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PIGOUVIAN CYCLES

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Keywords: Identification of shocks, TFP news, noise shocks, the Great Recession, Bayesian estimation, labor market trends, employment gap

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Pigouvian Cycles*

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Abstract

Low-frequency variations in current and expected unemployment rates are important to identify TFP news shocks and to allow a general equilibrium rational expectations model to generate Pigouvian cycles: a large fraction of the comovement of output, consumption, investment, employment, and real wages is explained by changes in expectations unrelated to TFP fundamentals. The model predicts that the start (end) of most U.S. recessions is associated with agents realizing that previous enthusiastic (lukewarm) expectations about future TFP would not be met.

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1 Introduction

The fascinating idea that business fluctuations could be driven by private-sector expectations that are unrelated to fundamentals has attracted interest from many generations of economists starting with Beveridge (1909), Pigou (1927), and Keynes (1936). In recent years, there has been a revival of interest in this topic and scholars have applied modern time-series models to investigate the role of expectations, starting from the seminal contributions by Beaudry and Portier (2004, 2006). This literature has reached very different conclusions regarding the role of anticipated shocks and beliefs in business cycles. Furthermore, the correlation of estimated TFP news shocks across a number of papers surveyed by Ramey (2016, Table 10 p.144) turns out to be very low. These dismal results call for a better understanding of which data can sharpen the identification of news shocks.

To this end, we conjecture that current and expected unemployment rates carry useful information to identify TFP news shocks. This conjecture is motivated by Figure 1, which shows the five-year moving average of the unemployment rate and the utilization-adjusted TFP growth rate as measured in Basu, Fernald, and Kimball (2006) and Fernald (2014). Periods during which TFP growth is slow (fast) are often periods of high (low) rates of unemployment, suggesting that the average unemployment rate is influenced by TFP. If so, expectations about future unemployment are directly informative about expected TFP and hence about TFP news shocks.[1] The fact that changes in the average unemployment rate sometimes lead and other times lag average TFP growth may facilitate the task of disentangling news shocks from surprise shocks to TFP. There are times, such as the Great Recession and the ensuing recovery, when the link between unemployment and TFP appears to weaken. Changes in the average unemployment rate that are not justified by variations in future fundamentals might provide valuable information to identify movements in private sector expectations unrelated to fundamentals, which were considered by Pigou as an important driver of business cycles.

We construct a dynamic general equilibrium model with labor market frictions in which agents receive noisy signals about future shocks to TFP. Signals trigger revisions of agents' expectations about future TFP changes. Noise shocks bring about those revisions of expectations that are not backed by any actual future change in TFP fundamentals and thereby can be interpreted as the driver of business cycles envisioned by Pigou. As standard in the literature (e.g., Blanchard et

[1] There are potentially other measures of real activity that could be helpful in identifying TFP news shocks in the data, yet the unemployment rate is particularly appealing for a number of reasons. The unemployment rate is a business-cycle measure that does not need to be detrended, unlike employment, hours, vacancies or GDP. Furthermore, the relationship between labor productivity and unemployment has received the attention of some influential scholars (e.g., Bruno and Sachs 1985; Phelps 1994; Blanchard, Solow, and Wilson 1995; Blanchard and Wolfers 2000; Benigno, Ricci, and Surico 2015). Notice that in Figure 1 the rate of TFP growth is adjusted for the composition of employment using the methodology of Aaronson and Sullivan (2002), so the critique by Francis and Ramey (2009) that the link between productivity and unemployment may be driven by demographics does not apply.

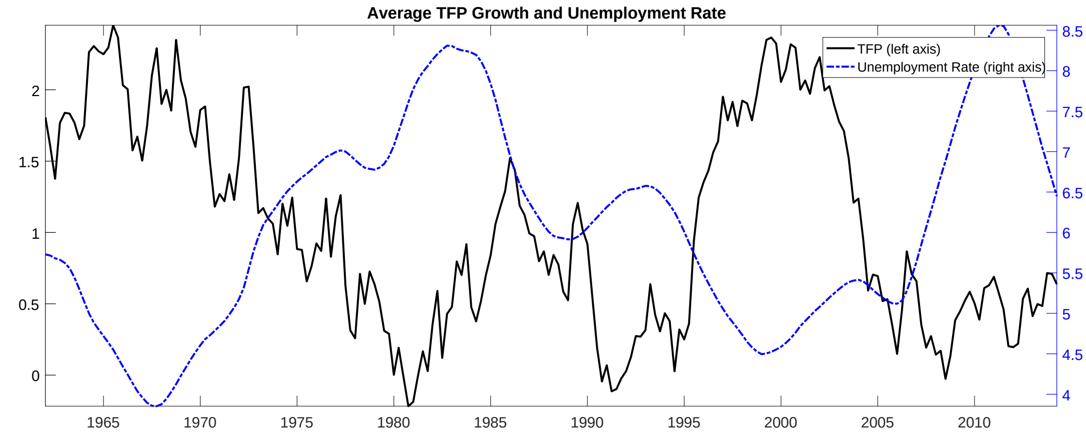

Figure 1: Five-year centered moving average of the unemployment rate and TFP growth rates. The time series are the U.S. civilian unemployment rate from the U.S. Bureau of Labor Statistics and the growth rate of TFP adjusted for capital utilization computed by Fernald (2014).

al. 2013), we estimate the model's observationally equivalent news representation, which can be solved with fast and reliable off-the-shelf techniques. Then we tease out the implied parameters of our model following Chahrour and Jurado (2017a).[2]

We estimate the news representation of the model with likelihood methods by using current and expected unemployment rates from the Survey of Professional Forecasters (SPF) and TFP growth among other macroeconomic time series. Even though the model features an array of shocks, it turns out that our conjecture is verified: TFP news shocks explain a large fraction of the variability of unemployment rates at the low end of the business-cycle frequencies and at even lower frequencies. The low-frequency swings in unemployment rates improve the identification of TFP news shocks by considerably reducing the econometrician's uncertainty about the estimates of these shocks. We achieve a significantly better estimation accuracy than that in leading studies with the same news structure.

Accurate identification of TFP news shocks is instrumental in attaining a precise identification of noise shocks. In the news representation, TFP news shocks capture revisions of agents' expectations about future TFP shocks. In our model, these same revisions are explained by the signals, which are driven by a combination of future TFP shocks and noise shocks. Identifying whether these revisions of expectations are due to future TFP shocks or noise shocks hinges on the extent to which future TFP actually changes, which we observe in the data.[3]

Low-frequency changes in unemployment rates help identify TFP news shocks because in the estimated news representation, employment responds persistently to these shocks, and with a gradual buildup. This result is hard to obtain in standard general equilibrium models, as the

[2] The model's news representation is identical to the model except for replacing the signals about future TFP shocks with news shocks to TFP.

[3] In the news representation of our model, the effects of noise shocks are reproduced by news shocks that are eventually offset by future shocks to TFP.

presence of wealth effects leads to a sharp drop in hours worked after favorable TFP news (Barro and King 1984). We overcome this issue by assuming that hiring entails a short-run disruption in production as resources are diverted from production into recruitment and training activities in the spirit of Merz and Yashiv (2007). The mechanism works as follows: The wealth effect owing to an anticipated improvement in TFP, combined with a low estimate of investment adjustment costs, weakens households' aggregate demand. Because of nominal rigidities, prices cannot fall enough to clear the market for goods. Firms can forgo the excess production by hiring more workers, since hiring entails output losses. The resulting increase in labor demand counteracts the negative wealth effect on labor supply, preventing a sharp contraction in employment at the time the news arrives. In addition, the labor frictions induce firms to anticipate the rise in labor demand so as to smooth out hiring costs. As a result of these two combined forces, employment does not respond much on impact, and then gradually rises before the actual improvement in TFP takes place. We emphasize that the rise of employment in the longer run is due to the improvement in TFP and is not very related to price rigidities. In fact, the cost of adjusting prices falls quickly with the anticipation horizon of the news shocks.

In the news representation, the identified TFP new shocks contribute very marginally to the fluctuations in the unemployment rate at the high end of the business-cycle frequencies. Yet, when we map the estimated parameters of the news representation into the parameters of our model, we find that noise shocks explain a substantial fraction of changes in the unemployment rate at every frequency of the business cycle. Noise shocks jointly account for the business-cycle variation in GDP, consumption, investment, employment and real wages with similar quantitative importance, thereby generating *Pigouvian cycles.* To our knowledge, this is the first rational expectations model in which noise shocks explain a large share of the comovement of all key business-cycle variables. This result is hard to obtain in models with a rich structure of shocks like ours as these models typically rely on a combination of shocks to explain the comovement of business-cycle variables. For instance, this is the case of the structural analysis of Blanchard et al. (2013), who find that noise matters for output and consumption, but not for investment. Thus, our finding represents an important econometric validation of the Pigouvian insight.

In our model, noise shocks play a prominent role in business cycles because they generate *boom-bust responses* in the key macroeconomic aggregates. At the beginning, these shocks trigger a buildup in output, consumption, investment, and employment as agents expect a future improvement in TFP. These initial effects of noise shocks are very similar to those brought about by TFP news shocks and arise for the same reasons, which we explained above. When agents realize that their expectations are not going to materialize, they reduce investment and hiring and the economy goes through a persistent recession. Unlike in Blanchard et al. (2013), the phases of boom and bust of output, employment, and investment are very well synchronized and this feature appears to be critical for our estimated model to generate Pigouvian cycles. We find that the boom-bust pattern associated with noise shocks has contributed to the beginning of most of the recessions and expansions in the U.S. postwar period. We believe that this is the first paper that offers this historical decomposition and shows that too enthusiastic or too lukewarm expectations about future TFP developments often precede the turning points of the business cycle.[4]

The empirical relevance of hiring frictions as forgone output has been backed by microeconomic evidence in various studies (e.g., Bartel et al. 2014, Cooper, Haltiwanger, and Willis 2015, Faccini and Yashiv 2019), which we review in the paper. Furthermore, this type of hiring frictions provides a way to counterbalance the wealth effect associated with news shocks without muting its magnitude through the adoption of specific households' preferences (Jaimovich and Rebelo 2009). Thus, our approach is consistent with the evidence provided by Mertens and Ravn (2011), which supports the existence of sizeable wealth effects.

The persistent response of employment to TFP news shocks is consistent with the findings of Faccini and Melosi (2019), who estimate a vector autoregressive (VAR) model and identify TFP news shocks consistently with how these shocks propagate in the structural model of this paper. In Appendix A, we describe the identification strategy and the impulse response functions to TFP news shocks in that paper.[5] Moreover, the most recent reduced-form literature finds little evidence that the impact effect of TFP news shocks on hours worked is positive (e.g., Barsky, Basu, and Lee 2015). In line with these findings, the estimated news representation of our model predicts that the impact response of employment to TFP news shocks is virtually zero.[6]

How does our model interpret the decoupling between the average unemployment rate and TFP growth during and after the Great Recession, which is shown in Figure 1? The model interprets this pattern as evidence that noise shocks have recently played a more important role in explaining the changes in expectations about future TFP shocks (i.e., the TFP news shocks in the news representation). The model predicts that in 2010 agents started to realize that the bad TFP news received during the Great Recession was partially exaggerated. This prompted firms to hire more workers and hence contributed to raising the employment rate in the post-Great

[4] With the terms "too enthusiastic" or "too lukewarm" we mean that agents' expectations about future TFP growth will turn out to be incorrect. We do not mean that agents are irrational and do not use the correct model to form their beliefs about future contingencies.

[5] TFP news shocks identified using the approach proposed by Barsky and Sims (2011) and Barsky, Basu, and Lee (2015) lead to a rise in TFP after one or two quarters, which is inconsistent with how TFP news shocks propagate in the news representation of our model. Faccini and Melosi (2019) identify TFP news shocks as those shocks that *(i)* do not increase the level of TFP for two years and *(ii)* raise consumption, the University of Michigan's confidence index, and stockmarket prices (S&P 500) over the next eight quarters following the realization of TFP news shocks. Except for the response of TFP, the response of the key business-cycle variables to TFP news shocks in Faccini and Melosi (2019) is qualitatively similar to those in Barsky, Basu, and Lee (2015). We show the results of Faccini and Melosi (2019) in the appendix because we are currently writing the first draft of that paper.

[6] If we introduced TFP news shocks with longer anticipation horizons, employment would slightly fall on impact and then gradually increase before the actual improvement in TFP materializes. For reasonable anticipation horizons, our results would not significantly change.

Recession recovery. Since 2013, the rise in the employment rate has been sustained by favorable TFP news, which failed to materialize due to the recent slowdown in TFP growth shown in Figure 1. Our model predicts that noise shocks have been the most important factor behind the recovery in the employment rate and the labor market boom of 2014.[7] The University of Michigan's Index of Consumer Sentiment supports the model's prediction that the private sector has started receiving good news about the economy since 2013. Since this index is not used in the estimation, this result provides external validation to this prediction by the model.

Why do we use expected unemployment in the estimation as opposed to expectations of other variables, such as expected GDP, or the confidence index? Unlike expectations of the level of GDP or employment, the expected unemployment rates do not need to be detrended. Pre-filtering the data is well-known to arbitrarily affect the predictions of estimated models in general (e.g., Gorodnichenko and Ng 2010; and Hamilton 2018) and turns out to exacerbate the problem of identifying TFP news shocks in our particular application. Using the confidence index is problematic because it is a survey measure that cannot be precisely mapped into any model's variable.

In the model, TFP shocks are the only type of shocks agents receive signals about. This modeling choice is consistent with the fact motivating our paper: news shocks are hard to identify in the data. Having signals on multiple shocks implies anticipated shocks of many types in the news representation and would raise the challenge of achieving an adequate identification of all these news shocks and hence of the noise shocks. Furthermore, one may wonder why we pick the TFP shock as the only anticipated shock instead of other types of shocks. The reason is that the TFP growth rate is measured in the data (Basu, Fernald, and Kimball 2006 and Fernald 2014), which allows us to exactly identify noise shocks conditional on the estimated TFP news shocks. To see this, recall that noise shocks are revisions in agents' expectations about future TFP that are independent of observed variations in TFP at any lead and lag. Hardly any of the standard structural shocks in empirical macroeconomics can be directly identified by observable time series.[8]

Our paper belongs to the literature that develops and estimates medium-scale general equilibrium models with news or noise shocks, which was pioneered by Schmitt-Grohe and Uribe (2012). It is therefore connected to the work of Lorenzoni (2009), Christiano et al. (2010), Barsky and Sims (2012), Blanchard et al. (2013), Nguyen and Miyamoto (2014), Avdjiev (2016),

[7]Noise explains one third of the observed fall in the rate of unemployment during the post-Great Recession recovery. The remaining two-thirds has been driven by a significant drop in the labor force participation rate. The model explains this fall in participation with changes in a low-frequency exogenous factor (namely, shocks to households' disutility to participate in the labor market), capturing long-lasting demographic and social changes in the U.S. labor force.

[8]An exception is the investment-specific-technology (IST) shock, which can arguably be identified using the inverse of the relative price of equipment (Fisher 2006). Khan and Tsoukalas (2012) estimate a New Keynesian model with anticipated IST shocks and find that these shocks play a negligible role in business fluctuations. These results are reminiscent of the findings in Justiniano, Primiceri, and Tambalotti (2011).

and Theodoridis and Zanetti (2016). A novel feature of our paper is to estimate a dynamic general equilibrium model with noisy signals about future TFP shocks using unfiltered current and expected unemployment rates and to show that these series significantly contribute to identifying these shocks. While this is not the first paper relying on labor market data to estimate a model of this type, the literature has typically pre-filtered these data in order to remove demographic and social trends that are not explained by standard macroeconomic models (e.g., Schmitt-Grohe and Uribe 2012 and Blanchard et al. 2013). However, pre-filtering labor market data turns out to also throw away the frequencies that are most useful for identifying TFP news shocks. We show that had we estimated our model using the HP-filtered rate of employment or the growth rates of employment, we would have obtained results that are very similar to Schmitt-Grohe and Uribe (2012) and Nguyen and Miyamoto (2014), who estimate their model using the growth rate of hours and find a small role for TFP news shocks and noise shocks in business cycles.[9]

Blanchard et al. (2013) estimate a structural model in which TFP has both a permanent and transitory component. Agents observe the sum of these two components as well as a noisy signal about the permanent component. As in this paper, these scholars find evidence in favor of the expectations-driven business cycle hypothesis. Nevertheless, in their estimated model noise shocks do not explain much of the business-cycle fluctuations in investment. Moreover, in Blanchard et al. (2013) the assumption of a frictionless labor market implies that employment adjusts significantly as news about future TFP arrives. As previously discussed, this feature does not align with the reduced-form evidence that typically finds that labor market variables respond with a delay and gradually buildup to TFP news. This response closely resembles the one predicted by our model. Like Barsky and Sims (2011), we rely on expectations data (they use the University of Michigan Confidence Index) to identify news shocks. Yet, these scholars do not use labor market data for their empirical exercise and conclude that noise shocks are unimportant for the business cycle.

Chahrour and Jurado (2017a) prove a representation theorem that can be used to recast models with news and noisy signals into an observationally equivalent model with only news shocks (news representation) or into observationally equivalent models with noisy signals (noise representation). These scholars recompute the contribution of noise shocks to business cycles in three leading studies. Chahrour and Jurado (2017a) do not propose a new model to empirically assess the role of news and noise shocks in explaining the business cycle, nor do they analyze which data may improve identification of these shocks, as we do in this paper.

Our paper is also connected to the literature that studies the role of TFP news in business cycles using VAR models. The original contributions of Beaudry and Portier (2006), Beaudry and Lucke (2010), and Beaudry, Nam, and Wang (2011) suggested that business cycles might be, to a significant extent, driven by expectations. Subsequent works by Barsky and Sims (2011),

[9]Chahrour and Jurado (2017a) evaluate the role of noise shocks in Schmitt-Grohe and Uribe (2012).

Kurmann and Mertens (2014), Forni, Gambetti, and Sala (2014), and Barsky, Basu, and Lee (2015) have challenged these conclusions by using alternative identification strategies. It should be noted that both strands of this literature focus on anticipated TFP shocks and do not identify their noise component. Chahrour and Jurado (2017b) propose an approach to identify the effect of noise shocks in VAR models.

Our paper is related to the young and rising literature on the structural estimation of dynamic general equilibrium models with labor market frictions (e.g., Christiano, Eichenbaum and Trabandt 2016). Faccini and Yashiv (2019) investigate the role of hiring frictions modelled as forgone output for the propagation of traditional, unanticipated shocks in a simpler model. They abstract from news shocks altogether as well as from structural estimation.

The paper is structured as follows. In Section 2, we present the model. In Section 3, we discuss the estimation and the evaluation of the model as well as how TFP news shocks are identified in the data. We evaluate the Pigouvian hypothesis in Section 4. In Section 5, we run a number of robustness checks. We present our conclusions in Section 6.

2 The Model

The economy is populated by a continuum of households, and each household comprises a unit measure of members whose labor market status can be classified as inactive, unemployed, or employed. We assume full sharing of consumption risk across households' members. Intermediate goods firms are monopolistically competitive and produce differentiated goods by renting capital from the households in a perfectly competitive market, by hiring workers in a frictional labor market, and by setting prices subject to Rotemberg adjustment costs. Final goods firms package these differentiated goods into a homogeneous composite good that is sold to the households and the government under perfect competition. The wage is set according to a simple surplus splitting rule with wage inertia à la Hall (2005). The government levies lump-sum taxes and issues one-period government bonds to the households so as to finance its purchases of final goods and to repay its maturing government bonds. The monetary authority adjusts the nominal interest rate following a standard Taylor rule. All agents are rational, observe past and current shocks, and receive signals about future shocks to TFP.

The Labor Market. Unemployed workers search for jobs and firms open vacancies in a frictional labor market. The total number of hires per period, or matches, is given by the standard Cobb−Douglas matching function $H_t = mU_{0,t}^l V_t^{1-l}$, where the parameter $m > 0$ denotes the efficiency of the matching function, $U_{0,t}$ denotes the workers who are unemployed at the beginning of the period, and V_t denotes vacancies. The parameter l governs the elasticity of the matching function to the mass of job seekers. The vacancy filling rate is given by $q_t = \frac{H_t}{V_t} = m\left(\frac{V_t}{U_{0,t}}\right)^{-l}$, and the job finding rate is $x_t = \frac{H_t}{U_{0,t}} = m\left(\frac{V_t}{U_{0,t}}\right)^{1-l}$, where $\frac{V_t}{U_{0,t}}$ denotes labor market tightness.

The Representative Household. The fraction of household workers who actively participate in the labor market is given by $LF_t = N_t + U_t$, where N_t and U_t denote the stock of workers who are respectively employed and unemployed at the end of the period. The law of large numbers implies that the measure of new hires in each period t is given by $x_t U_t^0$. These workers are assumed to start working in the same time period, implying that $U_t = (1 - x_t)U_t^0$. Under the assumption that employed workers lose their job with probability δ_N at the end of each period, N_t obeys the law of motion: $N_t = (1 - \delta_N)N_{t-1} + x_t U_t^0$.[10]

The household enjoys utility from the aggregate consumption index C_t, reflecting the assumption of full sharing of consumption risk among members. It also suffers disutility from a labor supply index $L_t = N_t + \varpi U_t$, where the parameter $\varpi \in [0, 1]$ captures the marginal disutility generated by an unemployed member relative to an employed one. The period utility function is given by $\mathcal{U}_t = \eta_t^p \ln\left(C_t - \vartheta \bar{C}_{t-1}\right) - \eta_t^l\left(\chi/1 + \varphi\right) L_t^{1+\varphi}$, where ϑ is a parameter capturing external habits in consumption, φ is the inverse Frisch elasticity of labor supply, χ is a scale parameter, $\bar{C}_{t-1}$ denotes aggregate consumption, and η_t^p and η_t^l denote exogenous autoregressive (AR) processes with Gaussian shocks, which will be referred to as preference shocks and labor disutility shocks, respectively.

