Search Frictions, Labor Supply and the Asymmetric Business Cycle*

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Abstract

We develop an equilibrium business cycle model with search frictions in the labor market à la Diamond-Mortensen-Pissarides and a labor supply decision that yields the cyclical asymmetry between peaks and troughs in the unemployment rate and the symmetric fluctuations in the labor force participation rate as in U.S. data. We find that fluctuations in the extent of search frictions are the sole responsible for the peak-trough asymmetry in the data. Participation decisions contribute to the fluctuations in search frictions by changing the size and composition of the pool of job-seekers, which in turn affect the tightness ratio and thereby slack in the labor market. Absent labor supply responses to shocks, the participation rate would be counterfactually asymmetric.

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Keywords: Asymmetric business cycles; Labor supply; Search frictions; Employment; Unemployment rate; Labor force participation rate.

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1 Introduction

In the United States, cyclical fluctuations in the employment-to-population ratio display a striking asymmetry: deviations below trend ("troughs") are larger than deviations above trend ("peaks"). This asymmetry between peaks and troughs produces significant higher-order moments, such as negative skewness in the distribution of the employment-to-population ratio in deviations from trend. Sichel (1993) first refers to this phenomenon as "deepness," which since then has become one of the stylized facts of the U.S. business cycle (McKay and Reis, 2008).

The large and growing literature on the topic studies this phenomenon through the lens of a Diamond-Mortensen-Pissarides (DMP) model in which search frictions generate unemployment (Diamond, 1982; Mortensen, 1982; Pissarides, 1985). This approach uses a two-state representation of the labor market, which abstracts from participation decisions altogether (Andolfatto, 1997; Abbritti and Fahr, 2013; Dupraz, Nakamura and Steinsson, 2020; Ferraro, 2017, 2018; Hairault, Langot and Osotimehin, 2010; Petrosky-Nadeau and Zhang, 2013, 2017; Pizzinelli, Theodoridis and Zanetti, 2020).

By contrast, in this paper, labor force participation decisions take center stage. We begin with documenting a new, overlooked fact: cyclical fluctuations in the labor force participation rate are symmetric around the trend, which implies that deepness in the U.S. employment-to-population ratio is accounted for solely by the unemployment rate. Given these observations, one might be tempted to conclude that participation or *labor supply* decisions, and thus worker flows in and out of the labor force are inconsequential for the study of cyclical asymmetry.

There are however at least two reasons to be skeptical about this view; one of them is empirical, the other is theoretical. First, worker flows in and out of the labor force account for around one-third of the cyclical volatility in the unemployment rate (Elsby, Hobijn and Şahin, 2015). Also, workers' transition probabilities from nonparticipation to unemployment and from unemployment to nonparticipation are respectively countercyclical and procyclical. Thus, during recessions, a larger share of individuals who would have left the labor force remains unemployed, and a larger share of nonparticipants who would have stayed out of the labor force enters the unemployment pool. Such cyclical patterns exacerbate congestion in the labor market during recessions, contributing to generate deepness.

Second, in the context of a DMP model extended to allow for an active participation margin the lack of cyclical asymmetry in the participation rate is somewhat puzzling.

In a three-state model, a key object impinging on the decision to enter the labor force is the probability of finding a job. In the data, cyclical fluctuations in such probability display significant deepness (Ferraro, 2018). Thus a model that successfully reproduces the observed deepness in the probability of finding a job would naturally generate a sharp fall in the individuals' willingness to the enter the labor force during recessions. At the same time, such labor supply decisions change the size and arguably the composition of the pool of job-seekers competing for jobs, which affects vacancy posting and the extent of slack in the labor market.

To quantify these mechanisms, we develop an equilibrium business cycle model that reconciles the deepness in the employment rate (defined as one minus the unemployment rate) with the symmetric fluctuations in the labor force participation rate. Our model combines search frictions with endogenous vacancy posting à la DMP with an active participation margin, akin to a labor supply decision with indivisible labor, as in Rogerson (1988) and Hansen (1985). In the model, individuals differ in terms of home productivity (or value of leisure), which changes over time due to persistent idiosyncratic shocks, while they have the same market productivity. Aggregate fluctuations are driven by symmetric and persistent shocks to productivity.[1]

The model embodies two propagation mechanisms of productivity shocks: (i) shifts in the individuals' willingness to work; (ii) fluctuations in the extent of frictions, i.e., the speed at which job-seekers meet employers posting vacancies, which depends on market tightness (the ratio of vacancies to job-seekers). Unlike the DMP model, in our setting, the market tightness ratio is determined in equilibrium by posted job vacancies (labor demand) jointly with participation decisions (*desired* labor supply). Actual and desired labor supply differ due to search frictions.

First, individual participation decisions are described by a separation and a search cutoff on home productivity that determine whether an individual is out of the labor force, attached, or non-attached to the labor force. An individual attached to the labor force is either employed or unemployed and searching for a job, whereas a nonattached individual participates insofar as he or she is employed. The response of the two cutoffs to productivity shocks, keeping the tightness ratio and so the level of frictions fixed, is what we refer to as the *"labor supply channel,"* which captures the partial-equilibrium adjustment of individual labor supply to productivity shocks.

Second, the market tightness ratio falls in response to a negative productivity shock,

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[1] Altuğ, Ashley and Patterson (1999) find no evidence for nonlinearity in measured TFP using aggregate-level U.S. data. Ilut, Kehrig and Schneider (2017) confirm this finding in establishment-level data.

generating slack in the labor market. We refer to this mechanism as the *"slackness channel,"* which captures the equilibrium feedback effect between firms' vacancy posting and individuals' participation decisions. Notably, equilibrium vacancies are determined based on the size and composition of the pool of job-seekers: the participation margin directly contributes to the cyclical movements in labor market frictions. This channel is absent in the DMP model, where all individuals are participants at all times.

We calibrate the model to U.S. data. As a test of the model, we check whether, with the same parameter values, the model accounts for the deepness in the unemployment rate and the lack thereof in the participation rate. We find that, to a large extent, it does. Furthermore, our model captures the key features of the cyclical movements in gross worker flows, a well-known challenge for existing three-state models of the labor market (see, e.g., Tripier, 2004; Veracierto, 2008; Shimer, 2013).

To study the role of labor supply vis-à-vis search frictions, we propose a structural quantitative accounting exercise. Specifically, we generate two counterfactual time series for the unemployment and the labor force participation rate, keeping the same realization of productivity shocks. In the first counterfactual, we drop the indifference conditions determining the separation and search cutoffs, fix the two cutoffs on home productivity at their steady-state values, and let the tightness ratio vary in response to shocks as implied by the free-entry condition. In the second counterfactual, we drop instead the free-entry condition, fix the tightness ratio at its steady-state value, and let the cutoffs vary.[2]

We find that the slackness channel and so fluctuations in the extent of frictions are the key driving force of deepness in the employment rate. In the model, the matching process is subject to congestion due to random search, implying that the probability that a job-seeker meets an employer falls more in response to bad shocks than it rises in response to good shocks. Such asymmetric responses to shocks yield that the troughs are deeper than the peaks are tall.

In other words, if the labor supply channel was the only driving force of fluctuations, we would observe no deepness asymmetry in employment. In this sense, our model reproduces the symmetric fluctuations in labor generated by frictionless models in the RBC tradition. To be sure, this is not to say that the labor force participation margin is inconsequential for cyclical asymmetry. On the contrary, in a three-state model like ours,

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[2] Such a decomposition cannot be implemented solely with data on labor market stocks and average transition probabilities as in, say, Elsby, Hobijn and Şahin (2015). The reason is that observed transition probabilities are equilibrium objects jointly determined by the individuals' willingness to work for a given level of market tightness, and the probability of finding a job, which in turn depends on the collection of individuals' participation decisions and job vacancies.

individuals' flows in and out of the labor force depend on market tightness, and they all contribute to the stocks of employment, unemployment, and nonparticipation, and so to the mass of job-seekers competing for jobs. During recessions, in the model, as in the data, unemployed individuals are less likely to drop out of the labor force, and individuals out of the labor force are more likely to enter the labor force as unemployed. Accounting for the cyclicality of these gross worker flows is key for the model to generate the cyclical asymmetry in the data.

Furthermore, absent the labor supply channel, the labor force participation rate would be markedly asymmetric, mirroring the cyclical asymmetry in the probability of finding a job, which is at odds with the data. The lack of asymmetry in the participation rate is not hard-wired into the model, rather it is the result of equilibrium forces inherent to the joint determination of market tightness and the cutoffs on home productivity.

The rest of the paper is organized as follows. In Section 2, we discuss the related literature. Section 3 briefly presents the observations that motivate the paper. Section 4 presents the model. In Sections 5 and 6, we take the model to the data and study its quantitative properties. Finally, Section 7 concludes. Appendices A, B, and C contain data sources, derivations, and additional results.

2 Related Literature

This paper contributes to the literature on business cycle asymmetry. In the RBC tradition, Hansen and Prescott (2005) explain the negative skewness in U.S. market hours worked (in deviations from trend) in the context of a neoclassical growth model with occasionally-binding capacity constraints. Van Nieuwerburgh and Veldkamp (2006) study asymmetry in output growth rates using an RBC model augmented with learning about technology shocks. At the end of a boom, agents have accurate estimates of the state of technology so that a negative productivity shock prompts abrupt actions, leading to a sharp fall in investment and hours. Jovanovic (2006) explain the negative skewness in output growth rates through the adoption of technologies of uncertain skill requirements. Quadratic costs in skill mismatch imply that a good match rises output by less than a bad match reduces it, such that output growth rates are negatively skewed. McKay and Reis (2008) show that a model with asymmetric adjustment costs in employment and a choice of when to scrap old technologies reconciles the brevity and violence of the contractions in employment with the nearly symmetric fluctuations in output. Ordonez (2013) singles out financial frictions as an explanation for the observation that cyclical asymmetry is stronger in countries with less developed financial systems.

Using a search-theoretic model, Andolfatto (1997) argues that asymmetric fluctuations in the job destruction rate can qualitatively account for the fast rises and slow declines in the U.S. unemployment rate. Petrosky-Nadeau and Zhang (2013) argue that a DMP model, calibrated to match the cyclical volatility in the unemployment rate, produces the asymmetry between peaks and troughs in the data. Building on this result, Petrosky-Nadeau and Zhang (2017) show that a first-order approximation of the DMP equilibrium dynamics neglects important nonlinearities in the propagation of shocks. Ferraro (2018) develops a search-and-matching model with heterogeneous workers in productivity/skills that reconciles the cyclical asymmetry in the unemployment rate with the nearly symmetric fluctuations in output. Abbritti and Fahr (2013) and Dupraz, Nakamura and Steinsson (2020) study cyclical asymmetry in a DMP model with downward nominal wage rigidity. This body of work abstracts from participation decisions altogether.

Our work also relates to the literature that studies the aggregate implications of three-state models of the labor market. The bulk of this body of work considers steady-state outcomes only (Garibaldi and Wasmer, 2005; Pries and Rogerson, 2009; Krusell et al., 2008, 2010, 2011). A few attempts have been made to confront these models with the cyclical properties of labor market outcomes (Tripier, 2004; Veracierto, 2008; Shimer, 2013; Cairó, Fujita and Morales-Jiménez, 2019). Only recently, Krusell et al. (2017) show that a model with idiosyncratic risk, incomplete markets, and labor market frictions can account for the cyclical volatility and comovement of the U.S. gross worker flows. In their setting, job-finding rates are *exogenous* stochastic processes. By contrast, in our setting, job-finding rates are endogenously determined as an equilibrium outcome, based on the individuals' participation decisions and the free-entry condition for vacancy posting. This property of the equilibrium is instrumental in quantifying the role of search frictions as the source of cyclical asymmetry.

Our contribution to the literature is twofold. First, we formulate and quantify a three-state model that accounts for the deepness asymmetry in the unemployment rate and the symmetric fluctuations in the labor force participation rate, alongside key features of gross worker flows. Second, we quantify the importance of labor supply vis-à-vis search frictions for the cyclical volatility and asymmetry in the employment-to-population ratio, a question that previous studies have not addressed.

