The Role of News about TFP in U.S. Recessions and Booms*

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Abstract

We develop a general equilibrium model to study the historical contribution of TFP news to the U.S. business cycle. Hiring frictions provide incentives for firms to start hiring ahead of an anticipated improvement in technology. For plausibly calibrated hiring costs, employment gradually rises in response to positive TFP news shocks even under standard preferences. TFP news shocks are identified mainly by current and expected unemployment rates since periods in which average unemployment is relatively high (low) are also periods in which average TFP growth is slow (fast). We work out the noise component of the identified TFP news shocks. Noise captures changes in agents' beliefs about future TFP shocks that do not materialize. These autonomous changes in beliefs have induced fluctuations in the unemployment rate within a two-percentage-point range across the post-war recessions and expansions. After the Great Recession, noise about TFP growth has been the most important factor behind the rise in the employment rate. The index of consumer sentiment and the dismal TFP growth in recent years support these predictions.

Keywords: Unemployment rate; hiring frictions; beliefs; the Great Recession; 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 has attracted interest from many generations of economists starting from Beveridge (1909), Pigou (1927), and Clark (1934). An appealing feature of this theory is that booms and busts can happen absent large changes in fundamentals and technological regress is not required to generate recessions. In recent years, there has been a revival of interest in this topic and scholars have applied modern time series models to investigate the validity of this hypothesis, starting from the seminal contributions by Beaudry and Portier (2004 and 2006). This literature has predominantly focused on how much of the volatility of business-cycle variables is explained by beliefs about future fundamentals (news shocks) and how much is explained by noise (pure beliefs). Nevertheless, very little is known about the historical contributions of pure beliefs to each expansion and recession. This matter is complicated because it requires careful estimation of news shocks and their noise component in the data.

We tackle this issue from a new angle by conjecturing that current and expected unemployment rates carry useful information to estimate TFP news shocks. This conjecture is motivated by Figure 1 that shows the five-year moving average of the unemployment rate and of the utilization-adjusted TFP growth rate measured as in Fernald (2012) and Basu, Fernald, and Kimball (2006). Periods during which TFP growth was slow (fast) are also periods of high (low) rates of unemployment, with the notable exception of the last ten years when this relationship is no longer visible. While the reasons for this recent decoupling will be investigated later in the paper, we emphasize that the relationship between the average unemployment rate and TFP growth appears to have been fairly stable over most of the post-war period. Indeed, scholars have long recognized that the dynamics of productivity and unemployment are closely connected (e.g., Bruno and Sachs 1985; Phelps 1994; Blanchard, Solow, and Wilson 1995; Blanchard and Wolfers 2000; Benigno, Ricci, and Surico 2015). Figure 1 provides suggestive evidence that the rate of unemployment appears to be influenced by TFP. If so, then unemployment rates carry useful information to identify TFP shocks and, to the extent that these shocks are anticipated, also to TFP news.[1] Furthermore, if unemployment carries information about TFP, then expectations about future unemployment are informative about expected TFP and hence about TFP news shocks.

[1]Stock market prices have predictive power on the average growth rate of TFP over the next five years. We use the time series for the growth rate of TFP and the log-difference of real S&P500 (Shiller CAPE: Real S&P 500 Composite Index, ssp500r@usecon, from Haver). The data series span the period 1962Q1:2008Q3. We reject the null that S&P500 does not Granger cause the average TFP growth rate over the next five years with a p-value of 0.0007. When we test the reversed causal link we cannot reject the null. Results are robust to permutations across various lags. Moreover, the recent VAR literature finds that TFP news shocks are a key determinant of low-frequency TFP dynamics (Beaudry and Portier 2006; Barsky and Sims 2011; and Basu, Barsky, and Lee 2015). In some specifications, anticipated shocks to TFP account for as much as over 40% of the forecast error variance decomposition of TFP at twenty quarters.

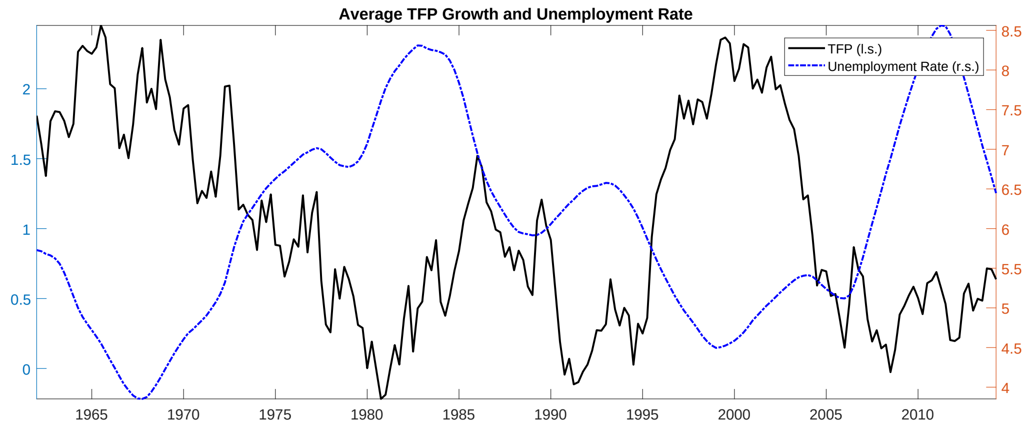

Figure 1: Five-year centered moving average of the unemployment rate and TFP growth rate, The time series are the U.S. civilian unemployment rate from the Bureau of Labor Statistics and the growth rate of TFP adjusted for capital utilization computed by Fernald (2012).

To study the historical contribution of pure beliefs to 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 news have to bring about a positive and persistent increase in the employment rate. However, it is well-known that positive responses of employment are hard to obtain in standard dynamic general equilibrium models (Barro and King 1984 and 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 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 (Merz and Yashiv 2007). This type of frictions is supported by various empirical micro-labor studies suggesting that hiring entails a temporary loss of firm-level production efficiency (Bartel 1995, Krueger and Rouse 1998, Cooper, Haltiwanger, and Willis 2015 etc.). The mechanism is based on the interaction between 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. Other frictions, such as consumption habits and wage inertia, complement hiring frictions in explaining the build-up in employment after positive TFP news shocks. Nevertheless, we can show that the estimated model would predict a fall in employment following the news if the magnitude of hiring costs was half of its estimated value, suggesting that hiring frictions are essential to counterbalance the wealth effect.

The model is estimated with likelihood methods by using current and expected unemployment rates and TFP growth among other macroeconomic time series. The unemployment rate responds sluggishly to TFP news shocks. Furthermore, the dynamics of unemployment and expected unemployment play a key role in estimating TFP news shocks in the U.S. post-war period. The model interprets the 1960s as a period in which favorable technological news have pushed unemployment rates below their long run average. The 1970s and 1980s have instead been two decades dominated by lackluster news about TFP, which considerably raised unemployment rates. Finally, the 1990s and 2000s have been dominated again by positive news about technology and, hence, lower unemployment rates.

In the model, agents continuously receive news about future TFP developments. Sometimes this anticipated information actually materializes while other times it turns out to be just noise. In other words, news shocks carry information about noise shocks, which capture changes in agents' beliefs that are not backed by future changes in TFP. In this sense, noise shocks can be interpreted as autonomous changes in agents' beliefs, which some scholars have pointed out to be a potentially important source of business fluctuations (Pigou 1927, Blanchard 1993, Hall 1993, Beaudry and Portier 2004 and 2006). In line with this view, boom-bust responses of GDP, consumption, investment and the unemployment rate occur in response to noise in the estimated model. The bust occurs when agents realize that TFP news are 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 slowly falls. As a result, output contracts and stays below its steady-state level for a fairly long period of time, suggesting that noise may lead to long-lasting recessions or booms.

We then tease out the historical series of noise shocks from the estimated news shocks and find that these exogenous changes in beliefs have contributed positively to the growth of consumption, investment, and GDP in all booms and recessions with the only exception of the first recession of the 1980s. Noise shocks have accounted for fluctuations of unemployment rates within a band of about two percentage points over the post-war period.

When we extend the analysis to include the Great Recession and the following recovery, we find that noise shocks have played an unprecedented, crucial role in explaining the fall in the rate of unemployment from the fourth quarter of 2009 and on.[2] In 2010 the 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. According to our analysis, the aftermaths of the Great Recession has been the first time in which exogenous shifts in beliefs have been the leading driver of business cycle dynamics. 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 estimate the model using the sentiment index, this finding provides an important external validation for the model.

Why did noise shocks start contributing so significantly to employment after the Great Recession? The reason is in Figure 1: the link between unemployment and TFP that has characterized the post-war period breaks down in the latest part of the sample. As 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 turn 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) shows that the correlation of news shocks identified across a number of studies is very low. We tackle this problem by showing that current and expected unemployment rates are key to identify TFP news shocks. Moreover, observing the actual TFP growth rate allows us to directly identify the noise components of TFP news shocks. Hardly any of the standard structural shocks in empirical macroeconomics can be directly identified by observable time series. An exception is the investment-specific-technology (IST) shock, which can be arguably identified using the inverse of the relative price of equipment (Fisher 2006).[3] Nonetheless, 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. They also find that surprise shocks to the marginal efficiency of investment (MEI) are important and, hence, we rather include these shocks in our model. These results are reminiscent of the findings in Justiniano, Primiceri, and Tambalotti (2011a) about the importance of surprise MEI shocks.

Our paper is connected to the literature that studies the role of TFP news in business cycles. The original contribution of Beaudry and Portier (2006) suggests that business cycles might be,

[2]Not all of the recent fall in the unemployment rate is explained by noise. The unemployment rate has also fallen since 2009 because the participation rate has dropped significantly. The model explains this fall in participation with changes in a low-frequency exogenous factor (namely, shocks to households' labor disutility) capturing long-lasting demographic and social changes to the U.S. labor force.

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

to a significant extent, expectation-driven. The issue at stake has been whether recessions could happen without technological regress, but rather stemming from downward revisions of beliefs about future technology. Subsequent works by Barsky and Sims (2011), Forni, Gambetti, and Sala (2014), Barsky, Basu, and Lee (2015) have challenged these conclusions on the grounds of alternative identification schemes for VAR analysis. Critics of the expectation-driven business-cycles-hypothesis have concluded that anticipated technology shocks might be an important propagation mechanism for low-frequency dynamics of macroeconomic variables, whereas their high-frequency effects are unclear. We offer a reconciliation for these two apparently conflicting views, by providing evidence in favor of the hypothesis that U.S. business cycles have been, to some extent, expectation-driven, while showing that TFP news shocks have also been a key determinant of trend unemployment rates.

