Contagious Unemployment

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Abstract

Recent micro evidence of how workers search for jobs is shown to have critical implications for the macroeconomic propagation of labor market shocks. Unemployed workers send over 10 times as many job applications in a month as their employed peers, but are less than half as likely per application to make a move. I interpret these patterns as the unemployed applying for more jobs that they are less likely to be a good fit for. During periods of high unemployment, it consequently becomes harder for firms to assert who is a good fit for the job. By raising the cost of recruiting, a short-lived adverse shock has a persistent negative impact on the job finding rate. I provide evidence that firms spend more time on recruiting when unemployment is high, quantitatively consistent with the theory.

JEL Codes: E24; E32; J63; J64

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1 Introduction

> While every job posting garnered an average of 250 applicants—which today, doesn't sound like the worst problem to have—[the Great Recession] led to increases in time to fill and cost per hire that were almost perfectly correlated with the increase in unemployment. This seems counterintuitive; if the supply is available, then one would assume that it would be easier and cheaper for recruiters to meet their employers' (limited) hiring demand. Instead, the inundation of active applicants created more noise for recruiters to sort through.[1]
>
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The Great Recession was associated with an initial burst of layoffs that contributed to a rapid increase in unemployment, without much or any fall in aggregate labor productivity. Standard theories of the labor market predict that, all else equal, such periods should be an excellent time for firms to recruit. The large supply of unemployed, who are likely to accept a firm's job offer and who can be bargained hard with, encourages firms to increase hiring. As a result, the unemployment rate quickly recovers.

Yet Human Resources (HR) professionals offer a different perspective on recruiting in recessions. Desperate, unemployed job seekers apply for any job they can find, and there are a large number of them in recessions. It becomes difficult to discern who is a good fit for the job. Effectively, the cost of recruiting rises with the unemployment rate, tempering firms' incentives to ramp up hiring. The job finding rate falls such that unemployment remains persistently high long after the initial spike in layoffs.

My main contribution is to propose and estimate an alternative theory of the labor market that is consistent with HR professionals' view of recruiting in recessions, and use it to reassess the sources of persistent labor market fluctuations. My main result is that worker job search behavior acts as a powerful propagating force of aggregate shocks. In particular, I find that fluctuations in the separation rate during the Great Recession account for a large share of the persistent fall in the job finding rate over this period.

The model is a version of the equilibrium search theory of Diamond (1982)–Mortensen and Pissarides (1994) (henceforth DMP), designed to account for the rich patterns of worker search behavior evident in recent micro data. Unemployed and employed workers decide how hard to search for jobs in a common labor market, while firms chose how many job openings to advertise. Worker-firm matches differ ex post in productivity, which unemployed and employed workers sample from the same offer distribution. When a worker learns of a job opening, she observes a signal of the underlying productivity of the potential match. Based on the signal, she has to decide whether to apply for the job subject to a time cost of applying. If she does, the firm spends resources screening her application, which reveals the

[1] https://blog.allegisglobalsolutions.com/what-happens-to-recruiting-in-a-recession.

productivity of the match. Finally, positive surplus matches are formed and surplus is split via counter-offer bargaining (Dey and Flinn, 2005; Cahuc et al., 2006).

As in McCall (1970), workers adopt a reservation approach: apply for the job if and only if the signal of fit is sufficiently promising. Without a job and with a low opportunity cost of time, the unemployed apply for jobs that they are less likely to be a good fit for. In this environment, a greater share of unemployed job seekers—driven for instance by a higher separation rate or lower job finding rate in the past—impacts firms' incentives to create jobs through two channels. On the one hand, the unemployed are likely to accept a job offer and can be hired at a relatively low wage, encouraging job creation. On the other hand, because the unemployed are less selective in their application decision, firms' cost of recruiting rises with the unemployment rate, dissuading job creation. The strength of the second channel and hence the aggregate response of job creation depends critically on how large differences in search behavior between the unemployed and employed are at the micro level.

To quantify this novel mechanism, I exploit unique US data on worker search from the Survey of Consumer Expectations (SCE) collected by the Federal Reserve Bank of New York. As recently documented by Faberman et al. (2020), these data show large differences in job search behavior between unemployed and employed workers. For instance, the unemployed send over 10 times as many applications in a month relative to the employed, but are less than half as likely on a per-application basis to actually make a move. If anything, these patterns are even more pronounced when controlling for worker observable factors, including prior wages as a control for underlying unobservable skills. Although the model does not impose any exogenous differences in the job search technology available to the unemployed and employed, it matches well the large empirical differences in job search behavior between the unemployed and employed as the result of the optimizing choices workers make. In particular, the unemployed are endogenously less selective in terms of what jobs they apply to, because they anticipate that they are more likely to accept a job and they have a lower opportunity cost of time.

Although accounting for these new micro patterns of job search is of some interest in and of its own, the main goal of this paper is to quantify what they imply for the macroeconomic propagation of shocks. To this end, I introduce into the estimated model two types of aggregate shocks: separation and productivity shocks (Shimer, 2005). Solving for the dynamic evolution of the economy requires tracking the distribution of employment—an infinite-dimensional object—so I solve a perfect foresight transition experiment, focusing primarily on the 2008–2009 Great Recession and its aftermath. Changes in the aggregate separation rate that mimic the initial spike and subsequent gradual decline in the employment-to-unemployment (EU) rate between 2007–2015 give rise to a large, persistent fall in the unemployment-to-employment (UE) rate, accounting for 80 percent of its trough and a large share of its persistence. Moreover, they generate a strongly negative Beveridge curve—the locus of unemployment and vacancies—that shifts out during the recession, matching well the empirical pattern. In contrast, I find only a minor role for productivity shocks in driving US labor market dynamics over this period.

The proposed framework nests several benchmark models as special cases, including the extension of the DMP model to the case of screening costs developed by Pissarides (2009). I exploit this feature to show that there exists parameter values such that existing frameworks predict as large a trough in the UE rate as the estimated model in response to the same underlying shocks. The crucial difference is the persistence of the fall in the UE rate, which is much greater in the estimated model. Moreover, I find that the persistence of the UE rate depends critically on the ratio of the application-to-mobility rate of the unemployed relative to the employed. This ratio encodes important information on how selective the unemployed are in their search behavior relative to the employed. In the data, it is two. That is, the unemployed send twice as many applications per realized move as the employed. In the model estimated to this target, the UE rate takes 36 quarters to return to its pre-Great Recession level. In contrast, in existing benchmark models, this ratio coincides with the ratio of the mobility rate of the employed to the unemployed, which is about 0.15. In a version of the model recalibrated to match this value, the UE rate recovers in 16 quarters. These findings highlight the critical importance of using worker-level micro data to discipline the macroeconomic consequences of labor market shocks.

My findings are not driven by firms receiving a greater *quantity* of applications in recessions. In fact, holding composition fixed, firms prefer more applicants. Key is that the *quality* of the pool of applicants falls in recessions, as the unemployed are less selective in their application decision and more applicants are unemployed. Consequently, firms would not want to randomly discard applicants, as this would reduce quantity, but hold composition fixed. Instead, they would want to selectively toss out unviable matches prior to spending resources screening them, but the baseline model assumes that this is not possible. To assess the sensitivity of my results to this assumption, I extend the model to feature heterogeneity in the costs firms have to incur to screen an applicant. In particular, firms learn for free either the employment status or the productivity of the potential match for some applicants, and may choose to discard them. Remaining applicants that pass the initial cursory screening are called for a costly "interview." The impact of shocks is moderated, but only modestly. The reason is that the unemployed conduct 1.4 times as many interviews per realized move as the employed in the data. In contrast, in a version of the model without applications, this ratio would again be 0.15. In other words, the data remain an order of magnitude off the predictions of benchmark models.

Why is the impact of shocks so persistent? Based on a series of counterfactual exercises, I draw two main conclusions. First, key to the persistent fall in the UE rate during recessions is changes in firms' job creation, as opposed to changes in workers' search behavior, consistent with evidence in Mukoyama et al. (2018). Second, central to fluctuations in firms' incentives to create jobs are shifts in the pool of potential hires over the business cycle, in particular shifts toward the unemployed and workers further down the job ladder in recessions. Because such workers are less selective in their application behavior, these shifts serve to effectively make it more expensive for firms to hire. Moreover, such shifts in labor market stocks are slow to materialize and reverse, contributing critically to propagation of shocks.