3 Motivating Facts

In this section, we detail the empirical observations that motivate our work. Based on Sichel (1993), we measure cyclical asymmetry with the third standardized central moment or *skewness* of the cyclical component $\hat{x}_t$ of the time series x_t:

$$\text{skew}(\hat{x}_t) = \frac{\mathbb{E}\left[\left(\hat{x}_t - \mathbb{E}\left[\hat{x}_t\right]\right)^3\right]}{\sigma_{\hat{x}}^3},$$

where $\mathbb{E}$ denotes the mathematical expectation operator and $\sigma_{\hat{x}}$ the standard deviation of the cyclical component $\hat{x}_t$ expressed in percent deviations from trend. As customary in the literature, fluctuations at the business cycle frequency are identified as occurring between 2 and 32 quarters. Also, since there is no firm consensus on the filtering approach, we report skewness statistics based on two alternative bandpass methods due to Baxter and King (1999) and Christiano and Fitzgerald (2003), as well as the procedure in Hodrick and Prescott (1997). To test for asymmetry against the null hypothesis of symmetry, we use the test developed by Bai and Ng (2005).[3]

Table 1 reports skewness statistics, with associated p-values, for the U.S. employment-to-population ratio, the employment rate (one minus the unemployment rate), and the labor force participation rate, in the post-war period 1948-2016. To interpret the results, we consider the following decomposition of the employment-to-population ratio:

$$\frac{\text{emp}}{\text{pop}} = \underbrace{\left(1 - \frac{\text{unemp}}{\text{emp+unemp}}\right)}_{\text{employment rate}} \times \underbrace{\left(\frac{\text{emp+unemp}}{\text{pop}}\right)}_{\text{participation rate}}.$$

This decomposition shows that employment as a fraction of the working-age population equals the employment rate (fraction of employed workers in the labor force, one minus the unemployment rate) times the participation rate (fraction of the population in the labor force). Hence, in an accounting sense, cyclical asymmetry in the employment-to-population ratio may result from either the unemployment or participation rate, or both.

The results in Table 1 establish that cyclical fluctuations in labor force participation are virtually symmetric, which leaves the unemployment rate as the key driving force of asymmetry in the employment-to-population ratio. Specifically, the cyclical component of the employment-to-population ratio displays significant negative skewness. Note that

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[3] See Appendix A for details on data sources.

this negative skewness remains significant and of similar magnitude also in the pre-1980 period. Thus, cyclical asymmetry is not driven by the so-called jobless recoveries of the 1990s, 2000s, or the Great Recession of 2007-2009, rather it is a systematic feature of the U.S. labor market over the entire post-war period.

Table 1: Skewness in the U.S. Labor Market

	Skewness		
	Baxter-King	Christiano-Fitzgerald	Hodrick-Prescott
A. Sample period: 1948:Q1-2016:Q4			
Employment-to-population ratio	−0.44	−0.29	−0.32
	(0.02)	(0.08)	(0.03)
Employment rate	−0.85	−0.51	−0.70
	(0.00)	(0.00)	(0.00)
Participation rate	0.09	0.05	0.05
	(0.38)	(0.44)	(0.38)
B. Sample period: 1948:Q1-1980:Q4			
Employment-to-population ratio	−0.42	−0.34	−0.43
	(0.03)	(0.05)	(0.02)
Employment rate	−0.80	−0.62	−0.76
	(0.00)	(0.01)	(0.00)
Participation rate	0.12	0.03	−0.06
	(0.34)	(0.45)	(0.41)

Notes: For Baxter-King and Christiano-Fitzgerald, we consider frequencies between 2 and 32 quarters. The order of the moving average for the Baxter-King filter is set to 8 quarters. The smoothing parameter for the Hodrick-Prescott filter is 1,600. Variables are expressed in log-deviations from trend. P-values (one-sided test) in parentheses.

To understand what are the mechanisms that shape the cyclical asymmetry in the U.S. unemployment rate and the lack thereof in the participation rate, we build a quantitative model that incorporates employment, unemployment, and nonparticipation, and use it as a laboratory to carry out counterfactual analysis. We turn to these issues next.

4 Model

4.1 Environment

Time is discrete and continues forever, indexed by $t = 0, 1, 2, \ldots, \infty$. The economy is inhabited by two types of agents: individuals and employers. Both agents are infinitely lived, risk-neutral, and discount future values at the same rate $\beta \in (0, 1)$. The mass of individuals is normalized to one. An individual is endowed with one unit of time that can be allocated to three uses: market work, job search, and nonmarket work (e.g., leisure and home production). Market work and job search are mutually exclusive activities. An employer is either matched with an individual and producing output, or unmatched and posting job vacancies. The mass of employers is determined in free-entry equilibrium.

Preferences and budget constraints As standard in the literature, we assume that an individual has a linear utility function over consumption $c_t \geq 0$ and maximizes $\sum_{t=0}^{\infty} \beta^t c_t$ under the flow budget constraint that consumption equals the wage, $c_t = w_t$, if employed, it equals unemployment insurance (UI) benefits, $c_t = b$, if unemployed, and $c_t = y_t^h$ if nonparticipant, where $y_t^h(x_t, y_t)$ is home production, which depends on the individual's idiosyncratic home productivity x_t and aggregate market productivity y_t, in a way that we make precise below.

Heterogeneity and home productivity As in Garibaldi and Wasmer (2005), individuals are heterogeneous in home productivity, x_t. The value of x_t may change over time with probability λ. In that event, the new value x_{t+1} for the next period is drawn from a probability distribution function $f(\cdot)$, taken to be log-normal with parameters μ_x and σ_x, defined over the bounded support $x_t \in \left[x^{\min}, x^{\max}\right]$. With probability $1 - \lambda$, home productivity maintains its current value into the next period. Hence, at the individual level, home productivity is persistent, but conditional on a switch, its the current value does not affect its next period realization.[4]

Aggregate productivity shock Production requires a match between one employer and one individual. When a job-seeker and an employer meet and agree to create a match

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[4] We extend the work of Garibaldi and Wasmer (2005) along two important dimensions. First, we amend their model to allow for worker flows from nonparticipation to employment, which are both large and highly volatile in the data (see Krusell et al., 2017). This modification implies that the composition of the pool of job seekers contributes to determine labor market tightness. Second, we focus on transition dynamics triggered by business cycle shocks, rather than just focusing on steady-state outcomes.

(or, equivalently, a job), they produce output, y_t, which evolves stochastically over time according to an AR(1) process in logs:

$$\log(y_{t+1}) = (1-\rho_y)\ln(\bar{y}) + \rho_y \log(y_t) + \sigma_y \epsilon_{t+1}, \tag{1}$$

where $\bar{y}$ is the unconditional mean of output and $\epsilon_t \overset{iid}{\sim} \mathcal{N}(0,1)$ are innovations to the (log) output of a job. The parameters ρ_y and σ_y control the persistence and volatility of the innovations, ϵ_t, respectively. Shocks to y_t rise output in all matches, thus we interpret them as aggregate shocks.

Wage determination As in Shimer (2004) and many others, we assume an ad-hoc wage rule relating the wage to labor productivity:

$$w_t = \bar{w} y_t^{\eta}, \tag{2}$$

where $\bar{w}$ is a constant and the parameter η governs the cyclical sensitivity of the wage to labor productivity.

The benefit of this parsimonious specification is twofold. First, it considerably simplifies the solution of the model. As the firm's value of a job is independent of home productivity, only the share of unemployed and nonparticipant individuals (instead of the full cross-sectional distribution) is relevant for vacancy posting. In turn, this allows us to cleanly isolate the role of individual heterogeneity and labor supply decisions on labor market outcomes. Second, depending on the value of η, the wage schedule accommodates different degrees of wage flexibility.

Meeting technology and search friction The matching process between job-seekers and employers posting vacancies is subject to a search friction. As standard in the literature, we assume a constant-returns-to-scale meeting technology of the following form:

$$m_t = \chi \times s_t^{\varepsilon} \times v_t^{1-\varepsilon}, \tag{3}$$

where s_t and v_t are the mass of job-seekers and vacancies, respectively. The probability that a job-seeker meets a vacancy, $p(\theta_t) = \theta_t^{1-\varepsilon}$, is strictly increasing and concave in market tightness, $\theta_t \equiv v_t/s_t$, with $p(\theta_t) \to 0$ as $\theta_t \to 0$. Similarly, the probability that a vacancy meets a job-seeker, $q(\theta_t) = \theta_t^{-\varepsilon}$, is strictly decreasing and convex in θ_t.

In our setting, the pool of job-seekers consists of both unemployed individuals and a randomly selected group of nonparticipants. Unemployed individuals are "active" searchers as they incur the utility cost of job search. Nonparticipants that are randomly drawn in the pool of searchers are viewed as "passive" searchers; they enjoy home production and do not collect unemployment benefits, but with a constant probability ϕ are costlessly selected into the pool of searchers. Active and passive searchers meet a vacancy with the same probability $p(\theta_t)$. Note that our classification of active searchers as unemployed individuals and passive searchers as nonparticipants is consistent with the approach of the BLS (see Jones and Riddell, 1999, for further discussion). By introducing the concept of passive searchers into the model, we allow for worker flows from nonparticipation to employment, that are both large and highly volatile over the business cycle (see Krusell et al., 2017).[5]

Timing of events Within the period, events unfold as follows. At the beginning of the period, the aggregate (y_t) and idiosyncratic (x_t) states are realized. After these events, the period consists of two stages. In the first stage, separations, participation, and search decisions are made simultaneously. In the second stage, output is produced and wages are paid.

In our setting, there is a distinction between a meeting between a vacancy and job-seeker, and the creation of a job. Only if profitable for both parties, a meeting is converted into a job. The model uses the *"instantaneous hiring"* view in which new hires begin working right away rather than with a one-period delay. As discussed in Davis, Faberman and Haltiwanger (2006), this timing describes the U.S. labor market flows at a quarterly frequency.

4.2 Individual Agents' Problem

We formulate the individual agents' problem in recursive form at the production stage where idiosyncratic and aggregate states have realized, and the individual agents' current

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[5] We acknowledge that, in the data, some of the observed flows from nonparticipation to employment may be due to time aggregation. As labor market data are sampled at the monthly frequency, measured flows from nonparticipation to employment may be due to unmeasured flows from nonparticipation to unemployment and from unemployment to employment insofar as they occur within the month. Here, we follow Krusell et al. (2017) and introduce a constant exogenous probability of becoming a (passive) searcher. Nonetheless, the flows from nonparticipation to employment remain endogenous in the sense that the individuals optimally decide whether to accept a job, or remain out of the labor force, given the realizations of the state variables.

decisions of continuing, destroying, or creating a match have been made.

4.2.1 Individuals

At the beginning of each period, an employee decides whether to remain in the match and receive the wage or separate. And conditional on separating, the individual has the option to become either unemployed or nonparticipant, thus dropping out of the labor force. Similarly, a non-employed individual has the choice to search for a job or stay out of the labor force. Again, conditional on being out of the labor force, an individual cannot meet a job vacancy unless he or she receives a random job offer. In that event, the individual chooses whether to accept the job offer or remain out of the labor force. All flows across the three labor market states are thus endogenous.

At the production stage, the worker's value of employment depends on whether he or she is attached to the labor force. If the individual is attached to the labor force, the value of employment is

$$\begin{aligned} W_t^a = w_t &+ \beta E_t \left\{(1-\delta)[1-\lambda(1-F(x_{t+1}^v))]\right\} W_{t+1}^a \\ &+ \beta E_t \left\{\delta[1-\lambda(1-F(x_{t+1}^v))]p_{t+1}\right\} W_{t+1}^a \\ &+ \beta E_t \left\{[(1-\delta)\lambda + \delta\lambda\phi p_{t+1}] \int_{x_{t+1}^v}^{x_{t+1}^q} W_{t+1}^{na}(x) f(x) dx \right\} \\ &+ \beta E_t \left\{\delta[1-\lambda(1-F(x_{t+1}^v))](1-p_{t+1})U_{t+1}\right\} \\ &+ \beta E_t \left\{[\delta\lambda(1-\phi p_{t+1})] \int_{x_{t+1}^v}^{x_{t+1}^q} H_{t+1}^a(x) f(x) dx \right\} \\ &+ \beta E_t \left\{\lambda \int_{x_{t+1}^q}^{x^{\max}} H_{t+1}^{na}(x) f(x) dx \right\}, \end{aligned} \tag{4}$$

where x_t^v and x_t^q are the search and separation cutoffs, respectively, whose determination we describe below.

If the worker is nonattached to the labor force, the value of employment is

$$\begin{aligned} W_t^{na}(x) = w_t &+ \beta E_t \left\{ [(1-\delta)\lambda(F(x_{t+1}^v) + \delta\lambda(F(x_{t+1}^v))p_{t+1}]W_{t+1}^a \right\} \\ &+ \beta E_t \left\{ [(1-\delta)(1-\lambda) + \delta(1-\lambda)\phi p_{t+1}]W_{t+1}^{na}(x) \right\} \\ &+ \beta E_t \left\{ [(1-\delta)\lambda + \delta\lambda\phi p_{t+1}] \int_{x_{t+1}^v}^{x_{t+1}^q} W_{t+1}^{na}(x) f(x) dx \right\} \\ &+ \beta E_t \left\{ [\delta\lambda(F(x_{t+1}^v))(1-p_{t+1})]U_{t+1} \right\} \\ &+ \beta E_t \left\{ [\delta\lambda(1-\phi p_{t+1}) + \delta(1-\lambda)(1-\phi p_{t+1})] \int_{x_{t+1}^v}^{x_{t+1}^q} H_{t+1}^a(x) f(x) dx \right\} \\ &+ \beta E_t \left\{ \lambda \int_{x_{t+1}^q}^{x^{\max}} H_{t+1}^{na}(x) f(x) dx \right\}. \end{aligned} \tag{5}$$

After collecting the wage w, the individual can remain employed if the match survives exogenous separation (with probability $1-\delta$) and it is still viable, the latter event occurring with probability $1-\lambda[1-F(x^q)]$. If the match is destroyed, the individual can receive and accept a job offer, becoming worker attached or nonattached depending on its home productivity. If the match is dissolved for exogenous reasons, the individual decides whether to actively seek a job or leave the labor force. Note that only the value of employment for a nonattached worker depends on the flow value of home production x. This dependence reflects the value of nonparticipation in the next period.

