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Endogenous Labor Supply in an Estimated New-Keynesian Model: Nominal versus Real Rigidities*

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Abstract

The deep deterioration in the labor market during the Great Recession, the subsequent slow recovery, and the missing disinflation are hard to reconcile for standard macroeconomic models. We develop and estimate a New-Keynesian model with financial frictions, search and matching frictions in the labor market, and endogenous intensive and extensive labor supply decisions. We conclude that the estimated combination of the low degree of nominal wage rigidities and high degree of real wage rigidities, together with the small role of pre-match costs relative to post-match costs, are key in successfully forecasting the slow recovery in unemployment and the missing disinflation in the aftermath of the Great Recession. We find that endogenous labor supply data are very informative about the relative degree of nominal and real wage rigidities and the slope of the Phillips curve. We also find that none of the model-based labor market gaps are a sufficient statistic of labor market slack, but all contain relevant information about the state of the economy summarized in a new indicator for labor market slack we put forward.

JEL Classification: E32, J64, J20, E37.
Keywords: search and matching, labor supply, labor force participation, missing disinflation, Great Recession.

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1 Introduction

The Great Recession was characterized by a deep deterioration in labor market conditions followed by a lackluster recovery. Most models with labor market frictions face challenges in accounting for a weak job recovery after a large deterioration in labor market outcomes (Leduc and Liu, 2020). At the same time, high unemployment usually exerts disinflationary pressures as predicted by a traditional Phillips curve relationship. However, this relationship broke down during the Great Recession, when the slowdown in activity was paired up with subdued but stable inflation, resulting in what Stock (2011) dubbed the "missing disinflation." This paper shows that an estimated dynamic stochastic general equilibrium (DSGE) model with search and matching frictions, endogenous labor force participation and hours, together with financial frictions on investment, is able to deliver both key features of the aftermath of the Great Recession. The empirical performance of our model relies on *(i)* a combination of a low degree of nominal wage rigidities and a large degree of real wage rigidities, *(ii)* the higher importance of job-training costs (post-match recruiting costs) relative to vacancy-posting costs (pre-match recruiting costs), and *(iii)* the interaction between the labor market and a financial accelerator channel.

Labor market data are characterized by multiple margins of adjustment: hours, employment, and participation (or the labor force). Most of the theoretical literature focuses on one or two of these margins but on not all of them simultaneously. However, employment is the biggest component of the variation in total hours (Rogerson and Shimer, 2011), and the labor force explains between one-fourth and one-third of the cyclical variation in the unemployment rate (Barnichon and Figura, 2015; Elsby, Hobijn, and Şahin, 2010). An important contribution of this paper is to consider all three margins of labor market adjustment by developing a New-Keynesian model à la Smets and Wouters (2007) with search and matching frictions, extended to incorporate labor force participation decisions and the intensive margin of labor supply (hours worked), together with financial rigidities as in Del Negro, Gianonni, and Schorfheide (2015). In addition to introducing both the extensive and intensive margins of labor supply, our model features the following: *(i)* extended Jaimovich and Rebelo (2009) preferences that take into account decisions about consumption and the extensive and intensive margins of labor supply; *(ii)* a generic recruiting cost function that features pre- and post-match costs; and *(iii)* staggered nominal wage bargaining. We estimate the model with Bayesian techniques by not only using standard macroeconomic variables but also including a large set of labor market variables such as the unemployment rate, the LFPR, the workweek, and vacancies. The estimated model does a good job at capturing the volatility, autocorrelations, and the correlation with GDP of main macroeconomic variables and also of labor market variables, such as the unemployment rate, the LFPR, vacancies, and workweek. Our model also delivers model-based estimates for two key latent variables, the unemployment rate gap and the output gap, that are close to estimates from established sources, and we show that having both the LFPR and hours worked as endogenous variables in the model and in the observable set is key in assessing the underlying state of the economy.

We show that the estimated model can successfully account for the observed labor market and inflation dynamics during the Great Recession and the subsequent recovery. In particular, we assess the forecasting performance of the estimated model at two critical points in time: *(i)* 2008:Q4, which corresponds to the quarter with the largest drop in gross domestic product (GDP) growth and *(ii)* 2009:Q4, which corresponds to the quarter with the highest unemployment rate, using data up to those dates. In doing so we take into account the expected duration of the effective lower bound (ELB) constraint on the nominal interest rate as in Kulish, Morley, and Robinson (2017). Evaluating the forecasting performance at these two dates allows us to show that the model is able to account for the deep deterioration of the labor market conditions during the Great Recession and for the subsequent slow recovery. While our model expected a slightly larger deterioration in the unemployment rate during the Great Recession than what was observed, we can ex-post explain this by assessing the role of the ELB constraint during this period. By doing a shock decomposition analysis we find that the deterioration in labor market conditions was not as dire as the model predicted due to less-severe-than-expected effects of the ELB constraint. Our model also does a great job at forecasting other labor market variables during this period, including wages, vacancies, and workweek as well as GDP growth and investment growth. Moreover, the model is able to predict only a modest decrease in inflation in 2009 and 2010 and a relatively subdued path for inflation in the years following the Great Recession.

By generating counterfactual model projections, we identify three key features of the estimated model that contribute to the good forecasting properties of our model. First, a small degree of nominal wage rigidities but a relatively large degree of real wage rigidities.[1] To do so, our paper develops a novel and parsimonious decomposition of nominal wages which can be used in any model featuring search and matching frictions. This decomposition allows us to assess the relative importance of nominal and real wage rigidities in our model and to compare that with other papers in the literature. Real (instead of nominal) wage rigidities allow us to match the cyclicality of the labor force participation rate (LFPR) and hours in the data, as real wages are more sluggish with real rigidities, preventing labor supply from plunging in recessions. Second, a relatively larger importance of post-match recruiting costs than pre-match costs. Large post-match recruiting costs (relative to pre-match recruiting costs) dampen the decline in marginal costs, and as a consequence in inflation, during a downturn, and help to match the observed vacancy volatility, which would be predicted to be smaller than in the data with a sizable pre-match cost. Third, the inclusion of financial rigidities help generating a large and persistent decline in investment following the spike in credit spreads in 2008. Lower capital accumulation on the one hand reduces labor demand persistently, delaying the recovery in the labor market, but on the other hand increases the rental rate of capital, hence preventing inflation from falling too much.

Importantly, we find that the estimated degree of real versus nominal wage rigidities relies on the information contained in the LFPR and hours worked. Therefore, information on the extensive and intensive margins of labor supply plays a relevant role in delivering the sought-after smaller response of inflation during the Great Recession. The inference on the relative importance of the two components of the recruiting cost function is mostly driven by the dynamics of vacancies. We find that a higher degree of post-match costs relative to pre-match costs helps in delivering higher labor market volatility and persistence in labor market outcomes, allowing us to explain the high unemployment rate during the

[1] Cairó, Fujita, and Morales-Jiménez (2022) show that some degree of real wage rigidity may be needed to match the cyclicality of the LFPR.

Great Recession and its sluggish recovery thereafter. We also conclude that having a higher degree of post-match costs than pre-match costs helps in delivering lower inflation volatility and more persistent inflation dynamics, which are key characteristics of the dynamics of inflation during and after the Great Recession. Moreover, in our model financial rigidities play a significant role in accounting for the joint behavior of labor market variables and inflation during the recovery. In fact, by causing higher lending spreads, financial frictions generate a persistent decline in investment which, on the one hand, results in a prolonged weakness in labor demand, and, on the other hand, prevents inflation from falling too much by raising the rental cost of capital.

In addition to assessing the forecasting performance of the model, we also exploit the richness of the labor market block of the model to study cyclical properties of labor market gaps. We find that including endogenous labor supply in the model and labor supply data in the estimation *does* matter in inferring the cyclical position of the labor market. First, based on the historical data decomposition, we show that the LFPR and workweek are informative about the labor market gaps and the natural rate of unemployment, potentially explaining about a one percentage point fluctuation in the latter. Second, based on the historical shock decomposition, we show that exogenous shocks to labor supply are important drivers of the economy—particularly of the natural rate of unemployment. In addition, we compute multiple labor market gaps (employment, unemployment, unemployment rate, LFPR, workweek, total hours, and vacancies gaps), and we find that there is not a sufficient statistic of slack in the labor market. Even though all labor market gaps are highly correlated and become negative within two or three quarters during a recession; there is not a single labor market gap that always leads the deterioration or recovery of the labor market. Based on this result, we propose a measure that *summarizes* the slack of the labor market by taking the first principal component of all of our labor market gaps. We find that this indicator had led the three recessions in our sample period, peaking about six quarters before the start of the recession.

Related Literature This paper relates to four strands of literature. First, this paper builds on the literature that estimates medium-scale DSGE models to explain business cycle dynamics, in the spirit of Smets and Wouters (2007) and Christiano, Eichenbaum, and Evans (2005). Gertler, Sala, and Trigari (2008) extended the previous papers by including search and matching frictions in the labor market and staggered-nominal wage rigidities, but did not use labor market variables in their estimation. They found that nominal-wage rigidities significantly improve the model's ability to explain the data. More recently, Furlanetto and Groshenny (2016) include vacancies in the Bayesian estimation of a search and matching model, finding that matching efficiency shocks play a meaningful role in explaining fluctuations in the natural rate of unemployment. All of the previous papers assumed a fixed labor supply along the extensive margin and, in some cases, along the intensive and extensive margins. A key contribution of our paper is to build and estimate a DSGE model with financial rigidities and search and matching frictions featuring both the intensive and extensive margins of labor supply, which successfully accounts for key business cycle dynamics, including those related to the labor market.

Second, this paper also relates to the literature that studies endogenous labor supply decisions. In particular, Cairó, Fujita, and Morales-Jiménez (2022) and Krusell et al. (2017, 2020) study the cyclical fluctuations in the LFPR and transition rates, highlighting the important role of small labor supply elasticities and wage rigidities in explaining the weak procyclicality of the LFPR. Cacciatore, Fiori, and Traum (2020) study the cyclical behavior of hours in an estimated DSGE model and find that intensive-margin adjustments increase job losses during postwar recessions and delay job recoveries. Nucci and Riggi (2018) use a search and matching model with endogenous labor force participation and real wage rigidities to rationalize the divergent behavior of the LFPR between the United States and the euro area during the Great Recession. Relative to these papers, we develop a fully-fledged New Keynesian model with a rich labor market structure and estimate it using Bayesian techniques on an expanded data set that includes labor market variables.

Two other papers featuring medium-sized DSGE models with a labor supply decision include Christiano, Eichenbaum, and Trabandt (2015) and Christiano, Trabandt, and Walentin (2021). Christiano, Eichenbaum, and Trabandt (2015) endogenize the LFPR in a model with only the extensive margin of labor supply and financial-like wedges to study the Great Recession. Different from our paper, Christiano, Eichenbaum, and Trabandt (2015) abstract from nominal wage rigidities and assume a log-linear specification for the utility function, without disutility from labor, and thus they cannot parameterize the strength of short run wealth effects on the labor supply. In turn, Christiano, Trabandt, and Walentin (2021) present a model with an endogenous LFPR (though without search frictions) and conclude that using only employment or total hours in the estimation is not enough to explain the unemployment or the LFPR responses observed in the data. Different from our paper, both Christiano, Eichenbaum, and Trabandt (2015) and Christiano, Trabandt, and Walentin (2021) perform an impulse response matching estimation, consider a smaller set of the macroeconomic shocks, and do not focus on the role of real and nominal wage rigidities and pre-and post-match recruiting costs in explaining business cycle dynamics.

Third, our paper is also related to the literature that studies the role of real and nominal rigidities in models with search and matching frictions. Papers in this literature include, Kuester (2010) and Thomas (2011), which claim that strategic complementarities in price setting that arise when price setters are also subject to labor market frictions are necessary in delivering smaller responses of inflation to shocks in New Keynesian models with search and matching frictions. While these types of real price rigidities do not arise in our model, their findings are obtained within the context of simpler macroeconomic models that do not include a labor force participation decision as in our paper. The inclusion of both the LFPR and the workweek in our data set allows us to estimate a combination of the slope of the Phillips curve and the degree of real wage rigidities that delivers the sought-after smaller response of inflation during the Great Recession, as well as the sluggish recovery in the labor market.

Finally, this paper relates to recent papers that evaluate the performance of DSGE models during the Great Recession. In particular, Leduc and Liu (2020) show that search and matching models with a standard matching function fail to predict weak job recoveries following a deep labor market downturn. By introducing search intensity and recruiting intensity in an otherwise standard model, Leduc and Liu (2020) are able to account for the weak job recovery observed after the Great Recession. Our paper shows that a good forecasting performance can also be achieved by introducing two additional labor supply margins—LFPR and hours worked—while relying on a standard matching function. Our paper is also related to the literature investigating the causes for the the missing disinflation after the 2007-2009 financial crisis. Del Negro, Gianonni, and Schorfheide (2015) show that DSGE models can predict the missing disinflation when featuring financial frictions and a high degree of nominal rigidities in an environment with forward-looking agents. Gilchrist et al. (2017) develop a model in which financial frictions play a crucial role in explaining a more resilient path of inflation following the Great Recession, but they abstract from studying the behavior of labor market variables. The paper by Christiano, Eichenbaum, and Trabandt (2015) looks at the interaction between financial frictions and labor market dynamics in the wake of the financial crisis, but in their model financial wedges are exogenous rather than endogenous as in our framework.[2]

The rest of this paper is organized in the following way. Section 2 presents our model. Section 3 describes our estimation strategy, data, and results. Section 4 presents the results of forecasting with our model the labor market and inflation during the Great Recession. Section 5 analyzes the role of real versus nominal wage rigidities and pre-match versus post-match costs in our model. Section 6 presents a historical analysis of the labor market based on our estimated model. We present multiple labor market gaps, data and shock decompositions, and propose a measure that summarizes the slack in the labor market. Finally, Section 7 concludes.

2 Model Description

We build a quantitative general equilibrium model à la Smets and Wouters (2007) that features search and matching frictions in the labor market, and financial rigidities, as in Bernanke, Gertler, and Gilchrist (1999). The model incorporates several novelties. First, labor supply decisions encompass the standard intensive margin—hours worked—of New Keynesian models and the extensive margin, both through employment and labor force participation. While these margins were previously studied in isolation, our model is the first one to incorporate these three components of labor supply simultaneously in an estimated DSGE model. Second, we extend the Jaimovich and Rebelo (2009) preferences to incorporate the extensive margin of labor, enabling us to quantify the wealth effect in labor supply decisions. Third, in the spirit of Furlanetto and Groshenny (2016), we include a generic recruiting cost function that depends on both the number of vacancies posted and the number of new hires. Fourth, we extend the Nash bargaining process of Gertler, Sala, and Trigari (2008) by including hours and a generic recruiting cost function. All these features allow us to empirically evaluate the relationship among different labor market gaps over the business cycle and over history, the role of wealth in labor supply decisions, the relative importance of vacancy costs over hiring costs, and a rigorous treatment of nominal wage rigidities in the labor market.

The model economy is populated by a representative household, a representative final goods producer,

[2]Regarding alternative explanations for the missing disinflation see also Hall (2011), Coibion and Gorodnichenko (2015), and Harding, Lindé, and Trabandt (2022).

monopolistically competitive retailers, competitive intermediate goods producers, a representative capital producer, entrepreneurs, a government, and a monetary authority. Below, we present the key elements of the model environment and make available detailed derivations in the Online Appendix.

2.1 Households

There is a representative household made up of a continuum of members—who can be employed, unemployed, or out of the labor force at each point in time—with a mass normalized to 1. We assume perfect consumption insurance within the household, which implies that all members of the household seek to maximize the household's utility function and consume the same basket of goods. The total number of employed and unemployed workers are denoted by N_t and U_t, respectively, and together constitute the labor force, which is denoted by $L_t = N_t + U_t$. Thus, we have $1 = N_t + U_t + O_t = L_t + O_t$, where the total number of workers out of the labor force is denoted as O_t.

Unemployed workers receive real unemployment compensation equal to $b_t = b$. Employed workers receive a nominal hourly wage W_t and are exogenously separated from their jobs at a time-invariant rate δ_s. The timing of labor market decisions closely follows Campolmi and Gnocchi (2016). At the beginning of each period, a fraction δ_s of the employed are separated from their job. The newly separated workers, together with the unemployed and the nonparticipants, form the nonemployment pool $U_{t-1} + O_{t-1} + \delta_s N_{t-1} = 1 - (1-\delta_s)N_{t-1}$. Out of the nonemployment pool, some members will form the searching pool s_t, and the remaining ones will enter non-participation O_t. Therefore, $s_t + O_t = 1 - (1-\delta_s)N_{t-1}$, which implies $s_t = L_t - (1-\delta_s)N_{t-1}$. The searchers find a job with probability p_t, and we allow for contemporaneous hiring: Those who find a job are able to become employed immediately. Aggregate employment evolves as follows: $N_t = (1-\delta_s)N_{t-1} + p_t s_t$, and the unemployment rate is defined as $u_t \equiv \frac{U_t}{L_t}$.

As in Cacciatore, Fiori, and Traum (2020), we follow Jaimovich and Rebelo (2009) in assuming an instantaneous utility function for the household that allows for the parameterization of the strength of short-run wealth effects on the labor supply. However, unlike in Cacciatore, Fiori, and Traum (2020), the labor supply decision in our model entails both the extensive margin (through participation in the labor force) and the intensive margin (through hours worked). To accommodate both margins of labor supply, we propose the following extension of the utility function specification put forward by Jaimovich and Rebelo (2009):

$$\mathcal{U}(c_{t-1}, c_t, H_t, zh_t, X_t(h), X_t(l), N_t) = \frac{\left[c_t - hc_{t-1} + \chi_{lt}\frac{(1-H_t)^{1-\psi_l}}{1-\psi_l}X_t\left(l\right) - \chi_{ht}\frac{zh_t^{1+\psi_h}}{1+\psi_h}N_t X_t\left(h\right)\right]^{1-\sigma_c} - 1}{1-\sigma_c}, \tag{1}$$

where $H_t = N_t + \Gamma U_t$ denotes the total effort exerted by those members of the household in the labor force, zh_t stands for the average hours worked by each employee, $X_t\left(h\right) = \left(c_t - hc_{t-1}\right)^{\gamma_h} X_{t-1}\left(h\right)^{1-\gamma_h}$ is the process for the intensive labor margin—hours worked—, and $X_t\left(l\right) = \left(c_t - hc_{t-1}\right)^{\gamma_l} X_{t-1}\left(l\right)^{1-\gamma_l}$

is the process for the extensive margin—labor force participation. The marginal rate of substitution between market and home goods consumption is governed by a preference shock to the extensive margin of labor supply, χ_{lt}, which is assumed to follow $\log\chi_{l,t} = (1-\rho_{\chi_l})\log\chi_l + \rho_{\chi_l}\log\chi_{l,t-1} + \varepsilon_{\chi_l,t}/100$, with $\varepsilon_{\chi_l,t} \sim \mathcal{N}\left(0, \sigma^2_{\chi_l}\right)$. Similarly, a preference shock to the intensive margin of labor supply, χ_{ht}, governs the marginal rate of substitution between market good and intensive labor supply. The process for the labor supply shock – intensive margin is given by $\log\chi_{h,t} = (1-\rho_{\chi_h})\log\chi_h + \rho_{\chi_h}\log\chi_{h,t-1} + \varepsilon_{\chi_h,t}/100$, with $\varepsilon_{\chi_h,t} \sim \mathcal{N}\left(0, \sigma^2_{\chi_h}\right)$. For simplicity, we assume that all employees work the same number of hours, which is determined at the household level.

The household problem is given by the following:

$$\max_{c_t,B_t,s_t,U_t,L_t,H_t,zh_t,N_t,X_t(H),X_t(l)} E_0\sum_{t=0}^{\infty}\beta^t\mathcal{U}(c_{t-1},c_t,H_t,zh_t,X_t(h),X_t(l),N_t)$$

subject to

$$\begin{aligned}
s_t &= L_t-(1-\delta_s)N_{t-1}, && (2)\\
N_t &= (1-\delta_s)N_{t-1}+p_t s_t, && (3)\\
L_t &= s_t+(1-\delta_s)N_{t-1}, && (4)\\
U_t &= L_t-N_t, && (5)\\
H_t &= N_t+\Gamma U_t, && (6)\\
X_t(h) &= (c_t-hc_{t-1})^{\gamma_h}X_{t-1}(h)^{1-\gamma_h}, && (7)\\
X_t(l) &= (c_t-hc_{t-1})^{\gamma_l}X_{t-1}(l)^{1-\gamma_l}, && (8)\\
c_t+B_t &\leq w_tN_tzh_t+b_tU_t+\mu_t^{CY}R_{t-1}B_{t-1}+T_t+D_t, && (9)
\end{aligned}$$

where B_t is the total amount, in real terms, of risk-free government securities holdings, w_t is the overall hourly wage, with $w_t = \int_0^1\left[(W_{jt}/P_t)\cdot(n_{jt}/N_t)\right]dj$ where W_{jt} is the nominal hourly wage earned by employed workers at firm j, b_t stands for unemployment benefits, which are fully financed by lump-sum taxes, R_t is the real interest rate on the risk-free government security, T_t is lump-sum taxes, D_t is profits, and μ_t^{CY} is a convenience yield term, which captures the premium associated with the safety and liquidity characteristics of Treasury securities. We introduce this convenience yield term following the specification in Del Negro et al. (2017) such that the Euler equation for investing in risk-free government securities is given by

$$1 = E_t\left[\Lambda_{t,t+1}\mu_{t+1}^{CY}R_t\right], \tag{10}$$

where $\Lambda_{t,t+k}$ is the stochastic discount factor between period t and period $t+k$. We assume, like Del Negro et al. (2017), that the convenience yield is exogenous and follows the process $\log\mu_t^{CY} = (1-\rho_{CY})\log\mu^{CY}+\rho_{CY}\log\mu_{t-1}^{CY}+\varepsilon_{CY,t}/100$, with $\varepsilon_{CY,t}\sim\mathcal{N}\left(0,\sigma^2_{CY}\right)$.