Our paper also contributes to the literature on structural estimation of news and noise shocks, and is therefore connected to the work of Christiano, Ilut, Motto, and Rostagno (2010), Barsky and Sims (2011), Barsky and Sims (2012) , Schmitt-Grohe and Uribe (2012), Khan and Tsoukalas (2012), Blanchard, L'Huillier, and Lorenzoni (2013), Nguyen and Miyamoto (2014), Barsky, Basu, and Lee (2015), Theodoridis and Zanetti (2016), and Chahrour and Jurado (2017). Our work differs from those contributions in one or more of the following dimensions. First, we investigate the historical role that news and noise played across each of the booms and recessions that have characterized the postwar U.S. economy. The aforementioned papers assess the contribution of news and noise shocks by looking only at the fraction of the unconditional variance of GDP, consumption, investment, and hours explained by these shocks. Second, our study assesses the role of TFP news and noise during the Great Recession and the ensuing recovery. Third, the key identification mechanism for TFP news and noise shocks is based on observing the unfiltered rates of unemployment and their expectations, as well as the TFP growth rate. With the notable exception of Barsky and Sims (2012) and Nguyen and Miyamoto (2014), the existing literature does not use data on private sector's expectations to estimate the parameters of their model with news shocks. Fourth, we do not assume preferences à la Jaimovich and Rebelo (2009) that allow to parameterize the magnitude of the wealth effect. In our paper, preferences are standard. On the methodological side, we build on the important contribution by Chahrour and Jurado (2017), 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 shocks in causing macroeconomic events of interest (e.g., the Great Recession) without solving the model with noise.

We highlight the role of data on current and expected unemployment rates for the identification of news shocks and, jointly with observing the growth rate of TFP, noise shocks. In this respect, our paper connects to the aforementioned literature on the link between unemployment and TFP dynamics at low frequencies. In particular, Benigno, Ricci, and Surico (2015) use a model with asymmetric real wage rigidities to explain this link and its decoupling during the Great Recession by leveraging on the observation that the volatility of labor productivity rose during the most recent recession. In their model, higher volatility increases the probability of a significant adverse shock that makes the downward wage constraint binding, thus leading to higher long-run unemployment. Unlike Benigno, Ricci, and Surico (2015), the main focus of our paper is on the business cycle implications of TFP news shocks and of the associated noise. In our paper, the link between the unemployment rate and TFP growth is merely used for identifying TFP news shocks. Differently from that paper, we impute the instability of this link to the arrival of noise about future TFP dynamics. Our model is also related to the theoretical literature on news shocks that has attempted to overcome the Barro and King (1984) critique, following the lead of Jaimovich and Rebelo (2009). We propose a new propagation mechanism that hinges on hiring frictions. Finally, our paper is related to Faccini and Yashiv (2017), who investigate the role of hiring frictions modelled as forgone output for the propagation of traditional, unanticipated shocks in a simpler model. They abstract from news shocks altogether as well as from structural estimation.

The paper is structured as follows. Section 2 presents the model used in estimation. Section 3 discusses the estimation and the evaluation of the model. In Section 4, we analyze the historical role of noise in explaining the U.S. postwar business fluctuations. In Section 5, we run a number of robustness checks. Section 6 contains our concluding remarks.

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 a la Christiano, Eichenbaum, and Evans (2005), Smets and Wouters (2007), and Justiniano, Primiceri, and Tambalotti (2010), except for how hiring costs are modeled.[4] The economy is populated by a continuum of households, and each household comprises a unit measure of members, whose labor market status can be classified as inactive, unemployed or employed. We assume full sharing of consumption risk across households' members. Intermediate goods firms are monopolistically competitive and produce differentiated goods by renting capital from the households in a perfectly competitive market, by hiring workers in a frictional labor market, and by setting prices subject to Rotemberg adjustment costs. Final good firms package these differentiated goods into a homogeneous composite good that is sold to the households and the

[4]The model is a rich specification of the economy in Faccini and Yashiv (2017), extended to include, among other features, an endogenous participation margin and anticipated shocks to technology.

government under perfect competition. The wage is set according to a simple surplus splitting rule with wage inertia a 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 $U_t = (1 - x_t)U_t^0$. Assuming that employed workers lose their job with probability δ_N at the end of each period, N_t obeys the law of motion: $N_t = (1 - \delta_N)N_{t-1} + x_t U_t^0$.[5]

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

[5] 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. Indeed, if labor market frictions were unreasonably small, the wealth effect would have important implications for participation and employment. We will show that in the estimated model the wealth effect on labor supply and the effect of frictions on labor demand nicely balance out, giving rise to a response of employment to positive TFP news that is close to zero upon impact and then gradually builds up, in line with the VAR evidence (e.g., Barsky, Basu and Lee, 2015).

is a scale parameter, $\bar{C}_{t-1}$ denotes aggregate consumption, and η_t^p and η_t^l denote exogenous 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 (2011b), 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 below, 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 wage income W_t from employed workers, revenues from renting capital to the firms $R_t^K K_{t-1}$, dividends from firms Θ_t and pays lump sum government taxes T_t.[6] 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 price P_t.

Let β denote the discount factor. The intertemporal problem of the households is to choose state-contingent sequences for $\{C_{t+s}, I_{t+s}, B_{t+s+1}, LF_{t+s}, U_{t+s}\}_{s=0}^{\infty}$ 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 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 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

[6] 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. Moreover, as we will discuss in Section 3.4, we have estimated a version of the model with variable capacity utilization and obtained similar results.

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 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 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.[7]

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. Specifically, we assume that $\eta_t^A = A_t/A_{t-1}$ is a stochastic trend that follows the process

[7] 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, Muehlemann, Schenker, and Wolter (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, Beaulieu, Phibbs, and Stone (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.

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

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

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

where $\varepsilon_{a,t}^0$ is an iid unanticipated shock to TFP, and $\varepsilon_{a,t}^4$ and $\varepsilon_{a,t}^8$ denote iid innovations to the future value of TFP anticipated four and eight quarters in advance, respectively. This particular timing of anticipation of technology shocks follows Schmitt-Grohe and Uribe (2012).[8] It is worthy emphasizing that equation (6) implies that TFP news shocks capture revisions of expectations about future TFP innovations. This framework is quite general and is flexible enough to capture situations in which agents receive some favorable news about future TFP developments and after four or eight quarters they discover that the news does not pan out and, in fact, is just noise.[9]

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, among others, by Merz and Yashiv (2007), Gertler, Sala, and Trigari (2008), Christiano, Trabandt, and Walentin (2011) and Furlanetto and Groshenny (2016) 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.[10]

[8] The literature has developed different ways of modeling news shocks. We follow Schmitt-Grohe and Uribe (2012) because this is the simplest approach, which also leads to a very intuitive noise representation. Robustness of results to alternative approaches (e.g., that in Barsky and Sims, 2012) is discussed in Section 5.

[9] Chahrour and Jurado (2017) formalize the link between news and noise and show that our model with news shocks can be recast into an observationally equivalent model with noise (or noise representation). Being the two models 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.

[10] 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 more detailed discussion.

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 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:

$$E_t \sum_{s=0}^{\infty} \Lambda_{t,t+s} \left\{ \begin{array}{c} \frac{P_{i,t+s}}{P_{t+s}} Y_{i,t+s} - \frac{W_{i,t+s}}{P_{t+s}} N_{i,t+s} - \frac{R^K_{t+s}}{P_{t+s}} K_{i,t+s} \\ -\frac{\zeta}{2} \left(\frac{P_{i,t+s}}{(\Pi_{t+s-1})^{\psi} \left(\bar{\Pi}\right)^{1-\psi} P_{i,t+s-1}} - 1 \right)^2 Y_{t+s} \end{array} \right\}, \tag{8}$$

where the parameter ζ controls the degree of price rigidities à la Rotemberg, the parameter ψ governs inflation indexation and $\bar{\Pi}$ denotes the steady-state gross inflation rate. The problem of the intermediate 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, who are the owners of the firms.

2.4 Wage Bargaining

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

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

where ω is a parameter that governs wage rigidities.[11] 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:

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

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

where V_t^N and Q_t^N are the marginal values of jobs for households and firms, which are derived from the first order conditions of their respective maximization problems.[12]

2.5 Policymakers and Market Clearing

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

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

where $\tilde{Y}_t \equiv Y_t/A_t$, Y^* denotes the steady-state value of $\tilde{Y}_t$, the parameter ρ_r controls the degree of interest rate smoothing, $\Pi_t \equiv P_t/P_{t-1}$ is the actual gross rate of price inflation and r_y and r_π govern the response of the monetary authority to deviations of output and inflation from their target values, Y^* and Π_t^*, respectively. We assume that the monetary shock η_t^R follows an iid Gaussian process while Π_t^* captures persistent deviations from the long-run inflation target Π_*

$$\ln \Pi_t^* = (1 - \rho_\pi) \ln \Pi_* + \rho_{\Pi^*} \ln \Pi_{t-1}^* + \varepsilon_t^\pi.$$

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 illus-

[12]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 Groeshny 2016, and Christiano, Eichenbaum, and Trabandt 2016).

trated 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. 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 firm in (8):[13]

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

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

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, whereas ξ_t represents the 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 marginal revenue ξ_t. Note that the marginal revenue 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 prices are sticky, this fall in demand generates excess production, which in turn implies that the marginal revenue falls. A fall in the marginal revenue 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 marginal revenue is given by

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

and is proportional to the value of a job to the firm, and hence is increasing in the parameter governing the intensity of hiring frictions e. For values of hiring frictions that are in line with

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

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 the mechanism above? 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 instead, firms can use their workers to produce hiring services instead of output goods, which contributes to reabsorbing the initial excess production. The incentive to divert resources from production to hiring increases with the fall in hiring costs, which in itself increases with the magnitude of hiring frictions e. So the larger labor market frictions are, the higher the recruiting effort that follows an expansionary TFP news, 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 the above mechanism. Namely, 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 unique steady-state equilibrium. The list of the log-linearized equations of the model is reported in Appendix H. 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 (e.g., Fernandez-Villaverde and Rubio-Ramirez and An and Schorfheide 2007).

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 introduce the prior distribution for the model parameters in Section 3.3. The posterior moments, the fit of the model, and the contribution of TFP shocks to the variance of the business cycle 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.

3.1 Data and Measurement

The data set we use for estimation comprises sixteen observable variables for the U.S. economy at quarterly frequency: Real per-capita GDP growth, real per-capita consumption growth, real per-capita investment growth, the employment rate, the participation rate, 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, respectively adjusted and non-adjusted for variable capacity utilization, and three measures of inflation dynamics: GDP deflator, the consumer price index (CPI), and the personal consumption expenditure (PCE). Details on how these series are constructed are in Appendix D.

