News Shocks, Business Cycles, and the Disinflation Puzzle*

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Abstract

We argue that key findings of the recent empirical literature on the effects of news about future technology — including their tendency to generate negative comovement of macroeconomic aggregates, and their puzzling disinflationary nature — are due to measurement errors in total factor productivity (TFP). Reduced-form innovations to TFP, which are typically identified as unanticipated technology shocks, are found to generate anomalous responses that are inconsistent with the interpretation of these disturbances as supply shocks, thus hinting at the presence of an unpurged non-technological component in measured TFP. Such an impurity undermines existing identification schemes, which are based on the premise that measured TFP is entirely driven by surprise and news shocks to technology. In this paper, we estimate the macroeconomic effects of news shocks in the U.S. using an agnostic identification approach that is robust to measurement errors in TFP. We find no evidence of negative comovement conditional on a news shock, and the disinflation puzzle essentially vanishes under our identification strategy. Our results also indicate that news shocks have become an important driver of business-cycle fluctuations in recent years.

JEL classification: E20, C32, E32, O47
Key words: Identification, Measurement errors, News shocks, Sign restrictions, Technology, Total factor productivity.

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1 Introduction

A long-standing and fundamental question in macroeconomics is: what causes business-cycle fluctuations? Following the seminal work of Beaudry & Portier (2006), interest has been rekindled in Pigou (1927)'s theory of business cycles, according to which changes and revisions in expectations about future fundamentals can give rise to boom-bust cycles. A number of empirical studies — based on vector autoregressions (VARs) — have therefore attempted to gauge the importance of news shocks about future productivity in generating the type of positive comovement of macroeconomic aggregates observed in the data and in explaining their variability.[1]

Beaudry & Portier (2006) were the first to document using U.S. data that news shocks lead to positive comovement of consumption, hours worked, and investment, and account for the bulk of their variability at business-cycle frequencies. Beaudry & Lucke (2010) and Beaudry & Portier (2014) reach essentially the same conclusions. These findings have been challenged, however, by some scholars who questioned the underlying identification strategies.[2] Using an alternative, more flexible, identification approach, Barsky & Sims (2011) find that good news about future technology tend to raise consumption but to decrease output, hours worked, and investment in the short run.[3] They also find that inflation declines sharply and persistently in response to a positive realization of the news shock; a result deemed puzzling in light of the standard New Keynesian model.[4] Finally, though Barsky & Sims (2011) find that news shocks account for a significant fraction of output variability at business-cycle frequencies, they invoke the negative comovement to conclude that these shocks are unlikely to be a major driver of business cycles. These findings are confirmed by subsequent studies that propose alternative but related methodologies to Barsky & Sims' (e.g., Forni et al. (2014), Barsky et al. (2015), and Kurmann & Sims (2017)).

Existing empirical approaches to identify news shocks about future productivity are based on

[1] An alternative approach to evaluate the importance of news shocks has been to estimate/calibrate dynamic stochastic general-equilibrium (DSGE) models that feature anticipated shocks to technology. This approach has been pursued by Jaimovich & Rebelo (2009), Fujiwara et al. (2011), Karnizova (2012), Schmitt-Grohé & Uribe (2012), and Khan & Tsoukalas (2012).

[2] Beaudry & Portier (2006), Beaudry & Lucke (2010), and Beaudry & Portier (2014) estimate small-scale systems (two to five equations) in which news shocks are identified using a mix of short- and long-run restrictions. Kurmann & Mertens (2014) show that Beaudry & Portier (2006)'s identification scheme does not have a unique solution when applied to a Vector Error Correction Model (VECM) with more than two variables. This identification scheme is therefore uninformative about the effects of news shocks and their importance for business cycles. Kurmann & Mertens (2014) further point out that the validity of the identification strategy proposed by Beaudry & Lucke (2010) critically depends on the plausibility of zero restrictions for other non-news shocks necessary to identify news shocks. Finally, Forni et al. (2014) argue that small-scale VARs and VECMs do not contain enough information to recover anticipated technology shocks from observable variables, a problem commonly known as *non-fundamentalness*.

[3] Barsky & Sims (2011) identify the news shock as the shock that best explains future movements in total factor productivity not accounted for by its own innovation.

[4] See, for instance, Jinnai (2013), Barsky et al. (2015), and Kurmann & Otrok (2014).

the premise that total factor productivity (TFP) is entirely and exclusively driven by two orthogonal disturbances: unanticipated and news shocks, the latter generally affecting TFP with a lag. This assumption is consistent with the standard treatment of TFP in theoretical macroeconomic models. Hence, the above-mentioned studies invariably include a measure of TFP in the information set when attempting to identify news shocks from the data.

In this paper, we argue that the TFP measures typically utilized in the empirical literature contain important measurement errors that call into question the interpretation of TFP as a pure measure of technology. This is despite the corrections aiming at purging measured TFP of its non-technological component by controlling for unobserved variations in labor and capital. Most importantly, we demonstrate that the negative comovement of macroeconomic aggregates and the disinflation puzzle documented in recent empirical studies are spurious and are just an artifact of using a polluted measure of technology. In fact, we show that the news shocks identified in these studies are mostly picking up the effects of unanticipated technology shocks.

We document the severity of measurement errors in the adjusted TFP measure constructed by Fernald (2014) — which is the most widely used TFP series — by examining the dynamic effects of an unanticipated technology shock, identified as the reduced-form innovation to TFP, as is done in *all* existing VAR-based studies on news shocks.[5] The most revealing symptom of the presence of measurement errors is that unanticipated technological improvements are found to be inflationary, an outcome that runs against the conventional interpretation of surprise technology shocks as supply shocks, and violates the prediction of any sensible theory of aggregate fluctuations. A favorable surprise technology shock is also found to have counter-intuitive effects on stock prices and consumer confidence, which are initially unresponsive to the shock but fall persistently in the subsequent periods. We interpret these anomalous responses as an indication that the TFP series used in the empirical literature is an uncleansed measure of technology. Since a correct identification of news shocks hinges on the surprise technology shocks being properly identified, measurement errors in TFP are likely to undermine existing identification approaches.

We then propose an agnostic identification strategy that is robust to the presence of measurement errors in TFP. Our methodology relaxes the assumption that only technological shocks can affect measured TFP. Instead, we allow for the existence of non-technology shocks, which may capture measurement errors arising from the imperfect observability of inputs and their utilization rates, from the potential misspecification of the production function, and from aggregation bias. Non-technology shocks may affect measured TFP contemporaneously or at any future horizon, just

[5]The only exception is the study by Kurmann & Sims (2017), in which there is no attempt to identify surprise technology shocks.

like surprise technology shocks. To identify the latter, we rely on the sign-restriction approach proposed by Mountford & Uhlig (2009), imposing a negative sign on the inflation response to a positive shock. Hence, by construction, our strategy avoids the inflation anomaly engendered by identification schemes that associate surprise technology shocks with reduced-form innovations to TFP. We then extract the news shock as the linear combination of reduced-form innovations that is orthogonal to the surprise technology shock and that maximizes the contribution of the news shock to the forecast-error variance of TFP at a long but finite horizon. The argument underlying this criterion, originally proposed by Francis et al. (2014) and commonly referred to as the Max Share, is that the contribution of non-technology shocks to movements in TFP is likely to be negligible at very low frequencies.

We take our agnostic approach to the data by estimating a seven-variable VAR similar to that considered by Barsky & Sims (2011), first using their original data set, which spans the period 1960Q1–2007Q3, and then using an updated sample that extends the data coverage to 2016Q4. We find that non-technology shocks account for nearly half of the forecast error variance of Fernald's TFP series at the one-quarter horizon. This observation confirms the existence of non-trivial measurement errors in measured TFP and raises skepticism about available estimates of the effects of news shocks. Our results also show that the estimated effects of unanticipated technology shocks are remarkably consistent both with the predictions of the medium-scale New Keynesian model of Smets & Wouters (2007) and with the empirical evidence based on identification via long-run restrictions. In addition to being disinflationary by construction, an unanticipated technological improvement leads to a persistent and hump-shaped increase in consumption and output and to a short-term decline in hours worked. Moreover, the shock is found to have a positive effect on stock prices and consumer confidence.

Turning to the effects of news shocks, we find no evidence of negative comovement between consumption, output, and hours worked using our methodology. In the sample ending in 2007, a favorable news shock triggers an increase in consumption, but the initial response of output and hours worked is small and statistically indistinguishable from zero. In the updated sample, all three variables increase significantly and persistently in response to the shock. Importantly, this simultaneous increase — indicative of positive comovement — occurs even before TFP starts to rise, thus lending support to the view that aggregate fluctuations can be driven by expectations of higher productivity. Our results also indicate that the inflation response is mostly statistically insignificant in both samples. In other words, the disinflation puzzle essentially vanishes under our identification strategy. More generally, the effects of a news shock identified using our agnostic strategy differ markedly from Barsky & Sims' results. The latter turn out to be very similar to our estimated effects of a *surprise* technology shock, pointing to a misidentification of the news shock.

Finally, variance-decomposition results and the historical decomposition of the time series of consumption, output, and hours strongly suggest that news shocks are unlikely to have been a major contributor to business-cycle fluctuations before 2007. In the extended sample, however, we find that news shocks account for roughly 40 to 60 percent of the forecast error variance of consumption, output, and hours worked at business-cycle frequencies, and that they explain a significant share of the decline in these quantities during the recent U.S. downturns, including the Great Recession. Together, these findings indicate that TFP news shocks have become an important source of business-cycle fluctuations in recent years, a conclusion that contradicts the verdict of the recent empirical literature that builds on Barsky & Sims' methodology (e.g., Forni et al. (2014), Barsky et al. (2015), and Kurmann & Sims (2017)).

The presumption that TFP is measured with error is of course not new; it has been discussed, for instance, in Christiano et al. (2004), Basu et al. (2006), and Fernald (2014). In a contemporaneous paper closely related to ours, Kurmann & Sims (2017) also study the implications of measurement errors in TFP for the identification of news shocks. These authors, however, do not establish a link between the anomalous responses to a surprise technology shock and the existence of measurement errors in TFP. Instead, their suspicion of the presence of such errors is based on the sensitivity of the estimated effects of news shocks using Barsky & Sims' methodology to revisions in Fernald's TFP series. Kurmann & Sims (2017) document that these revisions mainly reflect changes in the estimate of factor utilization, and argue that mis-measured utilization invalidates the identifying restriction that news shocks do not affect adjusted TFP on impact. Based on an identification strategy that relaxes this restriction and relies on the Max Share criterion to extract the news shock, they obtain very similar results to those documented by Barsky & Sims (2011) — namely, a negative comovement between consumption and hours and a limited contribution of news shocks to business-cycle fluctuations — with the difference that the results remain robust to revisions in Fernald's TFP series.

A crucial assumption of Kurmann & Sims' identification scheme is that the news shock is not orthogonalized with respect to the surprise technology shock (which is not identified). The two shocks are therefore likely to be muddled up since they both affect TFP in the short and in the long run, making it impossible — without further assumptions — to disentangle their respective contribution to the forecast error variance of TFP at any given horizon. Importantly, when we impose the orthogonality between the news and the surprise technology shock while relaxing the zero-impact restriction, we find no evidence of negative comovement and a significant role of news shocks in explaining aggregate fluctuations at business-cycle frequencies in the updated sample.

In fact, our results are almost identical to those obtained by imposing the zero-impact restriction. This suggests that Kurmann & Sims' approach may be confounding news and surprise technology shocks.

The rest of this paper is organized as follows. Section 2 discusses the symptoms of measurement errors in TFP. Section 3 presents our agnostic identification strategy. Section 4 discusses the results based on Barsky & Sims (2011) original data and on an updated sample. Section 5 studies the robustness of our results when we relax the zero-impact restriction. Section 6 concludes.

2 The Inflation Anomaly and Other Symptoms of Measurement Errors in TFP

In this section, we illustrate the extent to which the effects of unanticipated technology shocks typically reported in the VAR-based "news" literature are inconsistent with the predictions of New Keynesian models and, for that matter, any sensible theory of aggregate fluctuations. We view these inconsistencies as symptoms of the presence of measurement errors in the TFP series commonly used in the literature.

2.1 Unanticipated technology shocks: measurement...

In the VAR-based literature on news shocks, unanticipated technology shocks are usually identified as the reduced-form innovations to TFP. Formally, let y_t be a $k \times 1$ vector of observables of length T, which includes TFP and which has the following moving-average (MA) representation

$$y_t = B(L)u_t,$$

where u_t is a $k \times 1$ vector of statistical innovations, whose variance-covariance matrix is denoted by Σ. Let ϵ_t be a $k \times 1$ vector of structural innovations, including the unanticipated technology shock, whose variance-covariance matrix is normalized to I_k. If a linear mapping between the statistical innovations, u_t, and the structural shocks, ϵ_t, exists, then we can write

$$u_t = A\epsilon_t,$$

where the impact matrix, A, must be such that $AA'= \Sigma$. Assuming (without loss of generality) that TFP is ordered first in y_t and that the unanticipated technology shock is ordered first in ϵ_t, a Cholesky decomposition of Σ ensures that the surprise technology shock is proportional to the statistical innovation to TFP.

