

# Pigouvian Cycles\*

Renato Faccini

Queen Mary, University of London  
Centre for Macroeconomics (LSE)

Leonardo Melosi

FRB Chicago  
European University Institute  
CEPR

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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.

*Keywords:* Identification of shocks; noise representation; the Great Recession; Bayesian estimation; labor market trends; employment gap.

*JEL codes:* C11, C51, E32.

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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), Clark (1934) 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 of 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, then expectations about future unemployment are directly informative about expected TFP and hence about TFP news shocks.<sup>1</sup> 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 average 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 that are unrelated to fundamentals.

We construct a dynamic general equilibrium model with labor market frictions and TFP news shocks. We estimate it with likelihood methods 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 a number of standard business-cycle shocks, it turns out that our conjecture is verified: TFP news shocks explain a large fraction of

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<sup>1</sup>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.

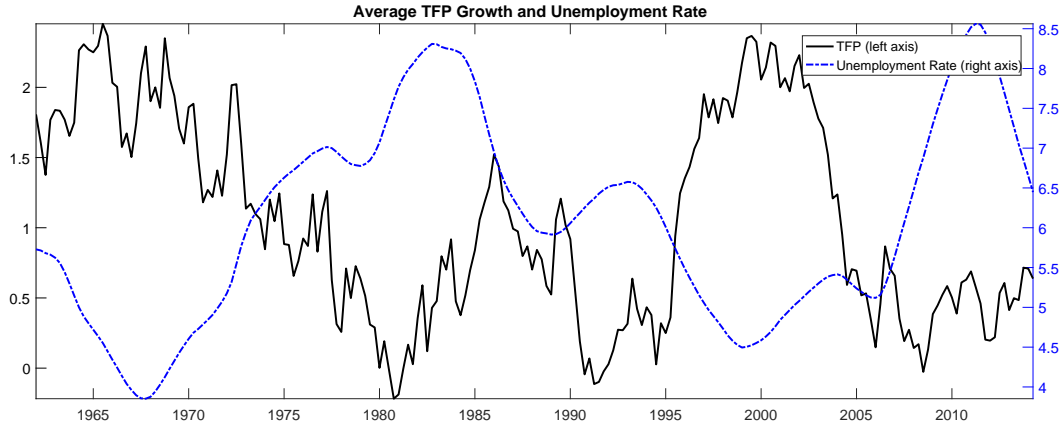


Figure 1: Five-year centered moving average of the unemployment rate and TFP growth rates. The time series are the U.S. civilian unemployment rate from the U.S. Bureau of Labor Statistics and the growth rate of TFP adjusted for capital utilization computed by Fernald (2014).

the variability of unemployment rates at the low end of the business-cycle frequencies and at even lower frequencies. Observing the unemployment rates improves the identification of TFP news shocks by lowering considerably the econometrician’s uncertainty about the estimates of these shocks. We achieve an estimation accuracy that is significantly larger than that in other studies with the same news structure (e.g., Schmitt-Grohe and Uribe 2012).

Low-frequency changes in unemployment rates help identify TFP news shocks because in the estimated model employment responds persistently to these shocks, and with a gradual buildup. This result is hard to obtain in standard general equilibrium models, as the presence of wealth effects leads to a sharp drop in hours worked after favorable TFP news. 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 wealth effect that follows an anticipated improvement in TFP 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 hits. 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 forces combined, 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 much related to price rigidities. In fact, firms’ cost of adjusting prices falls quickly with the anticipation horizon of the news shocks.

In the estimated model, the identified TFP news shocks contribute very marginally to the fluctuations in the unemployment rate at the high end of the business-cycle frequencies. Yet

when we derive the noise representation of the estimated model with TFP news shocks, we find that noise shocks explain a substantial fraction of changes in the unemployment rate at every frequency of the business cycle.<sup>2</sup> Noise shocks capture those movements in expectations about future TFP that are independent of variations in actual TFP fundamentals. Thus, these shocks can be thought of as capturing autonomous changes in agents' expectations, which were considered by Pigou (1927) as important drivers of business cycles.

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 the key business-cycle variables. This result is hard to obtain in models with a rich structure of shocks, like ours, and therefore represents an important econometric validation of the Pigouvian insight. 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, L'Huillier, and Lorenzoni (2013), who find that noise substantially matters for output and consumption, but not for investment.<sup>3</sup>

In our model, noise shocks play a prominent role in business cycles because they generate *boom-bust responses* in the key macroeconomic aggregates. These shocks trigger a persistent response of output, consumption, investment, and unemployment as agents expect a future improvement in TFP. 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, L'Huillier, and Lorenzoni (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 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.<sup>4</sup>

The empirical relevance of hiring frictions as forgone output has been backed by various empirical micro-labor studies (e.g., Bartel et al. 2014, Cooper, Haltiwanger, and Willis 2015, Muehlemann and Strupler Leiser 2018), which we review in the paper. Furthermore, this type of hiring frictions provides a way to counterbalance the wealth effect associated with news shocks (Barro and King 1984) without muting its magnitude through the adoption of specific

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<sup>2</sup>Chahrour and Jurado (2017a) show that models with news shocks admit an observationally equivalent noise representation, in which agents observe noisy signals about future shocks (in our case, about future TFP shocks).

<sup>3</sup>Their findings do not significantly change when one applies the same definition of noise as that used in our paper. See Chahrour and Jurado (2017a).

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

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 (2018), who estimate a vector autoregression (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.<sup>5</sup> 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, our estimated model predicts that the impact response of employment is virtually zero.<sup>6</sup>

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 realized noise shocks have become more important lately. 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 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.<sup>7</sup> 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 of the model.

Why do we use expected unemployment in the estimation as opposed to expectations of

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<sup>5</sup>TFP news shocks identified using the approach proposed by Barsky and Sims (2011) and Barsky, Basu, and Lee (2015) leads to a rise in TFP after one or two quarters, which is inconsistent with how we model TFP news shocks in our structural model. Faccini and Melosi (2018) 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 (2018) is qualitatively similar to those in Barsky, Basu, and Lee (2015). We show the results of Faccini and Melosi (2018) in the appendix because we are currently writing the first draft of that paper.

<sup>6</sup>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 because TFP news shocks are mainly identified by the low-frequency variation in current and expected unemployment rates.

<sup>7</sup>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.

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 anticipated shocks. This modeling choice is consistent with the fact motivating our paper: news shocks are hard to identify in the data.<sup>8</sup> Having multiple news shocks raises the challenge of achieving an adequate identification of these shocks. That said, one may be concerned that having only one type of anticipated shocks may lead our model to attribute too large of a role to anticipated shocks and hence to noise shocks. Nonetheless, one should keep in mind that our estimated model has an array of standard macroeconomic shocks (nine structural shocks in addition to the TFP news shocks), which compete with TFP news shocks to explain the moments of the data.

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 in the data conditional on the estimated TFP news shocks. To see this, recall that noise shocks are changes in expectations about future TFP that are independent of observed changes in TFP fundamentals at any lead and lag. Hardly any of the standard structural shocks in empirical macroeconomics can be directly identified by observable time series. An exception is the investment-specific-technology (IST) shocks, which can be arguably identified using the inverse of the relative price of equipment (Fisher 2006).<sup>9</sup> 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).

Our paper belongs to the literature that develops and estimates general equilibrium models with news or noise, and is therefore connected to the work of Lorenzoni (2009), Christiano et al. (2010), Barsky and Sims (2012), Schmitt-Grohe and Uribe (2012), Blanchard, L'Huillier, and Lorenzoni (2013), Nguyen and Miyamoto (2014), Avdjiev (2016), and Theodoridis and Zanetti (2016). A novel feature of our paper is to estimate a dynamic general equilibrium model with TFP news shocks using unfiltered current and expected unemployment rates and to show that these series significantly contribute to identifying these shocks as well as noise shocks. While

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<sup>8</sup>Nakamura and Steinsson (2018b) discuss about the importance of identification in several fields of empirical macroeconomics.

<sup>9</sup>The government spending shock is another exception. However, it commonly plays a limited role in business-cycle dynamics in structural studies.

this is not the first paper relying on labor market data to estimate a model with news, 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). 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 the model using the growth rate of hours and find a little role for TFP news shocks in business cycles. While these scholars consider multiple news shocks in addition to those to TFP, they find a modest contribution of noise shocks to explaining the comovement among business-cycle variables.<sup>10</sup>

Blanchard, L’Huillier, and Lorenzoni (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, L’Huillier, and Lorenzoni (2013) the assumption of a frictionless labor market implies that employment adjusts significantly as news about future TFP arrives. As previously discussed, this feature is at odds with the reduced-form literature that typically finds that labor market variables respond with a delay and fairly gradually to TFP news. Like Barsky and Sims (2011) we rely on expectations data (they use the 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.

To characterize the noise representation of our model, we rely on the pathbreaking work of Chahrour and Jurado (2017a). These scholars prove a representation theorem that allows them to recast models with news shocks into an observationally equivalent model with noisy signals about future fundamentals. They apply this method to 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 TFP 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 vector autoregression (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), Kurmann and Mertens (2014), Forni, Gambetti, and Sala

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<sup>10</sup>Chahrour and Jurado (2017a) evaluate the role of noise shocks in Schmitt-Grohe and Uribe (2012).

(2014), and Barsky, Basu, and Lee (2015) have challenged these conclusions by using alternative identification strategies. It should be noticed 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 (2017) 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 use the noise representation of the estimated model to 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

We construct a dynamic general equilibrium model that features hiring frictions and TFP news shocks. While the ultimate objective of the paper is to evaluate the Pigouvian hypothesis, which requires working out the noise representation of this model, we start by presenting the news representation because it allows us to be transparent about how we achieve identification of the TFP news shocks, which in turn pin down noise shocks. None of our results would change if we directly estimated the observationally equivalent model with noisy signals, which will be introduced in Section 4.

The framework is a baseline New Keynesian model à la Christiano, Eichenbaum, and Evans (2005), Smets and Wouters (2007), and Justiniano, Primiceri, and Tambalotti (2010) except for the presence of hiring costs. 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. Intermediate goods firms' production technology is hit by anticipated and unanticipated TFP shocks. 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.

## 2.1 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.

## 2.2 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  $\delta_N$  at the end of each period,  $N_t$  obeys the law of motion:  $N_t = (1 - \delta_N)N_{t-1} + x_t U_t^0$ .<sup>11</sup>

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  $\mathcal{U}_t = \eta_t^p \ln(C_t - \vartheta \bar{C}_{t-1}) - \eta_t^l (\chi/1 + \varphi) L_t^{1+\varphi}$ , where  $\vartheta$  is a parameter capturing external habits in consumption,  $\varphi$  is the inverse Frisch elasticity of labor supply,  $\chi$  is a scale parameter,  $\bar{C}_{t-1}$  denotes aggregate consumption, and  $\eta_t^p$  and  $\eta_t^l$  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  $\delta_K$  and accrues with investment,  $I_t$ , net of adjustment costs.

<sup>11</sup>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.

The law of motion for physical capital is therefore

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

where  $\eta_t^I$  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  $\Theta_t$ ; it also pays lump-sum government taxes  $T_t$ .<sup>12</sup> The budget constraint can therefore be written as:

$$P_t C_t + P_t I_t + \frac{B_{t+1}}{R_t} = R_t^K K_{t-1} + W_t N_t + B_t + \Theta_t - T_t, \quad (2)$$

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

Let  $\beta$  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.

## 2.3 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:  $Y_t = \left( \int_0^1 Y_{i,t}^{1/(1+\lambda_{f,t})} di \right)^{1+\lambda_{f,t}}$ , where  $\lambda_{f,t}$  denotes the mark-up shocks, which are assumed to follow an independent and identically distributed (i.i.d) stochastic process in logs. These firms sell their

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<sup>12</sup>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. 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.