We map GDP to the model's output net of hiring costs precisely because hiring costs entail production inefficiencies. We observe expectations about the rate of unemployment measured by the *Survey of Professional Forecasters*. We consider horizons of one, two, three, and four quarters for these expectations.[14] Since these four series start in 1968Q1, the Kalman filter will treat these unavailable data points as missing observations. To account for any discrepancy of these expectations from rationality (Coibion, Gorodnichenko, and Kamdar 2018), we introduce a measurement error for each of these four series.

The series for adjusted and non-adjusted TFP are computed following Fernald (2012) in a way that ensures model consistency. Specifically, we adjust TFP for employment in bodies rather than total hours, for consistency with the model's notion of labor input. 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.[15] 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 since standard ways of modeling capital utilization are easily rejected by data. Alternatively, we could rely on statistical methods to correct the series

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

[15] 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.

of TFP growth for capital utilization as Fernald (2012) and Basu, Fernald, and Kimball (2006) do, and then use only this adjusted series for measuring TFP in the model. One shortcoming of this approach is that Fernald's 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 materially affects the inference about the macroeconomic effects of TFP news shocks. We mitigate these problems by adopting a flexible approach based on observing both the unadjusted and the 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. This approach arguably reduces the impact of measurement errors and data revisions concerning the estimate of capital utilization on our analysis. Specifically, the observation equations for the two TFP growth rates read

$$\Delta \ln TFP_t^N = c_{TFP,unadj}^m + \lambda_{TFP,unadj}^m \left[\hat{a}_t - \hat{a}_{t-1} + \alpha \hat{\eta}_t^A + 100\alpha \ln \mu\right] + \eta_{TFP,t}^N, \tag{17}$$

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

where $\Delta \ln TFP_t^N$ and $\Delta \ln TFP_t^A$ denote the series of unadjusted and adjusted TFP growth expressed in percent quarterly rates, $\lambda_{TFP,unadj}^m$ 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, Evans, Fisher, and Justiniano (2012), Barsky, Justiniano, and Melosi (2014), Campbell, Fisher, Justiniano, and Melosi (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 the PCE inflation equal to one. Results will not be 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. The full list of measurement equations are shown in Appendix E.

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 also be useful for identifying TFP news shocks. The participation rates and the employment rates are nonstationary arguably because of demographics and social changes that have affected the U.S.

labor force over the last 50 years. This feature of these series poses a serious challenge to our stationary model. As we will show, we set up our prior so that the labor disutility shocks are aimed at capturing these low-frequencies in employment and participation rates. We will return to this point in Section 3.4.

3.2 Estimation Strategy

The federal funds rate was stuck at its effective lower bound from 2008Q4 through 2015Q3. 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 filters to evaluate the likelihood. These filters rely on MC methods and, hence, are more computationally intensive and arguably less accurate than the Kalman filter. A simpler way to go about this issue has been proposed by Campbell, Evans, Fisher, and Justiniano (2012) and followed by Barsky, Justiniano, and Melosi (2014), Campbell, Fisher, Justiniano, and Melosi (2017), Del Negro, Giannoni, and Patterson (2012), and Del Negro, Giannone, Giannoni, and Tambalotti (2017) among others. This approach amounts to append a number of i.i.d. news shocks (called forward guidance shocks) to the monetary policy reaction function (13) and use data on market-based future federal funds rate to estimate the model.[16] 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 after 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 evaluating the historical role played by news and noise shocks in the most recent period.

We construct the market expected federal funds rate from the overnight interest rate swap data (Wright 2017). In line with the standard practice in the literature, 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.[17]

As in aforementioned contributions, we estimate the model sequentially over two subsamples. We first estimate the model over a sample period that goes from 1962Q1 through 2008Q3 using the data described in the previous section. Then we re-estimate only the measurement

[16] Details on how this approach changes the monetary policy reaction function are provided in appendix.

[17] The forward guidance shocks in the Taylor rule are an array of iid shocks from the perspective of agents in the model. The factor model is just measurement. We run a principal component analysis so as to verify that a two-factor model is adequate to explain most of the comovement among the expected interest rates. This two-factor structure was originally introduced by Gürkaynak, Sack, and Swanson (2005).

parameters (see Panel C of Table 6 in Appendix H for a list of measurement parameters) and the forward guidance parameters over the second sample (2008Q4 through 2016Q4). All the structural parameters are set to their first-sample posterior mode (see Table 5 and Table 6: Panel A and B in Appendix H for a list of those 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 rationale for having this two-step approach is that the Great Recession period is likely to be the most volatile period in the sample. Consequently, if one merged the two samples into one long sample, the second sample would play a disproportioned role in informing the value of model's parameters. This is undesirable because it would distort our analysis about the historical role of news and noise during the period that precedes the Great Recession. 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. Moreover, note that forward guidance shocks expand the state vector of the model.

Prior and Posterior Distribution 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
$\mu 100$	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
u^*100	5.8539	5.8452	5.7192	5.9479	N	5.6000	0.1000
π^*100	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 "Type" indicate the prior density function: N, G, and B stand for Normal, Gamma, Beta, respectively. See Table 5 in Appendix H for a description of the parameters.

3.3 Priors

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

Prior and Posterior Distribution for the Parameters of Shocks 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 structural parameters. The letters in the column "Type" indicate the prior density function: N, G, B, and IG stand for Normal, Gamma, Beta, and Inverse Gamma, respectively. See Table 6 in Appendix H for a description of the parameters.

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. 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 and the posterior mode for the structural parameters of the model are reported in Table 1. Priors and posteriors 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 participation and the rate of employment.

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 (1962Q1:2008Q3). Results are reported in Tables 1 and 2. Then we generate 500,000 posterior draws via the Metropolis-Hastings algorithm. As 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

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 participation rates have been detrended by subtracting their respective trends implied by the labor disutility shock before computing their standard deviation. For 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 percents. Sample period: 1962Q1-2008Q3.

parameters estimated over the second sample (2008Q4:2016Q4) are not reported but they are available upon request. Recall that only the measurement parameters (see Panel C of Table 6 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 still 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.[18]

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 DSGE 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

[18]This result seems to contradict Barsky, Basu, and Lee (2015), who obtain Pigouvian responses to TFP news shocks by adding only real wage inertia to an otherwise standard New Keynesian model. Two features explain these divergent results. First, in that paper the anticipation horizon of news shocks is just one period. In fact, if we added a one-quarter-ahead TFP news shock, we would find similar results for its propagation. Second, in that paper news shocks are modeled as anticipated shocks to the drift of TFP growth. While the main results of our paper are robust to modeling TFP news shocks in a similar way, we find that following the approach in Schmitt-Grohe and Uribe (2012) makes the identification of noise more transparent.

	TFP Surprise Shocks	TFP News Shocks
GDP Growth Rate	36	51
Consumption Growth Rate	1	0
Investment Growth Rate	18	26
Employment Rate	31	40
Participation Rate	17	28
Unemployment Rate	31	39
Expected Unemployment Rate (1-quarter ahead)	34	42
Expected Unemployment Rate (2-quarter ahead)	34	46
Expected Unemployment Rate (3-quarter ahead)	32	49
Expected Unemployment Rate (4-quarter ahead)	30	54

Table 4: Variance decomposition at business cycle frequencies (6, 32 quarters) for various observable variables. The unemployment rate is not directly observed but it is implied by observing the employment and participation rates. Parameters are equal to their posterior modes for the sample period 1962Q1-2008Q3.

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.[19]

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 excess capacity induced by price rigidities has to be absorbed by either a jump in investment, or a sharp increase in hiring costs. By selecting a tiny estimate of investment adjustment costs, the likelihood favors outcomes where employment responds smoothly while 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 DSGE models with no frictions in the labor market. It turns out that labor market frictions lower the volatility of investment because of the complementarities between hiring and investment that are implied by the Cobb-Douglas production function.

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,

[19] Manning (2011), in a review of the hiring costs literature states that: "The bulk of these [hiring] costs are the costs associated with training newly-hired workers and raising them to the productivity of experienced workers". According to Silva and Toledo (2009), training costs are measured to be about ten times as large as recruiting costs, which are typically modelled as vacancy posting costs. Similar results are obtained by Muhlemann and Leiser (2015) using Swiss administrative establishment-level survey data.

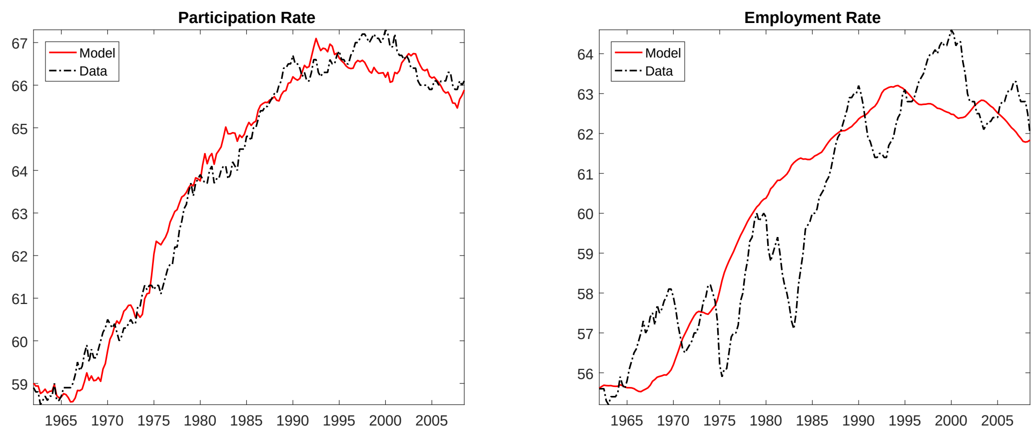

Figure 2: Detrending the rate of participation and the rate of employment. The black dashed-dotted lines denote the data and the red solid lines denote the two rates simulated from the estimated model by using only the filtered (one-sided) estimates for the labor disutility shocks. The estimated model's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

φ, is in line with the survey of micro evidence in Chetty, Guren, Manoli, and Weber (2013a), 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 participation in the post-war 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 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, Table 3 shows the standard deviations of the observable variables predicted by the estimated model and compares them to the data. Overall the estimated model matches well the empirical second moments. The volatility of investment is slightly overestimated, which implies that the volatility of output is also somewhat above its empirical counterpart. The volatility of adjusted TFP news shocks implied by the model is very close to the one measured in the data. 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 marginal revenues and marginal hiring costs conditional on technology shocks generates