The household accumulates wealth in the form of physical capital, K_t. The stock of capital depreciates at the exogenous rate δ_K and accrues with investment, I_t, net of adjustment costs. The law of motion for physical capital is therefore

$$K_t = (1 - \delta_K)K_{t-1} + \eta_t^I \left[1 - S\left(\frac{A_{t-1}I_t}{A_t I_{t-1}}\right)\right] I_t, \tag{1}$$

where η_t^I follows an exogenous AR process affecting the marginal efficiency of investment as in Justiniano, Primiceri, and Tambalotti (2011); A_t denotes a labor-augmenting state of technology; and S is an adjustment cost function that satisfies the properties $S(1) = S'(1) = 0$ and $S''(1) \equiv \phi$. The shock to the efficiency of investment is assumed to be stationary, whereas the labor-augmenting state of technology, described later, is characterized by a stochastic trend.

Every period, capital is rented to firms at the competitive rate of return R_t^K. The household can also invest in the financial market by purchasing zero-coupon government bonds at the present discounted value B_{t+1}/R_t, where R_t is the gross nominal interest rate set by the central bank. Each period, the household receives a nominal labor income $W_t N_t$ from employed workers, revenues from renting capital to the firms $R_t^K K_{t-1}$, and dividends from firms Θ_t; it also pays

[10] One could worry that the assumption of exogenous separation could hinder households' ability to reduce participation at will following a positive wealth effect. In fact, the separation rate is fixed in estimation at the corresponding value in U.S. data, which is high enough not to constrain households' decisions following a positive wealth effect.

lump-sum government taxes T_t.[11] The budget constraint can therefore be written as:

$$P_tC_t + P_tI_t + \frac{B_{t+1}}{R_t} = R_t^K K_{t-1} + W_tN_t + B_t + \Theta_t - T_t, \tag{2}$$

where it is assumed that both consumption and investment are purchases of the same composite good, which has a competitive price P_t.

Let β denote the discount factor. The intertemporal problem of the households is to choose state-contingent sequences for $\{C_{t+s}, I_{t+s}, B_{t+s+1}, LF_{t+s}, U_{0,t+s}\}_{s=0}^{\infty}$ in order to maximize the discounted present value of current and future utility, $E_t \sum_{s=0}^{\infty} \beta^s \mathcal{U}_{t+s}$ subject to the budget constraint, the participation constraint, and the laws of motion for employment and for capital.

Final goods firms. Final goods producers buy and transform a bundle of intermediate goods into a composite good Y_t by using the following constant-elasticity-of-substitution (CES) technology: $Y_t = \left(\int_0^1 Y_{i,t}^{1/\left(1+\lambda_{f,t}\right)} di\right)^{1+\lambda_{f,t}}$, where $\lambda_{f,t}$ denotes the mark-up shocks, which are assumed to follow an independent and identically distributed (i.i.d) Gaussian process in logs with mean $\ln \lambda_f$. These firms sell their composite good in a perfectly competitive market at the price index $P_t = \left(\int_0^1 P_{i,t}^{\frac{1}{\lambda_{f,t}}} di\right)^{-\lambda_{f,t}}$. The demand for good i from the final good producers is given by

$$Y_{i,t} = \left(\frac{P_{i,t}}{P_t}\right)^{-\frac{1+\lambda_{f,t}}{\lambda_{f,t}}} Y_t. \tag{3}$$

Intermediate goods firms. Intermediate goods firms face hiring frictions. In the spirit of Merz and Yashiv (2007), we model hiring frictions as a disruption in production or forgone output. As a result, the output produced by an intermediate goods firm net of hiring costs can be written as follows:

$$Y_{i,t} = f_{i,t}\left(1 - g_{i,t}\right), \tag{4}$$

where $f_{i,t}$ is the production function and $g_{i,t}$ is the fraction of production lost due to hiring.

We model hiring costs as non-pecuniary for two reasons. First, as we shall discuss in more detail in Section 3.4, modeling hiring frictions as forgone output contributes to boosting labor demand following a favorable TFP news shock. This mechanism helps the model overcome the wealth effects associated with anticipated shocks. Second, this way of modeling hiring costs is consistent with findings in the empirical micro-labor literature, which emphasizes that hiring costs

[11] Note that the model rules out the possibility of varying the utilization rate of physical capital. Introducing variable capital utilization turns out to shrink the determinacy region, making it harder to accurately estimate the parameters of the model and run robustness checks. Intuitively, expectations of higher aggregate demand induce firms to utilize capital more intensively. Because utilization costs are a purchase of the numeraire composite good, expectations of higher aggregate demand become self-fulfilling, leading to indeterminacy. These problems of indeterminacy are exhacerbated in the presence of hiring frictions. As we will discuss in Section 5, estimating a version of the model with variable capital utilization would lead to results very similar to the ones presented in the paper.

only rarely involve payments for third-party hiring services, such as head hunting or outsourced training services. In fact, the lion's share of hiring costs for firms is the opportunity cost of work incurred by the new hires, their team managers, and co-workers in connection with hiring activities. These activities imply that workers divert their work efforts away from production and into recruitment or training. These hiring activities, hence, turn out to negatively affect firms' productivity.[12]

The production function is assumed to be Cobb−Douglas: $f_{i,t} = a_t \left(A_t N_{i,t}\right)^{\alpha} \left(K_{i,t}\right)^{1-\alpha}$, where $K_{i,t}$ denotes capital rented from households at time t, a_t is a stationary technology-neutral shock (henceforth, TFP process) and A_t is a labor-augmenting technology shock that is stationary in the growth rate.[13] Specifically, we assume that $\eta_t^A = A_t/A_{t-1}$ is a stochastic trend that follows

$$\ln \eta_t^A = \left(1 - \rho^A\right) \ln \mu + \rho^A \ln \eta_{t-1}^A + \varepsilon_t^A, \tag{5}$$

where μ denotes the drift parameter of the labor-augmenting technology A_t. Moreover, the exogenous variable a_t follows the stochastic process:

$$\ln a_t = \rho^a \ln a_{t-1} + \theta_t^a,\ \theta_t^a \sim N\left(0, \sigma_\theta^2\right) \tag{6}$$

where θ_t^a is an i.i.d. Gaussian shock to TFP.

We postulate the same hiring cost function as in Sala, Soderstrom, and Trigari (2013):

$$g_{i,t} = \frac{e}{2} q_t^{-\eta^q} \left(\frac{H_{i,t}}{N_{i,t}}\right)^2, \tag{7}$$

where $H_{i,t} = q_t V_{i,t}$ and $\eta^q \in [0, 2]$ is a parameter. When $\eta^q = 0$, hiring costs depend only on the gross hiring rate $H_{i,t}/N_{i,t}$, a measure of worker turnover within the firm. These frictions are typically interpreted as capturing training costs. Formulations of hiring costs that are quadratic in the hiring rate have been adopted by Merz and Yashiv (2007), Gertler, Sala, and Trigari (2008), Christiano, Trabandt, and Walentin (2011), and Furlanetto and Groshenny (2016), among others, and are consistent with the empirical estimates in Yashiv (2016). When $\eta^q = 2$, instead, the function (7) depends only on the vacancy rate $V_{i,t}/N_{i,t}$ and can therefore be interpreted as capturing vacancy posting costs in the tradition of search and matching models of the labor

[12] Using detailed micro-data on the sources of hiring costs for a representative panel of German and Swiss firms, descriptive evidence reported by Faccini and Yashiv (2019) implies that non-pecuniary hiring costs account for around 80% of the total cost of hiring. Similarly, the review in Silva and Toledo (2009) based on U.S. data indicates that the bulk of hiring costs consists of forgone output. Moreover, Bartel et al. (2014) find that the arrival of a new nurse in a hospital is associated with lowered team-level productivity, and that this effect is significant only when the nurse is hired externally. Similarly, Cooper, Haltiwanger, and Willis (2015), using the Longitudinal Research Dataset on U.S. manufacturing plants, find that labor adjustment costs reduce plant-level production.

[13] The process of TFP and that of the labor-augmenting technology are separately identifiable because shocks to the latter are permanent.

market. Any intermediate value of η^q governs the relative importance of these two types of hiring costs.[14]

Following an argument similar to the one proposed by Gertler, Sala, and Trigari (2008), we note that by choosing vacancies, the firm directly controls the total number of hires $H_{i,t} = q_t V_{i,t}$, since it knows the job-filling rate q_t. Hence $H_{i,t}$ can be treated as a control variable in lieu of $V_{i,t}$. The problem faced by the intermediate goods firms is then to choose state-contingent series for $\{P_{i,t+s}, H_{i,t+s}, K_{i,t+s}\}_{s=0}^{\infty}$ in order to maximize current and expected discounted profits $E_t \sum_{s=0}^{\infty} \Lambda_{t,t+s} \Xi_{i,t+s} / P_{t+s}$, where nominal profits are given by

$$\Xi_{i,t} = \frac{P_{i,t}}{P_t} f_{i,t} \left(1 - g_{i,t}\right) - \frac{W_{i,t}}{P_t} N_{i,t} - \frac{R_t^K}{P_t} K_{i,t} - \frac{\zeta}{2} \left(\frac{P_{i,t}}{\left(\Pi_{t-1}\right)^{\psi} \left(\bar{\Pi}\right)^{1-\psi} P_{i,t-1}} - 1 \right)^2 Y_t. \tag{8}$$

In this equation, the parameter ζ controls the degree of price rigidities à la Rotemberg, the parameter ψ governs inflation indexation, and $\bar{\Pi}$ denotes the steady-state gross inflation rate. The problem of the intermediate goods firm is subject to the law of motion for labor,

$$N_{i,t} = (1 - \delta_N) N_{i,t-1} + H_{i,t}, \tag{9}$$

and the constraint that output must equal demand,

$$\left(\frac{P_{i,t}}{P_t} \right)^{-\frac{1+\lambda_{f,t}}{\lambda_{f,t}}} Y_t = f_{i,t} \left(1 - g_{i,t}\right), \tag{10}$$

which is obtained by combining equations (3) and (4). Note that $\Lambda_{t,t+s}$ denotes the stochastic discount factor of the households, which are the owners of the firms.

Wage Bargaining. We assume that real wages are sticky, and driven by a Hall (2005)-type wage norm:

$$\frac{W_t}{P_t} = \omega \frac{W_{t-1}}{P_{t-1}} \eta_t^A + (1 - \omega) \frac{W_t^{NASH}}{P_t}, \tag{11}$$

where ω is a parameter that governs wage rigidities.[15] The reference wage $\frac{W_t^{NASH}}{P_t}$ is assumed to maximize a geometric average of the households' and the firms' surplus weighted by the parameter γ, which denotes the bargaining power of the households:

$$\frac{W_t^{NASH}}{P_t} = \arg\max \left\{ \left(V_t^N\right)^{\gamma} \left(Q_t^N\right)^{1-\gamma} \right\}, \tag{12}$$

[14] These costs have also been defined in the literature as internal and external. External costs depend on aggregate labor market conditions (via the vacancy filling rate), whereas internal costs depend on the firm-level hiring rate. See Sala, Soderstrom, and Trigari (2013) for a detailed discussion.

[15] In Section 5, we will discuss the role played by wage inertia in our results.

where V_t^N and Q_t^N are the marginal values of jobs for households and firms, which are derived from the first-order conditions of their respective maximization problems.[16]

Policymakers, Aggregate Resource Constraint, and Market Clearing. The government budget constraint takes the following form: $P_t G_t - T_t = B_{t+1}/R_t - B_t$. Real government expenditures are given by $G_t = \left(1 - 1/\eta_t^G\right) Y_t$, where η_t^G is an AR process that determines the government's purchases of final goods. The monetary authority follows a standard Taylor rule:

$$\frac{R_t}{R^*} = \left(\frac{R_{t-1}}{R^*}\right)^{\rho_R} \left[\left(\frac{\Pi_t}{\Pi_t^*}\right)^{r_\pi} \left(\frac{\tilde{Y}_t}{Y^*}\right)^{r_y}\right]^{1-\rho_R} \eta_t^R, \tag{13}$$

where $\tilde{Y}_t \equiv Y_t/A_t$, Y^* denotes the steady-state value of $\tilde{Y}_t$; the parameter ρ_R controls the degree of interest rate smoothing; $\Pi_t \equiv P_t/P_{t-1}$ is the actual gross rate of price inflation; and r_y and r_π govern the response of the monetary authority to deviations of output and inflation from their target values, Y^* and Π_t^*, respectively. We assume that the monetary shock η_t^R follows an i.i.d. Gaussian process.[17] Moreover, as in Christiano, Eichenbaum, and Evans (2005), Del Negro et al., Smets and Wouters (2007), and Del Negro and Eusepi (2011), we assume that the variable Π_t^* captures persistent deviations from the long-run inflation target Π_*; that is, $\ln \Pi_t^* = (1 - \rho_{\Pi^*}) \ln \Pi_* + \rho_{\Pi^*} \ln \Pi_{t-1}^* + \varepsilon_t^\pi$. In our study, the only role played by the time-varying inflation target is to help the model fit the low-frequency movements of the inflation rate over our sample period.

The aggregate resource constraint reads:

$$Y_t \left[\frac{1}{\eta_t^G} - \frac{\zeta}{2}\left(\frac{\Pi_t}{\left(\Pi_{t-1}\right)^{\psi}\left(\bar{\Pi}\right)^{1-\psi}} - 1\right)^2\right] = C_t + I_t. \tag{14}$$

where Y_t denotes the aggregate output net of the aggregate hiring costs $\int g_{i,t} di$. Finally, market clearing in the market for physical capital implies that $K_{t-1} = \int K_{i,t} di$.

Agents' Information Set and Pigouvian Shocks. Agents are rational and observe all past and current shocks. Agents also observe signals about future TFP shocks θ_{t+h}^a. Specifically, in every period t, agents receive three signals $s_{8,t}$, $s_{4,t}$ and $s_{0,t}$ about the future realization of the

[16]The Nash bargaining problem in (12) assumes that hiring costs are sunk. That is, all costs of hiring are incurred before wages are bargained. This is the standard approach in the literature (cf. Gertler, Sala, and Trigari 2008; Pissarides 2009; Sala Soderstrom and Trigari 2013; Christiano, Trabandt and Walentin 2011; Furlanetto and Groshenny 2016; and Christiano, Eichenbaum, and Trabandt 2016).

[17]Faccini and Yashiv (2019) explore the transmission mechanism of monetary policy shocks in a stylized New Keynesian model with hiring frictions expressed as forgone output. They show that in such a setup monetary policy shocks can give rise to an unconventional propagation, whereby a monetary expansion leads to an initial contraction in employment and output. These results do not emerge in our estimated model.

TFP shock at time t, which are defined as

$$s_{8,t} = \theta^a_{t+8} + v_{8,t}, \quad (15)$$

$$s_{4,t} = \theta^a_{t+4} + v_{4,t}, \quad (16)$$

and $s_{0,t} = \theta^a_t$, with the noise shocks $v_{4,t}$ and $\nu_{8,t}$ following i.i.d., zero-mean Gaussian processes with standard deviations $\sigma_{4,v}$, and $\sigma_{8,v}$, respectively. The signal $s_{0,t}$ is fully revealing and hence it implies that agents perfectly observe the current realization of TFP shock θ^a_t.

The noise shocks $\nu_{4,t}$ and $\nu_{8,t}$ trigger movements in expectations about future TFP that are orthogonal to future changes in TFP fundamentals at all leads and lags. Hence, they can be thought of as capturing autonomous changes in agents' expectations, which were considered by Pigou (1927) as important drivers of business cycles.[18] Hence, we will sometimes refer to the noise shocks $v_{4,t}$ and $v_{8,t}$ as *Pigouvian shocks.*

3 Empirical Analysis

This section deals with the empirical analysis of the model with Pigouvian shocks presented in the previous section. The unit-root process followed by the labor-augmenting technology A_t causes some variables to be non-stationary. Hence, we first detrend the non-stationary variables and then we log-linearize the model equations around the steady-state equilibrium.[19] The log-linearized model is estimated using Bayesian techniques. The posterior distribution is a combination of our prior beliefs about parameter values and the model's likelihood function. The likelihood function is not available in closed form, and we use the Kalman filter to approximate it (Fernandez-Villaverde et al. 2016).

In Section 3.1, we introduce the data set used for estimation of the model parameters and discuss how the model variables are mapped to the data. Furthermore, we discuss how we handle the issue of the effective lower bound for interest rates, which becomes binding in our sample period, and how to work out the model's observationally-equivalent news representation that we estimate. We elicit the prior distribution for the parameters of the news representation in Section 3.2. The posterior moments for the model parameters and the fit of the model are analyzed in Section 3.3. The propagation of TFP news shocks and the variance decomposition of the business-cycle variables are analyzed in Section 3.4. In this section we also explain the novel mechanism based on labor market frictions that allows TFP news shocks to have persistent positive effects on the employment rate. The objective of Section 3.5 is to analyze the identification of anticipated and unanticipated TFP shocks.

[18] While in principle nothing prevents us from adding one-, two-, and three-quarters-ahead TFP signals, changes in these signals propagate very similarly in the model, which hinders their precise identification in the data.

[19] The list of the log-linearized equations of the model is reported in Appendix B.

3.1 Data, Measurement, and Estimation Strategy

The data set we use for estimation comprises sixteen variables for the U.S. economy observed over the period 1962:Q1 to 2016:Q4: real per-capita GDP growth; real per-capita consumption growth; real per-capita investment growth; the employment rate; the participation rate; the private sector's one-, two-, three-, four-quarters-ahead expectations about the unemployment rate;[20] the effective federal funds rate; real wage growth; two measures of TFP growth (one adjusted and the other unadjusted for variable capital utilization); and three measures of inflation dynamics – GDP deflator, the consumer price index (CPI), and the price index for personal consumption expenditures (PCE). Appendix C shows how these series are constructed.

We map GDP to the model's output net of hiring costs precisely because hiring costs entail production inefficiencies. Expectations about the rate of unemployment are obtained from the Survey of Professional Forecasters. Since the four unemployment expectations series from the SPF start in 1968:Q1, the Kalman filter will treat unavailable data points as missing observations. To account for any discrepancy between the SPF expectations and rationality (Jurado 2016 and Coibion, Gorodnichenko, and Kamdar 2018), we introduce an i.i.d. measurement error for each of these four series.

The TFP series adjusted and unadjusted for variable capital utilization are computed following Fernald (2014) in a way that ensures model consistency (Appendix D).[21] Ideally, TFP growth should be measured by adjusting for capital utilization. One way to do that is to have variable capital utilization in the model. However, this approach is likely to provide a fairly inaccurate adjustment because standard ways of modeling capital utilization are easily rejected by the data. Alternatively, we could rely on statistical methods to correct the series of TFP growth for capital utilization following Fernald (2014) and Basu, Fernald, and Kimball (2006), and then use the adjusted series for measuring TFP in the model. One shortcoming of this approach is that the available series of utilization-adjusted TFP growth is subject to periodic revisions based on new data and methodological refinements.[22] We mitigate these problems by adopting a flexible approach based on using both the observed unadjusted and adjusted series of TFP growth. This approach allows us to extract the common component between these two

[20] One may wonder if given these horizon structures, it would be more natural to also have TFP news shocks with one-, two-, and three-quarter anticipation horizons in equation (6). The problem with having news shocks with so similar anticipation horizons is that their propagation ends up being very similar, making it extremely challenging to precisely identify each of these shocks in the data. Data on two-year-ahead expectations about the unemployment rate are not available to the best of our knowledge.

[21] Note that we do not have to adjust Fernald's estimate of TFP for aggregate hiring costs g because these costs are modeled as forgone output. Hence, the measure of GDP in the data should be interpreted as already net of these costs. Moreover, we adjust Fernald's estimates by setting the elasticity of output to employment, α, to 0.66, which is consistent with how this parameter is calibrated in our empirical analysis (Section 3.2).

[22] For instance, Kurmann and Sims (2017) show that a recent revision concerning the estimate of factor utilization in Basu, Fernald, and Kimball (2006) materially affects the inference about the macroeconomic effects of TFP news shocks.

series of TFP growth rates and, in doing so, to filter out capital utilization. The flexibility of this approach arguably reduces the impact of measurement errors and data revisions concerning the estimate of capital utilization on our analysis. Details on how these series are constructed and how the model's TFP growth is mapped to both the adjusted and the unadjusted series are in Appendix D.

As in Campbell et al. (2012), Barsky, Justiniano, and Melosi (2014), and Campbell et al. (2017), we use the three series of the inflation rate to jointly measure the model's inflation rate. We assume that the employment rate is influenced by an i.i.d. measurement error to avoid stochastic singularity. The real wage growth rate is affected by an i.i.d. measurement error as well. The full list of measurement equations is shown in Appendix E.

We estimate the model using unfiltered data. It is well known that the application of filters to data can perversely affect the predictions of estimated models (Canova 1998; Burnside 1998; Gorodnichenko and Ng 2010; and Hamilton 2018). Furthermore, filtering the unemployment rate is likely to alter the low-frequency properties of the observed unemployment rates, which are key for identifying TFP news shocks, as we will show. We observe both the participation and employment rates, which allow us to identify the source of the observed changes in the unemployment rate in estimation. One issue is that the participation and the employment rates are non-stationary, which poses a serious challenge to our stationary model. As we will show in Section 3.3, we set up our prior so that the labor disutility shocks η_t^l can explain the low-frequency dynamics of employment and participation rates.

The federal funds rate was stuck at its effective lower bound from 2008:Q4 through 2015:Q3. Formally modeling the lower bound for the interest rate substantially raises the computational challenge of our empirical exercise because it would introduce a non-linearity in the model, which requires using non-linear Monte Carlo filters to evaluate the likelihood (Fernandez-Villaverde and Rubio-Ramirez 2004). A simpler approach is to use data on market-based future federal funds rates to estimate the model after the fourth quarter of 2008.[23] Agents' expectations about the future interest rates are informed by the market forecasts, which basically enforce the effective lower bound in the model. Therefore, agents in the model are not surprised about not seeing negative interest rates in every period during the Great Recession.

This approach has been introduced by Campbell et al. (2012) and followed by Barsky, Justiniano, and Melosi (2014), Campbell et al. (2017), Del Negro, Giannoni, and Patterson (2012), and Del Negro et al. (2017), among others. The basic idea is to append as many i.i.d. news shocks (called forward guidance shocks) to the monetary policy reaction function (equation 13) as the number of forward rates observed.[24] As done in those contributions, we assume that

[23]How we construct the series of the market-expected federal funds rate is identical to Campbell et al. (2017) and is explained in Appendix C.