The value of unemployment is independent of x and equal to

$$\begin{aligned} U_t = b &+ \beta E_t \left\{ [1-\lambda(1-F(x_{t+1}^v))]p_{t+1}W_{t+1}^a \right\} \\ &+ \beta E_t \left\{ \lambda\phi p_{t+1} \int_{x_{t+1}^v}^{x_{t+1}^q} W_{t+1}^{na}(x) f(x) dx \right\} \\ &+ \beta E_t \left\{ \delta[1-\lambda(1-F(x_{t+1}^v))](1-p_{t+1})U_{t+1} \right\} \\ &+ \beta E_t \left\{ \lambda(1-\phi p_{t+1}) \int_{x_{t+1}^v}^{x_{t+1}^q} H_{t+1}^a(x) f(x) dx \right\} \\ &+ \beta E_t \left\{ \lambda \int_{x_{t+1}^q}^{x^{\max}} H_{t+1}^{na}(x) f(x) dx \right\}. \end{aligned} \tag{6}$$

The first two lines on the right-hand side of (6) capture the individual's decision to create a match, at the beginning of next period. If the individual decides not to create a match, then he or she decides between remaining unemployed or leaving the labor force.

The last three lines in (6) capture instead the individual's decision to stay unemployed or leave the labor force in the event that either she or he does not meet an employer, or a meeting is exogenously destroyed, or the individual receives the exogenous shock λ dropping out of the labor force. The latter event occurs if the individual draws an x higher than x^q.

The value of nonparticipation for an attached individual is

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\begin{aligned}
H_t^a(x) = y_t^h &+ \beta E_t \left\{\lambda F(x_{t+1}^v) p_{t+1} W_{t+1}^a\right\} \\
&+ \beta E_t \left\{(1-\lambda)\phi p_{t+1} W_{t+1}^{na}(x)\right\} \\
&+ \beta E_t \left\{\lambda \phi p_{t+1} \int_{x_{t+1}^v}^{x_{t+1}^q} W_{t+1}^{na}(x) f(x) dx\right\} \\
&+ \beta E_t \left\{\lambda F(x_{t+1}^v)(1-p_{t+1}) U_{t+1}\right\} \\
&+ \beta E_t \left\{(1-\lambda)(1-\phi p_{t+1}) H_{t+1}^a(x)\right\} \\
&+ \beta E_t \left\{\lambda (1-\phi p_{t+1}) \int_{x_{t+1}^v}^{x_{t+1}^q} H_{t+1}^a(x) f(x) dx\right\} \\
&+ \beta E_t \left\{\lambda \int_{x_{t+1}^q}^{x^{\max}} H_{t+1}^{na}(x) f(x) dx\right\}, \qquad (7)
\end{aligned}
$$

where the home production technology is specified as $y_t^h = x_t y_t / \bar{y}$.[6]

The value of nonparticipation for a nonattached individual is

$$
\begin{aligned}
H_t^{na}(x) = y_t^h &+ \beta E_t \left\{\lambda F(x_{t+1}^v) p_{t+1} W_{t+1}^a\right\} \\
&+ \beta E_t \left\{(1-\lambda)\phi p_{t+1} W_{t+1}^{na}(x)\right\} \\
&+ \beta E_t \left\{\lambda \phi p_{t+1} \int_{x_{t+1}^v}^{x_{t+1}^q} W_{t+1}^{na}(x) f(x) dx\right\} \\
&+ \beta E_t \left\{[\lambda F(x_{t+1}^v)(1-p_{t+1})] U_{t+1}\right\} \\
&+ \beta E_t \left\{(1-\lambda)(1-\phi p_{t+1}) H_{t+1}^{na}(x)\right\} \\
&+ \beta E_t \left\{\lambda (1-\phi p_{t+1}) \int_{x_{t+1}^v}^{x_{t+1}^q} H_{t+1}^a(x) f(x) dx\right\} \\
&+ \beta E_t \left\{\lambda \int_{x_{t+1}^q}^{x^{\max}} H_{t+1}^{na}(x) f(x) dx\right\}, \qquad (8)
\end{aligned}
$$

---

[6] We scale home production by $\bar{y}$ so that in the deterministic steady state of the model $y_t^h = x_t$.

where again $y_t^h = x_t y_t / \bar{y}$ is home production. The first three rows on the right-hand side of (7) and (8) capture the passive searcher's choice between working and not-working at the beginning of the next period. Also, conditional on not-working, the passive searcher has the option to remain out of the labor force or become an active searcher (i.e., unemployed). The remaining rows capture the passive searcher's decision to become an active searcher or remain out of the labor force in the event that either he or she does not meet a job vacancy, or a meeting is exogenously destroyed.

4.2.2 Employers

From the employer's perspective, the value of being in an employment relationship (value of a job, for short) is always positive. This feature implies that employers never initiate job destruction. As argued above, however, individuals initiate job destruction when the value of nonparticipation exceeds the value of employment.

At the production stage, then, the value of a job is

$$J_t = y_t - w_t + \beta \mathbb{E}_t \left[(1 - d_{t+1}) J_{t+1} + d_{t+1} V_{t+1} \right], \tag{9}$$

where the individual's decision of destroying the match is subsumed in the indicator

$$d_t = \begin{cases} \delta & \text{if} \quad H_t < W_t \\ 1 & \text{if} \quad H_t \geq W_t \end{cases}, \tag{10}$$

where $\delta \in (0, 1)$ is an exogenous rate of job destruction.

The value of a posted job vacancy is

$$V_t = -k + q(\theta_t) \Omega_t J_t + (1 - q(\theta_t)) V_{t+1}, \tag{11}$$

where k is the per-period unit cost of opening and maintaining a job vacancy. Note that J_t is independent of x and Ω_t accounts for the selection into the pool of job searchers (akin to an inverse Mills ratio) and captures the share of job seekers that accepts a job offer. We emphasize that we do not need to keep track of the full cross-sectional distribution, but only of the share of job seekers that accept an eventual offer. Active and passive searchers (or unemployed or nonparticipant attached, respectively) accept job offers, while nonparticipant nonattached decline them. As a result, Ω_t is equal to $(u_t + \phi n_t^a) \,/\, [u_t + \phi(n_t^a + n_t^{na})]$, where u_t is the stock of unemployed, n_t^a the stock of nonparticipants attached to the labor force, and n_t^{na} the stock of nonparticipants nonattached.[7] Again, ϕ is the probability that nonparticipants are drawn into the pool of job seekers.

4.2.3 Free Entry

As in Pissarides (1985), and many others after that, employers post job vacancies until it is profitable to do so, which yields that the cost of posting a vacancy equals its expected benefit at all times, such that $V_t = 0$ for all realizations of the aggregate shock y_t. As a result, the market tightness θ_t is determined according to a forward-looking equation:

$$\frac{k}{q(\theta_t)\Omega_t} = y_t - w_t + \beta \mathbb{E}_t \left[\frac{k}{q(\theta_{t+1})\Omega_{t+1}} (1 - d_{t+1}) \right]. \tag{12}$$

As in the standard DMP model, the probability that a vacancy is filled depends on the probability of meeting a job seekers $q(\theta_t)$, however, unlike DMP, in our setting the job filling probability depends on the fraction of job-seekers who are willing to work and so accept a job offer as captured by Ω_t. Note that if $\phi = 0$ then $\Omega_t = 1$ at all times, which shuts down the composition of the pool of job-seekers channel altogether, nesting the free-entry condition in DMP.

4.3 Equilibrium

The equilibrium of the model is characterized by the solutions to the functional equations determining the value of work (4) and (5), unemployment (6), and nonparticipation (7) and (8), together with the free-entry condition (12), which yields market tightness, the separation and search cutoffs, and the labor market stocks. Unlike the standard DMP model, one needs to solve for the individual decision rules and market tightness ratio, *jointly* with the stocks of unemployment and nonparticipation. This obtains because job vacancy posting depends on the stocks of unemployed individuals, nonparticipants, and nonparticipants attached to the labor force through the share of job-seekers who accept a job offer and yield a positive surplus.

Since the value of nonparticipation is increasing in x, it is possible to determine two threshold values that uniquely identify the separation cutoff, x^q, and the search cutoff, $x^v \leq x^q$.

---

[7] All the stocks are computed at the beginning of the period after aggregate and idiosyncratic shocks have been realized but before offers are received and matches formed.

Separation and search cutoff An individual separates from a match when the value of nonparticipation exceeds the value of working. The indifference condition for separation

$$W^{na}(x_t^q, y_t) = H^a(x_t^q, y_t) = H^{na}(x_t^q, y_t) \tag{13}$$

implicitly defines the cutoff value x_t^q. Intuitively, the worker trade-offs the utility cost of market work with the benefit of market work, which equals the wage plus the expected discounted value of continuing the employment relationship. Given that the value of non-participation is increasing in x_t, job separation satisfies the reservation property. That is, there exists a unique separation cutoff, x_t^q, so that all matches with individuals whose value of nonmarket work is $x_t \geq x_t^q$ are endogenously destroyed. Hence, aggregate shocks induce job destruction.

The indifference condition for search

$$U(x_t^v, y_t) = H(x_t^v, y_t) \tag{14}$$

implicitly defines the cutoff value x_t^v. The marginal individual weighs the utility cost of job search against the benefit of job search, which equals the UI benefits, b, plus the expected discounted value of entering an employment relationship.

Dynamics of labor market stocks The stocks of employment (e_t), unemployment (u_t), and nonparticipation (n_t) evolve over time according to

$$\begin{bmatrix} e_{t+1} \\ u_{t+1} \\ n_{t+1} \end{bmatrix} = \begin{bmatrix} f_{t+1}^{ee} & f_{t+1}^{ue} & f_{t+1}^{ne} \\ f_{t+1}^{eu} & f_{t+1}^{uu} & f_{t+1}^{nu} \\ f_{t+1}^{en} & f_{t+1}^{un} & f_{t+1}^{nn} \end{bmatrix} \times \begin{bmatrix} e_t \\ u_t \\ n_t \end{bmatrix}, \tag{15}$$

where f_t^{ij} denotes the individual's transition probability from the labor market state i to j at time t. Here, we briefly describe the determination of these transition probabilities and refer the reader to Appendix B for details on their calculation.

Employed individuals separate from employers either exogenously with probability δ, or endogenously with probability $1 - F(x_t^q)$. Thus, δ and the separation cutoff x_t^q jointly determine the workers' transition probability from employment to unemployment, f_t^{eu}, from employment to nonparticipation, f_t^{en}, and the probability of remaining employed, f_t^{ee}, with the restriction that $f_t^{eu} + f_t^{en} + f_t^{ee} = 1$.

Unemployed individuals meet a posted vacancy with probability $p(\theta_t)$. Time variation in $p(\theta_t)$, resulting from changes in the tightness ratio, θ_t, captures endogenous fluctuations in the degree of labor market frictions. So, the meeting probability, $p(\theta_t)$, the separation, x_t^q, and participation, x_t^v, cutoffs jointly determine the workers' transition probability from unemployment to employment, f_t^{ue}, from unemployment to nonparticipation, f_t^{un}, and the probability of remaining unemployed, f_t^{uu}, with the restriction that $f_t^{ue} + f_t^{un} + f_t^{uu} = 1$.

Finally, nonparticipant individuals meet a posted vacancy with probability $\phi p(\theta_t)$. So, the meeting probability $\phi p(\theta_t)$, the separation, x_t^q, and participation, x_t^v, cutoffs jointly determine the transition probabilities from nonparticipation to employment, f_t^{ne}, from nonparticipation to unemployment, f_t^{nu}, and the probability of remaining nonparticipant, f_t^{nn}, so that $f_t^{ne} + f_t^{nu} + f_t^{nn} = 1$.

4.4 Basic Properties of the Model

To provide insight into the main forces at play in the model, here we discuss some basic properties of the deterministic steady state of the model where the productivity shock is $y = \bar{y}$ at all times, and the stocks of employment, unemployment, and nonparticipation are constant.

