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News and Noise in the Post-Great Recession Recovery*

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Abstract

We develop and estimate a general equilibrium model to study the historical contribution of beliefs about future total factor productivity (TFP) to the U.S. business cycle. In the model, hiring frictions cause a temporary loss in firms' efficiency because of recruiting and training activities. We show that such frictions induce firms to gradually hire more workers when they expect an improvement in future TFP. Using current and expected unemployment rates in estimation turns out to be crucial for identifying TFP news shocks, since periods in which the average unemployment rate is relatively high (low) are also periods in which average TFP growth is slow (fast). TFP news shocks cause fluctuations in beliefs about future TFP that mainly explain the trend unemployment rate. Yet, when we isolate those changes in beliefs that are orthogonal to TFP fundamentals, we find that these beliefs affect unemployment at business-cycle frequencies. After the Great Recession, these autonomous changes in beliefs have been the most important factor behind the rise in the employment rate and account for the labor market boom of 2014. The University of Michigan's Index of Consumer Sentiment and the dismal TFP growth in recent years support this prediction.

Keywords: Unemployment rate; hiring frictions; beliefs; labor market trends; employment gap; Bayesian estimation.

JEL codes: C11, C51, E32, J64.

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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 from Beveridge (1909), Pigou (1927), and Clark (1934). 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 predominantly focused on how much of the volatility of business-cycle variables is explained by beliefs about the future. Nevertheless, very little is known about the historical contribution of these beliefs (news) and their changes that are orthogonal to future fundamentals (noise) to every expansion and recession. This matter is complicated because it requires careful estimation of news and noise in the data.

We tackle this issue by conjecturing that current and expected unemployment rates carry useful information to estimate 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 measured as in Basu, Fernald, and Kimball (2006) and Fernald (2014). Periods during which TFP growth was slow (fast) are often periods of high (low) rates of unemployment, suggesting that the rate of unemployment appears to be influenced by TFP.[1] If so, then expectations about future unemployment are directly informative about expected TFP and hence about TFP news shocks. 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. Although the link between unemployment and TFP appears to be rather stable over the postwar period, there are times when it appears to weaken. For instance, this is the case in the early 1980s, when the two series move in the same direction and since 2006, when we observe a clear decoupling of their joint behavior. These changes in the average unemployment rate that are not justified by changes in future fundamentals may provide valuable information to identify noise.

To study the historical role of beliefs in the U.S. business cycle, we construct a dynamic general equilibrium model in which TFP news shocks are given a fair chance to explain the joint comovement of TFP and unemployment rates illustrated in Figure 1. For this to be the case, favorable TFP news has to bring about a persistent increase in the employment rate. However,

[1] There are potentially other measures of real activity that could be helpful in identifying TFP news shocks in the data. Yet the unemployment rate is particularly appealing for a number of reasons. The unemployment rate is a business cycle measure that does not need to be detrended, unlike employment, hours 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.

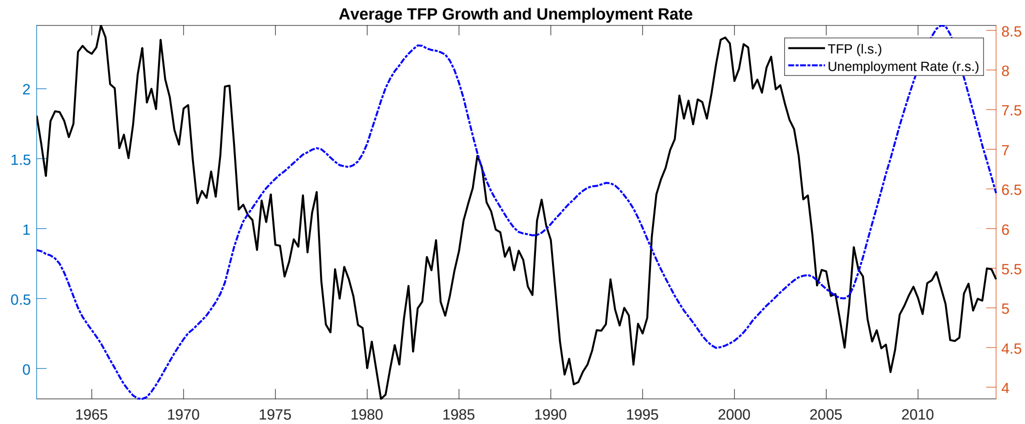

Figure 1: Five-year centered moving average of the unemployment rate and TFP growth rates. The time series are the U.S. civilian unemployment rate from the U.S. Bureau of Labor Statistics and the growth rate of TFP adjusted for capital utilization computed by Fernald (2012).

it is well known that positive responses of employment are hard to obtain in standard dynamic general equilibrium models (Barro and King 1984; Jaimovich and Rebelo 2009). The issue is that these shocks generate a sizable wealth effect on labor supply decisions that leads to a sharp contraction in hours before the anticipated improvement in TFP materializes. We build a model where hiring frictions provide incentives for firms to smooth out hiring over time, which implies that labor demand starts increasing before the anticipated change in TFP materializes, offsetting the negative effect on labor supply.

We model hiring costs in a way that provides an additional incentive for labor demand to expand after positive TFP news shocks. Specifically, we assume 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). Such frictions are supported by various empirical micro-labor studies suggesting that hiring entails a temporary loss of firm-level production efficiency (e.g., Bartel 1995; Krueger and Rouse 1998; Cooper, Haltiwanger, and Willis 2015). The additional incentive for labor demand to expand after a positive TFP news shock is based on the interaction of such hiring frictions and nominal rigidities. The wealth effect that follows an anticipated improvement in TFP weakens the 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 can be large enough to cause employment to grow in equilibrium. Indeed, for plausible values of hiring costs, employment increases gradually before the actual improvement in TFP takes place.[2] It should be noted that this mechanism helps

[2] Other frictions, such as consumption habits and wage inertia, complement hiring frictions in explaining the buildup in employment after positive TFP news shocks. Indeed, we can show that the estimated model would predict a fall in employment following the news shock if the magnitude of hiring costs was half of its estimated

overcome the wealth effect in the short run. 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, the cost of adjusting prices for firms falls quickly with the anticipation horizon of the news shocks.

The model is estimated with likelihood methods by using current and expected unemployment rates from the *Survey of Professional Forecasters* (SPF) and TFP growth among other macroeconomic time series. In the estimated model, the unemployment rate responds sluggishly to TFP news shocks. As a result, when we simulate the estimated model using only the historical realizations of TFP news shocks, we recover the low-frequency dynamics of unemployment rates rather than their business cycles.[3] This finding suggests that the dynamics of unemployment and expected unemployment play key roles in identifying TFP news shocks in the U.S. postwar period.[4] The model interprets the 1960s as a period in which favorable technological news has pushed unemployment rates below their long run average. According to the model, the 1970s and 1980s are interpreted instead as two decades mainly dominated by lackluster news about TFP, which considerably raised unemployment rates. Finally, the period ranging from the mid-1990s through mid-2000s is viewed as dominated again by positive news about technology and, hence, lower unemployment rates. It should be noted that the model we estimate features a broad set of standard structural shocks that compete with TFP news shocks in explaining unemployment dynamics.

News shocks affect not only beliefs but also future fundamentals. To evaluate the empirical relevance of beliefs-driven business cycles, we have to focus on those news shocks that are orthogonal to any future change in fundamentals. 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 those movements in beliefs that are independent of fundamentals at all horizons. Therefore, noise can be thought of as capturing *autonomous changes in agents' expectations,* which Pigou (1927) among other scholars considered to be a potentially important source of business fluctuations. In line with this view, our model predicts boom-bust responses of GDP, consumption, investment, and the unemployment rate to noise. The bust occurs when agents realize that TFP news will not be reflected in fundamentals. When agents expect a future increase in TFP, they start accumulating capital, and employment increases. When agents eventually realize that the good news will not pan out, households have accumulated too much capital and firms have accumulated too much employment. Consequently, households gradually lower investment so as to smooth out the transition of consumption to its steady-state level and both participation in the labor market and employment slowly fall. As a result, output contracts and stays below its

value, suggesting that hiring frictions are essential to counterbalance the wealth effect.

[3]We use the Kalman smoother to estimate the historical realizations of TFP news shocks.

[4]We also establish this result by applying a more formal test proposed by Iskrev (2018).

steady-state level for a fairly long period of time, suggesting that noise may lead to long-lasting recessions or expansions.

An important result of this paper is that news shocks capture changes in trend unemployment. Yet, when we tease out noise by orthogonalizing news shocks to future changes in fundamentals, we find that noise mostly matters at business-cycle frequencies. Indeed, these autonomous changes in beliefs have contributed to the behavior of consumption, investment, and GDP in all booms and recessions, with the exception of the first recession of the 1980s. Noise has played a significant role for cyclical employment fluctuations, which is reflected in oscillations of the unemployment rate within a band of about two percentage points over the postwar period.

When we extend the analysis to include the Great Recession and the following recovery, we find that noise has been the most important factor behind the recovery in the employment rate and the labor market boom of 2014.[5] In 2010, agents started to realize that the bad TFP news received during the Great Recession was largely exaggerated. This realization prompted firms to hire more workers, which increased the employment rate. Since 2013, the rise in the employment rate has been sustained by favorable TFP news, which failed to materialize, in accordance with Figure 1. The University of Michigan's Index of Consumer Sentiment supports the model's prediction that the private sector received good news about the economy starting in 2013. Since we do not use the Index of Consumer Sentiment in estimation, this result provides external validation for this finding.

Why did noise contribute so significantly to employment after the Great Recession? The reason is in Figure 1: the link between unemployment and TFP that has characterized the postwar period breaks down in the latest part of the sample. As we already emphasized, our model explains the recent increase in the rate of employment with positive TFP news shocks. Nonetheless, TFP growth in the data has been stagnant lately. The model reconciles these two patterns in the data with favorable TFP news that turns out to be noise.

In the model, TFP shocks are the only anticipated shocks. While this is a strong assumption, this modeling choice is driven by the fact that news shocks are extremely hard to identify in the data. For instance, Ramey (2016, Table 10 p.144) shows that the correlation of news shocks identified across a number of studies is very low. We address this problem by showing that current and expected unemployment rates are key to identifying TFP news shocks. Moreover, observing the actual TFP growth rate allows us to directly identify the noise component of TFP news shocks. Hardly any of the standard structural shocks in empirical macroeconomics

[5]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 to the labor market) capturing long-lasting demographic and social changes to the U.S. labor force.

can be directly identified by observable time series. An exception is the investment-specific-technology (IST) shock, which can be arguably identified using the inverse of the relative price of equipment (Fisher 2006).[6] 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).

Furthermore, Iskrev (2018) develops methods to formally assess the information content of observed variables with respect to unobserved shocks in structural macroeconomic models. This methodology relies on computing the reduction in uncertainty about a model's latent state variables due to observing additional series of data relative to the unconditional uncertainty. When Iskrev (2018) applies his methodology to a number of estimated models with multiple news shocks, he finds that the data used in estimation help only incrementally identify most of the anticipated shocks. These results call for caution in introducing multiple news shocks in structural models estimated using standard macroeconomic data sets when the goal is to conduct a historical evaluation of the role of these shocks. The key idea of our paper is to use current and expected unemployment rates to sharpen the identification of TFP news shocks. Using the methods introduced by Iskrev (2018), we find that these labor market data increase the information about the historical realizations of TFP news shocks by 60 percent for four quarters ahead and 36 percent for eight quarters ahead. Moreover, we obtain a precision of identification for TFP news shocks that is significantly better than that found in other studies with the same news structure surveyed by Iskrev (2018).