[24]If one did not augment the monetary policy reaction function with these news shocks, likelihood estimation would not be feasible because the model becomes stochastically singular.

the contemporaneous realizations of the forward guidance shocks are governed by a two-factor model, which is shown in Appendix E. This factor model is intended to parsimoniously capture the high correlation among forward rates across the considered horizons (i.e., one quarter through ten quarters).[25] Following this literature, we call the parameters of this factor model forward guidance parameters. While an analysis about the role of forward guidance and monetary policy during the Great Recession and afterward is beyond the scope of this paper, making sure that agents are not surprised by the lower bound for the interest rate in every period is crucial to precisely estimating the states and the shocks and, hence, to accurately evaluating the historical role played by noise shocks in the most recent period.

Forward guidance shocks are introduced when the federal funds rate became constrained by the effective lower bound and the following periods. We first estimate the model with no forward guidance shocks over a sample period that goes from 1962:Q1 through 2008:Q3 using the data set described earlier in this section. Then we introduce the forward guidance shocks and we reestimate the measurement parameters (see Panel C of Table 6 in Appendix L for a list of measurement parameters) over the second sample (2008:Q4 through 2016:Q4) using our data set augmented with the series of the market-based future federal funds rates, which are described in Appendix C. All other parameters are set to their first-sample posterior mode (see Table 5 and Panel A and Panel B of Table 6 in Appendix L for a list of those parameters) and are not re-estimated over the most recent period. The distribution of the model's state vectors at the beginning of the second sample is initialized by taking the filtered moments of the distribution of the state vector at the end of the first sample. This two-sample approach has been used by Campbell et al. (2012) among others before us.

The news representation We estimate the model's observationally-equivalent news representation. Solving the model's news representation can be done with standard solution methods that apply to linear rational expectations models and hence is substantially less time consuming than solving our model with noisy signals. The news representation is identical to the model with noisy signals except for two features. First, in the news representation, agents do not receive the signals $s_{0,t}$, $s_{4,t}$, and $s_{8,t}$. Second, in the news representation, the process of TFP in equation (6) becomes the following:

$$\ln a_t = \rho^a \ln a_{t-1} + \underbrace{\varepsilon^0_{a,t} + \varepsilon^4_{a,t-4} + \varepsilon^8_{a,t-8}}_{\theta^a_t}, \ \varepsilon^k_{a,t} \sim N\left(0, \sigma^2_{k,a}\right) \quad \text{for } k = \{0,4,8\}, \tag{17}$$

where $\varepsilon^0_{a,t}$ is an i.i.d. unanticipated shock to TFP and where $\varepsilon^4_{a,t-4}$ and $\varepsilon^8_{a,t-8}$ are i.i.d. shocks to

[25] The forward guidance shocks in the Taylor rule are an array of i.i.d. shocks from the perspective of agents in the model. The factor model is part of the measurement equations and is introduced to capture the strong correlation of interest rates across their maturity horizons. As standard, we run a principal component analysis so as to verify that two factors are enough to explain most of the comovement among the expected interest rates in the period 2008:Q4-2016:Q4.

Prior and Posterior for Structural Parameters							
Parameters	Post. Mode	Post. Median	5%	95%	Prior Type	Prior Mean	Prior Std
ϑ	0.8559	0.8581	0.8451	0.8694	B	0.6000	0.1000
$100\ln\mu$	0.4756	0.4721	0.4190	0.5121	N	0.5500	0.0500
φ	4.9154	4.9820	4.8229	5.1882	G	4.0000	0.2500
κ	0.0343	0.0372	0.0315	0.0509	N	0.0900	0.0150
$100u$	5.8040	5.8179	5.7157	5.9159	N	5.6000	0.1000
$100\ln\Pi_*$	0.6179	0.6160	0.5727	0.6585	N	0.6100	0.1000
e	4.1775	4.1415	3.8823	4.2484	N	2.5000	0.2500
ω	0.9394	0.9472	0.9353	0.9575	B	0.5000	0.1000
ϕ	0.0044	0.0018	0.0003	0.0045	N	3.5000	0.7500
ψ	0.2757	0.3030	0.2551	0.3466	B	0.2500	0.0500
l	0.5987	0.6162	0.5753	0.6648	B	0.6000	0.0500
η^q	0.0089	0.0114	0.0043	0.0211	G	0.1450	0.1000
$\bar{\omega}$	0.8303	0.8155	0.7785	0.8519	B	0.5000	0.1000
r_π	2.0051	1.9431	1.8540	1.9984	G	1.7500	0.1000
r_y	0.0259	0.0234	0.0217	0.0271	G	0.2500	0.1000
ρ_R	0.2346	0.2559	0.2211	0.2907	B	0.5000	0.1000

Table 1: Posterior modes, medians, 90 percent posterior confidence bands and prior moments for the structural parameters. Posterior moments are computed using every one hundredth posterior draw. The letters in the column with the heading "Prior Type" indicate the prior density function: N, G, and B stand for Normal, Gamma, and Beta, respectively. See Table 5 in Appendix L for a description of these parameters.

TFP that are known four and eight quarters in advance (TFP news shocks), respectively. Thus, in the news representation the TFP innovation at time t is denoted by θ_t^a and is given by the sum of the unanticipated and anticipated shocks to TFP.

We follow Chahrour and Jurado (2017a) and work out the mapping from the parameters of the news representation ($\sigma_{0,a}$, $\sigma_{4,a}$, and $\sigma_{8,a}$) to the parameters of the model with Pigouvian shocks (σ_θ, $\sigma_{4,v}$, and $\sigma_{8,v}$) that ensures observationally equivalence. This mapping is reported in Appendix G (Step 1). Once we have estimated the parameters of the news representation, we use this mapping to retrieve the value of the parameters of the model with noisy signals. Since the model with noisy signals and its news representation are observationally equivalent, the mapping exactly gives us the estimated parameters of the model with Pigouvian shocks.

3.2 Priors

To elicit the prior distributions for the model parameters, we follow the approach proposed by Del Negro and Schorfheide (2008). Some parameter values are fixed in estimation or implied by steady-state restrictions. We fix the value for the discount factor β so that the steady-state real interest rate is broadly consistent with its sample average. The parameter δ^N reflects the average rate of separation from employment, and is calibrated to match an average quarterly hiring rate of 12.76%, measured following Yashiv (2016). The quarterly rate of capital depreciation, δ^K, is set to target an investment rate of 2.5%. The parameter λ_f is calibrated to a 10% mark-up, in line with estimates by Burnside (1996) and Basu and Fernald (1997). The elasticity of output to

Prior and Posterior for the Parameters of Exogenous Processes and Measurement Equations							
Parameters	Post. Mode	Post. Median	5%	95%	Prior Type	Prior Mean	Prior Std
Panel A: Autoregressive Parameters							
ρ_a	0.9839	0.9808	0.9699	0.9864	B	0.5000	0.1000
ρ_μ	0.3859	0.3852	0.3451	0.4209	B	0.2500	0.1000
ρ_l	0.9961	0.9960	0.9946	0.9971	B	0.9950	0.0010
ρ_g	0.8958	0.8799	0.8192	0.9216	B	0.5000	0.1000
ρ_i	0.8078	0.8160	0.7889	0.8402	B	0.5000	0.1000
ρ_p	0.5381	0.5339	0.4730	0.5940	B	0.5000	0.1000
ρ_{Π^*}	0.9948	0.9947	0.9930	0.9962	B	0.9950	0.0010
Panel B: Shocks Standard Deviations							
$\sigma_{0,a}$	0.3942	0.3790	0.3475	0.4254	IG	0.5000	0.2000
$\sigma_{4,a}$	0.2613	0.2338	0.2004	0.2713	IG	0.5000	0.2000
$\sigma_{8,a}$	0.4160	0.4277	0.3902	0.4649	IG	0.5000	0.2000
σ_θ	0.6299	0.6201	0.5849	0.6532	-	-	-
$\sigma_{4,v}$	0.7135	0.7260	0.5887	0.8841	-	-	-
$\sigma_{8,v}$	0.7161	0.6446	0.5759	0.7540	-	-	-
σ_μ	0.3740	0.3506	0.3068	0.3994	IG	0.5000	0.2000
σ_l	1.6958	1.7835	1.6775	1.8823	IG	0.2500	0.2000
σ_g	0.9416	0.9633	0.8894	1.0459	IG	0.5000	0.2000
σ_i	0.8178	0.8442	0.7941	0.9119	IG	0.5000	0.2000
σ_p	3.1896	3.2785	3.1606	3.3208	IG	0.5000	0.2000
σ_{Π^*}	0.0957	0.0856	0.0684	0.1057	IG	0.0350	0.0350
σ_r	0.4341	0.4268	0.3805	0.4685	IG	0.5000	0.2000
$\sigma_{\lambda_{f,t}}$	0.2414	0.2626	0.2163	0.3099	IG	0.5000	0.2000
Panel C: Measurement Equations							
$\sigma^m_{u,1}$	1.0604	1.0696	1.0356	1.0961	IG	0.5000	0.2000
$\sigma^m_{u,2}$	0.7498	0.7876	0.7166	0.8157	IG	0.5000	0.2000
$\sigma^m_{u,3}$	0.4876	0.4894	0.4767	0.4986	IG	0.5000	0.2000
$\sigma^m_{u,4}$	0.9223	0.9529	0.9232	0.9820	IG	0.5000	0.2000
σ^m_E	0.3108	0.3161	0.3007	0.3384	IG	0.5000	0.2000
c^m_w	-0.1291	-0.1299	-0.1916	-0.0710	N	0.0000	0.5000
σ^m_w	0.5023	0.5146	0.4702	0.5629	IG	0.1000	0.0500
$c^m_{\pi,1}$	0.0006	-0.0015	-0.0578	0.0602	N	0.0000	0.1000
$c^m_{\pi,2}$	-0.0296	-0.0308	-0.0919	0.0296	N	0.0000	0.1000
$c^m_{\pi,3}$	0.0610	0.0613	-0.0092	0.1296	N	0.1400	0.1000
$\lambda^m_{\pi,1}$	0.8874	0.8885	0.8481	0.9274	N	1.0000	0.5000
$\lambda^m_{\pi,3}$	1.1287	1.1246	1.0868	1.1656	N	1.0000	0.5000
$\sigma^m_{\pi,1}$	0.2004	0.2043	0.1858	0.2235	IG	0.1000	0.0500
$\sigma^m_{\pi,2}$	0.0801	0.0732	0.0590	0.0914	IG	0.1000	0.0500
$\sigma^m_{\pi,3}$	0.2101	0.2116	0.1943	0.2342	IG	0.1000	0.0500
$c^m_{TFP,unadj}$	-0.0414	-0.0417	-0.1199	0.0337	N	0.0000	0.1000
$c^m_{TFP,adj}$	-0.0405	-0.0333	-0.1052	0.0455	N	0.0000	0.1000
$\lambda^m_{TFP,adj}$	0.3475	0.3825	0.2722	0.4793	N	1.0000	0.5000
$\sigma^m_{TFP,unadj}$	0.6985	0.6994	0.6542	0.7405	IG	0.1000	0.0500
$\sigma^m_{TFP,adj}$	0.7093	0.7040	0.6663	0.7465	IG	0.1000	0.0500

Table 2: Posterior modes, medians, 90 percent posterior confidence bands and prior moments for the parameters of exogenous processes and measurement equations. Posterior moments are computed using every one hundredth posterior draw. The letters in the column with the heading "Prior Type" indicate the prior density function: N, G, B, and IG stand for Normal, Gamma, Beta, and Inverse Gamma, respectively. See Table 6 in Appendix L for a description of these parameters. Some parameters are introduced in Appendix D and E.

employment in the production function α is set to the standard value of 0.66. The parameter η^G, which is the constant of the exogenous government-spending process η_t^G, is calibrated to match a ratio of government expenditures to GDP of 0.22. Finally, the bargaining power parameter, γ, and the scale parameter in the utility function χ are implied in estimation by the target values for the steady-state participation rate and the unemployment rate, which are set to 65% and 5.6%, respectively.

The prior distribution for the structural parameters of the model are reported in the last three columns of Table 1. Priors for the parameters governing shocks and measurement equations are reported in Table 2. Prior distributions are quite standard and in line with what the literature has used. As we shall show, the parameter governing the intensity of hiring frictions, e, and the parameter affecting the type of hiring costs, η^q, are key for the propagation of shocks, and deserve special attention. Evidence reported by Silva and Toledo (2009) shows that average training costs are equal to 55% of quarterly wages, whereas average recruiting costs are only about 5%. Taken together, these values suggest that the average cost of hiring a worker is approximately equal to seven weeks of wages, and that vacancy costs are less than one-tenth of the average cost of a hire. For the steady-state economy to match these two target values, we would need to set the prior mean of e to 5.5 and the prior mean of η^q to 0.145. In setting the prior, we rather follow a conservative strategy. So while we do set the prior mean of η^q to 0.145, following Sala, Soderstrom, and Trigari (2013), we set a fairly loose prior for e, centered at 2.5, which implies that average hiring costs are only about three weeks of wages. This value lies at the lower end of the spectrum of estimates reported in the literature. We set a dogmatic prior for the autocorrelation parameter for labor disutility shocks (ρ_l), reflecting the beliefs that these shocks explain the low-frequency changes in the rate of labor force participation and the rate of employment. The prior moments for the forward guidance parameters are the same as those in Campbell et al. (2012) and Barsky, Justiniano, and Melosi (2014).

3.3 Posterior Estimation and Model Evaluation

We use a Newton-Rapson type minimization routine to compute the posterior mode for the model parameters in the first sample (1962:Q1−2008:Q3). The results are reported in Tables 1 and 2. Then we generate 500,000 posterior draws via the Metropolis−Hastings algorithm. As is standard, we use these posterior draws for approximating the posterior moments of the parameters. Tables 1 and 2 report the posterior median and the 90 percent posterior credible set for the model parameters estimated over the first sample. Posterior mode and moments for the model parameters estimated over the second sample (2008:Q4−2016:Q4) are in line with previous works and are not reported in the interest of space. Recall that only the measurement parameters (see Panel C of Table 6 in Appendix L) and the forward guidance parameters are re-estimated in the second sample.

Statistic	Y	C	I	FFR	$EMPL$	$PART$	E_tU_{t+1}	E_tU_{t+2}
Data	0.68	0.49	2.92	0.81	2.28	0.79	22.01	21.10
Model	0.80	0.57	3.26	0.79	1.88	0.80	18.81	18.30
Statistic	E_tU_{t+3}	E_tU_{t+4}	W/P	P^{def}	P^{pce}	P^{cpi}	TFP^{adj}	TFP^{unadj}
Data	20.32	18.59	0.61	0.59	0.62	0.73	0.75	0.87
Model	17.58	16.70	0.45	0.72	0.72	0.72	0.69	0.69

Table 3: Unconditional standard deviations of the observable variables and their model counterparts. The model's standard deviations are obtained under the assumption that measurement errors are shut down and loadings for the multiple indicators are one for every variable. The observable series for employment and labor force participation rates have been detrended by subtracting their respective trends implied by the labor disutility shock before computing their standard deviation. For the sake of consistency, the standard deviations of employment and participation in the model are obtained by shutting down the contribution of the labor disutility shocks. All standard deviations are expressed in logs and in percent.

The posterior mode for the parameter governing the intensity of hiring frictions, e, takes a value of roughly 4, which implies that the average cost of hiring is between five and six weeks of wages. This is slightly below the value that would be implied by the micro-evidence reviewed in Silva and Toledo (2009). So while the estimation favors values of hiring frictions that are high relative to our conservative prior, we are confident that the dynamics of the model generated at the posterior mode do not rely on implausibly large hiring costs.

The posterior estimate for the hiring cost parameter η^q is tiny, suggesting that hiring costs are mainly driven by disruption associated with worker turnover at the firm level rather than by the costs of posting vacancies. This result is reminiscent of those in Christiano, Trabandt, and Walentin (2011), who, based on the estimation of a dynamic general equilibrium model of the Swedish economy, argue that hiring costs are a function of hiring rates, not vacancy posting rates. Other empirical macro papers, such as Yashiv (2000) and Sala, Soderstrom, and Trigari (2013) find similar results, though not as stark. The estimated value for the parameter η^q is broadly in line with findings in the micro literature. See, for instance, Silva and Toledo (2009) and Manning (2011).[26] The reason why the estimated value of η_t^q is so tiny is to boost the countercyclicality of hiring costs conditional on TFP shocks, which helps fit the volatility of unemployment in the data.

Table 2 reports the posterior moments for the standard deviations of TFP and noise shocks (σ_θ, $\sigma_{4,\nu}$, and $\sigma_{8,\nu}$) implied by the posterior distribution for the parameters of the model's news representation ($\sigma_{0,a}$, $\sigma_{4,a}$, and $\sigma_{8,a}$). The implied (posterior mode for the) Kalman gain parameters associated with the four- and eight-quarters-ahead signals are 0.3053 and 0.4362, respectively.[27]

The cost of varying the investment flow, governed by the parameter ϕ, is estimated to be

[26] Manning (2011), in a review of the hiring costs literature, states that: "The bulk of these [hiring] costs are the costs associated with training newly-hired workers and raising them to the productivity of experienced workers." According to Silva and Toledo (2009), training costs are measured to be about ten times as large as recruiting costs, which are typically modelled as vacancy posting costs. Similar results are obtained by Faccini and Yashiv (2019) using German and Swiss administrative establishment-level survey data.

[27] The formula to compute the Kalman gains is shown in Appendix G.

negligible. As we will explain in Section 3.4, this low cost of adjusting investment, combined with non-pecuniary hiring costs and nominal rigidities, has strong implications for the propagation of TFP news shocks to employment and investment. Specifically, by selecting such a tiny estimate of investment adjustment costs, the likelihood favors outcomes where employment does not fall in response to positive TFP news shocks.

One may be concerned that with a small cost of adjusting investment, the model would over-predict the volatility of investment in the data. Yet, the standard deviation of the growth rate of investment implied by the estimated model is 3.26%, which is close to the 2.92% observed in the data. This result would not extend to standard dynamic general equilibrium models with no frictions in the labor market. Complementarities between hiring and investment decisions imply that labor market frictions lower the volatility of hiring and, in so doing, the volatility of investment. Moreover, as shown in Appendix K, the small estimate of investment adjustment costs does not come to the detriment of the model's ability to account for the empirical auto-correlation of the observables. In particular, the estimated model also matches fairly well the autocorrelation of the growth rates of output, consumption and investment in the data.

In the estimated model the degree of wage inertia is on the large side. This value has important implications for the propagation of anticipated technology shocks. A high degree of inertia reduces the strength of the wealth effect. In Section 5, we show that while wage inertia complements hiring frictions in causing the employment rate to respond positively and sluggishly to TFP news shocks, wage inertia alone is not enough to deliver this pattern.

The posterior mode and median for the other parameters are quite similar to what is found in other structural studies of the U.S. economy. The inverse Frisch elasticity of labor supply, φ, is in line with the survey of micro evidence in Chetty et al. (2013), which points to elasticities of labor supply on the extensive margin of around 0.25. The slope of the Phillips curve, κ, is broadly in line with estimates in the literature. The degree of inflation indexation, ψ, is on the low side, while the Taylor rule parameters reveal a limited degree of smoothing.

A key challenge of using unfiltered labor market data to estimate a structural model is to account for the trends in the rates of employment and labor force participation in the postwar period. Recall that we set a dogmatic prior that restricts the value for the autocorrelation parameter of labor disutility shocks to be close to unity. The idea is to introduce an almost-unit-root process so as to endow the model with a persistent exogenous process that can account for these labor market trends. Figure 2 shows the U.S. rates of participation and employment (black dashed-dotted lines) along with their counterfactuals simulated from the estimated model using only the one-sided filtered labor disutility shocks (solid red lines).[28] This picture suggests that labor disutility shocks effectively detrend the employment and participation rates in estimation.

[28]Simulating the model using the two-sided estimates of the shocks would not materially change the solid red line in Figure 2. We work with the one-sided estimates because they are obtained from the filter that we use to evaluate the likelihood of the model and to estimate the model parameters.

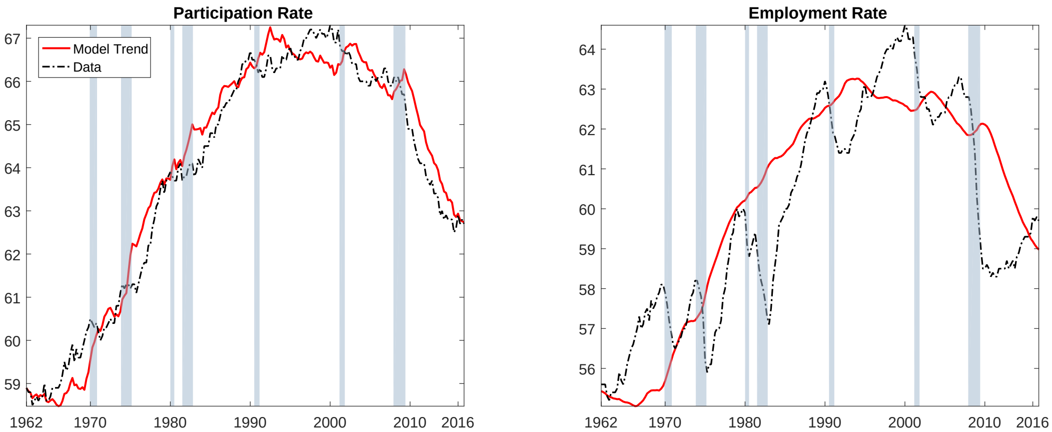

Figure 2: Detrending the rate of participation and the rate of employment. The black dashed-dotted lines denote the data and the red solid lines denote the two rates simulated from the estimated model by using only the filtered (one-sided) estimates for the labor disutility shocks. The estimated model's parameters are set to their values at the posterior mode, which are reported in Tables 1 and 2. Shaded areas denote NBER recessions.