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

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

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:

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

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 2.6, 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 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.<sup>13</sup>

The production function is assumed to be Cobb–Douglas:  $f_{i,t} = a_t (A_t N_{i,t})^\alpha (K_{i,t})^{1-\alpha}$ , 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.<sup>14</sup> Specifically, we assume that  $\eta_t^A = A_t/A_{t-1}$  is a stochastic trend that follows

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

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<sup>13</sup>Using detailed micro-data on the sources of hiring costs for a representative panel of Swiss firms, descriptive evidence reported by Muehleemann and Strupler Leiser (2018) implies that non-pecuniary hiring costs account for around 86% of the total cost of hiring. Similarly, the reviews in Silva and Toledo (2009) and Blatter et al. (2016) indicate 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.

<sup>14</sup>The process of TFP and that of the labor-augmenting technology are separately identifiable because shocks to the latter are permanent.

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

$$\ln a_t = \rho^a \ln a_{t-1} + \underbrace{\varepsilon_{a,t}^0 + \varepsilon_{a,t-4}^4 + \varepsilon_{a,t-8}^8}_{\theta_t^a}, \quad \varepsilon_{a,t}^k \sim N(0, \sigma_{k,a}^2) \quad \text{for } k = \{0, 4, 8\}, \quad (6)$$

where  $\varepsilon_{a,t}^0$  is an i.i.d. unanticipated shock to TFP and where  $\varepsilon_{a,t-4}^4$  and  $\varepsilon_{a,t-8}^8$  are i.i.d. shocks to the value of TFP at time  $t$  anticipated four and eight quarters in advance, respectively.<sup>15</sup> The TFP innovation at time  $t$  is denoted by  $\theta_t^a$  and is given by the sum of the unanticipated and anticipated shocks to TFP. As shown by Schmitt-Grohe and Uribe (2012), This framework is quite general and is flexible enough to capture situations in which agents receive some news about a future TFP innovation, and after four or eight quarters, they discover that the news does not pan out and, in fact, was just noise.

This particular way of modelling anticipated shocks in equation (6) mimics the approach in Schmitt-Grohe and Uribe (2012) and implies that TFP surprise and news shocks are stationary. This approach simplifies the interpretation of noise shocks, as we will discuss in Section 4. In Section 5, we will show that allowing news shocks to have permanent effects on TFP as in Barsky and Sims (2011, 2012) would strengthen our results.

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

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

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 Groshehny (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 market. Any intermediate value of  $\eta^q$  governs the relative importance of these two types of hiring costs.<sup>16</sup>

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  $H_{i,t} = q_t V_{i,t}$ ,

<sup>15</sup>While in principle nothing prevents us from adding one-, two-, and three-quarters-ahead TFP news shocks, these shocks propagate very similarly in the model, hindering their precise identification.

<sup>16</sup>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.

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

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

In this equation, the parameter  $\zeta$  controls the degree of price rigidities à la Rotemberg, the parameter  $\psi$  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,

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

and the constraint that output must equal demand,

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

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.

## 2.4 Wage Bargaining

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

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

where  $\omega$  is a parameter that governs wage rigidities.<sup>17</sup> 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  $\gamma$ , which denotes the bargaining power of the households:

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

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.<sup>18</sup>

<sup>17</sup>In Section 5, we will discuss the role played by wage inertia in our results.

<sup>18</sup>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;

## 2.5 Policymakers 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  $G_t = (1 - 1/\eta_t^G) Y_t$ , where  $\eta_t^G$  is an AR process that determines the government's purchases of final goods. The monetary authority follows a standard Taylor rule:

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

where  $\tilde{Y}_t \equiv Y_t/A_t$ ,  $Y^*$  denotes the steady-state value of  $\tilde{Y}_t$ ; the parameter  $\rho_R$  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  $r_\pi$  govern the response of the monetary authority to deviations of output and inflation from their target values,  $Y^*$  and  $\Pi_t^*$ , respectively. We assume that the monetary shock  $\eta_t^R$  follows an i.i.d. Gaussian process.<sup>19</sup> 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  $\Pi_t^*$  captures persistent deviations from the long-run inflation target  $\Pi_*$ ; 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 these shocks is to help the model fit the heightened inflation rate in the 1970s.

The aggregate resource constraint reads:

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

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  $K_{t-1} = \int K_{i,t} di$ .

## 2.6 Inspecting the Mechanism

It is well known that with standard logarithmic preferences, as assumed in our model, favorable news about TFP induces a positive wealth effect, which in turn implies that consumption increases and labor supply falls. In our model, 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

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Furlanetto and Goshenny 2016; and Christiano, Eichenbaum, and Trabandt 2016).

<sup>19</sup>Faccini and Yashiv (2017) 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.

adjustment costs over time.<sup>20</sup> 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 2.3:<sup>21</sup>

$$Q_t^N = \xi_t (f_{N,t} - \bar{g}_{N,t}) - \frac{W_t}{P_t} + (1 - \delta_N) E_t \Lambda_{t,t+1} Q_{t+1}^N, \quad (15)$$

$$Q_t^N = \xi_t \bar{g}_{H,t}. \quad (16)$$

Here we let  $Q_t^N$  and  $\xi_t$  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  $\xi_t$  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 (15) equals the marginal product of employment  $\xi_t (f_{N,t} - \bar{g}_{N,t})$  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 (16). In turn, the latter is given by the intermediate firms' output lost  $\bar{g}_{H,t}$  multiplied by the shadow value of output  $\xi_t$ . 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. Since the state of technology is unchanged on impact of news shocks, households expect a fall in income, and hence, aggregate demand falls. 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.<sup>22</sup> A fall in this shadow value reduces both the expected profits of a match in equation (15) and the expected cost in equation (16), with a priori ambiguous effects on job creation. The sensitivity of marginal hiring costs to the shadow value of output is given by

$$\frac{\partial (\xi_t \bar{g}_{H,t})}{\partial \xi_t} = \bar{g}_{H,t} = e \frac{H_t}{N_t} = \frac{Q_t^N}{\xi_t}, \quad (17)$$

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<sup>20</sup>It should be noted that this mechanism is at work independent of the presence of price rigidities. We can show that in a standard New Keynesian model, employment rises when the anticipated technological improvement hits the economy. This is because firms have already adjusted their prices by that time.

<sup>21</sup>We drop the subscript  $i$  because firms are identical.

<sup>22</sup>Notice that with flexible prices, the shadow value of output is a constant. So the mechanism we have described would not arise.

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.

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 an expansionary technology shock, 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. We note that 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.

The value of the parameter  $\eta^q$ , governing the share of hiring costs that depend on vacancy rates or hiring rates, matters for propagation. 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 an expansionary technology shock. However, congestion externalities in the matching function would increase the cost of hiring, partially 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  $\eta^q$  decreases the sensitivity of the marginal hiring costs to changes in the vacancy filling rate, muting this feedback effect from aggregate labor market conditions. Since the nature of hiring costs matters for propagation, we let the data decide on their relative importance by estimating the parameter  $\eta^q$ .

### 3 Empirical Analysis

This section deals with the empirical analysis of the structural model 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.<sup>23</sup> 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

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<sup>23</sup>The list of the log-linearized equations of the model is reported in Appendix B and is obtained using methods such as the ones described in Schmitt-Grohe and Uribe (2004).



function is not available in closed form, and we use the Kalman filter to approximate it (see, e.g., Fernandez-Villaverde and Rubio-Ramirez 2004 and An and Schorfheide 2007; Fernandez-Villaverde et al. 2010; Fernandez-Villaverde et al. 2016).<sup>24</sup>

In Section 3.1, we introduce the data set used for estimation and discuss how the model variables are mapped to the data and this paper’s estimation strategy. We elicit the prior distribution for the model parameters in Section 3.2. The posterior moments for the parameters and the fit of the model are analyzed in Section 3.3. The propagation of TFP news shocks is analyzed in Section 3.4. The objective of Section 3.5 is to analyze the identification of anticipated and unanticipated TFP shocks.

### 3.1 Data 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;<sup>25</sup> 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 (as shown by 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).<sup>26</sup> 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. Nonetheless, this approach is likely to provide a fairly

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<sup>24</sup>The consequences of the use of approximated likelihoods are studied in Fernandez-Villaverde et al. (2006).

<sup>25</sup>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.

<sup>26</sup>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,  $\alpha$ , to 0.66, which is consistent with how this parameter is calibrated in our empirical analysis (Section 3.2).

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 as Fernald (2014) and Basu, Fernald, and Kimball (2006) do, 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. 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. 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 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 series of unemployment, 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. Nonetheless, the participation rate and the employment rate are non-stationary, and this characteristic 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  $\eta_t^l$  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 way to address this issue is to use data on market-based future federal funds rates to estimate the model after the fourth quarter of 2008.<sup>27</sup>

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<sup>27</sup>How we construct the series of the market-expected federal funds rate is identical to Campbell et al. (2017)

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 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 (eq. 13) as the number of forward rates observed.<sup>28</sup> As done in those contributions, we assume that 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).<sup>29</sup> 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 news and noise shocks in the most recent period.

Similarly to Campbell et al. (2012), Barsky, Justiniano, and Melosi (2014), and Campbell et al. (2017), we estimate the model sequentially over two subsamples. 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 re-estimate only the measurement parameters (see Panel C of Table 6 in Appendix L for a list of measurement parameters) and the forward guidance 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. 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.

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and is explained in Appendix C.

<sup>28</sup>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.

<sup>29</sup>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) and used by several papers since then, including Nakamura and Steinsson (2018a).

Prior and Posterior for Structural Parameters							
Parameters	Post. Mode	Post. Median	5%	95%	Prior Type	Prior Mean	Prior Std
$\vartheta$	0.8559	0.8578	0.8448	0.8694	B	0.6000	0.1000
$100\ln \mu$	0.4756	0.4734	0.4246	0.5136	N	0.5500	0.0500
$\varphi$	4.9154	4.9549	4.8350	5.1608	G	4.0000	0.2500
$\kappa$	0.0343	0.0457	0.0323	0.0666	N	0.0900	0.0150
$100u$	5.8040	5.8112	5.7118	5.9138	N	5.6000	0.1000
$100\ln \Pi_*$	0.6179	0.6009	0.5379	0.6512	N	0.6100	0.1000
$e$	4.1775	3.9416	3.4423	4.2328	N	2.5000	0.2500
$\omega$	0.9394	0.9481	0.9366	0.9572	B	0.5000	0.1000
$\phi$	0.0044	0.0014	0.0002	0.0042	N	3.5000	0.7500
$\psi$	0.2757	0.2915	0.2101	0.3407	B	0.2500	0.0500
$l$	0.5987	0.6053	0.5671	0.6570	B	0.6000	0.0500
$\eta^q$	0.0089	0.0104	0.0034	0.0200	G	0.1450	0.1000
$\bar{\omega}$	0.8303	0.8026	0.7675	0.8473	B	0.5000	0.1000
$r_\pi$	2.0051	1.9846	1.8601	2.1634	G	1.7500	0.1000
$r_y$	0.0259	0.0233	0.0193	0.0267	G	0.2500	0.1000
$\rho_R$	0.2346	0.2485	0.1945	0.2856	B	0.5000	0.1000

Table 1: Posterior modes, medians, 90 percent posterior confidence bands and prior moments for the structural parameters. 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.

