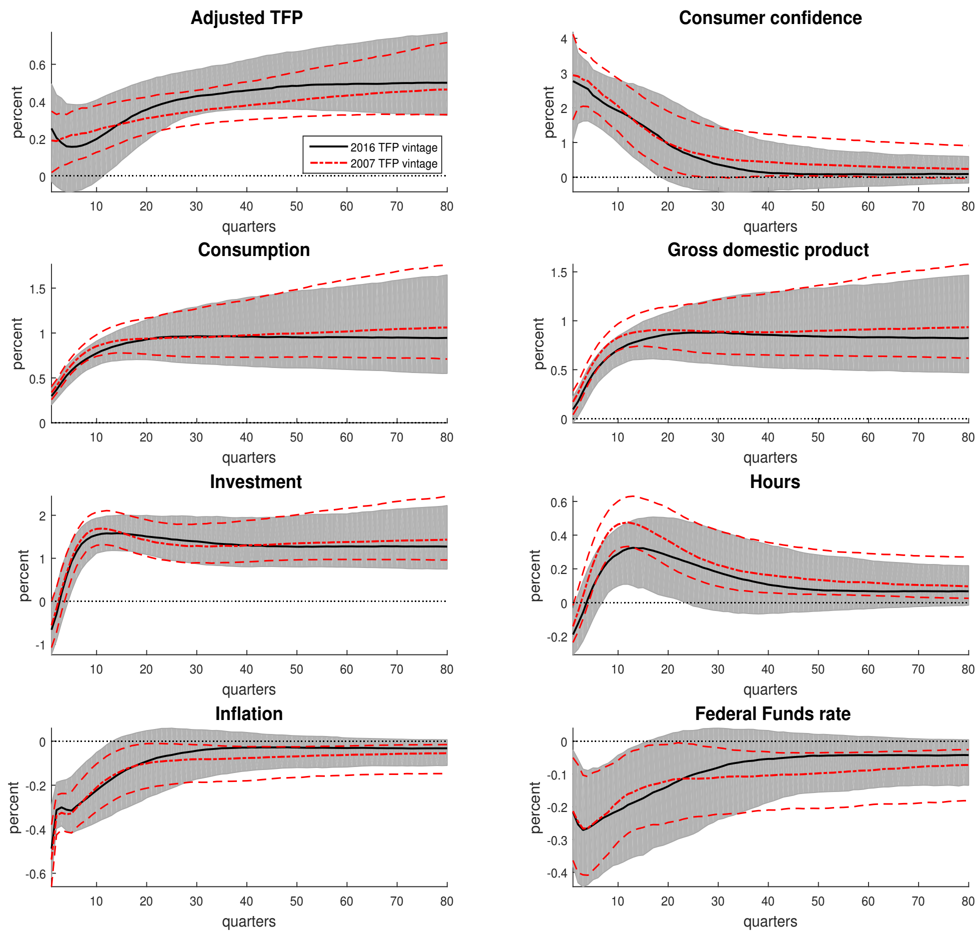
Figure 7: Empirical Responses, BS Identification, Eight Variable VAR, 2007 vs. 2016 Vintage of Adjusted TFP



Notes: Solid black lines are the posterior median estimates from the VAR system estimated with the 2016 vintage of adjusted TFP. The gray bands correspond to the 16 to 84 percent posterior coverage intervals. The red dash-dotted lines are the posterior median estimates for the system estimated with the 2007 vintage of adjusted TFP. The red dashed lines correspond to the 16 to 84 percent posterior coverage intervals. The impulse responses are identified using the BS identification.

Figure 8 repeats this exercise, but uses our alternative identification, which does not impose impact orthgonality between the news shock and adjusted TFP and which maximizes the variance share due to news at a 80 quarter horizon. As in Figure 6, and unlike what is shown in Figure 7, the estimated responses are much more similar for the two different vintages of the adjusted TFP series. Investment and hours decline on impact, while output rises slightly (albeit insignificantly). Furthermore, inflation and the Funds rate decline significantly on impact with both vintages.