The optimality conditions for labor supply to firm j, labor force participation, and hours worked are given by the following:[3]

$$
\begin{aligned}
V_{jt}^{h} &= w_{jt}zh_t - [b_t + (1-\Gamma)\mu_t + \mathcal{U}_t^{-\sigma_c} X_t(h) \frac{\chi_{ht}}{V_{ct}} \frac{zh_t^{1+\psi_h}}{1+\psi_h}] + E_t[(1-\delta_s)\Lambda_{t,t+1}V_{jt+1}^{h}] \\
&\quad - E_t[(1-\delta_s)p_{t+1}\Lambda_{t,t+1}\bar{V}_{t+1}^{h}] + (1-\delta_s)\,E_t\left[\Lambda_{t,t+1}V_{jt+1}^{n}\right] - E_t\left[\Lambda_{t,t+1}p_{t+1}(1-\delta_s)\bar{V}_{t+1}^{n}\right], \\
p_t\bar{V}_t^{h} &= \Gamma\mu_t - b_t, \\
0 &= V_{zh,t} + V_{c,t}w_tN_t,
\end{aligned}
$$

where $\mu_t = (V_{h,t}/V_{c,t})$ is the value of non-working activities in terms of consumption, $\bar{V}_t^h \equiv \int_0^1 \left[(v_{jt}/v_t)\, V_{jt}^h\right] dj$ is the average employment offer, $V_{zh,t}$ is the marginal dis-utility of hours worked, and $V_{c,t}$ is the marginal utility of consumption. Let us define the flow opportunity cost of employment as $\Omega_t = \mathcal{U}_t^{-\sigma_c} \frac{\chi_{ht} X_t(h)}{V_{ct}} \frac{zh_t^{1+\psi_h}}{1+\psi_h} + b_t + (1-\Gamma)\mu_t$.

2.2 Labor Market

The total number of matches in the economy, m_t, is a function of the total number of vacancies, v_t, and job searchers, s_t:

$$
m_t(v_t, s_t) = \overline{\sigma}_{m,t} v_t^{1-\sigma_m} s_t^{\sigma_m}, \tag{11}
$$

where σ_m is the matching function elasticity with respect to unemployment, and $\overline{\sigma}_{m,t}$ is a time-varying scale parameter that captures matching efficiency. Following Furlanetto and Groshenny (2016), we assume the process for matching efficiency shocks is given by $\log \overline{\sigma}_{m,t} = (1-\rho_{\sigma_m}) \log \overline{\sigma}_m + \rho_{\sigma_m} \log \overline{\sigma}_{m,t-1} + \varepsilon_{\sigma_m}/100$, with $\varepsilon_{\sigma_m} \sim \mathcal{N}\left(0, \sigma_{\sigma_m}^2\right)$. The job-finding rate—$p_t \equiv p(\theta_t)$—and vacancy-filling rate—$q_t \equiv q(\theta_t)$—are given by the following:

$$
p_t = \frac{m_t(v_t, s_t)}{s_t} = \overline{\sigma}_{m,t}\theta_t^{1-\sigma_m}, \tag{12}
$$

$$
q_t = \frac{m_t(v_t, s_t)}{v_t} = \overline{\sigma}_{m,t}\theta_t^{-\sigma_m}, \tag{13}
$$

where $\theta_t \equiv v_t/s_t$ is the labor market tightness.

2.3 Firms

There are five types of firms in the model economy: *(i)* final goods producers, *(ii)* retailers, *(iii)* intermediate goods producers, *(iv)* capital producers, and *(v)* entrepreneurs. The representative final goods producer aggregates the differentiated goods produced by retailers into a final good that is sold for consumption and capital production in a competitive market. Using intermediate goods, retailers produce differentiated goods that are sold to the final goods producer in a monopolistically competitive market. Intermediate goods producers use capital and labor as inputs to produce the intermediate good that is sold to retailers in a competitive market. The representative capital producer uses a strictly concave

[3] See the online appendix for details.

production function to transform the final goods into raw capital goods. These raw capital goods are sold in a perfectly competitive market to entrepreneurs. Entrepreneurs, who are subject to financial frictions, produce effective units of capital and rent them out to intermediate goods producers in a perfectly competitive market.

2.3.1 Final Goods Producer

There is a representative final goods producer that aggregates the differentiated goods produced by retailers, $Y_{z,t}$, using a Kimball aggregator.[4] The final good, Y_t, is produced according the following function:

$$\int_0^1 \mathcal{G}_t\left(\frac{Y_{z,t}}{Y_t}, \epsilon_t^p\right) dz = 1, \tag{14}$$

where $\mathcal{G}$ is strictly increasing and strictly concave, with $\mathcal{G}(1) = 1$, and ϵ_t^p is a markup shock moving the elasticity of substitution. The process for the markup shock is given by $\log \epsilon_t^p = \rho_\epsilon \log \epsilon_{t-1}^p + \varepsilon_{\epsilon,t}/100 - \theta_\epsilon \varepsilon_{\epsilon,t-1}/100$. From cost minimization, we obtain the implied demand function for intermediate good z

$$Y_{z,t} = \mathcal{G}_t^{\prime -1}\left(\frac{P_{z,t}}{P_t}\tau_t\right) Y_t, \tag{15}$$

where P_t is the aggregate price index and τ_t is given by

$$\tau_t = \int_0^1 \mathcal{G}_t^{\prime}\left(\frac{Y_{z,t}}{Y_t}\right) \frac{Y_{z,t}}{Y_t} dz. \tag{16}$$

2.3.2 Retailers

There is a continuum of retailers, with a mass normalized to 1, that is indexed by z. Retailers produce differentiated goods combining intermediate goods using a linear production function. These differentiated goods are sold in a monopolistically competitive market to the final goods producer. We assume that retailers face nominal price rigidities in the form of Calvo prices. Each period, an exogenous fraction $(1 - \lambda_p)$ of retailers are able to adjust prices, while the remaining firms partially index their prices to past inflation. A retailer's price in period t is given by

$$P_{z,t} = \begin{cases} P_{z,t}^* & \text{with probability } 1 - \lambda_p \\ P_{z,t-1}\pi_{t-1}^{\gamma_p}\pi^{1-\gamma_p} & \text{with probability } \lambda_p \end{cases} \tag{17}$$

where $P_{z,t}^*$ is the optimal reset price, $\pi_t = P_t/P_{t-1}$ is the aggregate inflation rate, γ_p is the degree of indexation, and π is (aggregate) trend inflation. Given this environment, a retailer that reoptimizes its price in period t chooses a reset price $P_{z,t}^*$ that maximizes the expected present value of the profits

[4] The Kimball aggregator is a generalization of the Dixit–Stiglitz aggregator that assumes elasticities of substitution that vary with market shares. This assumption introduces real complementarities into the model and helps match key inflation dynamics in the data, especially, in a model with search and matching frictions.

generated while the price remains effective.

$$
\begin{aligned}
&\max_{P^*_{z,t}} E_t \left[\sum_{i=0}^{\infty} \lambda_p^i \Lambda_{t,t+i} \left(\frac{P^*_{z,t}}{P_{t+i}} \Pi_{k=1}^{i} \pi_{t+k-1}^{\gamma_p} \pi^{1-\gamma_p} - \frac{P^m_{t+i}}{P_{t+i}} \right) Y^*_{z,t+i} \right], \\
&\text{subject to} \qquad (18) \\
&Y^*_{z,t+i} = \mathcal{G}'^{-1} \left(\frac{P^*_{z,t}}{P_{t+i}} \left(\Pi_{k=1}^{i} \pi_{t+k-1}^{\gamma_p} \pi^{1-\gamma_p} \right) \tau_{t+i} \right) Y_{t+i}.
\end{aligned}
$$

The first-order condition for the retailer is

$$
E_t \sum_{i=0}^{\infty} \lambda_p^i \Lambda_{t,t+i} \left[(1+\Theta_t) \frac{P^*_t}{P_{t+i}} \prod_{k=1}^{i} (\pi_{t+k-1})^{\gamma_p} - \Theta_t p^m_{t+i} \right] Y^*_{z,t+i} = 0, \tag{19}
$$

where

$$
\Theta_t = -\frac{1}{\mathcal{G}_t'^{-1}\left(\frac{P_{z,t}}{P_t}\tau_t\right)} \frac{\mathcal{G}_t' \left[\mathcal{G}_t'^{-1}\left(\frac{P_{z,t}}{P_t}\tau_t\right) \right]}{\mathcal{G}_t'' \left[\mathcal{G}_t'^{-1}\left(\frac{P_{z,t}}{P_t}\tau_t\right) \right]}. \tag{20}
$$

2.3.3 Intermediate Goods Firms

There is a continuum of intermediate goods firms, with a mass normalized to 1, that is indexed by j. Intermediate goods firms produce an homogeneous good using capital, k_{jt}, and labor, n_{jt}, in a Cobb–Douglas production function. Intermediate goods are sold in a perfectly competitive market to retailers at real price p^m_t. To hire labor, firms post vacancies in a frictional labor market subject to a strictly convex recruiting cost function $\kappa(\cdot)$. Vacancies are filled with probability q_t, and it is assumed that new matches become productive immediately. Capital rental decisions are assumed to be frictionless. The optimization problem for intermediate goods firm j is given by

$$
F(\tilde{w}_{jt}, n_{jt-1}, s_t) = \max_{k_{jt}, n_{jt}, v_{jt}} \left\{ p^m_t y_{jt} - A_t \tilde{w}_{jt} n_{jt} - \kappa(v_{jt}, n_{jt-1}) - r^k_t k_{jt} + E_t[\Lambda_{t,t+1} F(\tilde{w}_{jt+1}, n_{jt}, s_{t+1})] \right\}
$$

subject to

$$
\begin{aligned}
y_{jt} &= k_{jt}^{\alpha} (A_t n_{jt})^{1-\alpha}, && (21) \\
n_{jt} &= (1-\delta_s) n_{jt-1} + q_t v_{jt}, && (22) \\
\kappa(v_{jt}, n_{jt-1}) &= \underbrace{\frac{\kappa_1 A_t}{1+\psi_1} \left(\frac{q_t v_{jt}}{n_{jt-1}} \right)^{1+\psi_1} n_{jt-1}}_{\text{post-match costs}} + \underbrace{\frac{\kappa_2 A_t}{1+\psi_2} \left(\frac{v_{jt}}{n_{jt-1}} \right)^{1+\psi_2} n_{jt-1}}_{\text{pre-match costs}}. && (23)
\end{aligned}
$$

where A_t is technological progress. We introduce exogenous growth into the model by assuming that $\gamma_t = \frac{A_t}{A_{t-1}}$ with $\log \gamma_t = (1-\rho_\gamma) + \rho_\gamma \log \gamma_{t-1} + \varepsilon_{\gamma,t}/100$.

As in Yashiv (2000) and Furlanetto and Groshenny (2016), we consider a generalized recruiting cost function, equation (23), with two components: pre-match and post-match hiring costs. The pre-match component is the cost of posting vacancies, such as the costs of advertising, screening, and selecting new workers, and its importance in overall recruiting costs is governed by the parameter κ_2. The post-match component is the cost of adjusting the hiring rate, such as training costs, and its importance in overall recruiting costs is governed by the parameter κ_1. It is well known in the existing literature that the relative importance of pre-match hiring costs in overall recruiting costs is key in shaping the role of matching efficiency costs in driving the natural rate of unemployment. In Section 3, we estimate the relative share of both types of recruiting costs, as well as the parameters ψ_1 and ψ_2, which govern the convexity of the recruiting cost function.

The optimality conditions for capital and vacancies are given by the following:

$$\begin{aligned} r_t^k &= p_t^m mpk_{jt}, &(24)\\ \frac{\partial \kappa(v_{jt}, n_{jt-1})}{\partial v_{jt}} &= \kappa_{vt} = q_t J_{jt}, &(25) \end{aligned}$$

where $mpk_{jt} = \alpha \frac{y_{jt}}{k_{jt}}$, J_{jt} is the value of a filled vacancy and

$$J_{jt} = p_t^m mpl_{jt} - \frac{W_{jt}^n}{P_t} z h_t + E_t\left[\Lambda_{t,t+1}\kappa_{nt+1}\right] + E_t\left[\Lambda_{t,t+1}(1-\delta_s)J_{jt+1}\right], \tag{26}$$

with $mpl_{jt} = (1-\alpha)\frac{y_{jt}}{n_{jt}}$ and $\kappa_{nt} = -\frac{\partial \kappa(v_{jt}, n_{jt-1})}{\partial n_{jt-1}}$. Also, let us define $z_{jt} = \frac{q_t v_{jt}}{n_{jt-1}}$.

Wages Wages are renegotiated at the beginning of each period with probability $1-\lambda^w$; otherwise, they are partially indexed to past inflation:

$$W_{jt+1} = \begin{cases} W_{jt+1}^*, & \text{with probability } 1-\lambda^w \\ \bar{\gamma}\pi_t^{\gamma_{wp}} W_{jt}, & \text{with probability } \lambda^w \end{cases}$$

where γ_{wp} is the indexation degree to inflation. We introduce the term $\bar{\gamma} = \gamma\pi^{1-\gamma_{wp}}$ to ensure that nominal rigidities do not distort the steady state. Under Nash bargaining, the contract wage W_t^* is chosen to maximize the Nash product $\left\{V_t(W_t^*)^{\eta_t} \cdot J_t(W_t^*)^{1-\eta_t}\right\}$, where $V_t(W_t^*)$ denotes the worker's surplus and $J_t(W_t^*)$ is the value of a filled vacancy for the intermediate goods firm defined in equation (26). We assume that workers' bargaining power, η_t, evolves exogenously as $\log \eta_t = (1-\rho_\eta)\log\eta + \rho\eta \log \eta_{t-1} + \varepsilon_\eta/100$. The wage derivations are available in the online appendix.

2.3.4 Capital Producers

There is a representative capital producer who solves the following optimization program

$$\max_{\{I_t\}_{t=0}^{\infty}} \quad E_0\left\{\sum_{t=0}^{\infty}\Lambda_{0,t}\left[q_t^k I_t \mu_t^I\left(1 - f\left(I_t/I_{t-1}\right)\right) - I_t\right)\right\} \tag{27}$$

where q_t^k is the price of investment goods, I_t is the units of the final good used in the production of the capital good, μ_t^I is an investment-specific technology shock that evolves as $\log\mu_t^I = \left(1-\rho_{\mu^I}\right)\log\mu^I +$

$\rho_{\mu^I} \log \mu^I_{t-1} + \varepsilon_{\mu^I}/100$, and $f(\cdot)$ is an increasing and convex function capturing adjustment costs in investment. In particular, we assume $f(x) = \frac{\gamma_k}{2}(x-\gamma)^2$.

2.3.5 Entrepreneurs

Following Bernanke, Gertler, and Gilchrist (1999), we assume there is a continuum of infinitely lived, risk-neutral entrepreneurs indexed by e. Entrepreneurs purchase physical capital, $K_{e,t}$, at price q^k_t, invest their own net worth, $NW_{e,t}$, and use external financing, $B_{e,t}$. After buying $K_{e,t}$ units of raw capital, entrepreneurs produce $\omega_{e,t}K_{e,t}$ units of capital services, where $\omega_{e,t}$ is an idiosyncratic productivity shock that has a unit-mean log normal distribution. Following Christiano, Motto, and Rostagno (2014), we assume that the standard deviation of $\log \omega_{e,t}$ denoted by $\sigma_{\omega,t}$, is time-varying and that it follows the process $\log \sigma_{\omega,t} = (1-\rho_{\sigma_\omega}) \log \sigma_\omega + \rho_{\sigma_\omega} \log \sigma_{\omega,t-1} + \varepsilon_{\sigma_\omega,t}/100$. This entrepreneurial risk shock captures the degree of cross-sectional dispersion in idiosyncratic productivity. In this environment, financial rigidities arise because there is asymmetric information between borrowers and lenders: While entrepreneurs observe the realization of their idiosyncratic productivity shock, lenders must pay monitoring costs to observe an individual borrower's realized return. In this environment, a debt contract is characterized by the amount of the loan, $B_{e,t}$, the contractual rate, $R^b_{e,t}$, and a schedule of state-contingent threshold values of the idiosyncratic shock, $\bar{\omega}^n_{e,t+1}$, where n refers to the state of nature. For values of the idiosyncratic productivity shock above the threshold, the entrepreneur is able to repay the lender at the contractual rate. For values below the threshold, the entrepreneur defaults and lenders only recover a fraction $(1-\widehat{\mu})$ of the realized entrepreneurial revenue, where $\widehat{\mu}$ is referred to as the marginal bankruptcy cost.

After observing the realization of the idiosyncratic productivity shock, entrepreneurs choose the capital utilization rate, $u^k_{e,t}$, such that the capital services rented to intermediate good producers are given by $k_{e,t} = u^k_{e,t}\omega_{e,t}K_{e,t}$. The capital services demand for entrepreneur e is, then, given by the gross real return on holding one unit of capital from t to $t+1$ given by

$$R^k_{e,t} = \frac{u^k_{e,t} r^k_{e,t} - a(u^k_{e,t}) + (1-\delta_k) q^k_t}{q^k_{t-1}}, \tag{28}$$

where δ_k is the capital depreciation rate, which is assumed to be identical for all entrepreneurs, and $a(u^k_t) = \iota_{u,0}\left[e^{\iota_{u,1}\left(u^k_t - 1\right)} - 1\right]$ is the utilization cost function. As the capital utilization problem is static, all entrepreneurs chose the same level of capital utilization.

Let us define the leverage of entrepreneur e as $\phi_{e,t} = q^k_t K_{e,t}/NW_{e,t}$. Then, the optimization problem faced by entrepreneurs is given by

$$\max_{\phi_{e,t},\bar{\omega}_{e,t+1}} \qquad E_t \left\{1 - \hat{\Gamma}_t(\bar{\omega}_{e,t+1})\right\} \frac{R^k_{t+1}}{\mu^{CY}_{t+1} R_t} \phi_{e,t} NW_{e,t}$$

subject to

$$\mathbb{E}_t \left(\left[\hat{\Gamma}_t(\bar{\omega}_{e,t+1}) - \hat{\mu}\hat{G}_t(\bar{\omega}_{e,t+1})\right] R^k_{e,t+1}\phi_{e,t}\right) \quad \geq \quad (\phi_{e,t}-1)\,\mu^{CY}_{t+1} R_t, \tag{29}$$

where $\hat{\Gamma}_t(\bar{\omega}_{e,t+1}) = \hat{G}(\bar{\omega}_{e,t+1}) + \left[1 - \hat{F}_t\left(\bar{\omega}_{e,t+1}\right)\right]\bar{\omega}_{e,t+1}$, $\hat{G}_t(\bar{\omega}_{e,t+1}) = \int_0^{\bar{\omega}_{e,t+1}} \omega_{t+1} d\hat{F}_t(\omega)$, and $\hat{F}_t(\bar{\omega}_{e,t+1}) = \int_0^{\bar{\omega}_{e,t+1}} d\hat{F}_t(\omega)$. Note that the spread between the entrepreneurs' expected return on capital and the return on risk-free bonds depends on entrepreneurial leverage, the wedge linked to the financial rigidity, and the wedge arising from the convenience yield.

We assume that entrepreneurs exit with probability $(1-\hat{\gamma})$ and new entrants start off with an endowment equal to W_t^e. The law of motion for aggregate entrepreneurial net worth (average net worth across entrepreneurs) if given by

$$NW_t = \hat{\gamma}\left\{\phi_{t-1}\left[\left(1-\hat{\mu}\hat{G}_t(\bar{\omega}_t)\right)R_t^k - \mu_t^{CY}R_{t-1}\right] + \mu_{t-1}^{CY}R_{t-1}\right\}NW_{t-1} + W_t^e. \tag{30}$$

2.4 Monetary Policy

We assume that the monetary authority follows an inertial Taylor–type rule that responds to deviations of inflation from the inflation target $\pi_t^\star$, to the output gap, defined as the ratio of aggregate output in the economy Y_t to output in the flexible economy, Y_t^f, and to the growth rate in the output gap. The flexible economy is defined as the model economy but with flexible prices and wages, constant workers' bargaining power, and constant price markup. We also assume that the ELB on the nominal interest rate is not binding. The monetary policy rule is thus given by the following:

$$i_t = i_{t-1}^{\rho_i}\left[(R\pi)\left(\frac{\pi_t}{\pi_t^\star}\right)^{\kappa_\pi}\left(\frac{Y_t}{Y_t^f}\right)^{\kappa_y}\left(\frac{Y_t/Y_t^f}{Y_{t-1}/Y_{t-1}^f}\right)^{\kappa_{gy}}\right]^{(1-\rho_i)}\mu_t^m, \tag{31}$$

where i_t is the nominal interest rate, R and π are the steady state values for the real interest rate and inflation, respectively, and μ_t^m stands for the monetary policy shock, which is assumed to evolve as $\log\mu_t^m = (1-\rho_m)\log\mu^m + \rho_m\log\mu_{t-1}^m + \varepsilon_{m,t}/100$. The ex-ante real interest rate is given by the Fisher equation:

$$R_t = \frac{i_t}{E_t\pi_{t+1}}. \tag{32}$$

2.5 Capital Stock Dynamics, Aggregate Resource Constraint and Government Spending

Taking into account investment adjustment costs and the effects of variable capital utilization on depreciation, the evolution of capital in this economy is given by the following:

$$K_t = (1-\delta_{k,t})K_{t-1} + \mu_t^I I_t\left(1 - f\left(I_t/I_{t-1}\right)\right). \tag{33}$$

Given that recruiting costs are pecuniary, the aggregate resource constraint can be written as:

$$Y_t = C_t + I_t + \kappa(v_t, N_{t-1}) + (1 - 1/(Gov_t))GDP_t + a(u_t^k)K_{t-1} + A_t\Phi, \tag{34}$$

where government spending, Gov_t, is an exogenous time-varying fraction of GDP and Φ is a fixed cost paid by any of the producers to help the model match the investment-to-GDP ratio observed in the data. The government–spending shock is assumed to follow the process $\log Gov_t = (1 - \rho_G) \log Gov + \rho_G \log Gov_{t-1} + \varepsilon_{Gov,t}/100 + \theta_{Ga}\varepsilon_{\gamma,t}/100$.

3 Estimation

We estimate the model using Bayesian techniques on a rich dataset that includes, unlike other estimation exercises in the existing literature, multiple labor market variables: the LFPR, the workweek, the unemployment rate, and vacancies. In this section, we first describe the data, the measurement equations, and the exogenous processes in the model. Second, we discuss the assumptions on the prior distributions for the parameters and their estimated posterior distributions. We close the section with an overview of model fit and an external–validity exercise for two key latent variables of the model: the unemployment rate gap and the output gap.