We use the strategy above to measure the effects of a surprise technology shock within a seven-variable VAR similar to that estimated by Barsky & Sims (2011). The vector of observables includes adjusted TFP, output, consumption, hours, inflation, stock prices, and consumer confidence, measured at a quarterly frequency. We start by using Barsky and Sims' original data, which span the period 1960Q1–2007Q3; we then update the sample by extending it to 2016Q4.[6]

The results are shown with solid black lines in Figure 1.[7] The (one-standard-error) confidence intervals around the estimated impulse responses are computed using the bias-corrected bootstrap procedure proposed by Kilian (1998). A surprise technology shock triggers a transitory increase in TFP, output, and consumption. In all three cases, the estimated response is rather monotonic and the variable reverts to its pre-shock level rather rapidly. In contrast, hours worked exhibit a relatively muted — and mostly statistically insignificant — response. The Figure also shows that, in response to the identified surprise technology shock, inflation rises persistently and in a hump-shaped manner, with a peak occurring at around 10 quarters after the shock. Stock prices and consumer confidence, in contrast, are unresponsive on impact and eventually fall below their pre-shock levels for a prolonged period of time. Very similar results are reported by Forni et al. (2014), Barsky et al. (2015), and Fève & Guay (2016).

When we extend the sample to 2016Q4, two notable differences with respect to the results above stand out (see Figure 2). First, hours worked now fall initially in response to the shock, but their response remains mostly statistically insignificant. Second, stock prices and consumer confidence now rise for about three quarters after the shock, but they continue to decline persistently during the subsequent quarters. These two exceptions aside, the results based on the updated sample are very similar to the original ones. In particular, the response of TFP, output and consumption are transitory, inflation rises persistently and in a hump-shaped manner, and consumer confidence falls persistently with a delay.

2.2 … and theory

How do the empirical findings discussed in the previous section compare with the predictions of New Keynesian theory of aggregate fluctuations? We answer this question by studying the effects of unanticipated technology shocks both within the simplest version of the New Keynesian model and the more realistic medium-scale version proposed by Smets & Wouters (2007). To do so, we

[6] The series used in estimation are constructed as follows. Adjusted TFP is the quarterly series constructed by Fernald (2014), which controls for unobserved input variation. Output is measured by the log of real GDP in the non-farm business sector. Consumption is measured by the log of real personal spending on non-durables and services. Hours are measured by the log of total hours worked in the non-farm business sector. Output, consumption and hours are expressed in per capita terms by dividing them by the civilian, noninstitutional population, age 16 and over. Inflation is measured by the percentage change in the CPI for all urban consumers. Stock prices are measured by the log of the S&P index. Consumer confidence is retrieved from the Michigan Survey of Consumers.

[7] These results are based on a VAR with 3 lags. Alternative lag lengths yield similar results.

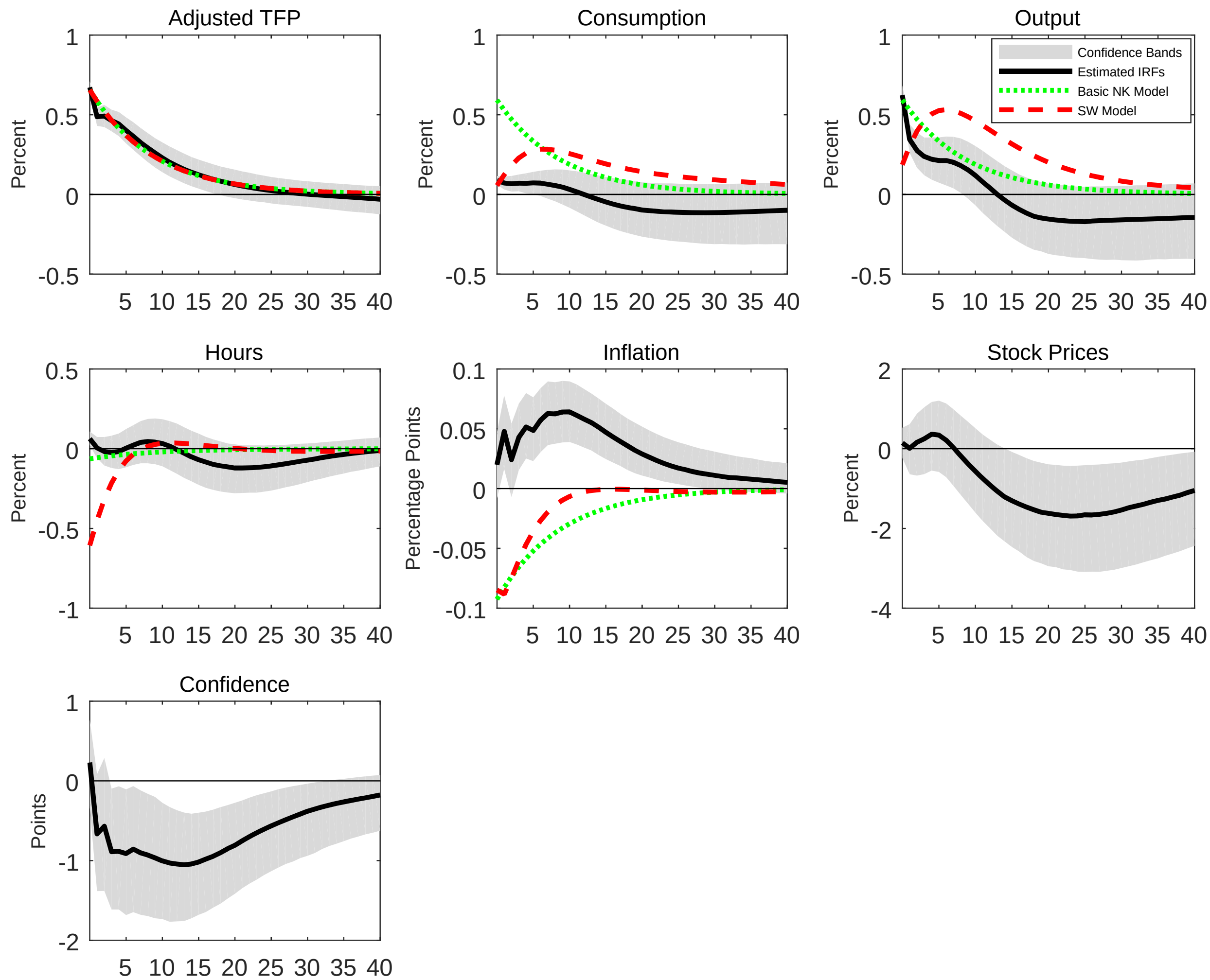

Figure 1: Impulse responses to a surprise technology shock. Sample: 1960Q1–2007Q3.

Notes: The figure shows the impulse responses to a surprise technology shock. The solid lines are the median impulse responses estimated based on the reduced-form innovation to TFP. The 68 percent confidence bands are the bias-corrected bootstrap confidence intervals computed using Kilian (1998)'s procedure with 2000 replications. The dotted lines are the impulse responses obtained from the standard New Keynesian model. The dashed lines are the impulse responses obtained from the Smets & Wouters (2007) model.

assume that the log of TFP (in deviation from its mean), a_t, is governed by the following process:

$$a_t = \rho_a a_{t-1} + x_{t-1} + \epsilon_t^s, \qquad (1)$$

$$x_t = \rho_x x_{t-1} + \epsilon_t^n, \qquad (2)$$

where ϵ_t^s and ϵ_t^n are, respectively, the surprise and anticipated (or news) technology shocks, and $0 \leq \rho_a, \rho_x < 1$. Notice that ρ_x is irrelevant to the dynamic effects of the surprise shock and

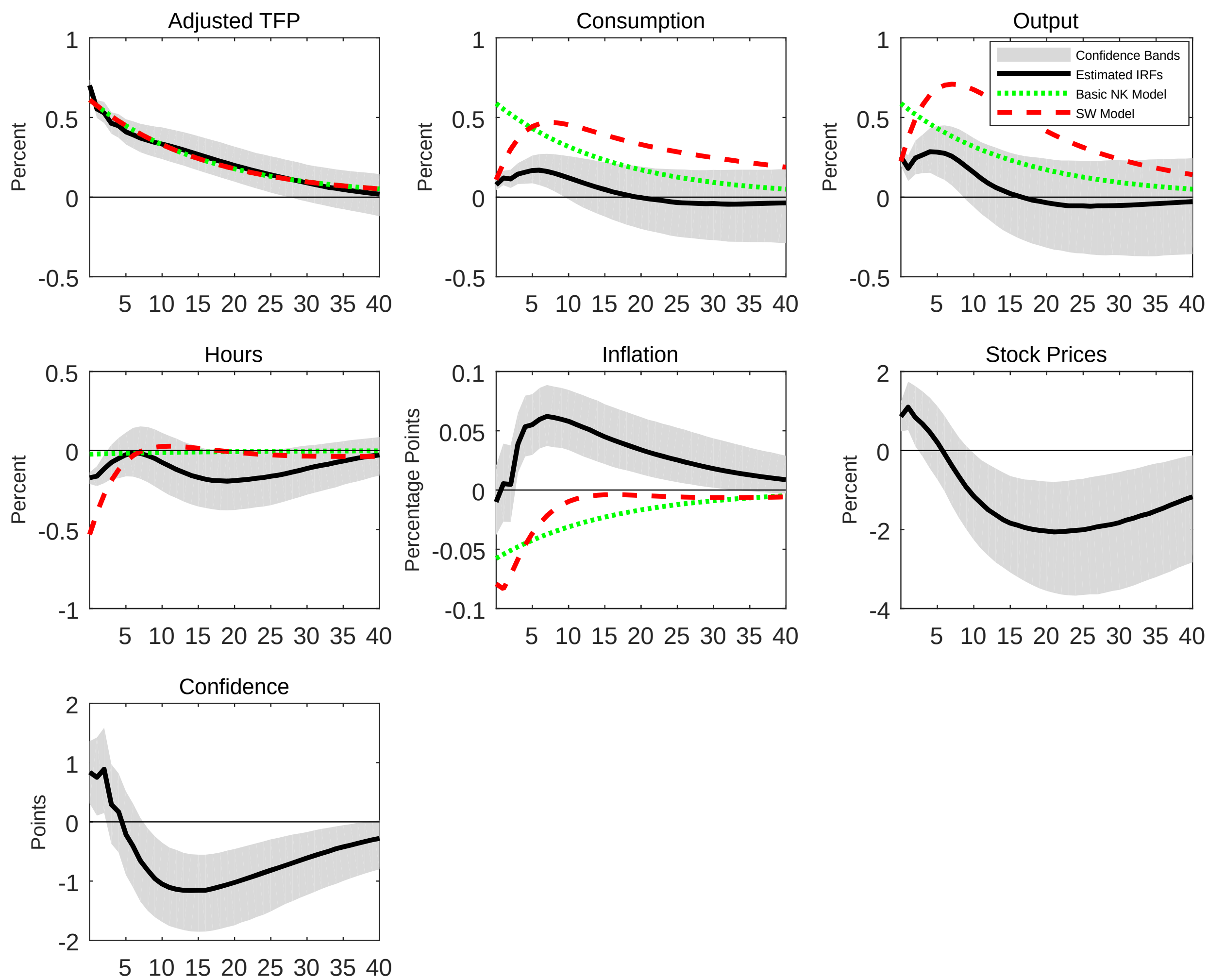

Figure 2: Impulse responses to a surprise technology shock. Sample: 1960Q1–2016Q4.

Notes: The figure shows the impulse responses to a surprise technology shock. The solid lines are the median impulse responses estimated based on the reduced-form innovation to TFP. The 68 percent confidence bands are the bias-corrected bootstrap confidence intervals computed using Kilian (1998)'s procedure with 2000 replications. The dotted lines are the impulse responses obtained from the standard New Keynesian model. The dashed lines are the impulse responses obtained from the Smets & Wouters (2007) model.

thus ρ_a and the size of the disturbance ϵ_t^s are the only parameters that one needs to calibrate to study those effects. We choose those two parameters such that the implied response of TFP to the surprise technology shock mimics as closely as possible the response estimated from the data. The model-based responses of TFP, consumption, output, hours, and inflation are superimposed on their empirical counterparts in Figures 1 and 2.