## 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  $\beta$  so that the steady-state real interest rate is broadly consistent with its sample average. The parameter  $\delta^N$  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,  $\delta^K$ , is set to target an investment rate of 2.5%. The parameter  $\mu$  is calibrated to a 10% mark-up, in line with estimates by Burnside (1996) and Basu and Fernald (1997). The elasticity of output to employment in the production function  $\alpha$  is set to the standard value of 0.66. The parameter  $\eta^G$ , which is the constant of the exogenous government-spending process  $\eta_t^G$ , is calibrated to match a ratio of government expenditures to GDP of 0.22. Finally, the bargaining power parameter,  $\gamma$ , and the scale parameter in the utility function  $\chi$  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. The parameter governing the intensity of hiring frictions,  $e$ , and the parameter affecting the type of hiring costs,  $\eta^q$ , are key for the propagation of shocks, and deserve

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
<i>Panel A: Autoregressive Parameters</i>							
$\rho_a$	0.9839	0.9810	0.9712	0.9868	B	0.5000	0.1000
$\rho_\mu$	0.3859	0.3599	0.2988	0.4174	B	0.2500	0.1000
$\rho_l$	0.9961	0.9960	0.9944	0.9971	B	0.9950	0.0010
$\rho_g$	0.8958	0.8850	0.8375	0.9183	B	0.5000	0.1000
$\rho_i$	0.8078	0.8068	0.7537	0.8368	B	0.5000	0.1000
$\rho_p$	0.5381	0.5060	0.4548	0.5875	B	0.5000	0.1000
$\rho_{\Pi^*}$	0.9948	0.9946	0.9928	0.9961	B	0.9950	0.0010
<i>Panel B: Shocks Standard Deviations</i>							
$\sigma_{0,a}$	0.3942	0.3867	0.3512	0.4310	IG	0.5000	0.2000
$\sigma_{4,a}$	0.2613	0.2463	0.2090	0.2851	IG	0.5000	0.2000
$\sigma_{8,a}$	0.4160	0.4263	0.3838	0.4906	IG	0.5000	0.2000
$\sigma_\mu$	0.3740	0.3702	0.3118	0.4218	IG	0.5000	0.2000
$\sigma_l$	1.6958	1.8476	1.6868	2.0901	IG	0.2500	0.2000
$\sigma_g$	0.9416	0.9575	0.8850	1.0445	IG	0.5000	0.2000
$\sigma_i$	0.8178	0.8555	0.7968	0.9216	IG	0.5000	0.2000
$\sigma_p$	3.1896	3.2376	3.1438	3.3172	IG	0.5000	0.2000
$\sigma_{\Pi^*}$	0.0957	0.0917	0.0709	0.1311	IG	0.0350	0.0350
$\sigma_r$	0.4341	0.4278	0.3790	0.4653	IG	0.5000	0.2000
$\sigma_{\lambda_{f,t}}$	0.2414	0.2721	0.2198	0.3347	IG	0.5000	0.2000
<i>Panel C: Measurement Equations</i>							
$\sigma_{u,1}^m$	1.0604	1.0415	0.9629	1.0915	IG	0.5000	0.2000
$\sigma_{u,2}^m$	0.7498	0.7742	0.7137	0.8157	IG	0.5000	0.2000
$\sigma_{u,3}^m$	0.4876	0.4947	0.4783	0.5217	IG	0.5000	0.2000
$\sigma_{u,4}^m$	0.9223	0.9564	0.9252	0.9994	IG	0.5000	0.2000
$\sigma_E^m$	0.3108	0.3143	0.2987	0.3361	IG	0.5000	0.2000
$c_w^m$	-0.1291	-0.1277	-0.1887	-0.0673	N	0.0000	0.5000
$\sigma_w^m$	0.5023	0.5123	0.4589	0.5635	IG	0.1000	0.0500
$c_{\pi,1}^m$	0.0006	-0.0050	-0.0633	0.0576	N	0.0000	0.1000
$c_{\pi,2}^m$	-0.0296	-0.0362	-0.1004	0.0279	N	0.0000	0.1000
$c_{\pi,3}^m$	0.0610	0.0515	-0.0293	0.1293	N	0.1400	0.1000
$\lambda_{\pi,1}^m$	0.8874	0.8896	0.8497	0.9295	N	1.0000	0.5000
$\lambda_{\pi,3}^m$	1.1287	1.1279	1.0872	1.1746	N	1.0000	0.5000
$\sigma_{\pi,1}^m$	0.2004	0.2029	0.1835	0.2232	IG	0.1000	0.0500
$\sigma_{\pi,2}^m$	0.0801	0.0767	0.0602	0.1051	IG	0.1000	0.0500
$\sigma_{\pi,3}^m$	0.2101	0.2118	0.1929	0.2339	IG	0.1000	0.0500
$c_{TFP,unadj}^m$	-0.0414	-0.0420	-0.1192	0.0323	N	0.0000	0.1000
$c_{TFP,adj}^m$	-0.0405	-0.0338	-0.1080	0.0459	N	0.0000	0.1000
$\lambda_{TFP,adj}^m$	0.3475	0.3900	0.2783	0.4799	N	1.0000	0.5000
$\sigma_{TFP,unadj}^m$	0.6985	0.7114	0.6677	0.7501	IG	0.1000	0.0500
$\sigma_{TFP,adj}^m$	0.7093	0.7056	0.6690	0.7512	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. 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.

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  $\eta^q$  to 0.145. In setting the prior, we rather follow a conservative strategy. So while we do set the prior mean of  $\eta^q$  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 ( $\rho_l$ ), 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.

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.

In the estimated model the degree of wage inertia is on the large side. This result 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

Statistic	$Y$	$C$	$I$	$FFR$	$EMPL$	$PART$	$E_t U_{t+1}$	$E_t U_{t+2}$
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	$E_t U_{t+3}$	$E_t U_{t+4}$	$W/P$	$P^{def}$	$P^{pce}$	$P^{cpi}$	$TFP^{adj}$	$TFP^{unadj}$
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.

sluggishly to TFP news shocks, wage inertia alone is not enough to deliver this pattern.

The posterior estimate for the hiring cost parameter  $\eta^q$  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  $\eta^q$  is broadly in line with findings in the micro literature. See, for instance, Silva and Toledo (2009) and Manning (2011). The reason why the estimated value of  $\eta_t^q$  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.<sup>30</sup>

The cost of varying the investment flow, governed by the parameter  $\phi$ , is estimated to be virtually negligible. This result has important implications for the propagation of TFP news shocks to employment. The Euler equation governing consumption and savings decisions implies that anticipated jumps in consumption cannot be optimal, as households wish to smooth consumption over time. Consequently, when a positive TFP shock hits the economy, the increase in production has to be met by either a jump in investment, which increases aggregate demand, or a sharp increase in hiring costs, which lowers firms' output in the short run. By selecting a tiny estimate of investment adjustment costs, the likelihood favors outcomes where employment responds smoothly and investment is relatively more responsive. One may be concerned that with a small cost of adjusting investment, the model would overpredict the volatility

<sup>30</sup>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 Muhlemann and Leiser (2015) using Swiss administrative establishment-level survey data.

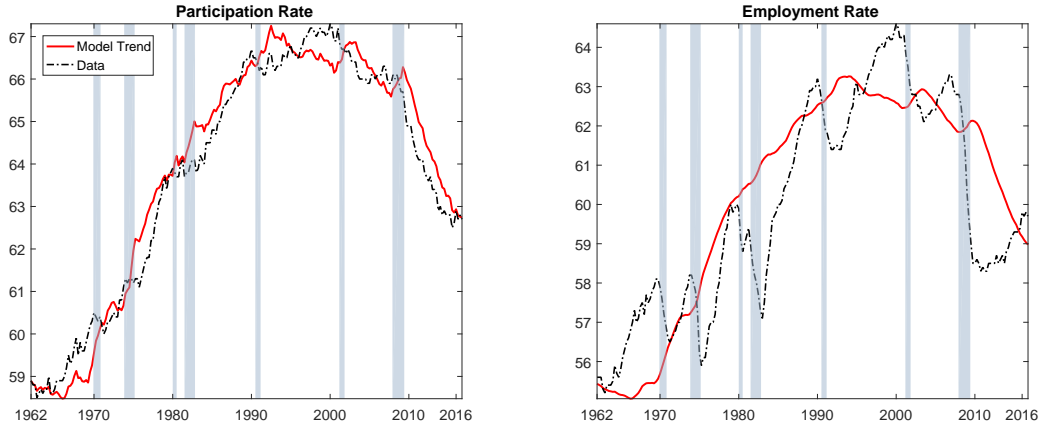


Figure 2: Detrending the rate of participation and the rate of employment. The black dashed-dotted lines denote the data and the red solid lines denote the two rates simulated from the estimated model by using only the filtered (one-sided) estimates for the labor disutility shocks. The estimated model’s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

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.

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,  $\varphi$ , 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,  $\kappa$ , is broadly in line with estimates in the literature. The degree of inflation indexation,  $\psi$ , 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 generated by the estimated model using only the one-sided filtered labor disutility shocks (solid red lines).<sup>31</sup> This picture suggests that labor disutility shocks effectively detrend the employment and participation rates in estimation.

<sup>31</sup>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.



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. 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

The propagation of the unanticipated TFP shock (black dotted-dashed line), the four-quarters-ahead TFP news shock (blue dashed line), and the eight-quarters-ahead TFP news shock (red solid line) are compared 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. Second, the longer the anticipation 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 very gradual buildup thereafter. A similar argument applies to the other macroeconomic aggregates reported in the figure. Third, after a news shock, most of the buildup in employment and fall in unemployment occur ahead of the actual change in TFP. The responses of employment and unemployment peak near to the time where the new technology is implemented, either four or eight quarters after the news arrives.

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 (2018), who identify TFP news shocks consistently with 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. We can show that estimating a model in which TFP news shocks are serially correlated would lead to smooth, hump-shaped responses of these variables to TFP news shocks, as also shown by Leeper and Walker (2011).

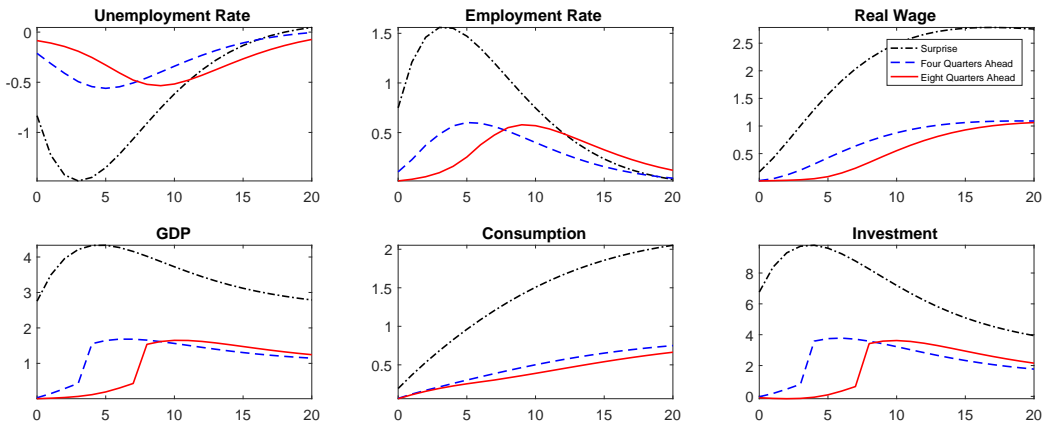


Figure 3: Impulse response of the unemployment rate, the employment rate, real wages, GDP, consumption, and investment to surprise TFP shocks (black dotted-dashed line), four-quarters-ahead shocks (blue dashed line), and eight-quarters-ahead TFP shocks (red solid line). The responses of unemployment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

As discussed in Section 5, the results of this paper would be strengthened by having persistent news shocks. Nevertheless, serially correlated news would make the characterization of the role of noise in business cycles a bit more complicated and certainly less intuitive.

The mechanism based on the interaction between hiring frictions and nominal rigidities is at work because the firms' shadow value of output,  $\xi_t$ , drops as the news shock hits and stays negative throughout the anticipation period, leading to a prolonged fall in marginal hiring costs, as discussed in Section 2.6.<sup>32</sup> 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 these 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.

The first two columns of Table 4 show how much of the variance of output, consumption, and investment (in deviations from their stochastic trend) is explained by TFP surprise and TFP news shocks. 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.