3.1 Data

In addition to the standard macroeconomic data in the estimation of DSGE models—the growth rate of real GDP per capita, the growth rate of real consumption per capita, the growth rate of real investment per capita, inflation, and the federal funds rate—we use credit spreads, defined as the difference between the Baa corporate rate and the 10-year Treasury yield, and a rich set of labor market variables that includes data on the extensive margin—the unemployment rate and LFPR—, the intensive margin—the workweek—, a vacancies index, and the growth rate of real wage per capita. Following Barsky, Justiniano, and Melosi (2014), we do not match the model's concept of price and wage inflation to one observed series but rather use factor structures to match the model's concept of price and wage inflation to two indicators for each model variable. A detailed description of the data sources and transformations is available in Appendix A. The quarterly data sample spans from 1987:Q1 to 2010:Q2. We do not include additional years in order to prevent our estimates from being distorted by the ELB constraint on nominal interest rates and other nonlinearities. However, in Section 4, we use our estimated parameters to filter the data up to 2019:Q4 to study the behavior of the variables of interest beyond the estimation period.[5]

We first provide the measurement equations for all variables but price and wage inflation. Given the complexity of the model and the richness of the data set, we introduce measurement errors for all observable variables but those for which we observe the exact values: the federal funds rate and the corporate spread.[6] We map the model's concept of spread to the observed spread, which is defined as the corporate Bba rate over the 10-year yield, using the 10-year average of the model-implied quarterly

[5] In Section 4, we follow the methodology proposed by Kulish, Morley, and Robinson (2017) to take into account the ELB constraint on nominal interest rates.

[6] Guerron-Quintana (2010) argues that given that the exact values of interest rates are observed contemporaneously, there is no need to include a measurement error in its corresponding measurement equation.

excess returns.

$$
\begin{aligned}
\text{Output growth} &= 100 \cdot \left[\log \widetilde{Y}_t - \log \widetilde{Y}_{t-1} + \log \gamma_t\right] + \varepsilon_t^y, \\
\text{Consumption growth} &= 100 \cdot \left[\log \widetilde{C}_t - \log \widetilde{C}_{t-1} + \log \gamma_t\right] + c_{dc} + \varepsilon_t^c, \\
\text{Investment growth} &= 100 \cdot \left[\log \widetilde{I}_t - \log \widetilde{I}_{t-1} + \log \gamma_t\right] + c_{di} + \varepsilon_t^i, \\
\text{FFR} &= 100 \cdot \log i_t, \\
\text{Unemployment rate} &= 100 \cdot u_t + \varepsilon_t^u, \\
\text{Labor force participation rate} &= 100 \cdot L_t + \varepsilon_t^L, \\
\text{Log-Workweek} &= \log\left(zh_t/zh_\star\right) + \varepsilon_t^{zh}, \\
\text{Vacancies} &= 100 \cdot \log\left(v_t/v_\star\right) + \varepsilon_t^v, \\
\text{Spread} &= 100 * \sum_{j=1}^{40} (1/40) \cdot \left(E_t R_{t+j}^k - R_{t+j-1}\right),
\end{aligned}
$$

where $\widetilde{x}$ refers to detrended variables, γ_t is the growth rate of the economy, c_{dc} is a constant equal to the observed difference in sample means between the growth rates for consumption and output, c_{di} is a constant equal to the observed difference in sample means between the growth rates of investment and output, $i_\star$ is the steady-state level of net nominal interest rates, $v_\star$ is the steady-state value for vacancies, and ε_t^x stands for the measurement error of observable x. Following Guerron-Quintana (2010), we assume that measurement errors are $i.i.d$ and Gaussian $\varepsilon_t^x \sim \mathcal{N}\left(0, \sigma_{\varepsilon^x}\right)$.

Following Barsky, Justiniano, and Melosi (2014), we use factor structures in the measurement equations for price and wage inflation. We consider two observable variables for price inflation—the log difference of the GDP deflator and core PCE inflation—and specify the corresponding measurement equations as follows:

$$
\begin{aligned}
\text{Inflation rate GDP deflator} &= \Lambda_{\pi,p}\left[100 \cdot \log\left(\pi_t\right)\right] + \varepsilon_t^{defl}, \\
\text{Inflation rate Core PCE} &= 100 \cdot \log\left(\pi_t\right) + \varepsilon_t^{pce},
\end{aligned}
$$

where $\Lambda_{\pi,p}$ is the factor loading for core PCE inflation in the model's concept of inflation, ε_t^{defl} is the measurement error for inflation measured by the GDP deflator, and ε_t^{pce} is the measurement error for inflation measured by core PCE inflation.

For real wage inflation growth, we use two measures, average hourly wages and compensation per hour, and the measurement equations are given by the following:

$$
\begin{aligned}
\text{Growth rate compensation per hour} &= 100\left[\log \tilde{w}_t - \log \tilde{w}_{t-1} + \log \gamma_t\right] + c_{dw} + \varepsilon_t^{cph}, \\
\text{Growth rate average hourly earnings} &= \Lambda_{\pi,w}\left(100\left[\log \tilde{w}_t - \log \tilde{w}_{t-1} + \log \gamma_t\right]\right) + c_{\pi,w} + \varepsilon_t^{ahe},
\end{aligned}
$$

where $\Lambda_{\pi,w}$ is the factor loading for average hourly earnings in the model's concept of wage growth, c_{dw} and $c_{\pi,w}$ are constants capturing the difference in estimated means between output and wage growth computed using compensation per hour and average hourly earnings, respectively, and ε_t^{cph} and ε_t^{ahe} are

Table 1: Calibrated Parameters

Capital depreciation	δ_k	0.025
Capital share	α	0.33
Share of government spending in GDP at the steady state	$\frac{Gov_\star}{Y_\star}$	0.20
Share of investment in GDP at the steady state	$\frac{I_\star}{Y_\star}$	0.20
TFP growth at the steady state	$\gamma_\star$	1.004
Net inflation at the steady state (quarterly)	$\pi_\star$	0.005
100*Spread at steady state	$100 \cdot \left(R^k - R\right)$	0.5085
Kimball aggregator	Θ	5.19
Job–filling rate at the steady state	$q_\star$	0.95
Survival rate for firms	$\widehat{\gamma}$	0.975
100*Entrepreneurial default rate at steady state	$100 \cdot \widehat{F}\left(\overline{\omega}\right)$	0.56
Constant in the consumption meas. equation	c_{dc}	0.13
Constant in the investment meas. equation	c_{dc}	-0.29
Constant in the comp. per hour meas. equation	c_{dw}	-0.02
Constant in the average hourly earnings meas. equation	c_{ahe}	-0.20

Notes: The constants in the measurement equations are computed as the average of the differences in the growth rates of the corresponding variable and output.

the measurement errors for compensation per hour and average hourly earnings, respectively.

3.2 Prior and Posterior Distributions

The parameter space can be partitioned into three sets: *(i)* parameters with degenerate priors, *(ii)* estimated parameters, and *(iii)* endogenous parameters, which are obtained conditional on parameters in sets *(i)* and *(ii)*.

The set of parameters with degenerate priors, reported in Table 1, contains parameters usually calibrated, such as the capital depreciation rate, the capital share, or government spending as a share of GDP at the steady state, which are set equal to $0.025, 0.33$, and 0.20, respectively. We also set the steady–state value of the share of investment in GDP equal to 0.20. Moreover, we use sample averages of observable variables as degenerate priors for the steady–state values of total factor productivity (TFP) growth, net inflation, and the spread to overcome the well-known difficulty of DSGE models to match them. We calibrate the Kimball aggregator such that the markup is equal to 1.238, which is along the lines of Christiano, Eichenbaum, and Evans (2005). We also calibrate two key parameters for financial rigidities: the entrepreneurs' survival rate, $\widehat{\gamma}$, and the entrepreneurial default rate at the steady state, $100 \cdot \widehat{F}\left(\bar{\omega}\right)$. We set $\widehat{\gamma}$ equal to 0.975, which lies in between the 0.973 in Bernanke, Gertler, and Gilchrist (1999) and 0.985 in Christiano, Motto, and Rostagno (2014). We set $100 \cdot \widehat{F}\left(\bar{\omega}\right)$ equal to 0.56, which is the estimated value for the parameter in Christiano, Motto, and Rostagno (2014). Finally, we set the constants in the measurement equations equal to the average of the differences in the growth rates of the corresponding variable and output.

We estimate 65 parameters, which are reported in Table 2 in the main text and in Tables B.1 to B.4 in Appendix B. Our estimates for standard economic parameters, reported in Table B.1 in Appendix B,

Table 2: ESTIMATED ECONOMIC PARAMETERS: LABOR FRICTIONS RELATED PARAMETERS

PARAMETER		*PRIOR*	*POSTERIOR*	
			Mode	*St. Dev.*
Steady–state unemployment rate	u_{ss}	$\mathcal{N}\,(0.05, 0.10)$	0.06	0.00
Steady–state labor force participation rate	L_{ss}	$\mathcal{N}\,(0.64, 0.02)$	0.66	0.00
Steady–state job finding rate	p_{ss}	$\mathcal{N}\,(0.75, 0.03)$	0.83	0.02
Matching elasticity with respect to unemployment	σ_m	$\mathcal{B}\,(0.84, 0.10)$	0.81	0.03
Ratio of vacancy posting costs parameters	$\log \kappa_{21}$	$\mathcal{N}\,(0.00, 5.00)$	-6.49	2.47
Hiring–rate cost elasticity	ψ_1	$\mathcal{N}\,(1.00, 1.00)$	1.53	0.38
Vacancy–rate cost elasticity	ψ_2	$\mathcal{N}\,(1.00, 1.00)$	1.17	0.86
SS ratio of outside option to MPL plus hiring cost	Ω_p	$\mathcal{B}\,(0.72, 0.05)$	0.83	0.03
SS ratio of b plus utility cost of employ to outside option	Γ^{Ω}	$\mathcal{B}\,(0.50, 0.10)$	0.43	0.05
SS ratio of b to the participation component of outside option	b^0	$\mathcal{B}\,(0.50, 0.25)$	0.98	0.03
Log of JR parameter for hours	$\log \gamma_h$	$\mathcal{N}\,(-0.70, 0.75)$	-2.56	0.29
Log of JR parameter for participation margin	$\log \gamma_l$	$\mathcal{N}\,(-0.70, 0.75)$	-3.29	0.39
Inverse employment elasticity	ψ_l	$\mathcal{G}\,(5.00, 5.00)$	1.86	0.29
SS workers' bargaining power	η	$\mathcal{B}\,(0.50, 0.10)$	0.57	0.08
Nominal wage rigidity	λ_w	$\mathcal{B}\,(0.50, 0.20)$	0.04	0.03

Notes: $\mathcal{B}$ stands for Beta distribution. $\mathcal{N}$ stands for Normal distribution. $\mathcal{G}$ stands for Gamma distribution. SS stands for steady state. MPL stands for marginal product of labor. JR stands for Jaimovich-Rebelo.

are consistent with the literature. We use identical location and dispersion parameters in the prior distribution for all structural shocks, as shown in Table B.3 in Appendix B. Following Ferroni, Grassi, and Leon-Ledesma (2019), we assume Gaussian priors centered at 0 for the size of the measurement errors, as reported in Table B.4 in Appendix B.

In the main text, we focus our discussion on the parameters related to the labor frictions in the model, reported in Table 2, and also steady–state values for relevant variables. In particular, we estimate the steady–state value for the unemployment rate, the LFPR, and the probability of employment. The estimated values are consistent with sample averages.

Unlike Furlanetto and Groshenny (2016) and Cacciatore, Fiori, and Traum (2020), who use a degenerate prior for the matching elasticity with respect to unemployment, σ_m, we estimate this parameter. Given that our model and data are at quarterly frequency, the matching elasticity in the model will be higher than in studies using monthly data.[7] Therefore, we choose a location parameter for the Beta distribution in the prior specification equal to 0.84, which is in the upper end of the range of values reported in the survey by Petrongolo and Pissarides (2001). Indeed, as shown in Table 2, the estimated value for the matching elasticity is higher than the standard values in monthly models.

Instead of estimating the two coefficients loading the two components of the recruiting cost function defined in equation 23, we define $\kappa_{21} = \frac{\kappa_2}{\kappa_1}$. Redefining the coefficients in equation (23) allows us to have

[7] As discussed in Appendix E, because newly separated workers are immediately able to search, the pool of searchers in this model is much larger than in models where only the previously unemployed are able to search, while percent deviations in the number of searchers are less volatile. Consequently, we expect the weight on searchers in the matching function to be appreciably higher than in models without immediate search by the recently separated. Note also that the location parameter of the prior distribution for σ_m and its posterior mode are consistent with Barnichon and Figura (2015).

a system of linear equations when solving the steady state. If instead we were to use the two coefficients κ_1 and κ_2 separately, the system of equations at the steady state would be nonlinear, which complicates solving the model a multiple of times as required by the posterior sampler in the estimation. We use a pretty agnostic prior for $\log \kappa_{21}$, but, as shown in Table 2, the posterior clearly favors the hiring or post-match component of the cost function over the vacancy or pre-match component, with the weight of the latter at virtually zero (see Table 3). Furlanetto and Groshenny (2016) also find that their data favor a large post-match component, which accounts for about two–thirds of the overall hiring costs. As we discuss further in Section 6.3, the relative importance of the pre-match component of the cost hiring function is key in determining the drivers of the natural rate of unemployment in our model. We choose priors centered at quadratic functions for both the vacancy–rate and hiring–rate cost elasticities, ψ_1 and ψ_2, respectively, but allow for a relatively large dispersion. These elasticities determine the degree of convexity of each of the components of the recruiting cost function. Given the estimated value for $\log \kappa_{21}$, although the posterior estimates for both elasticities are similar (see Table 2), only the hiring–rate cost elasticity is relevant for overall recruiting costs.

Our preference specification contains four preference parameters associated with labor supply decisions: *(i)* the parameter governing the magnitude of the short-run wealth effect on the supply of hours, γ_h; *(ii)* the parameter governing the magnitude of the short-run wealth effect on participation, γ_l; *(iii)* the parameter governing the disutility of the extensive margin of labor supply, ψ_l, or inverse employment elasticity; and *(iv)* the parameter governing the disutility of the intensive margin of labor supply, ψ_h.[8] We estimate a log-transformation of the first two parameters to add flexibility to the posterior–optimization routine. The implied priors for the parameters associated with the short-run wealth effect on labor supply are centered approximately at 0.50. The implied values at the posterior mode for γ_h and γ_l are quite low: 0.11 and 0.05, respectively. Note that the limiting case of no wealth effects would be $\gamma_h \to 0$ and $\gamma_l \to 0$. While we estimate the inverse employment elasticity, ψ_l, by imposing a relatively loose prior, we solve endogenously for the parameter governing the disutility of the intensive margin of labor supply, ψ_h. As reported in Table 3, at the posterior mode, the parameter linked to the disutility of the extensive margin of labor supply is almost twice as large as the one governing the disutility of the intensive margin of labor supply.

Following Gertler, Sala, and Trigari (2008), we set the location and dispersion parameters in the prior distribution for the workers' Nash bargaining power at the steady state, η, equal to 0.5 and 0.1, respectively. Our estimate of the workers' bargaining power is 0.56, which is within the range of values considered in the literature—$[0.5, 0.7]$—and similar to the recent estimation results in Cacciatore, Fiori, and Traum (2020). Following the literature, we choose a relatively loose prior for the parameter governing nominal wage rigidities, λ_w. Our estimation points to a relatively small value of the nominal wage rigidity. However, as we point out below, the model displays a significant degree of real wage rigidities.

We estimate three parameters that govern steady–state relationships linked to workers' outside option in the bargaining process and that, ultimately determine the degree of real wage rigidities: *(i)* the steady

[8]This parameter, ψ_h, corresponds to the inverse Frisch elasticity of labor supply with standard preferences.

Table 3: ENDOGENOUS PARAMETERS EVALUATED AT THE POSTERIOR MODE

Steady–state pref parameter extensive margin	χ_l	0.070
Steady–state pref parameter intensive margin	χ_h	0.950
Separation rate	δ_s	0.338
Elasticity of intensive labor supply	ψ_h	1.054
Effort parameter	Γ	0.984
Steady–state matching efficiency	$\bar{\sigma}_m$	0.854
Post-match cost parameter	κ_1	0.855
Pre-match cost parameter	κ_2	0.001
Steady–state leverage	ϕ_e	4.269
Steady–state entrepreneurial risk	σ_ω	0.105
Steady–state entrepreneurial endowment	W_e	0.001
Fixed cost	Φ	0.055
Scale factor for capital utilization costs	$\iota_{u,0}$	0.043

state–ratio of the workers' outside option to the sum of the marginal product of labor and hiring costs, Ω_p; *(ii)* the steady–state ratio of the flow opportunity cost of moving from unemployment to employment to the workers' outside option, Γ^{Ω}; and *(iii)* the steady state ratio of unemployment benefits to the participation component of the workers' outside option, b^0.[9] These parameters determine the estimated degree of real wage rigidities at the steady state, as shown below.

Table 3 reports the endogenous parameters when evaluating the estimated parameters at the posterior mode. When optimizing the posterior and running Markov Chain Monte Carlo (MCMC), we impose the condition that the model-implied level of leverage at the steady state is between 1 and 8 to avoid exploring unreasonable areas of the parameter space. As shown in Table 3, at the posterior mode, the steady–state value for leverage is 4.3, which is within the range of sample averages of the equity-to-debt ratio reported in Christiano, Motto, and Rostagno (2014).

3.2.1 Measuring the Degree of Nominal and Real Wage Rigidities

In this paper, we propose a parsimonious way of measuring the degree of nominal and real wage rigidities in any search and matching model. In particular, we propose the decomposing of the nominal wage in search and matching models into the weighted average of the past nominal wage, W_{t-1}, the marginal product of labor ($\mathcal{P}_t$), a real term ($\mathcal{F}_t$), a cyclical component ($\mathcal{C}_t$), and a term that depends on labor market frictions ($\mathcal{L}_t$):

$$W_t = a_1 W_{t-1} + a_2 \mathcal{P}_t + a_3 \mathcal{F} + a_4 \mathcal{C}_t + a_5 \mathcal{L}_t, \tag{35}$$

where the coefficients a_1, a_2, a_3, a_4, and a_5 are often interrelated.[10] The expression above allows us to quantify the relative importance of each component and evaluate the degrees of nominal wage rigidities

[9] The flow opportunity cost of moving from unemployment to employment consists of the forgone unemployment benefits and the forgone consumption value of nonworking time.

[10] For example, a higher estimate off the degree of nominal wage rigidities increases a_1 and lowers the rest of the coefficients.

Table 4: Real and Nominal Rigidities in Wage Setting

	N^w	R^w	$\mathcal{P}$	$\mathcal{C}$	$\mathcal{L}$
Baseline model	0.04	0.15	0.56	0.21	0.05
Shimer (2005)	0	0.11	0.73	0	0.15
Hagedorn and Manovskii (2008)	0	0.94	0.05	0	0
Gertler, Sala, and Trigari (2008)	0.72	0.02	0.25	0	0.01
Gertler and Trigari (2009)	0	0.92	0.05	0	0.03

Notes: N^w stands for the degree of nominal wage rigidity, R^w is the degree of real wage rigidity, $\mathcal{P}_t$ is the marginal product of labor, $\mathcal{F}$ is a fixed real term, $\mathcal{C}$ is a cyclical component, and $\mathcal{L}$ is a term that depends on labor market frictions. The contributions may not sum up to 1 because of rounding.

(N_t^w) and of real wage rigidities (R_t^w) in any search and matching model as follows:

$$N_t^w = \frac{a_1 W_{t-1}}{W_t}, \tag{36}$$

$$R_t^w = \frac{a_3 \mathcal{F}}{W_t}. \tag{37}$$

In our model, we can write equation (35) as

$$\begin{aligned} W_t =& \delta^w \bar{\gamma} \pi_t^{\gamma_{wp}} W_{t-1} + (1-\delta^w)\chi p_t^m mpl_t \\ &+ (1-\delta^w)(1-\chi) \underbrace{\left[b_t + (1-\Gamma)\mu_t + \mathcal{U}_t^{-\sigma_c} \frac{\chi_{ht} X_t(h)}{V_{ct}} \frac{z h_t^{1+\psi_h}}{1+\psi_h} \right]}_{\Omega_t} \\ &+ (1-\delta^w)\chi\beta \left[\kappa_{nt+1} + \frac{p_{t+1}}{q_{t+1}} (1-\delta)\kappa_{vt+1} \right]. \end{aligned} \tag{38}$$

Hence,

$$\mathcal{P}_t = p_t^m mpl_t, \tag{39}$$

$$\mathcal{F}_t = b_t, \tag{40}$$

$$\mathcal{C}_t = \mathcal{U}_t^{-\sigma_c} \frac{\chi_{ht} X_t(h)}{V_{ct}} \frac{z h_t^{1+\psi_h}}{1+\psi_h} + (1-\Gamma)\mu_t, \tag{41}$$

$$\mathcal{L}_t = \kappa_{nt+1} + \frac{p_{t+1}}{q_{t+1}} (1-\delta_s)\kappa_{vt+1}. \tag{42}$$

Given our estimated parameters, the model-implied real and nominal wage rigidities at the steady state are reported in Table 4, where we also report the values for seminal papers in the literature. We conclude that our estimation implies a larger relative importance of real wage rigidities and a low degree of nominal wage rigidities. While Riggi (2010) argues that models (without endogenous labor supply) tend to better explain empirical macroeconomic dynamics when nominal wage rigidities are assumed; Cairó, Fujita, and Morales-Jiménez (2022) show that some degree of real wage rigidity may be needed to explain the dynamics of labor supply. The implied level for real rigidities for our model is along the lines of the value computed for Shimer (2005) despite this latter model not allowing for nominal rigidities. Among the

Table 5: Business Cycle Statistics

	GDP	c	I	π	w	i	u	LFPR	v	ww	spread
Panel A: U.S. Data, 1987:Q1 to 2010:Q2											
Mean				1.01		1.01	0.057	0.66			
Std. Dev.	0.022	0.015	0.083	0.002	0.019	0.004	0.178	0.005	0.174	0.006	0.245
Autocorr.	0.96	0.94	0.98	0.44	0.95	0.96	0.97	0.89	0.95	0.88	0.87
Corr. with GDP	1	0.92	0.96	0.26	0.67	0.63	-0.91	0.54	0.82	0.67	-0.29
Panel B: Model											
Mean				1.00		1.01	0.065	0.66			
Std. Dev.	0.015	0.008	0.035	0.001	0.006	0.003	0.137	0.004	0.142	0.005	0.330
Autocorr.	0.94	0.96	0.96	0.83	0.81	0.94	0.94	0.87	0.90	0.87	0.75
Corr. with GDP	1	0.75	0.90	0.16	0.61	0.38	-0.80	0.69	0.72	0.75	-0.30

Notes: To compute volatilities and correlations, we express the variables in logs as deviations from an Hodrick-Prescott trend with a smoothing parameter of 10^5. C stands for consumption, I for investment, π for inflation, w for real wages, i for the nominal interest rate, u for unemployment rate, LFPR for the labor force participation rate, v for vacancies, and ww for the workweek.

references included in the table, the only case allowing for nominal and real rigidities is Gertler, Sala, and Trigari (2008). In this case, the relative weight of nominal rigidities versus real rigidities is substantially higher than in our baseline model.