Figure 8: Empirical Responses, Alternative Identification, Eight Variable VAR, 2007 vs. 2016 Vintage of Adjusted TFP



Notes: Solid black lines are the posterior median estimates from the VAR system estimated with the 2016 vintage of adjusted TFP. The gray bands correspond to the 16 to 84 percent posterior coverage intervals. The red dash-dotted lines are the posterior median estimates for the system estimated with the 2007 vintage of adjusted TFP. The red dashed lines correspond to the 16 to 84 percent posterior coverage intervals. The impulse responses are identified using the BS identification.

Our proposed identification of news shock, which differs primarily from Barsky and Sims (2011) in not imposing impact orthogonality between the news shock and adjusted TFP, delivers consistent, robust results regardless of the vintage of the adjusted TFP series. This is true in both a small and larger dimensional VAR system. We find that hours worked and investment decline on impact, as do inflation and the Federal Funds rate. In contrast, consumption and consumer confidence increase. As such, news shocks are unlikely to be a major driver of business cycle dynamics. Furthermore, our estimated responses are broadly consistent with the theoretical responses to a news shock in a conventionally specified medium scale DSGE model.

7 Conclusion

An almost universally imposed assumption in the empirical literature on news shocks is that a news shock impacts productivity only with a delay. This assumption is not necessarily consistent with a broader view of slow technology adoption, and may be violated empirically if one's measure of productivity does not perfectly align with true technology.

In this paper, we have proposed an alternative identification of news shocks which does not impose that a news shock have no impact effect on productivity. We have shown that our procedure performs well in a Monte Carlo experiment, and is more robust to misspecifications with respect to the data generating process than an identification assumption which imposes impact orthogonality between a news shock and productivity. Applied to the data, we find that the estimated response of a measure of utilization-adjusted TFP to our shock is consistent with a news interpretation – measured TFP increases slowly and with a significant lag. Hours worked declines on impact, while consumption rises. Inflation and the Fed Funds rate significantly decline in response to good news. These results are robust to using different vintages of Fernald (2014)'s popular utilization-adjusted TFP series, which is not the case with the Barsky and Sims (2011) identification approach which imposes impact orthogonality between news and TFP.

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A A Medium Scale DSGE Model

For the Monte Carlo experiments considered in the paper, we use as a laboratory a conventionally specified medium scale DSGE model. The model features sticky prices and wages, capital accumulation, habit formation in consumption, an investment adjustment cost, variable capital utilization, and a central bank which implements monetary policy according to a Taylor rule. The model is very similar to Christiano, Eichenbaum, and Evans (2005), Smets and Wouters (2007), and Justiniano, Primiceri, and Tambalotti (2010). As such, we only list the full set of equilibrium conditions here, rather than fully laying out the decision problems of each type of agent in the model.

The full set of equilibrium conditions are listed below. A brief discussion of each expression follows.

$$\lambda_t = (C_t - bC_{t-1})^{-1} - \beta b E_t (C_{t+1} - bC_t)^{-1} \tag{A.1}$$

$$\lambda_t = \beta(1+i_t)E_t\lambda_{t+1}(1+\pi_{t+1})^{-1} \tag{A.2}$$

$$\lambda_t R_t = \xi_t(\delta_1 + \delta_2(u_t - 1)) \tag{A.3}$$

$$\xi_t = \beta E_t\left[\lambda_{t+1}R_{t+1}u_{t+1} + (1-\delta(u_{t+1}))\xi_{t+1}\right] \tag{A.4}$$

$$\lambda_t = \xi_t Z_t \left[1 - \frac{\kappa}{2}\left(\frac{I_t}{I_{t-1}} - g_I\right) - \kappa\left(\frac{I_t}{I_{t-1}} - g_I\right)\frac{I_t}{I_{t-1}}\right] + \beta E_t \xi_{t+1} Z_{t+1}\kappa\left(\frac{I_{t+1}}{I_t} - g_I\right)\left(\frac{I_{t+1}}{I_t}\right)^2 \tag{A.5}$$

$$w_t^{\#} = \frac{\epsilon_w}{\epsilon_w - 1}\frac{f_{1,t}}{f_{2,t}} \tag{A.6}$$