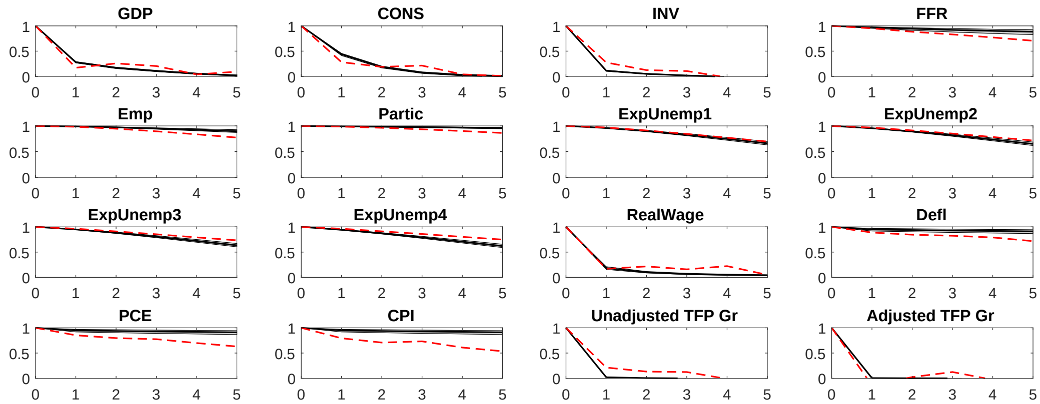

Figure 3: Posterior autocorrelation functions computed for every 100 posterior draws. The red dashed line denotes the empirical autocorrelation function and the solid black line denotes the posterior median for the autocorrelation implied by the model. The gray areas denote the 90-percent posterior credible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

a powerful amplification mechanism.[20] As discussed in Section 2.6, standard models instead predict a procyclical hiring costs, which makes it difficult to account for the volatility of labor market outcomes. 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 inflation, employment, and participation.

Table 4 shows the variance decomposition for a number of observable variables at business cycle frequencies (6 quarters to 32 quarters). This table highlights the role of TFP news, and more in general the relative importance of technology in driving key macroeconomic variables at business cycle frequencies. Because in the model the marginal cost of hiring is countercyclical conditional on technology shocks, and procyclical conditional on demand shocks, technology shocks are relatively more important than demand shocks as a determinant of cyclical labor market dynamics.

The key take-away from the table is that anticipated and unanticipated technology shocks are important drivers of the business cycle. Notice also that the contribution of TFP news shocks increases as the horizon of the expected unemployment rate rises. Conversely, surprise TFP shocks are relatively less important in explaining the variance of expected unemploy-

[20] 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 because amplification is driven by the countercyclicality of marginal hiring costs.

ment rates at longer horizons. All in all, labor market variables are largely explained by TFP shocks, in particular by anticipated TFP shocks. Labor market frictions make hiring decision forward-looking and, in doing so, raise the contribution of anticipated shocks to the dynamics of employment and unemployment. Technology shocks explain 85% of the volatility in GDP growth and 44% of the volatility of investment growth. Consumption growth is mainly explained by the preference shocks (88%).

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 so as to help show the difference in propagation rather than in relative size across the three shocks. There are three important points that emerge from comparing these impulse response functions. First, all three shocks produce over time an expansionary response of labor market variables, output and its components, which 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 build-up thereafter. A similar argument applies to the other macroeconomic aggregates reported in the figure. Third, after a news shock most of the build-up in employment and fall in unemployment occurs 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 VAR evidence in Beaudry and Portier (2006), 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' marginal revenue, ξ_t, drops as the news shock hits and stays negative throughout the anticipation period, leading to a prolonged fall in marginal hiring costs. The arrival of news ends up depressing aggregate demand which provides an incentive for firms to hire more workers even in this model with several sources of frictions (e.g., wage inertia). If the magnitude of the parameter governing 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 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 build-up in employment in Figure 4.

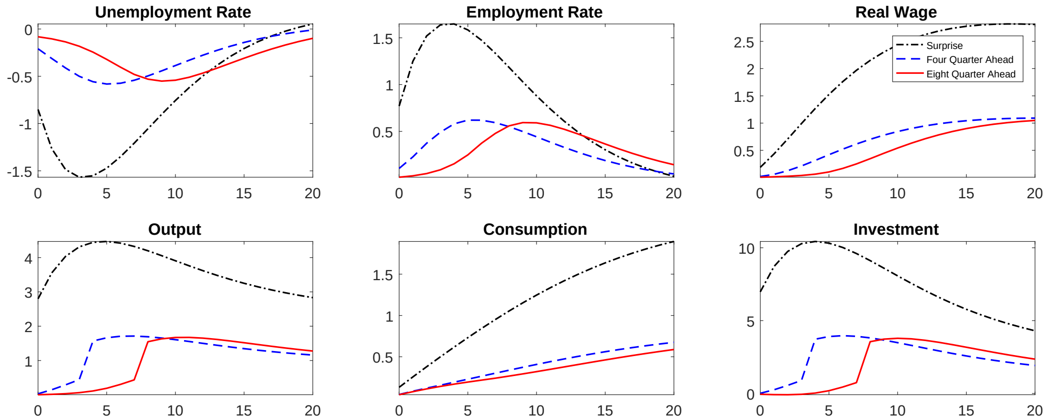

Figure 4: Estimated response of unemployment rates, employment rates, real wages, output, consumption, and investment to surprise TFP shocks (black dotted-dashed line), four-quarter-ahead shocks (blue dashed line), and eight-quarter-ahead TFP shocks (red solid line). The responses of unemployment and employment 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. Parameter values are set to their posterior modes, shown in Table 1 and 2.

It should also be noted that investment and output rise before the anticipated TFP shock 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 results, 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 responses of investment and output to TFP news shocks. 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 pure beliefs in business cycles less intuitive.

What are the effects of a TFP news shock that eventually does not pan out? In other words, what is the effect of a noise shock that captures changes in agents beliefs about future TFP that are orthogonal to actual changes in TFP? We find that this type of shocks can generate *boom-bust dynamics*. The effects are plotted in Figure 5. These impulse responses describe the propagation of an eight-quarter-ahead TFP shock that agents discover to be just noise eight quarters later. To construct the impulse responses to this noise shock 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.[21] As a result, the

[21] We have used the word "noise shock" with some abuse of terminology. As we will show in Section 4.1, eight-quarters-ahead noise shocks implied by the noise representation exhibit slightly different dynamics due to the revision of expectations after four quarters. In practice, such revision is minimal, and we ignore it here for the sake of exposition.

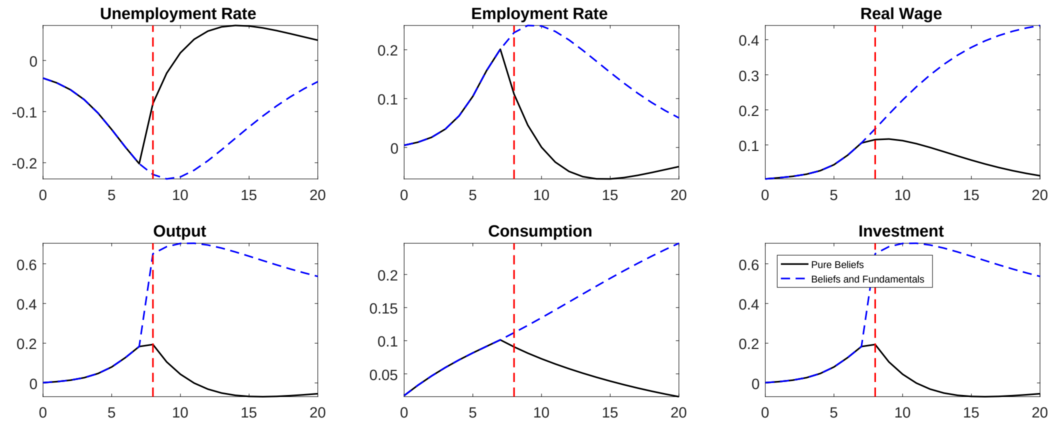

Figure 5: Estimated response of unemployment rate, employment rate, real wage, output, consumption, and investment to a TFP new shock (blue dashed line) and a TFP noise shock (black solid line), both anticipated eight quarters ahead. The responses of unemployment and employment are expressed in percent deviations from their steady-state rate. All other responses are in percentage deviations from their steady-state value. The size of the initial shock is one standard deviation. Parameter values are set to their posterior modes, shown in Table 1 and 2.

effect of this combination of shocks is generated purely by beliefs.

Figure 5 shows the propagation of this noise shock (solid black line) and compares it to the propagation of an eight-quarter-ahead TFP news shock (blue dashed line). Not surprisingly, the propagation of these two shocks is 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 noise shock. The bust occurs when agents realize that TFP news are 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 slowly falls. Therefore, output falls and remains below its steady-state level for a fairly long period of time, suggesting that noise may lead to long-lasting recessions and expansions (if the initial news is negative). It should be 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 in the wake of the fall in investment that drives down aggregate demand.

3.6 Estimation of TFP News and Surprise Shocks

We have conjectured that changes in the unemployment rate carry important information to identify 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-quarter and eight-quarter ahead TFP news shocks (red solid lines).[22] As we conjectured, these shocks appear to have been a key driver of the rate of unemployment at lower frequencies over the post-war period. In particular, anticipated TFP shocks appear to have induced relatively low rates of unemployment in 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 last part of the sample, and lackluster growth in between. Data on expected unemployment rates help identify TFP news shocks in a similar way (see Figures 10 and 11 in Appendix G). There are two main reasons why the model explains the dynamics of current and expected unemployment rates with TFP news shocks. 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.[23]

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 affect not only beliefs but also actual TFP (fundamentals). To test the Pigouvian hypothesis, one needs to isolate the noise component of these identified TFP news shocks, which we call noise shocks or pure beliefs for brevity. Like TFP news shocks, noise shocks affect expectations about future TFP changes but, unlike TFP news, they are not backed by any actual change in future TFP. As we will show more formally in the next section, noise shocks can be thought of as specific linear combinations of news and surprise shocks. To see why, recall the example in the previous section where we constructed a noise shock by engineering a negative surprise shock offsetting a previously anticipated positive shock. Thus, to understand the role of pure beliefs in business cycles one has to look also at the

[22] The smoothed shocks are conditioned on the first-sample observations only.

[23] 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 are modeled as i.i.d. shocks. We do not find support for this third potential explanation. Judging from the autocorrelation function of the smoothed estimate of TFP news shocks, it appears 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 corrrelation of the eight-quarter ahead shocks is statistical significant but very low, 0.18.