As far as the empirical fit of the model is concerned, we report in Table 3 the standard deviations of the observable variables predicted by the estimated model and compare them with the data. Overall, the estimated model matches well the empirical second moments. The volatility of investment is slightly overestimated, which implies that the volatility of output is also somewhat above its empirical counterpart. The volatility of adjusted TFP news shocks implied by the model is very close to the one measured in the data. As we shall explain in the next section, the countercyclicality of the shadow value of output and marginal hiring costs conditional on technology shocks allows the model to generate volatility in unemployment rates that comes close to the data. To provide further evidence on the ability of the model to fit the data, in Appendix K we show that the model does well at matching the empirical autocorrelation functions, overestimating only slightly the persistence of the rates of inflation and participation.

3.4 Propagation of News Shocks and Variance Decomposition

To understand how TFP news shocks are identified in the data, it is useful to look at how these shocks propagate in the estimated news representation of our model. The propagation of the four-quarters-ahead TFP news shock (blue dashed line) and the eight-quarters-ahead TFP news shock (red solid line) are compared to the effects of the unanticipated TFP shock (black dotted-dashed line) in Figure 3. We set the parameter values to the posterior mode (Table 1 and Table 2) and the size of the initial shock to 1% to facilitate comparison. There are three important points that emerge from comparing these impulse response functions. First, all three shocks produce over time an expansionary response of labor market variables, output and its components, which is fairly persistent. We will explain why the model does not predict a fall in employment due to the wealth effects (Barro and King 1984) later in this section. Second, the longer the anticipation

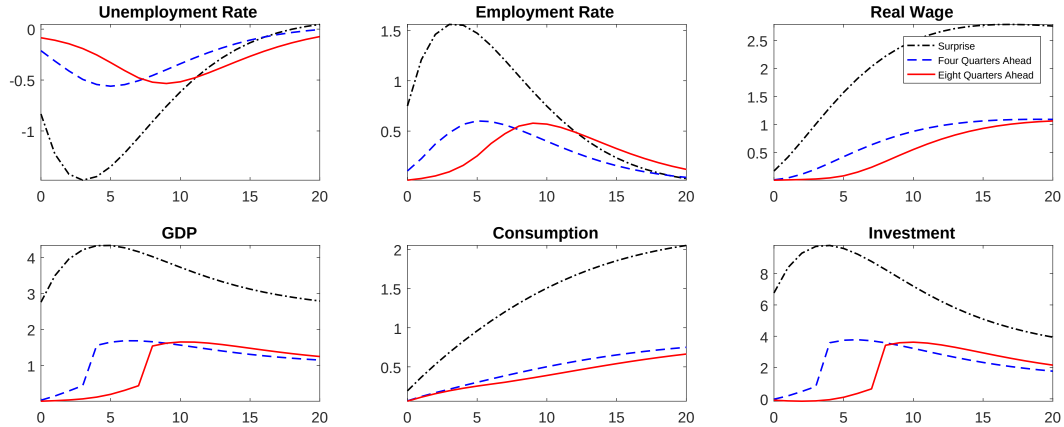

Figure 3: Impulse response of the unemployment rate, the employment rate, real wages, GDP, consumption, and investment to a one-percentage point surprise TFP shock (black dotted-dashed line), four-quarters-ahead TFP shock (blue dashed line), and eight-quarters-ahead TFP shock (red solid line). The responses of unemployment and employment rates are expressed in percentage points. All other responses are in percentage deviations from their stochastic trend. Parameter values are set to their posterior modes, shown in Tables 1 and 2.

horizon of the news, the more delayed and persistent is the expansion. A surprise shock to TFP induces a strong sudden increase in employment, whereas a shock anticipated eight quarters ahead leads to a rather minimal response on impact and a gradual buildup thereafter. A similar argument applies to the other macroeconomic aggregates reported in the figure. Third, in the aftermath a news shock, beliefs play a very important role in the response of employment and unemployment. Indeed, most of the buildup in employment and the fall in unemployment occur ahead of the actual change in TFP.

As discussed in Beaudry (2011), these smooth responses of employment are hard to obtain, even in the presence of search and matching frictions in the labor market. Furthermore, these dynamics are in line with the VAR evidence in Faccini and Melosi (2019), who identify TFP news shocks consistently with the news representation of our structural model and find that employment rises in anticipation of a favorable TFP shock. An excerpt of this paper is in Appendix A. Nevertheless, most of the adjustment in GDP and investment happens when the anticipated shock hits the economy. This pattern does not seem to be in line with the VAR literature. Serially correlated TFP shocks θ_t^a would cause anticipated TFP shocks to become serially correlated in the news representation and hence would help the model reproduce the responses of GDP and investment implied by VAR models. However, we prefer keeping TFP shocks i.i.d. to put more emphasis on the endogenous mechanism based on labor market frictions, which will be discussed next.

Wealth Effects of TFP News on Labor Supply. It is well known that with standard logarithmic preferences, as assumed in our model, a positive news shock about TFP induces a wealth effect that leads employment to fall. Nonetheless, employment rises after positive news about TFP shocks in Figure 3. The reason is that hiring frictions operate so as to increase labor demand in a way that counteracts the wealth effect on labor supply. This increase in labor demand stems from two separate mechanisms. The first one is the canonical mechanism illustrated by Den Haan and Kaltenbrunner (2009), whereby if firms expect to increase their workforce when the anticipated TFP shock materializes, they anticipate hiring so as to smooth adjustment costs over time. This mechanism has a hard time generating strong anticipation effects in isolation (Beaudry, 2011).

The second mechanism relies on an interaction between price rigidities and hiring frictions modeled as forgone output. To understand its workings, consider the optimality conditions for hiring, which are obtained from the problem of the intermediate goods firm in Section 2:[29]

$$Q_t^N = \xi_t \left(f_{N,t} - \bar{g}_{N,t} \right) - \frac{W_t}{P_t} + (1 - \delta_N) E_t \Lambda_{t,t+1} Q_{t+1}^N, \tag{18}$$

$$Q_t^N = \xi_t \bar{g}_{H,t}. \tag{19}$$

Here we let Q_t^N and ξ_t denote the Lagrange multipliers associated with the law of motion for employment (9) and with the constraint that output equals demand (10), respectively. Hence, Q_t^N represents the marginal value of a job to the firm and ξ_t represents the shadow value of output, or marginal revenue, which in equilibrium equals the real marginal cost. We let $f_{X,t}$ and $\bar{g}_{X,t}$ denote the derivative of the functions f_t and $\bar{g}_t \equiv g_t f_t$ with respect to a variable X.

The value of a marginal job in equation (18) equals the marginal product of employment $\xi_t \left(f_{N,t} - \bar{g}_{N,t} \right)$ less the real wage $\frac{W_t}{P_t}$, plus a continuation value, which is the future value of a job Q_{t+1}^N discounted at rate $E_t \Lambda_{t,t+1}$ and conditional on no separation, $1 - \delta_N$. In equilibrium, optimization implies that the marginal value of a job Q_t^N is equalized to the real cost of the marginal hire, as per equation (19). In turn, the latter is given by the intermediate firms' output lost $\bar{g}_{H,t}$ multiplied by the shadow value of output ξ_t. Note that this shadow value affects marginal hiring costs because hiring frictions are modeled as forgone output.

The propagation of TFP news shocks works as follows: households want to consume more and reduce participation in the labor market because of a wealth effect. If investment adjustment costs are small enough, as it is indeed the case in estimation, households respond to positive TFP news by lowering investment in such a way that more than compensates for the increase in consumption, leading to a fall in aggregate demand. Because of nominal rigidities, prices cannot fall enough to clear the market for goods, which in turn implies that the shadow value of output falls.[30] A fall in this shadow value reduces both the expected profits of a match in equation (18) and the expected cost in equation (19), with a priori ambiguous effects on job creation. The

[29] We drop the subscript i because firms are identical.

[30] Notice that with flexible prices, the shadow value of output is a constant. So the mechanism we have described would not arise.

sensitivity of marginal hiring costs to the shadow value of output is given by the derivative

$$\frac{\partial\left(\xi_t \bar{g}_{H,t}\right)}{\partial \xi_t} = \bar{g}_{H,t} = e\frac{H_t}{N_t} = \frac{Q_t^N}{\xi_t}, \tag{20}$$

and is proportional to the value of a job to the firm. Hence, this sensitivity is increasing in the parameter governing the intensity of hiring frictions e. For values of hiring frictions that are in line with the micro-evidence, the fall in the marginal cost of hiring is larger than the fall in marginal profits, leading to an increase in labor demand. In equilibrium, the increase in labor demand more than compensates for the fall in labor supply, leading to an increase in employment, which in turn sustains investment through the complementarities of the production function.

What is the intuition behind this mechanism we just described? In the standard New Keynesian model with a frictionless labor market, workers can only be used to produce, which implies that following a drop in aggregate demand, a fall in labor demand is required to clear the output market. In our model, firms can instead use their workers to produce hiring services rather than output goods, which contributes to reabsorbing the initial excess production. The incentive to divert resources from production to hiring increases with the fall in marginal hiring costs $(\xi_t \bar{g}_{H,t})$, which itself increases with the magnitude of hiring frictions e. So the larger the labor market frictions are, the higher the recruiting effort that follows news of expansionary TFP, and the higher the increase in labor demand. While the Taylor rule parameters matter for the equilibrium response of real interest rates and thus for the quantitative response of any endogenous variable, the qualitative mechanism presented here does not impinge on any specific parameterization.

As explained above, this mechanism relies on the fall in aggregate demand, and the associated drop in the shadow value of output which prompts firms to hire more workers. It may seem bizarre that aggregate demand falls following positive TFP news, since standard New Keynesian models typically predict the opposite. The reason for this difference is the tiny estimated magnitude of investment adjustment costs in our model.

Even though the model features several sources of real rigidities and frictions, the presence of hiring frictions as forgone output is key for generating a positive response of employment to TFP news shocks. If the magnitude of hiring frictions, e, was half the estimated value and all other parameters were kept equal to the posterior mode, employment would fall upon the arrival of a positive eight-quarters-ahead news shock and would remain negative for as long as six quarters. This suggests that all of the additional frictions and real rigidities end up complementing the central mechanism of our model, but they could not account on their own for the buildup in employment in Figure 3.[31]

[31] The value of the parameter η^q, governing the share of hiring costs that depend on vacancy rates or hiring rates, matters for propagation too. If vacancy costs were the only friction in the labor market ($\eta^q = 2$), firms would still have an incentive to divert their workforce to vacancy posting activities following a positive TFP noise shock. However, congestion externalities in the matching function would increase the cost of hiring, partially

	TFP Shocks							
	Baseline		First Difference		HP Detrended		Baseline	
	Surprise	News	Surprise	News	Surprise	News	Fundamental	Noise
GDP	0.2790	0.4301	0.0216	0.0256	0.3248	0.1815	0.2658	0.4433
Consumption	0.2002	0.3162	0.0017	0.0021	0.0249	0.0148	0.1937	0.3227
Investment	0.2391	0.3417	0.0353	0.0408	0.1854	0.0988	0.2173	0.3635

Table 4: Variance of GDP, consumption, and investment in deviation from their stochastic trend explained by TFP surprise and news shocks in the news representatrion and by fundamental and noise shocks in our model. The forward guidance shocks, which are introduced in the second sample, are not added to the decomposition. This decomposition is computed for the model estimated with the data set described in Section 3.1 (Baseline), and for the model estimated with a data set in which the only labor market data are the growth rate of employment (First Difference) or the HP-detrended employment rate (HP Detrended). The variance jointly explained by surprise and news shocks must be the same as the variance jointly explained by fundamental and noise shocks. See Appendix G in which equations (34) and (36) express noise shocks as linear combinations of surprise and news shocks.

How does this mechanism differ from the approach proposed by Jaimovich and Rebelo (2009)? Our mechanism does not directly suppress wealth effects through the adoption of suitable preferences, and is therefore consistent with empirical evidence provided by Mertens and Ravn (2011), which supports the view that such effects are sizeable. Furthermore, in our model, the wealth effect that follows an anticipated improvement in TFP weakens households' aggregate demand, putting downward pressure on price inflation.

Variance Decomposition. The first two columns of Table 4 show how much of the variance of output, consumption, and investment (in deviations from the their stochastic trend) is explained by TFP surprise and TFP news shocks (It also shows the contribution of fundamental θ_t^{α} and noise shocks, which will be discussed in Section 4). News shocks four and eight quarters ahead, together, account for 40% of the variance of GDP, around 30% of the fluctuations in consumption and investment and 56% of the fluctuations in real wages around its trend (not shown). While these are big numbers, we will show that most of this variability turns out to be at the low end of the business-cycle frequencies and at even lower frequencies. Surprise shocks to technology also play an important role, contributing to around 30% of the variation in these key macroeconomic aggregates.

3.5 Identification of TFP News and Surprise Shocks

We started this paper by conjecturing that current and expected unemployment rates carry important information for identifying TFP news shocks. Now we check the validity of this conjecture. Our (somehow informal) first step to address this matter is to compare the first two columns of Table 4 to the variance decomposition that we would have obtained if we had estimated the model with employment growth (third and fourth columns) or with an HP-filtered measure of employment (fifth and sixth columns) as the only labor market variable in the data

offsetting this mechanism. Specifically, having more aggregate vacancies raises the expected time required to fill any single vacancy, increasing the marginal cost of hiring. A lower value of η^q decreases the sensitivity of the marginal hiring costs to changes in the vacancy filling rate, muting this feedback effect from aggregate labor market conditions.

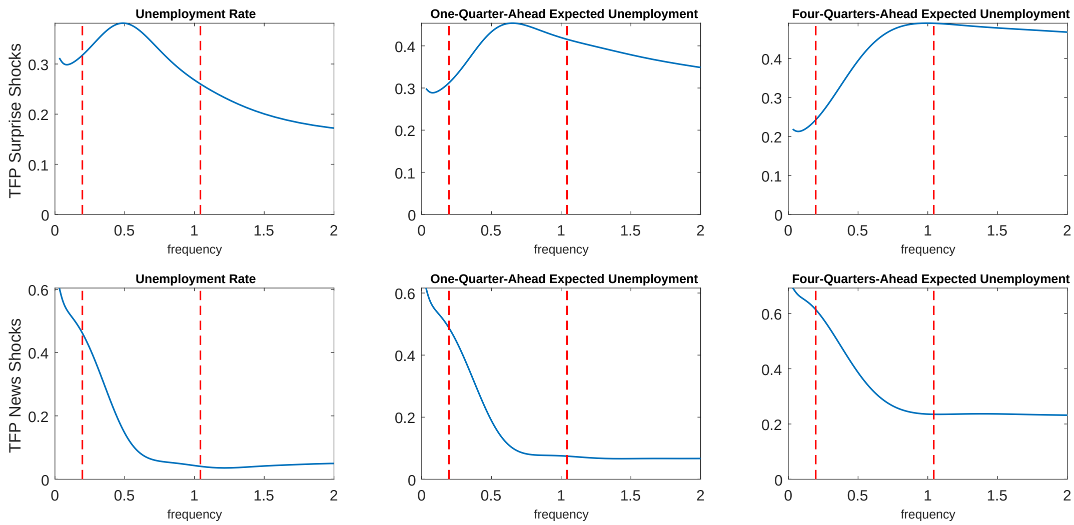

Figure 4: Variance share of current and expected unemployment rate (one quarter and four quarters ahead) due to TFP surprise (first row) and news shocks (second row) as a function of the spectrum frequencies. The vertical dashed lines mark the frequency band associated with business cycles, which includes frequencies between $\frac{2\pi}{32} = 0.19$ and $\frac{2\pi}{6} = 1.05$.

set. This comparison shows that as we remove the variability of labor market data at low frequencies, the contribution of anticipated technology shocks becomes marginal. Indeed, the loss of low-frequency information is particularly severe when taking the first differences. This finding suggests that observing unfiltered labor market data as well as the current and expected unemployment rates is critical to identifying technology shocks. Furthermore, the contribution of TFP news shocks when the model is estimated using the growth rate of employment as the only labor market observable is similar to that obtained by Schmitt-Grohe and Uribe (2012). Those scholars estimate a structural model with a frictionless labor market using the growth rate of hours as an observable variable, and find small role for TFP news shocks.

Now we turn our attention to how the identification of TFP shocks is affected by the variations in the observed current and expected unemployment rates at different frequencies. In Figure 4 we show the contribution of surprise (upper plots) and anticipated (lower plots) TFP shocks to the variation in current and expected unemployment rates across various frequencies.[32] The red dashed vertical lines indicate conventional business-cycle frequencies between 6 and 32 quarters. In the upper plots, the TFP surprise shocks explain the unemployment rate mainly at business-cycle frequencies. In contrast, the lower plots show that TFP news shocks explain very little of the high-frequency variations in unemployment rates, and appear to matter mostly for the frequencies at the lower end of the business cycle and at even lower frequencies. Comparing the two right plots of Figure 4 reveals the stark difference between the contribution of the unanticipated and the anticipated TFP shocks to the four-quarters-ahead expectations about unemployment. The

[32]The plots for the two- and three-quarters-ahead expectations about the rate of unemployment are not shown because they are similar to the ones in the figure. These plots are available upon request.

contribution of these two shocks to the variability of the four-quarter-ahead expectations across frequencies is flipped. This figure underscores that TFP news shocks are mainly identified by the dynamics of unemployment at the lower spectrum of business-cycle frequencies.

Figure 4 introduces an important qualification to the results in the previous section: while TFP news shocks seem to be an important contributor to business cycles in Table 4, this contribution is not evenly distributed across the typical business-cycle frequencies. In fact, these shocks seem to be fairly unimportant at the higher frequencies.

The historical analysis of the role of TFP news shocks is also very useful to understand the role of news shocks in business cycles and to see what features in the data drive their identification. The right plot in Figure 5 reports the U.S. unemployment rate (black dashed-dotted line) along with the counterfactual time series obtained by simulating the news representation of the model using only the smoothed estimates of the four- and eight-quarters-ahead TFP news shocks (red solid lines). These shocks appear to have been a key driver of the rate of unemployment at lower frequencies over the postwar period, in line with the insights of Figure 4. In particular, anticipated TFP shocks appear to have induced relatively low rates of unemployment in the 1960s, relatively high unemployment rates from the early 1970s through the mid-1990s, and low unemployment rates again thereafter. These dynamics have been driven by strong anticipated TFP growth in the first and in the last part of the sample, and lackluster expected growth in between. TFP news shocks affect the expected unemployment rates similarly, as shown in Appendix J.

There are two main reasons why the dynamics of current and expected unemployment rates are picked up by TFP news shocks in the estimation. First, unemployment rates and TFP growth negatively comove in the data, as shown in Figure 1. Second, in the estimated news representation of the model, anticipated TFP shocks have fairly persistent effects on the unemployment rate, as shown in Figure 3. The smoothed estimates of TFP news shocks, which are used to simulate the unemployment rate in the right plot of Figure 5, are not implausibly big. In Appendix I, we show that these estimates lie within a two-standard-deviation range around the zero mean in every quarter of the sample period (1962Q1-2016Q4) except two. The autocorrelation function of the smoothed estimate of the two TFP news shocks shows no or very small serial correlation.[33]

Quite interestingly, the right plot of Figure 5 shows that TFP news shocks almost systematically fail to account for the behavior of the unemployment rate during the NBER recessions, which are highlighted by the gray areas, and in the first quarters of the ensuing recoveries. This finding is consistent with Figure 4: the contribution of TFP news shocks to changes in the unemployment rates drops precipitously at the high end of business-cycle frequencies. In our sample, recessions are short and hence the observed variations in the unemployment rate in downturns are

[33]The serial correlation of the four-quarters-ahead TFP news shocks is not statistically significantly different from zero, whereas the serial correlation of the eight-quarters-ahead shocks is statistically significant but very low (0.18).

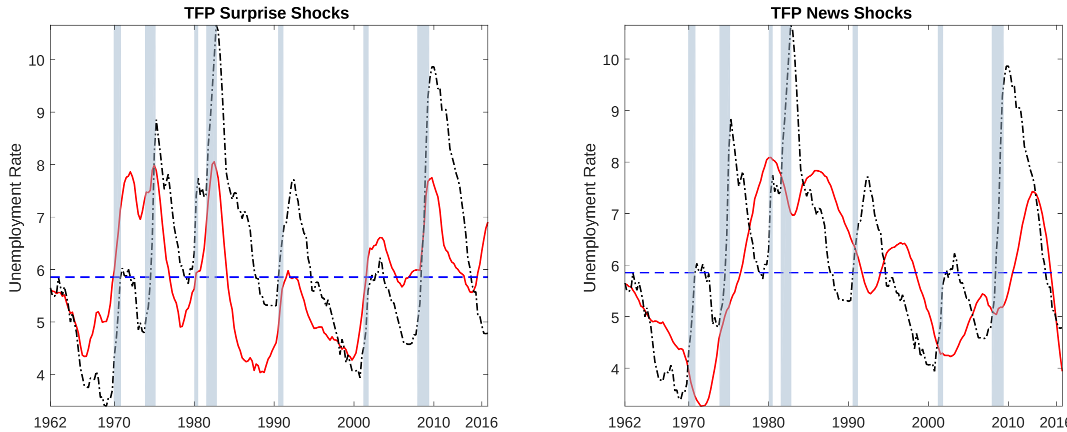

Figure 5: Historical role of TFP shocks to the U.S. unemployment rate. Left plot: The U.S. unemployment rate (black dashed-dotted line) implied by the observed series of the employment and participation rates, along with the counterfactual unemployment rate obtained by simulating the model using only the smoothed estimate of the surprise TFP shocks (red solid line). Right plot: The counterfactual series of the unemployment rate is obtained by simulating the model using only the smoothed estimate of the four-quarters- and eight-quarters-ahead TFP news shocks. The counterfactual series are computed by setting the model parameters to their posterior modes, which are reported in Table 1 and Table 2. The gray areas denote NBER recessions.

dominated by the unanticipated shocks. For the same reason, TFP news shocks often contribute to raising the unemployment rate at the beginning of the recoveries.

If we had estimated the model without the observed rates of labor force participation, employment, and expected unemployment, TFP news shocks would have played a negligible role. Specifically, the red solid line in the right plot of Figure 5 would have been very close to the zero line over the sample period. This result again underscores the importance of using unfiltered labor market data to identify TFP news shocks.