3.3 Model Fit

We finish this section with an overview of model fit. Panel A in Table 5 presents business cycle moments computed using U.S. data from 1987:Q1 to 2010:Q2, while panel B reports these moments for the model counterparts, evaluating the model parameters at the posterior mode. Overall, the model does a good job of capturing the volatility, autocorrelations, and the correlation with GDP of key main macroeconomic variables. Regarding labor market variables, the model is able to explain most of the observed volatility of the unemployment rate, the LFPR, vacancies, and workweek, as well as their correlation with output.[11]

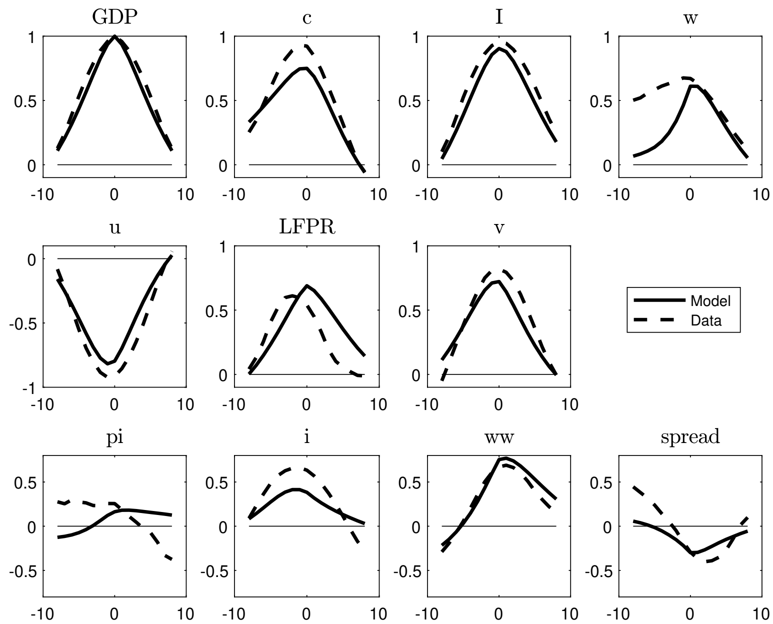
An alternative way of assessing the ability of the model to capture key features in the data is by comparing the autocorrelation functions of the model variables with their data counterparts. Figure 1 reports the autocorrelation functions up to eight leads and lags for the observable variables (dashed lines) and for their model-implied counterparts evaluated at the posterior mode (solid lines). Overall, the model does a very good job capturing the dynamics of most of the variables, with perhaps the exception of the inflation beyond lead/lag equal to two quarters.

3.4 External Validity

In this section, we do an external validation exercise for the model-based estimates of two key latent variables of the model: the unemployment rate gap and the output gap. In particular, we perform two exercises. First, we compare our model-based estimates with the estimate from established sources such as the Congressional Budget Office (CBO) and the most recent public estimates from the Board of Governors of the Federal Reserve System (FRB). Second, we compare our model-based estimates with estimates from

[11] Table C.1 in the Appendix presents cross correlations for all variables for both the data and the model.

Figure 1: Cross-Correlations with GDP of Selected Variables—Data vs. Model



Notes: c stands for consumption, I for investment, w for real wages, u for the unemployment rate, LFPR for the labor force participation rate, v for vacancies, pi for inflation, i for the nominal interest rate, and ww for the workweek. The data series for wages is real compensation per hour.

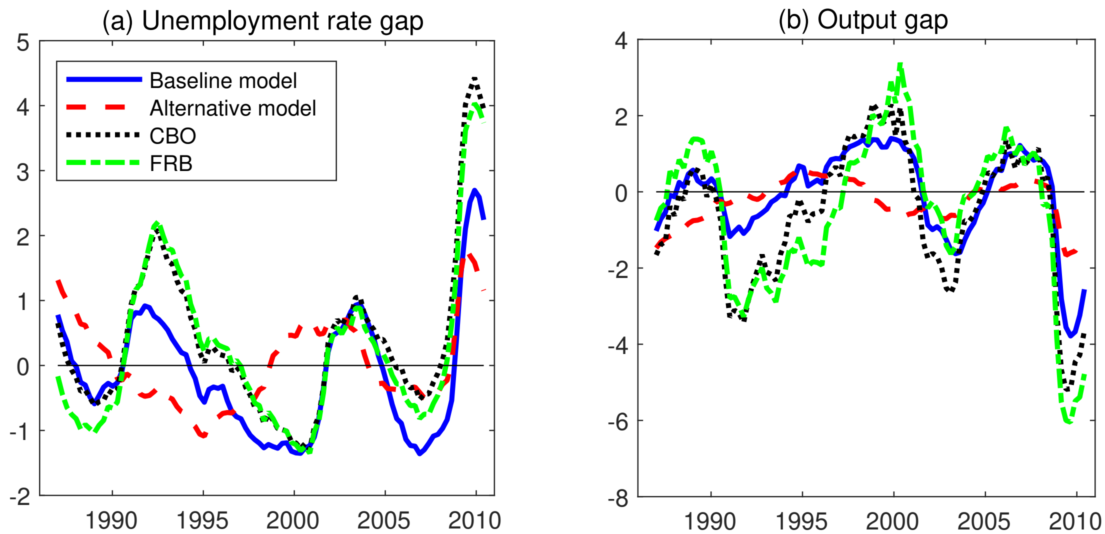
an alternative model that does not feature the labor force participation margin and the hours margin in order to establish the role of these new features in estimating the unemployment rate gap and the output gap.[12]

Figure 2 reports the model-based and CBO or FRB estimated unemployment rate and output gaps. The unemployment rate gap is computed as the difference between the observed unemployment rate and the natural rate of unemployment estimated by the model, the CBO, or the FRB. The model-based output gap is computed as the percent difference between the level of output in the model economy and the corresponding one in the flexible economy. The CBO/FRB output gap is computed as the percent difference between the observed real GDP and the real potential GDP estimated by the CBO/FRB.[13] As shown in Figure 2, the CBO and FRB estimates, the dotted black and dash-dotted green lines, respectively, are highly correlated—the correlation is 0.98 for the unemployment rate gap and 0.95 for the output gap. The baseline model-based measures of economic slack, in solid blue, are similar to the ones estimated by the CBO and the FRB. In particular, the correlation between the model-based measure of the unemployment rate gap and the corresponding CBO and FRB estimates ranges between 0.87 and 0.91. The corresponding values for the output gap are also very high—in the range of 0.82 to 0.92. There are, however, periods with notable differences.

[12]The alternative model is identical to the baseline model, but we impose that the LFPR and hours worked are constant and equal to their steady–state values. Moreover, we shut off the preference shock to participation or home production and the preference shock to hours. That is, we set equal to zero the two shocks affecting the additional margins of labor supply introduced in the baseline model. When estimating the alternative model, we use a reduced information set because the observed LFPR and the workweek data series are not included as observables.

[13]See Appendix A.2 for additional details on the CBO and FRB estimates.

Figure 2: External Validity for Model-based Gaps



Notes: Baseline and alternative models are defined in the text. *CBO* stands for Congressional Budget Office estimates and *FRB* stands for the Federal Reserve Board staff estimates.

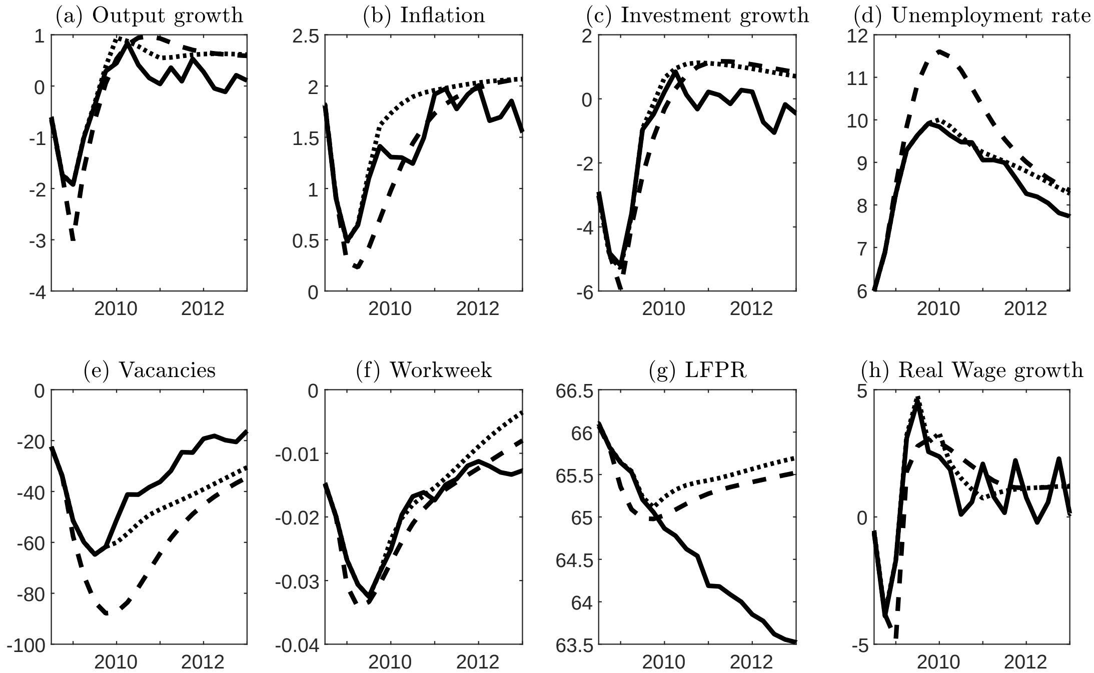
We assess the role of the two new labor supply margins in our model (the LFPR and hours) by comparing the model-implied gaps in the baseline model, in solid blue in Figure 2, and the alternative model without these two margins, in dashed red. Given the differences between the estimated gaps for these two models, we conclude that the estimates for the natural rate of unemployment and the flexible level of output are quite different in these two models. These results suggest that having both the LFPR and hours worked as endogenous variables in the model and in the observable set is key in assessing the underlying state of the economy summarized by the unemployment rate gap and the output gap.

4 Forecasting Performance of the Model

The significant deterioration of labor market conditions during the Great Recession was followed by a jobless recovery. In turn, the response of inflation was muted during the Great Recession, and the subsequent recovery featured a long-lasting period of subdued inflation. In this section, we assess the ability of the estimated model in delivering jointly a deterioration of labor market conditions and a small response in inflation in addition to a jobless recovery and inflation persistently subdued. To do so, we examine the forecasting performance of our estimated model for key labor market variables and inflation at two critical points during the Great Recession: *(i)* 2008:Q4, which is the quarter with the largest drop in GDP growth, and *(ii)* 2009:Q4, which is the quarter with the highest unemployment rate. In these forecasting exercises, we use the Kulish, Morley, and Robinson (2017) methodology to control for the binding ELB on the federal funds rate.[14]

[14] Kulish, Morley, and Robinson (2017) show that the dynamics at the ELB can be well approximated by a time-varying linear policy function for a given expected ELB duration. Technical details about the solution method, ELB, and shock decomposition can be found in Appendix D.

Figure 3: Model Forecast: 2008:Q4 and 2009:Q4

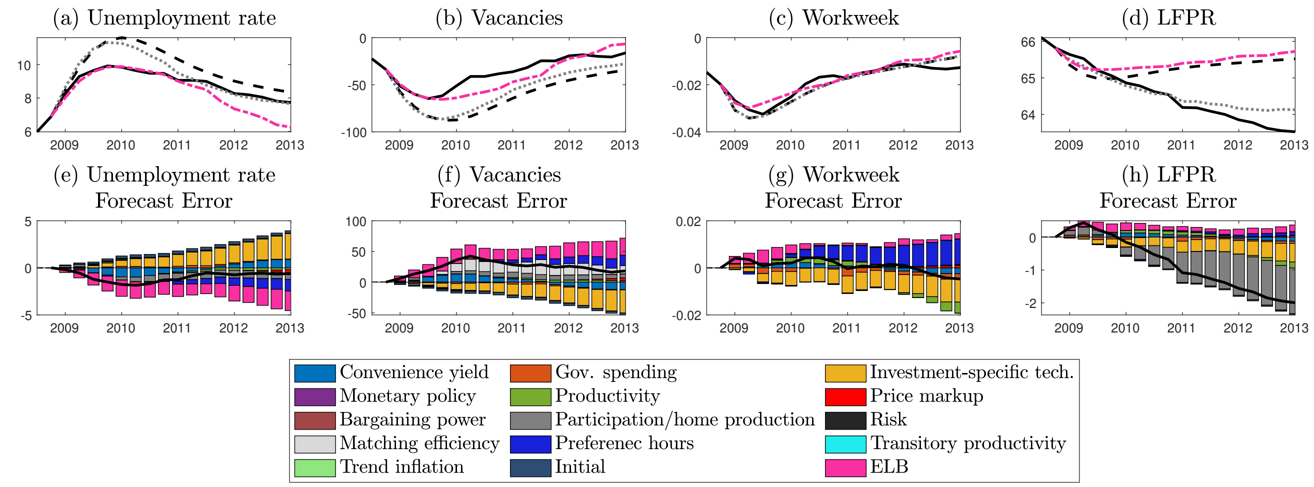


Notes: Solid lines represent the dynamics for the unemployment rate, the LFPR, the workweek, vacancies, real wage growth and inflation between 2008 and 2013. Dashed and dotted lines represent the model forecast based on data up to 2008:Q4 and 2009:Q4, respectively.

4.1 Description of the Model Forecast

The solid lines in Figure 3 report the observed variables, the dashed lines show the model forecast conditional on data up to 2008:Q4, and the dotted lines report the model forecast conditional on data up to 2009:Q4. Conditional on 2008:Q4 data (the dashed lines), the model does a good job at predicting the behavior of output and investment. In addition, the model predicts a significant deterioration in labor market conditions during 2009 and early 2010, with a slow recovery thereafter. However, the actual deterioration in the unemployment rate and vacancies was not as dire as expected. For example, as shown in panel (d), our model predicted that the unemployment rate would peak above 11 percent in 2010, above the realized peak of 10 percent, but the timing of the peak was closely predicted. As shown in panel (e), the model paired the projected increase in the unemployment rate with a larger decline in vacancies than in the data. By contrast, panel (f) shows that the size of the dip projected for the workweek was indeed similar to the one observed. Moreover, panels (d), (e), and (f) suggest that the model can match reasonably well the pace of the recovery in these labor market variables in the aftermath of the Great Recession. The model is also able to predict the initial fall of the LFPR in 2009 and 2010 (see panel (g)), but it fails to predict the secular downward trend (structural decline). We explore the sources behind the misses in the LFPR forecast in Section 4.2, where we illustrate the role of preference shocks to participation in explaining the downward trend in the LFPR. Despite the dire forecast of the

Figure 4: LABOR MARKET FORECAST: 2008:Q4



Notes: The solid black lines in the top panels present the dynamics for the unemployment rate, the LFPR, the workweek, and vacancies between 2008 and 2013. The black dashed lines are the model's forecast based on data up to 2008:Q4. The gray dotted lines are the model's forecast plus the χ_l contributions to the forecast error. The pink dashed-dotted lines are the model's forecast in the absence of the ELB constraint. The bottom panels present the forecast error ($Y_{t+s} - E_t [Y_{t+s}]$) decomposition.

labor market, the model does not predict a large wage and price disinflation, as shown in panels (b) and (h) of Figure 3. The model's predictions are similar to those observed in the data. Therefore, we argue that the model does not exhibit the missing disinflation puzzle.

Conditional on data available up to 2009:Q4 (the dotted lines), which is after the peak unemployment rate during the Great Recession, we evaluate the forecasting performance on the persistence during the recovery for the unemployment rate, vacancies, and the workweek. As shown in Figure 3, the model matches very well the observed size and pace of the recovery in these labor market variables. For example, between 2010 and 2013 the model predicts a decline of about 2 percentage points in the unemployment rate, a similar decline to the one observed in the data.

In the remainder of this section, we analyze the drivers of the model projections conditional on data up to 2008:Q4.[15]

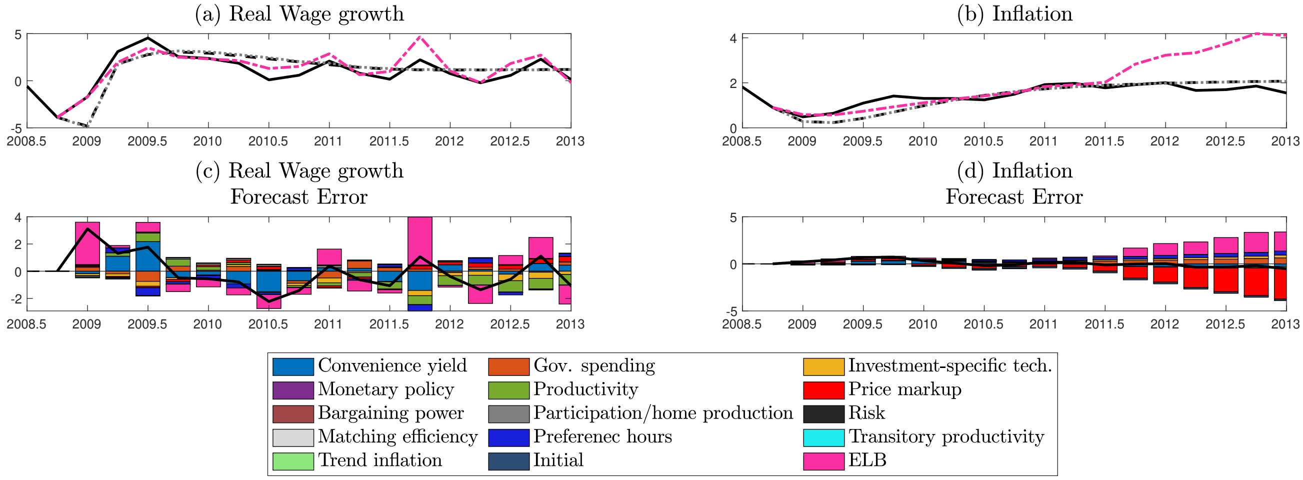
4.2 Understanding the Model Forecast Using a Shock Decomposition Approach

As discussed before, the model predicts a sizable deterioration in the labor market during the Great Recession and a plausible subsequent recovery. We rely on the forecast error shock decomposition to better understand the model forecast.[16] Figure 4 reports the model forecast for labor market variables conditional on data available in 2008:Q4 (the dashed lines) in the upper row and the forecast error shock decomposition in the bottom row. For the unemployment rate and vacancies, the bulk of the forecast errors during the Great Recession is accounted for by the ELB constraint on the nominal interest

[15]The analysis conditional on data up to 2009:Q4 is available in Appendix C.2.

[16]The forecast error for variable Y in period $t+s$ is defined as $Y_{t+s} - E_t [Y_{t+s}]$.

Figure 5: REAL WAGE AND INFLATION FORECAST: 2008:Q4



Notes: The solid black lines in the top panels present the dynamics for the annualized real-wage growth and the annualized price inflation between 2008 and 2019. The black-dashed lines are the model's forecast based on data up to 2008Q4. The gray dotted lines are the model's forecast plus the χ_l contributions to the forecast error. The pink dash-dotted lines are the model's forecast in the absence of the ELB constraint. The bottom panels present the forecast error ($Y_{t+s} - E_t [Y_{t+s}]$) decomposition.

rate (pink bars). For the LFPR, shocks to participation/home production (dark gray bars) are key in accounting for the secular trend.[17] We assess the role of the ELB and participation shocks by computing two counterfactual model projections: *(i)* a projection that adds in the contributions of participation shocks to the forecast error of a given variable (the gray dotted lines) and *(ii)* a projection that abstracts from the ELB constraint (pink dash-dotted lines).

First, when including the shocks to the participation margin to the forecast for the LFPR (gray dotted line), the model is able to reproduce the secular trend observed in the data. Implicitly, we argue that a forecaster could use existing projections on demographic trends to inform the model and improve the LFPR forecast. Also, during the recovery period adding the participation shocks improves the forecasting performance for the unemployment rate and vacancies.

Second, taking into account the ELB constraint (pink dash-dotted lines) suffices in delivering the size of the increase in the unemployment rate and the decline in vacancies during the Great Recession. The contributions of the ELB constraint in the forecast error decomposition have two sources: *(i)* the amplification of shocks (relative to a linear response) and *(ii)* an ELB duration that is longer than initially expected (see Appendix D for details). For the unemployment rate and vacancies, the lower-than-expected severity of the ELB constraint is the main source of the ELB contribution to the forecast errors.

Unlike other New Keynesian DSGE models, our model is also able to forecast the "missing disinflation" observed in the aftermath of the Great Recession. Using Figure 5, we study the role of the ELB constraint for the forecast of inflation and the real wage growth. We find that the forecast for inflation and real wage growth is somewhat improved when taking into account the expected ELB constraint. Specifically,

[17] For a discussion on the structural decline in the LFPR after the Great Recession, see, e.g., Aaronson et al. (2014).

the less-severe-than-expected ELB constraint explains part of the "small" missed disinflation and allows the model to not predict a further decline in real wage growth.

The findings discussed in this section are not enough to explain why the model can jointly forecast both the worsening of labor market conditions and the subdued response of inflation in the aftermath of the crisis—a key question that we explore next.

4.3 Understanding the Model Forecast Using a Structural Approach

Figure 3 has shown that our model successfully simultaneously predicts a modest decline in wage and price inflation and a severe deterioration in the labor market followed by a prolonged recovery. We argue that three distinctive features of our estimated model are key in delivering jointly the observed patterns: *(i)* the relatively high degree of real wage rigidities; *(ii)* the small or nonexistent role of pre-match costs in the recruiting cost function; and *(iii)* the presence of financial rigidities.[18] We proceed by generating counterfactual projections in which we can better illustrate the specific role played by each of these features in delivering the baseline projection.