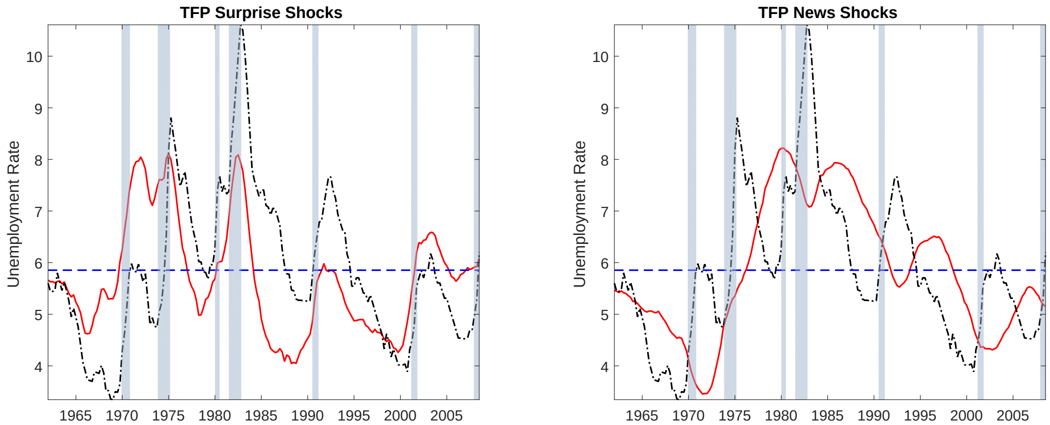

Figure 6: Left Plot: The U.S. unemployment rate (black dashed-dotted line) implied by the observed series of the employment and participation rates, along with the counterfactual unemployment rate obtained by simulating the model using only the smoothed estimate of the surprise TFP shocks (red solid 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. Sample period 1962Q1:2008Q3. The gray areas denote the NBER recessions.

behavior of TFP surprise shocks. To this end, 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 surprise TFP shocks have significantly contributed to unemployment dynamics during the postwar recessions and booms. We will return to the link with noise in the next section.

It is very important to emphasize that if we had estimated the model without observing the rates of participation, employment, and expected unemployment, TFP news and surprise shocks would have played a negligible role in estimation. Specifically, the contribution of these shocks to the variance of GDP growth, consumption growth, and investment growth would have been close to zero. These results underscore the importance of observing labor market data to identify TFP shocks.

Furthermore, if the model were estimated without observing 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. In contrast, simulation with only smoothed TFP surprise shocks would make the two lines very similar in the left plot, suggesting that surprise shocks play a dominant role in explaining the unemployment rate in this case. This finding seems consistent with the variance decomposition in Table 4, where TFP news shocks play a particularly important role in explaining the variance of expected unemployment in the data. This is not surprising given that news shocks directly affect the expectations about future TFP. These results lend support to the importance of forward-looking data on the rate of unemployment for identifying the historical realizations of TFP news shocks.

4 The Historical Role of Noise about TFP

So far, most of our analysis has focused on the role of TFP news shocks. These shocks can be interpreted as revisions in agents' expectations about future TFP innovations. We have estimated a dynamic general equilibrium model with TFP news shocks and found that changes in the observed unemployment rates are key to identifying these shocks. Moreover, we showed that noise shocks lead to a boom-bust-type propagation in employment, output, consumption, and investment. Noise shocks are those shocks that, like TFP news shocks, affect beliefs about future TFP growth. However, unlike TFP news shocks, noise shocks never actually manifest themselves in TFP. Therefore, given the historical realizations of TFP news shocks, which is identified by the changes in the unemployment rate (Section 3.6), the observed TFP growth rate pins down the historical realizations of noise shocks. Since, by construction, noise shocks will never affect TFP fundamentals, they can be thought of as capturing *autonomous changes in agents' expectations,* which according to Pigou (1927) are important drivers of business cycles.

This section is organized as follows. Section 4.1 shows 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 business cycle fluctuations over the first sample of estimation (1962Q1-2008Q3). In Section 4.3, we extend the analysis of the previous section to the Great Recession period and after.

4.1 Identifying 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 towards the maintained goal in three steps. We first characterize the noise representation of the estimated model with TFP news shocks by using the formalization introduced by the pathbreaking paper of Chahrour and Jurado (2017). Second, with the parameter values of the noise representation at hand, we use the two-sided filtered series of TFP news shocks over the full sample 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 2017). The empirical model with news is observationally equivalent to the noise representation in which the TFP process follows the process: $a_t = \rho_a a_{t-1} + \eta_t^a$. Agents receive signals $s_{8,t}$, $s_{4,t}$ and $s_{0,t}$ at time t that are defined as

$$
\begin{aligned}
s_{8,t} &= \eta_{t+8}^{a} + v_{8,t}, && (19)\\
s_{4,t} &= \eta_{t+4}^{a} + v_{4,t}, && (20)
\end{aligned}
$$

and conventionally $s_{0,t} = x_t^a$ with

$$
\begin{bmatrix} \eta_t^a \\ v_{4,t} \\ v_{8,t} \end{bmatrix} \overset{iid}{\backsim} N\left(\begin{bmatrix} 0 \\ 0 \\ 0 \end{bmatrix}, \begin{bmatrix} \sigma_\eta^2 & 0 & 0 \\ 0 & \sigma_{4,v}^2 & 0 \\ 0 & 0 & \sigma_{8,v}^2 \end{bmatrix} \right). \tag{21}
$$

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

$$
\sigma_{8,v}^2 = \left(\sigma_{0a}^2 + \sigma_{4a}^2 + \sigma_{8a}^2\right)\left(\frac{\sigma_{0a}^2 + \sigma_{4a}^2}{\sigma_{8a}^2}\right), \tag{22}
$$

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

and

$$
\sigma_\eta^2 = \sigma_{a,0}^2 + \sigma_{4,a}^2 + \sigma_{8,a}^2 \tag{24}
$$

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

Step 2: Teasing Out the Historical Realizations of Noise Shocks. Realize that, in the news representation, expectations revisions in period t, $t+4$, and $t+8$ are captured by the realization of news shocks $\varepsilon_{a,t}^i$ with $i \in \{0, 4, 8\}$, respectively. In symbols,

$$
\begin{aligned}
E_t \eta_{t+8}^a &= \varepsilon_{a,t}^8, && (25)\\
E_{t+4}\eta_{t+8}^a - E_t \eta_{t+8}^a &= \varepsilon_{a,t+4}^4, && (26)\\
\eta_{t+8}^a - E_{t+4}\eta_{t+8}^a &= \varepsilon_{a,t+8}^0. && (27)
\end{aligned}
$$

Therefore, by denoting the two-sided filter TFP news shocks as $\hat{\varepsilon}_{0,t}^a$, $\hat{\varepsilon}_{4,t}^a$, and $\hat{\varepsilon}_{8,t}^a$ we can write the solution to the time-t signal extraction problem concerning the technology innovation at time $t+8$ as follows:

$$
E_t \eta_{t+8}^a = \kappa_8 \left(\eta_{t+8}^a + v_{8,t}\right) = \hat{\varepsilon}_{a,t}^8, \tag{28}
$$

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 shocks. Substituting $\eta_{t+8}^a = \hat{\varepsilon}_{a,t+8}^0 + \hat{\varepsilon}_{a,t+4}^4 + \hat{\varepsilon}_{a,t}^8$

in equation (28) and rearranging terms leads to the implied series of noise shocks $\hat{v}_{8,t}$:

$$\kappa_8 \hat{v}_{8,t} = (1-\kappa_8)\,\hat{\varepsilon}^8_{a,t} - \kappa_8\left(\hat{\varepsilon}^0_{a,t+8} + \hat{\varepsilon}^4_{a,t+4}\right). \tag{29}$$

Let us write the solution to the time-t signal extraction problem concerning the technology innovation at time $t+4$ as follows:

$$\begin{aligned} E_t\eta^a_{t+4} - E_{t-4}\eta^a_{t+4} &= \kappa_4\left(x^a_{t+4} + v_{4,t} - E_{t-4}\eta^a_{t+4}\right), \\ &= \kappa_4\left(x^a_{t+4} + v_{4,t} - \hat{\varepsilon}^8_{a,t-4}\right) = \varepsilon^4_{a,t}, \end{aligned} \tag{30}$$

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 shocks. In the last row we made use of the fact $E_{t-4}\eta^a_{t+4} = \hat{\varepsilon}^8_{a,t-4}$. Substituting $\eta^a_{t+4} = \varepsilon^0_{a,t+4} + \varepsilon^4_{a,t} + \varepsilon^8_{a,t-4}$ in equation (30) and rearranging terms leads to the following equation that gives us the implied series of noise shocks $\hat{v}_{4,t}$:

$$\kappa_4 \hat{v}_{4,t} = (1-\kappa_4)\,\hat{\varepsilon}^4_{a,t} - \kappa_4\hat{\varepsilon}^0_{a,t+4}. \tag{31}$$

Equations (29) and (31) show that noise shocks are a particular linear combinations of TFP news shocks and future surprise shocks.

Step 3: Assessing the Historical Contribution of Noise Shocks. We compute the revisions in expectations only due to the estimated noise shocks $\hat{v}_{4,t}$ and $\hat{v}_{8,t}$ by using the solution to the signal extraction problems at horizon 4 and 8 periods; that is, equations (28) and (30). Since news shocks capture revisions in expectations, we can use the estimated noise shocks from Step 2 to compute the counterfactual TFP news shocks as follows:[24]

$$\tilde{\varepsilon}^8_{a,t} = \kappa_8 \hat{v}_{8,t}, \tag{32}$$

$$\tilde{\varepsilon}^4_{a,t} = \kappa_4 \hat{v}_{4,t} - k_4 k_8 \hat{v}_{8,t}, \tag{33}$$

and

$$\tilde{\varepsilon}^0_{a,t} = -\kappa_4\left(\hat{v}_{4,t-4} - \kappa_8\hat{v}_{8,t-8}\right) - \kappa_8 v_{8,t-8}. \tag{34}$$

These counterfactual news shocks can be used to simulate the estimated model with news and obtain the sought contribution of noise shocks to business fluctuations. Note that noise shocks have no effect on TFP innovations since $\tilde{\varepsilon}^0_{a,t} + \tilde{\varepsilon}^4_{a,t-4} + \tilde{\varepsilon}^8_{a,t-8} = 0$ for every t in our sample period.

[24] 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.