<sup>32</sup>The shadow value of output is also equal to the real marginal cost, which is the key determinant of inflation, and it falls following both a surprise and an anticipated TFP shock.

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 as well as fundamental and noise shocks (noise representation). The forward guidance shocks 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).

### 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 first step 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 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 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 little 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.<sup>33</sup> 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

<sup>33</sup>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.

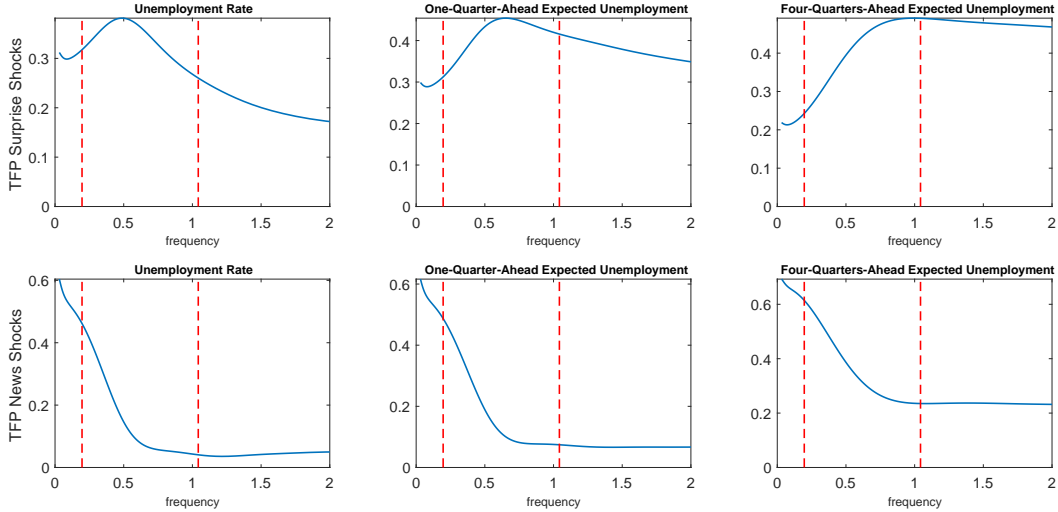


Figure 4: Variance share of current and expected unemployment rate (one quarter and four quarters ahead) due to TFP surprise (first row) and news shocks (second row) as a function of the spectrum frequencies. The vertical dashed lines mark the frequency band associated with business cycles, which includes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

frequencies. Comparing the two right plots of Figure 4 highlights the stark difference between the contribution of the unanticipated and the anticipated TFP shocks to the four-quarters-ahead expectations about unemployment. The importance of these two contributions 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 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.

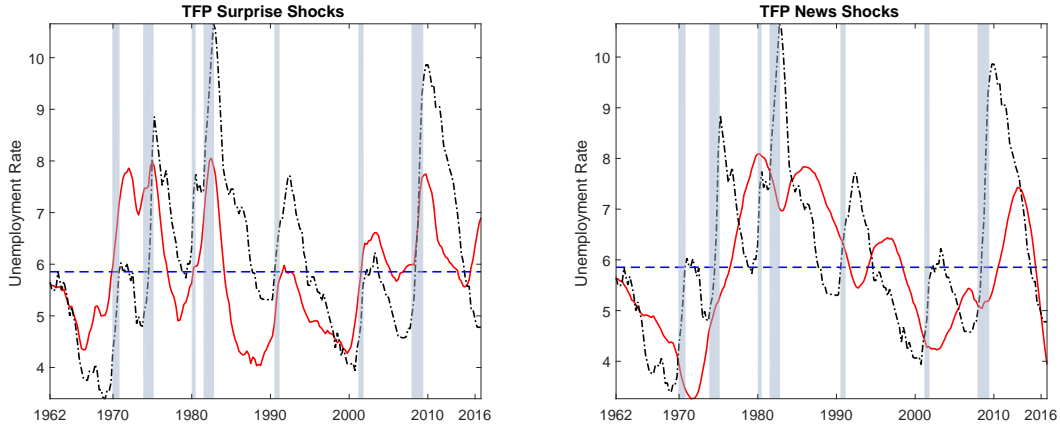


Figure 5: Historical role of TFP shocks to the U.S. unemployment rate. Left plot: The U.S. unemployment rate (black dashed-dotted line) implied by the observed series of the employment and participation rates, along with the counterfactual unemployment rate obtained by simulating the model using only 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.

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 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. Furthermore, the autocorrelation function of the smoothed estimate of the two TFP news shocks shows no or very little serial correlation.<sup>34</sup>

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

<sup>34</sup>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).

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 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 important 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 the labor market is affected by implausibly large changes in actual TFP fundamentals. Recall that in our model, TFP innovations  $\theta_t^a$  are given by the sum of current surprise shocks,  $\varepsilon_{a,t}^0$ , and past TFP news shocks,  $\varepsilon_{a,t-4}^4$  and  $\varepsilon_{a,t-8}^8$ . In Appendix I, we show that the magnitude of the estimated TFP innovations  $\theta_t^a$  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 isolate the component of these TFP news shocks that is orthogonal to any actual change in future TFP, which will be done in the next section. This component can be expressed as specific linear combinations of news and surprise shocks.

**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).<sup>35</sup> If shocks were observed or implied by the data, the uncertainty conditional

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<sup>35</sup>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

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 significantly larger than those found in other studies with the same news structure and several anticipated shocks (Schmitt-Grohe and Uribe 2012), in which the information content of the data set used for estimation is only around 2% for the TFP news shocks (Iskrev 2018).

## 4 Evaluating the Pigouvian Hypothesis

So far, our analysis has focused on the role of TFP news shocks. However, news shocks affect not only beliefs about future TFP shocks but also the future actual changes in TFP. In order to evaluate the empirical validity of the Pigouvian hypothesis, we need to correct the role of news shocks in business cycles for their effects on future TFP. One way to do so is to characterize the noise representation of the estimated model as proposed by Chahrour and Jurado (2017a) and then consider the importance of noise shocks. These shocks isolate precisely those movements in expectations about future TFP that are orthogonal to future changes in fundamentals at all horizons. 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.

**Definition of noise shocks.** Chahrour and Jurado (2017a) prove that models with news shocks, such as our model, admit an observationally equivalent noise representation in which TFP follows the process:  $a_t = \rho_a a_{t-1} + \theta_t^a$ , where  $\theta_t^a$  denotes the TFP shock. In every period  $t$ , agents receive three signals  $s_{8,t}$ ,  $s_{4,t}$  and  $s_{0,t}$  about the future realization of the TFP shock at time  $t$ , which are defined as

$$s_{8,t} = \theta_{t+8}^a + v_{8,t}, \quad (18)$$

$$s_{4,t} = \theta_{t+4}^a + v_{4,t}, \quad (19)$$

and  $s_{0,t} = \theta_t^a$ , with the fundamental TFP shocks  $\theta_t^a$  and the noise shocks  $v_{4,t}$  and  $v_{8,t}$  following i.i.d., zero-mean Gaussian processes with standard deviation  $\sigma_\theta$ ,  $\sigma_{4,v}$ , and  $\sigma_{8,v}$ , respectively. Note that agents perfectly observe the fundamental shock to TFP  $\theta_t^a$  at time  $t$ .

As shown by Chahrour and Jurado (2017a), there exists a mapping from the parameters of the estimated model with news (specifically,  $\sigma_{0,a}$ ,  $\sigma_{4,a}$ , and  $\sigma_{8,a}$ ) to those of its noise representa-

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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.

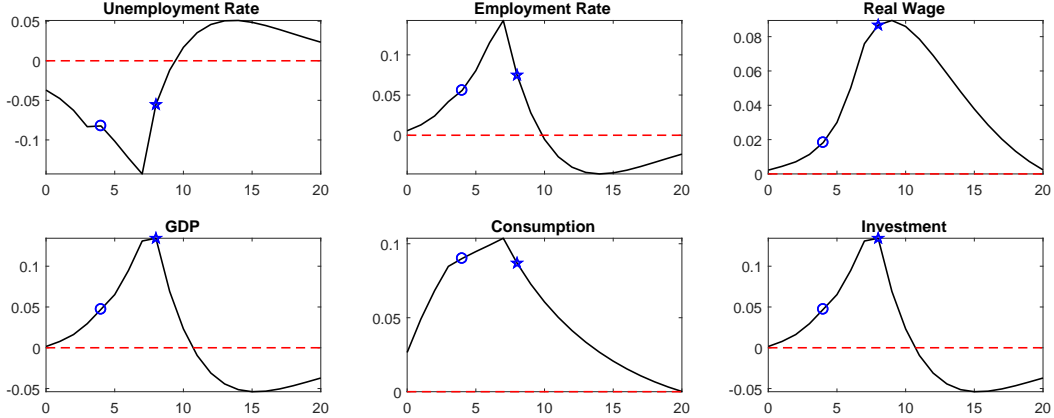


Figure 6: Impulse response of the unemployment rate, the employment rate, the real wage, GDP, consumption, and investment to a noise shock affecting the signal about the eight-quarter-ahead TFP shocks. The circle mark denotes the time at which agents receive the second signal  $s_{t+4}$ . The star mark denotes the time at which agents learn that actual TFP does not change at time  $s_{t+8}$ . 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).

tion (specifically  $\sigma_\theta$ ,  $\sigma_{4,v}$ , and  $\sigma_{8,v}$ ). This mapping is analytical and shown in Appendix G (Step 1). Since the noise representation of our model is observationally equivalent to the estimated model with news shocks, there is no need to estimate the noise representation.

To test the Pigouvian hypothesis, we conduct the following three exercises. First, we show how noise shocks propagate to the key macroeconomic variables of our model. Second, we compute the fraction of the observable variables' variance explained by the noise shocks  $\nu_{8,t}$  and  $\nu_{4,t}$ . This analysis will precisely quantify how important changes in beliefs that are orthogonal to future fundamentals are for the business cycle in population. Third, we assess whether there is any specific U.S. recession or expansion where it is possible to detect a significant contribution of noise shocks. We carry out this third exercise by estimating the historical realizations of the noise shocks  $\nu_{8,t}$  and  $\nu_{4,t}$  out of the historical estimates of TFP news and surprise shocks. Indeed, we will show that noise shocks can be expressed as specific linear combinations of news and surprise shocks. With these series of noise shocks at hand, we then evaluate their contribution to recessions and booms over the postwar period.

**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  $\nu_t^8$  concerning the eight-quarters-ahead realization of the fundamental shock to TFP,  $\theta_{t+8}^a$ .<sup>36</sup> The noise shock  $\nu_{8,t}$  gives rise to *boom-bust dynamics* in the key business-cycle variables. The responses of real wages and consumption are more persistent those of other

<sup>36</sup>The size of the shock is comparable to the anticipated shock to TFP  $\varepsilon_{a,t}^8$  shown in Figure 3. Details on how to compute the impulse response functions to noise shocks are provided in Appendix H. The impulse response function to a noise shock  $\nu_t^4$  affecting the four-quarters-ahead expectations of  $\theta_{t+4}^a$  is shown in Appendix H.



variables. Nonetheless, they become negative twenty quarters after the shock.

It should be noted that agents revise their expectations about the TFP shock  $\theta_{t+8}^a$  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  $\theta_{t+8}^a$ .<sup>37</sup> These mid-term revisions apparently have very little 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,  $s_{0,t+8} = \theta_{t+8}^a = 0$ , 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. When, at time  $t + 8$ , they 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 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 to 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). Thus, noise shocks account for *full Pigouvian cycles*. This finding is different from the one in Blanchard, L’Huillier, and Lorenzoni (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.