The left plot of Figure 5 shows the unemployment rate simulated from the estimated news representation of our model by using only the smoothed estimate of surprise TFP shocks. This counterfactual series of unemployment strongly comoves with the observed one, suggesting that surprise TFP shocks significantly contribute to business-cycle fluctuations in the observed unemployment rate. Nevertheless, this pattern of positive comovement breaks down in the most recent years. We will return to this point when we analyze the link between surprise TFP shocks and noise shocks in the next section.

The finding that surprise TFP shocks play such an important role in driving unemployment fluctuations does not imply that implausibly large shocks to TFP. In Appendix I, we show that the magnitude of the estimated TFP innovations θ_t^a is not too big, in that the large majority of the historical realizations of these shocks fall within the two-standard-deviation bands around their zero mean.

To sum up, TFP news shocks do not contribute to the high-frequency volatility of business-cycle variables and almost always contribute to *lowering* the unemployment rate during the postwar NBER recessions. These findings should not be interpreted as evidence against the expectations-driven business-cycle hypothesis. The reason is that the estimated TFP news shocks used in the simulation affect not only beliefs but also actual TFP (fundamentals). To evaluate the validity of the Pigouvian intuition, one needs to study the properties of the models with signals introduced in Section 2.

How accurately are TFP shocks identified? We formally evaluate how accurate our estimates of TFP news shocks are. To do so, we compute the reduction in the econometrician's uncertainty (measured by the variance) about the in-sample estimates of the two news shocks due to observing our entire data set relative to their unconditional variance (i.e., if no data were observed).[34] If shocks were observed or implied by the data, the uncertainty conditional on the data would be zero and this ratio would be equal to unity. If the data conveyed no information whatsoever about the shocks, then the conditional uncertainty would be equal to the unconditional uncertainty and the ratio would be equal to zero. The information content of our data set is 79%, 38%, and 61% for the TFP surprise shocks, the four-quarters-ahead TFP news shocks, and the eight-quarters-ahead TFP news shocks, respectively. These numbers are one order of magnitude larger than those found in leading studies with the same news structure, in which the information content about TFP news shocks is only 2% (Iskrev 2018).

4 Evaluating the Pigouvian Hypothesis

So far, our empirical analysis has focused on the news representation of our model and the role of TFP news shock. However, news shocks are not Pigouvian shocks in that they affect future TFP fundamentals. In order to evaluate the empirical validity of the Pigouvian hypothesis, we need to go back to our model with noisy signals, presented in Section 2. To do this, we map the estimated parameters of the news representation ($\sigma_{0,a}$, $\sigma_{4,a}$, and $\sigma_{8,a}$) into the parameters of the model with Pigouvian shocks (σ_{θ}, $\sigma_{4,v}$, and $\sigma_{8,v}$), as done in Chahrour and Jurado (2017a) (Appendix G, Step 1). The value of the posterior mode for the former standard deviations are reported in Table 2. We can then use the estimated model to study the role of noise shocks in explaining the business cycles, which is the central question of this paper.

Propagation of noise shocks. Figure 6 shows the impulse response functions of the unemployment rate, the employment rate, the real wage, GDP, consumption, and investment to a 1% noise shock ν_t^8 concerning the eight-quarters-ahead realization of the fundamental shock to TFP, θ_{t+8}^a.[35] The noise shock $\nu_{8,t}$ gives rise to boom-bust dynamics in the key business-cycle

[34] This analysis is conditional on the posterior mode of the model parameters, which is shown in Table 1 and Table 2, and abstracts from parameter uncertainty, which is very small. The unconditional variance of the shocks depends on the estimated values of the model parameters. The conditional variance of the shocks is computed by running the Kalman smoother. Since the smoother is a two-sided filter, it returns the uncertainty of the shocks in every period conditional on the entire data set described in Section 3.1. To correct for the relatively larger uncertainty at the beginning and at the end of the sample period, we take the smallest value of the variances in the sample. Results would not change if we used the median of the variances instead.

[35] The size of the shock is comparable to the anticipated shock to TFP $\varepsilon_{a,t}^8$ shown in Figure 3. Details on how

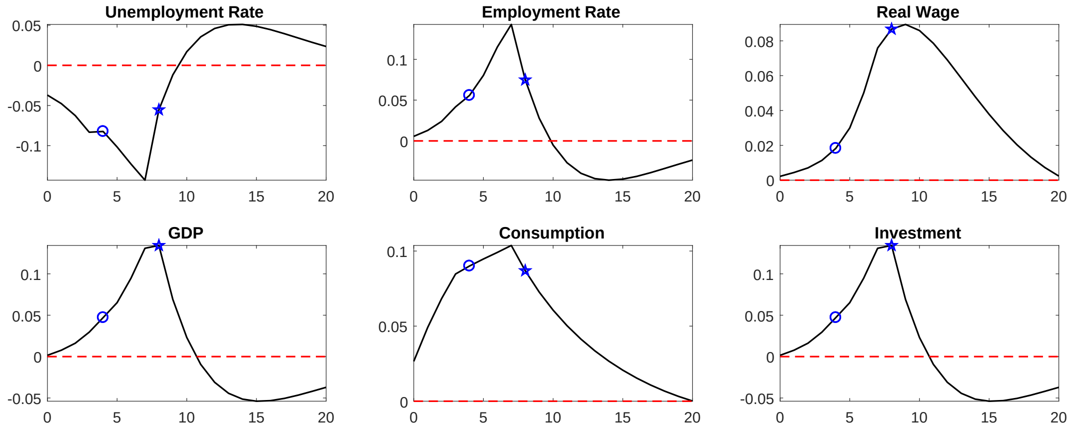

Figure 6: Impulse response of the unemployment rate, the employment rate, the real wage, GDP, consumption, and investment to a noise shock affecting the signal about the eight-quarter-ahead TFP shocks. The circle mark denotes the time at which agents receive the second signal s_{t+4}. The star mark denotes the time at which agents learn that actual TFP does not change in period $t+8$. The responses of unemployment and employment rates are expressed in percentage points. All other responses are in percentage deviations from their trend. The size of the initial shock is one percent. Parameter values are set to their posterior modes (Table 1 and 2).

variables. The responses of real wages and consumption are more persistent than those of other variables. Nonetheless, they become negative twenty quarters after the shock.

It should be noted that agents revise their expectations about the TFP shock θ^a_{t+8} at time $t = 4$, denoted by a circle in the graph. At that time, agents receive a signal $s_{4,t+4}$ equal to 0, which they use to update their expectations about the future innovation θ^a_{t+8}.[36] These mid-term revisions apparently have very small impact on the propagation of the noise shocks $\nu_{8,t}$. In period $t + 8$, marked with a star, agents learn that the innovation to TFP is zero, that is, $s_{0,t+8} = \theta^a_{t+8} = 0$, and hence realize that their past expectations were only reflecting noise. This realization brings about a persistent fall in employment, investment, and output. Employment adjusts more quickly than investment because of the slow response of real wages.

Why do noise shocks $\nu_{8,t}$ cause boom-bust responses of the key business-cycle variables? When agents expect a future increase in TFP (i.e., from period 0 through period 7), they start accumulating capital and employment increases. As discussed in Section 3.4, this response of employment stems from the interaction between non-pecuniary labor market frictions, small investment adjustment costs, and nominal rigidities which counter the strong wealth effects associated with noise shocks. When, at time $t + 8$, agents realize that the good news was in fact just noise, households have accumulated too much capital and firms have accumulated too much employment. Consequently, households gradually lower their investment so as to smooth out the transition of consumption to its steady-state level, and employment falls. Therefore, output also

to compute the impulse response functions to noise shocks are provided in Appendix H. The impulse response function to a noise shock ν^4_t affecting the four-quarters-ahead expectations of θ^a_{t+4} is shown in Appendix H.

[36] The signal $s_{4,t+4}$ is equal to zero because the realization of noise ν^4_{t+4} is 0 (the shock ν^4_{t+4} is by construction orthogonal to the initial noise shock ν^8_t) and the future fundamental shock to TFP θ^a_{t+8} is not affected by the initial noise shock ν^8_t and, hence, $\theta^a_{t+8} = 0$.

falls and remains below its steady-state level for a fairly long period of time, suggesting that noise may lead to long-lasting recessions (or expansions if the initial news is negative). This finding challenges the conventional wisdom, according to which the macroeconomic effects of noise are short lived. Furthermore, when agents realize that positive news is just noise, employment undershoots. This is caused by firms lowering labor demand so as to reduce production and meet the fall in aggregate demand due to the drop in investment.

Variance decomposition of noise shocks. The results of the second exercise are shown in the last two columns of Table 4. Noise shocks account for a large fraction of fluctuations in GDP, consumption, and investment. These shocks also explain 49% and 58% of the variation in the unemployment rate and in real wages (not shown). Furthermore, the contribution of noise shocks is more evenly distributed across business-cycle frequencies than that of TFP news shocks in Figure 4. Thus, noise shocks account for full Pigouvian cycles.

This finding is different from the one in Blanchard et al. (2013), who show that noise shocks contribute a fair amount to fluctuations in GDP, consumption, and hours but only marginally to fluctuations in investment. What we find is typically hard to obtain in estimated medium-scale DSGE models, which are characterized by a rich shock structure (nine fundamental shocks in our case) and thus tend to use different shocks to explain separately the dynamics of each business-cycle variable. Therefore, our findings provide a strong econometric validation to the Pigouvian theory of business cycles.

One can show that fundamental shocks (θ_t) and noise shocks (ν_t^4 and ν_t^8) in our model can be expressed as linear combinations of surprise and news shocks defined in the news representation (Chahrour and Jurado 2017a).[37] Consequently, the variance of any observable explained by noise shocks may exceed the variance explained by only news shocks in the news representation. One can show that the variance of any observable jointly explained by noise shocks and fundamental shocks must sum up to the total variance of the observables jointly explained by TFP surprise and news shocks. We note that the importance of noise shocks in the estimated model follows from observing the low-frequency fluctuations in the unemployment rate. Had we reduced information on the low-frequency oscillations of labor market aggregates by observing the HP-filtered employment rates, or removed it by taking first differences, as is typically done in the literature, we would have found a negligible role for these shocks (see the discussion in Section 3.5).

Identification of Noise Shocks. For the news representation to be observationally equivalent to our model, expectations about future TFP shocks in our model must be always identical to those in the estimated news representation. For the case of the eight-quarters-ahead expectations about TFP innovations $E_t\theta^a_{t+8}$, this implies that

$$\kappa_8\left(\theta^a_{t+8} + \upsilon_{8,t}\right) = E_t\theta^a_{t+8} = \varepsilon^8_{a,t}, \tag{21}$$

[37] Equations (32) and (34) in Appendix G show the analytical linear decomposition of noise shocks into surprise and news shocks.

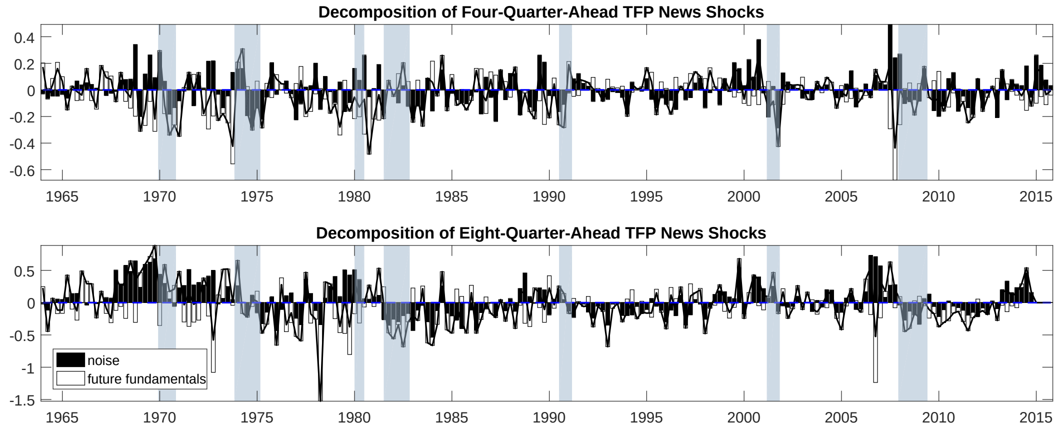

Figure 7: Decomposition of TFP news shocks (black solid line) into actual changes in future TFP (white bars) and noise shocks (black bars). Both components are rescaled by the relative Kalman gain as in equation (20). Shaded areas denote NBER recessions.

where κ_8 is the Kalman gain associated with the eight-quarters-ahead expectations. The expressions on the left-hand side and on the right-hand side capture the expectations of future TFP innovations in our model and in its news representation, respectively. Hence, equation (21) allows us to decompose the eight-quarters-ahead TFP news shocks $\varepsilon^8_{a,t}$ into two parts: future TFP fundamentals θ^a_{t+8} and noise shocks $\nu_{8,t}$ that is -by construction- orthogonal to past, present, and future changes in TFP.

Equation (21) precisely shows how we achieve identification of the noise shocks $\nu_{8,t}$. As we showed in Section 3.4, news shocks $\varepsilon^8_{a,t}$ are identified by the low-frequency fluctuations in current and expected unemployment rates. Combining the identified news shocks $\varepsilon^8_{a,t}$ with the *realized* changes in TFP at time $t+8$, θ^a_{t+8}, which we observe in the data, allows us to identify noise shocks through equation (21). A similar equation allows us to identify the four-quarter-ahead noise shocks $\nu_{4,t}$ (see Appendix G for more details).

To sum up, accurate identification of TFP news shocks is instrumental in attaining a precise identification of noise shocks. In the news representation, TFP news shocks capture revisions of agents' expectations about future TFP shocks (the right part of equation (21)). In our model with noisy signals, these same revisions are explained by the signals, which are driven by a combination of future TFP shocks and noise shocks, as shown in the left part of equation (21). Identifying whether these revisions of expectations are due to future TFP shocks or noise shocks hinges on the extent to which future TFP actually changes, which we observe in the data.

Historical analysis. Equation (21) can be used to tease out the historical series of noise shocks $\nu_{8,t}$ by combining the smoothed estimates of TFP news shocks $\varepsilon^8_{a,t}$ and the smoothed estimates of future TFP fundamentals $\theta^a_{t+8} \equiv \varepsilon^8_{a,t} + \varepsilon^4_{a,t+4} + \varepsilon^0_{a,t+8}$ in the news representation of the model. A similar equation allows us to retrieve the historical series of $\nu_{4,t}$ (see Appendix G for more details).

The lower panel of Figure 7 shows the historical realizations of eight-quarters-ahead TFP

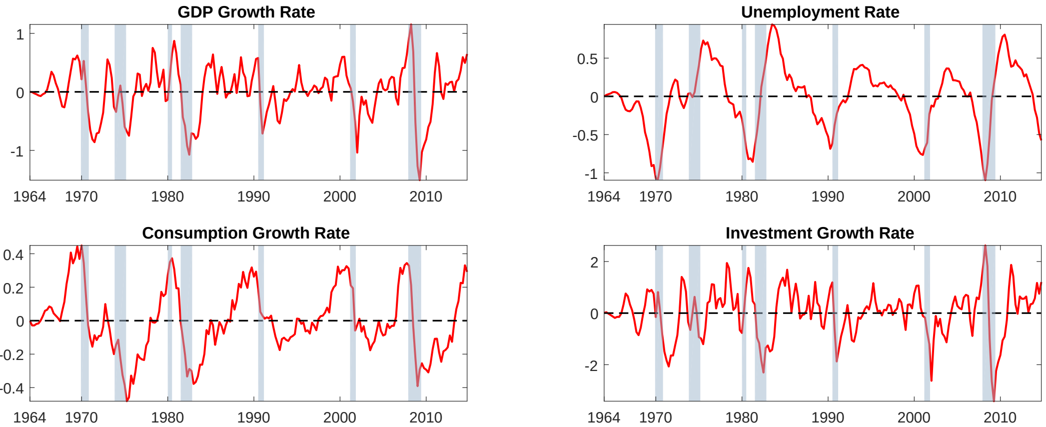

Figure 8: GDP growth rate, unemployment rate, consumption growth rate, and investment growth rate only due to noise shocks. All rates are in percent; growth rates are annualized. Shaded areas denote NBER recessions.

news shocks $\varepsilon^8_{a,t}$ (black solid line) and their decomposition into future fundamentals $\kappa_8\theta^a_{t+8}$ (white bars) and noise shocks $\kappa_8\nu_{8,t}$ (black bars) based on equation (21). The upper panel shows the historical realizations of four-quarters-ahead TFP news shocks $\varepsilon^4_{a,t}$ (black solid line) and their decomposition into future fundamentals $\kappa_4\theta^a_{t+4}$ (white bars) and noise shocks $\kappa_4\nu_{4,t}$ (black bars). The figure shows that noise shocks often characterize the periods immediately before the turning points of the business cycle. Overly enthusiastic beliefs relative to the future realization of TFP shocks (positive noise shocks) typically intensify at the end of most of the postwar-period expansions and were particularly relevant in the late 1960s, during the dot-com bubble, and in the years that preceded the Great Recession. Similarly, we can observe overly negative beliefs (negative noise shocks) in many recessions, including the Great Recession. Due to the boom-bust propagation of noise shocks, the intensification of excessively enthusiastic (lukewarm) beliefs about future TFP improvements often contributes to driving the economy to a recession (boom) later on, when the private sector figures out that the favorable (negative) news does not pan out.

While in Figure 7 noise shocks build up before the peaks and troughs of business cycles, the correlogram of the estimated series of the these shocks does not suggest any significant serial correlation. Furthermore, the size of the historical realizations of noise shocks in Figure 7 lies between a two-standard-deviation range around the zero mean except for a handful of realizations (Appendix I). This suggests that the historical realizations of these shocks are broadly in line with their distribution in the estimated model. Hence, the smoother does not need to engineer realizations of noise shocks that are systematically bigger than what agents expect. If this were the case, this would imply a violation of rationality because the estimated noise variance affects the Kalman gains that determine the sensitivity of rational agents' expectations to noise shocks.

We can now address the following question: is there any specific U.S. recession or expansion that has been caused by the private sector's autonomous changes in beliefs (i.e., noise shocks)? Noise shocks have contributed to business cycles in a way that is fairly regular over time. Figure 8 shows the historical contribution of these noise shocks to the unemployment rate, GDP growth, consumption growth, and investment growth over the full sample 1962−2014.[38] Noise shocks have played a role in lowering (raising) GDP growth and its components as well as in increasing (decreasing) the unemployment rate in all recessions (expansions), with the only exception being the recession that occurred at the very beginning of the 1980s, which turns out to be dominated by monetary shocks. Quantitatively, noise shocks have contributed to a quarterly fall of at most one percentage point in annualized output growth. The role of noise is particularly significant for labor market outcomes, and is reflected in the cyclical fluctuations of the unemployment rate that oscillate within a two-percentage-point band.

To sum up, anticipated TFP shocks mainly explain the trend unemployment rate, as shown in Figure 5. Yet, when we look at the contribution of changes in beliefs that are orthogonal to TFP fundamentals (noise shocks), we find that they affect unemployment at business-cycle frequencies, as shown in Figure 8. The main reason behind this finding is the different propagation of news and noise shocks. While TFP news shocks give rise to persistent adjustments in employment, noise shocks generate boom-bust macroeconomic dynamics, as shown in Figure 6.

The Great Recession and Its Aftermath (2008:Q4-2014:Q4). The left panel of Figure 9 plots the observed unemployment rate (solid black line with circles) along with the unemployment rate implied only by the estimated series of noise shocks (red solid line) over the Great Recession and its aftermath. The figure shows that noise shocks have contributed to about half of the increase in the unemployment rate trough-to-peak, and about a third of the subsequent recovery.[39] The center plot shows that noise shocks have accounted for most of the recovery in the employment rate, including the boom in the labor market of 2014. The long-run rate of employment, as implied by the estimated series of labor disutility shocks (the blue dashed-dotted line), has dropped significantly since 2010. This fall is driven by the dramatic drop in labor force participation, as shown in the right panel of Figure 9. The actual employment rate crossed its trend from below, and this recovery has been largely driven by noise.

The belief-driven increase in employment that starts around 2011 is the result of negative expectations at the time of the Great Recession and its immediate aftermath, which turned out to be exaggerated. As shown in Figure 7, the solid lines, which capture expectations about future TFP innovations, lie in negative territory during the Great Recession and the following years. The black bars capture the extent to which these negative expectations turned out to be

[38] It should be noted that the smoothed estimates of noise shocks depend on the smoothed estimates of future realizations of TFP innovations θ^a_{t+h}. Since our sample ends in the fourth quarter of 2016, we can estimate a series for the noise shocks $v_{8,t}$ and $\nu_{4,t}$ only up to the fourth quarter of 2014 and the fourth quarter of 2015, respectively.

[39] The level difference between the data and the contribution of noise is due to other shocks that have pushed unemployment up during the Great Recession − mainly preference shocks and monetary shocks, which were contractionary because of the binding zero lower bound constraint.

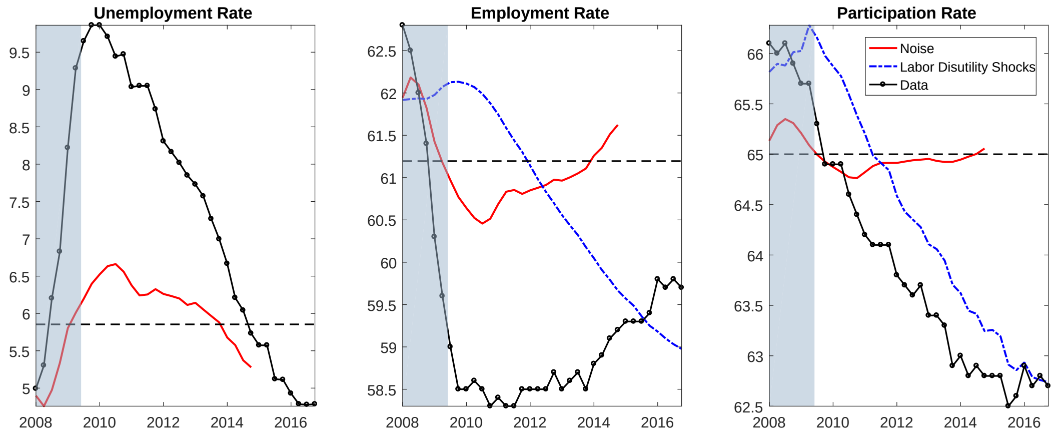

Figure 9: The effects of noise shocks and labor supply shocks to labor market dynamics during the Great Recession and its aftermath. The red solid lines refer to the counterfactual time series generated using only the smoothed estimate of noise shocks. The black lines with circles indicate actual data. The dashed-dotted blue lines indicate the conterfactual series for employment and participation rates obtained by simulating the model only with the smoothed labor disutility shocks.

exaggerated.[40] Since 2013, the rise in the employment rate has been sustained by favorable TFP news, which has turned out not to be backed by any actual TFP improvement.