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 (2011, 2012), Schmitt-Grohe and Uribe (2012), Blanchard, L'Huillier, and Lorenzoni (2013), Nguyen and Miyamoto (2014), Barsky, Basu, and Lee (2015), Jurado (2016), Avdjiev (2016), Theodoridis and Zanetti (2016), and Chahrour and Jurado (2017a). Our work differs from those contributions in one or more of the following dimensions. First, the key identification mechanism for TFP news and noise is based on using the unfiltered rates of unemployment and their expectations, as well as the TFP growth rate as observables. We believe that this is the first paper that does so. Second, we investigate the historical role that news and noise played across each of the economic expansions and recessions that have characterized the postwar U.S. economy. The aforementioned papers assess the contribution of news and noise by looking only at the fraction of the unconditional variance of GDP, consumption, investment, and hours explained by these shocks. Third, our study assesses the role of TFP news and noise during the Great Recession and the ensuing recovery. To our knowledge, this is the first paper that specifically focuses on the role of news during the Great Recession and

[6] The government spending shock is another exception. However, it commonly plays a limited role in business cycle dynamics in structural studies.

the following recovery. Fourth, we do not assume preferences à la Jaimovich and Rebelo (2009) that allow us to parameterize the magnitude of the wealth effect on the labor supply. In our model, preferences are standard. We propose a new propagation mechanism that hinges on hiring frictions, which counteracts the wealth effect on labor supply and generates a gradual buildup in employment. Moreover, we show that because of their complementarities with other real frictions, hiring frictions contribute to generating positive comovements among the main business-cycle variables.

On the methodological side, we build on the important contribution by Chahrour and Jurado (2017a), who show how models with news shocks can be recast in observationally equivalent models with noisy signals about the future realization of fundamentals. We extend their results in two ways. First, we show how to derive the historical realizations of noise from an estimated model with news. Second, we show how to evaluate the role played by noise in causing macroeconomic events of interest (e.g., the Great Recession) without solving the model with noise, which would be more complicated computationally.

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 (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. The recent study by Chahrour and Jurado (2017b) proposes an approach to identify the effect of noise shocks using VAR models.

Our paper is related to the young and rising literature on structural estimation of dynamic general equilibrium models with labor market frictions (e.g., Christiano et al. 2016). To our knowledge, this is the first paper to study the role of TFP news shocks in this class of models. 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. Finally ,we highlight the role of data on current and expected unemployment rates in identifying news shocks and (jointly with the growth rate of TFP observed) noise. In this respect, our paper is connected to the aforementioned literature on the link between unemployment and labor productivity dynamics at low frequencies. Unlike that literature, the main focus of our paper is on the identification of TFP news shocks and noise and on the business-cycle implications of these shocks.

The paper is structured as follows. In Section 2, we present the model used in the estimation. Then, in Section 3, we discuss the estimation and the evaluation of the model. Next, we analyze the historical role of noise in explaining the U.S. postwar business fluctuations 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 to investigate the historical role played by anticipated TFP innovations in the U.S. economy. 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 how hiring costs are modeled. 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 good 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 that 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 δ_N at the end of each period, N_t obeys the law of motion: $N_t = (1 - \delta_N) N_{t-1} + x_t U_t^0$.[7]

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

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

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

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

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

[7] One could worry that the assumption of exogenous separation could hinder the 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 US data, which is high enough not to constrain households' decisions following a positive wealth effect.

lump-sum government taxes T_t.[8] The budget constraint can therefore be written as:

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

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

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

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: $Y_t = \left(\int_0^1 Y_{i,t}^{1/\left(1+\lambda_{f,t}\right)} di\right)^{1+\lambda_{f,t}}$, where $\lambda_{f,t}$ denotes the mark-up and is assumed to follow an exogenous AR(1) stochastic process in logs. These firms sell their composite good in a perfectly competitive market at the price index $P_t = \left(\int_0^1 P_{i,t}^{\frac{1}{\lambda_{f,t}}} di\right)^{-\lambda_{f,t}}$. The demand of good i from the final good producers is given by

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

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

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

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

We model hiring costs as non-pecuniary for two reasons. First, as we shall discuss in more detail in Section 2.6, modeling hiring frictions as forgone output contributes to boosting labor

[8] 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. Moreover, as we will discuss in Section 5, we have estimated a version of the model with variable capital utilization and obtained similar results.

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 are opportunity costs 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.[9]

The production function is assumed to be Cobb−Douglas: $f_{i,t} = a_t \left(A_t N_{i,t}\right)^{\alpha} \left(K_{i,t}\right)^{1-\alpha}$, where $K_{i,t}$ denotes capital rented from households at time t, a_t is a stationary technology-neutral shock (henceforth, TFP process) and A_t is a labor-augmenting technology shock that is stationary in the growth rate.[10] Specifically, we assume that $\eta_t^A = A_t/A_{t-1}$ is a stochastic trend that follows

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

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

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

where $\varepsilon_{a,t}^0$ is an independent and identically distributed (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. The TFP innovation at time t is denoted by θ_t^a and is given by the sum of the unanticipated and anticipated shocks to TFP. It is worth emphasizing that equation (6) implies that TFP news shocks capture revisions of expectations about future TFP innovations θ^a. 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.[11]

[9] Using personnel records of US companies, Krueger and Rouse (1998) and Bartel (1995) find that the forgone cost of production related to training activities was much higher than the direct costs of training, measured as expenses related to course material and external teachers salaries. Similarly, the reviews in Silva and Toledo (2009) and Blatter et al. (2016) compute hiring costs as forgone output. The latter study provides evidence of some expenses being incurred for external advisors/headhunters, but these costs are very small. 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 US manufacturing plants, find that labor adjustment costs reduce plant-level production.

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

[11] Chahrour and Jurado (2017a) formalize the link between news and noise and show that our model with

This particular timing of anticipation of technology innovations follows Schmitt-Grohe and Uribe (2012) and implies that TFP surprise and news shocks are stationary. In the robustness section, we discuss the case in which TFP news shocks have permanent effects following Barsky and Sims (2011, 2012). We stick to the case in which news shocks have stationary effects because it simplifies the interpretation of noise.

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

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

where $H_{i,t} = q_t V_{i,t}$ and $\eta^q \in [0, 2]$ is a parameter. When $\eta^q = 0$, hiring costs depend only on the gross hiring rate $H_{i,t}/N_{i,t}$, a measure of worker turnover within the firm. These frictions are typically interpreted as capturing training costs. Formulations of hiring costs that are quadratic in the hiring rate have been adopted by Merz and Yashiv (2007), Gertler, Sala, and Trigari (2008), Christiano, Trabandt, and Walentin (2011), and Furlanetto and Groshenny (2016), among others, and are consistent with the empirical estimates in Yashiv (2016). When $\eta^q = 2$, instead, the function (7) depends only on the vacancy rate $V_{i,t}/N_{i,t}$ and can therefore be interpreted as capturing vacancy posting costs in the tradition of search and matching models of the labor market. Any intermediate value of η^q governs the relative importance of these two types of hiring costs.[12]

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

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

In this equation, the parameter ζ controls the degree of price rigidities à la Rotemberg, the parameter ψ governs inflation indexation, and $\bar{\Pi}$ denotes the steady-state gross inflation rate.

news shocks can be recast into an observationally equivalent model with noise (or noise representation). Given that the two models are observationally equivalent, the data cannot tell us anything about which model is more plausible. Furthermore, once the model with news is estimated, there is no point in estimating its noise representation. We will return to this crucial link between news and noise more formally in Section 4.1.

[12] 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.

The problem of the intermediate goods firm is subject to the law of motion for labor,

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

and the constraint that output must equal demand,

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

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

2.4 Wage Bargaining

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

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

where ω is a parameter that governs wage rigidities.[13] The reference wage $\frac{W_t^{NASH}}{P_t}$ is assumed to maximize a geometric average of the households' and the firms' surplus weighted by the parameter γ, which denotes the bargaining power of the households:

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

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.[14]

2.5 Policymakers and Market Clearing

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

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

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

[14] 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 et al. 2013; Christiano, Trabandt and Walentin 2011; Furlanetto and Groshenny 2016; and Christiano, Eichenbaum, and Trabandt 2016).

where $\tilde{Y}_t \equiv Y_t/A_t$, Y^* denotes the steady-state value of $\tilde{Y}_t$; the parameter ρ_R controls the degree of interest rate smoothing; $\Pi_t \equiv P_t/P_{t-1}$ is the actual gross rate of price inflation; and r_y and r_π govern the response of the monetary authority to deviations of output and inflation from their target values, Y^* and Π_t^*, respectively. We assume that the monetary shock η_t^R follows an i.i.d. Gaussian process.[15] Moreover, as in Christiano, Eichenbaum, and Evans (2005), Del Negro, Schorfheide, Smets, and Wouters (2007), Smets and Wouters (2007), and Del Negro and Eusepi (2011), we assume that the variable Π_t^* captures persistent deviations from the long-run inflation target Π_*; that is, $\ln \Pi_t^* = (1-\rho_{\Pi^*}) \ln \Pi_* + \rho_{\Pi^*} \ln \Pi_{t-1}^* + \varepsilon_t^\pi$. In our study, the only role played by these shocks is to help the model fit the heightened inflation rate in the 1970s.

The aggregate resource constraint reads:

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

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

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 raise their workforce when the anticipated TFP shock materializes, they anticipate hiring so as to smooth adjustment costs over time.[16] It should be noted that this mechanism does not hinge on modeling hiring frictions as forgone output.

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):[17]

[15] 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 the estimated model.

[16] 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.

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

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

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

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

The value of a marginal job in equation (15) equals the marginal product of employment $\xi_t \left(f_{N,t} - \bar{g}_{N,t} \right)$ less the real wage $\frac{W_t}{P_t}$, plus a continuation value, which is the future value of a job Q_{t+1}^N discounted at rate $E_t \Lambda_{t,t+1}$ and conditional on no separation, $1 - \delta_N$. In equilibrium, optimization implies that the marginal value of a job Q_t^N is equalized to the real cost of the marginal hire, as per equation (16). In turn, the latter is given by the intermediate firms' output lost $\bar{g}_{H,t}$ multiplied by the shadow value of output ξ_t. Note that this shadow value affects marginal hiring costs because hiring frictions are modeled as forgone output.

The propagation of TFP news shocks works as follows: households want to consume more and reduce participation in the labor market because of a wealth effect. 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.[18] 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

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

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 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 that 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

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

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.

Finally, we note that the precise value of the parameter η^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 η^q decreases the sensitivity of the marginal hiring costs to changes in the vacancy filling rate, muting this feedback effect from aggregate labor market conditions. Since the precise nature of hiring costs matters for propagation, we let the data decide on their relative importance by estimating the parameter η^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.[19] The log-linearized model is estimated using Bayesian techniques. The posterior distribution is a combination of our prior beliefs about parameters values and the model's likelihood function. The likelihood function is not available in closed form, and we use the Kalman filter to approximate it (see, e.g., Fernandez-Villaverde and Rubio-Ramirez 2004 and An and Schorfheide 2007; Fernandez-Villaverde et al. 2010; Fernandez-Villaverde et al. 2016).[20]

This section is organized in the following order: In Section 3.1, we introduce the data set used for estimation. In Section 3.2, we explain the estimation strategy. We elicit the prior distribution for the model parameters in Section 3.3. The posterior moments for the parameters and the fit of the model are analyzed in Section 3.4. The propagation of TFP news shocks and noise is analyzed in Section 3.5. The objective of Section 3.6 is to analyze the role of labor market data in the identification of anticipated and unanticipated TFP shocks.

[19] The solution to the agents' problem is shown in Appendix A.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).

[20] The consequences of the use of approximated likelihoods are studied in Fernandez-Villaverde et al. (2006).

3.1 Data and Measurement

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-quarter-ahead expectations about the unemployment rate; 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*.[21] 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 a 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. Specifically, we compute TFP growth using the number of employed workers rather than 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, $\hat{\eta}_t^A$.

Ideally, TFP growth should be measured by adjusting for capital utilization.[22] One way to do that is to have variable capital utilization in the model. Nonetheless, this approach is likely to provide a fairly inaccurate adjustment because standard ways of modeling capital utilization are easily rejected by the data. Alternatively, we could rely on statistical methods to correct the series of TFP growth for capital utilization 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

[21] One may wonder if given these horizon structures, it would be more natural to also have news shocks with one-, two-, and three-quarter 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.

[22] 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.