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

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<sup>37</sup>The signal  $s_{4,t+4}$  is equal to zero because the realization of noise  $\nu_{t+4}^4$  is 0 (the shock  $\nu_{t+4}^4$  is by construction orthogonal to the initial noise shock  $\nu_t^8$ ) and the future fundamental shock to TFP  $\theta_{t+8}^a$  is not affected by the initial noise shock  $\nu_t^8$  and, hence,  $\theta_{t+8}^a = 0$ .

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 only found a much lower role for these shocks (see the discussion in Section 3.5).

Furthermore, the contribution of noise shocks to these business-cycle variables is not very skewed toward the low end of business-cycle frequencies. Noise shocks explain roughly 20% of the variations in the rate of unemployment at the high end of business-cycle frequencies. This result underscores that the large contribution of noise to business cycles shown in Table 4 is not primarily concentrated at the lower frequencies as is the case with TFP news shocks. The contribution at the lower frequencies rises with the horizon of the SPF expectations. Noise explains around 50% of the fluctuations in the four-quarters-ahead expectations about the unemployment rate and this contribution varies only slightly across business-cycle frequencies.

**Historical analysis.** To carry out the third and last exercise of this section, we tease out the historical series of noise shocks implied by the estimated model with news. We use the following intuition to do so. For the model with news to be observationally equivalent to its noise representation, expectations about future TFP innovations in the noise representation must be identical to those in the estimated model with news in every period. For the case of the eight-quarters-ahead expectations about TFP innovations  $E_t\theta_{t+8}^a$ , this implies that

$$\kappa_8 (\theta_{t+8}^a + v_{8,t}) = E_t\theta_{t+8}^a = \varepsilon_{a,t}^8, \quad (20)$$

where  $\kappa_8$  is the Kalman gain associated with the eight-quarters-ahead expectations. The expressions on the right-hand side and on the left-hand side capture the expectations of future TFP innovations in the model with news shocks and in its noise representation, respectively. Hence, equation (20) allows us to decompose the eight-quarters-ahead TFP news shocks  $\varepsilon_{a,t}^8$  into two parts: future TFP fundamentals  $\theta_{t+8}^a$  and noise shocks  $\nu_{8,t}$  that is -by construction- orthogonal to past, present, and future TFP fundamentals.

Equation (20) can be used to tease out the historical series of noise shocks  $\nu_{8,t}$  by combining the smoothed estimates of TFP news shocks  $\varepsilon_{a,t}^8$  and the smoothed estimates of future TFP fundamentals  $\theta_{t+8}^a \equiv \varepsilon_{a,t}^8 + \varepsilon_{a,t+4}^4 + \varepsilon_{a,t+8}^0$ . A similar equation allows us to retrieve the historical series of  $\nu_{4,t}$  (see Appendix G for more details). Since news shocks  $\varepsilon_{a,t}^8$  are accurately identified by the low-frequency fluctuations in current and expected unemployment rates, observing actual TFP at time  $t + 8$  ( $\theta_{t+8}^a$ ) allows us to identify the historical realizations of the noise shock at time  $t$  via equation (20).

Noise shocks often characterize the periods immediately before the turning points of the business cycle. The lower panel of Figure 7 shows the historical realizations of eight-quarters-ahead TFP news shocks  $\varepsilon_{a,t}^8$  (black solid line) and their decomposition into future fundamentals  $\kappa_8\theta_{t+8}^a$  (white bars) and noise shocks  $\kappa_8\nu_{8,t}$  (black bars) based on equation (20). The upper

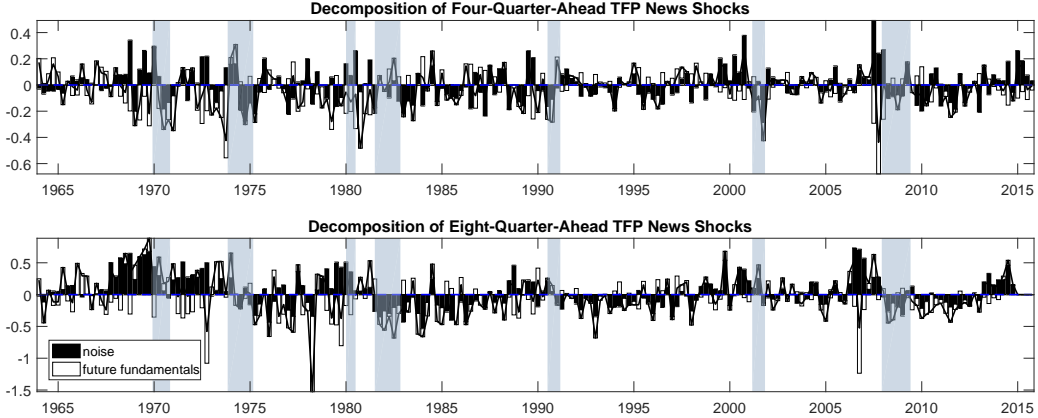


Figure 7: Decomposition of TFP news shocks (black solid line) into actual changes in future TFP (white bars) and noise shocks (black bars). Both components are rescaled by the relative Kalman gain as in equation (20). Shaded areas denote NBER recessions.

panel shows the historical realizations of four-quarters-ahead TFP news shocks  $\varepsilon_{a,t}^4$  (black solid line) and their decomposition into future fundamentals  $\kappa_4 \theta_{t+4}^a$  (white bars) and noise shocks  $\kappa_4 \nu_{4,t}$  (black bars). 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 builds up before the peaks and troughs of business cycles, the correlogram of the estimated series of the noise 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. This would imply a violation of rationality because the estimated noise variance affects the Kalman gain that determines 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)? Figure 8 shows the historical contribution of these noise shocks to the unemployment rate,

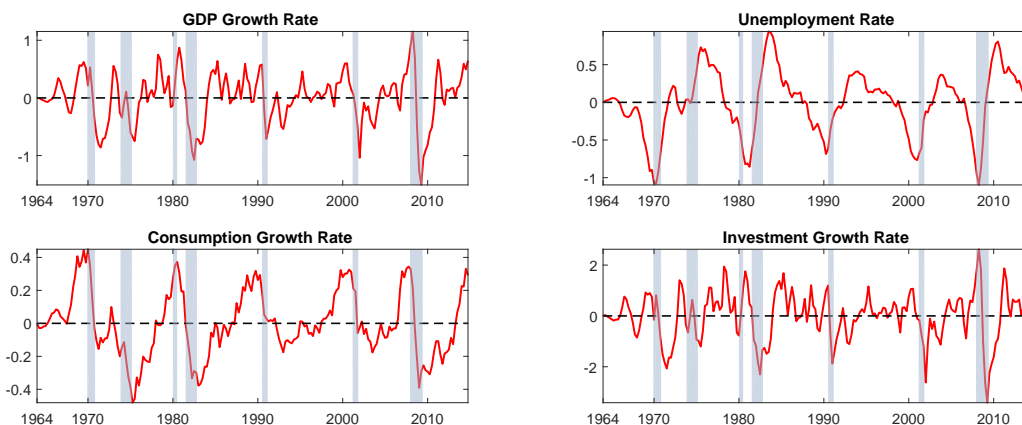


Figure 8: GDP growth rate, unemployment rate, consumption growth rate, and investment growth rate only due to noise shocks. All rates are in percent; growth rates are annualized. Shaded areas denote NBER recessions.

GDP growth, consumption growth, and investment growth over the full sample 1962–2014.<sup>38</sup> Noise shocks have contributed to business cycles in a way that is fairly regular over time. They 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.

As shown in Figure 7, recessions are often preceded by positive noise shocks that temporarily sustain employment and output and subsequently produce a sharp contraction when the expected positive news fails to materialize. This result is driven by the boom-bust pattern that follows a noise shock, shown in Figure 6.

To sum up, anticipated TFP shocks mainly explain the trend unemployment rate, as shown in Figure 5. Yet, when we isolate those changes in beliefs that are orthogonal to TFP fundamentals, 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

<sup>38</sup>It should be noted that the smoothed estimates of noise shocks depend on the smoothed estimates of future realizations of TFP innovations. 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.

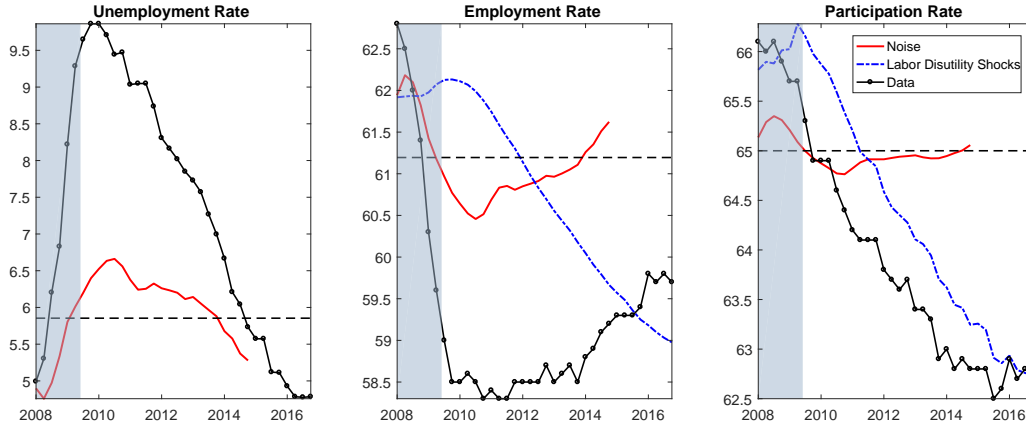


Figure 9: The effects of noise shocks and labor supply shocks to labor market dynamics during the Great Recession and its aftermath. The red solid lines refer to the counterfactual time series generated using only the smoothed estimate of noise shocks. The black lines with circles indicate actual data.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

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.<sup>39</sup> 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. Note also that the trend employment rate, 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 almost exclusively 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 were exaggerated.<sup>40</sup> 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

<sup>39</sup>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 due to the zero-lower-bound constraint.

<sup>40</sup>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, as illustrated in Figure 6.

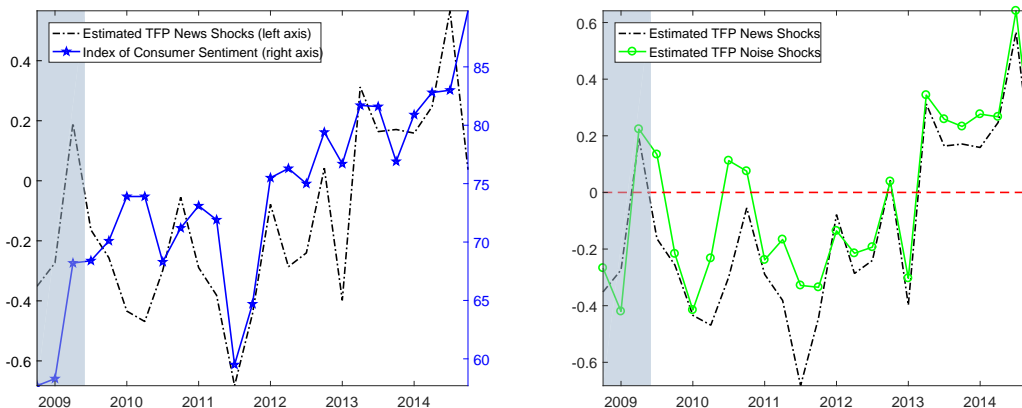


Figure 10: Estimated noise shocks, news shocks and the index of consumer sentiment. Estimated TFP news shocks are the sum of the news shocks received in every quarter. Noise shocks are rescaled by the relative Kalman gain and are computed analogously to the estimated TFP news shocks.

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 in 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 similarity between the estimated series of news and noise in the right plot.

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 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 model 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 estimated model with wage inertia. These weaker responses imply that TFP news shocks play a reduced role in explaining the dynamics of the unemployment rate and all the results of the paper would be quantitatively smaller. 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 are not enough.