Was there really any good news released in 2013 and in the following years? To answer this question we look at the University of Michigan's Index of Consumer Sentiment. The left plot of Figure 10 reports the sum of the two-sided estimates of the four- and eight-quarters-ahead TFP news shocks on the left axis along with the consumer sentiment index on the right axis. This figure shows that positive news shocks estimated by the model matches nicely with the rise in the Index of Consumer Sentiment. This result is noticeable and provides external validation to the model's predictions during the post-Great-Recession recovery, since the sentiment index is not used in the estimation. This result is mainly driven by the large negative comovement between the index and the SPF expectations about future unemployment rates. Finally, the right plot of Figure 10 shows that this stream of good news about TFP has turned out to be mostly noise. This can be seen in the right plot where the estimated series of news and noise shocks closely mimic each other.

Why such an important role for noise shocks during the Great Recession and the following recovery? As shown in Figure 1, the relationship between the average unemployment rate and TFP has noticeably broken down in the most recent period. Specifically, while in recent years the average unemployment rate has dramatically fallen to reach record-low values, average TFP growth has languished and has remained substantially lower than its levels recorded in previous periods when the average unemployment rate was similarly low. To account for these diverging

[40] Note that the counterfactual series of employment generated only by noise shocks (the solid red line in Figure 9) starts to recover at the beginning of 2011, even if the years 2011 and 2012 have been characterized by a sequence of negative noise shocks, as shown by the black bars in Figure 7. This is because noise shocks affect employment in a boom-bust fashion, which introduces delays in the effects of these shocks, as illustrated in Figure 6.

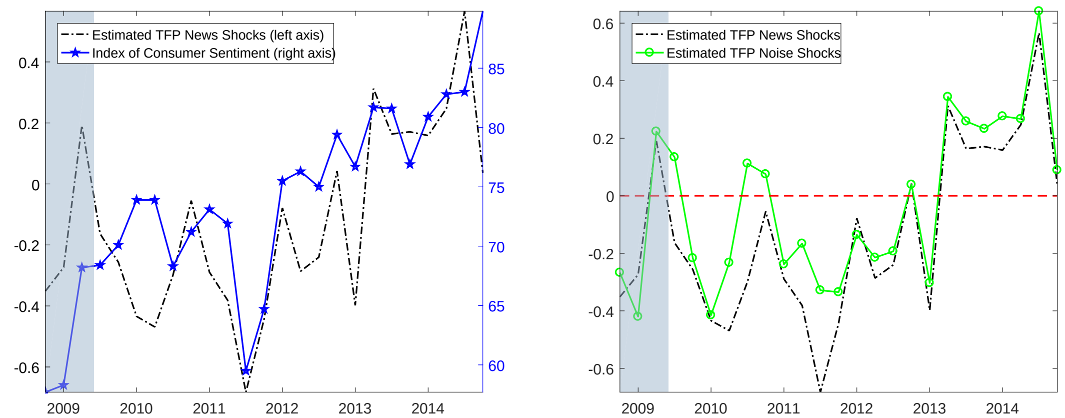

Figure 10: Estimated noise shocks, news shocks and the index of consumer sentiment. Estimated TFP news shocks are the sum of the news shocks received in every quarter. Noise shocks are rescaled by the relative Kalman gain and are computed analogously to the estimated TFP news shocks.

patterns between average unemployment rates and the TFP growth rate, the model resorts to noise shocks. It is important to notice that the model has several non-TFP shocks that could have explained the recent drop in the U.S. unemployment rate.

To sum up, noise accounts for most of the recovery in the employment rate in post-Great Recession recovery. What accounts for the remaining two-thirds of the recovery in the unemployment rate is the fall in the rate of labor force participation, which reflects the very low-frequency dynamics engendered by the labor disutility shock (the blue dashed-dotted line in Figure 9).

5 Robustness

One may be concerned that real wage inertia might be the single most important factor behind the positive response of the employment rate to news shocks. First, when the model is estimated with the parameter controlling the degree of wage inertia set equal to zero, the estimated news representation still delivers positive and gradual responses of the employment rate to TFP news shocks. Nonetheless, the response of the employment rate is substantially smaller than that in the model with wage inertia. Furthermore, if we halve the size of hiring frictions (e) while keeping all the other parameter values at their posterior mode, the response of employment to an eight-quarters-ahead TFP news shocks is negative for the first six quarters. The outcomes of these exercises lend support to the view that real wage inertia complements hiring frictions to deliver a gradual and significant response of employment to TFP news shocks but wage setting frictions alone would not be enough.

We also test the robustness of our results when TFP news shocks are modeled à la Barsky and Sims (2012), who model news shocks as anticipated information about the future drift in

TFP growth.[41] Under this specification, our results are generally strengthened. Namely, TFP news shocks explain even a larger fraction of the volatility of the unemployment rate and the contribution of noise to the business cycle is generally larger. This finding is mainly driven by the fact that TFP news shocks are now more persistent and hence are better suited to capture the low-frequency variations in unemployment rates. Very similar results are obtained if we allow for serial correlation of TFP news shocks. In our estimated model, TFP news shocks successfully capture the changes in the unemployment rate at lower frequencies mainly because of the endogenous mechanism based on labor market frictions. We also estimate the model allowing for signals with shorter anticipation horizons (i.e., we add signals about one-, two-, and three-quarters-ahead TFP shocks). We cannot precisely identify these shocks (and the associated TFP news shocks), since their propagation to the observable variables is too similar.

Finally, we estimate a model in which households choose the utilization rate of physical capital and lend the utilized (or effective) capital to firms. While this extension shrinks the determinacy region and hence complicates both the search for the posterior mode and the implementation of the posterior simulator, our results do not materially change.

6 Concluding Remarks

We have developed and estimated a general equilibrium model with non-pecuniary labor market frictions and Pigouvian shocks regarding future TFP changes. Unemployment gradually adjust after a TFP news shock. We show that anticipated TFP shocks are the key drivers of the low-frequency dynamics of the unemployment rate during the postwar period. Noise shocks, which capture changes in beliefs that are orthogonal to future fundamentals and thereby resemble the Pigou's sources of business cycles, give rise to boom-bust responses of output and employment. These changes in beliefs significantly contribute to jointly explaining the observed fluctuations in GDP, consumption, investment, the unemployment rate, and real wages. We find that most U.S. recessions begin (end) when agents start realizing that previous enthusiastic (lukewarm) expectations about future TFP would not be met. The role of these expectations has intensified in recent years due to the decoupling between the unemployment rate, whose recent record-low values have strengthened beliefs about future TFP improvements, and the observed TFP growth.

[41] One can achieve such a news representation by assuming that TFP shocks θ_t^a in the model with noisy signals are serially correlated in a particular way. See Chahrour and Jurado (2017a).

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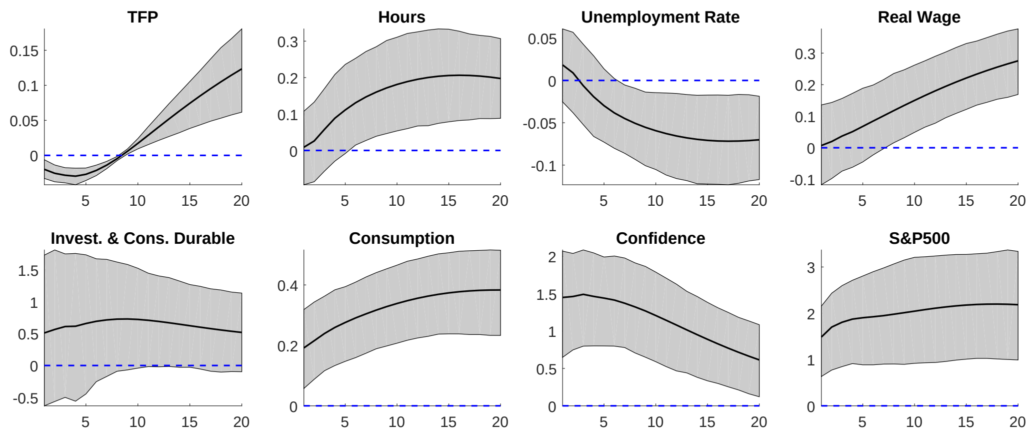

Figure 11: Response of macroeconomic variables to TFP news shocks identified using signed restrictions as in Faccini and Melosi (2018). All responses are expressed in percentage points. The size of the news shock is one standard deviation. The gray areas mark the sixty-eight-percent posterior credible sets.

Appendix (for online publication)

A The Transmission of Anticipated TFP Shocks in SVARs

In this appendix, we investigate the propagation properties of TFP news shocks using reduced-form VAR analysis. What follows is an excerpt from Faccini and Melosi (2019).

We use the same data set as that in Barsky, Basu, and Lee (2015), with the addition of unemployment rates and real wages. We use standard national income accounts data on gross investment, purchases of consumer durables, and consumption of nondurables and services (aggregated into a single index). Each variable is expressed in percapita terms, dividing by the civilian non-institutional population. Hours worked are the Bureau of Labor Statistics (BLS) measure of aggregate non-farm payroll hours, again on a percapita basis. The stock price variable is Shiller's real S&P 500 index, the interest rate is the three-month Treasury bill rate, and inflation is measured by the CPI-U. The consumer confidence measure is from the Michigan Survey of Consumers. Data on quarterly utilization-adjusted TFP are from Fernald (2014), who uses a subset of the procedures proposed by Basu, Fernald and Kimball (2006) to create a quarterly TFP series purged of the endogenous utilization component. We convert the growth rates in Fernald's TFP series to an index in log levels. We take logs of the quantity variables and the stock price.

We estimate a VAR model with four lags using Bayesian methods.[42] We identify TFP news

[42]Compared to the frequentist approach, which is dominant in this field, the Bayesian methodology allows us to more reliably estimate VAR models with a larger number of observables because of the prior shrinkage. Furthermore, this approach does not lead to spurious estimates when non-cointegrated data are used (Sims and Uhlig1991). We adopt a unit-root prior (Sims and Zha 1998) for the parameters of this empirical model with a presample of four quarters. As is standard, the number of lags and the five hyperparameters pinning down the prior are chosen so as to maximize the marginal likelihood. We perform Bayesian estimation of this VAR model

shocks in a way that is consistent with our DSGE model, in which agents receive news about four- and eight-quarters-ahead TFP shocks as in Schmitt-Grohe and Uribe (2012). Our identification strategy is based on imposing the following set of sign restrictions: *(i)* TFP news shocks do not increase the level of TFP for eight quarters. *(ii)* TFP news shocks raise consumption, the confidence index, and the S&P500 for the next eight quarters after their realization.[43]

The impulse responses to positive news about TFP are reported in Figure 11. The response of TFP is to significantly fall in the aftermath of the news. The rate of unemployment does not respond on the impact of the shocks, but starts to fall gradually, soon after a favorable TFP news. Similarly, hours do not respond significantly on impact, but then slowly build up, turning significantly positive after a few quarters. Overall, we find that news shocks induce a delayed tightening of labor market conditions along with a delayed increase in real wages, consumption, investment and stock market prices. The key finding is that the expansionary effects of TFP news start to materialize well in advance of technological improvements.[44] This finding lends support to the view that TFP news shocks largely propagate through adjustments in private sector's beliefs, as in our estimated model.

To sum up, the findings in Faccini and Melosi (2019) have two main implications. First, labor market variables seem to respond with a delay to TFP news shocks in VAR models. This feature is hard to find in the existing dynamic general equilibrium models. For instance, the model developed by Blanchard et al (2013) implies that the impact effect of news-driven beliefs is large and positive. Second, structural models that predict a gradual adjustment in macro variables in anticipation of the effects of TFP news shocks are not necessarily at odds with the VAR evidence.

B List of log-linearized equations

In this Appendix we list the log-linearized equations of the model introduced in Section 2. Let barred variables denote steady-state values, and the hat over a lower case variable denote log-deviations from the steady-state value, i.e., let $\hat{n}_t = \ln N_t - \ln \bar{N}$ denote log-deviations of employment from the steady-state. For variables that grow along the balanced growth path, such as consumption C_t, we denote by $\tilde{C}_t = \frac{C_t}{A_t}$ the stationarized variable and by $\tilde{C}$ the value it takes along the balanced growth path. In such a case $\hat{c}_t = \ln \tilde{C}_t - \ln \tilde{C}$.

with four lags and the ten observable variables described earlier.

[43] Identification of structural shocks via sign restrictions has been pioneered by Uhlig (2005). See also Baumeister and Hamilton (2015).

[44] This result was emphasized in Portier (2015), who, using the identification scheme proposed by Barsky, Basu, and Lee (2015) and a smaller scale frequentist VAR, has noticed the importance of the anticipation horizon in recovering the shock originally identified in Beaudry and Portier (2006). Similar results have also been obtained by Miranda-Agrippino, Hoke, and Bluwstein (2018).

1. Labor force

$$\widehat{lf}_t = \frac{\bar{N}}{\bar{N}+\bar{U}}\hat{n}_t + \frac{\bar{U}}{\bar{N}+\bar{U}}\hat{u}_t.$$

2. Consumption Euler equation

$$\begin{aligned}-\hat{R}_t &= \left[\frac{1}{\mu-\vartheta} + \frac{\vartheta}{(\mu-\vartheta)\,\mu}\right]\mu\hat{c}_t - \frac{\vartheta}{\mu-\vartheta}\hat{c}_{t-1} - \frac{\mu}{\mu-\vartheta}E_t\hat{c}_{t+1} \\ &\quad -\eta_t^p + E_t\eta_{t+1}^p + \frac{\vartheta}{\mu-\vartheta}\eta_t^A - \frac{\mu}{\mu-\vartheta}E_t\eta_{t+1}^A - E_t\pi_{t+1}.\end{aligned}$$

3. Marginal utility of consumption

$$\hat{\lambda}_t = -\frac{1}{1-\frac{\vartheta}{\mu}}\hat{c}_t + \frac{\frac{\vartheta}{\mu}}{1-\frac{\vartheta}{\mu}}\left(\hat{c}_{t-1} - \eta_t^A\right) + \hat{\eta}_t^p.$$

4. Law of motion for employment

$$\hat{n}_t = (1-\delta_N)\,\hat{n}_{t-1} + \delta_N\hat{h}_t.$$

5. Hiring

$$\hat{h}_t = \hat{u}_t + \frac{1}{1-\bar{x}}\hat{x}_t.$$

6. Labor participation decision

$$\begin{aligned}\hat{v}_t^N + (1-\bar{x})^{-1}\,\hat{x}_t &= \left(\eta_t^l + \varphi\hat{l}_t - \eta_t^p\right) \\ &\quad + \left[\frac{\mu}{\mu-\vartheta}\hat{c}_t - \frac{\vartheta}{\mu-\vartheta}\left(\hat{c}_{t-1} - \eta_t^A\right)\right].\end{aligned}$$

7. Value of employment to households

$$\frac{\varpi\,(1-\bar{x})+\bar{x}}{\varpi\,(1-\bar{x})}\left[\hat{v}_t^N + \frac{\bar{x}\left[\varpi\,(1-\bar{x})+\bar{x}\right]}{1-\bar{x}}\hat{x}_t\right]$$

$$= \left\{\frac{\varpi\,(1-\bar{x})+\bar{x}}{\varpi\,(1-\bar{x})} - (1-\delta_N)\,\beta\right\}\hat{w}_t^r + (1-\delta_N)\,\beta\left(\hat{\pi}_{t+1} - \hat{R}_t + \hat{v}_{t+1}^N + \eta_{t+1}^A\right).$$

8. Production function

$$\hat{f}_t = \hat{a}_t + \alpha\hat{n}_t + (1-\alpha)\left(\hat{k}_{t-1} - \hat{\eta}_t^A\right).$$

9. Output function

$$\hat{y}_t = \frac{\tilde{f}}{\tilde{f}-\tilde{g}}\hat{f}_t - \frac{\tilde{g}}{\tilde{f}-\tilde{g}}\hat{g}_t.$$

10. Adjustment cost function

$$\hat{g}_t = 2\left(\hat{h}_t - \hat{n}_t\right) - \eta^q \hat{q}_t + \hat{a}_t + \alpha \hat{n}_t + (1-\alpha)\left(\hat{k}_{t-1} - \hat{\eta}_t^A\right).$$

11. Derivative of adjustment cost function (∂H_t):

$$\hat{g}_{H,t} = -\eta^q \hat{q}_t + \hat{h}_t - 2\hat{n}_t + \hat{f}_t.$$

12. Derivative of adjustment cost function (∂K_t):

$$\hat{g}_{K,t} = \hat{g}_t - \hat{k}_{t-1} + \hat{\eta}_t^A.$$

13. Derivative of adjustment cost function (∂N_t):

$$\tilde{g}_{N,t}\hat{g}_{N,t} = -e_2 q^{-\eta^q} \delta_N^2 \frac{\tilde{f}}{N}\left(-\eta^q \hat{q}_t + \hat{f}_t - 3\hat{n}_t + 2\hat{h}_t\right) + \frac{\alpha \tilde{g}}{\bar{N}}\left(\hat{g}_t - \hat{n}_t\right).$$

14. Vacancy filling rate:

$$\hat{q}_t = -\frac{l}{1-l}\hat{x}_t.$$

15. Law of motion for capital

$$\hat{k}_t = (1-\delta_K)\frac{1}{\mu}\left(\hat{k}_{t-1} - \hat{\eta}_t^A\right) + \frac{\tilde{I}}{\tilde{K}}\left(\hat{\imath}_t + \hat{\eta}_t^I\right).$$

16. FOC capital

$$\begin{aligned}\hat{q}_t^K \quad = \quad & E_t\hat{\pi}_{t+1} - \hat{R}_t + \frac{\frac{\bar{\Pi}}{\bar{R}}\left[\bar{\xi}(\tilde{f}_K - \tilde{g}_K)\right]}{\bar{Q}^K} E_t m\hat{c}_{t+1} \\ & + \frac{\frac{\bar{\Pi}}{\bar{R}}\bar{\xi}\tilde{f}_K}{\bar{Q}^K} E_t\hat{f}_{K,t+1} - \frac{\bar{\Pi}}{\bar{R}\bar{Q}^K}\bar{\xi}\tilde{g}_K E_t\hat{g}_{K,t+1} + \frac{\bar{\Pi}}{\bar{R}}\left[(1-\delta_K)\right] E_t\hat{q}_{t+1}^K.\end{aligned}$$

17. FOC employment

$$\begin{aligned}\bar{\xi} \quad & \left(\tilde{g}_K - \tilde{f}_N + \tilde{g}_N\right)\widehat{\xi}_t + \bar{\xi}\tilde{g}_H \cdot \hat{g}_{H,t} = \\ & \bar{\xi}\tilde{f}_N \cdot \hat{f}_{N,t} - \bar{\xi}\tilde{g}_N \cdot \hat{g}_{N,t} - \tilde{W}^r \hat{w}_t^r \\ & +(1-\delta_N)\frac{\bar{\Pi}}{\bar{R}}\bar{\xi}\tilde{g}_H \mu \left[E_t\hat{\pi}_{t+1} - R_t + E_t\widehat{\xi}_{t+1} + E_t\hat{g}_{H,t+1} + E_t\hat{\eta}_{t+1}^A\right].\end{aligned}$$

18. Resource constraint

$$\frac{\tilde{Y}}{\eta^G}\left(\hat{y}_t - \hat{\eta}_t^G\right) = \tilde{C}\hat{c}_t + \tilde{I}\left(\hat{\eta}_t^q + \hat{I}_t\right).$$

19. Phillips curve

$$\left[1 + \frac{\bar{\Pi}\mu}{\bar{R}}\psi\right]\hat{\pi}_t = \psi\hat{\pi}_{t-1} + \frac{\epsilon - 1}{\zeta}\cdot\widehat{\xi}_t + \frac{\bar{\Pi}\mu}{\bar{R}}E_t\hat{\pi}_{t+1} + \hat{\eta}_t^{mkp}.$$

20. Real wage equation

$$\begin{aligned}\tilde{W}^{r,NASH}\hat{w}_t^{r,NASH} &= \gamma\bar{\xi}\left[\left(\tilde{f}_N - \tilde{g}_N\right)\widehat{\xi}_t + \tilde{f}_N\hat{f}_{N,t} - \tilde{g}_N\hat{g}_{N,t}\right] \\ &\quad + (1-\gamma)\frac{\chi\overline{L}^{\varphi}}{\tilde{\lambda}_*}\left(\eta_t^l + \varphi\hat{l}_t - \hat{\lambda}_t\right).\end{aligned}$$

21. Inertial wage

$$\hat{W}_t^r = \omega\hat{W}_{t-1}^r + (1-\omega)\hat{W}_t^{r,NASH}.$$

22. Taylor Rule

$$\hat{R}_t = \rho_R\hat{R}_{t-1} + (1-\rho_R)r_\pi\hat{\pi}_t + (1-\rho_R)r_y\hat{y}_t + \hat{\eta}_{r,t}.$$

23. Marginal productivity of labor

$$\hat{f}_{N,t} = \hat{f}_t - \hat{n}_t.$$

24. Marginal productivity of capital

$$\hat{f}_{K,t} = \hat{f}_t - \hat{k}_{t-1} + \hat{\eta}_t^A.$$

25. Tobin's Q for capital

$$\hat{q}_t^K + \hat{\eta}_t^I = \hat{\eta}_t^q + S''(1+\beta)\hat{\imath}_t - S''\hat{\imath}_{t-1} - \beta S''\hat{\imath}_{t+1}. \tag{22}$$

26. Tobin's Q for employment

$$\hat{Q}_t^N = \widehat{\xi}_t + \hat{g}_{H,t}.$$

C The Data Set

Nominal consumption includes personal consumption expenditures: nondurable goods (PCND) and personal consumption expenditures in services (PCESV), which are computed by the U.S. Bureau of Economic Analysis (BEA) (NIPA tables). Nominal investments include personal consumption expenditures in durable goods (PCDG) and gross private domestic investment (GPDI), which are computed by the BEA (NIPA tables). We deflate GDP, consumption, and investment by using the implicit price deflator index (GDPDEF), computed by the BEA (NIPA tables) and then we divide the resulting variable by the civilian non-institutional population (CNP16OV), measured by the U.S. Bureau of Labor Statistics (BLS).