4.4.1 Search and Separation Cutoffs

Figure 1 shows the cross-sectional distribution of home productivity alongside search and separation cutoffs for a calibrated version of the model, that we later use for our quantitative analysis.

The steady state features three regions. First, individuals whose home productivity (or, equivalently, value of leisure) exceeds the separation cutoff, x^q, are nonparticipants. Second, individuals with home productivity smaller than the search cutoff, x^v, are either employed or unemployed. These individuals are attached to the labor force. Third, for home productivity between the search and separation cutoffs, individuals are employed or nonparticipants; they are attached to the labor force.

4.4.2 Market Tightness

Size of the pool of job-seekers Participation decisions affect the *size* of the pool of job-seekers in two ways. First, for a given pool of unemployed individuals, a fraction ϕ of

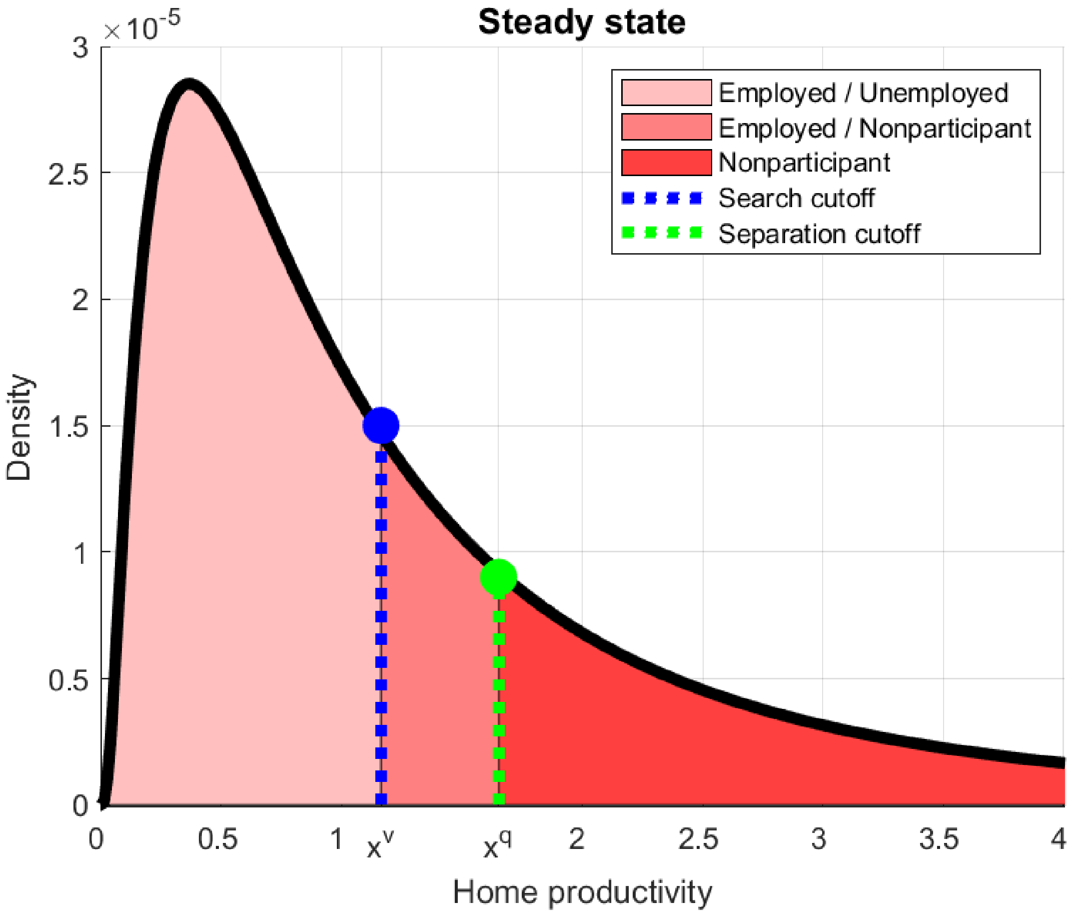

Figure 1: The figure shows the cross-sectional distribution of home productivity in the deterministic steady state of the model where the productivity shock is $y = \bar{y}$. See Section 5 for details on the parametrization of the model.

nonparticipants is drawn into the pool of job-seekers; these are passive searchers who congest the labor market, which reduces the probability that an unemployed individual seeking work finds a job. Given that a job-seeker's meeting probability is concave in the tightness ratio, this congestion effect is relatively more important during recessions when the incentives to post job vacancies are depressed. This channel becomes self-evident if one uses the definition of the market tightness ratio, which gives job vacancies as $v = \theta \times (u + \phi n)$ where $u + \phi n$ is the size of the pool of job-seekers. Hence, cyclical fluctuations in the measure of nonparticipants directly affect congestion insofar as $\phi > 0$. In the calibrated model, as in the data, the participation rate is procyclical implying that n rises in recessions and falls in expansions which exacerbates congestion.

Second, we emphasize that in the model the pool of unemployed individuals itself is affected by participation decisions. This occurs because during recessions, in the model, as in the data, unemployed individuals tend to remain unemployed at a higher rate, and individuals out of the labor force are more likely to transit into unemployment. Overall, the effect of the flows from and to unemployment leans towards a higher congestion of the labor market during recessions. Everything else equal, these two effects increase the probability that an employer posting vacancies meets a job-seeker and depresses the probability that a job-seeker finds a job.

Composition of the pool of job-seekers Participation decisions affect the *composition* of the pool of job-seekers, too. To clarify this channel, using $\beta = 1/(1+r)$ where r is the real interest rate, in the deterministic steady state we rewrite the free-entry condition (12) as

$$\frac{k}{q(\theta)\Omega} = \frac{1+r}{r+\delta}\left(\bar{y} - \bar{w}\bar{y}^{\eta}\right), \tag{16}$$

where again $\Omega = (u + \phi n^{a})/(u + \phi n)$ is the share of job-seekers who are willing to work at the steady-state wage $w = \bar{w}\bar{y}^{\eta}$. Unlike the DMP model, in our model, an active labor supply decision implies that individual participation decisions endogenously determine the composition of the pool of job-seekers. Whether composition amplifies or dampens the fluctuations in the tightness ratio θ depends on the cyclicality of Ω. Notably, if Ω is procyclical, fluctuations in θ are amplified; conversely, if Ω is countercyclical, fluctuations in θ are dampened. In the calibrated model, Ω is countercyclical, thus contributing to dampen fluctuations in market tightness. We note that the countercyclicality of Ω is not hard-wired into the model, rather it critically depends on getting the right comovement between unemployment and nonparticipation with output.

5 Parametrization

To parametrize the model, we exogenously set the values of a subset of parameters and jointly calibrate the remaining parameters using the method of moments. This calibration exercise involves solving the model's deterministic steady state and finding parameter values so that the model matches a set of targeted moments in actual data.

We are to assign values to 15 parameters related to frictions in the labor market (η, k, ϕ, $\bar{w}$, ε, δ, and χ), preferences (β), UI benefits (b), idiosyncratic and aggregate stochastic processes (μ_x, σ_x, λ, $\bar{y}$, σ_y, and ρ_y). The length of a model period is set to one month as crucial labor market targets are available at a monthly frequency, taken from Krusell et al. (2017). The sample period runs from 1978:M1 to 2012:M9. Table 2 summarizes the parametrization of the model.

5.1 Exogenously Set Parameters

We use standard values for the parameters β, η, b, ε, ρ_y, and σ_y based on commonly accepted values in the literature.

The time discount factor β is set to 0.997 so that the annual risk-free interest rate of our economy equals 4%. This is a standard value in the literature (see, e.g., McGrattan and Prescott, 2003; Gomme, Ravikumar and Rupert, 2011). We set the wage elasticity to labor productivity $\eta = 0.7$ to match microeconomic estimates of wage flexibility in Haefke, Sonntag and van Rens (2013). We set b to obtain a 50 percent replacement rate relative to the steady-state wage, a value consistent with the generosity of the unemployment benefits system in the United States. We set the elasticity of matches to job-seekers in the meeting function, ε, to 0.6, the midpoint of the estimates in Petrongolo and Pissarides (2006).

Transitory shocks to the productivity of a job are the source of aggregate fluctuations. Importantly, we assume that the stochastic process for log productivity follows an AR(1) process, such that it exhibits symmetric fluctuations around its steady-state value, $\bar{y}$. We set the persistence of the log productivity, ρ_y, to be 0.975, and its conditional volatility, σ_y, to 0.5%, so that the model reproduces the cyclical properties of the quarterly series of labor productivity in the data. To be sure, other shocks may hit the economy at different times and with different intensities (see Ramey, 2016, for an overview). While our analysis can accommodate other real shocks, we target productivity shocks as they have been the focus of much of the business cycle research.

5.2 Calibrated Parameters

The remaining parameters are calibrated to match targeted moments in U.S. data. While none of the parameters has a one-to-one relationship to a specific moment, it is instructive to describe the calibration as a few distinct steps.

After the normalization of the steady-state value of the market tightness ratio, we jointly calibrate the following 7 model objects using 7 data moments:

1. Steady-state value of f^{eu} (0.014);
2. Steady-state value of f^{en} (0.014);
3. Steady-state value of $f^{n^a e}$ (0.12);
4. Steady-state value of f^{ue} (0.23);
5. Steady-state labor force participation rate (66.8%);
6. Steady-state share of nonparticipant attached (8%);
7. Elasticity of f^{ue} with respect to labor productivity (3.09).

As in Shimer (2005), the cost of posting a job vacancy, k, is set to 0.10 so that the market tightness ratio equals 1 in the deterministic steady state in which $y = \bar{y}$. We then calibrate the arrival rate of the idiosyncratic shock, λ, the scale parameter of the meeting function, χ, the probability that a nonparticipant is drawn in the pool of job-seekers, ϕ, and the exogenous separation rate, δ, so that the deterministic steady state of the model jointly reproduces: (i) the average transition probability from employment to nonparticipation, $\bar{f}^{en}$; (ii) the average transition probability from unemployment to nonparticipation, $\bar{f}^{un}$; (iii) the probability that a nonparticipant attached becomes employed, as reported by Jones and Riddell (2019); (iv) the average transition probability from employment to unemployment, $\bar{f}^{eu}$.

To match a labor force participation rate of 66.8% and the 8% share of nonparticipant attached (Barnichon and Figura, 2016), we set the steady-state value of labor productivity $\bar{y}$ and the real wage scale parameter $\bar{w}$ to 1.72 and 1.67, respectively.

Finally, the distribution of idiosyncratic shocks captures unobserved heterogeneity in home production (or leisure values). This is an inherently latent object. To proceed, we assume that the idiosyncratic component of home production x_t is log-normally distributed with parameters μ_x (scale) and σ_x (shape). We normalize $\mu_x = 0$, and set $\sigma_x = 1$ so that

Table 2: Parametrization

Parameter	Description	Value	Comments
A. Labor market frictions			
η	Wage fcn: elasticity	0.700	Haefke, Sonntag and van Rens (2013)
$\bar{w}$	Wage fcn: scale	1.668	Method of moments
ϵ	Meeting fcn: elasticity	0.600	Petrongolo and Pissarides (2006)
χ	Meeting fcn: scale	0.231	Method of moments
κ	Unit vacancy cost	0.105	Steady-state tightness
ϕ	Prob. of passive searching	0.521	Method of moments
δ	Exogenous separation rate	0.022	Method of moments
B. Individual preferences and UI benefits			
β	Time discount factor	0.997	Real interest rate (4%)
b	UI benefits	$0.5\bar{w}$	Replacement rate (50%)
C. Market productivity shock			
$\bar{y}$	AR(1): mean	1.715	Method of moments
ρ_y	AR(1): persistence	0.975	Fit to AR(1), HP-filtered labor prod.
σ_y	AR(1): volatility	0.005	Fit to AR(1), HP-filtered labor prod.
D. Home productivity shock			
μ_x	Log-normal: scale	0	Normalization
σ_x	Log-normal: shape	1	Method of moments
λ	Arrival rate	0.032	Method of moments

the model replicates the elasticity of the transition probability from unemployment to employment with respect to labor productivity of 3.09.[8]

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[8] The lagged elasticity of the transition probability from unemployment to employment with respect to labor productivity, $\eta^{f^{ue}}_{y_{-1}}$, is estimated by running the regression $\log(f^{ue}_t) = \text{constant} + \eta^{f^{ue}}_{y_{-1}} \log(y_{t-1}) + u_t$ on actual and artificial data simulated from the model. Data on output per worker are from Hagedorn and Manovskii (2011).