We also test the robustness of our results to how TFP news shocks are modeled. For instance, when we estimate our model with TFP news shocks à la Barsky and Sims (2012), who model news shocks as anticipated information about the future drift in TFP growth, 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 news shocks with shorter anticipation horizons (i.e., we add one-, two-, and three-quarters-ahead TFP news shocks). We cannot precisely identify these 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 TFP news shocks. After a positive TFP news shock, firms face lower costs of hiring and, hence, aggregate labor demand expands. Under plausibly calibrated hiring frictions, the increase in labor demand is larger than the fall in labor supply and, hence, employment grows. In the estimated model, unemployment and employment rates 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, give rise to boom-bust responses of output and employment. These autonomous changes in beliefs significantly contribute to 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. As a result, noise shocks have contributed almost entirely to the recovery in the employment rate after the Great Recession.

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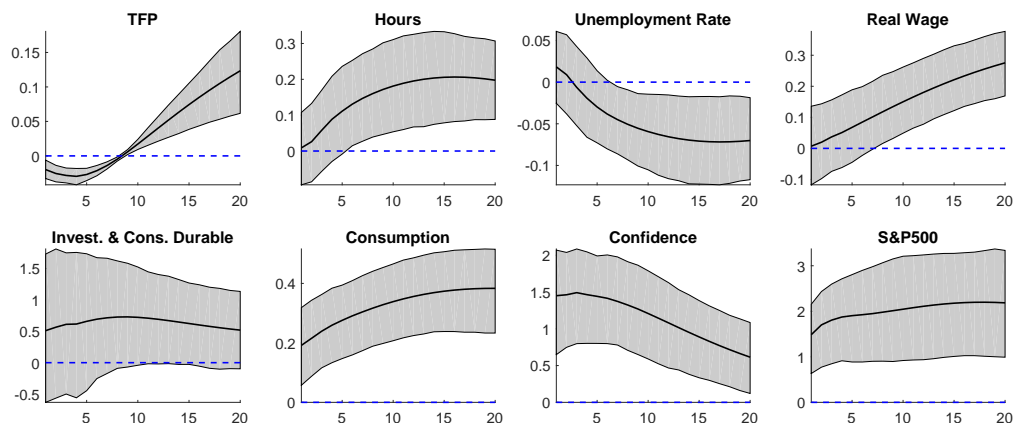


Figure 11: Response of macroeconomic variables to TFP news shocks identified using signed restrictions as in Faccini and Melosi (2018). All responses are expressed in percentage points. The size of the news shock is one standard deviation. The gray areas mark the sixty-eight-percent posterior credible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

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.<sup>41</sup> We identify TFP

<sup>41</sup>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

news 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.<sup>42</sup>

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.<sup>43</sup> This finding lends support to the view that TFP news shocks largely propagate through adjustments in private sector’s beliefs ahead as in our estimated model.

To sum up, the findings in Faccini and Melosi (2018) 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, L’Huillier, and Lorenzoni (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

Let a barred variable denote a steady-state value, and the hat over a lower case variable denote log-deviations from the steady state, 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  $\hat{c}_t = \ln \tilde{C}_t - \ln \tilde{C}$ .

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the prior are chosen so as to maximize the marginal likelihood. We perform Bayesian estimation of this VAR model with four lags and the ten observable variables described earlier.

<sup>42</sup>Identification of structural shocks via sign restrictions has been pioneered by Uhlig (2005). See also Baumeister and Hamilton (2015).

<sup>43</sup>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).



1. Labor force

$$\hat{l}f_t = \frac{\bar{N}}{\bar{N} + \bar{U}} \hat{n}_t + \frac{\bar{U}}{\bar{N} + \bar{U}} \hat{u}_t.$$

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

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

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

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

7. Value of employment to households

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

8. Production function

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

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 ( $\partial H_t$ ):

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

12. Derivative of adjustment cost function ( $\partial K_t$ ):

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

13. Derivative of adjustment cost function ( $\partial N_t$ ):

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

14. Vacancy filling rate:

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

15. Law of motion for capital

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

16. FOC capital

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

17. FOC employment

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

18. Resource constraint

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

19. Phillips curve

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

20. Real wage equation

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

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

$$\hat{q}_t^K + \hat{\eta}_t^I = \hat{\eta}_t^q + S'' (1 + \beta) \hat{i}_t - S'' \hat{i}_{t-1} - \beta S'' \hat{i}_{t+1}. \quad (21)$$

26. Tobin's Q for employment

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

## 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).<sup>44</sup> 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.<sup>45</sup>

## 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,  $\alpha$ , to 0.66, which is consistent with how this parameter is calibrated in our analysis.

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<sup>44</sup>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.

<sup>45</sup>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) and used by several papers, including Nakamura and Steinsson (2018a).

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.

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

$$\Delta \ln TFP_t^N = c_{TFP,unadj}^m + \lambda_{TFP,unadj}^m [\hat{a}_t - \hat{a}_{t-1} + \alpha \hat{\eta}_t^A + 100\alpha \ln \mu] + \eta_{TFP,t}^N, \quad (22)$$

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

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  $\mu$ .

## 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

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

### 3. Real Investment

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

### 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 ( $u_* = 0.056$ )<sup>46</sup>

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

7. Unemployment rate ( $u_* = 0.056$ )<sup>47</sup>

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

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

$$\begin{aligned} 100 \ln PartR_t &= 100 \ln \frac{LF_t}{Pop_t} \\ &= \hat{l}f_t + 100 \ln lf_*. \end{aligned}$$

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

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

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<sup>46</sup>To get this, observe that

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

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

<sup>47</sup>To get this, observe that

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

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

10. FFR (quarterly and in percent)

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

11. Multiple indicator for TFP growth adjusted for capital utilization  $\Delta TFP_t^A$  and non-adjusted for capital utilization  $\Delta TFP_t^N$

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

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

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

where  $f_T$  and  $f_P$  are two i.i.d. Gaussian factors with standard deviations  $\sigma_{f,T}$  and  $\sigma_{f,P}$ ,  $\Lambda_T$  and  $\Lambda_P$  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 model with news can be used to tease out the historical series of TFP 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

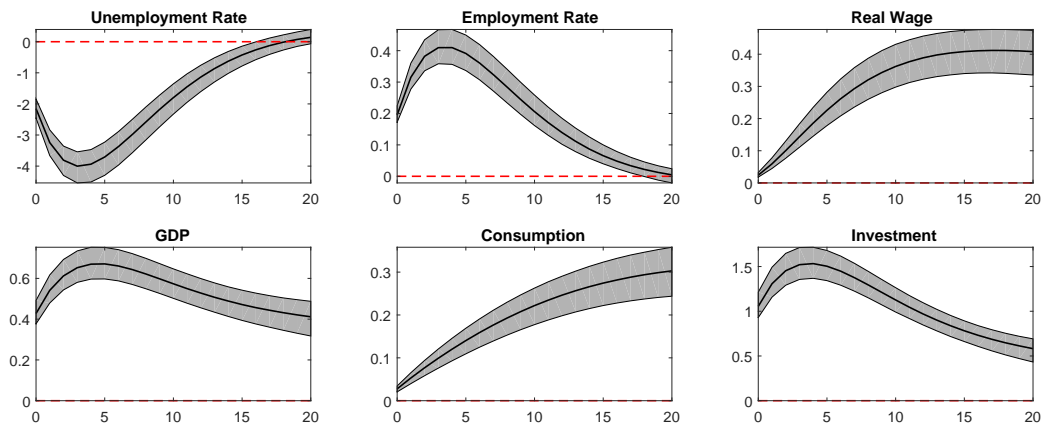


Figure 12: Posterior median of the response of unemployment rate, employment rate, real wage, GDP, consumption, and investment to a surprise shock to TFP. The gray areas denote the sixty-eight-percent posterior credible sets. The responses of unemployment and employment rates are expressed in percentage 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.

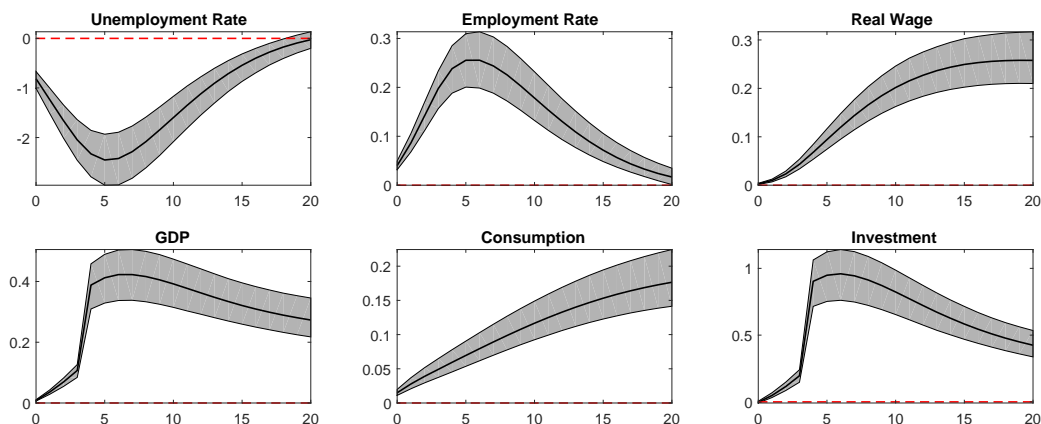


Figure 13: Posterior median of the response of unemployment rate, employment rate, real wage, GDP, consumption, and investment to a four-quarter-ahead shock to TFP. The gray areas denote the sixty-eight-percent posterior credible sets. The responses of unemployment and employment rates are expressed 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.

representation theorem introduced by Chahrour and Jurado (2017a) to characterize the noise representation of the estimated model with TFP news shocks. Second, with the parameter values of the noise representation at hand, we use the two-sided filtered series of TFP news and surprise shocks to tease out the implied series of noise shocks. Third, we construct the historical dynamics of the business cycle variables implied by the noise shocks.

### Step 1: Characterizing the Noise Representation (Chahrour and Jurado 2017a)

The estimated model with news is observationally equivalent to the noise representation in



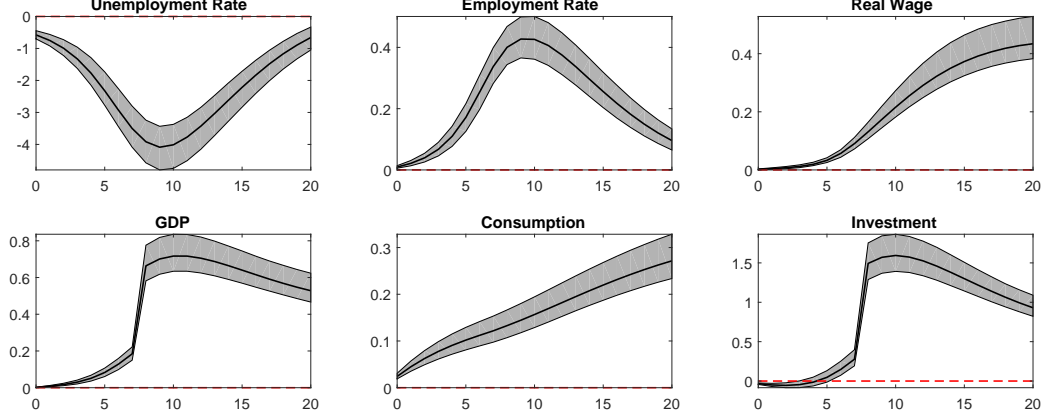


Figure 14: Posterior median of the response of unemployment rate, employment rate, real wage, GDP, consumption, and investment to an eight-quarter-ahead shock to TFP. The gray areas denote the sixty-eight-percent posterior credible sets. The responses of unemployment and employment rates are expressed 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.