First, regarding wage rigidities, Del Negro, Gianonni, and Schorfheide (2015) show that a model featuring a high degree of nominal rigidities can explain the muted response of inflation during 2010 and 2011. However, our model, which can also explain the "missing disinflation," features a low degree of nominal rigidities and a high degree of real wage rigidities. To show the relative role of real wage rigidities in the inflation forecast, we reduce the degree of real wage rigidities and increase the degree of nominal wage rigidities in our model, keeping the overall degree of wage rigidities, as reflected in Table 4, constant. In particular, we set the relative size of the unemployment benefits (b^0), the Calvo parameter (λ_w), the relative size of the outside option (Ω_p), and workers' bargaining power (η) such that nominal wage rigidities are more important than real wage rigidities, keeping the other components in Table 4 constant.[19]

Second, regarding pre-match costs, Leduc and Liu (2020) conclude that search intensity and recruiting intensity—which in their model entail pre-match costs—are quantitatively important in explaining the weak job recovery in the aftermath of the Great Recession. However, their model does not feature nominal rigidities and, hence, has no role for inflation. In our estimated model, pre-match costs are negligible. Thus, to examine the possible role of pre-match costs that are larger than we estimate, we increase the role of pre-match costs in the recruiting cost function. In particular, we increase the κ_2/κ_1 ratio from 0 to 0.5 in our estimated model.

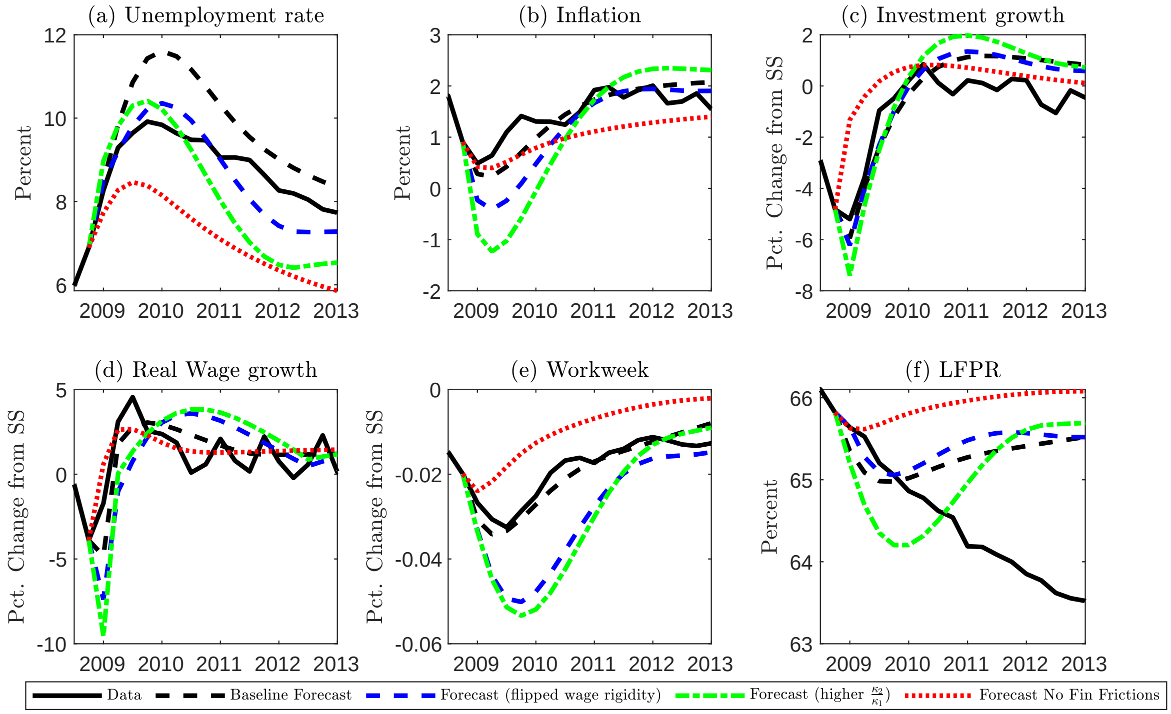
Third, regarding financial frictions, Gilchrist et al. (2017) argue that financial frictions play a relevant role in accounting for the missing disinflation during the Great Recession.[20] In our model, financial

[18] In Nucci and Riggi (2018), the effect of wage rigidity on inflation is almost offset by the countercyclicality of the LFPR, which implies that the degree of real wage rigidities is irrelevant for inflation dynamics in their calibrated model with endogenous participation. In our model, as in the data, the LFPR is procyclical, which implies that the degree of real wage rigidities plays a relevant role in defining the inflation dynamics.

[19] The implied values for the parameters are $b^0 = 0.34$, $\Omega_p = 0.77$, $\lambda = 0.15$, and $\eta = 0.66$.

[20] Also Christiano, Eichenbaum, and Trabandt (2015) develop a model with a rich labor market in which the missing disinflation is due to a financial wedge which pushes up firms' cost of working capital. However, in their model there are no endogenous financial frictions on investment, and the financial wedge is assumed to be an exogenous process.

Figure 6: Alternative Model projections



Notes: Solid black lines correspond to the observed variables for investment growth, unemployment rate, workweek, and LFPR. Solid black lines correspond to the model-implied (net of measurement error) PCE inflation and real compensation per hour. Dashed black lines report the baseline model forecast conditional on data available in 2008:Q4 data. Dotted red lines represent the counterfactual model projection without financial frictions. Blue dashed lines report the counterfactual model projection with smaller real wage rigidities but higher nominal wage rigidities. Green dash-dotted lines show the counterfactual model projection with a larger role for pre-match costs.

frictions affecting the entrepreneurial sector generate an endogenous inverse relationship between capital accumulation and spreads that would be missing in the absence of these frictions. We explore the implications of the latter by turning off the financial frictions in the model.[21]

Figure 6 shows the observed variables (solid black), the baseline model forecast conditional data available in 2008:Q4 data (dashed black), and the three counterfactual model projections: *(i)* the counterfactual projection when the relative importance of real and nominal wage rigidities is flipped (dashed blue), *(ii)* the counterfactual projection with a larger role for pre-match costs in the recruiting cost function (dash-dotted green), and *(iii)* the counterfactual projection without financial frictions (dotted red). As shown in panel (a) and panel (c), the counterfactual projections with flipped wage rigidities (dashed blue) and higher pre-match costs (dash-dotted green) predict a larger deterioration of economic activity than in the baseline paired with a smaller unemployment peak and a larger decline in hours worked as shown in panel (e). The peak unemployment rate projected in these two counterfactuals is closer to the observed one than the baseline model—but, at the expense of predicting a pace for the recovery that is

[21]In particular, in order to preserve the same steady state as in the baseline, we assume the presence of a fixed spread between the return on capital and the real interest rate, while in our model the spread moves endogenously in response to shocks and movements in the entrepreneurial net worth.

faster than the observed one and faster than the projected pace in the baseline model. Therefore, there is a trade-off between predicting the size of the peak and the pace of the recovery in unemployment. However, as shown in panel (b) and panel (d), the relative success in forecasting the unemployment rate comes at the cost of projecting substantial price and wage disinflation during the Great Recession. Note that the declines in price and wage inflation are projected even with the flat Phillips curve we estimated. Therefore, the model economies characterized by either a lower degree of real wage rigidities or a relatively more prominent role for the pre-match component of recruiting costs than in our estimation (all other parameters equal) are subject to the missing disinflation puzzle ubiquitous in standard New Keynesian DSGE models. In Section 5, we show that the combination of the high level of real wage rigidities and the small role of pre-match costs makes the marginal cost less cyclical, preventing inflation from falling too much in recessions. Moreover, these two features allow the model to match the cyclicality of the LFPR and the unemployment rate. Our results are consistent with Cairó, Fujita, and Morales-Jiménez (2022) that show that some degree of real wage rigidities is needed to match the cyclicality of the LFPR in the data. In addition, we show that a small role of pre-match costs allow us to match the observed unemployment volatility conditional on the observed vacancy volatility.

As shown in panel (c) in Figure 6, absent financial frictions (dotted red), the model fails to forecast the large and persistent decline in investment. The faster recovery of capital in the model without financial frictions leads to two counterfactual patterns in the recovery after the Great Recession. First, higher capital results in higher labor demand and consequently in a much faster recovery in the unemployment rate, in hours, and in the LFPR. Second, in our baseline model, the expected low path for capital implies a higher expected capital rental rate, putting upward pressure on marginal costs and on inflation. Interestingly, the absence of this channel in the model without financial frictions results in a shallower path for inflation, despite a faster recovery in the labor market.

5 Key Labor Market Mechanisms in the Model

As stated earlier, the role of financial rigidities in accounting for the missing disinflation during the Great Recession was already explored by Gilchrist et al. (2017) and in delivering labor market dynamics by Christiano, Eichenbaum, and Trabandt (2015). Therefore, in this section, we focus on further exploring the role played by the key labor market mechanisms, that is, the higher degree of post-match costs relative to pre-match costs in our estimated model and the higher degree of real wage rigidities relative to nominal wage rigidities. To do so, we use the estimation results from two alternative settings. First, we re-estimate the model using the same data set but impose a significant weight on the pre-match portion of the generic recruiting cost function. This exercise allows us to isolate the role played by this parameter. Second, we re-estimate the model by imposing a fixed labor supply on a data set that excludes the LFPR and the workweek from the observable set. In this case, the estimated vector is characterized by a flatter Phillips curve, a lower degree of real wage rigidities, and a higher degree of nominal rigidities. Therefore, we can study the role played by real versus nominal rigidities in the model-implied dynamics.

5.1 The Importance of Pre- versus Post-Match Recruiting Costs

To study the relative importance of the two components of the recruiting cost function, we explore the role they play in the dynamics of the marginal cost. The (detrended) marginal cost in the model economy (see Appendix F) is given by

$$p_t^m = \frac{1}{\left(\gamma_t^T\right)^{1-\alpha}} \left[\frac{\left(\frac{\tilde{\mathbf{W}}_t}{z_{ht}}\right)^{1-\alpha} \left(r_t^k\right)^{\alpha}}{\alpha^\alpha (1-\alpha)^{1-\alpha}} \right], \tag{43}$$

where $\frac{\tilde{\mathbf{W}}_t}{z_{ht}}$ is the detrended marginal labor cost and $\tilde{\mathbf{W}}_t$ is the detrended marginal cost of hiring a worker, which is given by:

$$\tilde{\mathbf{W}}_t = \tilde{w}_{jt} z_{ht} + \frac{\tilde{\kappa}_{vt}}{q_t} - \gamma_t \Lambda_{t,t+1} \tilde{\kappa}_{nt+1} - \gamma_t \Lambda_{t,t+1} \frac{\tilde{\kappa}_{vt+1}}{q_{t+1}}, \tag{44}$$

where

$$\begin{aligned} \tilde{\kappa}_{vt} &= \kappa_1 q_t^{1+\psi_1} \left(\frac{v_{jt}}{n_{jt-1}}\right)^{\psi_1} + \kappa_2 \left(\frac{v_{jt}}{n_{jt-1}}\right)^{\psi_2}, \\ \tilde{\kappa}_{nt} &= \left[\kappa_1 \frac{\psi_1}{1+\psi_1} q_t^{1+\psi_1} \left(\frac{v_{jt}}{n_{jt-1}}\right)^{1+\psi_1} + \kappa_2 \frac{\psi_2}{1+\psi_2} \left(\frac{v_{jt}}{n_{jt-1}}\right)^{1+\psi_2} \right]. \end{aligned} \tag{45}$$

Therefore, if a firm hires a new worker, it has to pay her wages $w_{jt} z_{ht}$ and the recruiting cost $\frac{\kappa_{vt}}{q_t}$. However, the firm saves on recruiting costs in the next period as the number of employees increases κ_{nt+1} and it can retain a fraction of the new workers hired today—κ_{vt+1}. Note that we use observable variables for all the endogenous variables affecting $\frac{\tilde{\mathbf{W}}_t}{z_{ht}}$ because we have data on the workweek, z_{ht}, vacancies, v_{jt}, unemployment, $1 - n_{jt}$, and wage growth, $\Delta\tilde{\mathbf{W}}_t$. Thus, conditioning on the observed volatility of these variables, the model parameters determine the volatility and cyclicality of the marginal labor cost. Given that labor market tightness, $\left(\frac{v_{jt}}{n_{jt-1}}\right)$, enters into equation (44), the cyclicality of labor costs is a function of the relative importance of the pre-match component in overall recruiting costs. For example, if the pre-match component is relatively more important than the post-match component—κ_2 is higher than κ_1—then labor costs are very cyclical and the cyclicality of hiring is low.

In our estimation, post-match costs are much more important than pre-match costs, which has relevant implications for the dynamics of labor market variables and inflation. We explore the extent of the influence of this result on model dynamics by estimating a version of the model with a fixed coefficient that governs the relative importance of the two types of recruiting costs. In particular, we fix $\log \kappa_{21} = 2$.[22] This value implies parameters values for $\kappa_1 = 0.014$ and $\kappa_2 = 0.105$, which are very different from the estimated values $\kappa_1 = 0.855$ and $\kappa_2 = 0.001$ in our baseline model. The estimation exercise uses the same data set and the same prior choices for the other parameters as in the baseline estimation. Tables B.5 to B.10 in Appendix B report the estimation results for this version.[23]

[22] In the baseline estimation, the estimated parameter value was $\log \kappa_{21} = -6.55$.

[23] The posterior odds for the baseline model over the alternative discussed here are above 30 log points.

Table 6: Cyclical Volatilities for Labor Market Variables and Inflation

	π	w	u	LFPR	v	ww
Panel A: U.S. Data, 1987:Q1 to 2010:Q2						
Std. Dev.	0.002	0.019	0.178	0.005	0.174	0.006
Relative Std. Dev.	0.07	0.88	8.19	0.22	8.04	0.26
Panel B: Baseline Model						
Std. Dev.	0.001	0.006	0.137	0.004	0.142	0.005
Relative Std. Dev.	0.09	0.41	9.29	0.26	9.61	0.34
Panel C: Alternative Model with Higher Pre-Match Costs						
Std. Dev.	0.002	0.012	0.098	0.005	0.096	0.011
Relative Std. Dev.	0.07	0.55	4.68	0.22	4.59	0.54

Notes: See notes to Table 5. Relative volatility is computed as the standard deviation of each variable relative to output.

Table 6 reports cyclical volatilities for labor market variables and inflation. The higher value for pre-match costs imposed on the alternative model implies volatilies for the labor market variables (the LFPR, the unemployment rate, and vacancies) that are well below the sample standard deviations, thus explaining why our estimated model prefers very small pre-match costs. In the estimation, other parameters that also affect the volatilities of these variables are estimated; hence, they can adjust to compensate for the direct effect of the higher relative share of pre-match costs. In fact, the estimated values for parameters governing the convexity of the recruiting cost function and the workers' outside option suggest higher volatility for the variables of interest.[24] However, the effect on cyclical volatilities of more prevalent pre-match costs dominates those of the remaining labor market parameters as shown when comparing panel B and panel C in Table 6 where the volatilities of the unemployment rate and vacancies are about half of those in the baseline estimation and the data.

Because wages become more responsive to labor market tightness in the alternative model, the volatility of working hours increases exceeding the volatility in the baseline model and the data. Therefore, the lower volatility of the extensive margin of the labor decisions is compensated by higher volatility of the intensive margin of labor supply.

Despite the differences in labor market volatilities between the baseline model and the alternative estimation presented here, the volatility of inflation is similar. The higher volatility of marginal cost in the alternative estimation is compensated by an even flatter estimated slope of the Phillips curve compared with the baseline model.[25] In addition, we show in Section 5.2 that estimating the relative importance of pre- and post-match recruiting costs is key in assessing the relative importance of real wage rigidities versus nominal rigidities.

[24] The estimated parameters governing the convexity of the recruiting cost function (ψ_1 and ψ_2) are almost zero, suggesting linearity on both of its components, which, ceteris paribus, increases the cyclicality of the unemployment rate and vacancies. The estimated higher value of workers' outside option relative to the sum of the marginal product of labor and hiring costs also generates additional volatility in labor market variables.

[25] The slope of the Phillips curve is estimated to be 0.66 in the alternative model versus 1.10 in our baseline model.

Table 7: REAL AND NOMINAL RIGIDITIES IN WAGE SETTING

	N^w	R^w	$\mathcal{P}$	$\mathcal{C}$	$\mathcal{L}$
Baseline model	0.04	0.15	0.56	0.21	0.05
Alt. model with higher degree of pre-match costs	0.27	0.10	0.48	0.13	0.03
Alt. model without LFPR and hours decisions	0.33	0.09	0.38	0.16	0.04

Notes: N^w stands for the degree of nominal wage rigidity, R^w is the degree of real wage rigidity, $\mathcal{P}$ is the marginal product of labor, $\mathcal{F}$ is a real term, $\mathcal{C}$ is a cyclical component, and $\mathcal{L}$ is a term that depends on labor market frictions. The contributions may not sum up to 1 because of rounding.

5.2 The Importance of Real Wage Rigidities versus Nominal Wage Rigidities

As we have seen so far, our model can jointly explain the evolution of labor market variables and inflation during and after the Great Recession. In Section 4, we argued that this result hinges on our estimated low degree of nominal wage rigidities and high degree of real wage rigidities. In this section, we further investigate the role of nominal and real rigidities in our baseline model by evaluating the relative importance of nominal and real wage rigidities in the baseline vis-à-vis two alternative models using the decomposition put forward in Section 3. The first alternative model, presented in Section 5.1, imposes a larger importance on pre-match hiring costs than post-match costs. The second alternative model explores the importance of the two additional margins of labor supply we have introduced in the paper: participation and hours worked. To do so, we fix participation and hours worked to their steady state values and we estimate this alternative model by removing the LFPR and the workweek from the dataset. This second alternative model allows us to isolate the role of endogenous labor supply decisions and data on labor supply in informing the model about the degree of nominal and real wage rigidities. The estimation results for this second alternative model are characterized by substantially different estimates for the slope of the Phillips curve (*slope* is equal to 1.10 in the baseline versus 4.75 in the alternative estimation), the nominal wage rigidity parameter (λ_w is 0.04 in the baseline versus 0.33 in the alternative), and one of the parameters governing the outside option (b^0 is 0.98 in the baseline versus 0.79 in the alternative).[26]

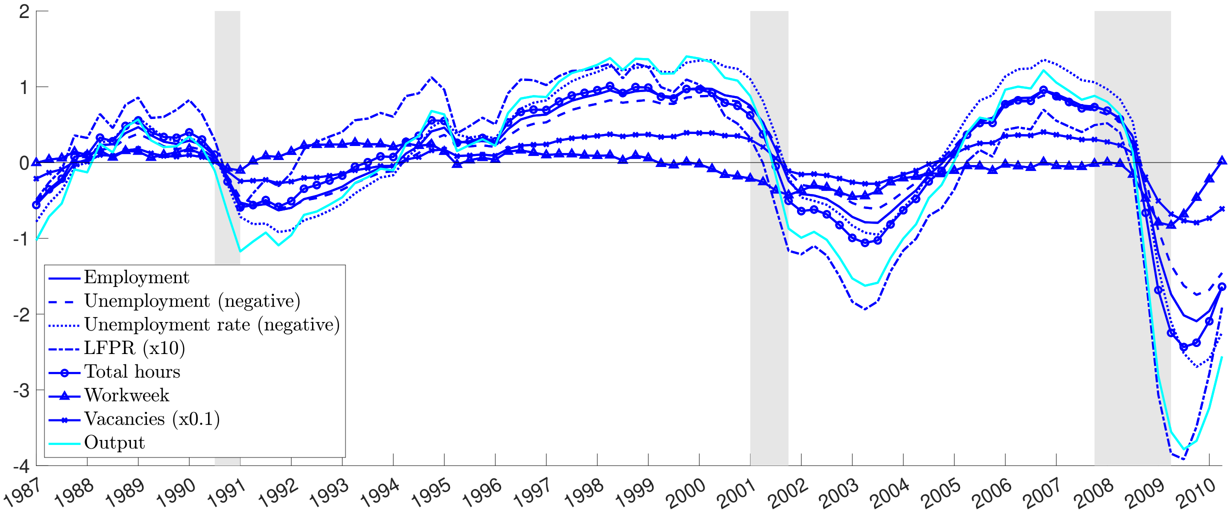
When comparing the first two columns of Table 7, we conclude that the two alternative models present substantially higher levels of nominal rigidities than the baseline model and a lower degree of real rigidities. Therefore, while the baseline model displays a larger relative importance of real wage rigidities, the two alternatives rely more on nominal wage rigidities. Comparing the estimates and implied levels of nominal versus real wage rigidities for the baseline model and for the model with fixed labor supply, we conclude that data on both the LFPR and the workweek are informative in identifying the degree of (nominal and real) wage rigidities and the slope of the price Phillips curve.

6 Model-Based Labor Market Gaps

This section presents an analysis of the main model-based labor market gaps featured in our model economy. We start with a historical analysis of model-based latent variables for the labor market. We

[26]Estimation results for the alternative models are available in Tables B.5 and B.6 in Appendix B.

Figure 7: A Comparison of Model-Based Labor Market Gaps



Notes: The flexible-price gap for the labor market variable x is defined as $100 \cdot (x - x^{flex})$, where the superscript $flex$ denotes variables in the flexible-price economy. For comparison purposes, the LFPR gap is multiplied by 10, the unemployment gap and the unemployment rate gap are multiplied by -1, and the vacancies gap is multiplied by 0.1. The output gap is defined as the percentage deviation of output with respect to its flexible-price counterpart times 100. The shaded areas represent NBER recessions.

show that none of the model-based labor market gaps are a sufficient statistic of labor market slack. However, all labor market gaps contain important information about the state of the economy, which we summarize in a labor market indicator constructed using principal components analysis. Finally, we show that data on the intensive and extensive margins of labor supply are important drivers of the natural rate of unemployment, which summarizes the state of the labor market.