Table 3: Business Cycle Statistics – Labor Market Stocks

	y	θ	v	EPOP	ER	PR
A. Standard deviation						
Data	0.0225	24.01	13.15	0.99	0.90	0.26
Model: baseline	0.0225	8.21	7.59	0.40	0.34	0.07
Model: no link market-home productivity	0.0225	8.63	7.99	0.53	0.35	0.20
B. Correlation with output						
Data	0.55	0.89	0.88	0.83	0.86	0.21
Model: baseline	0.99	0.97	0.95	0.97	0.96	0.86
Model: no link market-home productivity	0.98	0.95	0.92	0.93	0.97	0.75
C. Autocorrelation						
Data	0.75	0.92	0.91	0.92	0.93	0.69
Model: baseline	0.75	0.67	0.64	0.84	0.84	0.87
Model: no link market-home productivity	0.75	0.68	0.65	0.87	0.85	0.91
D. Beveridge curve						
Data	-0.92					
Model: baseline	-0.92					
Model: no link market-home productivity	-0.91					

Notes: y is labor productivity; θ is labor market tightness; v is vacancies; EPOP is the employment-to-population ratio; ER is the employment rate (one minus the unemployment rate); PR is the participation rate. Variables are quarterly averages of monthly series expressed in log-deviations from the Hodrick-Prescott trend with smoothing parameter 1,600. See Appendix A for data sources.

6 Quantification

In this section, we study the quantitative properties of the calibrated model. To this goal, we solve the deterministic steady state, and compute the model's dynamics in response to productivity shocks using an approximation of the model equilibrium conditions around the deterministic steady state accurate to the second order.[9]

Operationally, we perform 200 simulations, each 870 periods long. We simulate the

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[9] We numerically solve the model by relying on a second-order approximation to the solution around the deterministic steady state (see, e.g., Schmitt-Grohé and Uribe, 2004).

Table 4: Business Cycle Statistics – Transition Probabilities

	f^{eu}	f^{en}	f^{ue}	f^{un}	f^{ne}	f^{nu}
A. Average						
Data: AZ-adjusted	0.014	0.014	0.228	0.135	0.022	0.021
Model: baseline	0.014	0.014	0.230	0.015	0.013	0.015
Model: no link market-home productivity	0.014	0.014	0.228	0.015	0.013	0.015
B. Standard deviation						
Data: AZ-adjusted	0.089	0.083	0.088	0.106	0.103	0.072
Data: De*NUN*ified	0.069	0.036	0.076	0.066	0.041	0.063
Model: baseline	0.011	0.002	0.036	0.002	0.027	0.013
Model: no link market-home productivity	0.012	0.007	0.038	0.008	0.030	0.007
C. Correlation with output						
Data: AZ-adjusted	−0.630	0.430	0.760	0.610	0.520	−0.230
Data: De*NUN*ified	−0.660	0.290	0.810	0.550	0.570	−0.560
Model: baseline	−0.974	0.929	0.964	0.811	0.826	−0.982
Model: no link market-home productivity	−0.950	−0.979	0.949	−0.961	0.825	−0.943
D. Autocorrelation						
Data: AZ-adjusted	0.590	0.290	0.750	0.620	0.380	0.300
Data: De*NUN*ified	0.700	0.220	0.850	0.580	0.480	0.570
Model: baseline	0.680	0.856	0.670	0.821	0.530	0.705
Model: no link market-home productivity	0.683	0.731	0.679	0.699	0.557	0.667

Notes: f^{ij} is the transition probability from labor market state i to j; e is employment, u is unemployment, $n = 1 - e - u$ is nonparticipation. Variables are quarterly averages of monthly series expressed in log-deviations from the Hodrick-Prescott trend with smoothing parameter 1,600. See Appendix A for data sources.

model at a monthly frequency and then construct quarterly series by averaging the data over three consecutive non-overlapping periods. We discard 40% of the initial simulated series, so we are left with 420 observations that once aggregated at the quarterly frequency match the length of the sample period in Krusell et al. (2017). For each simulation, we compute moments and report the median of those moments across the 200 simulations.

6.1 Standard Business Cycle Moments

We now turn to examine the time-series properties of the calibrated economy in terms of first- and second-order moments of labor market stocks and transition probabilities across the three states of the labor market in deviations from trend.

6.1.1 Labor Market Stocks

Table 3 reports business cycle statistics calculated on artificial data simulated from the model, aggregated to a quarterly frequency, logged, and HP-filtered with a smoothing parameter of 1,600. First, the model generates 40% of the volatility of the employment-to-population ratio and 27% of the volatility of the participation rate in the data. Note that by construction the model matches the volatility of labor productivity in the data. Also, the model reproduces approximately 34% and 58% of the volatility of the tightness ratio and job vacancies, respectively, accounting for a nontrivial share of the fluctuations in what the model identifies as determinants of search frictions. Here we stress that as a number of shocks of varying nature and magnitude hits the U.S. economy over time, it is not surprising that a model with only productivity shocks like ours does not account for the entirety of the cyclical volatility in the data.[10]

In light of these considerations, we compare some of the model's predictions related to the elasticities of labor market stocks and workers' transition probabilities with respect to labor productivity with their empirical counterparts. In terms of labor market stocks, and focusing on CPS data for the non-farm business sector, the contemporaneous and lagged estimated elasticities of the employment-to-population ratio to output per worker are 0.25 and 0.4, respectively. Running the same regressions on artificial data simulated from the model, we find elasticities of 0.35 that are remarkably close to the untargeted estimates in actual data. The model also does reasonably well in accounting for the elasticities of job vacancies, tightness, and employment rate to labor productivity, all untargeted moments.[11]

The model also accounts for the comovement and persistence in the data, measured as the contemporaneous correlation with output and autocorrelation, respectively. Note that none of these moments is a target of our calibration, thus one can assess how well

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[10] Mortensen and Nagypal (2007) propose a similar argument in the context of the "unemployment volatility puzzle," in reference to the inability of the DMP model to reproduce the cyclical volatility in the U.S. unemployment rate.

[11] Table C.1 in Appendix C reports the estimated elasticities for labor market stocks, tightness, and job vacancies in the model and in the data for several labor productivity series.

the model does against a rich set of overidentifying restrictions. The positive and strong comovement of job vacancies with output is to a large degree not surprising. Intuitively, in the model, shocks to the output of a job are the only source of aggregate fluctuations, so job vacancies are bound to be highly correlated with output. In this sense, a close match with the data along that dimension cannot be viewed as a success. By contrast, the positive comovement of the employment-to-population ratio is not hard-wired into the model, but crucially depends upon the configuration of parameter values. Our calibrated model generates the strength of the comovement between the unemployment rate and output in the data, and it produces a correlation of the participation rate with output. We stress that even accounting for the *sign* of the comovement of both unemployment and participation rates has been a challenge for equilibrium models of the aggregate labor market (see, e.g., Veracierto, 2008; Shimer, 2013).

The model does reasonably well in accounting for the persistence of job vacancies. In the model, job vacancies have an autocorrelation of 0.64 which is comparable to the 0.91 in the data. The lack of persistence in vacancies is a well-known problem in search-and-matching models of the labor market. As shown by Fujita and Ramey (2006), one way to tackle this shortcoming is to extend the model with sunk costs in vacancy posting. In our setting, though, the introduction of sunk costs in vacancy posting dramatically increases the state space of the model as the stocks of employed (attached and nonattached, separately), unemployed, and nonparticipants become endogenous state variables, thus enormously complicating the computation of the equilibrium.

Finally, the model generates a downward-sloping Beveridge curve – i.e., the negative empirical relationship between job vacancies and unemployment. This is a well-known challenge for three-state models of the labor market (see, e.g., Tripier, 2004; Veracierto, 2008). Our results along this dimension are in line with Arseneau and Chugh (2012).

6.1.2 Transition Probabilities

Table 4 shows averages and business cycle statistics for the transition probabilities across employment, unemployment, and nonparticipation in the model and data. We report statistics based on data adjusted for classification errors as in Abowd and Zellner (1985) as well as "de*NUN*ified" data as constructed in Elsby, Hobijn and Şahin (2015).

The model matches the calibration targets of the average transition probabilities from employment to unemployment $\bar{f}^{eu} = 0.014$, from employment to nonparticipation $\bar{f}^{en} = 0.014$, and from unemployment to employment $\bar{f}^{ue} = 0.228$. As a by product then, the model matches the average probability of staying employed $\bar{f}^{ee} = 1 - \bar{f}^{eu} - \bar{f}^{en} = 1 - 0.014 - 0.014 = 0.972$. Hence, in the model, as in the data, employment is a very persistent state. The model does reasonably well for other untargeted moments too, such as the average probability from nonparticipation to employment $\bar{f}^{ne}$ (0.022 in the data, 0.013 in the model), and from nonparticipation to unemployment $\bar{f}^{nu}$ (0.021 in the data, 0.015 in the model).

Our calibrated model accounts well for the cyclical properties of the workers' transition probabilities across the three labor market states. Notably, it captures (i) the countercyclicality of the transition probabilities into unemployment (f^{eu}, f^{nu}), (ii) the procyclicality of the transition probabilities out of unemployment (f^{ue}, f^{un}), and (iii) the procyclicality of the transition probability from nonparticipation to employment, f^{ne}. The model is successful in reproducing the *procyclicality* of the transition probability from employment to nonparticipation f^{en}, and that from unemployment to nonparticipation f^{un}, as in the data. This is typically a challenge for three-state models of the labor market in which market productivity shocks are the only driving force of aggregate fluctuations. A positive productivity shock rises the match surplus across the board, so that individuals either continue working at a higher wage, or continue seeking work at a higher expected value of future employment. Overall, these two forces induce countercyclical movements in both f^{en} and f^{un}. Indeed, a version of our model in which home productivity is *not* scaled by market productivity suffers from the same drawback, suggesting that the *procyclicality* of the opportunity cost of employment is critical for the model to reproduce the procyclicality of f^{en} and f^{un}.[12]

Finally, by virtue of our calibration strategy, the model matches the lagged elasticity of the probability of finding a job f^{ue} with respect to labor productivity, a key model object determining the extent of slack in the labor market. The model does reasonably well in terms of the elasticity of f^{ne} to labor productivity, and it reproduces the negative sign of the estimated elasticities of f^{en} and f^{un}, however, it greatly undershoots the strong countercyclicality of the transition probability from employment to unemployment, f^{eu}.[13]

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[12] Chodorow-Reich and Karabarbounis (2016) find that the opportunity cost of employment is procyclical and volatile over the business cycle.

[13] Table C.2 in Appendix C reports the estimated elasticities for the transition probabilities in the model and in the data for several labor productivity series.

6.2 Cyclical Skewness - Deepness

We now turn to evaluate the model's ability to generate the cyclical asymmetry in the data, as measured by the skewness of a time series in deviations from trend or "deepness" (Sichel, 1993). Note that, since the skewness is not a target of our calibration, a close match to the data constitutes an additional validation of the model.

Table 5 reports skewness statistics for three different filtering or detrending methods: Hodrick-Prescott (HP), Baxter-King (BK), and Christiano-Fitzgerald (CF) filters. Overall, the model is successful in reproducing the deepness in the employment-to-population ratio in the data, and crucially the negative skewness in the employment rate and the lack of it in the labor force participation rate.

Focusing on the results based on the HP filter to streamline exposition, the skewness in the artificial employment-to-population ratio generated by the model is -0.24, which is 75% of the skewness in the data. The model reproduces the disconnect between the asymmetry properties of unemployment and participation rates as well. In the model, cyclical fluctuations in the employment rate (one minus the unemployment rate) are left-skewed, with a skewness coefficient of -0.25, whereas those in the participation rate are symmetric, with a skewness coefficient of virtually zero. Similar results hold for the BK and CF filter.

6.3 Impulse Responses

To illustrate the propagation mechanism of productivity shocks embodied in the model, in this section we discuss impulse response functions (IRFs). All responses are expressed as log deviations from the deterministic steady-state levels.

IRFs: search and separation cutoffs An important part of the propagation mechanism of shocks embodied in the model is how labor force participation varies over the business cycle. In the model, the participation margin of employment adjustment is described by the response of the search and separation cutoffs to shocks and the mass of individuals at those cutoffs.

After a positive productivity shock, labor supply is affected by two contrasting forces. On the one hand, high *market* productivity results in higher wages, increasing, ceteris paribus, the return of working leading nonparticipant individuals to join the labor force. Similarly, an individual may postpone the separation decision and stay in the labor force.

Table 5: Skewness of Labor Market Stocks

	EPOP	ER	PR
A. Hodrick-Prescott (HP) filter			
Data	−0.32	−0.70	0.05
Model: baseline	−0.24	−0.25	−0.07
B. Baxter-King (BK) filter			
Data	−0.44	−0.85	0.09
Model: baseline	−0.25	−0.27	−0.09
C. Christiano-Fitzgerald (CF) filter			
Data	−0.29	−0.51	0.05
Model: baseline	−0.14	−0.14	−0.09

Notes: EPOP is the employment-to-population ratio; ER is one minus the unemployment rate; PR is the participation rate. Variables are quarterly averages of monthly series expressed in log-deviations from trend. The smoothing parameter for the Hodrick-Prescott filter is 1,600. For Baxter-King and Christiano-Fitzgerald filters, we consider frequencies between 2 and 32 quarters. The moving average order for Baxter-King is set to 8 quarters. See Appendix A for data sources.