2.2.1 The basic New Keynesian model

Consider first the basic New Keynesian model, summarized by the following log-linearized equations (around a zero-inflation steady state):[8]

$$c_t = y_t, \tag{3}$$

$$y_t = a_t + n_t, \tag{4}$$

$$mc_t = \sigma c_t + +\varphi n_t - a_t, \tag{5}$$

$$c_t = \mathbb{E}_t c_{t+1} - \sigma^{-1}(i_t - \mathbb{E}_t \pi_{t+1} - \ln\beta), \tag{6}$$

$$\pi_t = \beta \mathbb{E}_t \pi_{t+1} + \lambda mc_t, \tag{7}$$

$$i_t = \ln\beta + \phi_\pi \pi_t + \phi_y (y_t - y_t^f), \tag{8}$$

where c_t is consumption, y_t is output, n_t is hours worked, mc_t is real marginal cost, π_t is the inflation rate, i_t is the nominal interest rate, and $y_t^f = (1+\varphi)(\sigma+\varphi)^{-1} a_t$ is the flexible-price (or natural) level of output. All the variables are expressed as percentage deviations from their steady-state values except π_t and i_t, which are expressed in levels. The parameters are defined as follows: $\sigma > 0$ is the inverse of the elasticity of intertemporal substitution, $\varphi > 0$ is the inverse of the Frisch elasticity of labor supply, $0 < \beta < 1$ is the discount factor, $\lambda = (1-\theta)(1-\beta\theta)/\theta > 0$, $0 < \theta < 1$ is the Calvo probability of not changing prices, and $\phi_\pi, \phi_y > 0$ are the coefficients attached to inflation and the output gap in the interest rate rule.

Model (3)–(8) can be solved analytically to determine the effects of a surprise technology shock. Assuming that $\epsilon_t^n = 0$ for all t, one can use the method of undetermined coefficients to show that

$$\pi_t = -\frac{\sigma\lambda(1+\varphi)(1-\rho_a)}{\Delta_a} a_t,$$

where $\Delta_a = \lambda(\sigma+\varphi)(\phi_\pi - \rho_a) + (1-\beta\rho_a)[\sigma(1-\rho_a) + \phi_y] > 0$.[9] Since the numerator in the expression above is positive, an unanticipated technological improvement will cause inflation to fall persistently as long as $\rho_a < 1$. This disinflationary effect reflects the persistent fall in real marginal cost or, equivalently, the negative output gap resulting from the shock.[10] This can be seen by noticing that

$$mc_t = -\frac{\sigma(1+\varphi)(1-\rho_a)(1-\beta\rho_a)}{\Delta_a} a_t.$$

[8] This is essentially the model presented in Galí (2008). The only difference is that we assume (for simplicity) constant returns to scale in the production technology. This simplification has no impact on the results.

[9] The necessary and sufficient condition for the existence of a unique linear rational expectations equilibrium is given by $\lambda(\sigma+\varphi)(\phi_\pi - 1) + (1-\beta)\phi_y > 0$. It is straightforward to see that this condition implies that $\Delta_a > 0$.

[10] By iterating equation (7) forward, inflation can be expressed as a discounted sum of current and expected future real marginal costs.

The surprise technology shock has a positive effect on output (and thus consumption) but an ambiguous effect on hours worked. The solutions for these variables are given by

$$\begin{aligned} y_t &= \frac{(1+\varphi)\left[\lambda\left(\phi_\pi-\rho_a\right)+(\sigma+\varphi)^{-1}\left(1-\beta\rho_a\right)\phi_y\right]}{\Delta_a}a_t, \\ n_t &= \left\{\frac{(1+\varphi)\left[\lambda\left(\phi_\pi-\rho_a\right)+(\sigma+\varphi)^{-1}\left(1-\beta\rho_a\right)\phi_y\right]}{\Delta_a}-1\right\}a_t. \end{aligned}$$

Under plausible parameter values, however, hours worked fall in response to a positive unanticipated technology shock. The responses depicted in Figures 1 and 2 (with green dotted lines) are obtained using the following standard parameterization of the model: $\sigma=\varphi=1$, $\beta=0.99$, $\theta=0.75, \phi_\pi=1.5, \phi_y=0.125$. Under these parameter values, a positive surprise shock to technology raises output and consumption and decreases hours worked and inflation.

The dynamic responses implied by the model hardly match those estimated from the data, but the most striking discrepancy concerns the response of inflation, which has the opposite sign and a completely different shape relative to what is predicted by the VAR.

2.2.2 The Smets and Wouters (2007) model

Next, consider the medium-scale model developed by Smets & Wouters (2007). To conserve space, we only summarize the main features of the model and refer the reader to their paper for a more detailed description. The model features a representative household whose preferences exhibit habit formation in consumption. The final good is produced using an aggregator of intermediate goods that exhibits a non-constant elasticity of substitution. Intermediate goods are produced using a technology that depends on TFP, labor, and capital, and that exhibits variable capital utilization and fixed costs. Capital accumulation is subject to investment adjustment costs. Both prices and wages are set in a staggered fashion à la Calvo, whereby the non-optimizing agents partially index their prices and wages to past inflation, thus giving rise to a New Keynesian Phillips curve that depends not only on current and expected future inflation but also past inflation. Monetary policy follows an interest rate rule with a smoothing component. The model is estimated by Bayesian techniques using U.S. data over the period 1966Q1–2004Q4.

We use Smets and Wouters' posterior means for the structural parameters to generate the implied responses to an unanticipated positive technology shock, which are represented by the dashed red lines in Figures 1 and 2. Despite some quantitative differences, these responses are in line with the predictions of the basic New Keynesian model: output and consumption rise while hours worked and inflation fall in response to the shock. The fall in inflation persists for about eight quarters after the shock, which is in stark contrast with the positive response obtained from the VAR.[11] Notice also that the VAR-based responses of output and consumption lack the persistent and hump-shaped pattern implied by the model.

2.3 Discussion

As we have just shown, reduced-form innovation to TFP are found to be inflationary, an outcome that runs against the conventional interpretation of technology shocks as supply shocks, and contradicts the prediction of any sensible macroeconomic model. It is also at odds with the results reported by a number of empirical studies that rely on the long-run restriction approach proposed by Galí (1999) to identify exogenous technology shocks (e.g., Edge et al. (2003), Christiano et al. (2003), Fève & Guay (2010)). Moreover, the result that technology shocks have a delayed negative effect on stock prices and consumer confidence also appears hard to reconcile with the view that technology enhances efficiency and raises the productive capacity of the economy.

These observations cast serious doubt on the interpretation of reduced-form innovations to TFP as pure unanticipated technological improvements. The identified shocks appear to be contaminated by other non-technological disturbances that also affect measured TFP contemporaneously and whose effects are akin to those of a demand shock. Since a proper identification of news shocks about future productivity hinges on purging TFP of its non-technological component, the anomalous responses just discussed suggest that existing methodologies — albeit sound in theory — may still fail to correctly identify news shocks and their effects due to measurement errors in TFP.

In the models discussed in Section 2.2, TFP is assumed to be exogenous to the state of the economy and, as such, is not expected to be affected by demand shocks — note that this is precisely the identifying assumption underlying the empirical literature on news shocks. TFP, however, is not readily observable in the data and must be inferred from production and input use, a task that poses a number of measurement challenges. First, some inputs may not be observable or measurable; second, input utilization varies in response to non-technology shocks; third, the production technology may have non-constant returns to scale; fourth, aggregating inputs across heterogeneous production sectors may introduce a bias. Failing to eliminate any of these potential sources of measurement errors may result in an incorrect measure of TFP and thus a poor proxy for technology. In their seminal paper, Basu et al. (2006) went a long way towards constructing a purified annual measure of technology by adjusting TFP for observed and unobserved input variations and non-constant returns to scale. The quarterly TFP series used in the empirical literature on news

[11] A persistent decline in inflation following a favorable surprise technology shock is also predicted by the New Keynesian models estimated by Ireland (2004) and Altig et al. (2011), though the inflation response is relatively small in magnitude in the latter case.

shocks was constructed by Fernald (2014) following Basu et al. (2006)'s methodology but without correction for non-constant returns to scale since the industry level data needed for this correction are only available at an annual frequency.

To get a sense of how this impacts the measurement of TFP, we plot in Figure 3 annual TFP growth based on the measures constructed by Fernald (2014) and Basu et al. (2006) for the period 1960–1996.[12] Although there is some similarity between the two series, their correlation is modest (0.57), suggesting that the constant-returns-to-scale assumption underlying the construction of the quarterly TFP series is counterfactual and is likely to be one of the culprits for the anomalous responses documented above.

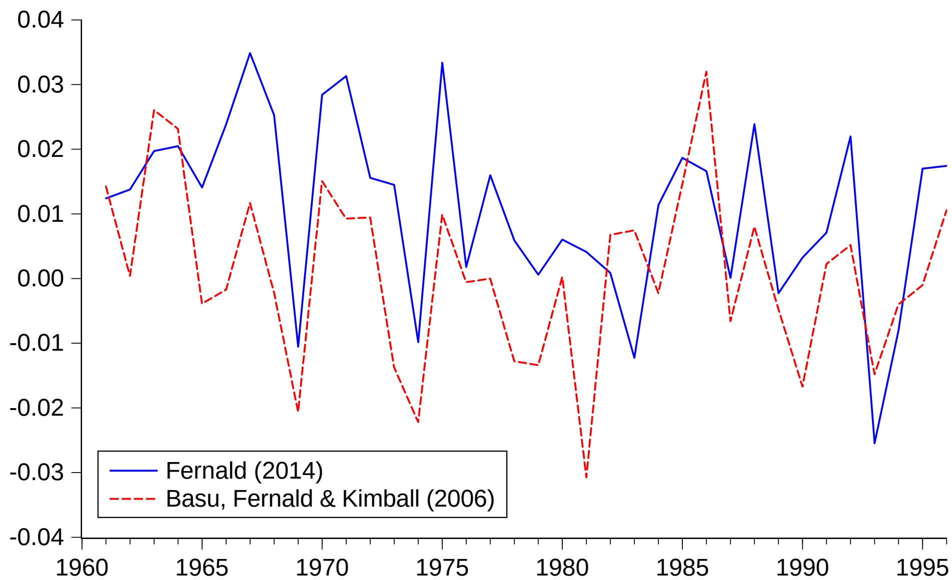

Figure 3: Annual TFP growth based on the series constructed by Fernald (2014) and Basu et al. (2006).

To further illustrate the importance of this assumption as a potential source of measurement errors, we estimate the effects of a surprise technology shock identified as the reduced form innovation to Basu et al. (2006)'s series using the same observable variables as in section 2.1, measured annually. The estimated impulse responses and their confidence bands are shown in Figure 4, in which a period corresponds to a year.[13] The figure shows that, following a positive technology shock,

[12]Basu et al. (2006)'s TFP series ends in 1996.

[13]The results reported in Figure 4 are based on a VAR with one lag. We obtain very similar results when we

output remains essentially unresponsive on impact but increases in a hump-shaped manner during the subsequent years, whereas hours worked fall significantly at the time of the shock. Inflation also falls sharply on impact, consistently with the expected disinflationary effect of a technological improvement, and in sharp contrast with the rise in inflation obtained using the quarterly TFP series. This observation hints at the fact that Basu et al. (2006)'s TFP series is less polluted by non-technological factors than Fernald (2014)'s quarterly series.

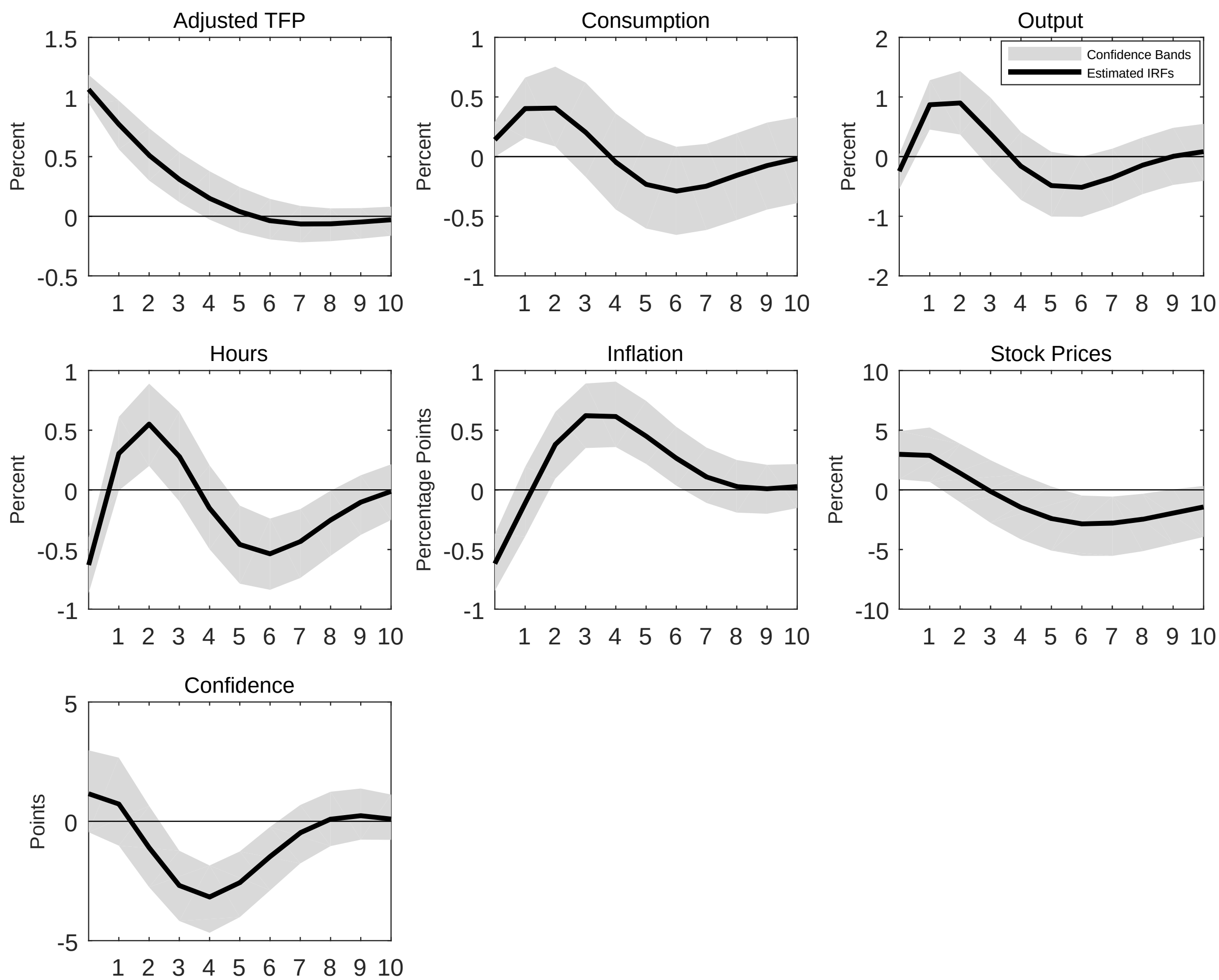

Figure 4: Impulse responses to a surprise technology shock based on Basu et al. (2006)'s annual TFP series.