In the last part of my analysis, I offer novel reduced-form support for two salient predictions of the theory. First, worker search behavior is weakly counter-cyclical. In particular, I estimate based on variation across state-years in the SCE that one percent higher unemployment is associated with workers submitting 0.5 percent more applications (versus 0.4 in the model). The reason is the shift in employment down the job ladder in recessions, which more than offsets the fall in the job finding rate to raise workers' probability of applying for a job. Second, firms receive more applications and spend more time on recruiting per vacancy when unemployment is high. In particular, I estimate in the Earnings and Opportunities Pilot Project (EOPP) across 28 US locations for 1978–1981 that one percent higher unemployment is associated with firms receiving 1.3 percent more applications per vacancy and spending 0.9 percent more hours on recruiting per vacancy (versus 1.3 and 0.8 percent, respectively, in the model). I conclude that—consistent with a widely shared view among HR managers—the cost of recruiting rises with unemployment, propagating the effect of shocks.

Related literature. Since Shimer (2005), an active debate focuses on the ability of the DMP model to match the empirical volatility of labor market outcomes. Two prominent approaches to generate greater volatility include a high flow value of leisure (Hagedorn and Manovskii, 2008) or a sticky wage (Hall, 2005a; Hall and Milgrom, 2008; Gertler and Trigari, 2009; Michaillat, 2012; Schoefer, 2015; Fukui, 2020; Gertler et al., 2020).[2] Chodorow-Reich and Karabarbounis (2016) argue, however, that even if one accepts that workers barely prefer work over unemployment, the flow value of leisure co-varies with productivity to largely offset the effect of a small surplus, while Kudlyak (2014) documents that the user cost of labor is quite flexible, at odds with amplification based on sticky wages. In any case, aside from the issue of whether these mechanisms find empirical support, they continue to generate little persistence of labor market outcomes, which is a central focus of this paper.[3]

[2] Other recently emphasized mechanisms that generate more amplification include, for instance, replacement hiring, whereby firms replace workers who quit to other employers (Elsby et al., 2019; Mercan and Schoefer, 2020).

[3] A related literature assesses the underlying drivers of fluctuations in labor market outcomes. An earlier literature emphasizes the role of separation shocks: "what is needed to create a theory of equilibrium unemployment is a theory of the impermanence of jobs" (Hall, 1979, p.155). Lilien (1982) views fluctuations in unemployment as the result of variation in the volatility of idiosyncratic demand in a Lucas and Prescott (1974) model, which necessitates the reallocation of labor across

A smaller literature has focused on the ability of the DMP framework to match the high persistence of labor market outcomes in the data (Moscarini and Postel-Vinay, 2018). As discussed by Hall and Kudlyak (2021), one approach is to make the exogenous force driving job creation incentives more persistent. In this spirit, Petrosky-Nadeau (2014) argues that paying for vacancies requires external financing, which is obtained subject to financial frictions. As financial conditions slowly improve during the recovery, the opportunity cost of job creation gradually falls, generating persistent labor market outcomes. Another approach involves an endogenous feedback from the labor market to the *return* to hiring. For instance, Nagypál (2007), Krause and Lubik (2010) and Eeckhout and Lindenlaub (2019) show that pro-cyclical on-the-job search contributes to a more pro-cyclical return to hiring than in the standard DMP model. Empirical evidence on the cyclicality of worker search, however, indicates that it if anything is counter-cyclical, although the magnitude is fairly modest (Mukoyama et al., 2018). Bradley (2020) obtains a more pro-cyclical return to hiring in a model in which the employed learn about more job openings than the unemployed, but workers can only apply for one job and hence the employed apply for better jobs. In Mercan et al. (2020), workers that differ in time since they were last unemployed are imperfectly substitutable in production. During recessions, many unemployed workers are hired at the same time, reducing their marginal product. Consequently, the return to hiring falls.

In contrast, I emphasize an endogenous feedback from the labor market to the *cost* of hiring, for which I provide direct empirical support in Section 6. Similarly, Fujita and Ramey (2007) and Coles and Kelishomi (2018) show that if there is a sunk component to vacancy costs, such that the elasticity of job creation is less than perfectly elastic, the DMP model can generate more persistent fluctuations. As unemployment rises, firms create more vacancies. Because vacancies are long-lasting and the cost of vacancies convex, however, firms do not scale up vacancy creation fast enough to replace the vacancies filled by the large number of unemployed looking for jobs. Consequently, although "new" vacancy creation rises, the stock of vacancies initially falls. Indeed, Coles and Kelishomi (2018) show that the elasticity of entry can be set such that separation shocks account for a large share of labor market volatility in US recessions. Although the aggregate predictions in these papers are similar to those in the current

sectors and firms. Abraham and Katz (1986) and Blanchard and Diamond (1989) provide early critiques of this view, arguing that it is inconsistent with the strongly negative Beveridge curve in the data. Shimer (2005) forcefully illustrates the issue. Since then, the literature has primarily focused on aggregate productivity shocks as the driver of labor market fluctuations. Labor productivity, however, did not fall in the past three recessions (Hall, 2007; McGrattan and Prescott, 2012), challenging this view. Recent papers instead show that financial shocks are an important driver of labor market fluctuations (Hall, 2017; Kehoe et al., 2019b,a), although Borovička and Borovičková (2018) note that the required magnitude of shocks are inconsistent with asset price dynamics and Martellini et al. (n.d.) argue that discount shocks are inconsistent with the joint behavior of the job finding and separation rates over the business cycle. Consistent with the view in this paper of "recessions as reorganizations" (Hall, 1991)—i.e. separation shocks are an important driver of business cycle fluctuations—Carrillo-Tudela and Visschers (2020) find that occupational switching is more pronounced in economic downturns, while Chodorow-Reich and Wieland (2020) document that sectoral reallocation is an important driver of unemployment dynamics.

paper, it is highly relevant from a policy perspective to differentiate between the two views. If the reason for labor market fluctuations is technological, there may be little a planner would want to do about it. If, on the other hand, the reason is thick externalities in the labor market, it increases the scope for policy. A key difference between these two views is that the vacancy cost in this paper is not convex at the micro-level. Consequently, the framework proposed here is entirely consistent with the observation that some firms—Amazon, Google, Facebook, etc—have grown very rapidly for several years. In contrast, Coles and Kelishomi (2018) find that vacancy creation must be perfectly *inelastic* to match labor market dynamics during the Great Recession, which is difficult to reconcile with the growth trajectories of Amazon and the likes. In addition, I provide in Section 6 direct evidence consistent with the particular mechanism highlighted here, which a model with convex hiring costs would not be able to capture.

This paper also relates to a literature on adverse selection in labor markets (Akerlof, 1970; Spence, 1973). Pries (2008) and Ravenna and Walsh (2012) assume that the pool of unemployed shifts toward low-ability workers during downturns, which amplifies the impact of shocks. In contrast, Nakamura (2008) and Mueller (2017) document that the pool of unemployed becomes less adversely selected during recessions, consistent with marginally *better* workers getting laid off in bad times. I abstract from permanent worker heterogeneity, implicitly assuming that firms can easily infer such differences, to focus on idiosyncratic heterogeneity in match quality. Moscarini (2001) develops a theory in which some workers apply selectively to a limited number of jobs where they are likely to be hired, whereas other workers apply broadly but are rarely chosen for the job. In a recession, lower overall job creation implies a higher opportunity cost of declining a job offer, since the worker would have to wait for longer for another job opportunity to arrive. As a result, a worker is more willing to settle for a second-best match. Consequently, matches are less successful and "excess worker reallocation" is higher. Hall (2005b) proposes in a model of unemployed search that shocks to how well-informed applicants are about their qualifications for jobs can give rise to labor market fluctuations when applicants are self-selective. In particular, if applicants are less selective, firms' cost of recruiting is higher.

Finally, although with a different objective—understanding secular trends—this paper also relates to Martellini and Menzio (2020), who argue that secular improvements in the job search technology may not have contributed to a fall in unemployment. In a similar spirit, the model in this paper may imply that if it becomes easier for workers to apply for jobs, unemployment may not necessarily decline.