In short, individuals with higher home productivity are led into the labor force. On the other hand, higher *home* productivity increases the opportunity cost of market work, prompting nonparticipants to stay out of the labor force, or employed individuals to drop out of it. Which of these two forces prevails depends on the parametrization of the model.

The IRFs in Figure 2 show that in the baseline model, in which home productivity is scaled by market productivity, the search (x^v) and separation (x^q) cutoffs fall in response to a technology shock that increases home and market productivity. By contrast, in the case of a “pure” market productivity shock, in which home productivity is *not* scaled by market productivity, the cutoffs x^v and x^q move in the opposite direction, which in turn makes the workers’ transition probabilities f^{en} and f^{un} to fall in response to a positive technology shock (see Figure C.1 in Appendix C). By assumption, home productivity is proportional to market productivity, implying that the opportunity cost of employment is procyclical, consistent with the evidence in Chodorow-Reich and Karabarbounis (2016).

As it turns out, the procyclicality of the opportunity cost of employment is critical for the model to replicate the procyclicality of f^{en} and f^{un} in the data.

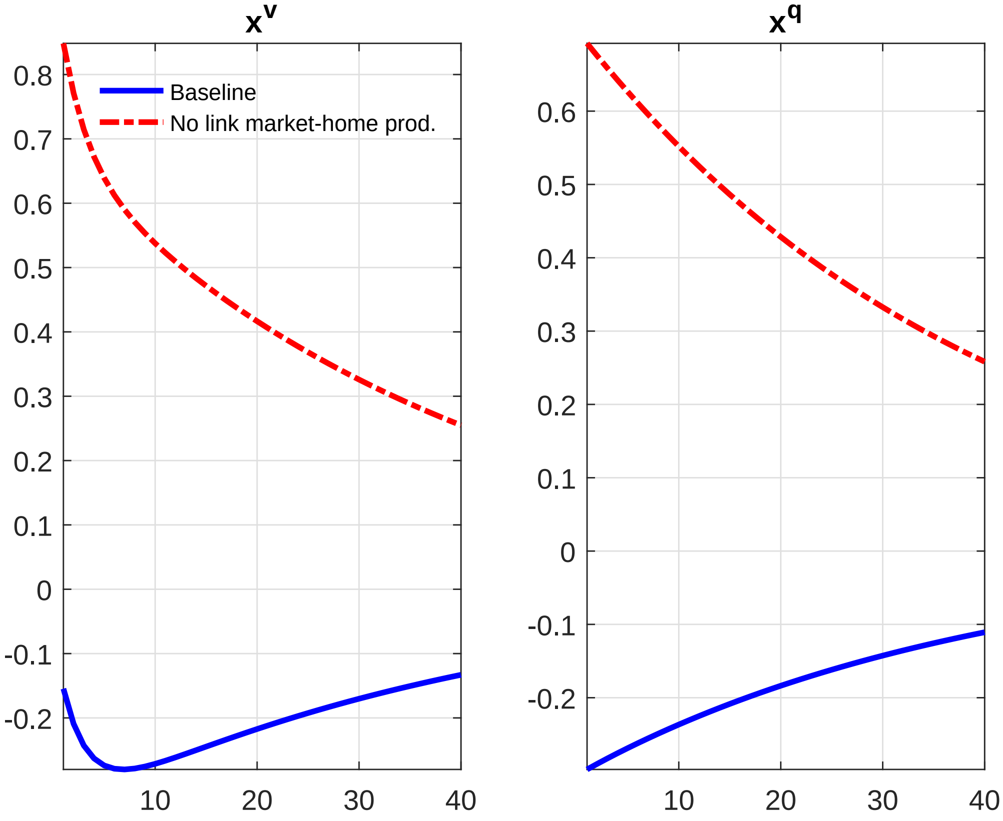

Figure 2: The figure shows the IRFs of the search (x^v) and separation (x^q) cutoffs to a productivity shock in the baseline model (solid line) and in a version of the model in which home productivity is not scaled by market productivity (dash-dotted line). All responses are expressed as log deviations from the deterministic steady-state levels. See Section 5 for details on the parametrization of the model.

IRFs: labor market stocks and transition probabilities Figures 3 and 4 show the IRFs of labor market stocks and workers' transition probabilities, respectively. Note that by assumption the productivity shock follows an AR(1) process, so that its IRF features a jump on impact and monotonic reversion towards the unconditional mean. In response to a positive productivity shock, labor market stocks exhibit hump-shaped dynamics.

Job vacancies and the market tightness ratio (θ) rise on impact and then revert back to their steady-state values, mirroring the dynamics of the productivity shock. The fraction of job-seekers accepting a job offer (Ω) instead displays hump-shaped dynamics; it falls in response to a productivity shock, slowly reverting to its steady-state level.

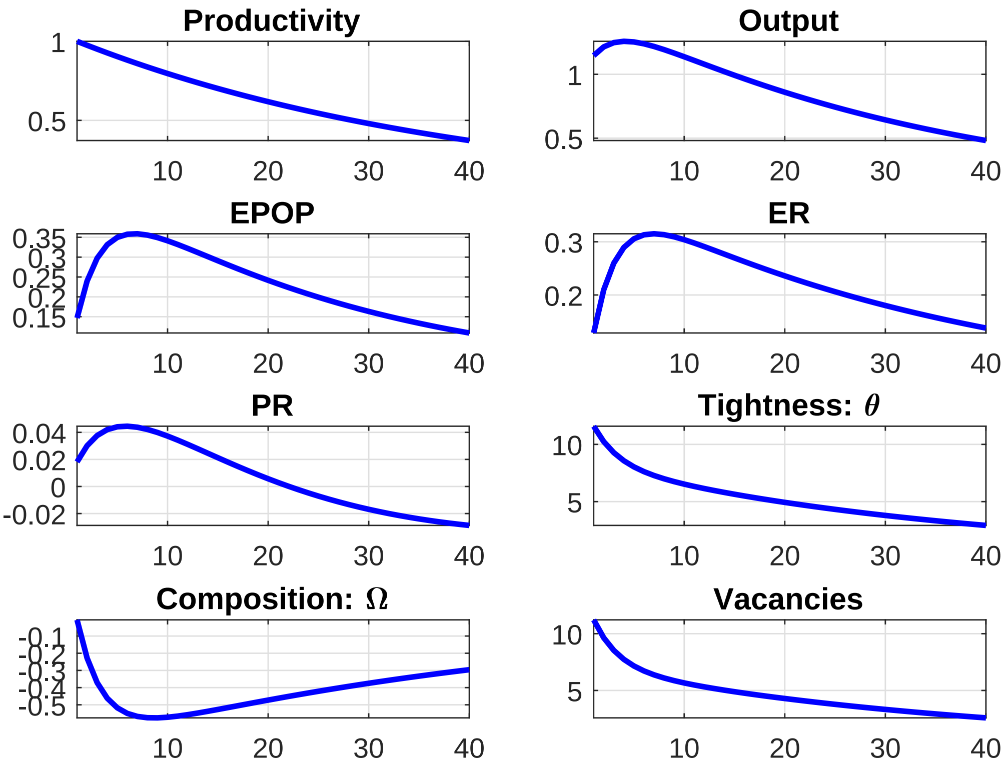

Figure 3: The figure shows the IRFs to a productivity shock. EPOP is the employment-to-population ratio; ER is the employment rate (one minus the unemployment rate); PR is the participation rate. $\Omega = \frac{u+\phi n^a}{u+\phi n}$ is the fraction of job-seekers that accepts a job offer. All responses are expressed as log deviations from the deterministic steady-state levels. See Section 5 for details on the parametrization of the model.

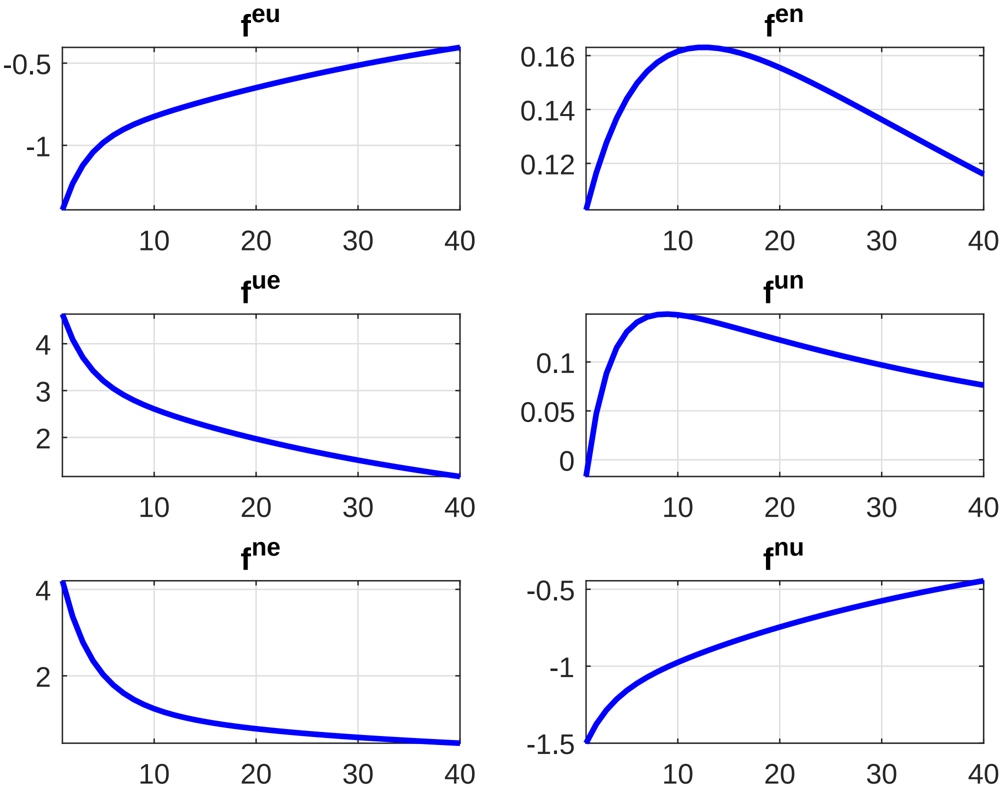

Figure 4: The figure shows the IRFs of the workers' transition probabilities to a productivity shock. All responses are expressed as log deviations from the deterministic steady-state levels. See Section 5 for details on the parametrization of the model.

6.4 Role of Labor Supply vs. Frictions

To gain further insight into the mechanism of fluctuations, we carry out a quantitative accounting exercise that leverages the structure of the model.

Labor supply and slackness channel To assess the importance of labor supply decisions vis-à-vis slack, we simulate two counterfactual economies in which crucially we keep the same parameter values and the same realizations of productivity shocks in the baseline economy. In the first counterfactual ("Ctrfl 1"), we re-solve the model by dropping the free-entry condition (12) and fix the market tightness ratio at its steady-state value in the baseline economy; search and separation cutoffs are allowed to vary in response to shocks as implied by the separation and search indifference conditions (13) and (14). This exercise produces counterfactual time series of labor market stocks and flows in which all the variation comes from the response of the two cutoffs to productivity shocks, namely the "labor supply channel."

Conversely, in the second counterfactual ("Ctrfl 2"), we re-solve the model by dropping the indifference conditions for separation and search and fix the values of the two cutoffs at their steady-state values in the baseline economy; the tightness ratio is allowed instead to vary as implied by the free-entry condition (12). This counterfactual isolates the role of fluctuations in the tightness ratio, namely the "slackness channel."[14]

We stress that this exercise is neither a test of whether a two-state model is a better abstraction than a three-state model, nor a way to discriminate between frictional and frictionless models of the labor market. The constructed counterfactual series for the unemployment rate and the participation rate are not the equilibrium outcome of nested economies. Specifically, fixing the cutoffs on home productivity at their steady-state values does not render a two-state model of the labor market. The counterfactual economy with fixed cutoffs continues to display flows in and out of the labor force. In addition, the transition probabilities from out of the labor force to either employment or unemployment, and the transition probability from unemployment to attached nonparticipation directly depend on the tightness ratio. Thus, movements in market tightness alone drive fluctuations not only in the flows between employment and unemployment, but also those in and out of the labor force.[15]

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[14] For each counterfactual, we re-compute the equilibrium of the model by relying on a second-order approximation to the solution around the deterministic steady state.