$$f_{1,t} = \varphi_t \psi \left(\frac{w_t}{w_t^{\#}}\right)^{\epsilon_w(1+\chi)} L_t^{1+\chi} + \beta\theta_w E_t \left(\frac{w_{t+1}^{\#}}{w_t^{\#}}\right)^{\epsilon_w(1+\chi)} \left(\frac{(1+\pi_t)^{\zeta_w}}{1+\pi_{t+1}}\right)^{-\epsilon_w(1+\chi)} f_{1,t+1} \tag{A.7}$$

$$f_{2,t} = \lambda_t \left(\frac{w_t}{w_t^{\#}}\right)^{\epsilon_w} L_t + \beta\theta_w E_t \left(\frac{w_{t+1}^{\#}}{w_t^{\#}}\right)^{\epsilon_w} \left(\frac{(1+\pi_t)^{\zeta_w}}{1+\pi_{t+1}}\right)^{1-\epsilon_w} f_{2,t+1} \tag{A.8}$$

$$R_t = \alpha mc_t A_t \widetilde{K}_t^{\alpha-1} N_t^{1-\alpha} \tag{A.9}$$

$$w_t = (1-\alpha)mc_t A_t \widetilde{K}_t^{\alpha} N_t^{-\alpha} \tag{A.10}$$

$$\frac{1+\pi_t^{\#}}{1+\pi_t} = \frac{\epsilon_p}{\epsilon_p - 1}\frac{x_{1,t}}{x_{2,t}} \tag{A.11}$$

$$x_{1,t} = \lambda_t mc_t Y_t + \beta\theta_p E_t(1+\pi_t)^{-\zeta_p\epsilon_p}(1+\pi_{t+1})^{\epsilon_p} x_{1,t+1} \tag{A.12}$$

$$x_{2,t} = \lambda_t Y_t + \beta\theta_p(1+\pi_t)^{\zeta_p(1-\epsilon_p)}E_t(1+\pi_{t+1})^{\epsilon_p - 1}x_{2,t+1} \tag{A.13}$$

$$Y_t v_t^p = A_t \widetilde{K}_t^{\alpha} L_t^{1-\alpha} - X_t F \tag{A.14}$$

$$v_t^p = (1+\pi_t)^{\epsilon_p}\left((1-\theta_p)(1+\pi_t^{\#})^{-\epsilon_p} + \theta_p(1+\pi_{t-1})^{-\epsilon_p\zeta_p}v_{t-1}^p\right) \tag{A.15}$$

$$K_{t+1} = Z_t\left[1 - \frac{\kappa}{2}\left(\frac{I_t}{I_{t-1}} - g_I\right)^2\right] I_t + (1-\delta(u_t))K_t \tag{A.16}$$

$$\delta(u_t) = \delta_0 + \delta_1(u_t - 1) + \frac{\delta_2}{2}(u_t - 1)^2 \tag{A.17}$$

$$Y_t = C_t + I_t \tag{A.18}$$

$$\widetilde{K}_t = u_t K_t \tag{A.19}$$

$$(1+\pi_t)^{1-\epsilon_p} = (1-\theta_p)(1+\pi_t^{\#})^{1-\epsilon_p} + \theta_p(1+\pi_{t-1})^{\zeta_p(1-\epsilon_p)} \tag{A.20}$$

$$w_t^{1-\epsilon_w} = (1-\theta_w)w_t^{\#,1-\epsilon_w} + \theta_w\left(\frac{(1+\pi_{t-1})^{\zeta_w}}{1+\pi_t}w_{t-1}\right)^{1-\epsilon_w} \tag{A.21}$$

$$i_t = (1-\rho_i)i + \rho_i i_{t-1} + (1-\rho_i)\left[\phi_\pi(\pi_t - \pi_t^*) + \phi_y(\ln Y_t - \ln Y_{t-1} - \ln g_Y)\right] \tag{A.22}$$

$$\ln Z_t = \rho_Z \ln Z_{t-1} + s_Z \varepsilon_{z,t} \tag{A.23}$$

$$\ln \varphi_t = \rho_\varphi \ln \varphi_{t-1} + s_\varphi \varepsilon_{\varphi,t} \tag{A.24}$$