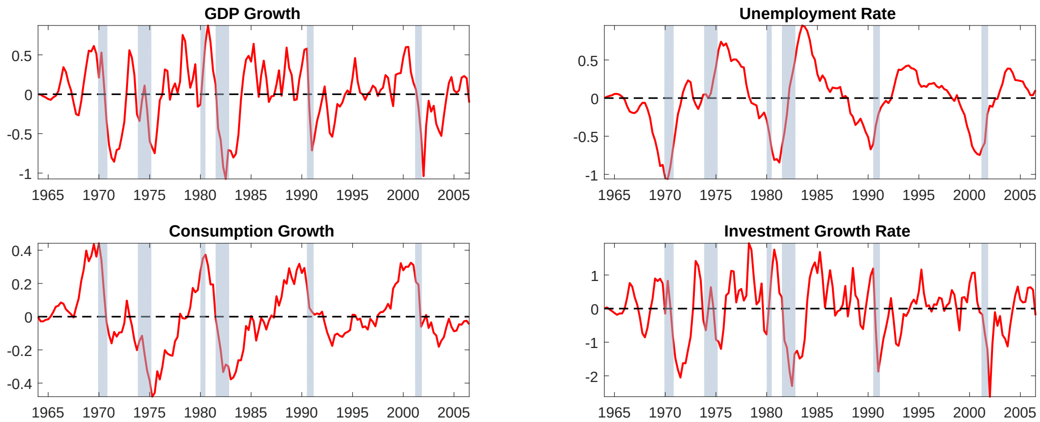

Figure 7: Counterfactual GDP growth rate, unemployment rate, consumption growth, and investment growth only due to noise shocks. All rates are in percent and growth rates are annualized. The growth rates of GDP, consumption, and investment are annualized. Sample period: 1962Q1-2008Q3. Shaded areas denote NBER recessions.

4.2 The Historical Role of Noise Shocks Before the Great Recession

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 shocks in the U.S. postwar period? Figure 7 provides the answers to these questions by showing plots of the historical contribution of noise shocks to the unemployment rate, GDP growth, consumption growth, and investment growth.[25] Pure changes in beliefs about TFP have contributed positively to the growth of consumption, investment and output during all the expansionary periods covered in our sample. We also find that pure beliefs played a role in lowering growth in output and its components in all recessions except the one occurring in the early 1980s, which turns out to be dominated by monetary shocks. Pure beliefs have contributed to a quarterly fall of at most one percentage point of annualized output growth. They have also contributed to the observed dynamics of the unemployment rate within a two percentage-point band.

4.3 The Great Recession and its Aftermaths (2008Q4 - 2014Q4)

While in the pre-Great-Recession period, pure beliefs have played a moderate role in driving the business cycle, their role has been particular important during the Great Recession and the ensuing recovery. The left panel of Figure 8 plots the observed unemployment rate (solid black line with circles) along with the unemployment rate implied only by noise shocks (red solid line). 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. The

[25]The smoothed shocks used for the simulations reported in Figure 7 are conditioned on the first-sample observations only.

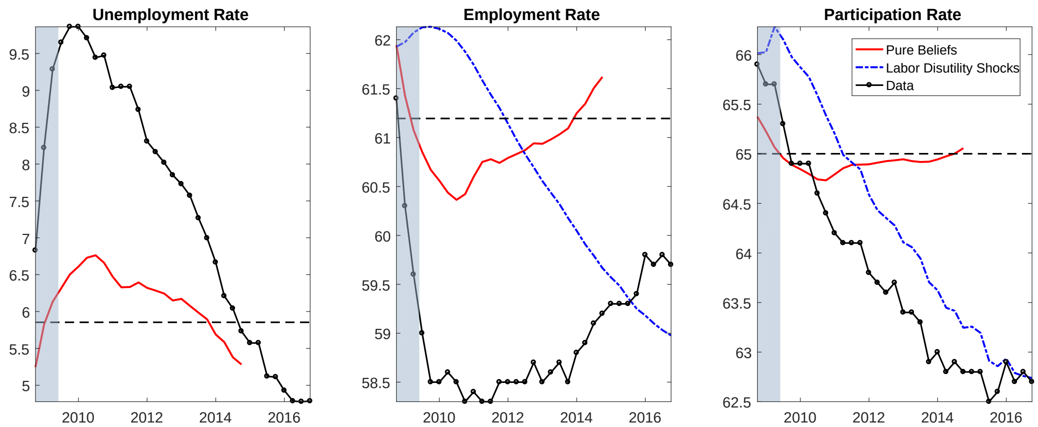

Figure 8: The effects of noise shocks and labor supply shocks to labor market dynamics in the Great Recession and its aftermath. The red solid lines refer to the counterfactual time series generated using only the smoothed estimate of noise shocks. The black lines with circles indicate actual data. The 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.

center plot shows that noise shocks have accounted for most of the recovery in the employment rate. This belief-driven increase in employment is the result of negative expectations at the time of the Great Recession and its immediate aftermaths, that turned out to be exaggerated. 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. Note also that the trend employment rate, as captured by the labor disutility shocks (the blue dashed-dotted line), has dropped significantly since 2010.[26] The employment rate crossed its long-run trend from below and this recovery has been almost exclusively driven by pure beliefs.

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.[27] The left plot of Figure 9 reports the sum of the two-sided estimates of the four-quarter-ahead and the eight-quarter-ahead TFP news shocks on the left axis along with the consumer sentiment index on the right axis. Recall that the TFP news shocks capture revisions of expectations about future TFP independently of whether these revisions turned out to be correct or not. 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

[26]Smoothed labor disutility shocks are mainly identified by the the common trend of both of the participation rate and the employment rate. The graph that shows this result is extremely similar to Figure 2 for the first sample and is available upon request.

[27]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.

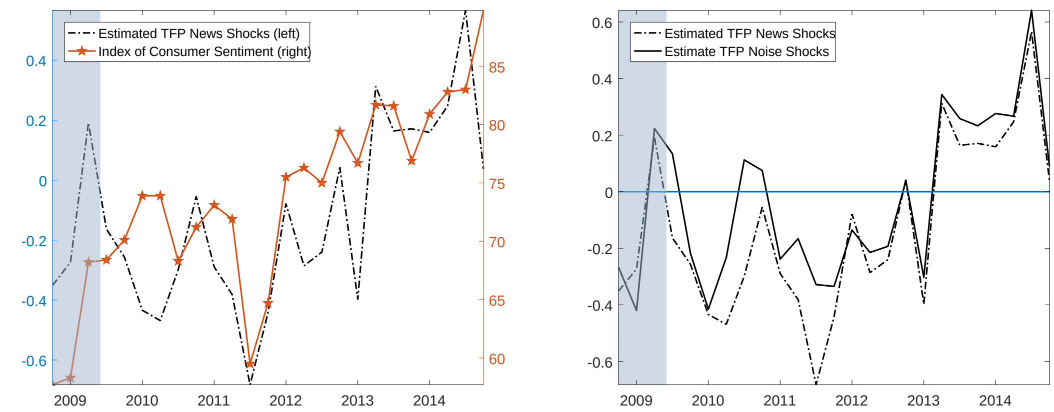

Figure 9: Estimated noise shocks, news shocks and the index of consumer sentiment. Noise shocks in the plot are rescaled by the Kalman gain and are defined as the sum of the four-quarter-ahead and the eight-quarter-ahead noise shocks. TFP news shocks are defined analogously.

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. Since we do not estimate the model using the sentiment index, this finding provides an important external validation for the model. Finally, the right plot of Figure 9 shows that this flow of good news about TFP has turned out to be mostly noise. This can be seen by observing how similar the estimated series of noise and news are in the right plot.[28]

Quantitatively, the role of pure beliefs in raising employment is large and unprecedented. This is the first example of exogenous shifts in beliefs being the leading driver of the business cycle in our sample period. What accounts for the remaining two-thirds of the recovery in the unemployment rate is the fall in the rate of participation, which reflects the very low-frequency dynamics engendered by the labor disutility shock (the blue dashed-dotted line).

Why such a big 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, which has been arguably fairy stable during the pre-Great-Recession period, has 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 average unemployment rate was similarly low. To explain 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.

[28]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.

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 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 unemployment rate and all the results of the paper would be quantitatively smaller. The outcomes of this exercise 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. 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.

We also test the robustness of our results to how TFP news shocks are modeled. For instance, we could follow Barsky and Sims (2012), who model news shocks as anticipated information about the future drift in TFP growth. When we estimate our model with TFP news shocks à la Barsky and Sims, our results generally strengthen. Now TFP news shocks explain even a larger fraction of volatility of the unemployment rate and the contribution of noise shocks to the business cycle is generally larger. This finding is largely 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. 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. Furthermore, the noise representation of our model is more intuitive. See Chahrour and Jurado (2017) who characterize the noise representation for both our model and for the model in Barsky and Sims (2012).

We also estimate a model in which households choose the utilization rate of physical capital and lend just 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 technological developments are the key drivers of the low-frequency cycles in unemployment rate during the post-war U.S. economy. Noise shocks, which capture changes in beliefs about future TFP innovations that will never actually materialize, give rise to boom-bust responses of output and employment. These autonomous changes in beliefs have played a moderate role over the business cycle. However, their role has intensified in recent years. The improvement in the employment rate that has been observed during the recent recovery has been almost entirely driven by changes in beliefs that are not backed by any changes in technological fundamentals. 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 TFP growth.

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Appendix

A Derivation of first order conditions for the simple model

The simple model is a streamlined version of the empirical model presented in Sections 2 and in Appendix B. The notation is the same in the two models.

Households: It is assumed that the household derives disutility from the fraction of workers who participate to the labor market L_t. Unlike in the empirical model, unemployed and employed workers generate the same disutility to the household. Hence the index of labor supply that enters the utility function is simply the participation rate.