The employment rate and the participation rate are the quarterly averages of the civilian employment-to-population ratio (EMRATIO) and the civilian labor force participation rate (CIVPART), respectively. We measure wage growth by using the quarterly average of the wage and salary disbursements received by employees (A576RC1) divided by the civilian employment level (CE16OV). We divide the resulting series by the GDP deflator to obtain our measure of real wages. TFP growth rates are adjusted and unadjusted to capital utilization (Fernald 2012). We have three measures of inflation (GDP deflator, CPI, and PCE) in estimation. See Campbell et al. (2012) for a thorough description of this approach. We take the logs of these series. All data used in estimation are quarterly and in percent.

For the second sample, which ranges from the fourth quarter of 2008 through the fourth quarter of 2016 we use the market-expected federal funds rates to enforce the effective lower bound of the nominal interest rate. We construct this time series from the overnight index swap (OIS) data as in Campbell et al. (2017).[45] As in that paper, we consider market expectations with forecasting horizons ranging from one quarter to ten quarters and introduce a two-factor model to parsimoniously capture the comovements of these expectations across horizons.[46]

D Using Multiple TFP Growth Rates in Estimation

To ensure model consistency of the TFP series adjusted and unadjusted for variable capital utilization computed by Fernald (2014), we compute TFP growth using the number of employed workers instead of total hours. We do not adjust the TFP series for variations in the quality of workers over time because this time series is not available. Changes in the quality of employment is picked up by the labor-augmenting technology process, $\hat{\eta}_t^A$. Furthermore, we set the elasticity of output to employment, α, to 0.66, which is consistent with how this parameter is calibrated in our analysis.

Note that we do not have to adjust Fernald's estimate of TFP for aggregate hiring costs g

[45]The funds rate paths implied by these contracts include a 1 basis point- per-month adjustment for term premiums through 2011:Q2. We do not apply any adjustments after this date, when it appears that term premiums disappeared or perhaps turned negative. The unadjusted data yield very similar results.

[46]The forward guidance shocks in the Taylor rule are an array of i.i.d. shocks from the perspective of agents in the model. The factor model is part of the measurement equations and is introduced to capture the strong correlation of interest rates across their maturity horizons. We run a principal component analysis so as to verify that two factors are enough to explain most of the comovement among the expected interest rates in the period 2008:Q4-2016:Q4. This two-factor structure was introduced by Gürkaynak, Sack, and Swanson (2005).

because these costs are modeled as forgone output. Hence, the measure of GDP in the data should be interpreted as already net of these costs.

The observation equations for the two TFP growth rates read as follows:

$$\Delta \ln TFP_t^N = c_{TFP,unadj}^m + \lambda_{TFP,unadj}^m \left[\hat{a}_t - \hat{a}_{t-1} + \alpha \hat{\eta}_t^A + 100\alpha \ln \mu\right] + \eta_{TFP,t}^N, \quad (23)$$

$$\Delta \ln TFP_t^A = c_{TFP,adj}^m + \lambda_{TFP,adj}^m \left[\hat{a}_t - \hat{a}_{t-1} + \alpha \hat{\eta}_t^A + 100\alpha \ln \mu\right] + \eta_{TFP,t}^A, \quad (24)$$

where $\Delta \ln TFP_t^N$ and $\Delta \ln TFP_t^A$ denote the observed series of unadjusted and adjusted TFP growth expressed in percent quarterly rates; $\lambda_{TFP,unadj}^m$ (normalized to unity) and $\lambda_{TFP,adj}^m$ denote the loadings associated with the unadjusted and the adjusted series; and $\eta_{TFP,t}^N$ and $\eta_{TFP,t}^A$ are i.i.d. Gaussian measurement errors with mean zero and standard deviation $\sigma_{TFP,unadj}^m$ and $\sigma_{TFP,adj}^m$, respectively. The parameters $c_{TFP,unadj}^m$ and $c_{TFP,adj}^m$ denote constant parameters. Furthermore, $\hat{a}$ denotes log of TFP ($\ln a_t$) and $\hat{\eta}_t^a$ denotes log deviations of the growth rate of the labor-augmenting technology from its trend μ.

E Measurement Equations

1. Real GDP growth

$$100\Delta \ln RGDP_t = \hat{y}_t - \hat{y}_{t-1} + \hat{\eta}_t^A + 100 \ln \mu.$$

2. Real Consumption

$$100\Delta \ln RConsump_t = \hat{c}_t - \hat{c}_{t-1} + \hat{\eta}_t^A + 100 \ln \mu.$$

3. Real Investment

$$100\Delta RINV_t = \hat{\imath}_t - \hat{\imath}_{t-1} + \hat{\eta}_t^A + 100 \ln \mu.$$

4. Inflation rate (multiple indicator)

$$100 \cdot GDPDEFL_t = c_{\pi,1}^m + \lambda_{\pi,1}\hat{\pi}_t + 100 \ln \Pi_* + \sigma_{\pi,1}^m \eta_{1,t}^\pi,$$

$$100\Delta PCE_t = c_{\pi,2}^m + \hat{\pi}_t + 100 \ln \Pi_* + \sigma_{\pi,2}^m \eta_{2,t}^\pi,$$

$$100\Delta CPI_t = c_{\pi,3}^m + \lambda_{\pi,3}\hat{\pi}_t + 100 \ln \Pi_* + \sigma_{\pi,3}^m \eta_{3,t}^\pi.$$

5. Real wage growth

$$100\Delta \ln RW_t = c_w^m + \hat{w}_t^r - \hat{w}_{t-1}^r + \hat{\eta}_t^A + 100 \ln \mu + \sigma_w^m \eta_{w,t}.$$

where the constant c_w^m accounts for the difference in sample means with the growth rate of

GDP, consumption, and investment.

6. Unemployment rate ($u_* = 0.056$)[47]

$$100 \ln UR_t = \hat{u}_t - \widehat{lf}_t + 100 \ln u_*.$$

7. Unemployment rate ($u_* = 0.056$)[48]

$$100 \ln E_t^{spf} UR_{t+h} = E_t \hat{u}_{t+h} - E_t \widehat{lf}_{t+h} + 100 \ln u_* + \sigma_{u,h}^m \eta_{h,t}^u, \quad h \in \{1, 2, 3, 4\}.$$

8. Participation rate ($lf_* = 0.65$)

$$\begin{aligned} 100 \ln PartR_t &= 100 \ln \frac{LF_t}{Pop_t} \\ &= \widehat{lf}_t + 100 \ln lf_*. \end{aligned}$$

9. Employment rate (n_* is implied by u_* and lf_*)

$$100 \ln ER_t = \hat{n}_t + 100 \ln n_* + \sigma_E^m \eta_{e,t}.$$

10. FFR (quarterly and in percent)

$$FFR_t = \ln R_t + 100 \ln R_*.$$

[47] To get this, observe that

$$\begin{aligned} 100 \ln \frac{UR_t^{\%}}{100} &= 100 \ln \frac{U_t}{LF_t} \\ &= 100 \ln \frac{U_t}{\overline{U}} - 100 \ln \frac{LF_t}{\overline{LF}} + 100 \ln \frac{\overline{U}}{\overline{LF}} \\ &= \hat{u}_t - \widehat{lf}_t + 100 \ln \overline{U}^r, \end{aligned}$$

where $\overline{U}^r \equiv \frac{\overline{U}}{\overline{LF}}$ denotes the steady-state unemployment rate.

[48] To get this, observe that

$$\begin{aligned} 100 \ln \frac{UR_t^{\%}}{100} &= 100 \ln \frac{U_t}{LF_t} \\ &= 100 \ln \frac{U_t}{\overline{U}} - 100 \ln \frac{LF_t}{\overline{LF}} + 100 \ln \frac{\overline{U}}{\overline{LF}} \\ &= \hat{u}_t - \widehat{lf}_t + 100 \ln \overline{U}^r, \end{aligned}$$

where $\overline{U}^r \equiv \frac{\overline{U}}{\overline{LF}}$ denotes the steady-state unemployment rate.

11. Multiple indicator for TFP growth adjusted for capital utilization ΔTFP_t^A and non-adjusted for capital utilization ΔTFP_t^N

$$
\begin{aligned}
100\Delta \ln TFP_t^A &= c_{TFP,adj}^m + \lambda_{TFP,adj}^m \left[\hat{a}_t - \hat{a}_{t-1} + \alpha\hat{\eta}_t^A + 100\alpha \ln \mu\right] + \eta_{TFP,t}^A, \\
100\Delta \ln TFP_t^N &= c_{TFP,unadj}^m + \lambda_{TFP,unadj}^m \left[\hat{a}_t - \hat{a}_{t-1} + \alpha\hat{\eta}_t^A + 100\alpha \ln \mu\right] + \eta_{TFP,t}^N.
\end{aligned}
$$

12. Expected future federal funds rate (only in the second sample): The forward guidance shocks in the Taylor rule, $\xi_{r,t}^l$ with $l \in \{0, ...10\}$ are disciplined by the following two-factor model

$$\xi_{r,t}^l = \Lambda_T f_T + \Lambda_P f_P + \eta_{l,t}^{FG}, \text{ with } l \in \{0, ...10\}$$

where f_T and f_P are two i.i.d. Gaussian factors with standard deviations $\sigma_{f,T}$ and $\sigma_{f,P}$, Λ_T and Λ_P are their respective loadings, and $\eta_{l,t}^{FG}$ are eleven i.i.d. measurement error shocks. We impose restrictions on the two vectors of loadings allowing us to identify the two factors: a target factor that moves the current policy rate and a path factor that moves the slope of the term structure of future interest rates (i.e., it moves only expected future rates). The crucial restrictions to interpret factors this way are that $\Lambda_T(0) = 1$ and $\Lambda_P(0) = 0$.

F Model's Impulse Response Functions to TFP Shocks

Figures 12-14 show the posterior median and the 68-percent credible set of the impulse response functions of unemployment rate, employment rate, real wages, GDP, consumption, and investment to a one-standard deviation surprise TFP shock, a one-standard deviation four-quarter-ahead news shock to TFP, a one-standard deviation eight-quarter-ahead news shock to TFP, respectively.

G Recovering Noise from the Estimated Models with News Shocks

The goal of this Appendix is to show how the estimated news representation can be used to tease out the historical series of noise shocks and assess their historical contribution to the U.S. business cycle. We will proceed toward this goal in three steps. We first apply the representation theorem introduced by Chahrour and Jurado (2017a) to obtain the implied parameter of the model ($\sigma_\theta, \sigma_{4,\nu}$, and $\sigma_{8,\nu}$) from the estimated parameters ($\sigma_{0,a}$, $\sigma_{4,a}$, and $\sigma_{8,a}$) defined in the news representation. Second, with the parameter values of our model with signals at hand, we use the two-sided filtered series of TFP news and surprise shocks (obtained using the estimated news representation of our model) to tease out the implied series of noise shocks. Third, we

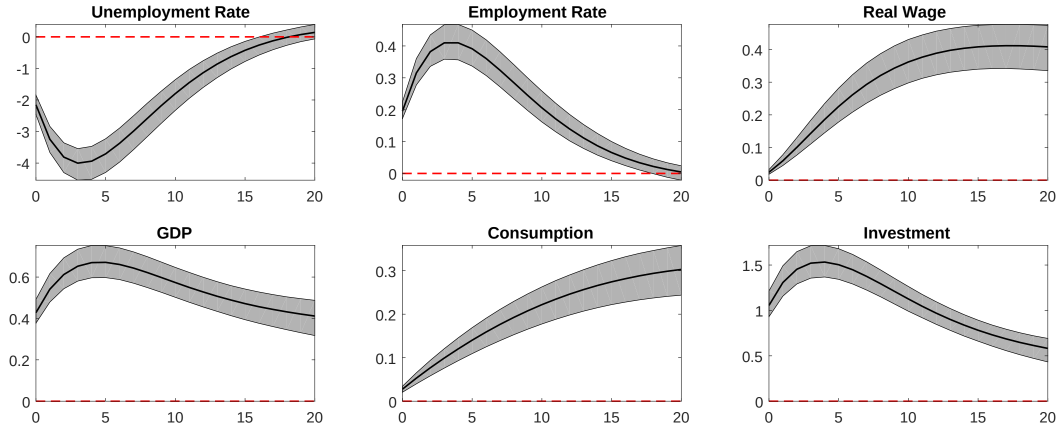

Figure 12: Posterior median of the response of unemployment rate, employment rate, real wage, GDP, consumption, and investment to a surprise shock to TFP. The gray areas denote the sixty-eight-percent posterior credible sets. The responses of unemployment and employment rates are expressed in percentage points deviations from the steady-state rate. All other responses are in percentage deviations from their steady-state value. The size of the initial shocks is one percentage point.

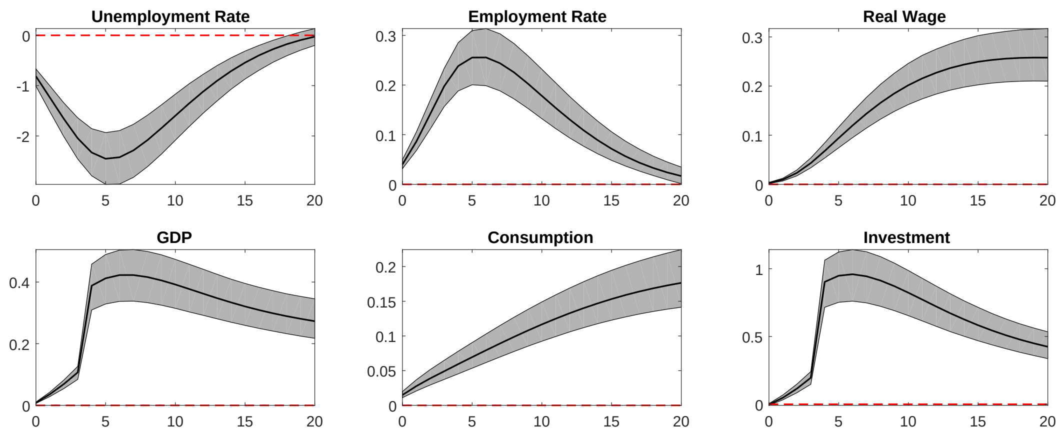

Figure 13: Posterior median of the response of unemployment rate, employment rate, real wage, GDP, consumption, and investment to a four-quarter-ahead shock to TFP. The gray areas denote the sixty-eight-percent posterior credible sets. The responses of unemployment and employment rates are expressed in percentage points deviations from the steady-state rate. All other responses are in percentage deviations from their steady-state value. The size of the initial shocks is one percentage point.

construct the historical dynamics of the business cycle variables implied by the estimated in-sample realizations of noise shocks alone.

Step 1: Fetching the Parameters of the Model from the Estimated News Representation (Chahrour and Jurado 2017a) The news representation of the model shares all the parameters of our model except for the standard deviations of TFP fundamentals and noise; that is, σ_θ, $\sigma_{4,\nu}$, and $\sigma_{8,\nu}$. As shown by Chahrour and Jurado (2017a), for given parameter values of the estimated news representation, the parameter values of the observationally equivalent model

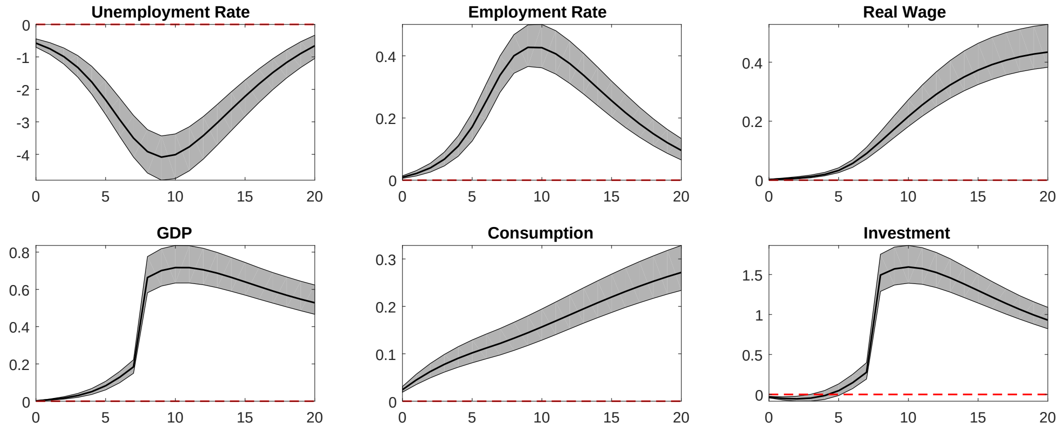

Figure 14: Posterior median of the response of unemployment rate, employment rate, real wage, GDP, consumption, and investment to an eight-quarter-ahead shock to TFP. The gray areas denote the sixty-eight-percent posterior credible sets. The responses of unemployment and employment rates are expressed in percentage points deviations from the steady-state rate. All other responses are in percentage deviations from their steady-state value. The size of the initial shocks is one percentage point.

with noisy signals are given by:

$$\sigma_{8,v}^2 = \left(\sigma_{0,a}^2 + \sigma_{4,a}^2 + \sigma_{8,a}^2\right)\left(\frac{\sigma_{0,a}^2 + \sigma_{4,a}^2}{\sigma_{8,a}^2}\right), \tag{25}$$

$$\sigma_{4,v}^2 = \left(\sigma_{0,a}^2 + \sigma_{4,a}^2\right)\frac{\sigma_{0,a}^2}{\sigma_{4,a}^2}, \tag{26}$$

and

$$\sigma_{\theta}^2 = \sigma_{a,0}^2 + \sigma_{4,a}^2 + \sigma_{8,a}^2. \tag{27}$$

We can use the estimated variance of TFP shocks ($\sigma_{a,0}^2$, $\sigma_{a,4}^2$, and $\sigma_{a,8}^2$) in the news representation to pin down the estimated variances for noise and fundamental shocks $\sigma_{4,v}^2$, $\sigma_{8,v}^2$, and σ_{θ}^2.

Step 2: Teasing Out the Historical Realizations of Noise Shocks In the estimated news representation, revisions of expectations about future TFP innovations θ_{t+8}^a in period t, $t+4$, and $t+8$ are given by the realizations of news and surprise shocks $\varepsilon_{a,t}^i$ with $i \in \{0,4,8\}$, respectively. In symbols, this would be as follows:

$$\begin{aligned} E_t\theta_{t+8}^a &= \varepsilon_{a,t}^8, & (28)\\ E_{t+4}\theta_{t+8}^a - E_t\theta_{t+8}^a &= \varepsilon_{a,t+4}^4, & (29)\\ \theta_{t+8}^a - E_{t+4}\theta_{t+8}^a &= \varepsilon_{a,t+8}^0. & (30) \end{aligned}$$

For the news representation to be observationally equivalent to our model with noisy signals, expectations about eight-quarter-ahead TFP changes in the model and in the estimated news representation must be identical. Therefore, we write the following condition:

$$\kappa_8 \left(\theta^a_{t+8} + \upsilon_{8,t}\right) = E_t \theta^a_{t+8} = \varepsilon^8_{a,t}, \tag{31}$$

where $\kappa_8 \equiv \left(\sigma^2_{0,a} + \sigma^2_{4,a} + \sigma^2_{8,a}\right) / \left(\sigma^2_{0,a} + \sigma^2_{4,a} + \sigma^2_{8,a} + \sigma^2_{8,v}\right)$ is the Kalman gain in terms of the estimated parameters of the news representation. The Kalman gain captures the precision of signals and depends on the parameter mappings (25)-(27) from the estimated news representation to our model with signals. Equation (31) decomposes the expectations about the eight-quarter-ahead TFP innovations, $E_t\theta^a_{t+8}$, into a fundamental component $\kappa_8\theta^a_{t+8}$, which will affect TFP in eight quarters, and a noise component $\kappa_8\nu_{8,t}$, which will never affect TFP. Substituting the estimated TFP innovations $\hat{\theta}^a_{t+8} = \hat{\varepsilon}^0_{a,t+8} + \hat{\varepsilon}^4_{a,t+4} + \hat{\varepsilon}^8_{a,t}$ in equation (31), we obtain the equation that can be used to tease out the noise component of the estimated eight-quarter-ahead TFP news shocks:

$$\kappa_8 \hat{\upsilon}_{8,t} = \left(1 - \kappa_8\right) \hat{\varepsilon}^8_{a,t} - \kappa_8 \left(\hat{\varepsilon}^0_{a,t+8} + \hat{\varepsilon}^4_{a,t+4}\right). \tag{32}$$

It should be noted that the noise component depends on the timing of information about θ^a_{t+8}, which is distributed from period t through $t+8$, and on the degree of imperfect information as captured by the Kalman gain $(1 - \kappa_8)$.

As far as the four-quarter-ahead expectation revisions, $E_{t+4}\theta^a_{t+8} - E_t\theta^a_{t+8}$, are concerned, we can analogously establish the following relation between the news representation and and the model:

$$\begin{aligned} E_t\theta^a_{t+4} - E_{t-4}\theta^a_{t+4} &= \kappa_4 \left(\theta^a_{t+4} + \upsilon_{4,t} - E_{t-4}\theta^a_{t+4}\right), \\ &= \kappa_4 \left(\varepsilon^0_{a,t+4} + \varepsilon^4_{a,t} + \upsilon_{4,t}\right) = \varepsilon^4_{a,t}, \end{aligned} \tag{33}$$

where $\kappa_4 \equiv \left(\sigma^2_{0,a} + \sigma^2_{4,a}\right) / \left(\sigma^2_{0,a} + \sigma^2_{4,a} + \sigma^2_{4,v}\right)$ is the Kalman gain in terms of the estimated parameters of the model with news. In the last row we made use of the fact $E_{t-4}\theta^a_{t+4} = \varepsilon^8_{a,t-4}$. Substituting the estimated TFP innovations $\hat{\theta}^a_{t+8} = \hat{\varepsilon}^0_{a,t+8} + \hat{\varepsilon}^4_{a,t+4} + \hat{\varepsilon}^8_{a,t}$ in equation (33), we obtain the equation that can be used to tease out the noise component of the estimated four-quarter-ahead TFP news shocks:

$$\kappa_4 \hat{\upsilon}_{4,t} = \left(1 - \kappa_4\right) \hat{\varepsilon}^4_{a,t} - \kappa_4 \hat{\varepsilon}^0_{a,t+4}. \tag{34}$$

Equations (32) and (34) show that noise shocks are a particular linear combination of TFP news shocks and future surprise shocks. Specifically, they depend on the magnitude of the news shocks realized today relative to the magnitude of the future news and surprise shocks. As a result, noise shocks will arise even if both news and surprise shocks are i.i.d, as their existence does not require any correlation between the two.