[15] Tables C.3 and C.4 in Appendix C report results for two additional experiments in which we fix one cutoff at the time.

Similarly, fixing the market tightness ratio at its steady-state value does not render a frictionless economy. This is because while the extent of frictions is not allowed to vary in response to shocks, the counterfactual economy with fixed tightness continues to display unemployment and fluctuations in the unemployment rate.[16]

Table 6: Labor Supply vs. Slackness

	Model	Ctrfl 1 (fixed tightness)	Ctrfl 2 (fixed cutoffs)
A. Standard deviation			
Employment-to-population ratio	0.40	0.06	0.43
Employment rate	0.34	0.01	0.35
Participation rate	0.07	0.07	0.09
B. Correlation with output			
Employment-to-population ratio	0.97	−0.24	0.96
Employment rate	0.96	0.90	0.97
Participation rate	0.86	−0.37	0.91
C. Skewness			
Employment-to-population ratio	−0.24	−0.05	−0.24
Employment rate	−0.25	0.04	−0.25
Participation rate	−0.07	−0.05	−0.18

Notes: "Ctrfl 1" refers to the counterfactual experiment where the model is simulated with the tightness ratio fixed at its steady-state value and varying search and separation cutoffs. "Ctrfl 2" refers to the counterfactual experiment where the model is simulated with cutoffs fixed at their steady-state values and varying tightness ratio. In all counterfactuals, we keep the same realizations of productivity shocks.

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[16] We note that since the model in nonlinear, the results of our quantitative accounting exercise are to be viewed as theory-based counterfactuals, as opposed to results of a linear additive decomposition.

Cyclical volatility and comovement Panels A and B of Table 6 show the results of the two experiments for the cyclical volatility and comovement of the labor market stocks with output. First, through the lens of the model, absent the response of the search and separation cutoffs to productivity shocks, fluctuations in the market tightness ratio account for the bulk of the cyclical volatility in the unemployment rate and are an important driver of the fluctuations in the participation rate, too.

Second, the counterfactual with a fixed tightness ratio yields the *wrong* comovement between the participation rate and output, which is positive in the data and in the baseline economy, and negative in the counterfactual. That is, in the counterfactual economy with fixed tightness, during a recession the labor force participation rate rises, instead of falling as in the data, which highlights the critical role of the fluctuations in the probability of finding a job for the cyclicality of the participation rate.[17]

Cyclical skewness (deepness) Panel C of Table 6 shows results for deepness, again, measured as skewness in deviations from trend. First, the slackness channel, captured by endogenous fluctuations in the market tightness ratio, accounts for virtually all the negative skewness in the employment rate. In fact, fluctuations in the cutoffs alone would generate fluctuations in the unemployment rate that are symmetric around the trend, which is strongly at odds with the data.

Second, the lack of skewness in the participation rate is the result of competing forces. Fluctuations in the tightness ratio alone generate negative skewness in the participation rate, while the labor supply channel counteracts that. Capturing the relative strength of these two channels is key for the model to replicate the observed disconnect between the asymmetry properties of unemployment and participation rates in the data.

7 Conclusion

In the United States cyclical fluctuations in the employment-to-population ratio exhibit “deepness,” which refers to the pattern that the deviations below trend (troughs) are larger than the deviations above trend (peaks). This phenomenon produces negative skewness in the distribution of the employment-to-population ratio in deviations from trend. Deepness is a stylized fact of the U.S. business cycle.

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[17] Panels B and C of Table C.4 in Appendix C report the standard deviations and the correlation with output of the workers’ transition probabilities across counterfactual experiments.

Our analysis starts with documenting a related, yet overlooked fact: deepness in the employment-to-population ratio is accounted for solely by the unemployment rate in that fluctuations in the labor force participation rate are symmetric. To explain these facts, we formulate an equilibrium business cycle model featuring frictional unemployment and a labor force participation decision. The model, restricted to fit key observations of U.S. data, accounts for the observed cyclical skewness in the unemployment rate and the lack thereof in the participation rate, as well as salient properties of gross worker flows across employment, unemployment, and nonparticipation.

Through the lens of a host of quantitative experiments, we find that cyclical fluctuations in the extent of search frictions, as measured by the speed at which job-seekers find job opportunities, account for the deepness in the employment-to-population ratio. Individuals' participation decisions contribute by affecting the size and the composition of the pool of job-seekers competing for jobs, which in turn affect the tightness ratio and thereby the amount of slack in the labor market. Absent labor supply responses to cyclical shocks, the labor force participation rate would display asymmetric fluctuations at odds with U.S. data, mirroring the asymmetry in the probability of finding a job.

Altogether, this paper provides a parsimonious model that combines the traditional view that business cycles are symmetric ups and downs around the trend at the core of frictionless models in the RBC tradition, arguably models of labor force participation, with the alternative view that nonlinearities from frictions in the labor market generate cyclical asymmetries and significant higher-order moments, often neglected in business cycle research.

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Appendix

A Data Sources

Data for the monthly and seasonally-adjusted unemployment rate (series LNS14000000) and participation rate (series LNS11300000) are from the Current Population Survey (CPS) of the Bureau of Labor and Statistics (BLS) and available at the BLS website at www.bls.gov. The employment-to-population ratio is obtained as one minus the unemployment rate times the participation rate. Data for monthly hazard rates across different states (employment, unemployment, and nonparticipation) are taken from Krusell et al. (2017). Data for job vacancies are the monthly composite Help-Wanted Index (HWI) constructed by Barnichon (2010) and available at the author's website at https://sites.google.com/site/regisbarnichon. Quarterly data are obtained by averaging non-overlapping monthly observations in a given quarter. Seasonally-adjusted quarterly data for real output per worker in nonfarm business sector are produced by the BLS and available at the Labor Productivity and Costs (LPC) home page at http://www.bls.gov/lpc.

B Derivations

Measurement of labor market stocks and transition probabilities We use f_t^{ij} to denote the worker's transition probability from labor market state i to j at time t, and the labels "a" and "na" to indicate "attached" and "nonattached" individuals, respectively.

The stocks of employment (e), unemployment (u), and nonparticipation (n) evolve over time according to:

$$e_{t+1}^{a} = f_{t+1}^{e_a e_a} e_t^a + f_{t+1}^{e_{na} e_a} e_t^{na} + f_{t+1}^{u e_a} u_t + f_{t+1}^{n_a e_a} n_t^a + f_{t+1}^{n_{na} e_a} n_t^{na}; \tag{B.1}$$

$$e_{t+1}^{na} = f_{t+1}^{e_a e_{na}} e_t^a + f_{t+1}^{e_{na} e_{na}} e_t^{na} + f_{t+1}^{u e_{na}} u_t + f_{t+1}^{n_a e_{na}} n_t^a + f_{t+1}^{n_{na} e_{na}} n_t^{na}; \tag{B.2}$$

$$u_{t+1} = f_{t+1}^{e_a u} e_t^a + f_{t+1}^{e_{na} u} e_t^{na} + f_{t+1}^{uu} u_t + f_{t+1}^{n_a u} n_t^a + f_{t+1}^{n_{na} u} n_t^{na}; \tag{B.3}$$

$$n_{t+1}^{a} = f_{t+1}^{e_a n_m} e_t^a + f_{t+1}^{e_{na} n_a} e_t^{na} + f_{t+1}^{u n_a} u_t + f_{t+1}^{n_a n_a} n_t^a + f_{t+1}^{n_{na} n_a} n_t^{na}; \tag{B.4}$$

$$n_{t+1}^{na} = f_{t+1}^{e_a n_n} e_t^a + f_{t+1}^{e_{na} n_{na}} e_t^{na} + f_{t+1}^{u n_{na}} u_t + f_{t+1}^{n_a n_{na}} n_t^a + f_{t+1}^{n_{na} n_{na}} n_t^{na}. \tag{B.5}$$

The workers' transition probabilities are calculated as:

$$f_{t+1}^{e_a e_a} = (1-\delta)\left\{1-\lambda\left[1-F\left(x_{t+1}^{v}\right)\right]\right\} + \delta\left\{1-\lambda\left[1-F\left(x_{t+1}^{v}\right)\right]\right\} p_{t+1}; \tag{B.6}$$

$$f_{t+1}^{e_{na} e_a} = (1-\delta)\lambda F\left(x_{t+1}^{v}\right) + \delta\lambda F\left(x_{t+1}^{v}\right) p_{t+1}; \tag{B.7}$$

$$f_{t+1}^{u e_a} = p_{t+1}\left\{1-\lambda\left[1-F\left(x_{t+1}^{v}\right)\right]\right\}; \tag{B.8}$$

$$f_{t+1}^{n_a e_a} = p_{t+1}\lambda F\left(x_{t+1}^{v}\right); \tag{B.9}$$

$$f_{t+1}^{n_{na} e_a} = p_{t+1}\lambda F\left(x_{t+1}^{v}\right); \tag{B.10}$$

$$f_{t+1}^{e_a e_{na}} = (1-\delta)\,\lambda[F\left(x_{t+1}^{q}\right) - F\left(x_{t+1}^{v}\right)] + \delta\lambda[F\left(x_{t+1}^{q}\right) - F\left(x_{t+1}^{v}\right)]\phi p_{t+1}; \tag{B.11}$$

$$f_{t+1}^{e_{na} e_{na}} = (1-\delta)\left\{1-\lambda F\left(x_{t+1}^{v}\right) - \lambda\left[1-F\left(x_{t+1}^{q}\right)\right]\right\} \tag{B.12}$$

$$+\,\delta\left\{1-\lambda F\left(x_{t+1}^{v}\right) - \lambda\left[1-F\left(x_{t+1}^{q}\right)\right]\right\}\phi p_{t+1}; \tag{B.13}$$

$$f_{t+1}^{u e_{na}} = \phi p_{t+1}\lambda\left[F\left(x_{t+1}^{q}\right) - F\left(x_{t+1}^{v}\right)\right]; \tag{B.14}$$

$$f_{t+1}^{n_a e_{na}} = \phi p_{t+1}\left\{1-\lambda\left[1-F\left(x_{t+1}^{q}\right)\right] - \lambda F\left(x_{t+1}^{v}\right)\right\}; \tag{B.15}$$

$$f_{t+1}^{n_{na} e_{na}} = \phi p_{t+1}\lambda\left[F\left(x_{t+1}^{q}\right) - F\left(x_{t+1}^{v}\right)\right]; \tag{B.16}$$

$$f_{t+1}^{e_a u} = \delta\left\{1-\lambda\left[1-F\left(x_{t+1}^{v}\right)\right]\right\}(1-p_{t+1}); \tag{B.17}$$

$$f_{t+1}^{e_{na} u} = \delta\lambda F\left(x_{t+1}^{v}\right)(1-p_{t+1}); \tag{B.18}$$

$$f_{t+1}^{uu} = (1-p_{t+1})\left\{1-\lambda\left[1-F\left(x_{t+1}^{v}\right)\right]\right\}; \tag{B.19}$$

$$f_{t+1}^{n_a u} = (1-p_{t+1})\lambda F\left(x_{t+1}^{v}\right); \tag{B.20}$$

$$f_{t+1}^{n_{na} u} = (1-p_{t+1})\lambda F\left(x_{t+1}^{v}\right); \tag{B.21}$$

$$f_{t+1}^{e_a n_a} = \delta\lambda\left[F\left(x_{t+1}^{q}\right) - F\left(x_{t+1}^{v}\right)\right](1-\phi p_{t+1}); \tag{B.22}$$

$$f_{t+1}^{e_m n_a} = \delta\left\{1-\lambda F\left(x_{t+1}^{v}\right) - \lambda\left[1-F\left(x_{t+1}^{q}\right)\right]\right\}(1-\phi p_{t+1}); \tag{B.23}$$

$$f_{t+1}^{u n_a} = (1-\phi p_{t+1})\lambda\left[F(x_{t+1}^{q}) - F(x_{t+1}^{v})\right]; \tag{B.24}$$

$$f_{t+1}^{n_a n_a} = (1-\phi p_{t+1})\left\{1-\lambda F\left(x_{t+1}^{v}\right) - \lambda\left[1-F(x_{t+1}^{q})\right]\right\}; \tag{B.25}$$

$$f_{t+1}^{n_{na} n_a} = (1-\phi p_t)\lambda\left[F(x_{t+1}^{q}) - F(x_{t+1}^{v})\right]; \tag{B.26}$$

$$f_{t+1}^{e_a n_{na}} = \lambda\left[1-F\left(x_{t+1}^{q}\right)\right]; \tag{B.27}$$

$$f_{t+1}^{e_{na} n_{na}} = \lambda\left[1-F\left(x_{t+1}^{q}\right)\right]; \tag{B.28}$$

$$f_{t+1}^{u n_{na}} = \lambda\left[1-F\left(x_{t+1}^{q}\right)\right]; \tag{B.29}$$

$$f_{t+1}^{n_a n_{na}} = \lambda\left[1-F\left(x_{t+1}^{q}\right)\right]; \tag{B.30}$$

$$f_{t+1}^{n_{na} n_{na}} = 1-\lambda F\left(x_{t+1}^{q}\right). \tag{B.31}$$

C Additional Results

Table C.1: Elasticity of Labor Market Stocks to Labor Productivity

l	θ	v	EPOP	ER	PR
A. Data, contemporaneous					
η^l_y: CPS, non-farm business	4.949	5.171	0.251	0.171	-0.016
η^l_y: CPS, all private	6.501	6.923	0.281	0.214	-0.052
η^l_y: LPC, non-farm business	2.597	2.910	0.035	0.054	-0.050
η^l_y: LPC, all private	4.244	4.723	0.112	0.108	-0.057
B. Data, lagged					
$\eta^l_{y_{-1}}$: CPS, non-farm business	6.204	6.427	0.396	0.244	0.012
$\eta^l_{y_{-1}}$: CPS, all private	8.349	8.769	0.488	0.315	-0.005
$\eta^l_{y_{-1}}$: LPC, non-farm business	4.570	4.873	0.223	0.159	-0.027
$\eta^l_{y_{-1}}$: LPC, all private	6.484	6.942	0.330	0.225	-0.025
C. Model, contemporaneous					
η^l_y: baseline	7.506	6.812	0.350	0.342	0.008
η^l_y: no link market-home productivity	8.244	7.181	0.674	0.375	0.301
D. Model, lagged					
$\eta^l_{y_{-1}}$: baseline	7.114	6.405	0.352	0.345	0.007
$\eta^l_{y_{-1}}$: no link market-home productivity	7.855	6.765	0.686	0.379	0.309