Section 2 develops the theory, which Section 3 brings to the SCE data. Section 4 uses the estimated framework to quantify the impact of separation shocks and Section 5 isolates various channels via a series of decomposition and counterfactual experiments. Finally, Section 6 confronts the theory with cross-sectional variation in workers' search behavior and firms' recruiting environment.

2 Model

This section develops an equilibrium search model in the Diamond (1982)–Mortensen and Pissarides (1994) tradition, in which workers search on and off the job and are selective in terms of what jobs they apply for, and firms pay to advertise jobs and screen applicants.

2.1 Environment

Time is continuous and infinite. I abstract for now from aggregate shocks to focus on an economy in its long run stationary state. To simplify the notation, I abstract from time as a state. A unit mass of homogenous workers and a positive mass of firms value a unique final good discounted at rate ρ.

The final good is produced by worker-firm matches, which differ in their idiosyncratic productivity $z \in [\underline{z}, \overline{z}]$. The technology becomes obsolete at rate δ, in which case the firm gets zero value and the worker becomes unemployed. The separation rate δ will later be the unique driver of business cycles.

Search and recruiting. At a point in time, a worker may be unemployed or employed, in the former case enjoying flow value of leisure b. From either state, she choses how hard to search for jobs. In return for search effort $zl^{1+\eta}/(1+\eta)$, she learns about openings at rate pl, where $\eta > 0$ and, abusing terminology, $z = b$ for the unemployed. The cost of search rises in productivity, reflecting the view that it is in terms of time (with opportunity cost equal to foregone production). The underlying productivity of a potential worker-firm match is sampled from an identical offer distribution, regardless of whether the worker is currently unemployed or employed. I denote by γ its probability density function (pdf), with upper case letters henceforth denoting the corresponding cumulative distribution functions (cdfs).

When a worker learns of an opening, she receives a signal $x \in [\underline{x}, \overline{x}]$ of how good a fit she would be for the job, which may depend on the underlying productivity of the match. I denote by $\psi(x|z)$ the conditional pdf of x given z. For instance, a worker may particularly enjoy some office cultures or have a passion for some firms, and the job posting gives her some sense of whether the job would fit her preferences. Such information, however, is hard for recruiting firms to immediately ascertain. For future reference, let $\phi(x)$ denote the unconditional pdf of signals x and $\omega(z|x) = \psi(x|z)\gamma(z)/\phi(x)$ the conditional pdf of productivity z given signal x. Based on the signal, the worker decides whether to apply for the job. Submitting an application costs az (again with $z = b$ for the unemployed). It also scales in current productivity, again reflecting the view that such costs are primarily in terms of time.

Firms advertise jobs subject to flow cost c_v per opening. All costs are in terms of the final good. A job opening contacts a job seeker at rate q. If the worker applies, the firm has to spend c_s to screen the applicant. This captures the time required to process the application, verify the applicant's information, and potentially interview the candidate. While in the benchmark all applications cost the same to screen, Section 4.4 extends the model to allow for heterogeneity in c_s (in particular allowing unemployed or less suitable applicants to be cheaper to screen). I assume that the risks associated with a bad match are so great that a firm never hires without first screening the worker. Screening reveals the productivity of the potential match to all parties, and the firm and worker decide whether to form the match.

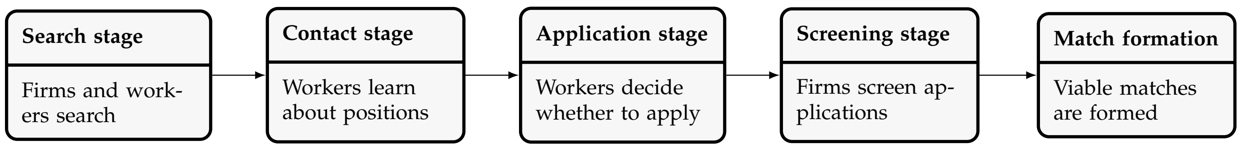
The labor market. If firms advertise V vacancies and workers search with total efficiency S, the number of contacts is $m(V, S) = \chi V^{\theta} S^{1-\theta}$, where χ is matching efficiency and $\theta \in (0, 1)$ is the elasticity of matches with respect to vacancies. Hence, the job finding rate is $p = \chi y^{\theta}$ and the worker contact rate is $q = \chi y^{\theta-1}$, where $y = V/S$ is labor market tightness.[4] A worker and firm bargain over the surplus of the match following the counter-offer bargaining protocol developed by Dey and Flinn (2005) and Cahuc et al. (2006). This results in an unemployed worker receiving a share β of the surplus of the match. An employed worker who gets an outside offer switches employer if the new employer is more productive than her old employer. Regardless of whether she stays or switches employer, she receives a pay increase equal to a share β of the difference in surplus between the two matches (subject to not being made worse off from receiving an offer). Note that I assume that a worker and firm can contract on search behavior. That is, the contract states how hard the worker is to search and what jobs to apply for. This ensures that matches maximize bilateral surplus and that the bargaining set is convex (Shimer, 2006). Without this assumption, worker search behavior would in general depend on the wage, greatly complicating the model. One interpretation is that firms look the other way when workers search for jobs on-the-job.

Timing. Figure 1 illustrates the timing assumptions. The search and matching process in the DMP model (extended to feature on-the-job search) can be viewed as having three stages: a *search stage*, during which workers and firms exert effort to locate each other; a *contact stage* when meetings take place; and a *match formation stage* in which viable matches are formed. The current framework adds two stages to this process. In the first *application stage*, the worker observes a signal of fit for the job and decides whether to apply. In the second *screening stage*, the firm screens the applicant, which reveals the productivity of the match. An appealing aspect of the current framework is that by setting some parameters to particular

[4] This specification implies that if one worker searches harder, it lowers the job finding rate of other workers, reflecting congestion in the labor market. An alternative would be that the job finding rate depends only on vacancies, $p = \chi V^{\theta}$, $\theta \in (0, 1)$, while worker congestion takes place at the application stage (Moscarini, 2001). I prefer the current specification as it nests several benchmark models in the literature, facilitating the comparison with previous work. In any case, my estimated curvature of job search, η, is so high that aggregate search intensity S barely varies over the business cycle. Hence from a practical point of view, congestion from worker search plays a second-order role in my quantitative results.

values, the application stage (no cost of applying, $a = 0$) and/or the screening stage (no cost of screening, $c_s = 0$) can be effectively shut down. That is, the theory nests several benchmark models as special cases, which I later exploit to contrast the predictions of the current framework to existing work.

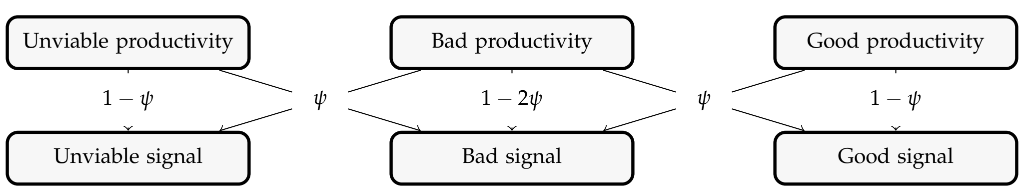
FIGURE 1. TIMING OF EVENTS



2.2 Analysis

To illustrate the workings of the model, I start by considering the comparative statics of a simplified version of the model. See Appendix A.1 for the value functions, Appendix A.2 for the laws of motion and Appendix A.3 for the equilibrium definition in the full-fledged version of the model. Suppose match productivity can take one of three values—good, z_g, bad, $z_b < z_g$, or unviable, z_u. The latter is assumed to be so low that the match is not formed. Let $\gamma_i = \gamma(z_i)$ be short-hand for the probability of drawing productivity z_i, for $i = \{u, b, g\}$. An unviable match sends a bad signal, x_b, with probability ψ and an unviable signal, x_u, with complementary probability. A bad match sends an unviable or good signal each with probability ψ and a bad signal with probability $1 - 2\psi$. A good match sends a bad signal with probability ψ and a good signal, x_g, with complementary probability. This structure of signals can be microfounded as uniform noise around the true productivity (Pries, 2004). Figure 2 illustrates.