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

$$\Delta \ln TFP_t^N = c_{TFP,unadj}^m + \lambda_{TFP,unadj}^m \left[\hat{a}_t - \hat{a}_{t-1} + \alpha \hat{\eta}_t^A + 100\alpha \ln \mu\right] + \eta_{TFP,t}^N, \tag{18}$$

$$\Delta \ln TFP_t^A = c_{TFP,adj}^m + \lambda_{TFP,adj}^m \left[\hat{a}_t - \hat{a}_{t-1} + \alpha \hat{\eta}_t^A + 100\alpha \ln \mu\right] + \eta_{TFP,t}^A, \tag{19}$$

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

Following Campbell et al. (2012), Barsky, Justiniano, and Melosi (2014), Campbell et al. (2017), the three measures of inflation (GDP deflator, CPI, and PCE) are jointly used for measuring inflation in the model. The approach is akin to what we do for the two measures of TFP growth. We set the loading of PCE inflation equal to one. The results are not affected by a different normalization. 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 similarly affected by an i.i.d. measurement error and a constant c_w^m that accounts for the difference in sample means with the growth rate of GDP, consumption, and investment. The full list of measurement equations are shown in Appendix D.

We use unfiltered data. It is well known that 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 could be useful for identifying TFP news shocks. Furthermore, using both the participation and employment rates as observables allows us to control the two channels that affect the unemployment rate when we estimate the structural shocks of our model. 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 3.4, we set up our prior so that the labor disutility shocks η_t^l can explain the low-frequency dynamics of employment and participation rates.

3.2 Estimation Strategy

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 because it would introduce a non-linearity in the model, which requires using non-linear Monte Carlo filters to evaluate the likelihood.[23] A simpler way to address this issue has been proposed 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. This approach amounts to appending a number of i.i.d. news shocks (called forward guidance shocks) to the monetary policy reaction function (13) and using data on market-based future federal funds rate to estimate the model.[24] Agents' expectations about the future interest rates are informed by the market forecasts, which basically enforce the zero lower bound in the model. Therefore, agents are not surprised about not seeing negative interest rates during the Great Recession. 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 shocks in the most recent period.

We construct the market-expected federal funds rates from the overnight index swap (OIS) data as in Campbell et al. (2017).[25] 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.[26]

Similarly to 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 described in the previous section. Then we re-estimate only the measurement parameters (see Panel C of Table 5 in Appendix H for a list of measurement parameters) and the forward guidance parameters over the second sample (2008:Q4 through 2016:Q4). All the structural parameters are set to their first-sample posterior mode (see Table 4 and Panel A and Panel B of Table 5 in Appendix H for a list of those

[23] Methods to implement one of these of filters are analyzed by Fernandez-Villaverde and Rubio-Ramirez (2007).

[24] Details on how this approach changes the monetary policy reaction function are provided in Appendix D.

[25] 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.

[26] 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 originally introduced by Gürkaynak, Sack, and Swanson (2005).

parameters) and are not re-estimated over the most recent period. We initialize the estimation of the model over the second sample period by using the filtered mean and variance of the states at the end of the first sample. The states for the expected interest rates and the two factors are initialized by using the OIS data in a presample period. We pick the 2008:Q4 as the initial observation for the second sample because this is the quarter when the federal funds rate hits its effective lower bound. The philosophy of the two-step estimation goes as follows: we estimate the structural parameters over a long sample period (i.e., the first sample) and assume that these parameters are structural and, hence, have not changed during the Great Recession.

Prior and Posterior for Structural Parameters

Parameters	Post. Mode	Post. Median	5%	95%	Prior Type	Prior Mean	Prior Std
ϑ	0.9094	0.9087	0.9003	0.9161	B	0.6000	0.1000
$100\ln\mu$	0.4786	0.4734	0.4330	0.5166	N	0.5500	0.0500
φ	4.9817	5.0172	4.9401	5.1211	G	4.0000	0.2500
κ	0.0337	0.0361	0.0299	0.0424	N	0.0900	0.0150
$100u$	5.8539	5.8452	5.7192	5.9479	N	5.6000	0.1000
$100\ln\Pi_*$	0.6171	0.6072	0.5602	0.6392	N	0.6100	0.1000
e	4.1754	4.0587	3.8792	4.2390	N	2.5000	0.2500
ω	0.9584	0.9597	0.9537	0.9653	B	0.5000	0.1000
ϕ	0.0037	0.0016	0.0002	0.0038	N	3.5000	0.7500
ψ	0.2770	0.2726	0.2416	0.3014	B	0.2500	0.0500
l	0.5977	0.6089	0.5788	0.6511	B	0.6000	0.0500
η^q	0.0090	0.0117	0.0079	0.0172	G	0.1450	0.1000
$\bar{\omega}$	0.8190	0.8138	0.7880	0.8525	B	0.5000	0.1000
r_π	2.0131	1.9996	1.9595	2.0304	G	1.7500	0.1000
r_y	0.0260	0.0290	0.0257	0.0308	G	0.2500	0.1000
ρ_R	0.2390	0.2379	0.2106	0.2539	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, Beta, respectively. See Table 4 in Appendix H for a description of the parameters.

3.3 Priors

To elicit the prior distributions for the model parameters, we follow the approach proposed by Del Negro and Schorfheide (2008). Some parameter values are fixed in estimation, or implied by steady-state restrictions. We fix the value for the discount factor β so that the steady-state real interest rate is broadly consistent with its sample average. The parameter δ^N reflects the average rate of separation from employment, and is calibrated to match an average quarterly hiring rate of 12.76%, measured following Yashiv (2016). The quarterly rate of capital depreciation, δ^K, is set to target an investment rate of 2.5%. The parameter μ 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 α is set to the standard value of 0.66.

Prior and Posterior for the Parameters of Exogenous Processes and Measurement Equations							
Parameters	Post. Mode	Post. Median	5%	95%	Prior Type	Prior Mean	Prior Std
Panel A: Autoregressive Parameters							
ρ_a	0.9819	0.9774	0.9745	0.9809	B	0.5000	0.1000
ρ_μ	0.3509	0.3482	0.3296	0.3669	B	0.2500	0.1000
ρ_l	0.9961	0.9960	0.9944	0.9972	B	0.9950	0.0010
ρ_g	0.9028	0.9148	0.9046	0.9339	B	0.5000	0.1000
ρ_i	0.8121	0.8100	0.7882	0.8314	B	0.5000	0.1000
ρ_p	0.4513	0.4552	0.4112	0.4786	B	0.5000	0.1000
ρ_{Π^*}	0.9948	0.9948	0.9927	0.9962	B	0.9950	0.0010
Panel B: Shocks Standard Deviations							
$\sigma_{0,a}$	0.3885	0.3859	0.3423	0.4330	IG	0.5000	0.2000
$\sigma_{4,a}$	0.2570	0.2434	0.2205	0.2690	IG	0.5000	0.2000
$\sigma_{8,a}$	0.4203	0.4324	0.3966	0.4865	IG	0.5000	0.2000
σ_μ	0.3758	0.3587	0.3272	0.3939	IG	0.5000	0.2000
σ_l	1.7428	1.7097	1.6041	1.8204	IG	0.2500	0.2000
σ_g	0.9405	0.9380	0.8838	0.984	IG	0.5000	0.2000
σ_i	0.8303	0.8808	0.7986	0.9759	IG	0.5000	0.2000
σ_p	4.9980	4.9956	4.9908	4.9993	IG	0.5000	0.2000
σ_{Π^*}	0.0963	0.1048	0.0813	0.1249	IG	0.0350	0.0350
σ_r	0.4289	0.4049	0.3672	0.4323	IG	0.5000	0.2000
$\sigma_{\lambda_{f,t}}$	0.2419	0.2323	0.2063	0.2527	IG	0.5000	0.2000
Panel C: Measurement Equations							
$\sigma^m_{u,1}$	1.0658	1.0659	1.0426	1.0859	IG	5.0000	1.0000
$\sigma^m_{u,2}$	0.7452	0.7179	0.6703	0.7554	IG	5.0000	1.0000
$\sigma^m_{u,3}$	0.4941	0.4748	0.4554	0.493	IG	5.0000	1.0000
$\sigma^m_{u,4}$	0.9077	0.8852	0.8575	0.9089	IG	5.0000	1.0000
σ^m_E	0.3071	0.3293	0.3127	0.3468	IG	5.0000	1.0000
c^m_w	-0.1283	-0.1274	-0.1841	-0.0639	N	0.0000	0.5000
σ^m_w	0.5009	0.5076	0.4477	0.5563	IG	0.1000	0.0500
$c^m_{\pi,1}$	0.0051	0.0066	-0.0500	0.0850	N	0.0000	0.1000
$c^m_{\pi,2}$	-0.0251	-0.0246	-0.0773	0.0680	N	0.0000	0.1000
$c^m_{\pi,3}$	0.0666	0.0641	-0.0012	0.1732	N	0.1400	0.1000
$\lambda^m_{\pi,1}$	0.8883	0.8960	0.8484	0.9382	N	1.0000	0.5000
$\lambda^m_{\pi,3}$	1.1287	1.1327	1.0859	1.1773	N	1.0000	0.5000
$\sigma^m_{\pi,1}$	0.2001	0.2018	0.1834	0.2229	IG	0.1000	0.0500
$\sigma^m_{\pi,2}$	0.0803	0.0902	0.0738	0.1053	IG	0.1000	0.0500
$\sigma^m_{\pi,3}$	0.2102	0.2108	0.1904	0.2321	IG	0.1000	0.0500
$c^m_{TFP,unadj}$	-0.0417	-0.0356	-0.1060	0.04340	N	0.0000	0.1000
$c^m_{TFP,adj}$	-0.0417	-0.0356	-0.1060	0.0434	N	0.0000	0.1000
$\lambda^m_{TFP,adj}$	0.3462	0.3487	0.2413	0.4395	N	0.5000	0.5000
$\sigma^m_{TFP,unadj}$	0.6986	0.7157	0.6729	0.7651	IG	0.1000	0.0500
$\sigma^m_{TFP,adj}$	0.7101	0.7338	0.6965	0.7635	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 5 in Appendix H for a description of the parameters. Some parameters are defined in Appendix D.

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

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

3.4 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

Statistic	Y	C	I	FFR	$EMPL$	$PART$	E_tU_{t+1}	E_tU_{t+2}
Data	0.68	0.49	2.92	0.81	2.29	0.81	22.01	21.10
Model	0.80	0.54	3.27	0.80	2.04	0.83	20.55	19.96
Statistic	E_tU_{t+3}	E_tU_{t+4}	W/P	P^{def}	P^{pce}	P^{cpi}	TFP^{adj}	TFP^{unadj}
Data	20.32	18.59	0.61	0.58	0.62	0.73	0.75	0.87
Model	19.23	18.37	0.45	0.72	0.72	0.72	0.68	0.68

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.

parameters (see Panel C of Table 5 in Appendix H) 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 substantial. 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 sluggishly to TFP news shocks, wage inertia alone is not enough to deliver this pattern.

The posterior estimate for the hiring cost parameter η^q is tiny, suggesting that hiring costs are mainly driven by disruption associated with worker turnover at the firm level rather than by the costs of posting vacancies. This result is remindful of those in Christiano, Trabandt, and Walentin (2011), who, based on the estimation of a dynamic general equilibrium model of the Swedish economy, argue that hiring costs are a function of hiring rates, not vacancy posting rates. Other empirical macro papers, such as Yashiv (2000), and Sala, Soderstrom, and Trigari (2013) find similar results, though not as stark. The estimated value for the parameter η^q is broadly in line with findings in the micro literature. See for instance, Silva and Toledo (2009) and Manning (2011). We note that the reason why our model estimates such a tiny value for η^q is to have a stronger countercyclicality of hiring costs, which in turn helps fit the volatility of unemployment in the data.[27]

[27] 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

The cost of varying the investment flow, governed by the parameter φ, is estimated to be quite tiny and virtually negligible. This result has important implications for the propagation of anticipated TFP shocks on 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 of investment in the data. As we shall discuss in the next section, the standard deviation of the growth rate of investment implied by the estimated model is 3.26%, which is close to 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 on the U.S. economy. The inverse Frisch elasticity of labor supply, φ, is in line with the survey of micro evidence in Chetty et al. (2013), which points to elasticities of labor supply on the extensive margin around 0.25. The slope of the Phillips curve, κ, is broadly in line with estimates in the literature. Finally, the degree of inflation indexation, ψ, is on the low side, while the Taylor rule parameters reveal a limited degree of smoothing and response to output combined with a relatively strong response to inflation.

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). This picture suggests that labor disutility shocks effectively detrend the employment and participation rates in estimation.

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

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.