Notes: The figure shows the impulse responses to a surprise technology shock. The solid lines are the median impulse responses estimated based on the reduced-form innovation to TFP. The 68 percent confidence bands are the bias-corrected bootstrap confidence intervals computed using Kilian (1998)'s procedure with 2000 replications.

include two lags. Because we are estimating a VAR with 7 variables using 36 annual observations, including more lags leaves too few degrees of freedom to obtain reliable estimates.

Yet, Figure 4 shows that even Basu et al. (2006)'s purified TFP measure generates some anomalies that are hard to reconcile with conventional wisdom about the effects of technology shocks. For instance, the initial disinflationary effect of the shock is followed by a protracted episode (of several years) during which inflation is above average. Moreover, while stock prices initially rise in response to a positive technology shock, they decline persistently during the subsequent years. Likewise, the shock triggers a delayed fall in consumer confidence that persists for a prolonged period of time. These responses cast doubt on the interpretation of the shock as a pure technological disturbance.

In sum, despite the colossal work carried out by Basu et al. (2006) and Fernald (2014) to construct a cleansed measure of technology, it is probably unrealistic to believe that the corrected TFP series is purged of all its non-technological factors, which in turn suggests that TFP-based measures of technology shocks will most likely be contaminated by measurement errors. This conclusion motivates the agnostic approach that we describe in the next section.

3 An Agnostic Identification Approach

3.1 Idea

The maintained assumption underlying the empirical identification of news shocks about future productivity is that measured TFP is exclusively driven by surprise and anticipated technology shocks, the latter affecting TFP only with a lag. The common approach to identify the news shock is then to select the linear combination of reduced-form innovations that best explains (or forecasts) future movement in TFP while being orthogonal to the surprise technology shock. This strategy will correctly identify news shocks only to the extent that surprise technology shocks are the only disturbances that affect measured TFP contemporaneously, which, as we just argued above, seems highly unlikely.

We propose an alternative empirical strategy based on the assumption that measured TFP is affected by two types of disturbances: technological and non-technological shocks. The latter capture measurement errors due to the imperfect observability of inputs and their utilization rates, to the potential misspecification of the production function, and to aggregation bias. From this perspective, it may be inappropriate to characterize these shocks as structural, given that they do not bear a clear economic interpretation. However, this is not a concern for our methodology since we need not identify these shocks; we simply allow them to affect measured TFP contemporaneously and at any future horizon, just as surprise technology shocks.

To identify the surprise technology shock, we adopt an agnostic strategy based on the sign-restriction approach proposed by Mountford & Uhlig (2009). More specifically, we select the impulse vector that (most markedly) satisfies the restriction that inflation falls for at least eight quarters after the shock, consistently with the prediction of the Smets & Wouters (2007) model. Hence, by construction, our strategy avoids the inflation anomaly engendered by identification schemes that associate surprise technology shocks with TFP innovations. We then identify the news shock as the linear combination of reduced-form innovations that is orthogonal to the surprise technology shock and that maximizes the contribution of the news shock to the forecast-error variance of TFP at a long but finite horizon, H. The latter criterion, initially proposed by Francis et al. (2014) and commonly referred to as the Max Share, differs from the one used by Barsky & Sims (2011), which involves maximizing the contribution of the news shocks to the forecast error variance of TFP over all horizons up to a finite truncation horizon. Barsky & Sims' approach has been criticized on the ground that it may confound shocks that have either permanent or temporary effects on TFP, and has been shown to be quite sensitive to the truncation horizon (see Beaudry et al. (2011)). Since our approach allows for the presence of non-technology shocks, whose effects on measured TFP are likely to be much more important at short horizons than at more distant ones, this makes the case for using the Max Share even stronger.

3.2 Implementation

Let $\tilde{A}$ denote the Cholesky decomposition of Σ and assume again that TFP is ordered first in y_t. Any impact matrix $A_0 = \tilde{A}D$, where D is an orthonormal matrix, also satisfies the requirement $A_0{A'}_0 = \Sigma$. Let γ_j denote the jth column of D, ϵ_1 denote the surprise technology shock, and ϵ_2 denote the news shock.

We identify the surprise technology shock by selecting the orthonormal matrix D that satisfies the requirement that inflation does not increase during the first eight quarters after the shock while yielding the largest response in the desired direction. Because the impulse vector to this shock is $\tilde{A}\gamma_1$ (the first column of $\tilde{A}D$), we only need to characterize γ_1.

Denote by $r_{j,i}(h)$ the impulse response of the jth variable to the ith column of $\tilde{A}$ at horizon h (that is, the reduced-form impulse response), and by $r_i(h)$ the $k-$dimensional column vector $[r_{1,i}(h), \cdots, r_{k,i}(h)]$. The $k-$dimensional impulse response $r_{\gamma_1}(h)$ to the impulse vector $\tilde{A}\gamma_1$ is given by

$$r_{\gamma_1}(h) = \sum_{i=1}^{k} \gamma_{i,1} r_i(h),$$

where $\gamma_{i,1}$ is the ith entry of γ_1.

Following Mountford & Uhlig (2009)'s approach, we select the vector γ_1 of unit length that solves the following minimization problem:

$$\min_{\{\gamma_1\}} \Psi(\tilde{A}\gamma_1),$$

with the criterion function, $\Psi(\tilde{A}\gamma_1)$, being given by

$$\Psi(\tilde{A}\gamma_1) \equiv \sum_{h=0}^{7} f\left(\frac{r_{\pi,\gamma_1}(h)}{s_\pi}\right),$$

where the loss function, f, is such that $f(x) = 100x$ if $x > 0$ and $f(x) = x$ if $x \leq 0$, and s_π is the standard deviation of the reduced-form innovation to inflation. The criterion $\Psi(\tilde{A}\gamma_1)$ therefore strongly penalizes impulse vectors that generate a positive inflation response at any given horizon. If multiple impulse vectors are consistent with the imposed sign restriction on the response of inflation, the unique solution to the minimization problem above will be the impulse vector that yields the largest fall in inflation over eight quarters.

Once the surprise technology shock, ϵ_1, is identified, we identify the news shock, ϵ_2, as the linear combination of the reduced-form residuals that is orthogonal to ϵ_1 and that explains the largest fraction of the forecast error variance of TFP at a long but finite horizon, H. The h-step ahead forecast error of vector y is

$$y_{t+h} - \mathbb{E}_t y_{t+h} = \sum_{\tau=0}^{h-1} B_\tau \tilde{A} D \epsilon_{t+h-\tau}.$$

Denoting by $\Omega_{i,j}(h)$ the share of the forecast error variance of variable i attributable to structural shock j at horizon h, this quantity is given by

$$\Omega_{i,j}(h) \equiv \frac{e_i^{'}\left(\sum_{\tau=0}^{h-1} B_\tau \tilde{A} D e_j e_j^{'} D^{'} \tilde{A} B_\tau^{'}\right) e_i}{e_i^{'}\left(\sum_{\tau=0}^{h-1} B_\tau \Sigma B_\tau^{'}\right) e_i} = \frac{\sum_{\tau=0}^{h-1} B_{i,\tau} \tilde{A} \gamma_j \gamma_j^{'} \tilde{A} B_{i,\tau}^{'}}{\sum_{\tau=0}^{h-1} B_{i,\tau} \Sigma B_{i,\tau}^{'}},$$

where

$$B_{i,\tau} = e_i^{'} B_\tau, \qquad \gamma_j = D e_j,$$

and e_i is a selection vector with 1 in the ith position and zero elsewhere. The identification of the news shock therefore amounts to selecting the vector γ_2 that solves the following maximization problem:

$$\max_{\{\gamma_2\}} \Omega_{1,2}(H) \equiv \frac{\sum_{\tau=0}^{H-1} B_{1,\tau} \tilde{A} \gamma_2 \gamma_2^{'} \tilde{A} B_{1,\tau}^{'}}{\sum_{\tau=0}^{H-1} B_{1,\tau} \Sigma B_{1,\tau}^{'}}$$

s.t.

$$\gamma_2(1) = 0, \qquad \gamma_2^{'}\gamma_1 = 0, \qquad \gamma_2^{'}\gamma_2 = 1.$$

The first constraint ensures that the news shock does not affect TFP contemporaneously; the second constraint ensures that the news shock is orthogonal to ϵ_1; and the third constraint ensures that γ_2 is a column vector of an orthonormal matrix. In practice, we choose $H = 80$ quarters.

4 Results

We apply our agnostic identification strategy to the same seven-variable VAR estimated by Barsky & Sims (2011). We consider two data sets: the one originally used by these authors, which spans the period 1960Q1–2007Q3, and an updated data set that extends the data coverage through 2016Q4. For each of these samples, we discuss the impulse responses to a surprise and an anticipated technology shock, the contribution of news shocks to the forecast error variance of macroeconomic aggregates, and their historical decomposition. In the process, we contrast our findings with those obtained using Barsky & Sims' methodology.

4.1 Sample period 1960Q1–2007Q3

Impulse responses We start by discussing the estimated impulse responses to a surprise and an anticipated technology shock. To gauge these responses from the standpoint of New Keynesian theory, we compare them with those implied by the Smets & Wouters (2007) model. To do so, we again assume that TFP is described by process (1)–(2) and calibrate the parameters ρ_a and ρ_x and the size of the disturbances ϵ_t^s and ϵ_t^n so as to replicate as closely as possible the estimated response of TFP to the surprise and the news shock. The confidence intervals around the estimated impulse responses are computed using Kilian (1998)'s bias-corrected bootstrap procedure.

The estimated impulse responses to a surprise technology shock are reported in the right column of Figure 5. For ease of comparison with the results based on reduced-form innovations to TFP (as in Barsky & Sims (2011) and the rest of the empirical literature on news shocks), the left column of Figure 5 reproduces the responses reported in Figure 1 using the same scale for each response as in the right column.

TFP increases on impact and remains persistently higher than its pre-shock level, a pattern that contrasts with the rapid return obtained when surprise technology shocks are identified as TFP innovations (shown in the upper left panel of Figure 5).[14] Consumption and output also increase persistently and in a hump-shaped fashion. The estimated responses are remarkably similar to those implied by the Smets & Wouters (2007) model (particularly for consumption), and sharply contrast with the small, transitory and rather monotonic pattern obtained from the identification scheme associating the shock with the TFP innovation.

[14]This is reflected in the larger estimate of the parameter ρ_a implied by our estimated response of TFP (0.956) than that implied by the TFP response estimated using Barsky and Sims' methodology (0.897).