which TFP follows the process:  $a_t = \rho_a a_{t-1} + \theta_t^a$ . Agents receive noisy signals  $s_{8,t}$ ,  $s_{4,t}$ , and  $s_{0,t}$  at time  $t$  that are defined as

$$s_{8,t} = \theta_{t+8}^a + v_{8,t}, \quad (24)$$

$$s_{4,t} = \theta_{t+4}^a + v_{4,t}, \quad (25)$$

and conventionally  $s_{0,t} = \theta_t^a$ , with the fundamental innovations  $\theta_t^a$  and the noise shocks  $v_t^4$  and  $v_t^8$  that follow i.i.d. Gaussian processes

$$\begin{bmatrix} \theta_t^a \\ v_{4,t} \\ v_{8,t} \end{bmatrix} \stackrel{iid}{\sim} N \left( \begin{bmatrix} 0 \\ 0 \\ 0 \end{bmatrix}, \begin{bmatrix} \sigma_\theta^2 & 0 & 0 \\ 0 & \sigma_{4,v}^2 & 0 \\ 0 & 0 & \sigma_{8,v}^2 \end{bmatrix} \right). \quad (26)$$

As shown by Chahrour and Jurado (2017a), for given parameter values of the model with news, the parameter values of the observationally equivalent noise representation are given by:

$$\sigma_{8,v}^2 = (\sigma_{0,a}^2 + \sigma_{4,a}^2 + \sigma_{8,a}^2) \left( \frac{\sigma_{0,a}^2 + \sigma_{4,a}^2}{\sigma_{8,a}^2} \right), \quad (27)$$

$$\sigma_{4,v}^2 = (\sigma_{0,a}^2 + \sigma_{4,a}^2) \frac{\sigma_{0,a}^2}{\sigma_{4,a}^2}, \quad (28)$$

and

$$\sigma_\theta^2 = \sigma_{a,0}^2 + \sigma_{4,a}^2 + \sigma_{8,a}^2. \quad (29)$$

We can use the variance of TFP shocks ( $\sigma_{a,0}^2$ ,  $\sigma_{a,4}^2$ , and  $\sigma_{a,8}^2$ ) of the estimated model with news to pin down the variances  $\sigma_{4,v}^2$ ,  $\sigma_{8,v}^2$ , and  $\sigma_\theta^2$ .

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

$$E_t \theta_{t+8}^a = \varepsilon_{a,t}^8, \quad (30)$$

$$E_{t+4} \theta_{t+8}^a - E_t \theta_{t+8}^a = \varepsilon_{a,t+4}^4, \quad (31)$$

$$\theta_{t+8}^a - E_{t+4} \theta_{t+8}^a = \varepsilon_{a,t+8}^0. \quad (32)$$

For the model with news to be observationally equivalent to its noise representation, expectations about eight-quarter-ahead TFP innovations in the noise representation and in the estimated model with news must be identical:

$$\kappa_8 (\theta_{t+8}^a + v_{8,t}) = E_t \theta_{t+8}^a = \varepsilon_{a,t}^8, \quad (33)$$

where  $\kappa_8 \equiv (\sigma_{0,a}^2 + \sigma_{4,a}^2 + \sigma_{8,a}^2) / (\sigma_{0,a}^2 + \sigma_{4,a}^2 + \sigma_{8,a}^2 + \sigma_{8,v}^2)$  is the Kalman gain in terms of the estimated parameters of the model with news. The Kalman gain captures the precision of signals and depends on the parameter mappings (27)-(29) from the estimated model with news to its noise representation. Equation (33) decomposes the expectation about the eight-quarter-ahead TFP innovations,  $E_t \theta_{t+8}^a$ , into a fundamental component  $\kappa_8 \theta_{t+8}^a$ , which will affect TFP in eight quarters, and a noise component  $\kappa_8 v_{8,t}$ , which will never affect TFP. Substituting the estimated TFP innovations  $\hat{\theta}_{t+8}^a = \hat{\varepsilon}_{a,t+8}^0 + \hat{\varepsilon}_{a,t+4}^4 + \hat{\varepsilon}_{a,t}^8$  in equation (33), we obtain the equation that can be used to tease out the noise component of the estimated eight-quarter-ahead TFP news shocks:

$$\kappa_8 \hat{v}_{8,t} = (1 - \kappa_8) \hat{\varepsilon}_{a,t}^8 - \kappa_8 (\hat{\varepsilon}_{a,t+8}^0 + \hat{\varepsilon}_{a,t+4}^4). \quad (34)$$

It should be noted that the noise component depends on the timing of information about  $\theta_{t+8}^a$ , which is distributed from period  $t$  through  $t+8$ , and on the degree of imperfect information as captured by the Kalman gain  $(1 - \kappa_8)$ . This is why we put so much emphasis on how we identify TFP news and surprise shocks in the data. See Section 3.5.

As far as the four-quarter-ahead expectation revisions,  $E_{t+4} \theta_{t+8}^a - E_t \theta_{t+8}^a$ , are concerned, we can analogously establish the following relation between the model with news and its noise

representation

$$\begin{aligned} E_t \theta_{t+4}^a - E_{t-4} \theta_{t+4}^a &= \kappa_4 (\theta_{t+4}^a + v_{4,t} - E_{t-4} \theta_{t+4}^a), \\ &= \kappa_4 (\varepsilon_{a,t+4}^0 + \varepsilon_{a,t}^4 + v_{4,t}) = \varepsilon_{a,t}^4, \end{aligned} \quad (35)$$

where  $\kappa_4 \equiv (\sigma_{0,a}^2 + \sigma_{4,a}^2) / (\sigma_{0,a}^2 + \sigma_{4,a}^2 + \sigma_{4,v}^2)$  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  $E_{t-4} \theta_{t+4}^a = \varepsilon_{a,t-4}^8$ . Substituting the estimated TFP innovations  $\hat{\theta}_{t+8}^a = \hat{\varepsilon}_{a,t+8}^0 + \hat{\varepsilon}_{a,t+4}^4 + \hat{\varepsilon}_{a,t}^8$  in equation (35), we obtain the equation that can be used to tease out the noise component of the estimated four-quarter-ahead TFP news shocks:

$$\kappa_4 \hat{v}_{4,t} = (1 - \kappa_4) \hat{\varepsilon}_{a,t}^4 - \kappa_4 \hat{\varepsilon}_{a,t+4}^0. \quad (36)$$

Equations (34) and (36) 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 (33) allows us to decompose eight-quarter-ahead news shocks into a fundamental component  $\kappa_8 \theta_{t+8}^a$ , 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 (35) allows for a similar decomposition of the four-quarter-ahead TFP news shocks. Equipped with the time series of noise shocks retrieved from equations (34) and (36), we can compute counterfactual series for TFP news and surprise shocks that generate revisions in expectations orthogonal to future fundamentals. Starting from the Kalman equation (33) and simply zeroing the fundamental component, we obtain

$$\tilde{\varepsilon}_{a,t}^8 = \kappa_8 \hat{v}_{8,t}. \quad (37)$$

Next, we substitute  $E_{t-4} \theta_{t+4}^a = \kappa_8 (\hat{\theta}_{t+4}^a + \hat{v}_{8,t-4})$  from equation (33) into the first line of equation (35) and then zero the realization of fundamentals  $\hat{\theta}_{t+4}^a$  to obtain the counterfactual series of the four-quarter-ahead TFP news shocks:

$$\tilde{\varepsilon}_{a,t}^4 = \kappa_4 \hat{v}_{4,t} - k_4 k_8 \hat{v}_{8,t-4}. \quad (38)$$

Analogously, combining equations (31), (32), (33), and (35) and then zeroing the funda-

mental component  $\theta_{t+8}^a$ , we get

$$\tilde{\varepsilon}_{a,t}^0 = -\kappa_4 (\hat{v}_{4,t-4} - \kappa_8 \hat{v}_{8,t-8}) - \kappa_8 \hat{v}_{8,t-8}. \quad (39)$$

These counterfactual news and surprise shocks can be used to simulate the estimated model with news and obtain the sought contribution of noise to business fluctuations.<sup>48</sup> Note that these counterfactual news and surprise shocks have no effect on time- $t$  innovation to TFP  $\theta_t^a$ , since  $\tilde{\varepsilon}_{a,t}^0 + \tilde{\varepsilon}_{a,t-4}^4 + \tilde{\varepsilon}_{a,t-8}^8 = 0$  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 (34) and (36). 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 ( $\kappa_8 \theta_{t+8}^a$  and  $\kappa_4 \theta_{t+4}^a$ ) given that we know the estimated TFP news shocks  $\hat{\varepsilon}_{a,t}^8$  and  $\hat{\varepsilon}_{a,t}^4$ , which capture the expectations revisions about future fundamentals in the noise representation. 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 (37), (38), and (39). Specifically, those equations give us the counterfactual news shocks that allow us to evaluate the historical contribution of noise shocks to the model's variables. Figure 8 plots the historical contribution of noise 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 the noise representation to compute the impulse response functions to noise shocks in Figure 6. We simulate the estimated model by using the TFP surprise and news shocks ( $\tilde{\varepsilon}_{a,t}^8, \tilde{\varepsilon}_{a,t+4}^4, \tilde{\varepsilon}_{a,t+8}^0$ ) implied by plugging the estimated noise shocks into equations (37)-(39). The estimated time series of noise shocks is obtained from the estimated news shocks in combination with equations (34) and (36) 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.

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<sup>48</sup>This is one way to assess the contribution of noise. Alternatively, one could simulate the model with noise in Step 1, using the series of noise shocks obtained in Step 2. However, our approach can be implemented by using only the estimated model with news with no need to solve the model with noise.

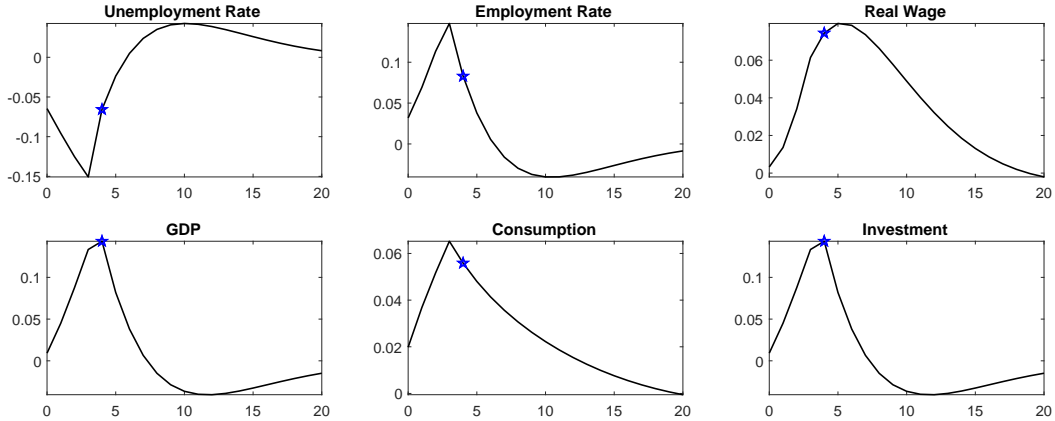


Figure 15: Estimated response of unemployment rate, employment rate, real wage, GDP, consumption, and investment to a noise shock affecting the signal about the four-quarter-ahead TFP shocks. The star mark denotes the time at which agents receive the last signal that reveals the true fundamental shock 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.

## 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 misspecification 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 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 noise representation, 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.