FIGURE 2. STRUCTURE OF SIGNALS



To simplify further, I restrict attention to the case in which application costs are small, $a \to 0$, and workers' bargaining power is low, $\beta \to 0$ (with the limits such that $\lim \frac{a}{\beta} = 0$). Furthermore, I assume that the elasticity of the search cost tends to infinity, $\eta \to \infty$ (with $\lim \eta\beta = 1$). Then,

Proposition 1. *Suppose that $a \to 0$, $\beta \to 0$ and $\eta \to \infty$, with $\lim \frac{a}{\beta} = 0$ and $\lim \eta\beta = 1$. Then, (i) unemployed workers apply regardless of the signal, while mismatched workers apply for any job that sends a bad or a good* *signal; (ii) unemployed and mismatched ($z = z_b$) workers search with unit intensity, while well-matched workers ($z = z_g$) do not search; and (iii) the surplus value $M_i = J(z_i) - U$ of a match with productivity $i \in \{b, g\}$ is*

$$M_i = \frac{z_i - b}{\rho + \delta}, \qquad i \in \{b, g\} \tag{1}$$

Proof. All proofs are in Appendix A.5. □

The Job Creation Curve. Firms advertise jobs until the cost of doing so, c_v, equals the expected return,

$$\frac{c_v}{q(y)} = \frac{u}{S}\Big(\gamma_b M_b + \gamma_g M_g - c_s\Big) + \frac{g_b}{S}\Big(\psi\gamma_u + (1-\psi)\gamma_b + \gamma_g\Big)\left(\frac{\gamma_g\Big(M_g - M_b\Big)}{\psi\gamma_u + (1-\psi)\gamma_b + \gamma_g} - c_s\right)$$

where $y = V/S$ is market tightness. If the open job contacts a potential hire, she is unemployed with probability u/S, where u is the number of unemployed, $S = u + g_b$ the number of searching workers, and g_b is the number of mismatched workers. Recall from proposition 1 that well-matched workers do not search. Unemployed workers always apply for the job. The firm screens the worker, productivity is revealed and the match is formed if productivity is bad or good. With probability g_b/S the potential applicant is mismatched. The worker applies for the position if the signal is bad or good, the firm pays the cost of screening and productivity is learned. Substituting using (1) yields a *Job Creation* (JC) curve,

$$\Big(\rho + \delta\Big)c_v\frac{y}{p(y)} = \gamma_g\Big(z_g - z_b\Big) - C_1 + \frac{u}{g_b}\left(\Big(\gamma_b + \gamma_g\Big)\Big(z_b - b\Big) - C_2\right) \tag{2}$$

where $C_1 = (\rho + \delta)c_s(\psi\gamma_u + (1-\psi)\gamma_b + \gamma_g)$ and $C_2 = (\rho + \delta)c_s((1-\psi)\gamma_u + \psi\gamma_b)$. The right hand side reflects the expected return to contacting a potential applicant. The firm gets $\gamma_g(z_g - z_b)$ from forming good matches, but has to pay cost C_1 associated with screening applicants for the position. Whenever the firm contacts an unemployed worker, it gets a premium $(\gamma_b + \gamma_g)(z_b - b)$ arising from the fact that the unemployed are more likely to accept an offer and they have a worse bargaining position. However, it has to pay additional screening cost C_2 to screen the additional applications sent by the unemployed.

Proposition 2. *The JC curve (2) increases in the ratio of unemployed applicants, $\frac{u}{g_b}$, if and only if*

$$\underbrace{(\gamma_b + \gamma_g)\frac{z_b - b}{\rho + \delta}}_{\textit{Excess return from screening unemployed}} > \underbrace{c_s\Big((1-\psi)\gamma_u + \psi\gamma_b\Big)}_{\textit{Excess cost from screening unemployed}} \tag{3}$$

The left hand side of (3) is the excess return to a hiring firm from an application from an unemployed worker relative to one from an employed worker. It reflects the fact that an unemployed applicant is more likely to accept the job and has a worse bargaining position. The right hand side is the additional cost to the firm from an unemployed applicant, where $(1-\psi)\gamma_u + \psi\gamma_b$ is the difference in the number of applications sent by the unemployed relative to the employed (conditional on learning about the job opening). This term stems from the fact that the unemployed apply for jobs that they are less likely to be good fits for and firms have to spend resources screening such applicants.

By assumption, firms cannot effortlessly infer applicants' employment status and based on this potentially discard some applicants. This assumption, however, is not necessary to obtain a downward-sloping JC curve (2). That is,

Proposition 3. *Suppose a firm could effortlessly learn an applicant's employment status and based on this choose to discard the applicant prior to spending any resources screening it. If,*

$$c_s - \gamma_g \frac{z_g - z_b}{\rho+\delta} \quad < \quad (\gamma_b + \gamma_g)\frac{z_b - b}{\rho + \delta} \quad < \quad c_s\Big((1-\psi)\gamma_u + \psi\gamma_b\Big) \tag{4}$$

then the JC curve (2) declines in the ratio of unemployed job seekers, $\frac{u}{g_b}$, yet the firm would want to screen an applicant who is known to be unemployed.

Free entry requires the expected net return to recruiting to be zero. At the point when a firm receives an application, however, it has already spent c_v for the chance to contact a potential applicant. Consequently, screening the applicant has a net positive expected return. When (4) holds, the firm would prefer the applicant to be employed, yet it would rather get the chance to screen *any* applicant than none, given that it spent c_v for a chance to do so. Put another way, a firm may not be willing to spend c_v for a chance to contact only unemployed applicants, but having already spent c_v for a chance to potentially meet an employed worker, it would find it optimal to proceed to screen also unemployed applicants.

The Beveridge Curve. The number of unemployed workers, u, and the number of mismatched workers, g_b, evolve according to the Kolmogorov Forward Equations (KFE),

$$\dot{u} \quad = \quad \delta(g_b + g_g) - p(y)(\gamma_b + \gamma_g)u, \qquad\qquad \dot{g_b} \quad = \quad p(y)\gamma_b u - \delta g_b - p(y)\gamma_g g_b$$

where the number of well-matched workers is $g_g = 1 - u - g_b$. Imposing steady-state—$\dot{u} = 0$ and $\dot{g_b} = 0$—and solving this system of equations, the stationary ratio of unemployed searchers is

$$\frac{u}{g_b} \quad = \quad \frac{\delta + \gamma_g p(y)}{\delta + \Big(\gamma_b + \gamma_g\Big)p(y)} \tag{5}$$

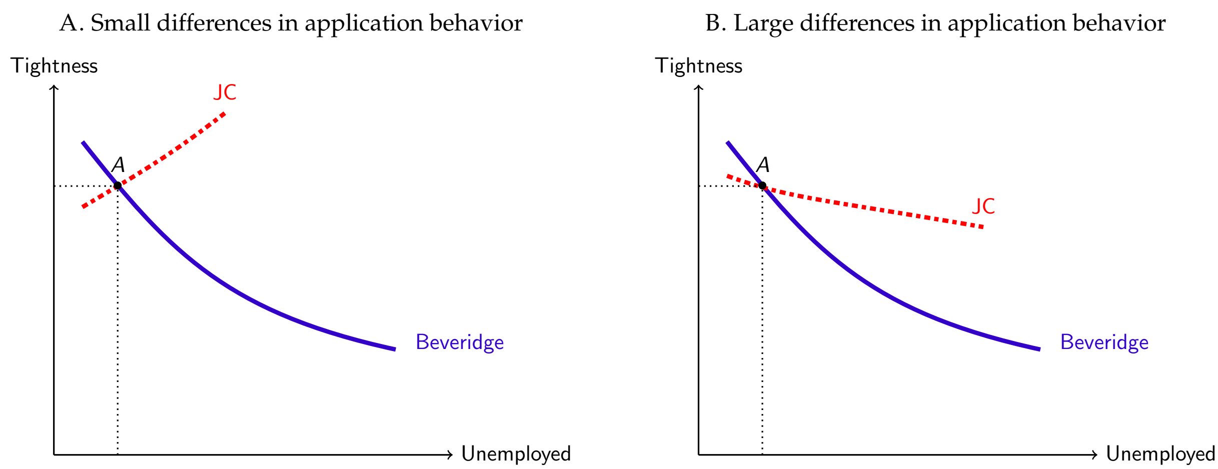
This augmented *Beveridge* curve relates the ratio of unemployed searchers to market tightness y. In particular, the ratio of unemployed searchers falls in tightness,

$$\frac{\partial \log \frac{u}{g_b}}{\partial \log y} = -X\,\xi, \qquad X = \frac{\delta \gamma_b p(y)}{\Big(\delta + \gamma_g p(y)\Big)\Big(\delta + (\gamma_b + \gamma_g) p(y)\Big)} > 0 \tag{6}$$

where $\xi = p'(y)y/p(y) \in (0,1)$ is the elasticity of the job finding rate with respect to tightness.