The maximization problem is

$$\max E_t \sum_{s=0}^{\infty} \beta^s \left\{ \ln C_{t+s} - \frac{\chi}{1+\varphi} L_{t+s}^{1+\varphi} \right\}$$

subject to the definition of labor force

$$L_t = N_t + U_t,$$

the budget constraint

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

the law of motion for capital

$$K_t = (1 - \delta_K) K_{t-1} + I_t,$$

and the law of motion for employment

$$N_t = (1 - \delta_N) N_{t-1} + x_t U_{0,t},$$

where

$$U_{0,t} = \frac{U_t}{1 - x_t}.$$

Form the Lagrangian:

$$\begin{aligned} \max \mathcal{L} = & E_t \sum_{s=0}^{\infty} \beta^s \left\{ \ln C_{t+s} - \frac{\chi}{1+\varphi} L_{t+s}^{1+\varphi} \right. \\ & + \Phi_{t+s} \left[N_{t+s} + U_{t+s} - L_{t+s} \right] \end{aligned}$$

$$-\lambda_{t+s} P_{t+s} \mathcal{V}^N_{t+s} \left[N_{t+s} - (1-\delta_N) N_{t+s-1} - x_{t+s} \frac{U_{t+s}}{1-x_{t+s}} \right]$$

$$-\lambda_{t+s} \left[P_{t+s} C_{t+s} + P_{t+s} I_{t+s} + \frac{B_{t+s+1}}{R_{t+s}} - R^K_{t+s} K_{t+s-1} - W_{t+s} N_{t+s} - B_{t+s} - \Upsilon_{t+s} + T_{t+s} \right]$$
$$-\lambda_{t+s} Q^K_{t+s} P_{t+s} \left[K_{t+s} - (1-\delta_K) K_{t+s-1} - I_{t+s} \right] \} .$$

The FOCs with respect to C_t, B_{t+1}, U_t and N_t are:

FOC K_t

$$\lambda_t P_t Q^K_t = \beta E_t \lambda_{t+1} \left[R^K_{t+1} + (1-\delta_K) P_{t+1} Q^K_{t+1} \right]$$
$$Q^K_t = \beta E_t \frac{P_{t+1}}{P_t} \frac{\lambda_{t+1}}{\lambda_t} \left[\frac{R^K_{t+1}}{P_{t+1}} + (1-\delta_K) Q^K_{t+1} \right] \tag{35}$$

FOC I_t

$$\lambda_t P_t = \lambda_t P_t Q^K_t \Rightarrow Q^K_t = 1 \tag{36}$$

FOC C_t

$$\lambda_t = \frac{1}{P_t C_t}, \tag{37}$$

FOC B_{t+1}

$$\frac{1}{R_t} = \beta E_t \frac{\lambda_{t+1}}{\lambda_t}, \tag{38}$$

FOC $L_{j,t}$

$$\Phi_t = -\chi L_t^{\varphi} \tag{39}$$

FOC U_t

$$\lambda_t P_t \mathcal{V}^N_t \frac{x_t}{1-x_t} = -\Phi_t \tag{40}$$

FOC N_t

$$\mathcal{V}^N_t = \frac{W_t}{P_t} - \frac{x_t}{1-x_t} \mathcal{V}^N_t + (1-\delta_N) \Lambda_{t,t+1} \mathcal{V}^N_{t+1}. \tag{41}$$

Using

$$E_t \Lambda_{t,t+1} \equiv \beta E_t \frac{\lambda_{t+1}}{\lambda_t} \frac{P_{t+1}}{P_t} = \frac{E_t \pi_{t+1}}{R_t},$$

and merging (35) and (36) and using the above expression for the discount factor we obtain:

$$1 = E_t \Lambda_{t,t+1} \left(\frac{R^K_{t+1}}{P_{t+1}} + 1 - \delta_K \right). \tag{42}$$

Merging (37) and (38) yields:

$$\frac{1}{R_t} = \beta E_t \frac{P_t C_t}{P_{t+1} C_{t+1}}.$$

Merging (39) and (40) we get:

$$\frac{x_t}{1-x_t}\mathcal{V}_t^N = \frac{\chi L_t^{\varphi}}{\lambda_t P_t},$$

which plugged into (41) yields:

$$\mathcal{V}_t^N = \frac{W_t}{P_t} - \frac{\chi L_t^{\varphi}}{\lambda_t P_t} + (1-\delta_N)\, E_t \Lambda_{t,t+1} \mathcal{V}_{t+1}^N. \tag{43}$$

Firms: The maximization problem is

$$\max E_t \sum_{s=0}^{\infty} \Lambda_{t,t+s} \left\{ \frac{P_{i,t+s}}{P_{t+s}} Y_{i,t+s} - \frac{W_{i,t+s}}{P_{t+s}} N_{i,t+s} - \frac{R_{t+s}^K}{P_{t+s}} K_{i,t+s} - \frac{\zeta}{2}\left(\frac{P_{i,t+s}}{P_{i,t+s-1}} - 1\right)^2 Y_{t+s} \right\} \tag{44}$$

subject to the definition of output net of hiring costs

$$Y_{i,t} = f_{it} - g_{it},$$

the law of motion for employment

$$N_{i,t} = (1-\delta_N) N_{i,t-1} + H_{i,t}, \tag{45}$$

and the demand function

$$Y_{i,t} = \left(\frac{P_{i,t}}{P_t}\right)^{-\epsilon} Y_t,$$

where $\epsilon = \frac{1}{\lambda}$ denotes the elasticity of substitution. See Appendix B for derivations of the demand function from the problem of final good producers.

The Lagrangian reads:

$$\max E_t \sum_{s=0}^{\infty} \Lambda_{t,t+s} \left\{ \begin{array}{c} \left(\frac{P_{i,t+s}}{P_{t+s}}\right)^{1-\epsilon} Y_{t+s} - \frac{W_{i,t+s}}{P_{t+s}} N_{i,t+s} \\ -\frac{R_{t+s}^K}{P_{t+s}} K_{i,t+s} - \frac{\zeta}{2}\left(\frac{P_{i,t+s}}{P_{i,t+s-1}} - 1\right)^2 Y_{t+s} \\ +Q_{i,t+s}^N \left[(1-\delta_N) N_{i,t+s-1} + H_{i,t+s} - N_{i,t+s}\right] \\ +\xi_{i,t+s} \left[\left(f(A_{t+s}, N_{i,t+s}, K_{i,t+s}) - g(A_{t+s}, H_{i,t+s}, N_{i,t+s}, K_{i,t+s}) - \left(\frac{P_{i,t+s}}{P_{t+s}}\right)^{-\epsilon} Y_{t+s} \right)\right] \end{array} \right\}$$

FOC $P_{i,t}$:

$$(1-\epsilon)\left(\frac{P_{i,t}}{P_t}\right)^{-\epsilon} \frac{Y_t}{P_t} - \zeta \left(\frac{P_{i,t}}{P_{i,t-1}} - 1\right) \frac{Y_t}{P_{i,t-1}} - E_t \Lambda_{t,t+1} \zeta \left(\frac{P_{i,t+1}}{P_{i,t}} - 1\right) Y_{t+1} \left(-\frac{P_{i,t+1}}{(P_{i,t})^2}\right) + \xi_t \epsilon \left(\frac{P_{i,t}}{P_t}\right)^{-\epsilon-1} \frac{Y_t}{P_t} = 0$$

$$(1-\epsilon)\left(\frac{P_{i,t}}{P_t}\right)^{-\epsilon}\frac{Y_t}{P_t}-\zeta\left(\pi_{i,t}\right)\frac{Y_t}{P_{i,t-1}}+E_t\Lambda_{t,t+1}\zeta\pi_{i,t+1}\frac{Y_{t+1}}{P_{i,t}}\left(1+\pi_{i,t+1}\right)+\xi_t\epsilon\left(\frac{P_{i,t}}{P_t}\right)^{-\epsilon-1}\frac{Y_t}{P_t}=0$$

Multiplying by P_t, dividing by Y_t and ζ and imposing symmetry:

$$\pi_t(1+\pi_t)=\frac{1-\epsilon}{\zeta}+\frac{\epsilon}{\zeta}\xi_t+E_t\Lambda_{t,t+1}\pi_{t+1}\left(1+\pi_{t+1}\right)\frac{Y_{t+1}}{Y_t}. \tag{46}$$

FOC N_t:

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

FOC H_t:

$$Q_t^N=\xi_t g_{H,t} \tag{48}$$

FOC K_t :

$$\xi_t\left(f_{K,t}-g_{K,t}\right)=\frac{R_t^K}{P_t}, \tag{49}$$

Merging the FOCs with respect to capital from the problems of households and firms, equations (35) and (49) respectively, we obtain:

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

Wage setting: Hiring costs are assumed to be sunk for the purpose of the bargaining. Wages are re-negotiated in every period and are assumed to maximize a geometric average of the household's and the firm's surplus weighted by the parameter γ, which denotes the bargaining power of the households:

$$W_t=\arg\max\left\{\left(V_t^N\right)^{\gamma}\left(Q_t^N\right)^{1-\gamma}\right\}. \tag{50}$$

The first order condition to this problem leads to the sharing rule:

$$(1-\gamma)V_t^N=\gamma Q_t^N. \tag{51}$$

Substituting (41) and (47) into the above equation and using the sharing rule (51) to eliminate the terms in Q_{t+1}^N and V_{t+1}^N one gets the following expression for the real wage[29]:

$$\frac{W_t}{P_t}=\gamma\xi_t\left(f_{N,t}-g_{N,t}\right)+(1-\gamma)\left[\chi C_t N_t^{\varphi}+\frac{x_t}{1-x_t}\frac{\gamma}{1-\gamma}Q_t^N\right]. \tag{52}$$

[29] We have solved a version of the model that allows for intrafirm bargaining, and found only minimal differences. If anything, the mechanism at play is magnified by the additional terms generated by the intrafirm bargaining assumption.

The model is closed assuming the same government budget constraint and Taylor rule.

Calibration: The calibration is quarterly. We set the discount factor β to equal 0.99. The inverse Frisch elasticity φ is set to 3.5 to match empirical estimates by Chetty, Guren, Manoli, and Weber (2013b) on the elasticity of labor supply on the extensive margin of employment. The capital depreciation rate is set at the conventional value of 2.5%, and the employment separation rate is set to 12.76%, to match a hiring to employment ratio measured following Yashiv (2016). The parameter α in the production function is set to the conventional value of 0.66. The elasticity of substitution ϵ is set to 11, which corresponds to a mark-up of 10%, in line with estimates by Basu and Fernald (1997). The Rotemberg parameter ζ is set to 120, which, together with the above value for the elasticity of substitution maps into a conventional Calvo parameter of 0.75. Finally, we calibrate the scale parameter χ governing the disutility of labor, the scale parameter governing the intensity of hiring frictions e and the bargaining power parameter γ to match: (i) a participation rate of 65% (ii) average hiring costs equal to 55% of quarterly wages, to match estimates of training costs in Silva and Toledo (2009); (iii) an unemployment rate of 5.6%. The Taylor rule coefficient for smoothing is set to 0.75 and the responses to inflation and output are set to 1.5 and 0.125, respectively. Finally, the parameter ρ_a governing the persistence of the TFP process is set to the standard value of 0.95.