## 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

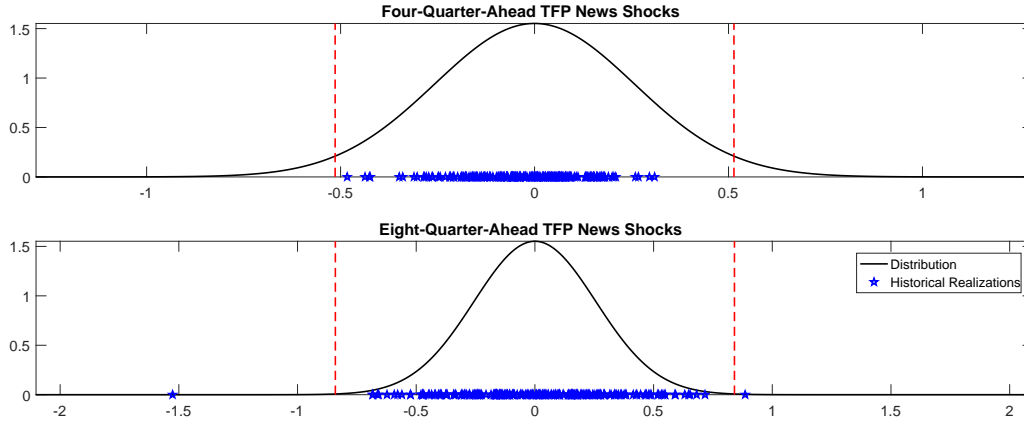


Figure 16: Distribution of the four- (top) and eight-quarter-ahead (bottom) TFP news shocks in the estimated model (black line). The blue stars mark the historical realizations of these shocks obtained from the Kalman smoother. The red dashed vertical lines denote the two-standard-deviation interval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

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.

## 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 estimated model with news shocks.

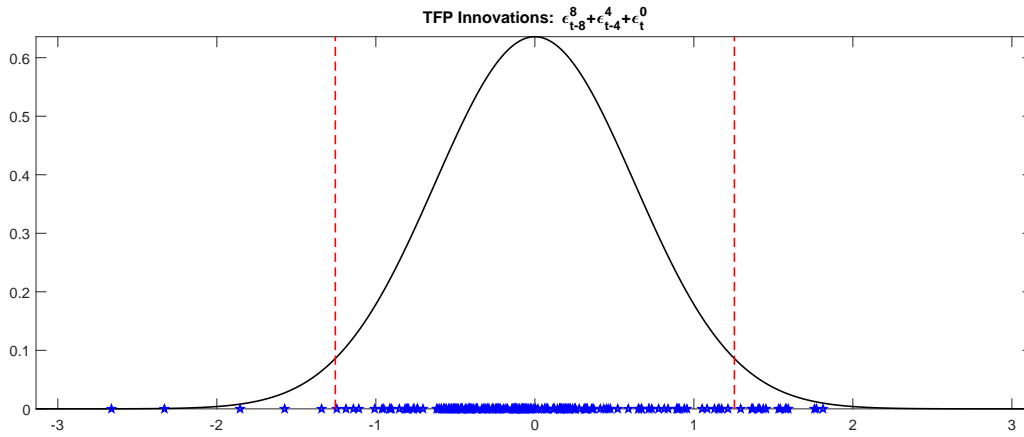


Figure 17: Distribution of the actual TFP innovations in the estimated model (black line). The blue stars mark the historical realizations of these shocks obtained from the Kalman smoother. The red dashed vertical lines denote the two-standard-deviation interval around the zero mean of these shocks.

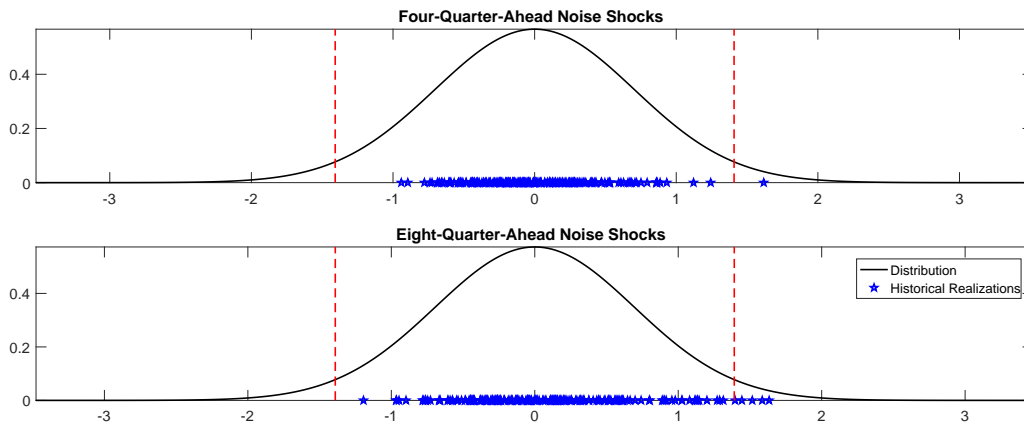


Figure 18: Distribution of the four- (top) and eight-quarter-ahead (bottom) noise shocks in the estimated model (black line). The blue stars mark the historical realizations of these shocks obtained from the Kalman smoother. The red dashed vertical lines denote the two-standard-deviation interval around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

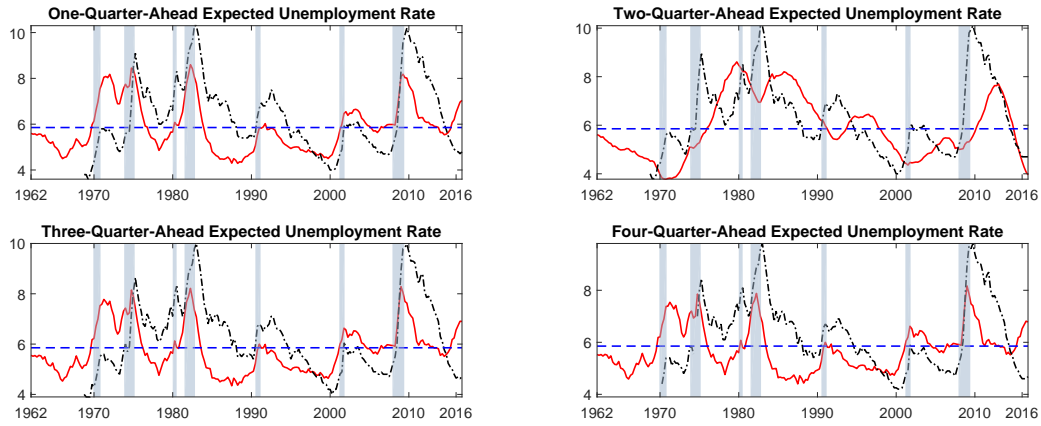


Figure 19: Expectations of U.S. unemployment rates (black dashed-dotted line), along with the counterfactual unemployment rate obtained by simulating the model using only the smoothed estimate of the surprise TFP shocks (red solid line). The counterfactual series are computed by setting the model parameters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

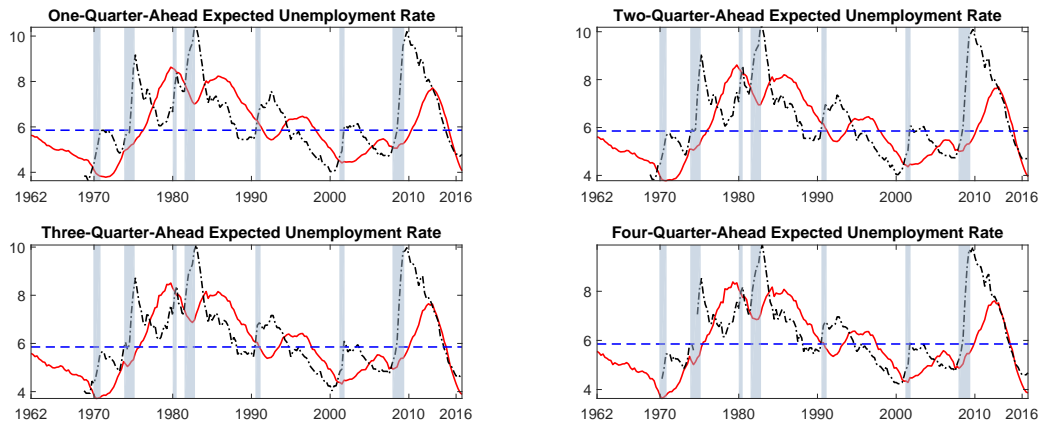


Figure 20: Expectations of U.S. unemployment rates (black dashed-dotted line), along with the counterfactual unemployment rate obtained by simulating the model using only the smoothed estimate of the four- and eight-quarter-ahead TFP news shocks (red solid lines). The counterfactual series are computed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



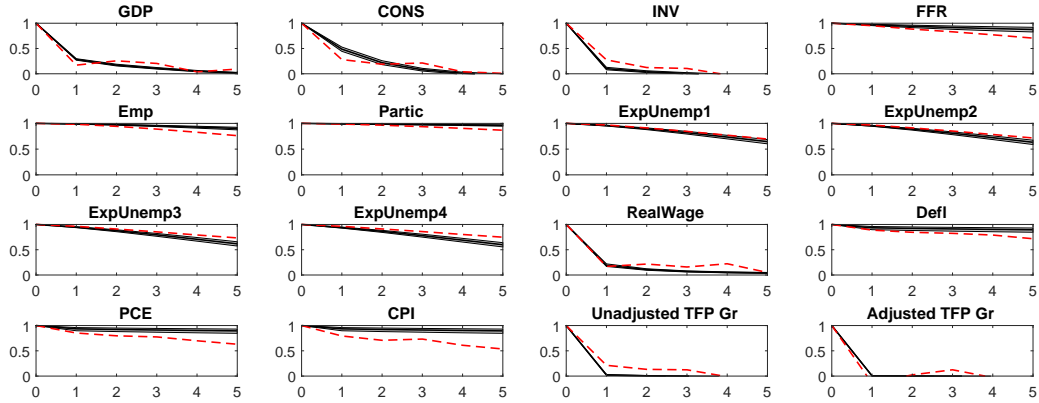


Figure 21: Posterior autocorrelation functions computed for every 100 posterior draws. The red dashed line denotes the empirical autocorrelation function and the solid black line denotes the posterior median for the autocorrelation implied by the model after shutting down its measurement errors. The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

Notation of Model Parameters	
	Parameters
Habit parameter	$\vartheta$
Steady-state growth rate	$\mu 100$
Inverse Frisch elasticity	$\varphi$
Slope Phillips curve	$\kappa$
Steady-state unemployment rate	$u^* 100$
Steady-state inflation rate	$\Pi^* 100$
Hiring cost parameter	$e$
Wage inertia	$\omega$
Investment adjustment cost	$\phi$
Inflation indexing parameter	$\psi$
Elasticity of the matching function	$l$
Weight of external hiring costs	$\eta^q$
Relative disutility of unemployment	$\bar{\omega}$
Taylor rule response to inflation	$r_\pi$
Taylor rule response to output	$r_y$
Taylor rule smoothing parameters	$\rho_R$

Table 5: Notations for the Model Parameters.

<b>Notation of Model and Measurement Parameters</b>	
	Parameters
<i>Panel A: Shocks Autoregressive Parameters</i>	
Technology, unanticipated	$\rho_a$
Technology, labor augmenting	$\rho_\mu$
Labor disutility	$\rho_l$
Government	$\rho_g$
Investment (MEI)	$\rho_i$
Preference	$\rho_p$
Inflation drift	$\rho\Pi^*$
<i>Panel B: Shocks Standard Deviations</i>	
Technology, unanticipated	$\sigma_a$
Technology, anticipated 4Q	$\sigma_a^4$
Technology, anticipated 8Q	$\sigma_a^8$
Technology, labor augmenting	$\sigma_\mu$
Labor disutility	$\sigma_l$
Government	$\sigma_g$
Investment (MEI)	$\sigma_i$
Preference	$\sigma_p$
Inflation drift	$\sigma\Pi^*$
Monetary	$\sigma_r$
Markup	$\sigma_{\lambda_{f,t}}$
<i>Panel C: Measurement Equations</i>	
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	$\sigma_E^m$
Wage compensation (constant)	$c_w^m$
Wage compensation (st.dev.)	$\sigma_w^m$
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.