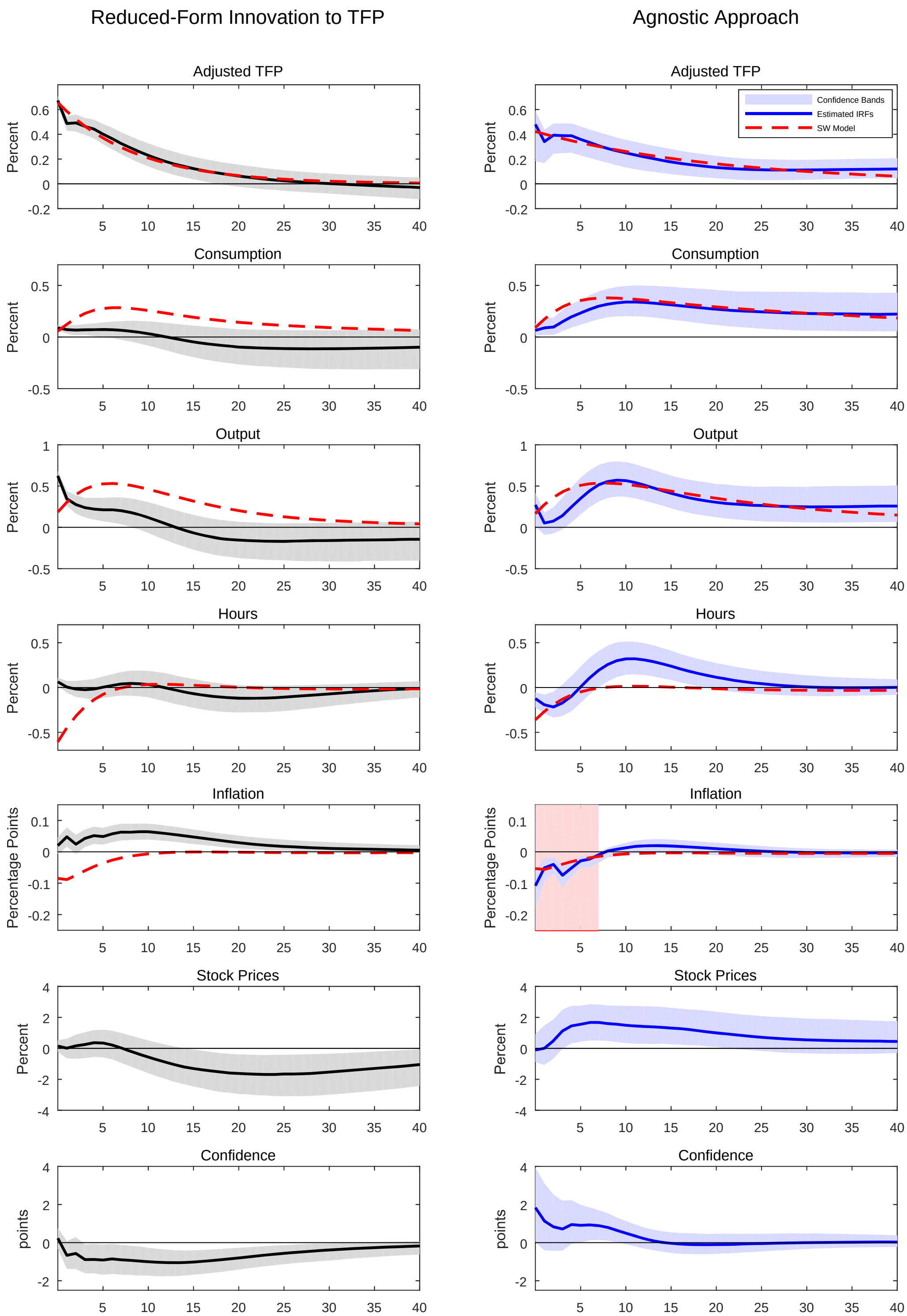

Figure 5: Impulse responses to a surprise technology shock. Sample: 1960Q1–2007Q3.

Notes: The figure shows the impulse responses to a surprise technology shock. The solid lines are the median impulse responses estimated based on the reduced-form innovation to TFP (left panels) and on the agnostic approach (right panels). The 68 percent confidence bands are the bias-corrected bootstrap confidence intervals computed using Kilian (1998)'s procedure with 2000 replications. The shaded red area indicates the horizons at which the inflation response is constrained to be negative. The dashed lines are the impulse responses obtained from the Smets & Wouters (2007) model.

Hours worked initially fall for about five quarters, then increase in a hump-shaped manner before converging to their pre-shock level from above. This pattern is consistent with the prediction of the Smets & Wouters (2007) model, at least qualitatively, and differs from the muted reaction shown in the corresponding left panel. The result that unanticipated technological improvement has a contractionary effect on employment in the short run has been documented in several studies using different empirical approaches.[15]

Our estimated response for inflation is, by construction, restricted to be negative for the first eight quarters after the shock, as indicated by the shaded red area. Beyond that horizon, the inflation response becomes small and statistically insignificant. Interestingly, although our identification strategy does not impose a precise numerical value for the inflation response, the estimated response is strikingly similar to that implied by the Smets & Wouters (2007) model. The latter lies within the estimated confidence band at almost any given horizon.

Our identified surprise technology shock raises stock prices and consumer confidence. Stock prices are initially unresponsive but increase significantly and persistently during the subsequent quarters. The increase in consumer confidence is more transitory and is only statistically significant on impact and between the sixth and eighth quarters after the shock. These responses are at variance with the persistent decline in stock prices and consumer confidence shown in the left panels of Figure 5.

In sum, these findings show that identifying surprise technology shocks by restricting their effect on inflation to be negative produces impulse responses that are more consistent with conventional wisdom and better grounded in theory than those obtained by using reduced-form innovations to TFP as a measure of surprise technology shocks. Interestingly, our estimated responses mimic remarkably well those implied by the Smets & Wouters (2007) model. The latter mostly lie within the confidence bands of the VAR-based responses.

The estimated responses to a news shock are illustrated in the right column of Figure 6. The response of TFP is similar in shape but significantly smaller in magnitude than that based on Barsky & Sims' approach. An important conclusion from Barsky & Sims' paper is that output and hours worked initially decline in response to a favorable news shock about future productivity (see the third and fourth panels on the left column of Figure 6), an outcome that violates the predictions of the Smets & Wouters (2007) model. Both variables then rise persistently during the subsequent quarters, although the rise in hours is mostly statistically insignificant. A similar pattern for hours is reported by Forni et al. (2014), Barsky et al. (2015), and Kurmann & Sims

[15]See Galí & Rabanal (2005) for a survey.

(2017).[16] The short-run contractionary effect of the news shock on aggregate output and hours worked no longer occurs, however, when we use our agnostic empirical methodology, as the output response is now statistically insignificant during the first two quarters after the shock, and that of hours worked is statistically indistinguishable from zero at any given horizon. In other words, we find no evidence of negative comovement between macroeconomic aggregates conditional on our identified news shock.[17]

Turning to the response of inflation, Barsky & Sims' approach implies that a favorable news shock about future technology decreases inflation sharply and persistently. This disinflationary effect, also documented by Forni et al. (2014), Barsky et al. (2015), Fève & Guay (2016), and Kurmann & Sims (2017), is puzzling in light of New Keynesian theory, as pointed out by Barsky & Sims (2009), Jinnai (2013), and Kurmann & Otrok (2014). In the context of the basic New Keynesian model presented in Section 2.2.1, it is possible to show (using the method of undetermined coefficients) that the initial response of inflation to a news shock is given by

$$\frac{d\pi_t}{d\epsilon_t^n} = \frac{\sigma\lambda(1+\varphi)\left[\lambda(\sigma+\varphi)(\phi_\pi - 1) + (1-\beta)\phi_y - \beta\sigma(1-\rho_a)(1-\rho_x)\right]}{\Delta_a \Delta_x},$$

where $\Delta_x = \lambda(\sigma+\varphi)\left(\phi_\pi - \rho_x\right) + (1-\beta\rho_x)\left[\sigma\left(1-\rho_x\right) + \phi_y\right] > 0$. While the sign of the expression above is, in principle, ambiguous, it typically tends to be positive under sufficiently high values of ρ_a and ρ_x and a plausible calibration of the remaining parameters. Using the estimated values of ρ_a and ρ_x and the calibration discussed in Section 2.2.1, the basic New Keynesian model predicts a positive response of inflation to a favorable TFP news shock. The Smets & Wouters (2007) model also implies that inflation rises temporarily after a positive news shock but the response is tiny and essentially indistinguishable from 0 at any given horizon. This disinflation puzzle has prompted some researchers to suggest modifications to the prototype New Keynesian model so as to reconcile its predictions with the empirical evidence.[18] Contrasting with the existing evidence, however, our results indicate that the inflation response to a favorable news shock is rather muted and

[16] Forni et al. (2014)'s approach is based on an estimated factor-augmented VAR in which the news shock is identified as the shock that best anticipates TFP at the 60-quarter horizon while being orthogonal to the reduced-form innovation in TFP. Barsky et al. (2015) identify the news shock as the innovation in the expectation of TFP at a fixed horizon in the future (20 quarters). Kurmann & Sims (2017) rely on the Max Share method (with $H = 80$) but without imposing the orthogonality of the news shock with respect to current TFP.

[17] Kurmann & Sims (2017) point out that the results based on Barsky & Sims' methodology are sensitive to revisions in Fernald's adjusted TFP series. Using the 2016 vintage of this series, they find, based on a four-variable VAR, that the response of hours worked to a favorable news shock is statistically insignificant during the first two quarters and positive thereafter. We also observed some sensitivity in the results based on our seven-variable VAR, though not to the extent documented by Kurmann & Sims (2017). Using the 2016 vintage of adjusted TFP, we found that hours worked fall for a single period after the shock, whereas the initial response of output is statistically insignificant. On the other hand, the results based on our agnostic strategy prove to be robust to the use of the revised TFP series. These results are not reported but are available upon request.

[18] See, for instance, Jinnai (2013), Barsky et al. (2015), and Kurmann & Otrok (2014).

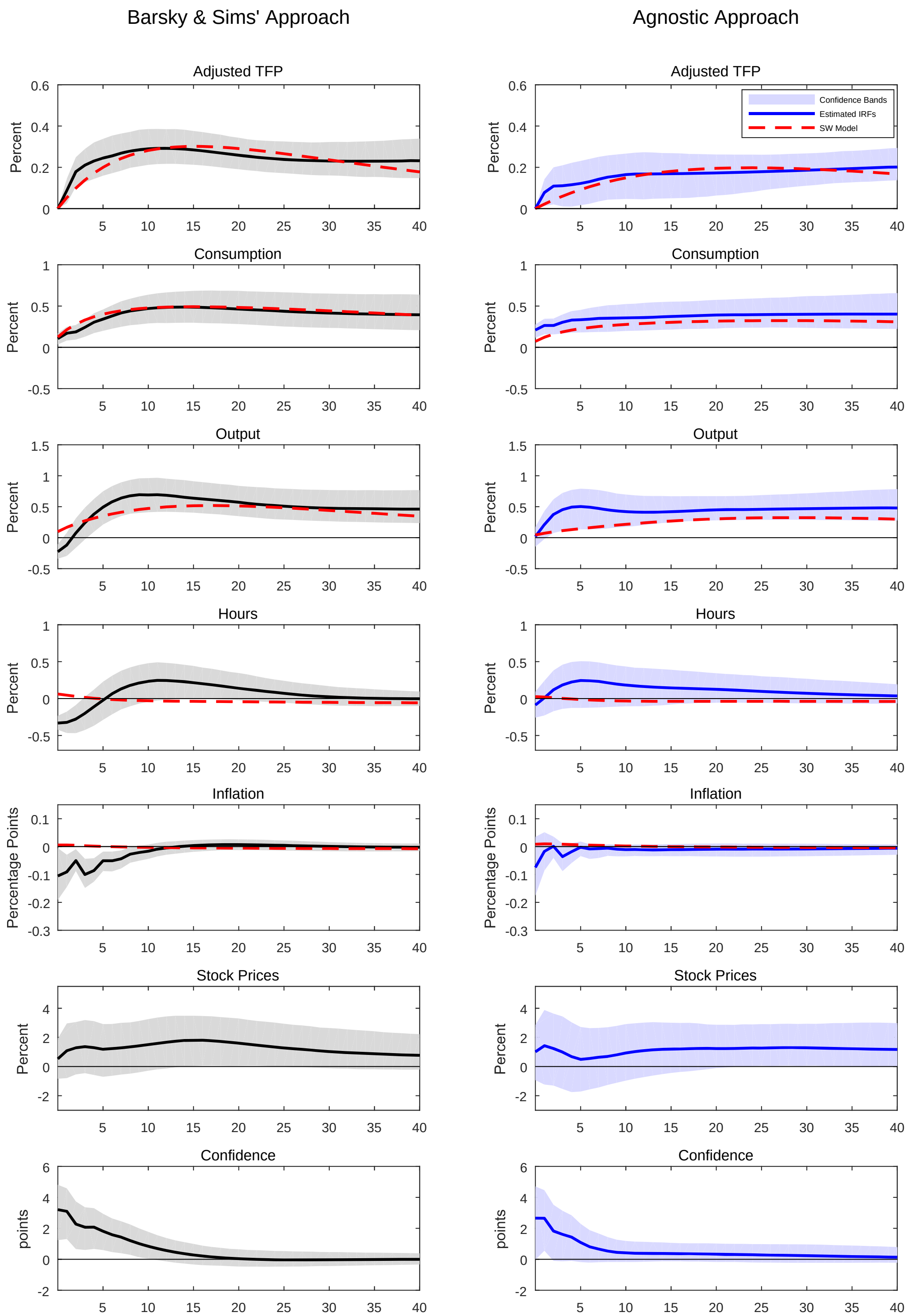

Figure 6: Impulse responses to a news shock. Sample: 1960Q1–2007Q3.