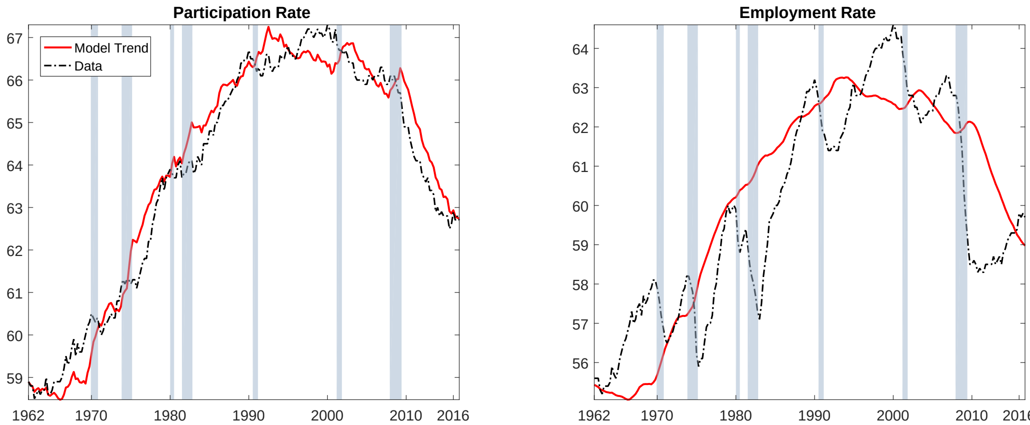

Figure 2: Detrending the rate of participation and the rate of employment. The black dashed-dotted lines denote the data and the red solid lines denote the two rates simulated from the estimated model by using only the filtered (one-sided) estimates for the labor disutility shocks. The estimated model's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

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. It is remarkable that the model matches the volatility of unemployment pretty well, despite the well-known difficulties that characterize models with frictional labor markets in this respect. Indeed, the countercyclicality of the shadow value of output and marginal hiring costs conditional on technology shocks generates a powerful amplification mechanism.[28] To provide further evidence on the ability of the model to fit the data, we show in Figure 3 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.

3.5 Propagation of News Shocks and Noise

The propagation of the unanticipated TFP shock (black dotted-dashed line), the four-quarter-ahead TFP news shock (blue dashed line), and the eight-quarter-ahead TFP news shock (red solid line) are shown in Figure 4. The size of the initial shock is equal to one percentage point to facilitate comparison.[29] There are three important points that emerge from comparing

[28] We note that our model matches the volatility of the unemployment rate despite the presence of a procyclical opportunity cost of work. Indeed, in our model, the opportunity cost of work is given by the marginal rate of substitution between consumption and leisure, which in turn is a positive function of consumption and the labor index, L. To the extent that both consumption and the labor index are procyclical, the opportunity cost of work is procyclical in our model. Chodorow-Reich and Karabarbounis (2016) have shown that the opportunity cost of work is indeed procyclical in the U.S. data, and under such a condition, leading models of unemployment dynamics fail to generate amplification. This result does not apply to our model also because amplification is driven by the countercyclicality of marginal hiring costs.

[29] The estimated impulse responses with the posterior credible bands are reported in Appendix E.

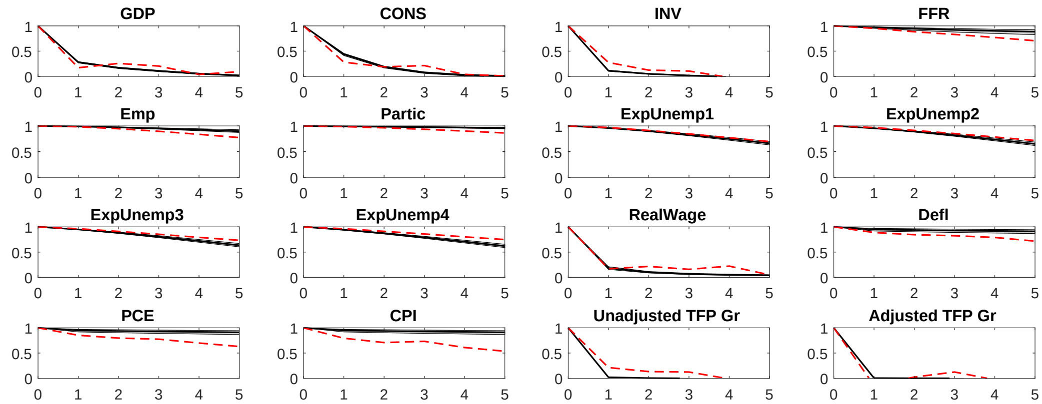

Figure 3: Posterior autocorrelation functions computed for every 100 posterior draws. The red dashed line denotes the empirical autocorrelation function and the solid black line denotes the posterior median for the autocorrelation implied by the model after shutting down its measurement errors. The gray areas denote the 90-percent posterior credible set. Sample period: 1962:Q1-2008:Q3)

these impulse response functions. First, all three shocks produce over time an expansionary response of labor market variables, output and its components, which are fairly persistent. Second, the longer is 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. This result implies that the macroeconomic effects of TFP news are largely driven by beliefs. 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. As discussed in Beaudry (2011), these dynamics, which are consistent with the VAR evidence in Beaudry and Portier (2006) and Portier (2015), are quite hard to be explained by structural models.

It is important to emphasize that the mechanism based on the interaction between hiring frictions and nominal rigidities is at work because the firms' shadow value of output, ξ_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. 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 news shock and would remain negative for as long as six quarters. This is suggestive that all 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 4.

It should also be noted that investment and output rise before the anticipated TFP shock

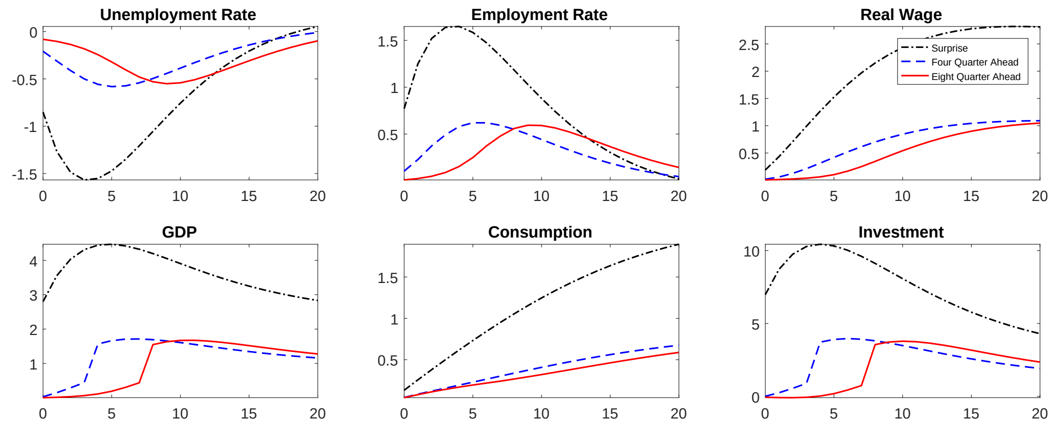

Figure 4: Estimated response of unemployment rate, employment rate, real wages, GDP, consumption, and investment to surprise TFP shocks (black dotted-dashed line), four-quarter-ahead shocks (blue dashed line), and eight-quarter-ahead TFP shocks (red solid line). The responses of unemployment and employment rates are expressed in percentage points deviations from the steady-state rate. All other responses are in percentage deviations from their respective steady-state values. The size of the initial shock is one percentage point. Parameter values are set to their posterior modes, shown in Tables 1 and 2.

hits the economy in period 8. However, most of the adjustment in these variables happens when the anticipated shock hits the economy. As noticed by Beaudry (2011), this may be an extreme result, which is not in line with the VAR literature. We can show that estimating a model in which TFP news shocks are serially correlated (possibly capturing technology diffusion) would lead to smooth, hump-shaped responses of investment and output to TFP news shocks, as also shown by Leeper and Walker (2011). 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.

What are the effects of a TFP news shock that eventually does not pan out? In other words, what are the effects of a TFP news shock that is orthogonal to future changes in TFP? We find that this type of shock can generate *boom-bust dynamics*. The effects are plotted in Figure 5. To construct these impulse responses, we engineer a combination of an expansionary eight-quarter-ahead news shock and a perfectly offsetting unanticipated shock to TFP that occurs eight quarters later. That is, we assume that $\varepsilon^8_{a,t} = -\varepsilon^0_{a,t+8}$, which implies that TFP remains constant throughout the impulse response horizon. These impulse responses describe the propagation of an eight-quarter-ahead TFP shock that agents discover to be just noise eight quarters later. This can be interpreted as the propagation of noise, which we will formally define in Section 4.1.[30]

[30] As we will discuss in Section 4.1, eight-quarters-ahead noise shocks implied by the noise representation exhibit slightly different dynamics because of the revision of expectations after four quarters. In estimated model, such a revision is minimal, and we ignore it here for the sake of exposition.

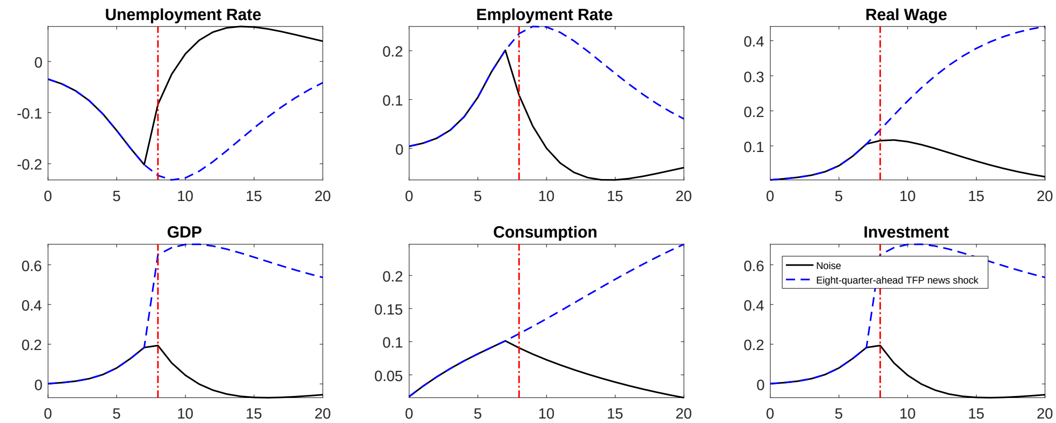

Figure 5: Estimated response of unemployment rate, employment rate, real wage, GDP, consumption, and investment to an eight-quarter-ahead TFP news shock (blue dashed line) and its related noise (black solid line). The vertical dashed-dotted line denotes the period when agents realize that the anticipated shock was just noise (i.e., when the surprise shock hits, offsetting the effect of the anticipated shock realized eight periods earlier on TFP). The responses of unemployment and employment rates are expressed in percent deviations from their steady-state rate. All other responses are in percentage deviations from their respective steady-state values. The size of the initial shock is one standard deviation. Parameter values are set to their posterior modes, shown in Tables 1 and 2.

Figure 5 shows the propagation of noise (solid black line) and compares it to the propagation of an eight-quarter-ahead TFP news shock (blue dashed line). The two propagations are identical for the first seven quarters. This is not surprising, since, as we have already emphasized, the propagation of TFP news shocks before they actually materialize is entirely driven by beliefs. The key result in Figure 5 is the boom-bust dynamics that follow the realization of noise. The bust occurs when agents realize that TFP news is in fact just noise. When agents expect a future increase in TFP, they start accumulating capital and employment increases. When agents eventually realize that the good news will not pan out, 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). It should be also noted that realizing that positive news is just noise brings about a gap in the labor market, with employment falling below its steady-state level. This undershooting of employment is caused by firms lowering labor demand so as to reduce production and to meet the fall in aggregate demand generated by the drop in investment.

When illustrating the propagation of noise in Figure 5, we assume that the surprise shock at time $t + 8$ exactly offsets the news shock so that TFP fundamentals are not affected. While this assumption is needed to heuristically illustrate the effects of noise, by no means does it imply that noise requires a negative correlation between current news shocks and future TFP surprise shocks, which would falsify the assumption of orthogonality between these two shocks. This point will be clarified in more details in Section 4.1.