Equilibrium. The equilibrium is determined by the intersection of the JC curve (2) and the Beveridge curve (5) as illustrated by Figure 3. It follows from (6) that the Beveridge curve is downward-sloping. Panel A plots the case in which the inequality (3) holds, i.e. application behavior is not that different between the unemployed and employed and/or screening costs are relatively unimportant. In this case, the JC curve is upward-sloping, and there is a unique stationary equilibrium.[5] If (3) does not hold, tightness falls in the ratio of unemployed job seekers. Although they are likely to accept the offer and they can be paid little, the unemployed apply for many positions that they are unlikely to be a good fit for, driving up the cost of recruiting. In this case, the JC curve is downward-sloping, as shown in Panel B. Indeed, the JC and Beveridge curves may cross multiple times, reflecting multiple stationary equilibria.

FIGURE 3. EQUILIBRIUM DETERMINATION



Note: JC: Equation (2). Beveridge: Equation (5). Tightness: Vacancies over efficiency number of searchers, $y = V/S$; Unemployed: Ratio of unemployed to mismatched job seekers, u/g_b.

A permanent fall in productivity/increase in the discount rate. Suppose that idiosyncratic match productivity shifts proportionally with aggregate productivity, Z, i.e. $\tilde{z}_i = Zz_i$ for $i = \{b, g\}$. Consider the

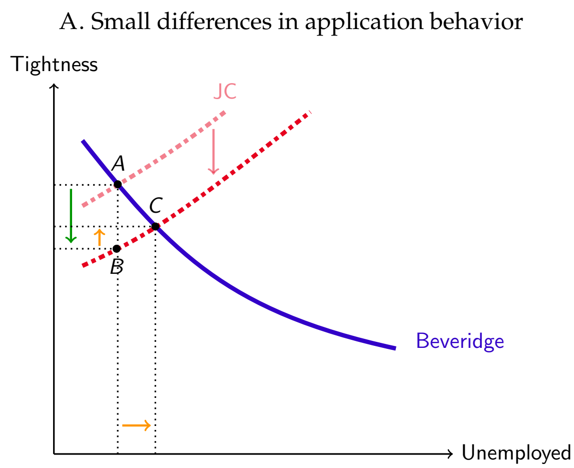
[5] Some additional regularity conditions are required to ensure that this equilibrium features positive job creation.

impact of a small, permanent change in aggregate productivity around $Z = 1$ or a small, permanent change in the discount rate ρ (these shifts are assumed small enough that low productive matches remain profitable). Aggregate productivity and the discount rate only affect the JC curve (2), but leaves the Beveridge curve (5) unaltered. In particular, a fall in productivity/rise in the discount rate shifts the JC curve (2) down, because job creation is discouraged by the lower discounted flow value of a match. Define the *direct* effect as the change in tightness holding fixed the composition of the labor force,

$$\underbrace{\left.\frac{d\log y}{d\log Z}\right|_{\frac{u}{g_b}}}_{\text{direct effect}} = \frac{1}{1-\xi}\frac{\gamma_g(z_g - z_b) + \frac{u}{g_b}(\gamma_b + \gamma_g)z_b}{\gamma_g(z_g - z_b) - C_1 + \frac{u}{g_b}((\gamma_b + \gamma_g)(z_b - b) - C_2)}, \qquad \underbrace{\left.\frac{d\log y}{d\log \rho}\right|_{\frac{u}{g_b}}}_{\text{direct effect}} = -\frac{1}{1-\xi}\frac{\rho}{\rho+\delta}$$

Figure 4 illustrates this direct effect as the fall in tightness from A to B.

FIGURE 4. IMPACT OF A PERMANENT FALL IN PRODUCTIVITY OR RISE IN THE DISCOUNT RATE



Note: Comparative-static equilibrium impact of a permanently lower productivity, Z, or permanently higher discount rate ρ. JC: Equation (2). Beveridge: Equation (5). Tightness: Vacancies over efficiency number of searchers, $y = V/S$; Unemployed: Ratio of unemployed to mismatched job seekers, u/g_b. Green arrow: Direct effect. Yellow arrow: Composition effect.

In equilibrium, as the job finding rate $p(y)$ changes, the composition of the labor force, $\frac{u}{g_b}$, changes—recall (5). In particular, the fall in the job finding rate raises the ratio of unemployed job seekers. This shift in the composition of the labor force in turn impacts job creation incentives through an equilibrium *compositon* effect. If differences in application behavior between the unemployed and employed are small, the rise in the ratio of unemployed job seekers encourages job creation. Panel A illustrates this scenario, in which case the composition effect—the movement from B to C—counters the direct effect. Panel B instead plots the case in which differences in application behavior between the unemployed and employed are large. In this case, the increase in the ratio of unemployed job seekers further discourages job creation, resulting in a larger overall effect than the direct effect.

A permanent rise in the separation rate. An increase in the separation rate shifts the JC curve (2) down via a direct effect, $\frac{d\log y}{d\log\delta}\Big|_{\frac{u}{g_b}} = -\frac{1}{1-\xi}\frac{\delta}{\rho+\delta}$, as illustrated by Figure 5, leading to a fall in tightness from A to B. The change in the composition of the labor force encourages job creation through the composition effect if differences in application behavior between the unemployed are small, as in panel A. If, on the other hand, differences are large as in panel B, the composition effect in equilibrium further discourages job creation. Abstracting from shifts in the Beveridge curve (5), the composition effect moves the economy from B to C. I refer to the total equilibrium effect of a change in the separation rate via the JC curve (2) as the *HJB* channel, holding fixed the Beveridge curve (5). In Figure 5, this is the movement A to C.

While the HJB channel is the only channel through which aggregate productivity and the discount rate impact the equilibrium, an increase in the separation rate also shifts the Beveridge curve (5) out—for a given tightness, more workers are unemployed since the separation rate is higher. I refer to the equilibrium change in tightness due to a change in the separation rate via only the Beveridge curve (5), holding the JC curve (5) fixed, as the *KFE* channel. This is the movement from A to D in Figure 5. With both the HJB and KFE channels active, the equilibrium shifts from A to E. Of this total effect, the direct effect is the movement from A to B. The composition effect is the movement from B to E.

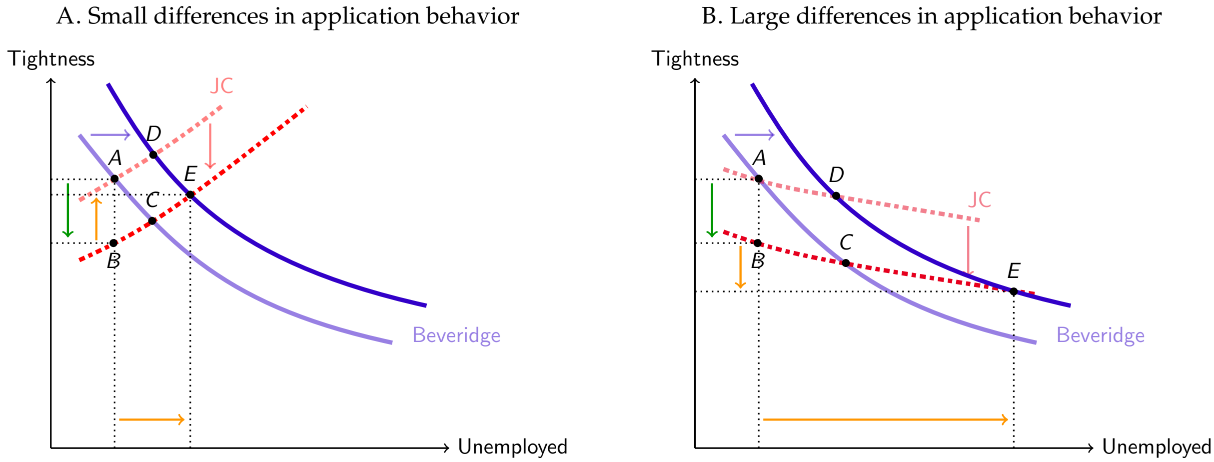
If differences in application behavior between the unemployed are small as in panel A, the KFE channel encourages job creation. In this case, the KFE channel goes in the same direction as the composition effect via the HJB channel, dampening the direct effect. As a consequence, a change in the separation rate may induce either a positive or negative correlation between the steady-state ratio of unemployed job seekers and tightness.[6] In this case, the KFE channel works to dampen the impact of a change in the separation rate relative to a change in productivity or the discount rate. This is exactly the reason why the previous literature has preferred productivity or discount shocks over separation shocks, because *ceteris paribus* higher unemployment encourages job creation in benchmark models. In contrast, if differences in application behavior are large as in panel B, the KFE channel and the composition effect of the HJB channel go in the same direction as the direct effect. In this case, the KFE channel amplifies the impact of a change in the separation rate relative to a change in productivity or the discount rate.