6.1 Is the Unemployment Rate a Sufficient Statistic for Labor Market Slack?

The richness of our labor market modeling allows us to compute several measures of labor market slack in the economy and evaluate whether the unemployment rate gap is a sufficient statistic for assessing the degree of labor market slack in the U.S. economy over the estimation sample. Figure 7 reports all the flexible-price labor market gaps featured in our model over the estimation period, alongside the flexible-price output gap.[27] As shown in Figure 7 and reported in Table 8, all gaps are highly correlated, with correlations ranging from 0.84 to 1 in absolute value, with the exception of the workweek gap, whose correlation with all gap measures but the LFPR gap is significantly smaller. The strong correlation between the flexible-price output gap and most flexible-price labor market gaps is also present in the scatter plots in Figure 8.

Moreover, from Figure 7 and Figure 8, we highlight the following six observations. First, not all labor market gaps are fully synchronized—that is, they do not become positive or negative at the same time. While all the labor gaps become negative within two or three quarters during recessions, the

[27] All gaps are the smoothed series computed when the model is evaluated at the posterior mode.

Table 8: Model-based Gaps: Correlation Matrix

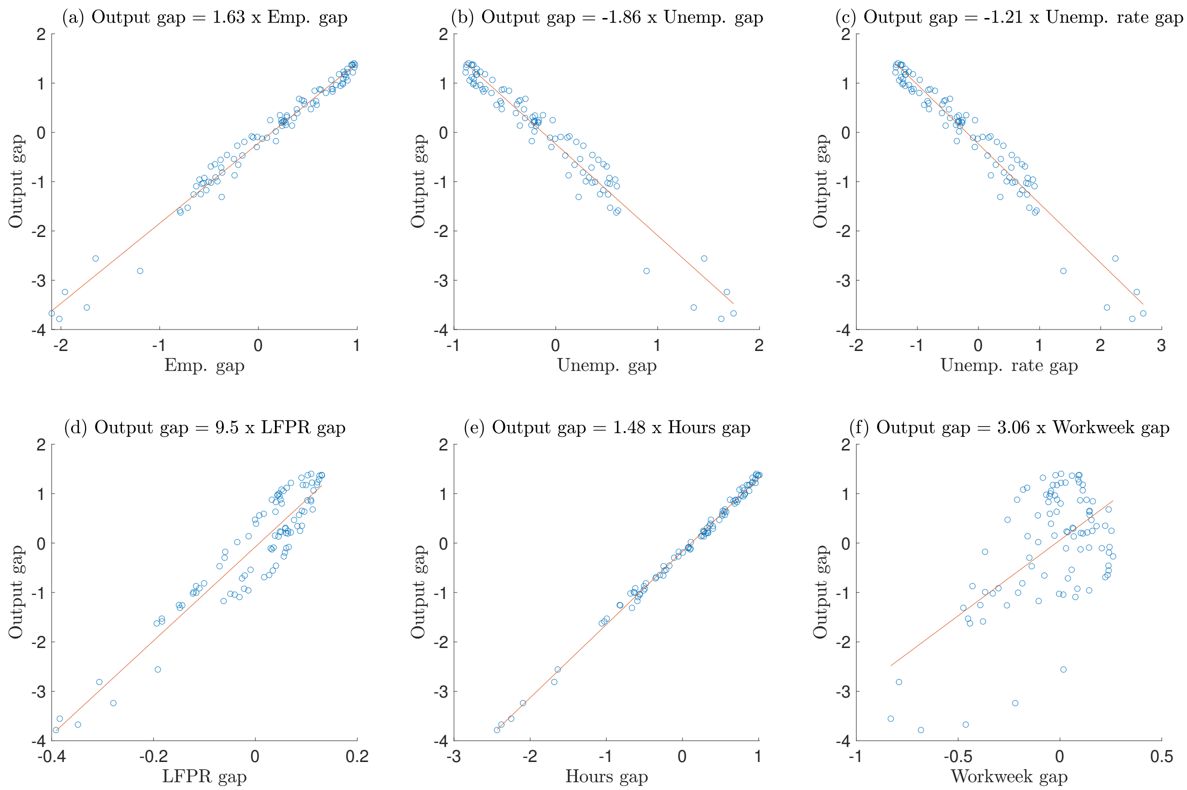
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
(1) Emp. gap	1	-0.996	-0.997	0.878	0.988	0.480	0.989
(2) Unemp. gap		1	1	-0.831	-0.971	-0.403	-0.974
(3) Unemp. rate gap			1	-0.835	-0.972	-0.408	-0.975
(4) LFPR gap				1	0.939	0.828	0.931
(5) Total hours gap					1	0.610	0.998
(6) Workweek gap						1	0.591
(7) Output gap							1

Notes: To compute correlations, we express the variables in logs as deviations from a Horick-Prescott trend with a smoothing parameter of 10^5.

timing of when the labor gaps become positive during recoveries is more heterogeneous. Indeed, it may take several quarters for all gaps to turn positive after the first gap becomes positive. Second, over the three recessionary periods in the estimation sample, the relative relationships among the labor market gaps are not constant. As shown in Figure 7, there is not a single labor market gap that always turns positive or negative first (or last). For example, the LFPR gap is the last gap to turn negative in the 1991 recession and the second to turn positive during the recovery. However, in the aftermath of the 2001 recession, the LFPR gap is the last gap to become positive. Third, from the estimated Okun's law coefficients reported in Figure 8, we conclude that the LFPR fluctuations matter for unemployment dynamics because the estimated Okun's law coefficient for the unemployment gap is close to 2 (see panel (b) in Figure 8), while the estimated Okun's law coefficient for the unemployment rate gap is around 1.2. Fourth, as shown in Figure C.2 in Appendix C, Okun's law errors tend to decline in recessions, implying that, in recessions, labor market gaps become relatively more negative than the output gap. Fifth, Figure C.2 in Appendix C shows that the Okun's law errors for the LFPR gap and for the workweek gap are quite cyclical. In particular, the turning points (peaks) in these errors—if you smooth through higher–frequency variations—lead recessions in our sample and could be a candidate for an early-warning indicator of recessions. Finally, as shown in Table 9, the labor market gap most tightly linked to the output gap is the total hours gap, as the Okun's law errors for that gap exhibit the smallest standard deviation.

Based on these results, we conclude that the unemployment rate gap is not a consistent indicator of broad labor market conditions, as it conveys only a partial view of overall labor market conditions. A positive or negative unemployment rate gap does not imply that all of the other labor market gaps are positive or negative. In addition, as shown in Table 9, the relationship between the output gap and the unemployment rate gap is more volatile than the relationship between the output gap and some of the other labor market gaps. Thus, the unemployment rate gap (or any other labor market gap) is not a sufficient indicator of labor market conditions nor the most accurate predictor of the output gap. As a consequence, no single labor market gap can accurately describe the state of broad labor-market conditions. From Figure C.2 and Table 9, the employment gap might be preferred as the single indicator of the current cyclical position of the economy because it can most accurately predict the output gap. However, it still does not encompass information from the total hours gap, which is also informative

Figure 8: Output Gap and Labor Market Gaps



Notes: This figure plots the flexible-price output gap against the flexible-price labor market gaps. Gaps are smoothed series when the model is evaluated at the posterior mode. Red lines represent the linear relationship between the output gap and the corresponding labor market gap.

Table 9: Okun's Law Errors: Standard Deviations

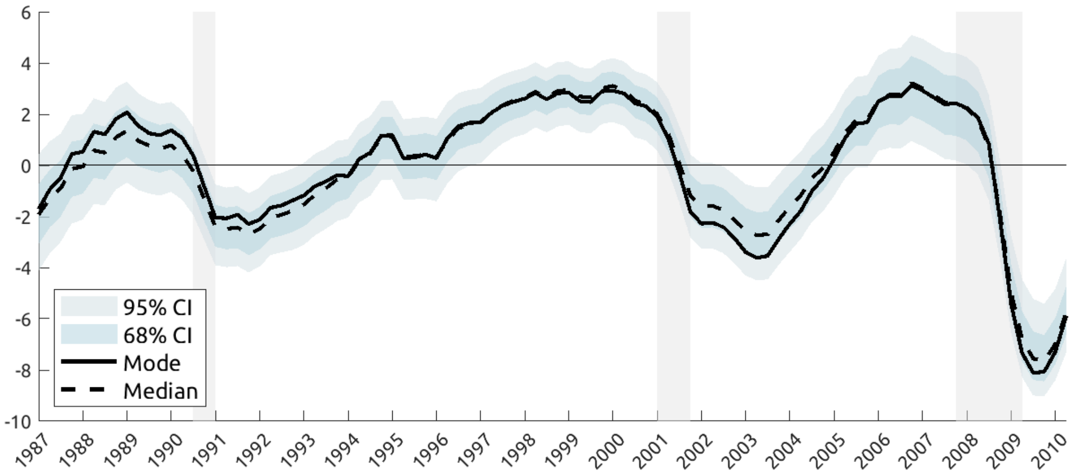
Emp. gap	Unemp. gap	Unemp. rate gap	LFPR gap	Total hours gap	Workweek gap
0.174	0.271	0.264	0.435	0.077	0.958

about the broad labor market conditions. In addition, at the onset of recessions, the output gap is usually smaller than implied by the estimated Okun's law relationships for most labor-market gaps, indicating the output recovery is actually slower than the recovery of the labor market.

6.2 Labor Market Conditions Indicator

Given our assessment on not having a single labor market gap that is a good summary statistic of the state of the economy, we proceed to compute a summary of the informational content in all labor market gaps using principal component analysis. Figure 9 reports the resulting first principal component series, representing the underlying state of the labor market. This series explains 88 percent of the total variability of labor market gaps and is the only principal component to explain at least one gap's worth of variability. Also, as shown in Table 10, the loading factors of the standardized labor market gaps are

Figure 9: Labor Market Conditions Indicator: Principal Component of all Model-based Labor Market Gaps



Notes: The principal component analysis is performed at the optimization mode and at each 10,000-th posterior draw so we can compute the median (dashed line) and credible intervals reported in the figure.

very similar, indicating that all gaps contribute significantly to this principal component.[28] As shown in Figure 9, the principal component peaks between one and one and a half years before a recession starts, suggesting that this aggregator of labor market conditions is a good leading indicator of recessions.

Following Chung et al. (2021), we decompose the principal component, which is a summary of latent variables in the model, into contributions of the structural shocks (shock decomposition) and contributions of the observable variables (data decomposition) in Figure 10. The solid line represents the estimated path for the principal component. For the shock decomposition, reported in panel (b), the bars above (below) the zero line correspond to the cumulative effects of shocks that increase (decrease) the principal component in a particular quarter. The data decomposition allows us to gauge which salient features of the data shape the alternative measures of slack in the labor market.

As stated earlier, the labor market gaps are defined as the difference between a given variable and its counterpart in the flexible-price economy. Consequently, most of the data drivers of a labor-market variable in the economy with nominal frictions are also the drivers of the flex-price counterpart. Thus, as shown in Figure C.3 in the Appendix, non-labor-market-related real and nominal variables, such as investment growth (in yellow), inflation (in red and dark brown), the federal funds rate (in dark gray), and spreads (in light green) are essential in defining the labor market gaps. However, there are two labor market variables with large information content about labor market gaps: the unemployment rate (in black) and the LFPR (in light gray). The relatively large role played by these two variables in driving the model-implied labor market gaps allows us to conclude that a model without the participation margin would have a hard time delivering sensible estimates of the labor market gaps. The fact that the workweek data are not very informative about our principal component (Figure 10) should not be confused with

[28]Standardized gaps refer to the gaps normalized by their respective mean and standard deviation.

Figure 10: Labor Market–Conditions Indicator: Historical Decompositions

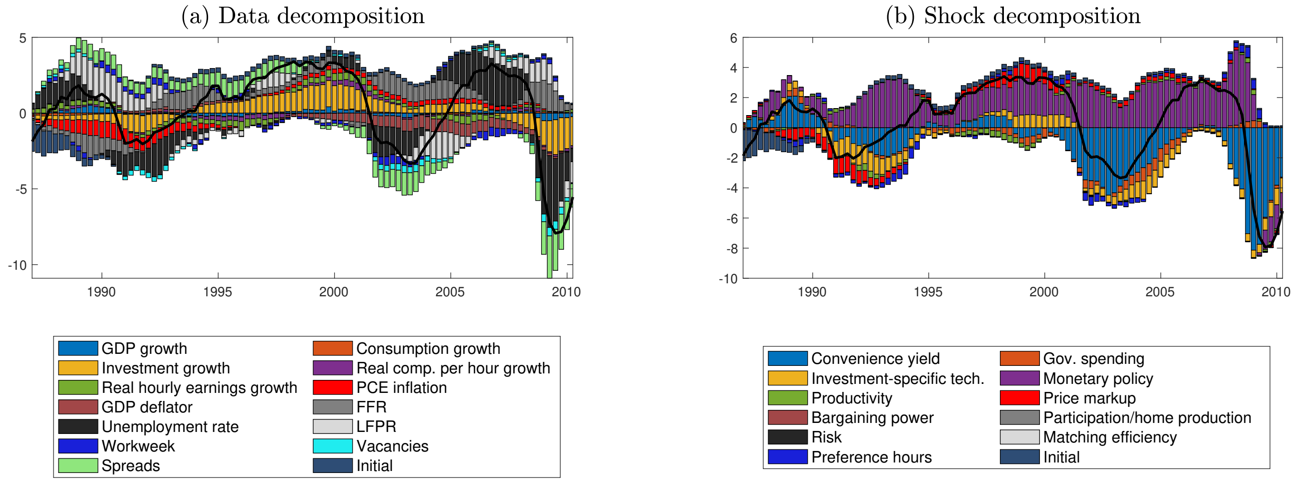


Table 10: Loading Factors Principal Component

Labor Market Gap	*Mode*	5*th*	*Median*	95*th*
Employment	0.3789	0.3627	0.3768	0.4056
Unemployment	-0.3723	-0.3988	-0.3700	-0.3594
Unemployment rate	-0.3729	-0.3993	-0.3706	-0.3597
LFPR	0.3365	0.1680	0.3278	0.3581
Total hours	0.3812	0.3650	0.3793	0.3980
Workweek	0.1966	0.0110	0.2343	0.3116
Vacancy	0.3761	0.3620	0.3737	0.4017
θ: LM tightness	0.3744	0.3610	0.3720	0.4004

Notes: This table reports the loading factors of the labor market gaps normalized by their historical mean and standard deviation. LM stands for labor market. The column titled "Mode" refers to the loading factors of the model evaluated at the optimization mode. The columns titled 5*th*, Median, and 95*th* represent the percentiles of the posterior draws.

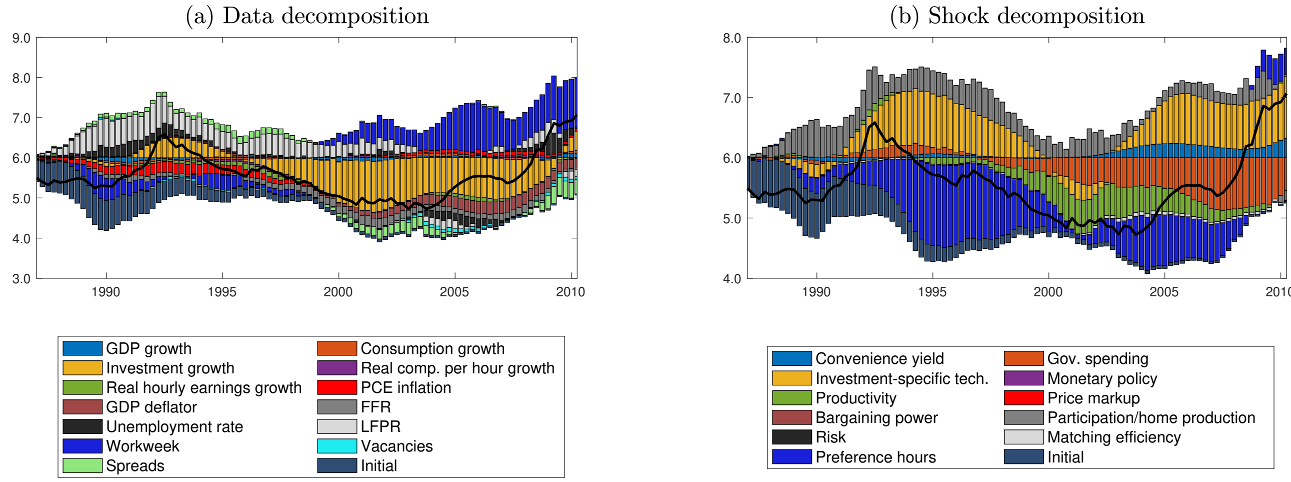
the fact that the workweek gap is informative about our principal component (Table 10).

6.3 Historical Decomposition of the Natural Rate of Unemployment

To further study the role of the new margins of labor supply in the estimated state of the economy, we focus on the historical shock and data decomposition of the natural rate of unemployment reported in Figure 11. As shown in panel (b), our model estimates that there are two main shocks that have been exerting upward pressure on the natural rate of unemployment: the investment-specific shock (in yellow)—especially during the mid-1990s period and from 2005 onwards—and, to a smaller extent, the participation shock (in dark gray). On the other hand, two other shocks exert downward pressure on the natural rate of unemployment: the hours preference shock (bright blue) and the government-spending shock (orange).

Previously, Furlanetto and Groshenny (2016) concluded that the main source of variation in the

Figure 11: Natural Rate of Unemployment: Historical Decomposition



natural rate of unemployment in a DSGE model with matching frictions and similar hiring cost function specifications is matching efficiency shocks. The role assigned to these shocks by our estimation results (light gray) is almost negligible. We have further studied the source of this discrepancy by estimating versions of our model that are closer to the Furlanetto and Groshenny (2016) specification and concluded that the relative role of matching efficiency shocks in driving the natural rate of unemployment depends on the relative size of pre-match hiring costs in the hiring costs function—in particular, the larger the size of pre-match hiring costs in the overall hiring cost function, the larger the contribution of matching efficiency shocks to the fluctuations of the natural rate of unemployment. Note that matching efficiency shocks only affect the unemployment rate when firms face pre-match hiring costs. While Furlanetto and Groshenny (2016) find a role for pre-matching hiring costs, our estimation provides an almost zero weight to this component of the hiring cost function.

7 Conclusion

In this paper, we develop a model with a rich treatment of the labor market that can account for the slowdown in labor market outcomes during the Great Recession, the subsequent slow recovery, and the missing disinflation. The main innovation of our theoretical model with respect to existing New-Keynesian models is the introduction of endogenous labor force participation and hours worked in a search and matching environment. Other relevant theoretical contributions include the following: *(i)* providing an extension of Jaimovich and Rebelo (2009) preferences, *(ii)* introducing a more flexible specification of a recruiting cost function, *(iii)* providing an extension of Gertler, Sala, and Trigari (2008) staggered nominal wage bargaining, and *(iv)* developing a decomposition of the nominal wage in search and matching models that allows us to quantify the degree of nominal and real wage rigidities. On the empirical side, our main contribution is using a wider set of labor market indicators to estimate the model than was previously used in the literature.

We show that a higher degree of post-match costs relative to pre-match costs not only delivers higher labor market volatility and persistence in labor market outcomes, but also helps in delivering lower inflation volatility and more persistent inflation dynamics. The ability of the model to account for the empirical evidence also relies on having a low degree of nominal wage rigidities and a high degree of real wage rigidities. These parameters are informed by the additional labor supply margins in the model and their corresponding observables. Our results show the key importance of incorporating both the participation contribution to the extensive margin of labor supply jointly with the intensive margin of labor supply to improve the forecasting performance of a New Keynesian DSGE model.

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Appendix

A Data Description

A.1 Data Used for Model Estimation

- *Growth rate of real per-capita GDP*. Data for nominal GDP are available from the Bureau of Economic Analysis (BEA) Survey of Current Businesses Table GDP.1.1.5, line 1 (Haver: $USNA/GDPX$). These data are deflated by the seasonally adjusted implicit price deflator found in the BEA Survey of Current Businesses Table GDP.1.1.9, line 1 (Haver: $USECON/DGDP$). This new series is divided by the quarterly average of the monthly civilian noninstitutional population (ages 16 and older) found in the Employment Situation release - Current Population Survey table A1, line 2 (Haver: $USECON/LNN$) to obtain per capita values. The data provided by the BEA are annualized. Growth rates are computed by taking 100*log differences (quarterly growth rate).

- *Growth rate of real consumption*. To get real consumption, we first sum "Personal Consumption Expenditures: Nondurable Goods"—available at BEA Survey of Current Businesses Table GDP.1.1.5, line 5 (Haver: $HAVER\_USNA/CNX$)—and "Personal Consumption Expenditures: Services"—found in the BEA Survey of Current Businesses Table GDP.1.1.5, line 6 (Haver: $HAVER\_USNA/CSX$). These resulting data are deflated by the seasonally adjusted implicit price deflator available at BEA Survey of Current Businesses Table GDP.1.1.9, line 1 (Haver: $USECON/DGDP$). This new series is divided by the quarterly average of the monthly civilian noninstitutional population (ages 16 and older)—available from the Employment Situation release - Current Population Survey table A1, line 2 (Haver: $USECON/LNN$)—to obtain per capita values. The data provided by the BEA are annualized. Growth rates are computed by 100*log differences (quarterly growth rate).

- *Growth rate of real investments*. To get real investment, we first sum private fixed investment—found in the BEA Survey of Current Businesses Table GDP.1.1.5, line 8 (Haver: $USNA/FX$)—and "Personal Consumption Expenditures: Durable Goods"—found in the BEA Survey of Current Businesses Table GDP.1.1.5, line 4 (Haver: $USNA/CDX$). These resulting data are deflated by the seasonally adjusted implicit price deflator available at BEA Survey of Current Businesses Table GDP.1.1.9, line 1 (Haver: $USECON/DGDP$). This new series is divided by the quarterly average of the monthly civilian noninstitutional population (16 years and older)—available from the Employment Situation release: Current Population Survey table A1, line 2 (Haver: $USECON/LNN$)—to obtain per capita values. The data provided by the BEA are annualized. Growth rates are computed by taking 100*log differences (quarterly growth rate).

- *Inflation*. To get inflation, we use two indicators: the implicit price deflator found in the BEA Survey of Current Businesses Table GDP.1.1.9, line 1 (Haver: $USECON/DGDP$) and core PCE inflation found in Table GDP 2.3.4, line 25 (Haver: $USECON/JCXFE$). Growth rates are computed by taking 100*log differences (quarterly growth rate).