B Derivation of first order conditions for the empirical model

Households:

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

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

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 yields the following list of equations:

$$\lambda_t = \frac{\eta^p_t}{P_t \left(C_t - \vartheta C_{t-1} \right)}, \tag{53}$$

$$\frac{1}{R_t} = \beta E_t \frac{\lambda_{t+1}}{\lambda_t}, \tag{54}$$

$$\frac{1}{\varpi} \frac{x_t}{1-x_t} \mathcal{V}^N_t = \frac{\eta^l_t \chi L^\varphi_t}{\lambda_t P_t} \tag{55}$$

$$\mathcal{V}^N_t = \frac{W_t}{P_t} - \frac{\eta^l_t \chi L^\varphi_t}{\lambda_t P_t} + (1-\delta_N) E_t \Lambda_{t,t+1} \mathcal{V}^N_{t+1}. \tag{56}$$

$$Q^K_t = E_t \Lambda_{t,t+1} \left[\frac{R^K_{t+1}}{P_{t+1}} + (1-\delta_K) Q^K_{t+1} \right] \tag{57}$$

$$Q^K_t = \frac{\eta^q_t - E_t \Lambda_{t,t+1} Q^K_{t+1} \eta^I_{t+1} S'\left(\frac{A_t I_{t+1}}{A_{t+1} I_t} \right) \frac{A_t}{A_{t+1}} \left(\frac{I_{t+1}}{I_t} \right)^2}{\eta^I_t \left[1 - S\left(\frac{A_{t-1} I_t}{A_t I_{t-1}} \right) - S'\left(\frac{A_{t-1} I_t}{A_t I_{t-1}} \right) \frac{A_{t-1} I_t}{A_t I_{t-1}} \right]} \tag{58}$$

where

$$E_t \Lambda_{t,t+1} = \frac{E_t \pi_{t+1}}{R_t}. \tag{59}$$

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 we can solve for the demand function

$$Y_{i,t} = \left(\frac{P_{i,t}}{P_t} \right)^{-\frac{1+\lambda_{f,t}}{\lambda_{f,t}}} Y_t. \tag{60}$$

Intermediate firms: Form the Lagrangian

$$E_t \sum_{s=0}^{\infty} \Lambda_{t,t+s} \left\{ \frac{P_{i,t+s}}{P_{t+s}} \left(\frac{P_{i,t+s}}{P_{t+s}} \right)^{-\frac{1+\lambda_{f,t+s}}{\lambda_{f,t+s}}} Y_{t+s} - \frac{W_{i,t+s}}{P_{t+s}} N_{i,t+s} - \frac{R^K_{t+s}}{P_{t+s}} K_{i,t+s} \right. , \tag{61}$$

$$-\frac{\zeta}{2} \left(\frac{P_{i,t+s}}{\left(\Pi_{t+s-1}\right)^{\psi} \left(\bar{\Pi}\right)^{1-\psi} P_{i,t+s-1}} - 1 \right)^2 Y_{t+s} \tag{62}$$

$$-Q^N_{i,t+s} \left[N_{i,t+s} - (1-\delta_N) N_{i,t+s-1} - H_{i,t+s} \right] \tag{63}$$

$$\left. +\xi_{i,t+s} \left[-\left(\frac{P_{i,t+s}}{P_{t+s}} \right)^{-\frac{1+\lambda_{f,t+s}}{\lambda_{f,t+s}}} Y_{t+s} + f_{i,t+s} - g_{i,t+s} \right] \right\} \tag{64}$$

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

$$\frac{R^K_t}{P_t} = \xi_t \left(f_{K,t} - g_{K,t} \right), \tag{65}$$

$$Q^N_t = \xi_t g_{H,t}, \tag{66}$$

$$Q^N_t = \xi_t \left(f_{N,t} - g_{N,t} \right) - \frac{W_t}{P_t} + (1-\delta_N) E_t \Lambda_{t,t+1} Q^N_{t+1}, \tag{67}$$

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

$$+\xi_t \frac{1+\lambda_{f,t}}{\lambda_{f,t}} \frac{1}{\zeta} + \left(\frac{\Pi_{t+1}}{(\Pi_t)^{\psi} \left(\bar{\Pi}\right)^{1-\psi}} - 1 \right) \frac{Y_{t+1}}{Y_t} \left(\frac{\Pi_{t+1}}{(\Pi_t)^{\psi} \left(\bar{\Pi}\right)^{1-\psi}} \right), \tag{68}$$

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

Consolidating (65) with (57) yields:

$$Q_t^K = E_t \Lambda_{t,t+1} \left[\xi_{t+1} \left(f_{K,t+1} - g_{K,t+1} \right) + (1-\delta_K) Q_{t+1}^K \right]. \tag{69}$$

C 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

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

3. Marginal utility of consumption

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

4. Law of motion for employment

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

5. Hiring

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

6. Labor participation decision

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

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

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

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

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

21. Inertial wage

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

22. Taylor Rule

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

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

$$\hat{q}_t^K + \hat{\eta}_t^I = \hat{\eta}_t^q + S'' (1 + \beta) \hat{\imath}_t - S'' \hat{\imath}_{t-1} - \beta S'' \hat{\imath}_{t+1}. \tag{70}$$

26. Tobin's Q for employment

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

D Data Set Construction

Nominal consumption includes personal consumption expenditures: nondurable goods (PCND) and personal consumption expenditures in services (PCESV), which are computed by the 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 BLS.

The employment rate and the participation rate are the quarterly averages of the civilian employment-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. Our measures of TFP growth are TFP the capital-utilization adjusted and unadjusted TFP growth rates as measured by Fernald (2012). We have three measures of inflation (GDP deflator, CPI, and PCE) and we use a multiple indicator to take the model to these three measures. See Campbell, Evans, Fisher, and Justiniano (2012) for a thorough description of this approach.

E Measurement Equations

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

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

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

4. Inflation
$$INFL_t = \hat{\pi}_t + 100 \ln \bar{\Pi}.$$

5. Real wage growth
$$WGR_t = \hat{w}_t^r - \hat{w}_{t-1}^r + \hat{\eta}_t^A + 100 \ln \mu.$$

6. Employment
$$100 \ln ER_t = \hat{n}_t + 100 \ln \bar{N}.$$

7. Unemployment[30]
$$100 \ln UR_t = \hat{u}_t - \widehat{lf}_t + 100 \ln \bar{U}.$$

8. Participation rate
$$\begin{aligned} 100 PartR_t &= 100 \ln \frac{LF_t}{Pop_t} \\ &= \widehat{lf}_t + 100 \ln \overline{lf}. \end{aligned}$$

9. FFR
$$FFR_t = \ln R_t + 100 \ln \bar{R}.$$

[30] 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.

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

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

where $\lambda_N = 1$ and the measurement errors $\eta_{A,t}^N$ and $\eta_{A,t}^A$ are i.i.d. Gaussian shocks with mean zero and standard deviation σ_{mN}^2 and σ_{mA}^2, respectively.

11. Expected Future Federal Funds Rate (from OIS):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 idd 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 iid measurement error shocks. We impose restrictions on the two vectors of loadings, which allows us to identify the two factors: a target factor that moves the current policy rate and a path factor that moves the slope of the term structure of future interest rates (i.e., it moves only expected future rates). The crucial restrictions to interpret factors this way are that $\Lambda_T(0) = 1$ and $\Lambda_P(0) = 0$.

F 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 Figures

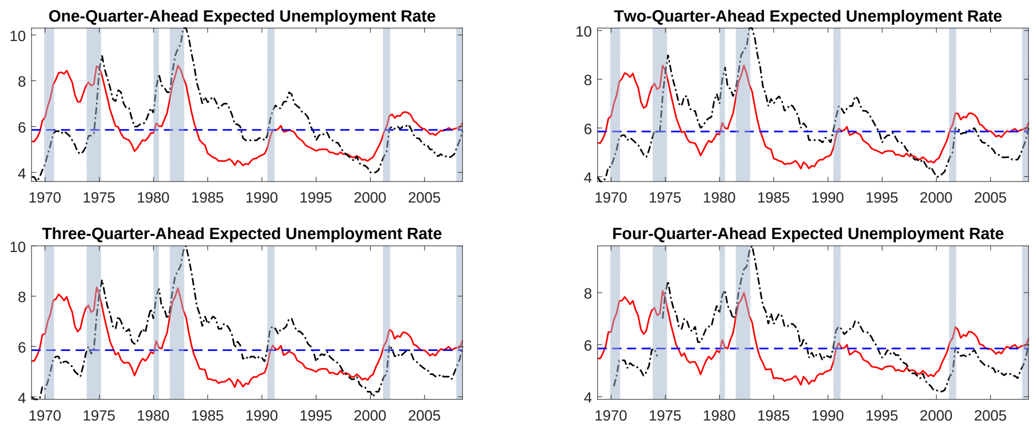

Figure 10: Expectations of U.S. unemployment rates (black dashed-dotted line), along with the counterfactual unemployment rate obtained by simulating the model using only the smoothed estimate of the surprise TFP shocks (red solid line). The counterfactual series are computed by setting the model parameters to their posterior modes, which are reported in Table 1 and Table 2. Sample period 1962Q1:2008Q3. The gray areas denote the NBER recessions.

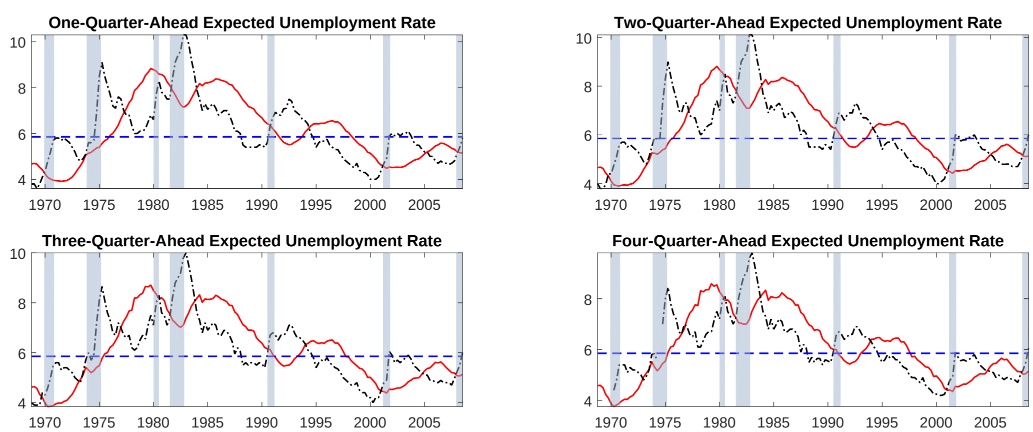

Figure 11: Expectations of U.S. unemployment rates (black dashed-dotted line), along with the counterfactual unemployment rate obtained by simulating the model using only the smoothed estimate of the four-quarter and eight-quarter-ahead TFP news shocks. The counterfactual series are computed by setting the model parameters to their posterior modes, which are reported in Table 1 and Table 2. Sample period 1962Q1:2008Q3. The gray areas denote the NBER recessions.

H Parameter List

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

Table 5: Notations for the Model Parameters.

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

Table 6: Notations for the Model Parameters.