[6]Formally, the elasticity of tightness with respect to the separation rate is

$$\frac{\partial \log y}{\partial \log \delta} \quad = \quad -\frac{1}{1-\xi\,(1-XY)}\left(\frac{\delta}{\delta+\rho}\,\frac{o-B}{o-B-C}-XY\right)$$

where $Y = \frac{u}{g_b}\left((\gamma_b+\gamma_g)(z_b-b)-C_2\right)\Big/\Big(\gamma_g(z_g-z_b)-C_1+\frac{u}{g_b}((\gamma_b+\gamma_g)(z_b-b)-C_2)\Big)$, $o = \gamma_g z_g + \frac{u}{e_b}(\gamma_b+\gamma_g)z_b$ is the expected output of a match, $B = \gamma_g z_b + \frac{u}{e_b}(\gamma_b+\gamma_g)b$ the expected outside value of a recruit, and $C = C_1 + \frac{u}{e}C_2$ the effective flow cost of screening.

FIGURE 5. IMPACT OF A PERMANENT INCREASE IN THE SEPARATION RATE



Note: Comparative-static equilibrium impact of a permanently higher separation rate, δ. JC: Equation (2). Beveridge: Equation (5). Tightness: Vacancies over efficiency number of searchers, $y = V/S$; Unemployed: Ratio of unemployed to mismatched job seekers, u/g_b. Green arrow: Direct effect. Yellow arrow: Composition effect.

2.3 Discussion

I briefly make three observations with respect to the modeling choices made. First, the theory abstracts from worker heterogeneity such as age, gender, race and education. An earlier literature has evaluated the impact of selection along such dimensions, with inconclusive findings. For instance, Pries (2008) and Ravenna and Walsh (2012) argue that such shifts serve to amplify shocks, while Nakamura (2008) and Mueller (2017) conclude that they dampen shocks. I instead focus on selection based on the idiosyncratic component of a new match. Implicitly, my assumption is that firms can easily screen observable factors such as age, gender, race and education, but learning about the idiosyncratic component—whether someone would enjoy the job, have the particular skills useful for the job, like the office culture, etc—is harder. Consistent with this assumption, I clean the data from observable factors in the next section. In fact, I find that the differences in search behavior by employment status emphasized in this paper are just as pronounced when conditioning also on a worker's prior wage as a proxy for unobservable factors.

Second, firms cannot effortlessly learn an applicant's employment status and based on this potentially discard unemployed applicants. As highlighted by Proposition 3, however, firms may prefer employed applicants, but still want to proceed to screen unemployed applicants. Moreover, many workers misrepresent their employment status on resumes, suggesting that it may not be that easy to quickly infer an applicant's employment status. For instance, BackgroundChecks.org reports that 53 percent of applications contain inaccuracies, of which dates of employment is one of the most common. In any case, Section 4.4 considers several extensions in which firms may discard either some unfit or some unemployed applicants at no cost. This moderates my conclusions but only modestly.

Third, as is standard in the DMP literature, firms face no capacity constraint in production. Consequently, there is no opportunity cost to the firm of filling a job, such that the higher worker contact rate in a recession does not induce a firm to be more selective in its hiring.[7] Two reasons lead me to follow the standard assumption in the DMP literature of no capacity constraint in production. First, the data I exploit in the next section are rich on the worker side, but contains little information on firms' recruiting outcomes. Hence, it would be difficult to identify such an alternative model. Second, if firms are able to select a better fit for the job in recessions, one would expect that match to last longer. Appendix A.6 finds, however, that the slopes of mobility-tenure profiles remain remarkably constant over the business cycle. Hence, I focus here on a richer understanding of worker search behavior. For a complementary assessment of the role of changes in firm hiring standards, see for instance Sedláček (2014), Hershbein and Kahn (2018), Wolthoff (2018), Acharya and Wee (2020) and Huckfeldt (2021), and for the role of changes in firm recruiting intensity, Kaas and Kircher (2015), Gavazza et al. (2018) and Leduc and Liu (2020).

That being said, Section 4.4 considers an extension in which firms pay a one time cost to set-up a job, in addition to a flow cost of advertising it. Because an open job is long lasting, firms face an opportunity cost when filling it. This does not change my results much, due to two offsetting forces. On the one hand, as an open job contacts more applicants in recessions, it raises the opportunity cost to a firm of filling the job. This force induces a firm to become more selective, raises its threat point in bargaining, and encourages job creation. On the other hand, the pool of applicants worsens, such that if the firm passes on a particular hire, it would have to spend more to eventually recruit someone for the position. This force induces a firm to be less selective, reduces its threat point, and discourages job creation. I also note that firms receive more applications in recessions in the baseline model. Hence in a reduced-form sense, firms *are* more selective in hiring in recessions, i.e. the chance that a given applicant is hired falls.

3 Estimation

To assess the impact of micro-level worker search behavior for the amplification and propagation of aggregate shocks, this section starts by estimating a steady-state version of the full-fledged model targeting novel moments on search behavior from the SCE. I estimate the continuous-time model on an equally spaced, discretized grid for (log) productivity in two steps (Appendix B.1 provides details).[8]

[7] The critical assumption is the absence of a capacity constraint, not that time is continuous as opposed to discrete. In discrete time, the absence of a capacity constraint implies that if an opening contacts multiple suitable applicants, the firm hires all of them. In continuous time, it implies that a higher worker contact rate does not induce firms to be more selective in hiring.

[8] The equilibrium may not be unique, but I have not found any evidence of multiplicity under the estimated values.

3.1 Data

The SCE data on worker search behavior is a supplement to the Federal Reserve Bank of New York's broader Survey of Consumer Expectations—see Appendix B.2 for a further data description. I focus on individuals aged 18–64 who are unemployed or employed. I exclude non-participants and the self-employed to align the data with the theory, which abstracts from these margins. I also exclude job search for additional jobs. See Appendix B.3 for a further discussion of how variables are defined.

Table 1 provides an overview of search and application behavior by employment status. The data cover just over three thousand employed and unemployed individuals. As noted by Faberman et al. (2020), the unemployed send a large number of applications relative to the employed, but are less than half as likely to convert an application into an actual move. These patterns are not primarily accounted for by differences in observable characteristics. In fact, as shown in the "unobservable" row, also controlling for a worker's wage in her previous job (previous month for the employed) as a measure of her unobserved ability if anything makes the patterns more pronounced. The implied mobility rates based on job offers and acceptance decisions correspond well with realized mobility rates, suggesting that the search questions capture what they are meant to. Appendix B.4 provides a comparison with the CPS.