3.6 Estimation of TFP News and Surprise Shocks

We have conjectured that changes in the unemployment rate carry important information for identifying TFP news shocks. Now we check the validity of this conjecture. The right plot in Figure 6 reports the U.S. unemployment rate (black dashed-dotted line) along with the counterfactual time series obtained by simulating the estimated model using only the smoothed estimate of the four- and eight-quarter-ahead TFP news shocks (red solid lines). As we conjectured, these shocks appear to have been a key driver of the rate of unemployment at lower frequencies over the postwar period. 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. Data on expected unemployment rates help identify TFP news shocks in a similar way (see Appendix G). There are two main reasons why the dynamics of current and expected unemployment rates are picked up by TFP news shocks in estimation. First, unemployment rates and TFP growth negatively comove in the data as shown in the introduction. Second, in the estimated model, anticipated TFP shocks have fairly persistent effects on the unemployment rate, as shown in Figure 4.[31]

Quite interestingly, Figure 6 shows that TFP news shocks systematically fail to account for the behavior of unemployment during the NBER recessions, which are highlighted by the gray areas, and during the following recoveries. This finding 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 do not affect only beliefs but also actual TFP (fundamentals). To evaluate the validity of the Pigouvian intuition, one needs to isolate the noise component of these identified TFP news shocks, which we call noise for sake of brevity. Like TFP news shocks, noise affects expectations about future TFP changes, but unlike TFP news shocks, it is orthogonal to any actual change in future TFP.

[31]In principle, there could be a third reason to explain why the average unemployment rate and TFP news shocks are so tightly related. The filter could extract a correlated series of TFP news shocks to explain the persistent dynamics of the unemployment rate. However, this would violate the assumption of rationality, since TFP news shocks are i.i.d. We do not find support for this third potential explanation. Judging from the autocorrelation function of the smoothed estimate of TFP news shocks, we find there to be none or very little serial correlation. The serial correlation of the four-quarter-ahead TFP news shocks is not statistically significant different from zero, whereas the serial correlation of the eight-quarter-ahead shocks is statistically significant but very low (0.18).

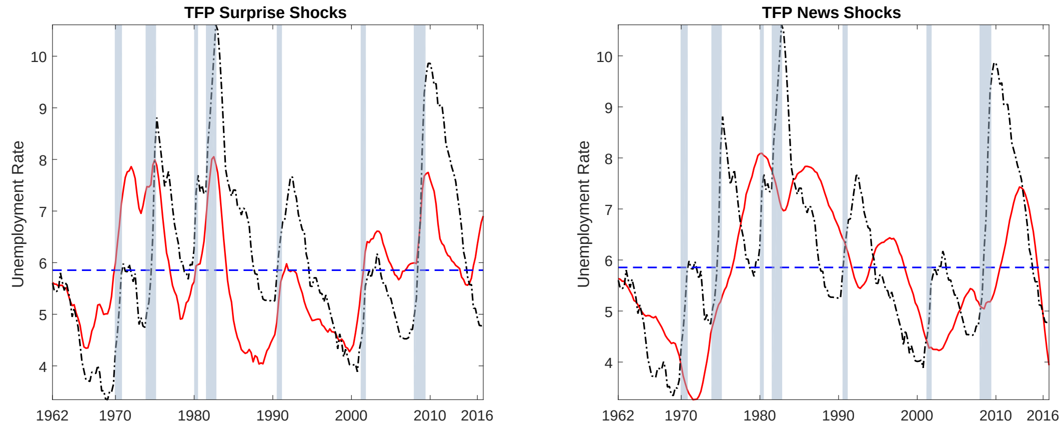

Figure 6: Left Plot: The U.S. unemployment rate (black dashed-dotted line) implied by the observed series of the employment and participation rates, along with the counterfactual unemployment rate obtained by simulating the model using only the smoothed estimate of the surprise TFP shocks (red solid line). Right Plot: the counterfactual series of the unemployment rate is obtained by simulating the model using only the smoothed estimate of the four-quarter and eight-quarter-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 the NBER recessions.

As we will show formally in the next section, noise can be thought of as specific linear combinations of news and surprise shocks. To see why surprise shocks may affect noise, recall the example in the previous section where we studied the propagation of noise by engineering a negative surprise shock offsetting a previously anticipated positive shock. The left plot of Figure 6 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 business-cycle fluctuations in the observed unemployment rate significantly contribute to identifying surprise TFP shocks. This pattern of positive comovement breaks in the most recent years. We will return to this important point and to the link between surprise TFP shocks and noise in the next section. Data on expected unemployment rates similarly contribute to the identification of TFP surprise shocks (see Appendix G).

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 shocks θ_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 principle, large realizations of the surprise TFP shocks could just offset previous news shocks, leaving TFP fundamentals unchanged.

It is very important to emphasize that 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 6 would have been very close to the zero line over the sample period. These results underscore the importance of using labor market data to identify TFP news shocks.

Furthermore, if the model were estimated without using observed expected unemployment rates, the role of TFP news shocks and hence that of noise would be diminished. The simulation of the model with only smoothed news shocks would not deliver the pronounced swings in trend unemployment rate that we observe in the right plot of Figure 6. This finding lends support to the importance of expectation data on the rate of unemployment for identifying the historical realizations of TFP news shocks.

Unemployment and Identification of TFP News Shocks: A Formal Assessment Iskrev (2018) introduces methods to evaluate how informative an observed time series is about the latent variables or shocks of a structural model. These methods are based on computing the reduction in uncertainty about a latent variable or shock, measured by its entropy, that is due to using the observed time series of interest. For linear and Gaussian models, uncertainty about state variables can be computed via the Kalman smoother. If the observables lead to a reduction in entropy equal to one, it means that the observables totally eliminate uncertainty about the historical realizations of the model's variable, and hence, the variable or shock is exactly identified in the data. This case always holds when the variable is observed. In our model, observing current and expected unemployment rates increases the information about the historical realizations of TFP news shocks by 60 percent for four quarters ahead and 36 percent for eight quarters ahead. There is a gain of 56 percent in information for TFP surprise shocks.

Iskrev (2018) also shows how to compute the information content of the entire data set used in estimation about shocks. This measure sheds light on how accurate the estimates of the shocks are in absolute terms. He proposes to compare the uncertainty about TFP shocks conditional on using the entire data set, to a measure of unconditional uncertainty (i.e., when no data are observed). The information content of our data set is 79%, 38%, and 63% for TFP surprise shocks, the four-quarter-ahead TFP shocks, and the eight-quarter-ahead TFP shocks, respectively. These numbers are significantly larger than those found in other studies with the same news structure surveyed by Iskrev (2018), in which the information content of the data set used for estimation is only around 2% for TFP news shocks.

4 The Historical Role of Beliefs-Driven Fluctuations

So far, most of our analysis has focused on the role of TFP news shocks. News shocks affect not only beliefs but also future fundamentals. To shed light on the importance of beliefs-driven business cycles, we have to focus on those news shocks that are orthogonal to any future change in fundamentals. 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. Noise shocks isolate precisely those movements in beliefs that are independent of fundamentals at all horizons. Since, by construction, noise shocks will never affect TFP fundamentals, they can be thought of as capturing *autonomous changes in agents' expectations,* which Pigou (1927) considered as important drivers of business cycles.

This section is organized as follows. In Section 4.1, we show how to tease out the series of noise shocks implied by the estimated model and how to assess their contribution to business cycles. In Section 4.2, we show the contribution of noise about TFP to U.S. business cycle fluctuations.

4.1 Recovering Noise from the Estimated Models with News Shocks

The goal of this section is to use the estimated model with news 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 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 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

$$\begin{aligned} s_{8,t} &= \theta^a_{t+8} + v_{8,t}, & (20)\\ s_{4,t} &= \theta^a_{t+4} + v_{4,t}, & (21) \end{aligned}$$

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

$$\begin{bmatrix} \theta_t^a \\ v_{4,t} \\ v_{8,t} \end{bmatrix} \overset{iid}{\backsim} N \left(\begin{bmatrix} 0 \\ 0 \\ 0 \end{bmatrix}, \begin{bmatrix} \sigma_\theta^2 & 0 & 0 \\ 0 & \sigma_{4,v}^2 & 0 \\ 0 & 0 & \sigma_{8,v}^2 \end{bmatrix} \right). \tag{22}$$

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:

$$\sigma_{8,v}^2 = \left(\sigma_{0,a}^2 + \sigma_{4,a}^2 + \sigma_{8,a}^2\right)\left(\frac{\sigma_{0,a}^2 + \sigma_{4,a}^2}{\sigma_{8,a}^2}\right), \tag{23}$$

$$\sigma_{4,v}^2 = \left(\sigma_{0,a}^2 + \sigma_{4,a}^2\right)\frac{\sigma_{0,a}^2}{\sigma_{4,a}^2}, \tag{24}$$

and

$$\sigma_{\theta}^2 = \sigma_{a,0}^2 + \sigma_{4,a}^2 + \sigma_{8,a}^2. \tag{25}$$

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 σ_{θ}^2.

Step 2: Teasing Out the Historical Realizations of Noise Shocks In the estimated model with news, revisions of expectations about future TFP innovations θ_{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:

$$\begin{aligned} E_t\theta_{t+8}^a &= \varepsilon_{a,t}^8, && (26)\\ E_{t+4}\theta_{t+8}^a - E_t\theta_{t+8}^a &= \varepsilon_{a,t+4}^4, && (27)\\ \theta_{t+8}^a - E_{t+4}\theta_{t+8}^a &= \varepsilon_{a,t+8}^0. && (28)\end{aligned}$$

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:

$$\kappa_8\left(\theta_{t+8}^a + v_{8,t}\right) = E_t\theta_{t+8}^a = \varepsilon_{a,t}^8, \tag{29}$$

where $\kappa_8 \equiv \left(\sigma_{0,a}^2 + \sigma_{4,a}^2 + \sigma_{8,a}^2\right) / \left(\sigma_{0,a}^2 + \sigma_{4,a}^2 + \sigma_{8,a}^2 + \sigma_{8,v}^2\right)$ 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 (23)-(25) from the estimated model with news to its noise representation. Equation (29) 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 $\kappa_8\nu_{8,t}$, 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 (29), we obtain the equation that can be used to tease out the noise component of the estimated eight-quarter-ahead TFP news shocks:

$$\kappa_8 \hat{\upsilon}_{8,t} = (1-\kappa_8)\,\hat{\varepsilon}^8_{a,t} - \kappa_8\left(\hat{\varepsilon}^0_{a,t+8} + \hat{\varepsilon}^4_{a,t+4}\right). \tag{30}$$

It should be noted that the noise component depends on the timing of information about θ^a_{t+8}, which is distributed from period t through $t+8$, and on the degree of imperfect information as captured by the Kalman gain $(1-\kappa_8)$. This is why we put so much emphasis on how we identify TFP news and surprise shocks in the data. See Section 3.6.