Step 3: Assessing the Historical Contribution of Noise Shocks Equation (31) allows us to decompose eight-quarter-ahead news shocks into a fundamental component $\kappa_8 \theta^a_{t+8}$, which will affect TFP in eight quarters, and a noise component $\kappa_8 \nu_{8,t}$, which is orthogonal to future changes in TFP. Equation (33) allows for a similar decomposition of the four-quarter-ahead TFP news shocks. Equipped with the time series of noise shocks retrieved from equations (32) and (34), we can compute the counterfactual series for TFP news and surprise shocks that generate revisions in expectations orthogonal to future fundamentals. Starting from the Kalman equation (31) and simply zeroing the fundamental component, we obtain

$$\tilde{\varepsilon}^8_{a,t} = \kappa_8 \hat{v}_{8,t}. \tag{35}$$

Next, we substitute $E_{t-4}\theta^a_{t+4} = \kappa_8 \left(\hat{\theta}^a_{t+4} + \hat{v}_{8,t-4}\right)$ from equation (31) into the first line of equation (33) and then zero the realization of fundamentals $\hat{\theta}^a_{t+4}$ to obtain the counterfactual series of the four-quarter-ahead TFP news shocks:

$$\tilde{\varepsilon}^4_{a,t} = \kappa_4 \hat{v}_{4,t} - k_4 k_8 \hat{v}_{8,t-4}. \tag{36}$$

Analogously, combining equations (29), (30), (31), and (33) and then zeroing the fundamental component θ^a_{t+8}, we get

$$\tilde{\varepsilon}^0_{a,t} = -\kappa_4 \left(\hat{v}_{4,t-4} - \kappa_8 \hat{v}_{8,t-8}\right) - \kappa_8 \hat{v}_{8,t-8}. \tag{37}$$

These counterfactual news and surprise shocks can be used to simulate the estimated news representation and obtain the sought contribution of noise shocks to business fluctuations.[49] Note that these counterfactual news and surprise shocks have no effect on time-t innovation to TFP θ^a_t, since $\tilde{\varepsilon}^0_{a,t} + \tilde{\varepsilon}^4_{a,t-4} + \tilde{\varepsilon}^8_{a,t-8} = 0$ for every t over our sample period. This is because these counterfactual shocks are orthogonal to fundamentals by construction.

The estimated time series of noise shocks is obtained from the estimated news shocks in combination with equations (32) and (34). The estimated series of noise shocks are the black bars in Figure 7 (after rescaling by the appropriate Kalman gain). The white bars are the remainder ($\kappa_8 \theta^a_{t+8}$ and $\kappa_4 \theta^a_{t+4}$) given that we know the estimated TFP news shocks $\hat{\varepsilon}^8_{a,t}$ and $\hat{\varepsilon}^4_{a,t}$, which capture the expectations revisions about future fundamentals in our model. The historical role of noise in the U.S. postwar period can be worked out by simulating the model using the estimated noise shocks in combination with equations (35), (36), and (37). Specifically, those equations give us the counterfactual news shocks that allow us to evaluate the historical

[49] This is one way to assess the contribution of noise. Alternatively, one could simulate the model with noisy signals in Step 1, using the series of noise shocks obtained in Step 2. However, our approach can be implemented by using only the observationally equivalent news representation with no need to solve the model with noisy signals.

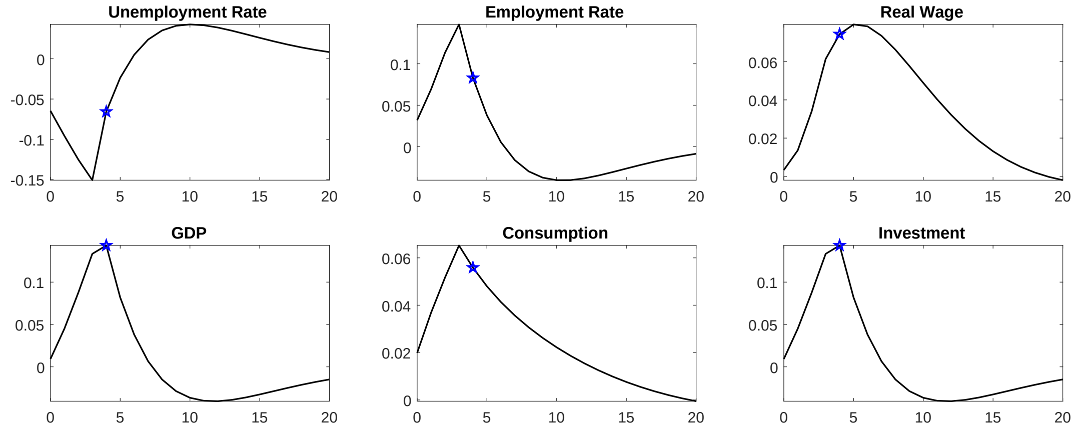

Figure 15: Estimated response of unemployment rate, employment rate, real wage, GDP, consumption, and investment to a noise shock affecting the signal about the four-quarter-ahead TFP shocks. The star mark denotes the time at which agents receive the last signal that reveals the true fundamental shock to TFP. The responses of unemployment and employment rates are expressed in percentage points. All other responses are in percentage deviations from their trend. The size of the initial shock is one standard deviation. Parameter values are set to their posterior modes, shown in Tables 1 and 2.

contribution of noise shocks to the model's variables. Figure 8 plots the historical contribution of noise shocks to the unemployment rate, GDP growth, consumption growth, and investment growth.

H Impulse Response Functions to Noise Shocks

We do not need to actually solve our model with noisy signals to compute the impulse response functions to noise shocks in Figure 6. We simulate the estimated news representation by using the counterfactual TFP surprise and news shocks $(\tilde{\varepsilon}^{8}_{a,t}, \tilde{\varepsilon}^{4}_{a,t+4}, \tilde{\varepsilon}^{0}_{a,t+8})$ implied by plugging the estimated noise shocks into equations (35)-(37). The estimated time series of noise shocks is obtained from the estimated news shocks in combination with equations (32) and (34) and is plotted in Figure 7 (the black bars).

Figure (15) plots the estimated response of the unemployment rate, the employment rate, the real wage, GDP, consumption and investment to a noise shock affecting the signal about the four-quarter-ahead TFP shocks. The star mark denotes the period in which agents learn that the signal they observed four periods earlier was just to noise.

I Historical Realizations of Shocks

Figure 16 shows the historical realizations (smoothed estimates) of four- and eight-quarter-ahead TFP news shocks along with their estimated distribution in the model. There are no realizations of these shocks lying in the tails of their distribution. When a large number of realizations lie in the tails of the distribution, it is often a symptom of mispecification and violation of rationality.

We conclude that the historical realizations of TFP news shocks are not too big. Figure 17 shows that similar conclusions apply when considering actual TFP shocks: the large majority of the historical realizations of these shocks fall within the two-standard-deviation bands around their zero mean.

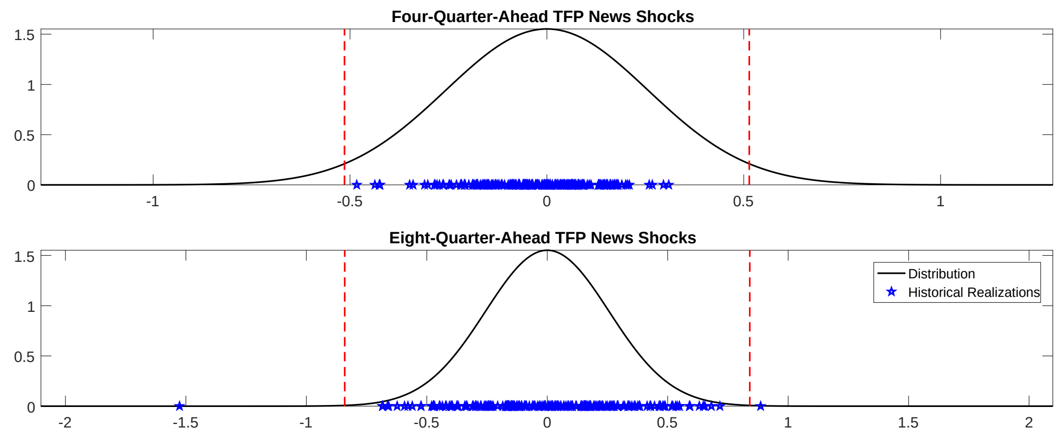

Figure 16: Distribution of the four- (top) and eight-quarter-ahead (bottom) TFP news shocks in the estimated model (black line). The blue stars mark the historical realizations of these shocks obtained from the Kalman smoother. The red dashed vertical lines denote the two-standard-deviation interval around the zero mean of these shocks.

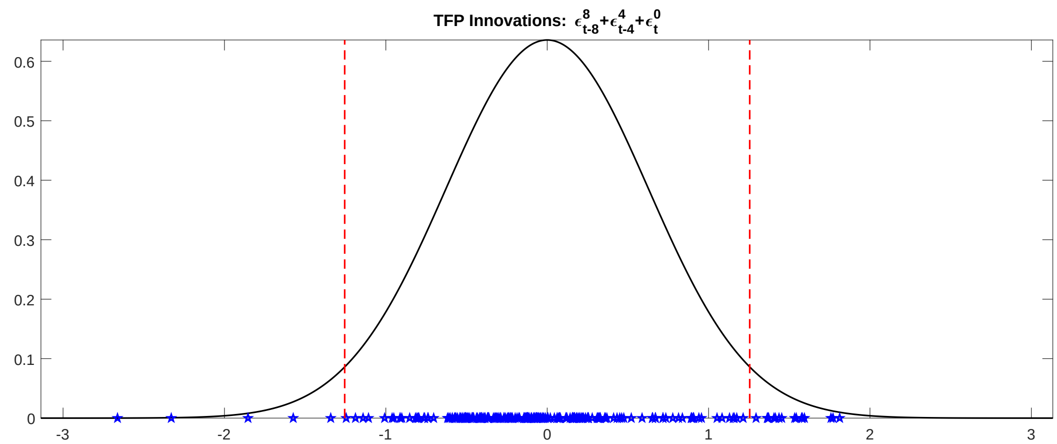

Figure 17: Distribution of the actual TFP innovations in the estimated model (black line). The blue stars mark the historical realizations of these shocks obtained from the Kalman smoother. The red dashed vertical lines denote the two-standard-deviation interval around the zero mean of these shocks.

Figure 18 compare the historical realizations of noise shocks to the estimated distribution of these shocks in the model. The realized noise shocks are not in the tails of their distribution. This check ensures that the Kalman gains in the model, which depends on the standard deviation of the Gaussian distribution of noise shocks, are consistent with the in-sample standard deviations of the estimated noise shocks.

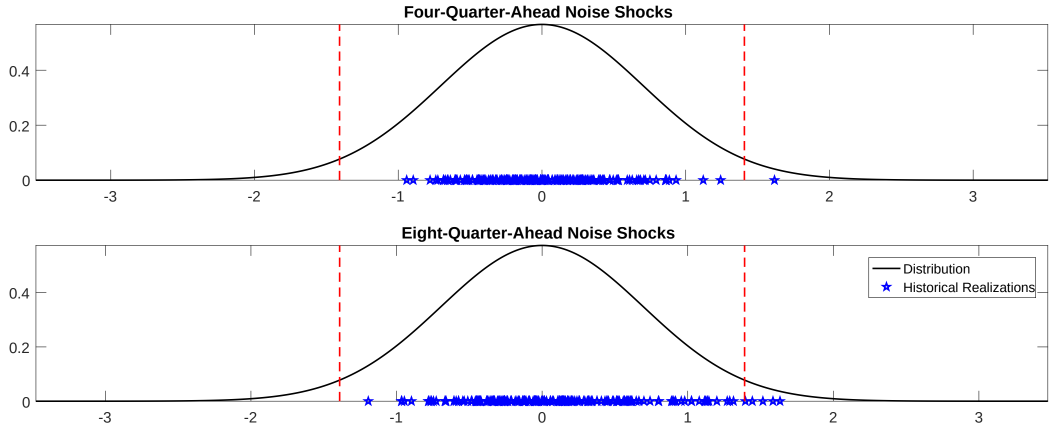

Figure 18: Distribution of the four- (top) and eight-quarter-ahead (bottom) noise shocks in the estimated model (black line). The blue stars mark the historical realizations of these shocks obtained from the Kalman smoother. The red dashed vertical lines denote the two-standard-deviation interval around the zero mean of these shocks.

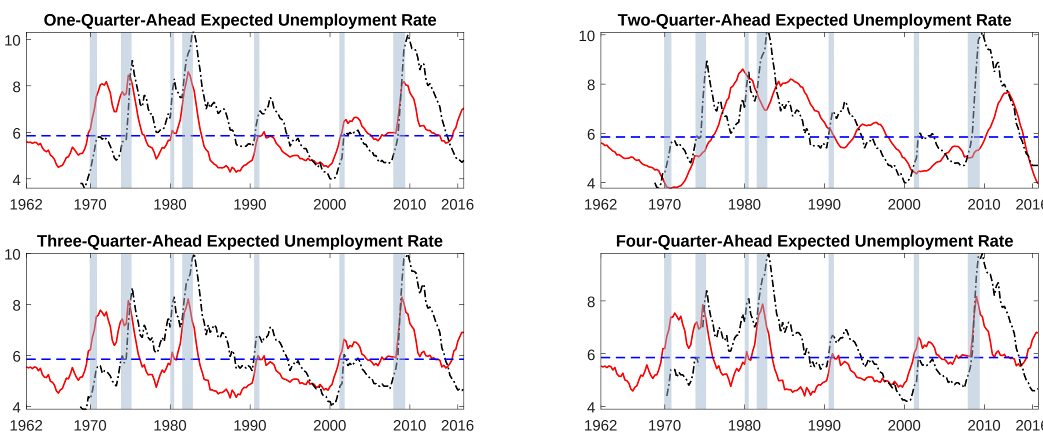

Figure 19: Expectations of U.S. unemployment rates (black dashed-dotted line), along with the counterfactual unemployment rate obtained by simulating the model using only the smoothed estimate of the surprise TFP shocks (red solid line). The counterfactual series are computed by setting the model parameters to their posterior modes, which are reported in Tables 1 and 2. Shaded areas denote NBER recessions.

J The Role of Expected Unemployment Rates in Identifying TFP Shocks

Figure 19 shows the U.S. expected unemployment rate (black dashed-dotted line) along with the counterfactual time series obtained by simulating the estimated model using only the smoothed estimate of the TFP surprise shocks (red solid lines). Figure 20 shows the counterfactual series of the expected unemployment rate when the estimated model is simulated using only the smoothed estimate of the four-quarter and eight-quarter ahead TFP news shocks.

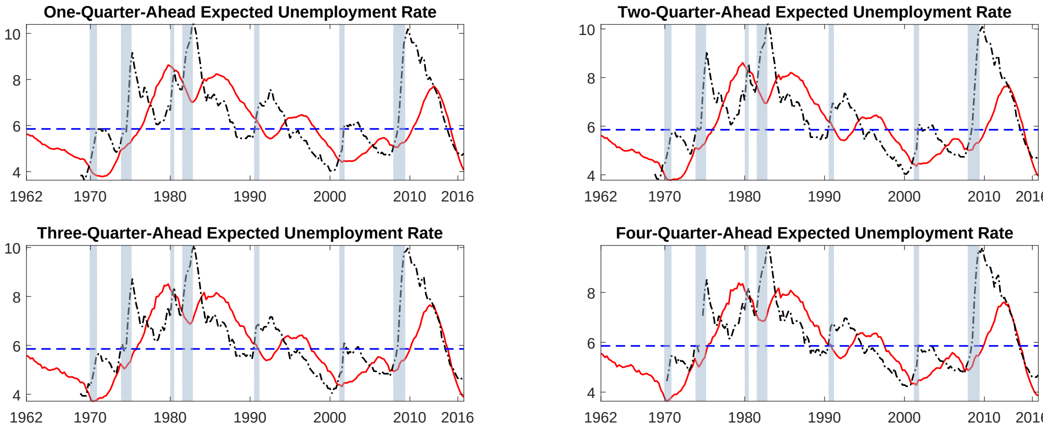

Figure 20: Expectations of U.S. unemployment rates (black dashed-dotted line), along with the counterfactual unemployment rate obtained by simulating the model using only the smoothed estimate of the four- and eight-quarter-ahead TFP news shocks (red solid lines). The counterfactual series are computed by setting the model parameters to their posterior modes, which are reported in Tables 1 and 2. Shaded areas denote NBER recessions.

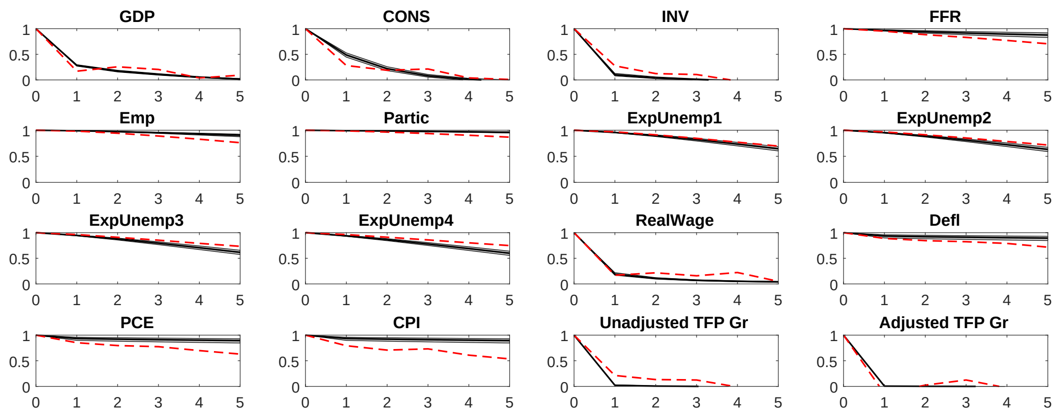

Figure 21: Posterior autocorrelation functions computed for every 100 posterior draws. The red dashed line denotes the empirical autocorrelation function and the solid black line denotes the posterior median for the autocorrelation implied by the model after shutting down its measurement errors. The gray areas denote the 90-percent posterior credible set. Sample period: 1962:Q1-2008:Q3)

K Autocorrelation Functions

To provide further evidence on the ability of the model to fit the data, we show in Figure 21 the autocorrelation functions for the endogenous variables. Overall, the model does well at matching these moments, overestimating only slightly the persistence of the rates of inflation and participation.

L Parameter List

Tables 5 and 6 list the parameters of the news representation of our model.

Notation of Model Parameters	
	Parameters
Habit parameter	ϑ
Steady-state growth rate	$\mu 100$
Inverse Frisch elasticity	φ
Slope Phillips curve	κ
Steady-state unemployment rate	$u^{*}100$
Steady-state inflation rate	$\Pi^{*}100$
Hiring cost parameter	e
Wage inertia	ω
Investment adjustment cost	ϕ
Inflation indexing parameter	ψ
Elasticity of the matching function	l
Weight of external hiring costs	η^{q}
Relative disutility of unemployment	$\bar{\omega}$
Taylor rule response to inflation	r_{π}
Taylor rule response to output	r_{y}
Taylor rule smoothing parameters	ρ_{R}

Table 5: Notations for the Model Parameters.

Notation of Model and Measurement Parameters	
	Parameters
Panel A: Shocks Autoregressive Parameters	
Technology, unanticipated	ρ_a
Technology, labor augmenting	ρ_μ
Labor disutility	ρ_l
Government	ρ_g
Investment (MEI)	ρ_i
Preference	ρ_p
Inflation drift	ρ_{Π^*}
Panel B: Shocks Standard Deviations	
Technology, unanticipated	σ_a
Technology, anticipated 4Q	σ_a^4
Technology, anticipated 8Q	σ_a^8
Technology, labor augmenting	σ_μ
Labor disutility	σ_l
Government	σ_g
Investment (MEI)	σ_i
Preference	σ_p
Inflation drift	σ_{Π^*}
Monetary	σ_r
Markup	$\sigma_{\lambda_{f,t}}$
Panel C: Measurement Equations	
Unemployment expectations 1Q	$\sigma_{u,1}^m$
Unemployment expectations 2Q	$\sigma_{u,2}^m$
Unemployment expectations 3Q	$\sigma_{u,3}^m$
Unemployment expectations 4Q	$\sigma_{u,4}^m$
Employment	σ_E^m
Wage compensation (constant)	c_w^m
Wage compensation (st.dev.)	σ_w^m
GDP deflator (constant)	$c_{\pi,1}^m$
PCE inflation (constant)	$c_{\pi,2}^m$
CPI inflation (constant)	$c_{\pi,3}^m$
GDP deflator (loading)	$\lambda_{\pi,1}^m$
CPI deflator (loading)	$\lambda_{\pi,3}^m$
GDP deflator (st.dev.)	$\sigma_{\pi,1}^m$
PCE inflation (st.dev.)	$\sigma_{\pi,2}^m$
CPI inflation (st.dev.)	$\sigma_{\pi,3}^m$
TFP unadjusted (constant)	$c_{TFP,unadj}^m$
TFP adjusted (constant)	$c_{TFP,adj}^m$
TFP adjusted (loading)	$\lambda_{TFP,adj}^m$
TFP unadjusted (st.dev.)	$\sigma_{TFP,unadj}^m$
TFP adjusted (st.dev.)	$\sigma_{TFP,adj}^m$

Table 6: Notations for the Model Parameters.