$$\ln S_t = \rho_S \ln S_{t-1} + s_S \varepsilon_{S,t} \tag{A.25}$$

$$\ln \Gamma_t - \ln \Gamma_{t-1} = (1-\rho_\Gamma)\ln g + \rho_\Gamma\left(\ln \Gamma_{t-1} - \ln \Gamma_{t-2}\right) + s_g \varepsilon_{g,t-q} \tag{A.26}$$

$$\mu_t = mc_t^{-1} \tag{A.27}$$

$$A_t = S_t \Gamma_t \tag{A.28}$$

In these equations λ_t is the Lagrange multiplier on the flow budget constraint of a household and ξ_t is the Lagrange multiplier on the capital accumulation equation. C_t denotes consumption, Y_t output, I_t investment, K_t physical capital, and L_t aggregate labor input. w_t is the aggregate real wage, and R_t is the real rental rate on capital services. u_t denotes capital utilization, with $\widetilde{K}_t = u_t K_t$ denoting capital services. π_t is the net inflation rate and i_t is the net nominal interest rate. v_t^p is a measure of price dispersion across firms. $w_t^{\#}$ is the reset real wage for a household given the opportunity to adjust its wage in a given period, while $\pi_t^{\#}$ is the reset inflation rate for firms given the opportunity to adjust their price. $f_{1,t}$ and $f_{2,t}$ are auxiliary variables related to optimal wage-setting, and $x_{1,t}$ and $x_{2,t}$ are auxiliary variables related to price-setting. mc_t is real marginal cost, the inverse of which is the price markup, μ_t. S_t is a stationary technology shock, while Γ_t is a non-stationary technology. A_t is technology, which is the product of these two terms. Z_t is a shock to the marginal efficiency of investment and φ_t is a shock to the disutility from labor. X_t is a trend factor, to be discussed below. g_I is the steady state gross growth rate of investment, and g_Y is the steady state gross growth rate of output.

(A.1) defines λ_t, the shadow value on the flow budget constraint facing a household. The parameter b measures internal habit formation and β is a discount factor. (A.2) is the Euler equation for bonds, which prices the nominal interest rate, i_t. (A.3) is the first order condition for capital utilization. The cost of capital utilization is faster depreciation of capital, which is governed by (A.17). δ_0 is the steady state depreciation rate, while δ_1 and δ_2 are parameters governing the linear and quadratic terms of the utilization adjustment cost function. The optimality condition for the choice of future capital is given by (A.4), while the first order condition for investment is given by (A.5). An investment adjustment cost is captured by the parameter κ. Each period, there is a $1-\theta_w$ probability that a household can adjust its wage. Optimal wage-setting for updating households is characterized by (A.6)-(A.8). ϵ_w is a parameter governing how much market power a household has in setting its wage, χ is the inverse Frisch labor supply elasticity, and ψ is a fixed parameter governing the disutility from labor. ζ_w is measures how much non-updated wages may be indexed to lagged inflation.

Cost-minimization by firms gives rise to factor demand curves for capital and labor in (A.9)-(A.10). α is the exponent on capital services in the production function, with $1-\alpha$ the exponent on labor. Because firms face the same factor prices, they all have the same real marginal cost and hire capital and labor in the same ratio. Each period, firms face a $1-\theta_p$ probability of being able to adjust their price. Optimal price-setting for updating firms is characterized by (A.11)-(A.13). ϵ_p measures the extent of monopoly power in price-setting. ζ_p is a parameter measuring how much non-updated prices are indexed to lagged inflation. The aggregate production function is given by (A.14). F is a fixed cost of production, scaled by X_t, which measures the economy's trend growth. v_t^p is a measure of price dispersion, the evolution of which is given by (A.15).

Physical capital accumulates according to the law of motion given in (A.16). The aggregate resource constraint is given by (A.18). The evolution of inflation and the aggregate real wage are governed by (A.20) and (A.21), respectively. Monetary policy is governed by a Taylor rule, (A.22), which features interest rate smoothing governed by the parameter of rho_i, a reaction of inflation, ϕ_π to deviations from a long run target, π^*, and a reaction to deviations of output growth from its steady state level, ϕ_y. The exogenous processes for the marginal efficiency of investment shock, the labor supply preference shock, and the stationary technology shock are given by (A.23)-(A.25). Each follows a stationary AR(1) process with steady state levels normalized to unity. The permanent productivity process is a stationary AR(1) in the growth rate and is given by (A.26). g denotes the steady state growth rate. The innovation is dated $t-s$, for $q \geq 0$. $q=0$ means that the technology improvement materializes immediately. $q>0$ means that agents observe the shock before it impacts productivity. The price markup is defined as the inverse of real marginal cost in (A.27), and composite technology is the composite of the stationary and non-stationary terms, given in (A.28).