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

$$\begin{aligned} E_t\theta^a_{t+4} - E_{t-4}\theta^a_{t+4} &= \kappa_4\left(\theta^a_{t+4} + \upsilon_{4,t} - E_{t-4}\theta^a_{t+4}\right), \\ &= \kappa_4\left(\varepsilon^0_{a,t+4} + \varepsilon^4_{a,t} + \upsilon_{4,t}\right) = \varepsilon^4_{a,t}, \end{aligned} \tag{31}$$

where $\kappa_4 \equiv \left(\sigma^2_{0,a} + \sigma^2_{4,a}\right) / \left(\sigma^2_{0,a} + \sigma^2_{4,a} + \sigma^2_{4,v}\right)$ is the Kalman gain in terms of the estimated parameters of the model with news. In the last row we made use of the fact $E_{t-4}\theta^a_{t+4} = \varepsilon^8_{a,t-4}$. Substituting the estimated TFP innovations $\hat{\theta}^a_{t+8} = \hat{\varepsilon}^0_{a,t+8} + \hat{\varepsilon}^4_{a,t+4} + \hat{\varepsilon}^8_{a,t}$ in equation (31), we obtain the equation that can be used to tease out the noise component of the estimated four-quarter-ahead TFP news shocks:

$$\kappa_4 \hat{\upsilon}_{4,t} = (1-\kappa_4)\,\hat{\varepsilon}^4_{a,t} - \kappa_4\hat{\varepsilon}^0_{a,t+4}. \tag{32}$$

Equations (30) and (32) show that noise shocks are a particular linear combinations 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 (29) allows us to decompose eight-quarter-ahead news shocks into a fundamental component $\kappa_8\theta^a_{t+8}$, which will affect TFP in eight quarters, and a noise component $\kappa_8\nu_{8,t}$, which is orthogonal to future changes in TFP. Equation (31) allows for a similar decomposition of the four-quarter-ahead TFP news shocks. Equipped with the time series of noise shocks retrieved from equations (30) and (32), 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 (29) and simply zeroing the fundamental component, we obtain

$$\tilde{\varepsilon}^8_{a,t} = \kappa_8\hat{\upsilon}_{8,t}. \tag{33}$$

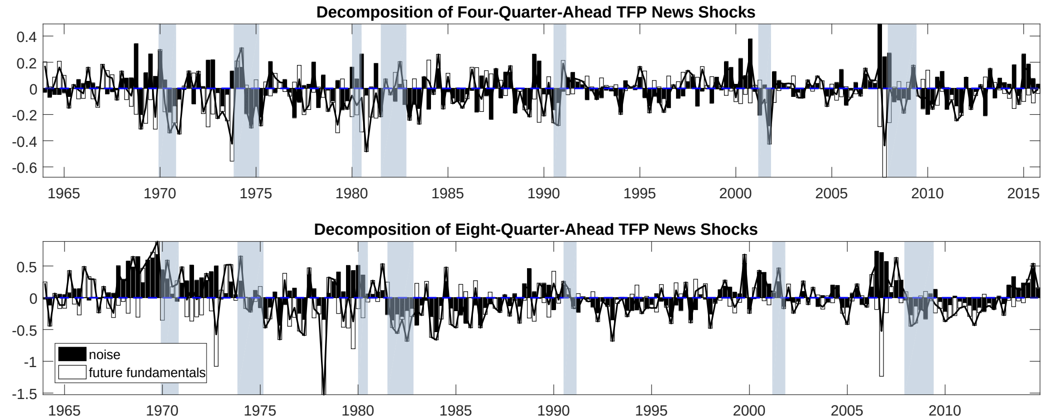

Figure 7: Decomposition of TFP news shocks (black solid line) into beliefs related to future fundamentals (white bars) and beliefs that are orthogonal to future fundamentals (black bars). Both components are rescaled by the relative Kalman gain. Shaded areas denote NBER recessions.

Next, we substitute $E_{t-4}\theta^a_{t+4} = \kappa_8\left(\hat{\theta}^a_{t+4} + \hat{v}_{8,t-4}\right)$ from equation (29) into the first line of equation (31) and then zero the realization of fundamentals $\hat{\theta}^a_{t+4}$ to obtain the counterfactual series of the four-quarter-ahead TFP news shocks:

$$\tilde{\varepsilon}^4_{a,t} = \kappa_4\hat{v}_{4,t} - k_4 k_8 \hat{v}_{8,t-4}. \tag{34}$$

Analogously, combining equations (27), (28), (29), and (31) and then zeroing the fundamental component θ^a_{t+8}, we get

$$\tilde{\varepsilon}^0_{a,t} = -\kappa_4\left(\hat{v}_{4,t-4} - \kappa_8\hat{v}_{8,t-8}\right) - \kappa_8\hat{v}_{8,t-8}. \tag{35}$$

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.[32] Note that these counterfactual news and surprise shocks have no effect on time-t innovation to TFP θ^a_t, since $\tilde{\varepsilon}^0_{a,t} + \tilde{\varepsilon}^4_{a,t-4} + \tilde{\varepsilon}^8_{a,t-8} = 0$ for every t over our sample period. This is because these counterfactual shocks are orthogonal to fundamentals by construction.

4.2 The Historical Role of Noise

Identification of Noise Shocks. We have shown through equations (29) and (31) that TFP news shocks (or changes in expectations about future TFP) have two main drivers: future TFP

[32]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.

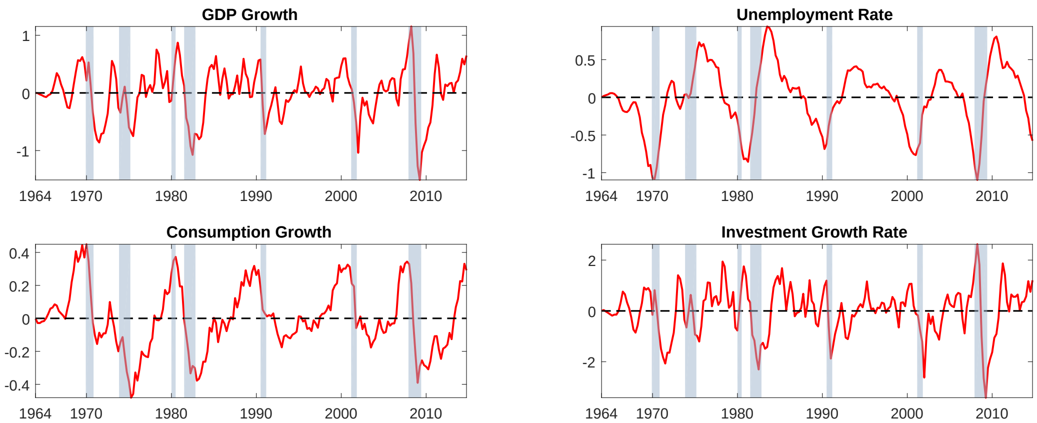

Figure 8: Counterfactual GDP growth rate, unemployment rate, consumption growth, and investment growth only due to noise shocks. All rates are in percent, and growth rates are annualized. The growth rates of GDP, consumption, and investment are annualized. Sample period: 1962:Q1-2008:Q3. Shaded areas denote NBER recessions.

fundamentals and noise, which captures those changes in expectations about future TFP that are orthogonal to any change in TFP fundamentals. Figure 7 shows the four- and eight-quarter-ahead TFP news shocks (black solid line) and their decomposition into future fundamentals and noise. Since the early 1990s, the contribution of noise to expectations (black bars) generally dominates the contribution of fundamentals (white bars). Expectations about future TFP (black solid line) are often revised upward at the end of expansions. In those periods, noise plays a major role in causing these revisions. This pattern suggests that noise has business cycle implications, raising employment and output at the end of booms and then suddenly generating a bust at the start of the recession when agents realize that the news was just noise. This type of dynamics was particularly relevant in the late 1960s, during the dot-com bubble, and in the years that preceded the Great Recession. The large negative contributions of future fundamentals (white bars) that preceded the recessions of 1974, the early 1980s, and the Great Recession capture the anticipated fall in TFP growth that occurred in those recessions.

How do we get identification of noise (i.e., the black bars in Figure 7)? As we have shown in Figure 6, the revisions of expectations about TFP, which are captured by TFP surprise and news shocks in the estimated model, are identified by observing the rate of unemployment. Disentangling the contributions of future fundamentals and noise to these revisions is achieved by directly observing TFP growth.

Full sample analysis. With the estimated noise shocks at hand, we can now answer the central question of this paper: What has been the historical role of noise in the U.S. postwar period? This can be worked out by simulating the model with the counterfactual estimates of the shocks $\tilde{\varepsilon}^0_{a,t}$, $\tilde{\varepsilon}^4_{a,t}$, and $\tilde{\varepsilon}^8_{a,t}$ in equations (33), (34), and (35). This is tantamount to producing the cumulated effects of noise shocks, which are the black bars in Figure 7 (after rescaling by the appropriate Kalman gain). Figure 8 plots the historical contribution of these noise shocks to the unemployment rate, GDP growth, consumption growth, and investment growth over the full sample 1962−2014.[33] A key result is that noise contributes to business cycles in a way that is fairly regular over time. Noise about TFP has contributed positively to the growth of consumption, investment, and output and to the fall in the unemployment rate during all the expansionary periods covered in our sample. We also find that noise played a role in lowering growth in output and its components and increasing unemployment in all recessions except the one occurring at the very beginning of the 1980s, which turns out to be dominated by monetary shocks. 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.

Quantitatively, noise has contributed to a quarterly fall of at most one percentage point of annualized output growth. The role of noise is particularly significant for labor market outcomes, and is reflected in cyclical fluctuations of the unemployment rate that oscillate within a two percentage-point band over the postwar period.

A remarkable result that comes out from our analysis is that TFP changes mainly explain trend unemployment rate. Yet, when we isolate those changes in beliefs that are orthogonal to TFP fundamentals, we find that they affect unemployment at business cycle frequencies. The main reason behind this finding is the different propagation of news and noise. While TFP news shocks give rise to persistent adjustments in employment, noise generates boom-bust macroeconomic dynamics as shown in Figure 5.

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 noise shocks (red solid line) over the Great Recession and its aftermath. The figure shows that noise shocks have contributed to about half of the increase in the unemployment rate through-to-peak, and about a third of the subsequent recovery.[34] 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 trend employment rate, as captured by the labor disutility shocks (the blue dashed-dotted line), has dropped significantly since 2010. This fall in the trend employment rate is driven by the dramatic drop in labor force

[33] It should be noted that noise shocks can be recovered using equations (30) and (32) based on the realizations of unanticipated shocks that will be observed in the future. Therefore, given that our sample ends in the fourth quarter of 2016, we are able to tease out 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.

[34] 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.

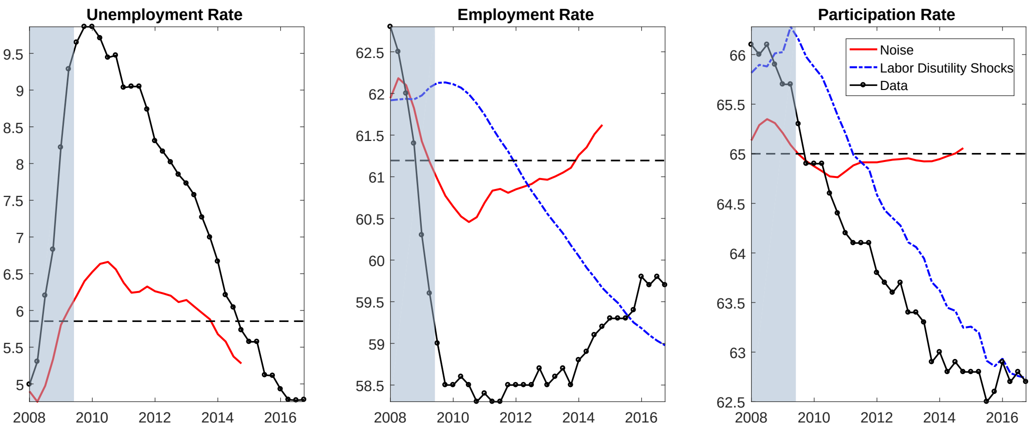

Figure 9: The effects of noise shocks and labor supply shocks to labor market dynamics in the Great Recession and its aftermath. The red solid lines refer to the counterfactual time series generated using only the smoothed estimate of noise shocks. The black lines with circles indicate actual data. The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

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 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 the negative territory during the Great Recession and the following years. The black bars capture the extent to which these negative expectations were exaggerated.

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 propagate to employment only slowly over time, as illustrated in Figure 5. Hence, the dynamics of employment over 2011 and 2012 are dominated by the sudden unraveling of the contractionary effect generated by the negative noise shocks that took place before 2011, rather than by the short-term effects of the negative noise shocks of 2011 and 2012. Since 2013, the rise in the employment rate has been sustained by favorable TFP news, which has turned out not to be backed by any actual TFP improvement.

Was there really any good news released in 2013 and in the following years? To answer this question we look at the University of Michigan's Index of Consumer Sentiment.[35] The left plot of Figure 10 reports the sum of the two-sided estimates of the four- and eight-quarter-ahead TFP news shocks on the left axis along with the consumer sentiment index on the right axis.

[35]This index seeks to find how consumers view (i) their own financial situation, (ii) the short-term general economy, and (iii) the long-term general economy. A more detailed description of how this index is constructed is in Appendix F.