- *Wage inflation.* To get wage inflation we use two indicators: compensation per hour—which is calculated as the ratio between total compensation of employees available at BEA Survey of Current Businesses Table GDP.1.12, line 2 (Haver: $USECON/YCOMPX$) and the quarterly average of civilian employment (ages 16 and over) found in the BLS Employment Situation release Table A1, line 5 (Haver: $USECON/LE$)—and average weekly earnings—which is calculated as "Average Weekly Earnings: Prod & Nonsupervisory: Total Private Industries" available as part of the BLS Employment Situation release (Haver: $USECON/LKPRIVA$). Growth rates are computed by taking 100*log differences (quarterly growth rate).

- *Federal funds rate.* We use the quarterly average of the monthly average of the yearly effective federal funds rate from the Selected Interest Rate Table H.15, line 1, published by the Board of Governors of the Federal Reserve System. We divide this series by 4 to make it quarterly.

- *Spreads.* Spreads are calculated by taking the difference between the quarterly average of the monthly average Moody's yield on "Seasoned Corporate Bonds: All industries, BAA" published in table 1.35, H.15, line 30 and the market yield on U.S. Treasury securities at 10-year constant maturity, quoted on investment basis available in the Selected Interest Rate Table H.15, published by the Board of Governors of the Federal Reserve System. We divide this series by 4 to make it quarterly.

- *Unemployment rate.* We use the quarterly average of the monthly Unemployment Rate: 16 Years+ series available from the Employment Situation release: Current Population Survey table A1, line 8 (Haver: $HAVER\_EMPL/RA16Q$).

- *Labor force participation rate.* We use the Civilian Participation Rate: 16 Years+ series available from the Employment Situation release: Current Population Survey table A1, line 4 (Haver: $USECON/LP$).

- *Vacancies.* The series for vacancies is calculated monthly using a methodology explained in Barnichon (2010). This series is then transformed to quarterly by taking the average. We take 100*log of the series that is divided by the population index such that we adjust for changes in population. Finally, we demean the series before using it in the estimation.

A.2 Estimates on Latent Variables from the CBO and the FRB

- *CBO estimate of the natural rate of unemployment.* The Congressional Budget Office (CBO) defines the natural rate of unemployment as the rate that results from all sources except fluctuations in aggregate demand, and it reflects the normal turnover of jobs and mismatches between the skills of available workers and the skills necessary to fill vacant positions. We retrieve the data from FRED (Federal Reserve Bank of St. Louis)—series NROUST.

- *CBO estimate of the output gap.* In order to compute the CBO estimate of the output gap, we first retrieve the CBO estimate of potential GDP from FRED—series GDPPOT. The CBO estimate of potential GDP is defined as the maximum sustainable output of the economy. We then compute the output gap as the ratio between real GDP and potential GDP. We retrieve real GDP from FRED—series GDPC1.

- *FRB estimate of the natural rate of unemployment.* We use the Federal Reserve staff's real-time estimates of the natural rate of unemployment. We retrieve those estimates from the Real-Time Data Research Center at the Federal Reserve Bank of Philadelphia: https://www.philadelphiafed.org/surveys-and-data/real-time-data-research/nairu-data-set. We use the latest available vintage, which corresponds to the December 2016 Tealbook estimates.

- *FRB estimate of the output gap.* We use the Federal Reserve staff's real-time estimates of the output gap. We retrieve those estimates from the Real-Time Data Research Center at the Federal Reserve Bank of Philadelphia: https://www.philadelphiafed.org/surveys-and-data/real-time-data-research/gap-and-financial-data-set. We use the latest available vintage, which corresponds to the December 2016 Tealbook estimates.

B Additional Estimation Results

B.1 Baseline Model

Table B.1 presents the posterior estimates of additional economic parameters for the baseline model. Tables B.2 and B.3 show the posterior estimates of all parameters related to the shock processes in the baseline model. Finally, Table B.4 presents the posterior estimates for measurement errors in the baseline model.

Table B.1: Estimated Economic Parameters: Other parameters

PARAMETER		*PRIOR*	*POSTERIOR*	
			Mode	*St. Dev.*
Discount factor	β	$\mathcal{B}\,(0.99, .001)$	0.9934	0.00
Intertemporal elast. of substitution	$1/\sigma_c$	$\mathcal{G}\,(1.00, 0.50)$	1.12	0.00
Habit parameter	h	$\mathcal{B}\,(0.50, 0.10)$	0.38	0.05
Capital utilization	$\iota_{u,1}$	$\mathcal{N}\,(1.00, 1.00)$	0.93	0.39
Capital adj. cost	γ_k	$\mathcal{N}\,(5.00, 3.00)$	5.91	1.34
Slope of the Phillips curve	$slope$	$\mathcal{G}\,(5.00, 3.00)$	1.10	0.43
Inflation indexation	γ_p	$\mathcal{B}\,(0.50, 0.10)$	0.39	0.09
Wage indexation to past inflation	γ_{wp}	$\mathcal{B}\,(0.50, 0.10)$	0.49	0.09
Inflation coefficient (Taylor rule)	κ_π	$\mathcal{N}\,(1.70, 0.30)$	1.48	0.23
Output gap coefficient (Taylor rule)	κ_y	$\mathcal{G}\,(0.13, 0.10)$	0.46	0.09
Output gap growth coefficient (Taylor rule)	κ_{yg}	$\mathcal{G}\,(0.13, 0.10)$	0.32	0.16
Taylor rule smoothing	ρ_i	$\mathcal{B}\,(0.75, 0.05)$	0.70	0.03
Fraction of capital diverted	$\widehat{\mu}$	$\mathcal{B}\,(0.15, 0.10)$	0.12	0.00

Notes: $\mathcal{B}$ stands for Beta distribution. $\mathcal{N}$ stands for Normal distribution. $\mathcal{G}$ stands for Gamma distribution.

Table B.2: Structural shocks

PARAMETER		*PRIOR*	*POSTERIOR*	
			Mode	*Std. Dev.*
Autocorrelations:				
Convenience yield shock	$\rho_{\mu^{CY}}$	$\mathcal{B}\,(0.50, 0.15)$	0.93	0.01
Participation/home production shock	ρ_{χ_l}	$\mathcal{B}\,(0.85, 0.10)$	0.98	0.01
Preference shock to hours	ρ_{χ_h}	$\mathcal{B}\,(0.85, 0.10)$	0.92	0.04
Price markup shock	ρ_{ϵ^p}	$\mathcal{B}\,(0.50, 0.15)$	0.90	0.06
Matching efficiency shocks	$\rho_{\bar{\sigma}_m}$	$\mathcal{B}\,(0.50, 0.10)$	0.95	0.02
Bargaining power shocks	ρ_η	$\mathcal{B}\,(0.50, 0.10)$	0.52	0.17
Productivity shocks	ρ_γ	$\mathcal{B}\,(0.50, 0.10)$	0.50	0.10
Investment-specific tech. shock	ρ_{μ^I}	$\mathcal{B}\,(0.50, 0.10)$	0.84	0.04
Risk shock	ρ_{σ_ω}	$\mathcal{B}\,(0.50, 0.10)$	0.50	0.12
Monetary policy shock	ρ_m	$\mathcal{B}\,(0.50, 0.10)$	0.79	0.07
Government spending shock	ρ_g	$\mathcal{B}\,(0.50, 0.10)$	0.95	0.06
MA component markup shock	θ_ε	$\mathcal{N}\,(0.90, 0.10)$	0.99	0.03
Correlation gov. spending shock – TFP shock	θ_{ga}	$\mathcal{N}\,(0.00, 0.50)$	-0.41	0.36
Factor loading for core PCE inflation	$\Lambda_{\pi,p}$	$\mathcal{N}\,(1.00, 0.50)$	1.00	0.03
Factor loading for average hourly earnings	$\Lambda_{\pi,w}$	$\mathcal{N}\,(1.00, 0.50)$	0.73	0.07

Notes: $\mathcal{B}$ stands for Beta distribution. $\mathcal{N}$ stands for Normal distribution.

Table B.3: Structural shocks: standard deviations

PARAMETER		*PRIOR*	*POSTERIOR*	
			Mode	*Std. Dev.*
Convenience yield shock	$\sigma_{\mu^{CY}}$	$\mathcal{IG}\,(0.15, 0.15)$	0.20	0.03
Participation/home production shock	σ_{χ_l}	$\mathcal{IG}\,(0.15, 0.15)$	0.51	0.10
Preference shock to hours	σ_{χ_h}	$\mathcal{IG}\,(0.15, 0.15)$	0.30	0.04
Price markup shock	σ_{ϵ^p}	$\mathcal{IG}\,(0.15, 0.15)$	0.05	0.01
Matching efficiency shocks	$\sigma_{\bar{\sigma}_m}$	$\mathcal{IG}\,(0.15, 0.15)$	0.65	0.10
Bargaining power shocks	σ_η	$\mathcal{IG}\,(0.15, 0.15)$	0.09	0.09
Productivity shock	σ_γ	$\mathcal{IG}\,(0.15, 0.15)$	0.15	0.04
Investment-specific tech. shock	σ_{μ^I}	$\mathcal{IG}\,(0.15, 0.15)$	1.89	0.32
Risk shock	σ_{σ_ω}	$\mathcal{IG}\,(0.15, 0.15)$	0.09	0.11
Monetary policy shock	σ_m	$\mathcal{IG}\,(0.15, 0.15)$	0.10	0.01
Government spending shock	σ_g	$\mathcal{IG}\,(0.15, 0.15)$	0.17	0.04

Notes: $\mathcal{IG}$ stands for Inverted Gamma distribution. We specify the distribution by reporting its mean and standard deviation.

Table B.4: Measurement errors: standard deviations

PARAMETER		*PRIOR*	*POSTERIOR*	
			Mode	*Std. Dev.*
Output growth	$\sigma_{\Delta y}$	$\mathcal{N}\,(0.00, 0.20)$	0.38	0.04
Consumption growth	$\sigma_{\Delta c}$	$\mathcal{N}\,(0.00, 0.20)$	0.40	0.03
Investment growth	$\sigma_{\Delta i}$	$\mathcal{N}\,(0.00, 0.20)$	0.99	0.08
Wage growth: Comp. per employee	$\sigma_{\Delta w}$	$\mathcal{N}\,(0.00, 0.20)$	0.55	0.04
Wage growth: Average weekly earnings	$\sigma_{\Delta AWE}$	$\mathcal{N}\,(0.00, 0.20)$	0.32	0.03
Inflation: GDP deflator	σ_{π}	$\mathcal{N}\,(0.00, 0.20)$	0.13	0.01
Inflation: PCE	σ_{π}	$\mathcal{N}\,(0.00, 0.20)$	0.11	0.02
Unemployment	σ_{u}	$\mathcal{N}\,(0.00, 0.20)$	0.03	0.01
Participation rate	σ_{lfpr}	$\mathcal{N}\,(0.00, 0.20)$	0.09	0.01
Workweek	σ_{ww}	$\mathcal{N}\,(0.00, 0.20)$	0.00	0.00
Vacancies	σ_{vobs}	$\mathcal{N}\,(0.00, 0.20)$	0.00	0.10

Notes: $\mathcal{N}$ stands for Normal distribution.

B.2 Alternative Models

This section presents the estimated model parameters for two alternative models discussed in Section 5 of the main text.

Table B.5: Estimated Economic Parameters for Alternative Models: Labor frictions related parameters

Parameter	Symbol	Alternative Model Pre-Match Costs		Alternative Model Fixed Labor Supply	
		Mode	Std. Dev.	Mode	Std. Dev.
Log of JR parameter for hours	$\log\gamma_h$	-3.66	0.16	-2.44	0.51
Log of JR parameter for participation	$\log\gamma_l$	-0.03	0.08	-2.00	0.25
Inverse employment elasticity	ψ_l	2.53	0.23	1.05	0.02
SS Workers' bargaining power	η	0.67	0.04	0.60	0.07
Wage rigidity	λ_w	0.27	0.07	0.33	0.06
Matching elasticity with respect to unemp.	σ_m	0.79	0.02	0.81	0.03
Ratio of vacancy posting costs parameters	$\log\kappa_{21}$			-4.52	0.84
Hiring rate cost elasticity	ψ_1	0.00	0.16	1.38	0.46
Vacancy rate cost elasticity	ψ_2	0.06	0.03	1.23	0.58
SS outside option to MPL plus hiring cost	Ω_p	0.85	0.03	0.82	0.03
SS b plus utility cost of emp/outside option	Γ^{Ω}	0.43	0.03	0.46	0.08
SS unemployment benefit	b^0	0.99	0.02	0.79	0.15
Steady-state unemp.. rate	u_{ss}	0.06	0.00	0.07	0.00
Steady-state LFPR	L_{ss}	0.065	0.01	0.64	0.02
Steady-state prob. of employ.	p_{ss}	0.75	0.02	0.82	0.03

Table B.6: Estimated Economic Parameters for Alternative Models: Other parameters

Parameter	Symbol	Alternative Model Pre-Match Costs		Alternative Model Fixed Labor Supply	
		Mode	Std. Dev.	Mode	Std. Dev.
Discount factor	β	0.99	0.00	0.99	0.00
Intertemporal elast. of substitution	$1/\sigma_c$	0.78	0.10	2.31	0.32
Habit parameter	h	0.43	0.05	0.49	0.10
Capital utilization	$\iota_{u,1}$	2.65	0.24	2.05	0.30
Capital adj. cost	γ_k	7.35	0.48	9.06	0.49
Slope of the Phillips curve	$slope$	0.66	0.10	4.75	0.71
Inflation indexation	γ_p	0.37	0.07	0.39	0.08
Wage indexation to past inflation	γ_{wp}	0.41	0.07	0.44	0.09
Inflation coefficient (Taylor rule)	κ_π	1.91	0.14	1.74	0.20
Output gap coefficient (Taylor rule)	κ_y	0.34	0.07	0.55	0.10
Output gap growth coefficient (Taylor rule)	κ_{yg}	0.06	0.09	0.23	0.16
Taylor rule smoothing	ρ_i	0.64	0.04	0.70	0.03
Fraction of capital diverted	$\widehat{\mu}$	0.13	0.00	0.12	0.00

Table B.7: Endogenous parameters evaluated at the posterior mode for Alternative Models

		Alternative Model Pre-Match Costs	Alternative Model Fixed Labor Supply
Steady-state pref. parameter extensive margin	χ_l	0.037	0.039
Steady-state pref. parameter intensive margin	χ_h	1.219	0.216
Separation rate	δ_s	0.203	0.324
Elasticity of intensive labor supply	ψ_h	1.031	1.153
Effort parameter	Γ	0.992	0.846
Steady-state matching efficiency	$\bar{\sigma}_m$	0.788	0.845
Post-match cost parameter	κ_1	0.014	0.828
Pre-match cost parameter	κ_2	0.105	0.009
Steady-state leverage	ϕ_e	3.842	4.607
Steady-state entrepreneurial risk	σ_ω	0.118	0.096
Steady state entrepreneurial endowment	W_e	0.000	0.000
Fixed cost	Φ	0.118	-0.005
Scale factor for capital utilization costs	$\iota_{u,0}$	0.016	0.019

Table B.8: Structural Socks Posterior Estimates for Alternative Models: Autocorrelations

		Alternative Model Pre-Match Costs		Alternative Model Fixed Labor Supply	
Shock	Symbol	Mode	Std. Dev.	Mode	Std. Dev.
Convenience yield shock	$\rho_{\mu^{CY}}$	0.91	0.01	0.91	0.02
Participation/home production shock	ρ_{χ_l}	0.99	0.01		
Preference shock to hours	ρ_{χ_h}	0.97	0.02		
Price markup shock	ρ_{ϵ^p}	0.86	0.06	0.51	0.15
Matching efficiency shocks	$\rho_{\bar{\sigma}_m}$	0.95	0.02	0.95	0.02
Bargaining power shocks	ρ_η	0.90	0.03	0.50	0.15
Productivity shocks	ρ_γ	0.15	0.07	0.52	0.07
Investment-specific tech shock	ρ_{μ^I}	0.92	0.02	0.84	0.07
Risk shock	ρ_{σ_ω}	0.50	0.11	0.50	0.14
Monetary policy shock	ρ_m	0.59	0.08	0.71	0.04
Government spending shock	ρ_g	0.53	0.10	0.63	0.11
MA component markup shock	θ_ε	1.01	0.03	0.88	0.09
Correlation gov. spending shock – TFP shock	θ_{ga}	0.16	0.05	0.03	0.06
Factor loading for core PCE inflation	$\Lambda_{\pi,p}$	1.00	0.03	1.01	0.03
Factor loading for average hourly earnings	$\Lambda_{\pi,w}$	0.71	0.07	0.79	0.08

Table B.9: Structural Socks Posterior Estimates for Alternative Models: Standard Deviations

		Alternative Model Pre-Match Costs		Alternative Model Fixed Labor Supply	
Shock	Symbol	Mode	Std. Dev.	Mode	Std. Dev.
Convenience yield shock	$\rho_{\mu^{CY}}$	0.21	0.03	0.22	0.03
Participation/home production shock	ρ_{χ_l}	1.01	0.08		
Preference shock to hours	ρ_{χ_h}	0.24	0.06		
Price markup shock	ρ_{ϵ^p}	0.05	0.01	0.05	0.01
Matching efficiency shocks	$\rho_{\bar{\sigma}_m}$	0.76	0.09	0.65	0.14
Bargaining power shocks	ρ_η	1.80	0.11	0.09	0.18
Productivity shocks	ρ_γ	0.65	0.06	0.38	0.05
Investment-specific tech shock	ρ_{μ^I}	2.08	0.13	1.05	0.27
Risk shock	ρ_{σ_ω}	0.09	0.06	0.09	0.07
Monetary policy shock	ρ_m	0.08	0.01	0.09	0.01
Government spending shock	ρ_g	0.08	0.01	0.06	0.01

Table B.10: Measurement Errors for Alternative Models: Posterior Estimates for Standard deviations

		Alternative Model Pre-Match Costs		Alternative Model Fixed Labor Supply	
Shock	Symbol	Mode	Std. Dev.	Mode	Std. Dev.
Output growth	$\sigma_{\Delta y}$	0.21	0.10	0.38	0.04
Consumption growth	$\sigma_{\Delta c}$	0.35	0.03	0.43	0.04
Investment growth	$\sigma_{\Delta i}$	1.05	0.06	0.94	0.07
Wage growth: Comp. per employee	$\sigma_{\Delta w}$	0.57	0.04	0.54	0.03
Wage growth: Average weekly earnings	$\sigma_{\Delta AWE}$	0.31	0.03	0.30	0.03
Inflation: GDP deflator	σ_{π}	0.13	0.01	0.12	0.01
Inflation: PCE	σ_{π}	0.11	0.01	0.12	0.01
Unemployment	σ_{u}	0.04	0.02	0.05	0.02
Participation rate	σ_{lfpr}	0.05	0.02		
Workweek	σ_{ww}	0.00	0.00		
Vacancies	σ_{vobs}	0.00	0.09	0.00	0.11

C Additional Model Results

C.1 Model Fit

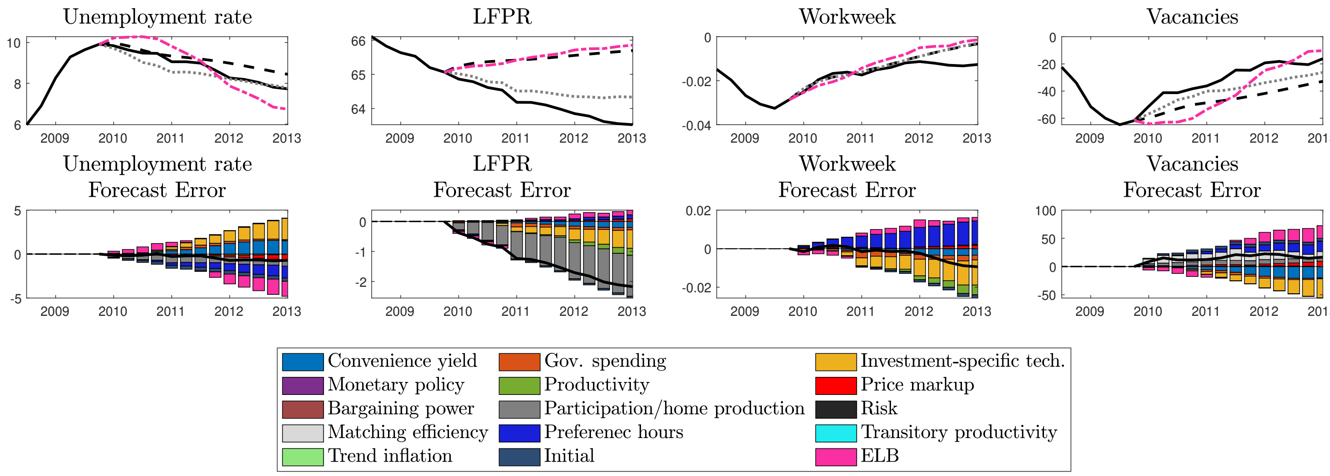
Table C.1: Business Cycle Statistics: Correlation Matrix

	GDP	c	I	π	w	i	u	LFPR	v	ww	spread
Panel A: U.S. Data, 1987:Q1 to 2010:Q2											
GDP	1	0.92	0.96	0.26	0.67	0.63	-0.91	0.54	0.82	0.67	-0.29
c		1	0.86	0.33	0.75	0.52	-0.82	0.52	0.65	0.48	-0.16
I			1	0.20	0.62	0.58	-0.90	0.42	0.83	0.69	-0.27
π				1	0.20	0.28	-0.20	-0.10	0.13	-0.11	-0.31
w					1	0.12	-0.46	0.23	0.32	0.15	0.28
i						1	-0.82	0.53	0.82	0.53	-0.49
u							1	-0.62	-0.94	-0.73	0.36
LFPR								1	0.54	0.49	-0.07
v									1	0.81	-0.41
ww										1	-0.40
spread											1
Panel B: Model											
GDP	1	0.78	0.89	0.16	0.61	0.38	-0.80	0.69	0.72	0.75	-0.30
c		1	0.61	0.03	0.64	0.01	-0.51	0.48	0.46	0.37	-0.04
I			1	0.23	0.43	0.53	-0.75	0.63	0.67	0.73	-0.33
π				1	0.13	0.36	-0.12	0.11	0.13	0.19	-0.23
w					1	0.05	-0.37	0.36	0.37	0.30	-0.39
i						1	-0.43	0.28	0.37	0.25	-0.52
u							1	-0.36	-0.84	-0.47	0.39
LFPR								1	0.37	0.55	-0.14
v									1	0.46	-0.36
ww										1	-0.15
spread											1

Notes: To compute correlations, we express the variables in logs as deviations from an HP trend with a smoothing parameter of 10^5.