TABLE 1. SUMMARY STATISTICS, DATA

	N	# applications	% with offer	% accept offer	Mobility (impl.)	Mobility (act.)
Employed	3,285	0.797	8.5%	27.4%	0.026	0.022
Unemployed	199	9.950	33.5%	38.6%	0.151	0.155
Observable	199	10.351	32.1%	41.8%	0.159	0.163
Unobservable	169	10.485	30.4%	40.0%	0.144	0.147

Note: Individuals aged 18–64. # applications: Average number of applications submitted in past 4 weeks; % with offer: Share of individuals who received at least one job offer in the past 4 weeks; % accept offer: Share of individuals who accepted at least one offer conditional on receiving at least one offer in the past 4 weeks; Mobility (impl.): Share of individuals who received at least one offer in the past 4 weeks that they accepted; Mobility (act.): Share of individuals who report that they switched employer/employment status in the past month. All search outcomes exclude search for additional jobs and are by employment status in the previous month. Observable: Unemployed controlling for age, education, gender, race and year, evaluated at the sample average values for these covariates. Unobservable: Unemployed controlling for observable factors and the prior wage, evaluated at the sample average values for these covariates. *Source:* SCE 2013–2017.

3.2 Method

I start by setting five parameters to standard values in the literature. The discount rate ρ corresponds to a five percent annual real interest rate. I introduce a small rate κ at which workers permanently exit the market (and are replaced by an equal mass of new unemployed workers), and set it to an average length of careers of 35 years.[9] Matching efficiency, χ, can be normalized. The curvature of the matching

[9] The death rate κ is inconsequential for any of the results in this paper (at least for reasonable values). The reason for introducing it is numerical, as it allows me to faster solve for the invariant distribution of workers across states.

function, θ, is set to 0.5 following Moscarini and Postel-Vinay (2018), who estimate that allowing for on-the-job search increases the weight on vacancies in the matching function. While a higher θ contributes to amplification, I show in Section 4.3 that a version of the model without applications and screening nevertheless fails to match the empirical volatility of labor market outcomes. Finally, I also set workers' bargaining power β to 0.5, consistent with a Hosios (1990) condition although no such condition is known to hold here. In fact, even under the condition $\theta = \beta$, the model is unlikely to be constrained efficient due to the additional externalities emphasized here. Appendix C.1 solves the model for a range of values for β, illustrating that in practice its exact value does not have a big impact on my conclusions.

I normalize the flow value of leisure b such that workers are indifferent between employment at the second grid point for productivity and unemployment. I parameterize the offer distribution over log productivity, $\hat{\gamma}(\log z)$ in the following way. With probability ξ, the potential match draws a log productivity from an exponential distribution with scale ζ. With complementary probability $1-\xi$ the potential match draws the lowest productivity on the grid, i.e. an unviable productivity under the normalized flow value of leisure b. The distribution of signals is assumed to be normal with a mean that corresponds to the true value, $x|z \sim \mathcal{N}(z, \sigma)$. As will become clear shortly, I estimate that worker search behavior is quite inelastic and hence varies little over the cycle. Consequently, I do not think that the particular parametric forms chosen for the offer distribution and the noise in the signal—in particular the shape of the density around these thresholds—play a critical role in the results in this paper.

This leaves eight parameters to estimate, which I inform using Simulated Method of Moments aiming to minimize the sum of squared percentage deviations between eight moments in the model and data,

$$\mathbf{p}^* \quad = \quad \underset{\mathbf{p}\in\mathscr{P}}{\arg\min} \sum_{m\in\mathscr{M}} \left(\frac{m^{\text{data}} - m^{\text{model}}}{m^{\text{data}}} \right)^2, \qquad \mathbf{p} \;=\; \left\{ \delta \,,\, \eta \,,\, \zeta \,,\, \xi \,,\, \sigma \,,\, a \,,\, c_v \,,\, c_s \right\}$$

The estimation is joint, but some moments particularly inform some parameters. The separation rate δ targets the unemployment rate. Changes in the probability that a worker looks for a job as a function of her residual wage informs the curvature of the search cost, η. If η is higher, search is less elastic and hence falls less with the wage. The scale of the offer distribution, ζ, is set to match residual wage dispersion. The share of potential matches that are viable, ξ, is informed by the application-to-mobility rate of the unemployed.[10] If ξ is higher, the unemployed move faster, such that their application-to-mobility rate is higher. The noise in the signal, σ, targets the application-to-mobility rate of the employed. If this is higher, the employed send more unsuccessful applications. The time cost of an application, a, is set to

[10] I use residual search and application outcomes controlling for age, education, gender and race, but not the prior wage. The reason is that the model abstracts from the former permanent characteristics, but the prior wage is an endogenous outcome in the model. As shown in Section 3.1, however, controlling for the prior wage does not much change the empirical patterns.

match the JJ rate. A higher a implies that the cost of applying rises faster with productivity, such that the employed apply less and hence move less.

I target for the cost of advertising jobs, c_v, the UE rate. If it is lower, more jobs are advertised such that the unemployed leave unemployment faster.[11] Finally, to inform the cost of screening, c_s, I target an estimate of the cost of screening relative to the sum of the cost of screening and advertising per hire. Since detailed recruiting cost data are unavailable for the US, I rely on Faccini and Yashiv (2019)'s analysis of two rich firm-level data sets from Germany and Switzerland. Table 2 decomposes hiring costs into advertising expenses and the cost of interviewing candidates.[12] As a higher screening cost share serves to amplify the impact of changes in the separation rate, I target a screening cost share of 50 percent, which is conservative based on this evidence. I present robustness with respect to this in Section 4.4.

TABLE 2. BREAK-DOWN OF COSTS PER HIRE, DATA

	Germany	Switzerland
Advertising costs	48.6%	39.9%
Interview costs	51.3%	60.1%
Number of firms	1,699	2,934

Note: Advertising cost includes advertising in print and online media, the costs of making enquiries with the Employment Office, internal job descriptions, posters, etc. Interview costs is hours needed to fill a vacancy, multiplied by the wage of the workers involved in the interview process. Germany: The survey on the costs and benefits of the training, recruitment and continuing training of skilled workers 2012–2013. Switzerland: Swiss Costs and Benefits Survey 2009. *Source:* Faccini and Yashiv (2019).

3.3 Estimates and model fit

Table 3 summarizes the estimated parameters as well as the targeted moments. Unless otherwise noted, the frequency is monthly. The model fits the data well. It understates somewhat the number of applications sent relative to the resulting mobility rate of the unemployed, and overstates somewhat that of the employed. The separation rate δ is somewhat higher than the empirical EU rate (but close to that in the CPS). Search is quite inelastic. I estimate such a low elasticity because the probability that a worker looks for a job does not decline much in her wage. For comparison, Faberman et al. (2020) estimate a much higher elasticity based on the same data, but targeting measures of the intensive margin of job search. As I demonstrate below, the current model is consistent with a much larger decline in hours on job search as workers move up the job ladder, since they spend less time filling out applications.

[11] In practice, I estimate the job finding rate, p, and recover the cost of advertising c_v such that p is consistent with free entry.

[12] These surveys also report training costs and "external consultancy costs" (costs for headhunters etc). I exclude the former to align the data with the theory. The latter, which correspond to 33 and 25 percent of total pre-hiring costs in Germany and Switzerland, respectively, may be associated with both advertising and screening applicants. I exclude also such costs, implicitly assuming that the breakdown of costs among external recruiters is similar to that among internal recruiters.

The share of viable matches, ξ, is just over one percent. A large number of potential matches must be inviable to match the high application-to-mobility rate in the data.[13] The variance of the signal, σ, is quite low, which is required to match large differences in the number of applications sent between the unemployed and employed. In contrast, if the signal had been completely uninformative, the unemployed and employed would be equally likely to apply for a job conditional on learning about it.

TABLE 3. PARAMETER VALUES, MODEL VS DATA

Parameter		Value	Moment	Data	Model
			A. Externally set/normalized parameters		
κ	Permanent exit rate	0.002	35 year average career		
$\tilde{\rho}$	Discount rate	0.004	5% annual real interest rate		
χ	Matching efficiency	1	Normalization		
θ	Elasticity of matches w.r.t. vacancies	0.5	Moscarini and Postel-Vinay (2018)		
β	Workers' bargaining power	0.5	Hosios (1990) condition		
			B. Internally normalized		
b	Flow value of leisure	1.159	Indifference at 2nd lowest grid point		
			C. Minimum distance routine		
δ	Separation rate	0.011	Unemployment rate	0.067	0.074
η	Curvature of search cost	16.576	Search in 5th wage quintile to 1st	0.681	0.798
ζ	Scale of offer distribution	0.509	St.d. of residual wages	0.721	0.731
ξ	Share of unviable matches	0.012	Application-to-mobility rate (unemp.)	65.737	62.972
σ	Variance of noise	0.284	Application-to-mobility rate (emp.)	30.555	35.920
a	Cost of applying	0.002	JJ rate	0.026	0.021
c_v	Cost of advertising	0.005	UE rate	0.151	0.169
c_s	Cost of screening	0.584	Screening share of total cost	0.500	0.504

Note: Individuals aged 18–64. When applicable, the frequency is monthly. Search in the 5th wage quintile to 1st quintile: Average share of workers looking for a job in the past 4 weeks in the 5th quintile of the wage distribution one month earlier relative to the 1st quintile. Empirical wage distribution is residual controlling for age, gender, education, race and year. Application-to-mobility rates and mobility rates are residual controlling for age, gender, education, race and year and evaluated at the sample mean for these covariates. Empirical moments are weighted using the provided survey weights. *Source:* Model and SCE 2013–2017.