Notes: The figure shows the impulse responses to a news shock. The solid lines are the median impulse responses estimated based on Barsky and Sims' approach (left panels) and on the agnostic approach (right panels). The 68 percent confidence bands are the bias-corrected bootstrap confidence intervals computed using Kilian (1998)'s procedure with 2000 replications. The dashed lines are the impulse responses obtained from the Smets & Wouters (2007) model.

statistically insignificant at all horizons, consistently with the theoretical prediction. In other words, the disinflation puzzle vanishes under our agnostic identification strategy. The disinflationary effect documented in earlier studies appears to be an artifact of the misidentification of anticipated technology shocks, due to measurement errors in TFP.

Variance decomposition Before evaluating the contribution of news shocks to the variability of macroeconomic variables, it is worth discussing the relative importance of the identified surprise technology shocks in explaining TFP. The results are reported in Table 1.[19] By construction, when surprise technology shocks are identified as the reduced-form innovations to TFP, they explain *all* of the forecast error variance of TFP at $h = 1$ (recall that the news shock does not affect TFP contemporaneously). Under our agnostic strategy, however, this need not be the case. In fact, our identified surprise technology shocks account for roughly half of the one-quarter ahead forecast error variance of TFP, thus implying that non-technological shocks (potentially reflecting measurement errors) account for the remaining half, which in turn raises a serious objection against the interpretation of the estimated TFP series as a purified measure of technology.

Table 1: Share of Forecast Error Variance of TFP attributed to Surprise Technology Shocks. Sample: 1960Q1–2007Q3.

	Horizon					
	$h = 1$	$h = 4$	$h = 8$	$h = 16$	$h = 24$	$h = 40$
Reduced-form innovation to TFP	1.000	0.976	0.783	0.502	0.632	0.537
Agnostic approach	0.519	0.559	0.562	0.502	0.447	0.373

Note: The Table reports the median fraction (across 2000 bootstrap replications) of the h-step ahead forecast error variance of TFP due to surprise technology shocks identified as the reduced-form innovations to TFP and using our agnostic approach.

Table 2 shows the contribution of news shocks to the h-step ahead forecast error variance of the series used in estimation. The table also reports the results implied by Barsky & Sims' methodology. Our identified news shocks explain less than 3 percent of the conditional variance of TFP at the one-year horizon and less than 25 percent at the ten-year horizon. They account for more than 35 percent of the forecast error variance of consumption but less than 2 percent of the forecast error variance of output at the one-year horizon. The contribution of news shocks to output variability rises steadily with the forecasting horizon, reaching 38 percent at the ten-year horizon. For hours worked, inflation, stock prices and consumer confidence, the share of the forecast error variance

[19]The results shown in the table are the median fractions across the 2000 bootstrap replication.

attributed to news shocks never exceeds 16 percent at any given horizon. Compared with the results based on Barsky & Sims' approach, we generally find a smaller contribution of the news shock to aggregate fluctuations at business-cycle frequencies.

Table 2: Share of Forecast Error Variance attributed to News Shocks. Sample: 1960Q1–2007Q3.

	Horizon					
	$h = 1$	$h = 4$	$h = 8$	$h = 16$	$h = 24$	$h = 40$
			Barsky & Sims' Approach			
TFP	0.000	0.068	0.157	0.311	0.394	0.459
Consumption	0.087	0.207	0.366	0.491	0.503	0.478
Output	0.079	0.073	0.199	0.385	0.428	0.425
Hours	0.419	0.171	0.128	0.155	0.162	0.160
Inflation	0.106	0.172	0.198	0.180	0.175	0.170
Stock Prices	0.040	0.068	0.083	0.112	0.124	0.133
Confidence	0.210	0.223	0.234	0.230	0.218	0.210
			Agnostic Approach			
TFP	0.000	0.027	0.049	0.105	0.154	0.233
Consumption	0.355	0.434	0.419	0.363	0.360	0.381
Output	0.019	0.143	0.219	0.244	0.268	0.313
Hours	0.071	0.091	0.125	0.132	0.137	0.150
Inflation	0.078	0.081	0.072	0.073	0.082	0.096
Stock Prices	0.091	0.100	0.100	0.104	0.112	0.136
Confidence	0.150	0.161	0.148	0.139	0.143	0.151

Note: The table reports the median fraction (across 2000 bootstrap replications) of the h-step ahead forecast error variance of each variable due to news shocks identified using Barsky & Sims' approach (top panel) and our agnostic approach (bottom panel).

Historical decomposition In order to further investigate the importance of news shocks in accounting for business-cycle fluctuations, we simulate the time paths of consumption, output, and hours worked from the estimated VAR assuming that the news shocks are the only stochastic disturbances driving the data. The median results (across 2000 bootstrap replications) are depicted in Figure 7, where the series are expressed in growth rates. The correlation between the actual and simulated series is high for consumption (0.72) but fairly low for output and hours worked (0.21 and 0.15, respectively). News shocks appear to have played a very limited role in explaining post-war U.S. recessions, especially the 1969–1970, 1973–1975, and 1981–1982 recessions.

Using the simulated series, we also compute the cross-correlations of the growth rates of consumption, output, and hours. The medians across the 2000 bootstrap replications are reported

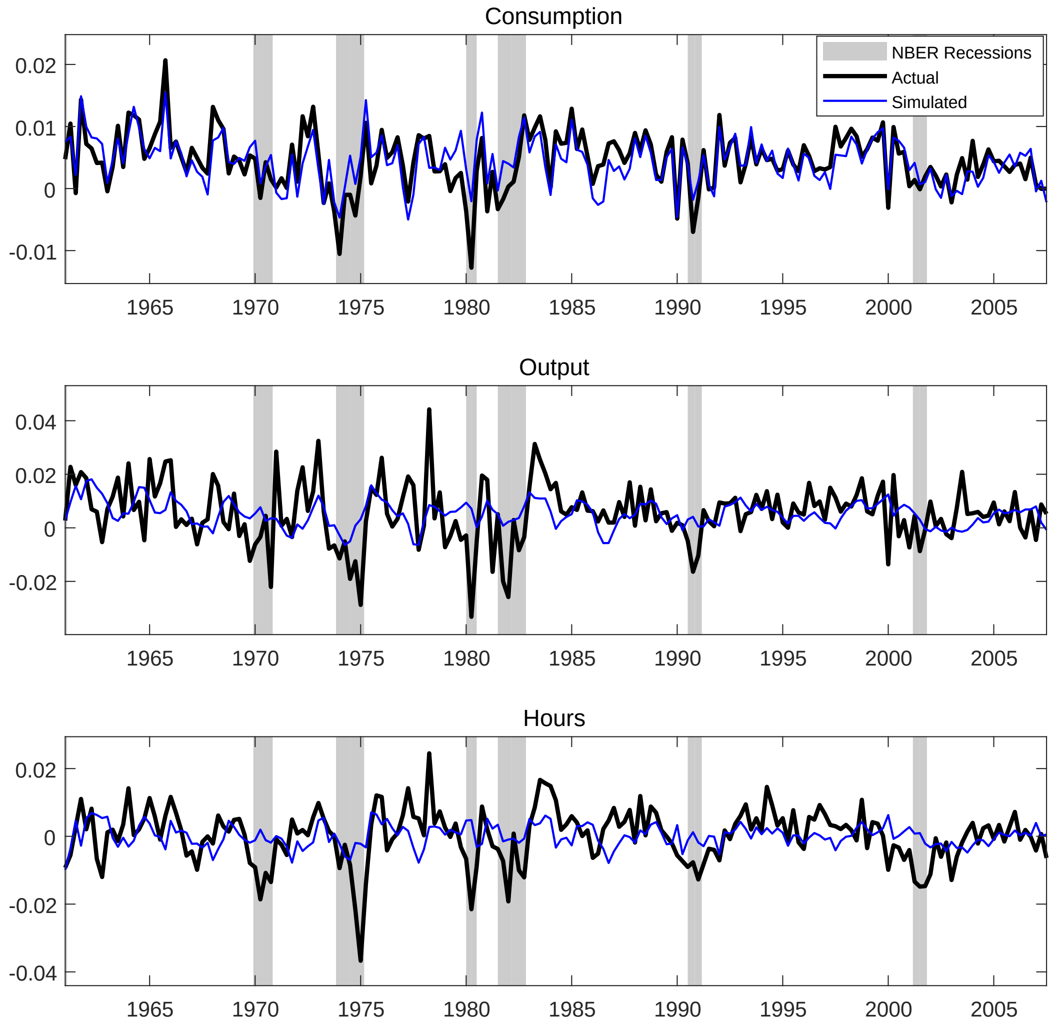

Figure 7: Historical decomposition. Sample: 1960Q1-2007Q3.

Notes: The figure shows the actual series (thick black lines) and the ones simulated from the VAR assuming that news shocks are the only stochastic disturbances (thin blue lines). The simulated series are the median across 2000 bootstrap replications. The shaded areas indicate the dates of the U.S. recessions identified by the NBER.

in Table 3. While there is positive comovement between consumption and hours worked in the data, the news shocks identified using Barsky & Sims' methodology imply negative comovement, consistently with the impulse responses shown in the left panels of Figure 6. Our agnostic strategy, on the other hand, implies a positive correlation between consumption and hours worked.

Together with the variance decomposition results discussed above, these observations lead us to conclude that news shocks are unlikely to have been a major driver of business-cycle fluctuations during the period 1960–2007. While this conclusion corroborates that reached by Barsky & Sims (2011), our argument for making such a claim differs from theirs. Indeed, Barsky & Sims (2011) base their conclusion on the fact that consumption co-moves negatively with output and hours worked in response to a news shock, a result that, as we have shown, is largely driven by measurement errors in TFP, just as the disinflationary effect of the shock. Instead, our conclusion is founded on the observation that news shocks explain only a modest fraction of the variability of output and hours worked at business-cycle frequencies.

Table 3: Comovement in the Data and Conditional on News Shocks. Sample: 1960Q1–2007Q3.

	U.S. Data	Barsky & Sims' Approach	Agnostic Approach
$Corr(\Delta \ln C_t,\, \Delta \ln Y_t)$	0.505	0.316	0.560
$Corr(\Delta \ln C_t,\, \Delta \ln N_t)$	0.387	-0.036	0.291
$Corr(\Delta \ln Y_t,\, \Delta \ln N_t)$	0.688	0.854	0.822

Notes: The table reports the historical correlations computed from the data and the ones based on the simulated series (medians across 2000 bootstrap replications) under the assumption that news shocks are the only stochastic disturbances. The variables C_t, Y_t, and N_t denote, respectively, consumption, output, and hours worked.

4.2 Sample period 1960Q1–2016Q4

Impulse responses The impulse responses based on the extended sample are reported in Figures 8 and 9 for the surprise and the news shock, respectively. As before, the left column of each figure shows the results based on Barsky & Sims' methodology while the right column shows the results based on our agnostic approach.

Starting with the surprise technology shock, the results based on the updated sample are very similar to those depicted in the right column of Figure 5. The shock has a long-lasting effect on TFP, consumption, and output. Hours worked fall significantly during the year following the shock, but their response is now statistically insignificant during the subsequent horizons. The inflation response to the surprise technology shock is negative by construction during the first eight quarters, and is virtually nil afterward. Stock prices exhibit a positive delayed response, while consumer confidence rises significantly for about ten quarters before returning to its pre-shock level.

Turning to the responses to the news shock, the left column of Figure 9 shows that one of Barsky & Sims' main results, namely the contractionary effect of an anticipated technology shock on output and hours, disappears when we apply their identification strategy to the updated sample. Output increases significantly and persistently but with a delay of three quarters, whereas the response of hours worked is mostly statistically insignificant. The rest of the responses are consistent with those based on the shorter sample. In particular, inflation falls significantly and persistently in response to a good news about future technology.