C.2 Forecast Conditional on 2009:Q4

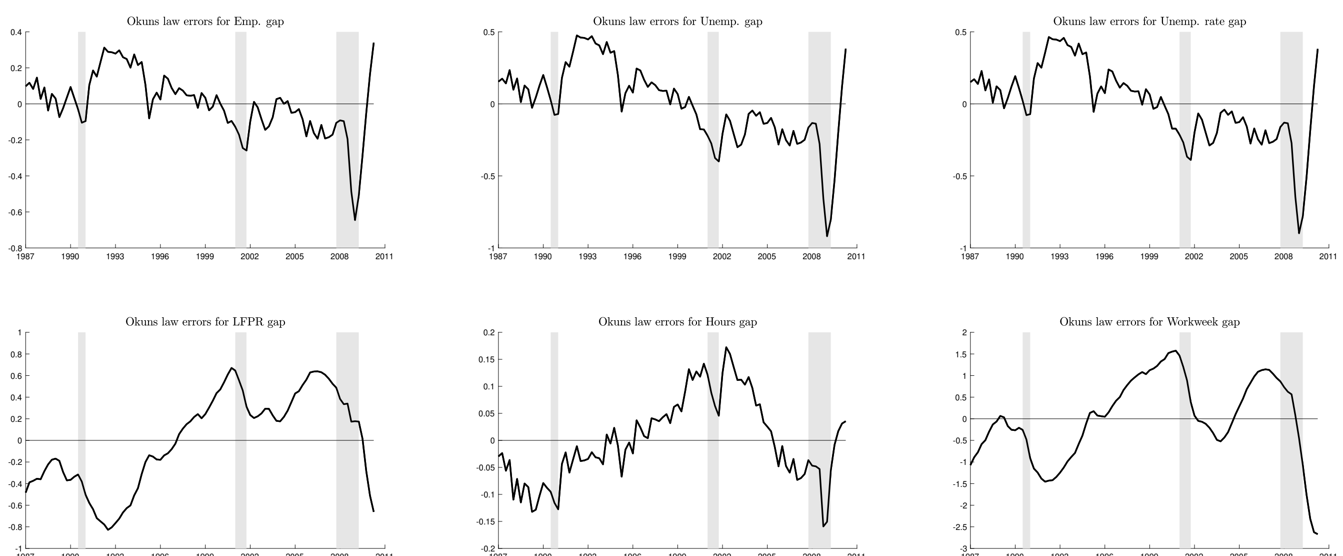
Figure C.1: Labor Market Forecast: 2009:Q4



Notes: The solid black lines in the top panels present the dynamics for the unemployment rate, the LFPR, the workweek, and vacancies between 2008 and 2013. The black dashed lines are the model's forecast based on data up to 2009:Q4. The gray dotted lines are the model's forecast plus the χ_l contributions to the forecast error. The pink dash-dotted lines are the model's forecast in the absence of the ELB constraint. Bottom panels present the forecast error $(Y_{t+s} - E_t[Y_{t+s}])$ decomposition.

C.3 Labor Market Gaps: Okun's Law Errors

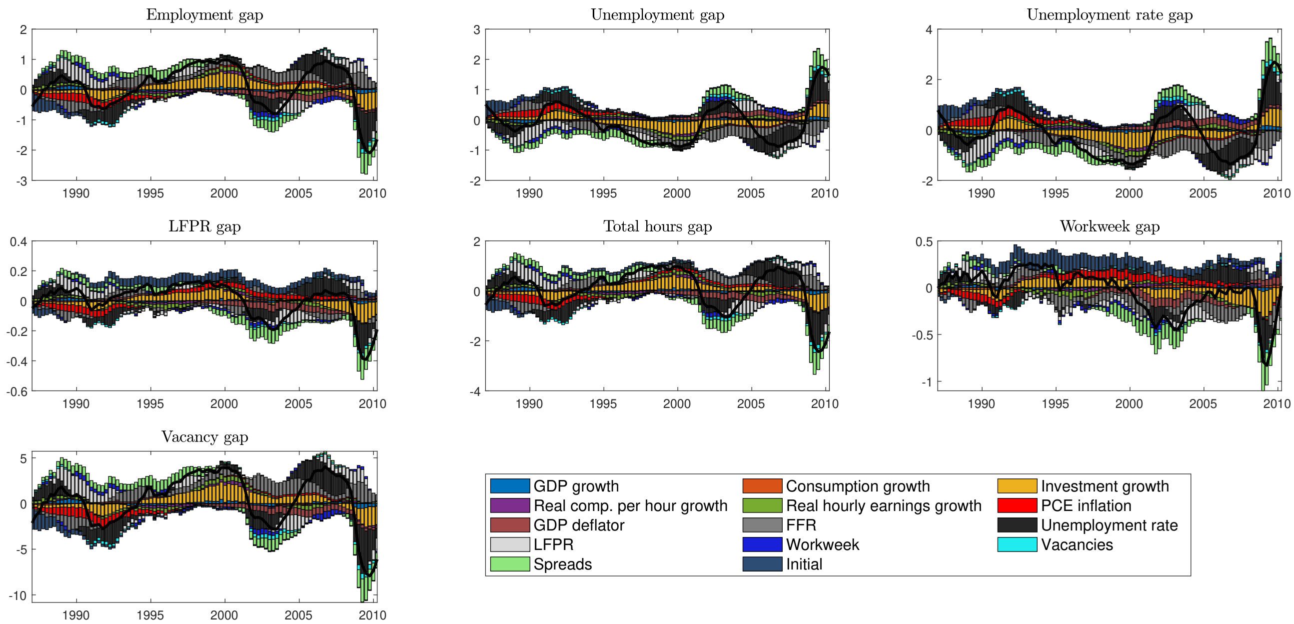
Figure C.2: Okun's Law Errors



Notes: This figure plots the Okun's law errors for each labor market gap. The shaded areas represent NBER recession dates.

C.4 Labor Market Gaps: Data Decomposition

Figure C.3: Labor Market Gaps: Data Decomposition



D Economic Dynamics at the ELB

If the effective lower bound (ELB) is binding in period t and the expected ELB duration is s periods at time t, Kulish, Morley, and Robinson (2017) show that the economic dynamics at time t are well approximated by the linear policy function:

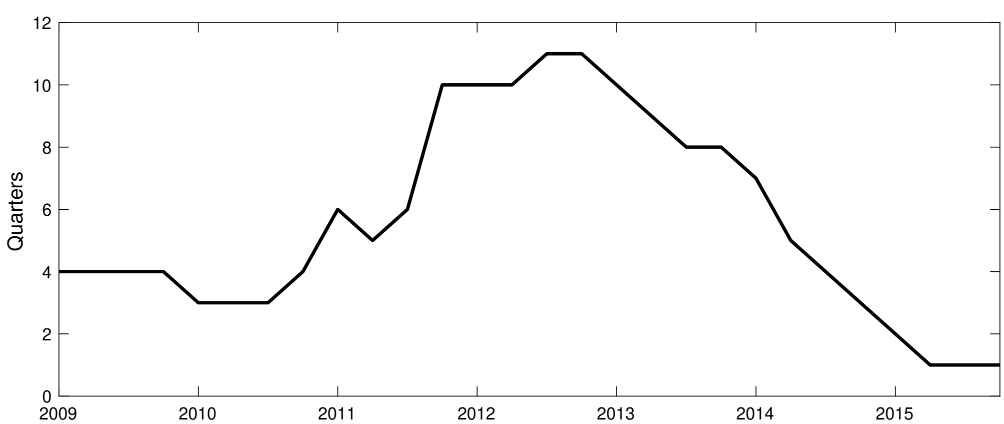
$$Y_{t+j} = C_{t+j} + P_{t+j}Y_{t+j-1} + D_{t+j}\epsilon_{t+j} \tag{D.1}$$

where matrices C, P, and D depend on the expected ELB duration at time t. If the ELB is not binding, those matrices are equal to their long-run values. Kulish, Morley, and Robinson (2017) show how to compute those matrices for each period in which the ELB is binding, given a sequence of expected ELB duration at each point in time. In this appendix, we show how we construct the sequence of expected ELB duration and how we compute the shock contributions in our forecasting exercise.

D.1 Expected ELB Duration

We calibrate the expected ELB duration based on Blue Chip data and the Survey of Primary Dealers. The Blue Chip is a monthly survey that asks about the expected federal funds rate for the next two years. This survey is available for the entire ELB period. However, between the end of 2011 and 2012, most of the Blue Chip participants were expecting the federal funds rate to be zero for the next two years, making it impossible to infer their expected ELB duration. The Survey of Primary Dealers asked participants about their expected ELB duration. However, that survey started in 2011. Given the limitations of both surveys, our measure of ELB duration is the implied median expected ELB duration from the Blue Chip participants between 2009 and 2010. Thereafter, we use the median expected ELB duration from the Survey of Primary Dealers. Figure C.4 plots our series for expected ELB duration. It is worth noting that this series is consistent with the estimated series of Kulish, Morley, and Robinson (2017).

Figure C.4: Calibrated Expected ELB Duration



Notes: The expected ELB duration is constructed based on Blue Chip data between 2009 and 2010 and the Survey of Primary Dealers between 2011 and 2015.

D.2 Shock Decomposition with the ELB

The policy rules of the log-linearized model are summarized by the following:

$$Y_t = S_1 Y_{t-1} + S_2 \epsilon_t, \tag{D.2}$$

where Y_t is the vector of endogenous variables and ϵ_t is the vector of exogenous shocks. S_1 and S_2 are fixed matrices. Following Kulish, Morley, and Robinson (2017), when the ELB is binding, the policy rule is given by the following:

$$Y_t = C_t + P_t Y_{t-1} + D_t \epsilon_t, \tag{D.3}$$

Hence, based on data up to $t+s$, we can decompose the level of the endogenous vector as follows:

$$\begin{aligned} Y_{t+s} =& \underbrace{S_1^s E_{t+s}\left[Y_t\right] + \tilde{S}_2 E_{t+s}\left[\epsilon^{t+s}\right]}_{\text{linear forecast}} \\ &+ \underbrace{\tilde{C}_{t+s|t+s} + \left(\tilde{P}_{t+s|t+s} - S_1^s\right) E_{t+s}\left[Y_t\right] + \left(\tilde{D}_{t+s|t+s} - \tilde{S}_2\right) E_{t+s}\left[\epsilon^{t+s}\right]}_{\text{non-linear forecast due to ELB}}, \end{aligned} \tag{D.4}$$

where $E_{t+s}\left[Y_t\right]$ and $E_{t+s}\left[\epsilon_{t+s}\right]$ are the expected level of Y_t and sequence of shocks up to $t+s$ based on data up to $t+s$. Similarly, matrices $\tilde{C}_{t+s|t+s}$, $\tilde{P}_{t+s|t+s}$, and $\tilde{D}_{t+s|t+s}$ are matrices at time $t+s$ given a sequence of expected ELB duration available at $t+s$.

Now, given data available at time t, the economy forecast is as follows:

$$E_t\left[Y_{t+s}\right] = S_1^s E_t\left[Y_t\right] + \tilde{C}_{t+s|t} + \left(\tilde{P}_{t+s|t} - S_1^s\right) E_t\left[Y_t\right]. \tag{D.5}$$

Hence, using equations (D.3) and (D.5),

$$\begin{aligned} Y_{t+s} - E_t\left[Y_{t+s}\right] = & S_1^s\left(E_{t+s}\left[Y_t\right] - E_t\left[Y_t\right]\right) + \tilde{S}_2 E_{t+s}\left[\epsilon^{t+s}\right] \\ &+ \underbrace{\left(\tilde{P}_{t+s|t+s} - S_1^s\right)\left(E_{t+s}\left[Y_t\right] - E_t\left[Y_t\right]\right) + \left(\tilde{D}_{t+s|t+s} - \tilde{S}_2\right) E_{t+s}\left[\epsilon^{t+s}\right]}_{\text{ELB amplification of shocks and revisions to initial conditions}} \\ &+ \underbrace{\left(\tilde{C}_{t+s|t+s} + \tilde{P}_{t+s|t+s} E_t\left[Y_t\right]\right) - \left(\tilde{C}_{t+s|t} + \tilde{P}_{t+s|t} E_t\left[Y_t\right]\right)}_{\text{difference in expected ELB duration}}. \end{aligned} \tag{D.6}$$

E Why is the Matching Elasticity so High?

The point estimate for the matching elasticity in the model is around 0.8, considerably higher than the conventional 0.5 in much of the literature on search and matching models of the labor market. In this section, we explain the reason for the higher matching elasticity and argue for its plausibility in the specific context of our model.

The job finding probability is a key part of the model's micro-foundations, and we discipline the model's estimates of this parameter with a tight normal prior centered around 0.75, based on microeconomic data for the quarterly transition rate from unemployment to employment. Moreover, as the dynamics of the model are specified at a quarterly frequency, we allow the newly separated to search within the quarter, because forcing newly separated labor force participants to wait a quarter before searching seems unrealistic. These two specification choices, along with our estimate of the steady-state unemployment rate, fix the steady-state separation rate δ_s via the equation

$$(1 - \bar{u} - \bar{p} + \bar{p}\bar{u})\delta_s = \bar{p}\bar{u} \tag{E.1}$$

For $\bar{p} = 0.75$, this equation would imply a separation rate of 0.25 and, for our modal estimate of $\bar{p} = 0.83$, an even higher separation rate of 0.34. For the wide range of plausible values, therefore, the separation rate is likely to be in the range of 25 percent or so.

With a separation rate in this range, however, the number of searchers $L_{t-1} - (1 - \delta_s)N_{t-1}$ is considerably larger than the conventional $L_{t-1} - N_{t-1}$ typically assumed in the literature – around six times as large with our modal parameter estimates. Consequently, percent deviations in the number of searchers relative to steady-state are much smaller than their counterparts in those models where only the previously unemployed search. To continue to fit variations in the job-finding probability like those implied by the data, therefore, the model requires a higher weight on searchers in the matching function.

F Marginal Cost

In this appendix, we derive the analytical expression for the marginal cost. The problem for the intermediate good firm is given by the following:

$$F_{jt} = \max_{k_{jt},v_{jt}} \quad p_t^m y_{tj} - \frac{W_{jt}^n}{P_t} z_{ht} n_{jt} - \kappa\left(v_{jt}, n_{jt-1}\right) - k_{jt} r_t^k + E_t\left[\Lambda_{t,t+1} F_{jt+1}\right] \tag{F.1}$$

s.t.

$$y_{tj} = k_{jt}^{\alpha}\left(A_t \gamma_t^T z_{ht} n_{jt}\right)^{1-\alpha} \tag{F.2}$$

$$n_{jt} = \left(1-\delta_s\right) n_{jt-1} + q_t v_{jt} \tag{F.3}$$

$$\kappa(v_{jt}, n_{jt-1}) = \frac{\kappa_1}{1+\psi_1}\left(\frac{q_t v_{jt}}{n_{jt-1}^{I_{cr}}}\right)^{1+\psi_1} n_{jt-1}^{I_{cr}} + \frac{\kappa_2}{1+\psi_2}\left(\frac{v_{jt}}{n_{jt-1}^{I_{cr}}}\right)^{1+\psi_2} n_{jt-1}^{I_{cr}} \tag{F.4}$$

Then, by cost minimization

$$TC_{jt} = \min_{k_{jt},v_{jt}} w_{jt} z_{ht} n_{jt} + \kappa\left(v_{jt}, n_{jt-1}\right) + k_{jt} r_t^k + E_t\left[\Lambda_{t,t+1} TC_{jt+1}\right] \tag{F.5}$$

s.t.

$$v_{jt} = \frac{n_{jt} - (1-\delta_s) n_{jt_1}}{q_t} \tag{F.6}$$

$$n_{jt} = \frac{1}{\underbrace{\left(A_t \gamma_t^T z_{ht}\right)}_{\tilde{A}_t}}\left(\frac{y_{jt}}{k_{jt}^{\alpha}}\right)^{\frac{1}{1-\alpha}} \tag{F.7}$$

$$\kappa(v_{jt}, n_{jt-1}) = \frac{\kappa_1}{1+\psi_1}\left(\frac{q_t v_{jt}}{n_{jt-1}^{I_{cr}}}\right)^{1+\psi_1} n_{jt-1}^{I_{cr}} + \frac{\kappa_2}{1+\psi_2}\left(\frac{v_{jt}}{n_{jt-1}^{I_{cr}}}\right)^{1+\psi_2} n_{jt-1}^{I_{cr}} \tag{F.8}$$

Then, the first-order condition with respect to capital is the following:

$$r_t^k + \underbrace{\left[w_{jt} z_{ht} + \frac{\kappa_{vt}}{q_t} - \Lambda_{t,t+1}\kappa_{nt+1} - \Lambda_{t,t+1}(1-\delta_s)\frac{\kappa_{vt+1}}{q_{t+1}}\right]}_{\mathbf{W}_t} \frac{\alpha}{1-\alpha}\frac{n_{jt}}{k_{jt}} = 0 \tag{F.9}$$

where, as defined before,

$$\kappa_{vt} = \frac{\partial\kappa(v_{jt}, n_{jt-1})}{\partial v_{jt}} = \kappa_1 A_t q_t^{1+\psi_1}\left(\frac{v_{jt}}{n_{jt-1}}\right)^{\psi_1} + \kappa_2 A_t\left(\frac{v_{jt}}{n_{jt-1}}\right)^{\psi_2},$$

$$\kappa_{nt} = -\frac{\partial\kappa(v_{jt}, n_{jt-1})}{\partial n_{jt-1}} = \left[\kappa_1 A_t \frac{\psi_1}{1+\psi_1} q_t^{1+\psi_1}\left(\frac{v_{jt}}{n_{jt-1}}\right)^{1+\psi_1} + \kappa_2 A_t \frac{\psi_2}{1+\psi_2}\left(\frac{v_{jt}}{n_{jt-1}}\right)^{1+\psi_2}\right]$$

$\mathbf{W}_t$ is the marginal cost of recruiting a worker. For each additional worker you hire today, you need to pay the recruiting cost ($\frac{\kappa_{vt}}{q_t}$) and wages ($w_{jt} z_{ht}$). However, each additional worker you hire today doesn't have to be re-hired next period ($\Lambda_{t,t+1}\frac{\kappa_{v+1}}{q_{t+1}}$) and saves you recruiting costs in the next period

$(\Lambda_{t,t+1}\kappa_{nt+1})$. Then, solving for n_{jt}

$$n_{jt} = \frac{1-\alpha}{\alpha}\frac{r_t^k}{\mathbf{W}_t}k_{jt} \tag{F.10}$$

Then, replacing in the production function and solving for capital

$$y_{jt} = k_{jt}^{\alpha}\left(\tilde{A}_t\frac{1-\alpha}{\alpha}\frac{r_t^k}{\mathbf{W}_t}\right)^{1-\alpha} \tag{F.11}$$

$$y_{jt} = k_{jt}\left(\tilde{A}_t\frac{1-\alpha}{\alpha}\frac{r_t^k}{\mathbf{W}_t}\right)^{1-\alpha} \tag{F.12}$$

$$k_{jt} = \frac{y_{jt}}{\tilde{A}_t^{1-\alpha}}\left[\frac{\alpha}{1-\alpha}\frac{\mathbf{W}_t}{r_t^k}\right]^{1-\alpha} \tag{F.13}$$

Then, replacing in equation (F.10)

$$n_{jt} = \frac{1-\alpha}{\alpha}\frac{r_t^k}{\mathbf{W}_t}\frac{y_{jt}}{\tilde{A}_t^{1-\alpha}}\left[\frac{\alpha}{1-\alpha}\frac{\mathbf{W}_t}{r_t^k}\right]^{1-\alpha} \tag{F.14}$$

$$n_{jt} = \frac{y_{jt}}{\tilde{A}_t^{1-\alpha}}\left[\frac{\alpha}{1-\alpha}\frac{\mathbf{W}_t}{r_t^k}\right]^{-\alpha} \tag{F.15}$$

Therefore, the marginal cost (p_t^m) equals the following:

$$p_t^m = \frac{\partial TC_{jt}}{\partial y_{jt}} \tag{F.16}$$

$$p_t^m = \mathbf{W}_t\frac{1}{\tilde{A}_t^{1-\alpha}}\left[\frac{\alpha}{1-\alpha}\frac{\mathbf{W}_t}{r_t^k}\right]^{-\alpha} + r_t^k\frac{1}{\tilde{A}_t^{1-\alpha}}\left[\frac{\alpha}{1-\alpha}\frac{\mathbf{W}_t}{r_t^k}\right]^{1-\alpha} \tag{F.17}$$

$$p_t^m = \frac{1}{\tilde{A}_t^{1-\alpha}}\left[\frac{\mathbf{W}_t^{1-\alpha}(r_t^k)^{\alpha}}{\alpha^{\alpha}(1-\alpha)^{1-\alpha}}\right] \tag{F.18}$$

$$p_t^m = \frac{1}{\left(A_t\gamma_t^T z_{ht}\right)^{1-\alpha}}\left[\frac{\mathbf{W}_t^{1-\alpha}(r_t^k)^{\alpha}}{\alpha^{\alpha}(1-\alpha)^{1-\alpha}}\right] \tag{F.19}$$

$$p_t^m = \frac{1}{(\gamma_t^T)^{1-\alpha}}\left[\frac{\left(\frac{\tilde{\mathbf{W}}_t}{z_{ht}}\right)^{1-\alpha}(r_t^k)^{\alpha}}{\alpha^{\alpha}(1-\alpha)^{1-\alpha}}\right] \tag{F.20}$$

where

$$\tilde{\mathbf{W}}_t = \frac{\mathbf{W}_t}{A_t} \tag{F.21}$$

$$\tilde{\mathbf{W}}_t = \tilde{w}_{jt}z_{ht} + \frac{\tilde{\kappa}_{vt}}{q_t} - \gamma_t\Lambda_{t,t+1}\tilde{\kappa}_{nt+1} - \gamma_t\Lambda_{t,t+1}\frac{\tilde{\kappa}_{vt+1}}{q_{t+1}} \tag{F.22}$$

and where $\frac{\tilde{\mathbf{W}}_t}{z_{ht}}$ is the marginal labor cost for the firm—the marginal cost of hiring an extra hour of work.