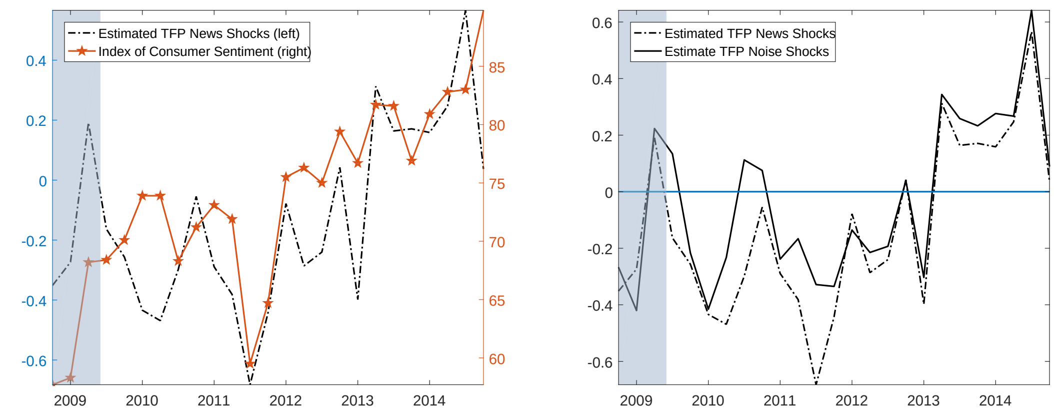

Figure 10: Estimated noise shocks, news shocks and the index of consumer sentiment. Noise shocks are rescaled by the relative Kalman gain and are defined as the sum of the four- and the eight-quarter-ahead noise shocks. Shaded areas denote NBER recessions.

Recall that TFP news shocks capture revisions of expectations about future TFP independent of whether these revisions turned out to be correct or not, so they seem a natural counterpart to the sentiment index. Moreover, since this index conflates expectations about the future state of the economy at different horizons, it is natural to compare it to the sum of news shocks at both four and eight quarters. While consumer sentiment attained the highest value since the onset of the Great Recession in early 2012, our model still predicts weak expectations about future TFP until the end of 2012. Since the first quarter of 2013 our model sees upward revisions of expectations about future TFP, and these predictions are supported by the Index of Consumer Sentiment.[36] This result is noticeable and provides external validation to this important finding, since we do not estimate the model using the sentiment index. The large negative comovement between the Index of Consumer Sentiment and the expectations about the future unemployment rate drives this result.[37] Finally, the right plot of Figure 10 shows that this flow of good news about TFP has turned out to be mostly noise. This can be seen in the similarity between the estimated series of noise and news in the right plot.[38]

Quantitatively, noise accounts for most of the recovery in the employment rate, and has therefore been the leading driver of the business cycle in this last part of the sample. 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).

[36] Values for the index above 80 are commonly observed in expansions.

[37] The correlation between the expected unemployment series used in estimation and the the Index of Consumer Sentiment ranges from -0.55 through -0.60. This negative correlation intensified after the 1970s. From 1980:Q1 through 2016:Q4, these correlations are equal to -0.66.

[38] Note that the noise shocks we plot are rescaled by the Kalman gain so that noise and TFP news are expressed in the same units.

Why such an important role for noise shocks during the Great Recession and the following recovery? As shown in Figure 1 the relationship between average unemployment rates 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 values observed during the 1990s, 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 TFP growth rate, the model resorts to noise shocks. It is important to realize that the model has several non-TFP shocks that could have explained the recent drop in the U.S. unemployment rate.

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-quarter-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 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 volatility of the unemployment rate and the contribution of noise to the business cycle is generally larger. This finding is essentially driven by the fact that TFP news shocks have a more persistent exogenous mechanism of propagation than under our approach that relies on i.i.d. news shocks. Very similar results are obtained if we allow for serial correlation of TFP news shocks (technology diffusion). 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-quarter-ahead

TFP news shocks). We cannot precisely identify these news shocks, since their propagation to the observable variables is too similar. This extended model gives us almost identical results.

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 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 cost 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 cycles in the unemployment rate during the postwar U.S. economy. 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 have played a role over the business cycle. Their role has intensified in recent years. For the first time since the 1960s noise has contributed almost entirely to the recovery in the employment rate after the Great Recession (including the labor market boom of 2014). This prediction is largely explained by the apparent decoupling between the unemployment rate, whose recent record-low values have strengthened beliefs about future TFP improvements, and the observed TFP growth.

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Appendix (for online publication)

A Derivation of first order conditions for the empirical model

Households:

$$
\begin{aligned}
\max \mathcal{L} = & E_t \sum_{s=0}^{\infty} \beta^s \Bigg\{ \eta^p_{t+s} \ln\left(C_{j,t+s} - \vartheta C_{t+s-1}\right) - \frac{\eta^l_{t+s}\chi}{1+\varphi} L^{1+\varphi}_{j,t+s} \\
& + \Phi_{j,t+s}\left[N_{j,t+s} + \varpi U_{j,t+s} - L_{j,t+s}\right] \\
& + \Omega_{j,t+s}\left[U_{j,t+s} + N_{j,t+s} - LF_{j,t+s}\right] \\
& - \lambda_{j,t+s} P_{t+s} \mathcal{V}^N_{j,t+s}\left[N_{j,t+s} - (1-\delta_N) N_{j,t+s-1} - x_{t+s}\frac{U_{j,t+s}}{1-x_{t+s}}\right]
\end{aligned}
$$

$$
\begin{aligned}
& -\lambda_{j,t+s}\left[P_{t+s}C_{j,t+s} + \eta^q_{t+s}P_{t+s}I_{j,t+s} + \frac{B_{j,t+s+1}}{R_{t+s}} - R^K_{t+s}K_{j,t+s-1} - W_{j,t+s}N_{j,t+s} - B_{j,t+s} - \Theta_{j,t+s} + T_{j,t+s}\right] \\
& -\lambda_{j,t+s}Q^K_{j,t+s}P_{t+s}\left[K_{j,t+s} - (1-\delta_K)K_{j,t+s-1} - \eta^I_{t+s}\left[1 - S\left(\frac{A_{t+s-1}I_{j,t+s}}{A_{t+s}I_{j,t+s-1}}\right)\right] I_{j,t+s}\right]\Bigg\}
\end{aligned}
$$

Taking first order conditions with respect to $C_{j,t}$, $B_{j,t+1}$, $L_{j,t}$, $U_{j,t}$, $LF_{j,t}$, $N_{j,t}$, $K_{j,t}$ and $I_{j,t}$ and rearranging them, we get the following list of equations:

$$\lambda_t = \frac{\eta^p_t}{P_t\left(C_t - \vartheta C_{t-1}\right)}, \tag{36}$$

$$\frac{1}{R_t} = \beta E_t \frac{\lambda_{t+1}}{\lambda_t}, \tag{37}$$

$$\frac{1}{\varpi}\frac{x_t}{1-x_t}\mathcal{V}^N_t = \frac{\eta^l_t \chi L^{\varphi}_t}{\lambda_t P_t} \tag{38}$$

$$\mathcal{V}^N_t = \frac{W_t}{P_t} - \frac{\eta^l_t\chi L^{\varphi}_t}{\lambda_t P_t} + (1-\delta_N) E_t \Lambda_{t,t+1}\mathcal{V}^N_{t+1}. \tag{39}$$

$$Q^K_t = E_t\Lambda_{t,t+1}\left[\frac{R^K_{t+1}}{P_{t+1}} + (1-\delta_K)Q^K_{t+1}\right] \tag{40}$$

$$Q^K_t = \frac{\eta^q_t - E_t\Lambda_{t,t+1}Q^K_{t+1}\eta^I_{t+1}S'\left(\frac{A_tI_{t+1}}{A_{t+1}I_t}\right)\frac{A_t}{A_{t+1}}\left(\frac{I_{t+1}}{I_t}\right)^2}{\eta^I_t\left[1 - S\left(\frac{A_{t-1}I_t}{A_tI_{t-1}}\right) - S'\left(\frac{A_{t-1}I_t}{A_tI_{t-1}}\right)\frac{A_{t-1}I_t}{A_tI_{t-1}}\right]} \tag{41}$$

where

$$E_t \Lambda_{t,t+1} = \frac{E_t \pi_{t+1}}{R_t}. \tag{42}$$

Firms

Final firms: Final firms maximize

$$\max P_t Y_t - \int_0^1 P_{i,t} Y_{i,t} di$$

subject to

$$Y_t = \left(\int_0^1 Y_{i,t}^{1/\left(1+\lambda_{f,t}\right)} di \right)^{1+\lambda_{f,t}}.$$

Taking first order conditions with respect to Y_t and Y_{it} and merging them, we can solve for the demand function

$$Y_{i,t} = \left(\frac{P_{i,t}}{P_t} \right)^{-\frac{1+\lambda_{f,t}}{\lambda_{f,t}}} Y_t. \tag{43}$$

Intermediate firms: Form the Lagrangian

$$\begin{aligned}
&E_t \sum_{s=0}^{\infty} \Lambda_{t,t+s} \Bigg\{ \frac{P_{i,t+s}}{P_{t+s}} \left(\frac{P_{i,t+s}}{P_{t+s}} \right)^{-\frac{1+\lambda_{f,t+s}}{\lambda_{f,t+s}}} Y_{t+s} - \frac{W_{i,t+s}}{P_{t+s}} N_{i,t+s} - \frac{R^K_{t+s}}{P_{t+s}} K_{i,t+s} \, , \\
&- \frac{\zeta}{2} \left(\frac{P_{i,t+s}}{\left(\Pi_{t+s-1}\right)^{\psi} \left(\bar{\Pi}\right)^{1-\psi} P_{i,t+s-1}} - 1 \right)^2 Y_{t+s} \\
&- Q^N_{i,t+s} \left[N_{i,t+s} - (1-\delta_N) N_{i,t+s-1} - H_{i,t+s} \right] \\
&+ \xi_{i,t+s} \left[- \left(\frac{P_{i,t+s}}{P_{t+s}} \right)^{-\frac{1+\lambda_{f,t+s}}{\lambda_{f,t+s}}} Y_{t+s} + f_{i,t+s} - g_{i,t+s} \right] \Bigg\}
\end{aligned} \tag{44}$$

Taking first order conditions with respect to $K_{i,t}$, $H_{i,t}$, $N_{i,t}$, and $P_{i,t}$ yields

$$\frac{R^K_t}{P_t} = \xi_t \left(f_{K,t} - g_{K,t} \right), \tag{45}$$

$$Q^N_t = \xi_t g_{H,t}, \tag{46}$$

$$Q^N_t = \xi_t \left(f_{N,t} - g_{N,t} \right) - \frac{W_t}{P_t} + (1-\delta_N) E_t \Lambda_{t,t+1} Q^N_{t+1}, \tag{47}$$

$$\left(\frac{\Pi_t}{(\Pi_{t-1})^{\psi}\left(\bar{\Pi}\right)^{1-\psi}}-1\right)\frac{\Pi_t}{(\Pi_{t-1})^{\psi}\left(\bar{\Pi}\right)^{1-\psi}}=\frac{1}{\zeta}\left(1-\frac{1+\lambda_{f,t}}{\lambda_{f,t}}\right)$$

$$+\xi_t\frac{1+\lambda_{f,t}}{\lambda_{f,t}}\frac{1}{\zeta}+\left(\frac{\Pi_{t+1}}{(\Pi_t)^{\psi}\left(\bar{\Pi}\right)^{1-\psi}}-1\right)\frac{Y_{t+1}}{Y_t}\left(\frac{\Pi_{t+1}}{(\Pi_t)^{\psi}\left(\bar{\Pi}\right)^{1-\psi}}\right), \tag{48}$$

where $\Pi_t \equiv P_t/P_{t-1}$.

Consolidating (45) with (40) yields:

$$Q_t^K = E_t\Lambda_{t,t+1}\left[\xi_{t+1}\left(f_{K,t+1}-g_{K,t+1}\right)+(1-\delta_K)Q_{t+1}^K\right]. \tag{49}$$

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 $\hat{c}_t = \ln \tilde{C}_t - \ln \tilde{C}$.

1. Labor force

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

2. Consumption Euler equation

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

3. Marginal utility of consumption

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

4. Law of motion for employment

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

5. Hiring

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

6. Labor participation decision

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

7. Value of employment to households

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

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

8. Production function

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

9. Output function

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

10. Adjustment cost function

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

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

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

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

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

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

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

14. Vacancy filling rate:

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

15. Law of motion for capital

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

16. FOC capital

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

17. FOC employment

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

18. Resource constraint

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

19. Phillips curve

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

20. Real wage equation

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

21. Inertial wage

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

22. Taylor Rule

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

23. Marginal productivity of labor

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

24. Marginal productivity of capital

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

25. Tobin's Q for capital

$$\hat{q}_t^K + \hat{\eta}_t^I = \hat{\eta}_t^q + S'' (1 + \beta) \hat{\imath}_t - S'' \hat{\imath}_{t-1} - \beta S'' \hat{\imath}_{t+1}. \tag{50}$$

26. Tobin's Q for employment

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

C Data Set Construction

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. All data used in estimation are quarterly.