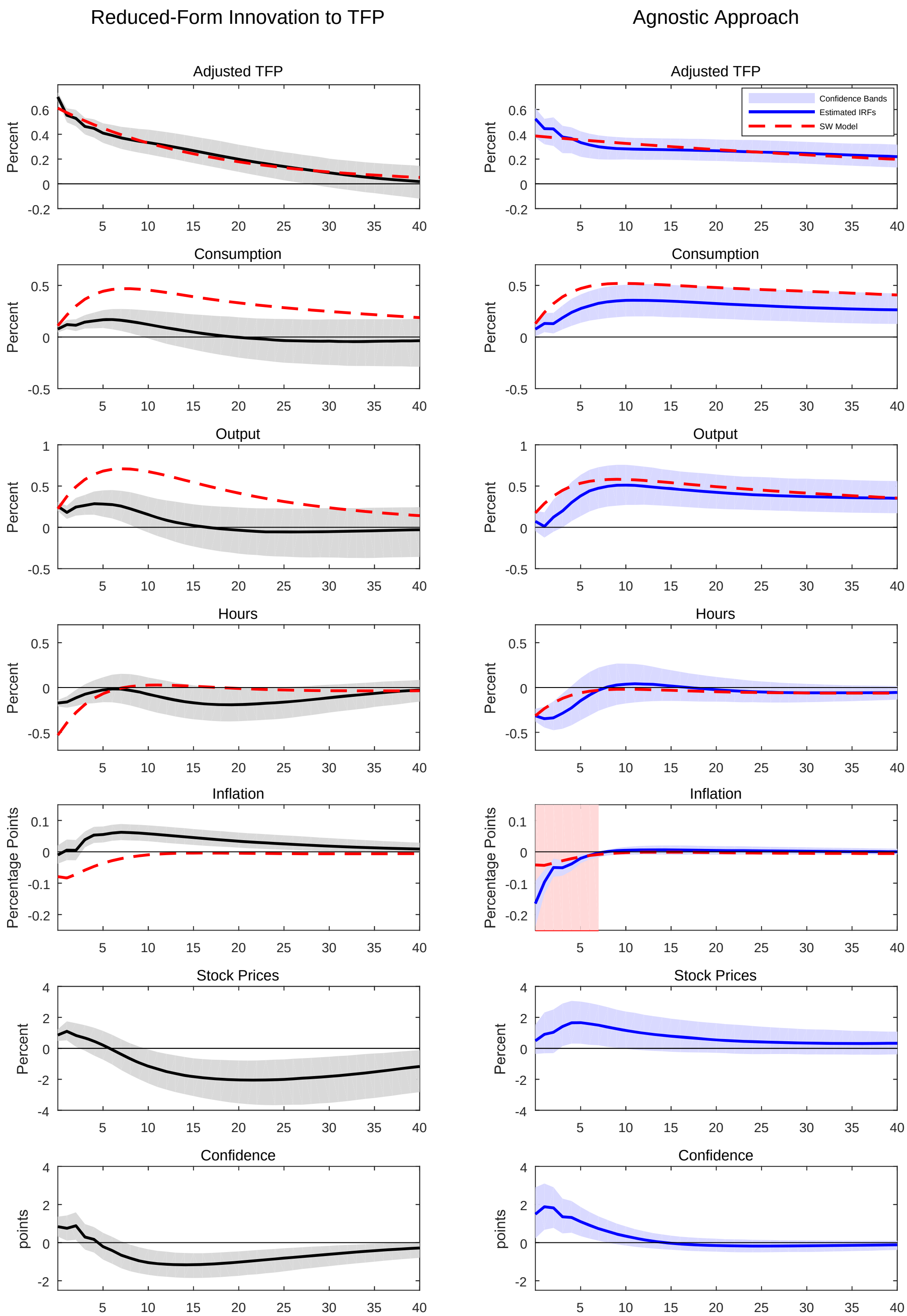

Figure 8: Impulse responses to a surprise technology shock. Sample: 1960Q1–2016Q4.

Notes: The figure shows the impulse responses to a surprise technology shock. The solid lines are the median impulse responses estimated based on the reduced-form innovation to TFP (left panels) and on the agnostic approach (right panels). The 68 percent confidence bands are the bias-corrected bootstrap confidence intervals computed using Kilian (1998)'s procedure with 2000 replications. The shaded red area indicates the horizons at which the inflation response is constrained to be negative. The dashed lines are the impulse responses obtained from the Smets & Wouters (2007) model.

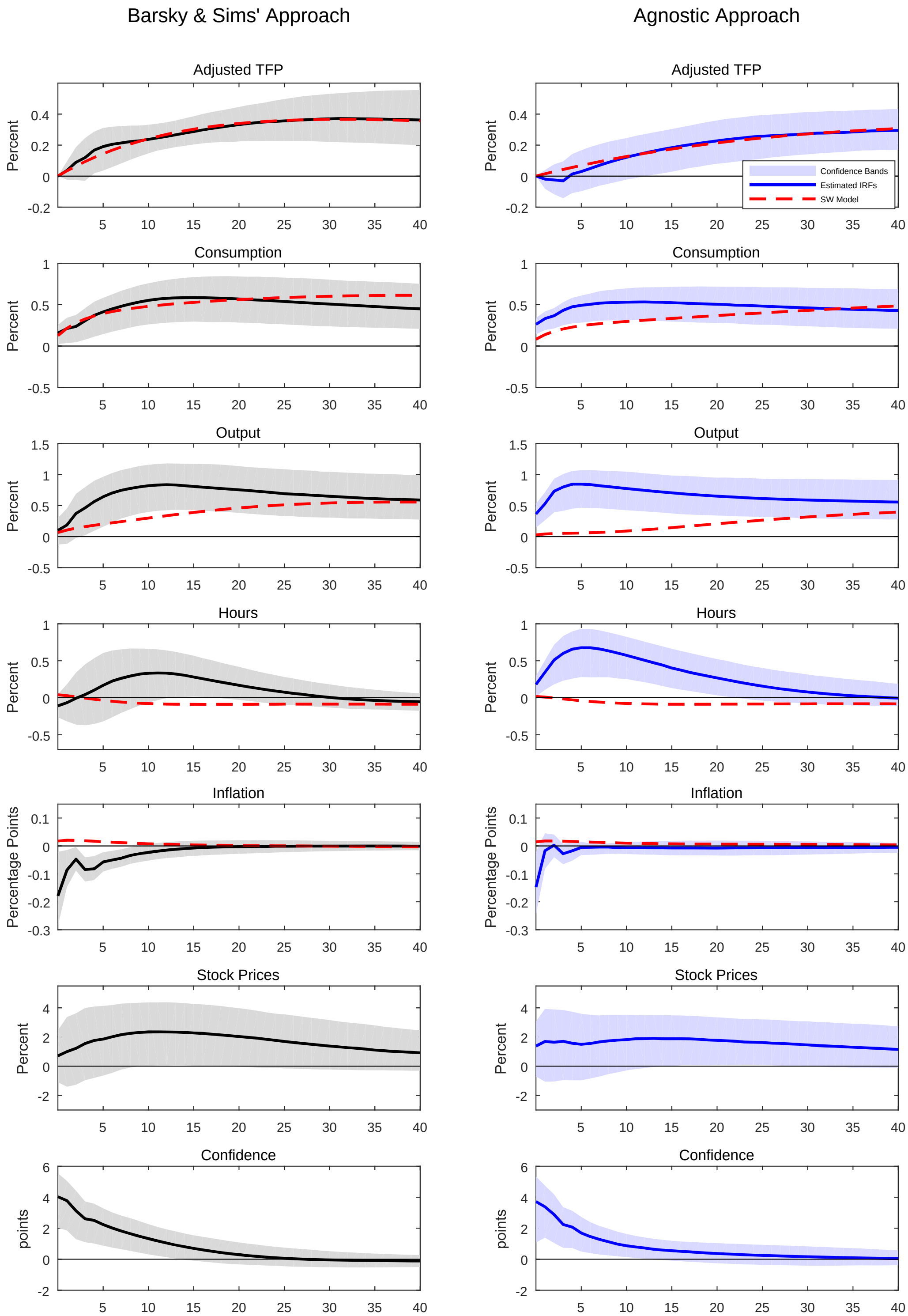

Figure 9: Impulse responses to a news shock. Sample: 1960Q1–2016Q4.

Notes: The figure shows the impulse responses to a news shock. The solid lines are the median impulse responses estimated based on Barsky and Sims' approach (left panels) and on the agnostic approach (right panels). The 68 percent confidence bands are the bias-corrected bootstrap confidence intervals computed using Kilian (1998)'s procedure with 2000 replications. The dashed lines are the impulse responses obtained from the Smets & Wouters (2007) model.

The results based on our agnostic identification strategy show important differences both with respect to those implied by Barsky & Sims' methodology and/or those based on the shorter sample. First, TFP exhibits a much more inertial response to the shock, starting to increase in a statistically significant manner only after about three years. This slowly diffusing process contrasts with the rapid increase in TFP estimated based on the shorter sample and using Barsky & Sims' methodology. Second, consumption, output, and hours worked increase significantly and persistently in response to the news shock. This simultaneous increase in macroeconomic aggregates — indicative of positive comovement — occurs well before TFP starts to rise; a result that corroborates Beaudry & Portier (2006)'s original findings. Third, inflation falls in response to the shock but its response exhibits very little persistence and is (barely) statistically significant only on impact. In other words, the disinflation puzzle appears to be much less acute under our identification strategy. Finally, unlike the results based on the shorter sample, the estimated impulse responses match rather poorly those implied by the Smets & Wouters (2007) model.

Variance decomposition Variance decomposition results for the updated sample are reported in Table 4. One of the striking differences with the results based on the shorter sample and on Barsky & Sims' methodology is that news shocks account for a relatively large fraction of the forecast error variance of output and hours worked at short horizons. At the one-year horizon, this fraction amounts to 42 percent for output and 28 percent for hours. At business-cycle frequencies, the contribution of news shocks to the variability of consumption, output, and hours worked ranges roughly between 40 and 60 percent. In contrast, Barsky & Sims' approach predicts that news shocks explain between 0.07 and 0.16 percent of the variability of hours worked at business-cycle frequencies. On the other hand, news shocks continue to explain a small fraction of the forecast error variance of inflation, stock prices, and, consumer confidence at business-cycle frequencies. Our agnostic approach continues to attribute a smaller role to news shocks in accounting for the conditional variance of these variables than does Barsky & Sims' methodology.

Historical decomposition Figure 10 shows the actual growth rates of consumption, output, and hours worked, along with their counterparts based on the artificial series simulated under the assumption that news shocks are the only underlying disturbances. The actual and simulated series for output and hours worked are more highly correlated than in the shorter sample, while actual and simulated consumption growth continue to track each other very closely.[20] The figure also

[20]The correlation between the actual and simulated series is 0.76 for consumption, 0.37 for output, and 0.38 for hours worked.

Table 4: Share of Forecast Error Variance attributed to News Shocks. Sample: 1960Q1–2016Q4.

	Horizon					
	$h = 1$	$h = 4$	$h = 8$	$h = 16$	$h = 24$	$h = 40$
	Barsky & Sims' Approach					
TFP	0.000	0.024	0.087	0.200	0.315	0.455
Consumption	0.137	0.226	0.355	0.493	0.531	0.527
Output	0.041	0.125	0.257	0.427	0.473	0.482
Hours	0.067	0.070	0.101	0.153	0.162	0.161
Inflation	0.188	0.206	0.219	0.212	0.193	0.181
Stock Prices	0.059	0.085	0.119	0.166	0.186	0.320
Confidence	0.291	0.360	0.388	0.372	0.342	0.210
	Agnostic Approach					
TFP	0.000	0.012	0.025	0.073	0.144	0.242
Consumption	0.372	0.498	0.534	0.597	0.484	0.452
Output	0.203	0.416	0.494	0.486	0.461	0.438
Hours	0.119	0.280	0.367	0.406	0.390	0.371
Inflation	0.130	0.103	0.092	0.088	0.096	0.105
Stock Prices	0.102	0.113	0.124	0.142	0.152	0.171
Confidence	0.251	0.296	0.288	0.265	0.252	0.246

Note: The table reports the median fraction (across 2000 bootstrap replications) of the h-step ahead forecast error variance of each variable due to news shocks identified using Barsky & Sims' approach (top panel) and our agnostic approach (bottom panel).

shows that news shocks account for a significant share of the decline in consumption, output, and hours worked during the recent U.S. recessions, including the Great Recession.

Table 5 reports the median cross-correlations of the growth rates of consumption, output, and hours worked based on the simulated series. The table confirms that the negative comovement between consumption and hours worked documented by Barsky & Sims (2011) vanishes when their methodology is applied to the extended sample period. Consistently with the impulse responses estimated using our agnostic strategy, the growth rates of consumption, output, and hours worked are highly correlated, implying strong positive comovement. These findings, along with the variance-decomposition results, suggest that news shocks have become an important driver of business-cycle fluctuations in recent years. In this respect, our agnostic identification strategy provides a sharply contrasting conclusion to that based on Barsky & Sims' methodology or variants of it used in recent empirical studies.