Notes: η^l_y and $\eta^l_{y_{-1}}$ denote the elasticity of $l \in \{\theta, v, \text{EPOP}, \text{ER}, \text{PR}\}$ to contemporaneous (y) and lagged (y_{-1}) output per worker, respectively. Contemporaneous and lagged elasticities are estimated by running the regressions $\log(l_t) = \text{constant} + \eta^l_y \log(y_t) + u_t$ and $\log(l_t) = \text{constant} + \eta^l_{y_{-1}} \log(y_{t-1}) + u_t$ on actual and artificial data simulated from the model. Data on output per worker are from Hagedorn and Manovskii (2011).

Table C.2: Elasticity of Transition Probabilities to Labor Productivity

l	f^{eu}	f^{en}	f^{ue}	f^{un}	f^{ne}	f^{nu}
A. Data, contemporaneous						
η_y^l: CPS, non-farm business	-4.005	2.032	2.144	2.626	2.891	-0.394
η_y^l: CPS, all private	-5.749	2.683	2.432	4.039	3.918	0.130
η_y^l: LPC, non-farm business	-3.632	0.685	0.191	1.259	1.725	0.389
η_y^l: LPC, all private	-5.128	1.324	0.735	2.383	2.813	0.762
B. Data, lagged						
$\eta_{y_{-1}}^l$: CPS, non-farm business	-3.639	2.716	3.093	3.853	3.751	-0.272
$\eta_{y_{-1}}^l$: CPS, all private	-4.843	3.768	4.273	5.269	5.741	0.166
$\eta_{y_{-1}}^l$: LPC, non-farm business	-3.444	2.042	1.548	2.904	2.834	0.177
$\eta_{y_{-1}}^l$: LPC, all private	-4.289	3.149	2.444	4.234	4.339	0.486
C. Model, contemporaneous						
η_y^l: baseline	-1.115	0.219	3.257	0.164	1.804	-1.273
η_y^l: no link market-home productivity	-1.113	-0.764	3.604	-0.790	2.334	-0.653
D. Model, lagged						
$\eta_{y_{-1}}^l$: baseline	-1.062	0.220	3.086	0.171	1.603	-1.219
$\eta_{y_{-1}}^l$: no link market-home productivity	-1.059	-0.740	3.434	-0.756	2.126	-0.620

Notes: η_y^l and $\eta_{y_{-1}}^l$ denote the elasticity of $l \in \{f^{eu}, f^{en}, f^{ue}, f^{un}, f^{ne}, f^{nu}\}$ to contemporaneous (y) and lagged (y_{-1}) output per worker, respectively. Contemporaneous and lagged elasticities are estimated by running the regressions $\log(l_t) = \text{constant} + \eta_y^l \log(y_t) + u_t$ and $\log(l_t) = \text{constant} + \eta_{y_{-1}}^l \log(y_{t-1}) + u_t$ on actual and artificial data simulated from the model. Data on output per worker are from Hagedorn and Manovskii (2011).

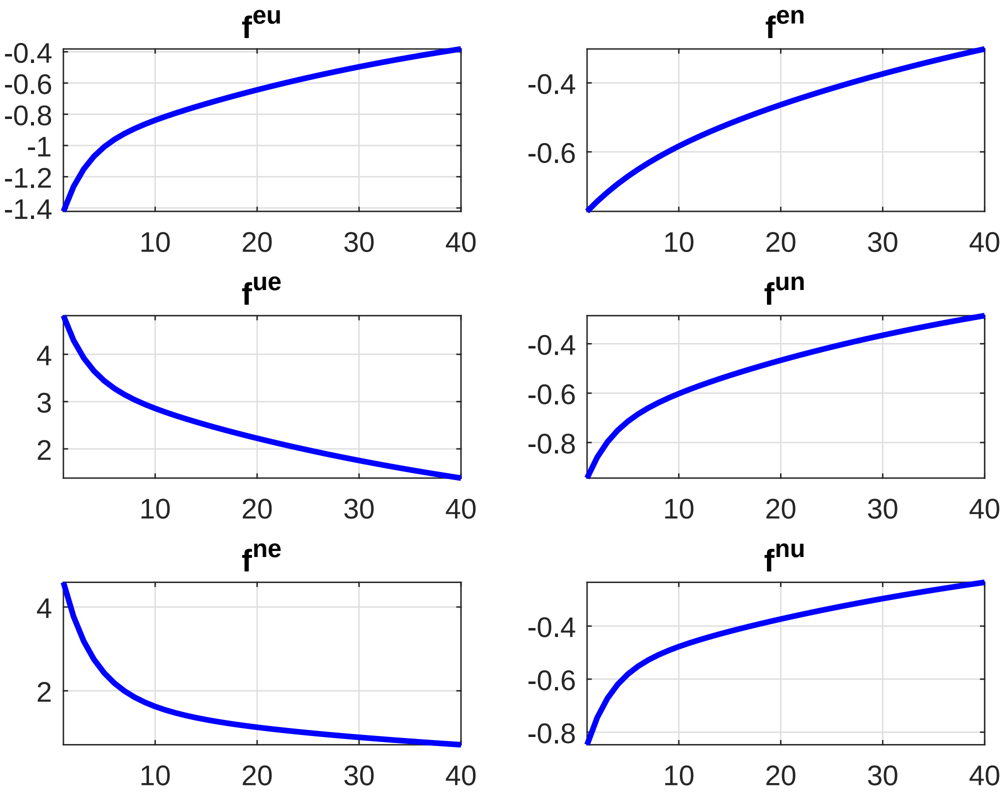

Figure C.1: The figure shows the IRFs of the workers' transition probabilities to a productivity shock in a version of the model in which home productivity is not scaled by market productivity. All responses are expressed as log deviations from the deterministic steady-state levels. See Section 5 for details on the parametrization of the model.

Table $C.3$: Business Cycle Statistics – Labor Market Stocks

	y	θ	v	EPOP	ER	PR
A. Standard deviation						
Data	0.0225	24.01	13.15	0.99	0.90	0.26
Model: baseline	0.0225	8.21	7.59	0.40	0.34	0.07
Ctrfl: θ fixed	0.0225	0.00	0.00	0.06	0.01	0.07
Ctrfl: x^v and x^q cutoffs fixed	0.0225	8.33	7.71	0.43	0.35	0.09
Ctrfl: x^v cutoff fixed	0.0225	8.24	7.63	0.41	0.34	0.07
Ctrfl: x^q cutoff fixed	0.0225	8.32	7.69	0.43	0.35	0.08
B. Correlation with output						
Data	0.55	0.89	0.88	0.83	0.86	0.21
Model: baseline	0.99	0.97	0.95	0.97	0.96	0.86
Ctrfl: θ fixed	1.00	0.95	0.72	-0.24	0.90	-0.37
Ctrfl: x^v and x^q cutoffs fixed	0.99	0.96	0.94	0.96	0.97	0.91
Ctrfl: x^v cutoff fixed	0.99	0.96	0.95	0.97	0.97	0.92
Ctrfl: x^q cutoff fixed	0.99	0.96	0.94	0.96	0.97	0.93
C. Autocorrelation						
Data	0.75	0.92	0.91	0.92	0.93	0.69
Model: baseline	0.75	0.67	0.64	0.84	0.84	0.87
Ctrfl: θ fixed	0.75	0.75	0.43	0.94	0.86	0.93
Ctrfl: x^v and x^q cutoffs fixed	0.75	0.67	0.64	0.85	0.84	0.88
Ctrfl: x^v cutoff fixed	0.75	0.67	0.64	0.84	0.84	0.87
Ctrfl: x^q cutoff fixed	0.75	0.67	0.64	0.85	0.84	0.87

Notes: y is labor productivity; θ is labor market tightness; v is vacancies; EPOP is the employment-to-population ratio; ER is the employment rate (one minus the unemployment rate); PR is the participation rate. Variables are quarterly averages of monthly series expressed in log-deviations from the Hodrick-Prescott trend with smoothing parameter 1,600. See Appendix A for data sources.

Table $C.4$: Business Cycle Statistics – Transition Probabilities

	f^{eu}	f^{en}	f^{ue}	f^{un}	f^{ne}	f^{nu}
A. Average						
Data: AZ-adjusted	0.014	0.014	0.228	0.135	0.022	0.021
Model: baseline	0.014	0.014	0.230	0.015	0.013	0.015
Ctrfl: θ fixed	0.014	0.014	0.228	0.015	0.013	0.015
Ctrfl: x^v and x^q cutoffs fixed	0.014	0.014	0.229	0.015	0.014	0.015
Ctrfl: x^v cutoff fixed	0.014	0.014	0.229	0.015	0.014	0.015
Ctrfl: x^q cutoff fixed	0.014	0.014	0.229	0.015	0.013	0.015
B. Standard deviation						
Data: AZ-adjusted	0.089	0.083	0.088	0.106	0.103	0.072
Data: De*NUN*ified	0.069	0.036	0.076	0.066	0.041	0.063
Model: baseline	0.011	0.002	0.036	0.002	0.027	0.013
Ctrfl: θ fixed	0.001	0.003	0.000	0.006	0.002	0.004
Ctrfl: x^v and x^q cutoffs fixed	0.012	0.001	0.036	0.001	0.028	0.012
Ctrfl: x^v cutoff fixed	0.011	0.001	0.036	0.001	0.027	0.011
Ctrfl: x^q cutoff fixed	0.012	0.001	0.036	0.002	0.028	0.014
C. Correlation with output						
Data: AZ-adjusted	−0.630	0.430	0.760	0.610	0.520	−0.230
Data: De*NUN*ified	−0.660	0.290	0.810	0.550	0.570	−0.560
Model: baseline	−0.974	0.929	0.964	0.811	0.826	−0.982
Ctrfl: θ fixed	−0.362	0.939	−0.998	0.998	0.097	−0.998
Ctrfl: x^v and x^q cutoffs fixed	0.682	0.601	0.673	0.674	0.544	0.674
Ctrfl: x^v cutoff fixed	0.676	0.836	0.671	0.653	0.531	0.672
Ctrfl: x^q cutoff fixed	−0.976	−0.518	0.961	0.796	0.861	−0.979
D. Autocorrelation						
Data: AZ-adjusted	0.590	0.290	0.750	0.620	0.380	0.300
Data: De*NUN*ified	0.700	0.220	0.850	0.580	0.480	0.570
Model: baseline	0.680	0.856	0.670	0.821	0.530	0.705
Ctrfl: θ fixed	0.936	0.792	0.747	0.747	0.879	0.747
Ctrfl: x^v and x^q cutoffs fixed	0.682	0.601	0.673	0.674	0.544	0.674
Ctrfl: x^v cutoff fixed	0.676	0.836	0.671	0.653	0.531	0.672
Ctrfl: x^q cutoff fixed	0.688	0.718	0.672	0.807	0.550	0.707

Notes: f^{ij} is the transition probability from labor market state i to j; e is employment, u is unemployment, $n = 1 - e - u$ is nonparticipation. Variables are quarterly averages of monthly series expressed in log-deviations from the Hodrick-Prescott trend with smoothing parameter 1,600. See Appendix A for data sources.