D Measurement Equations

1. Real GDP growth

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

2. Real Consumption

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

3. Real Investment

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

4. Inflation rate (multiple indicator)

$$100 \cdot GDPDEFL_t = c^m_{\pi,1} + \lambda_{\pi,1}\hat{\pi}_t + 100 \ln \Pi_* + \sigma^m_{\pi,1}\eta^{\pi}_{1,t},$$

$$100\Delta PCE_t = c^m_{\pi,2} + \hat{\pi}_t + 100 \ln \Pi_* + \sigma^m_{\pi,2}\eta^{\pi}_{2,t},$$

$$100\Delta CPI_t = c^m_{\pi,3} + \lambda_{\pi,3}\hat{\pi}_t + 100 \ln \Pi_* + \sigma^m_{\pi,3}\eta^{\pi}_{3,t}.$$

5. Real wage growth

$$100\Delta \ln RW_t = c^m_w + \hat{w}^r_t - \hat{w}^r_{t-1} + \hat{\eta}_t^A + 100 \ln \mu + \sigma^m_w \eta_{w,t}.$$

6. Unemployment rate ($u_* = 0.056$)[39]

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

[39] To get this, observe that

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

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

7. Unemployment rate ($u_* = 0.056$)[40]

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

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

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

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

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

10. FFR (quarterly and in percent)

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

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

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

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

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

where f_T and f_P are two i.i.d. Gaussian factors with standard deviations $\sigma_{f,T}$ and $\sigma_{f,P}$, Λ_T and Λ_P are their respective loadings, and $\eta_{l,t}^{FG}$ are eleven i.i.d. measurement error

[40] To get this, observe that

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

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

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 $\Lambda_P(0) = 0$.

E Impulse Response Functions to TFP Shocks

Figures 11-13 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.

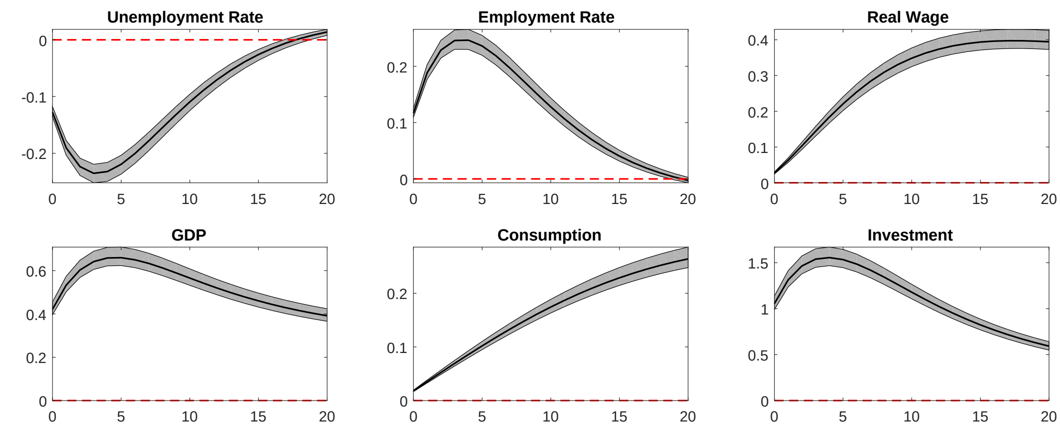

Figure 11: Posterior median of the response of unemployment rate, employment rate, real wage, GDP, consumption, and investment to a surprise shock to TFP. The gray areas denote the sixty-eight-percent posterior credible sets. The responses of unemployment and employment rates are expressed in percentage 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.

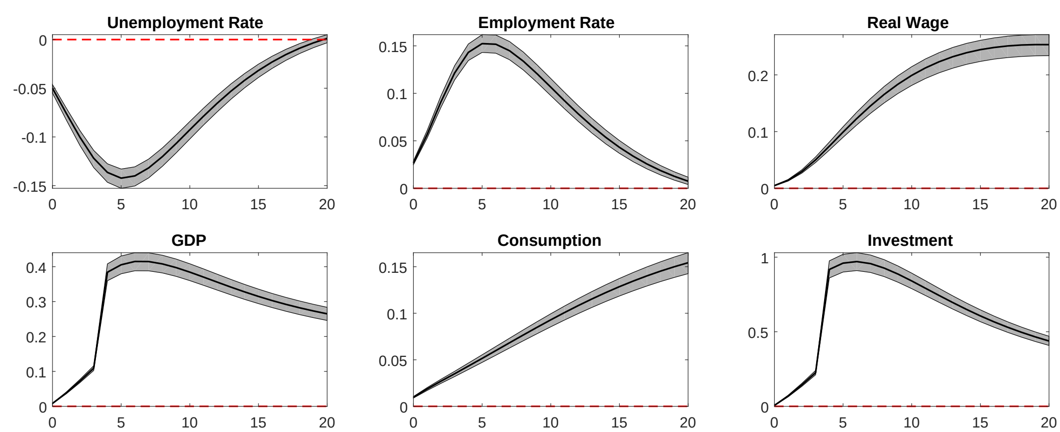

Figure 12: Posterior median of the response of unemployment rate, employment rate, real wage, GDP, consumption, and investment to a four-quarter-ahead shock to TFP. The gray areas denote the sixty-eight-percent posterior credible sets. The responses of unemployment and employment rates are expressed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

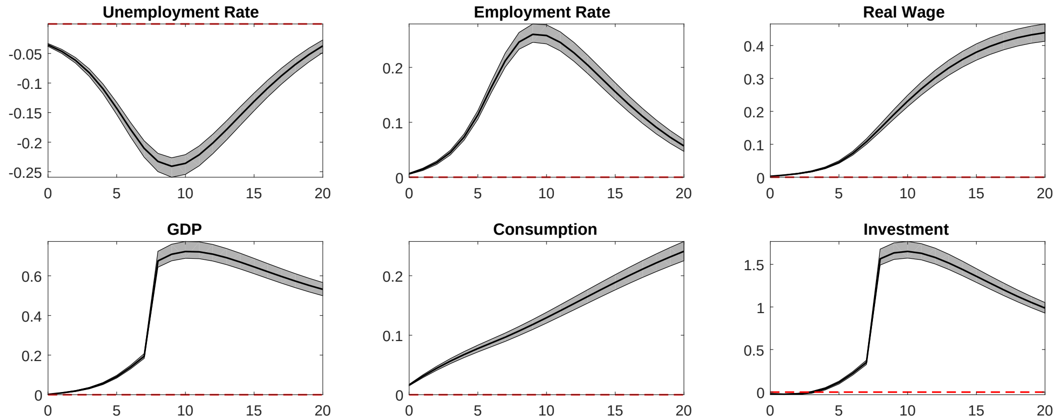

Figure 13: Posterior median of the response of unemployment rate, employment rate, real wage, GDP, consumption, and investment to an eight-quarter-ahead shock to TFP. The gray areas denote the sixty-eight-percent posterior credible sets. The responses of unemployment and employment rates are expressed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

F The Index of Consumer Sentiment

The Index of Consumer Sentiment (ICS) is derived from the following five questions:

1. "We are interested in how people are getting along financially these days. Would you say that you (and your family living there) are better off or worse off financially than you were a year ago?"

2. "Now looking ahead–do you think that a year from now you (and your family living there) will be better off financially, or worse off, or just about the same as now?"

3. "Now turning to business conditions in the country as a whole–do you think that during the next twelve months we'll have good times financially, or bad times, or what?"

4. "Looking ahead, which would you say is more likely–that in the country as a whole we'll have continuous good times during the next five years or so, or that we will have periods of widespread unemployment or depression, or what?"

5. "About the big things people buy for their homes–such as furniture, a refrigerator, stove, television, and things like that. Generally speaking, do you think now is a good or bad time for people to buy major household items?"

G The Role of Expected Unemployment Rates in Identifying TFP Shocks

Figure 14 shows the U.S. expected unemployment rate (black dashed-dotted line) along with the counterfactual time series obtained by simulating the estimated model using only the smoothed estimate of the TFP surprise shocks (red solid lines). Figure 15 shows the counterfactual series of the expected unemployment rate when the estimated model is simulated using only the smoothed estimate of the four-quarter and eight-quarter ahead TFP news shocks.

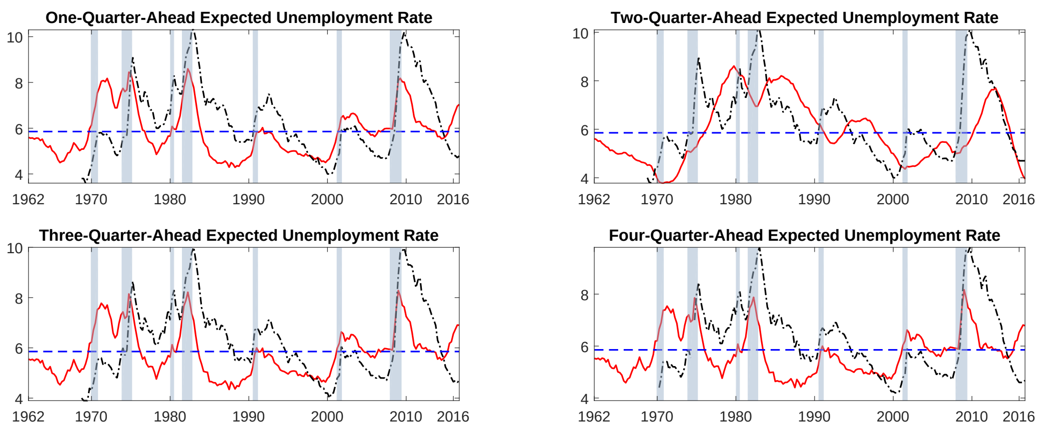

Figure 14: Expectations of U.S. unemployment rates (black dashed-dotted line), along with the counterfactual unemployment rate obtained by simulating the model using only the smoothed estimate of the surprise TFP shocks (red solid line). The counterfactual series are computed by setting the model parameters to their posterior modes, which are reported in Tables 1 and 2. Shaded areas denote NBER recessions.

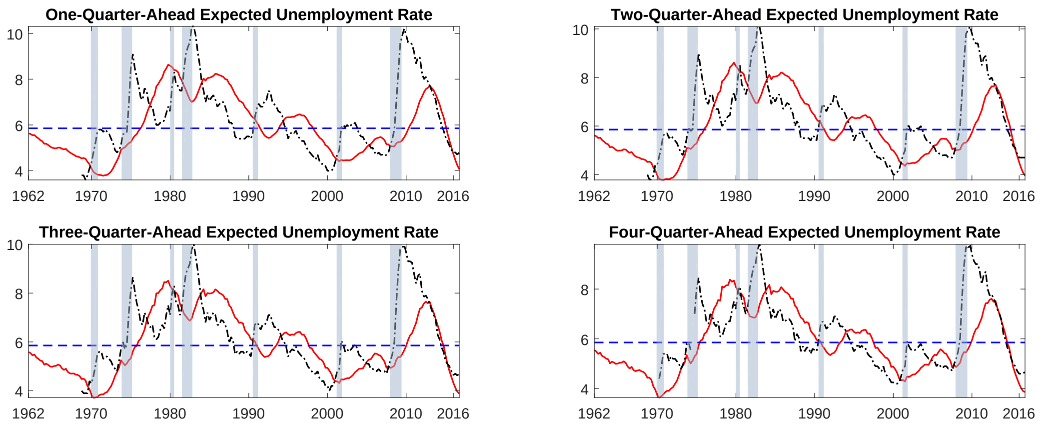

Figure 15: Expectations of U.S. unemployment rates (black dashed-dotted line), along with the counterfactual unemployment rate obtained by simulating the model using only the smoothed estimate of the four- and eight-quarter-ahead TFP news shocks (red solid lines). The counterfactual series are computed by setting the model parameters to their posterior modes, which are reported in Tables 1 and 2. Shaded areas denote NBER recessions.

H Parameter List

Tables 4 and 5 list the parameters of the estimated model with news shocks.

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

Table 4: Notations for the Model Parameters.

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

Table 5: Notations for the Model Parameters.