Many of the variables in the model inherit the stochastic trend from Γ_t. It is straightforward to show that the stochastic trend factor is $X_t = \Gamma_t^{\frac{1}{1-\alpha}}$. Re-scaling trending variables by this factor renders the model stationary, and permits solution of the model using standard techniques. We solve the model via linearization about the non-stochastic steady state in the re-scaled variables.

The parameters of the model are set to values listed in Table 1 below:

Table 1: Calibrated Parameters

Parameter	Value	Description
β	0.99	Discount factor
α	1/3	Capital's share
δ_0	0.025	Steady state depreciation
δ_1	$u^* = 1$	Utilization linear term
δ_2	0.025	Utilization squared term
ψ	$L^* = 1/3$	Labor disutility
π^*	0	Steady state inflation
ϕ_π	1.5	TR inflation
ϕ_y	0.3	TR output growth
ρ_i	0.85	TR smoothing
ϵ_p	11	Elasticity sub goods
ϵ_w	11	Elasticity sub labor
χ	1	Inverse Frisch
F	$\Pi^* = 0$ or 0	Fixed cost
θ_p	0.75	Calvo prices
θ_w	0.75	Calvo wages
ζ_p	0.00	Price indexation
ζ_w	0.00	Wage indexation
b	0.8	Habit formation
κ	1	Investment adjustment cost
g	1.0025	SS growth of productivity
ρ_Γ	0.6	AR productivity growth
ρ_A	0.85	AR surprise productivity
ρ_Z	0.80	AR investment
ρ_φ	0.90	AR labor supply
s_g	0.0031 or 0.0031	SD growth shock
s_A	0.0065 or 0.0069	SD surprise productivity
s_Z	0.0121 or 0.0131	SD investment shock

These parameter values are largely drawn from the literature and are therefore quite standard. The frequency of time is a quarter. The discount factor is set to 0.99 and the parameter α in the production function is 1/3. The steady state depreciation rate is set to 0.025. The linear parameter in the utilization adjustment cost function is set to be consistent with a normalization of steady state utilization to unity. The coefficient on the squared term in the utilization cost term is set to $\delta_2 = 0.025$. The disutility of labor parameter is chosen to be consistent with steady state hours worked of 1/3. The parameters ϵ_p and ϵ_w are chosen to be consistent with steady state price and wage markups of 10 percent. The Calvo price and wage parameters are both set to 0.75, implying that the average duration between price or wage changes is four quarters. We assume no backward indexation of prices or wages to lagged inflation. The habit formation parameter is set to $b = 0.8$, and the investment adjustment cost parameter is set to $\kappa = 1$. We assume that there is no trend inflation, so $\pi^* = 0$. The Taylor rule features significant interest smoothing and strong responses to both inflation and output growth. The steady state gross growth rate of productivity is set to 1.0025, which implies output growth of 1.5 percent per year in steady state. The fixed cost of production, F, is chosen so that profits are zero in steady state or the fixed cost is set to 0. We present results based on specifications both with and without a fixed cost.

We have less to guide us in terms of the parameterization of the shock processes. Our model features four stochastic shocks, which coincides with the number of variables included in our estimated VARs. As a benchmark, we assume that $q = 0$, so that the permanent productivity shock impacts the level of productivity in the period in which agents observe the shock. We set the autoregressive parameters in the shock processes to conventional values. We then choose the standard deviations of the shocks to generate a standard deviation of output growth of 0.01, a contribution to the unconditional variance share of output growth of 0.50 owing to the investment shock (this is based on Justiniano et al. 2010), a contribution to the unconditional variance share of output growth due to the growth shock of 0.25, and a contribution to the unconditional variance share of output of the labor supply shock of 0.125 (which means that the surprise productivity shock accounts for the remaining 0.125 of the variance of output growth).