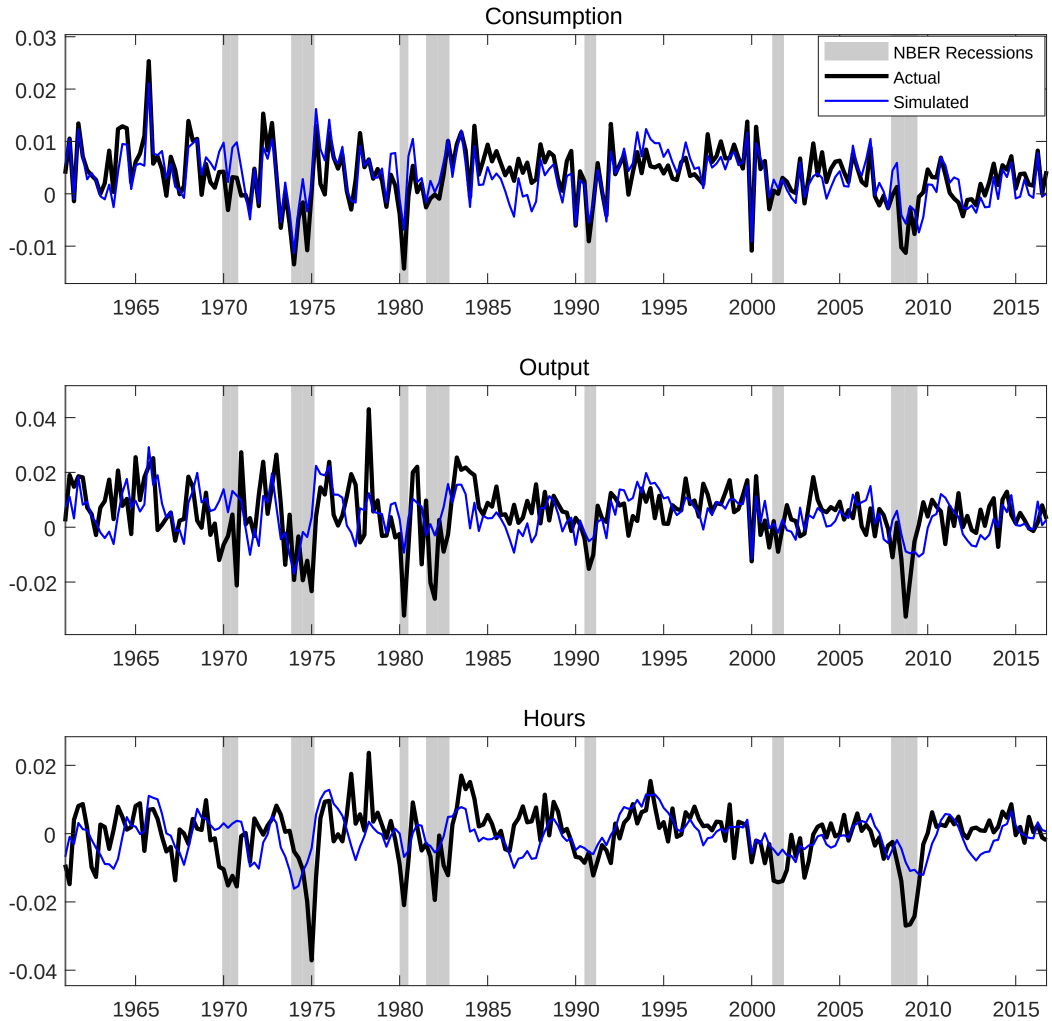

Figure 10: Historical decomposition. Sample: 1960Q1-2016Q4.

Notes: The figure shows the actual series (thick black lines) and the ones simulated from the VAR assuming that news shocks are the only stochastic disturbances (thin blue lines). The simulated series are the median across 2000 bootstrap replications. The shaded areas indicate the dates of the U.S. recessions identified by the NBER.

5 Robustness: Systematic Measurement Errors

The identification strategy proposed in this paper relies on the commonly used assumption that news shocks do not affect measured TFP contemporaneously. However, to the extent that non-technological shocks affecting TFP subsume systematic measurement errors in factor utilization, the zero-impact assumption may become unwarranted, since news shocks could affect measured TFP through their effects on input utilization. Based on the latter argument, Kurmann & Sims (2017) relax the assumption that measured TFP does not react contemporaneously to news shocks

Table 5: Comovement in the Data and Conditional on News Shocks. Sample: 1960Q1–2016Q4.

	U.S. Data	Barsky & Sims' Approach	Agnostic Approach
$Corr(\Delta \ln C_t,\, \Delta \ln Y_t)$	0.538	0.761	0.894
$Corr(\Delta \ln C_t,\, \Delta \ln N_t)$	0.391	0.363	0.743
$Corr(\Delta \ln Y_t,\, \Delta \ln N_t)$	0.667	0.757	0.884

Notes: The table reports the historical correlations computed from the data and the ones based on the simulated series (medians across 2000 bootstrap replications) under the assumption that news shocks are the only stochastic disturbances. The variables C_t, Y_t, and N_t denote, respectively, consumption, output, and hours worked.

and identify these shocks solely based on the Max Share criterion described above. Using this strategy, Kurmann & Sims (2017) find very similar effects of the news shock to those reported by Barsky & Sims (2011). In particular, they find that consumption rises while hours worked and inflation decline in response to a favorable news shock. Importantly, they show that these results remain robust when they use the 2016 vintage of Fernald's adjusted TFP series.

A crucial assumption of Kurmann & Sims' identification scheme is that the news shock is not orthogonalized with respect to the surprise technology shock. Because the latter is typically identified as the reduced-form innovation to TFP, imposing orthogonality with respect to this shock necessarily implies that the contemporaneous response of TFP to the news shock is nil,[21] which is precisely the restriction that Kurmann & Sims (2017) aim to relax (and to which we henceforth refer as the "zero-impact" restriction). This in turn suggests that Kurmann & Sims' strategy is likely to confound surprise and anticipated technological shocks, as both shocks affect TFP in the short and in the long run, making it impossible — without further assumptions — to disentangle their respective contribution to the forecast error variance of TFP at any given horizon.

Our agnostic approach, on the other hand, allows us to relax the zero-impact restriction while still imposing the orthogonality of the news shock with respect to the surprise shock, since the latter is identified via sign restrictions. The prior identification of the surprise shock enables us to identify the news shock by maximizing its contribution to the remainder of the forecast error variance of TFP at any given (range of) horizon(s).

We apply this variant of our agnostic approach to the two sample periods considered in the previous section. To do so, we relax the restriction $\gamma_2(1) = 0$ in the maximization problem described in Section 3.2. The impulse responses to a news shock based on this approach are shown in Figure 11. Interestingly, even though the zero-impact restriction is relaxed, the median initial response of adjusted TFP turns out to be equal to zero — with very little sampling uncertainty — regardless of

[21] Assuming again that TFP is ordered first in y_t, the impulse vector associated with the surprise technology shock has zeros everywhere except for the first element. For this impulse vector to be orthogonal to the one associated with the news shock, the latter must have zero as its first element.

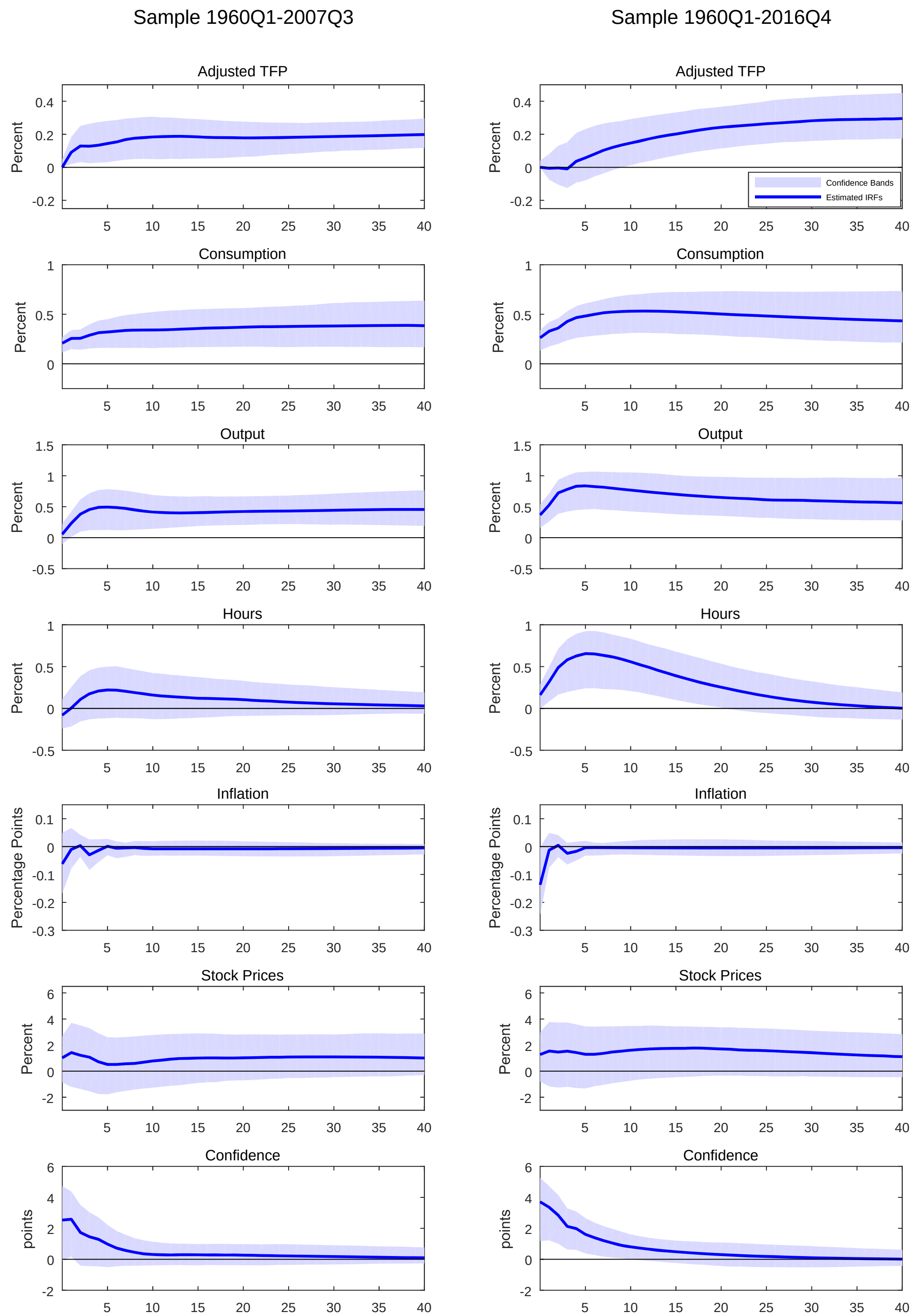

Figure 11: Impulse responses to a news shock: Relaxing the zero-impact restriction.

Notes: The figure shows the impulse responses to a news shock estimated using the agnostic strategy under the assumption that the news shock can affect TFP on impact. The solid lines are the median impulse responses. The 68 percent confidence bands are the bias-corrected bootstrap confidence intervals computed using Kilian (1998)'s procedure with 2000 replications.

the sample period. The estimated response of TFP during the subsequent quarters is remarkably similar to that estimated under the zero-impact restriction. This can be seen by comparing the upper left panel of Figure 11 with the upper right panel of Figure 6 for the 1960Q1–2007Q3 sample period, and the upper right panels of Figures 11 and 9 for the 1960Q1–2016Q4 sample period. Not surprisingly (given this similarity), the impulse responses of the remaining variables are hardly affected when the zero-impact restriction is relaxed. In particular, hours worked continue to be unresponsive to the news shock in the sample ending in 2007, and to increase significantly and persistently along with consumption and output in the updated sample, while the disinflation puzzle essentially vanishes in both samples. These findings contradict those reported by Kurmann & Sims (2017) and suggest that their identified news shock is partly picking up the effects of the unanticipated technology shock.

We also find that the variance-decomposition results and the historical decomposition of macroeconomic aggregates exhibit very little sensitivity to the zero-impact restriction,[22] thus confirming our main conclusions: news shocks contributed modestly to business-cycle fluctuations during the 1960Q1–2007Q3 period, but their importance has increased significantly in recent years.

6 Conclusion

Much of the recent VAR-based evidence on the effects of news shocks about future productivity casts doubt on the plausibility and importance of TFP-news-driven business cycles, as these shocks are found to generate negative comovement between consumption and hours worked. Another robust finding of this literature is that favorable news shocks tend to be associated with sharp and persistent declines in inflation.

In this paper, we have shown that these conclusions are spurious and are largely due to the presence of measurement errors in TFP. We have documented the severity of these errors by examining the effects of unanticipated technology shocks, usually identified as the reduced-form innovations to TFP. We found these effects to be inconsistent with the interpretation of unanticipated technological disturbances as supply shocks. We have then proposed an agnostic identification strategy that is robust to measurement errors, successfully isolating the technological component of TFP. We found no evidence of negative comovement between consumption and hours worked conditional on a news shock, and the disinflation puzzle essentially disappears under our identification strategy. Importantly, we found that news shocks have become a major source of business-cycle fluctuations in recent years, consistently with Beaudry & Portier (2006)'s original view.

[22] To conserve space, these results are not reported but are available upon request.

News about TFP, however, are clearly not the only factor that can cause changes in agents' expectations. Some recent studies have empirically examined the importance of changes in expectations caused by factors unrelated to TFP, such as news about investment-specific technology (e.g., Ben Zeev & Khan (2015)) or sentiments (e.g., Beaudry et al. (2011), Levchenko & Pandalai-Nayar (2015) and Fève & Guay (2016)). The identification of these shocks, however, usually relies on the prior identification of TFP news shocks, which implies that the empirical approaches developed in this strand of the literature are also likely to be plagued by measurement errors in TFP. By correctly identifying TFP news shocks, the empirical strategy developed in this paper can therefore help shed light on the relative importance of non-TFP news shocks for aggregate fluctuations.

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