Finally, the time cost of applying for a job, a, is also quite low. In particular, a worker spends about 20 minutes on an application (the estimated time cost, a, times work days per month times work hours per day, $0.002 \times 21.75 \times 8 = 0.35$ hours). Given that the noise in the signal is relatively low, the cost of applying must also be relatively low unless the employed stop applying almost completely.

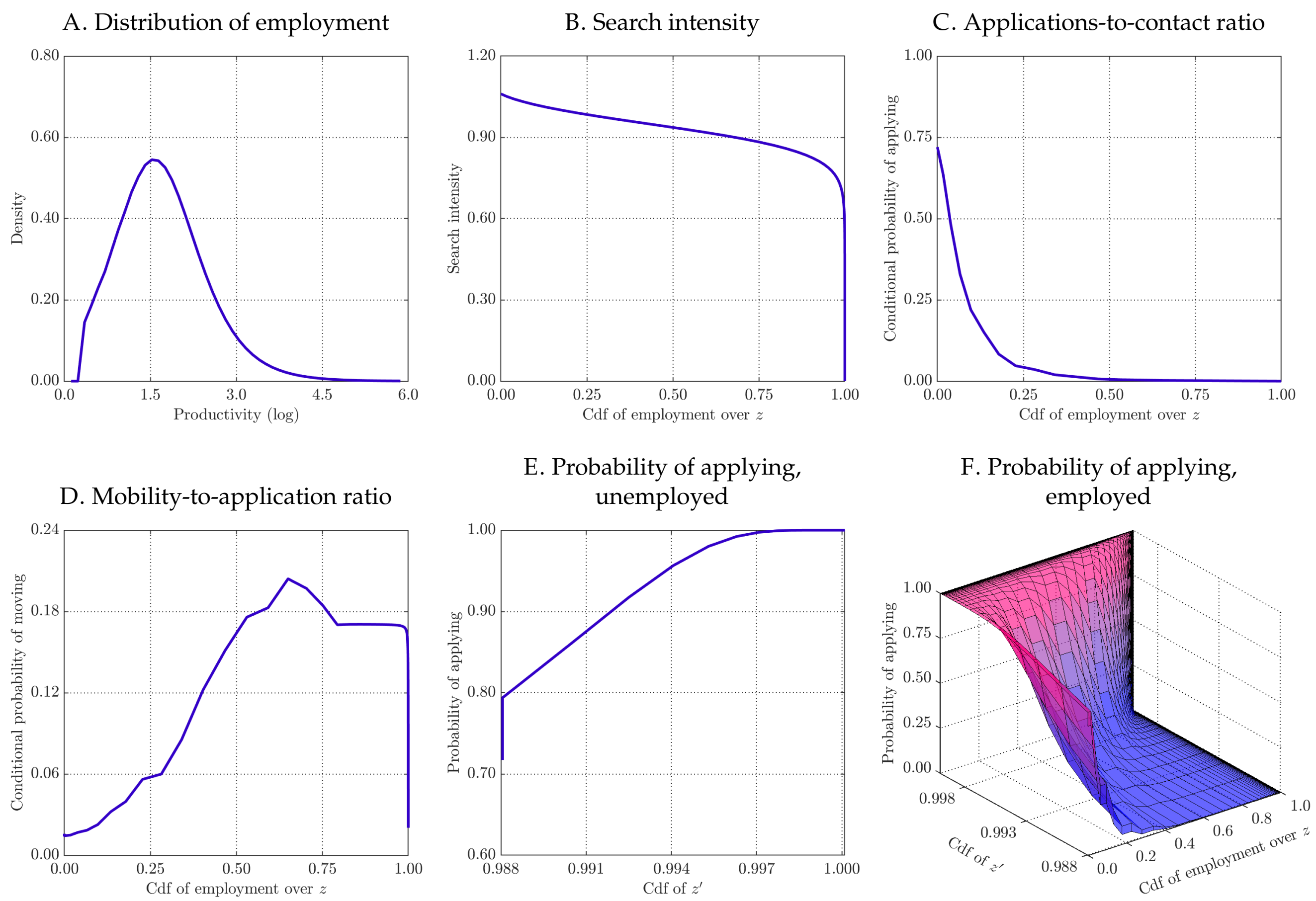
3.4 Understanding search and application behavior

Figure 6 illustrates the workings of the model. Workers in more productive matches search less, as the expected return to mobility is lower. The curvature of the search cost, η, is so high, though, that over most of the domain, search intensity varies little. Workers higher up the job ladder are much less likely

[13]The fact that 1.2 percent of matches are viable does not say anything about the job filling rate to firms, since the latter is the probability that a worker accepts the job offer (which is even less than 1.2 percent) *times* the worker finding rate, q.

to apply for a job, as they expect to be less likely to accept it. Because workers higher up the job ladder are more selective in terms of what jobs they apply for, they are more likely to move per application.

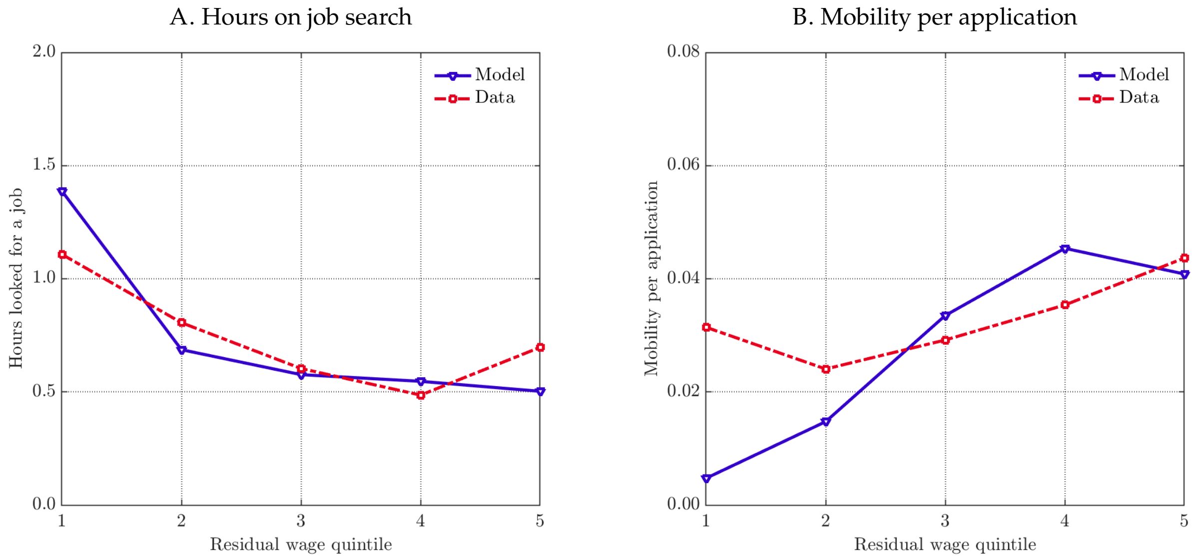
FIGURE 6. SEARCH AND APPLICATION BEHAVIOR, MODEL



Panel E plots the probability that an unemployed worker applies for a job of productivity z conditional on learning about it, $1 - \Psi(r|z)$, where r is the lowest signal that an unemployed worker applies to (see Appendix A.1). The unemployed apply for most jobs they learn of—even if underlying productivity is unviable (a large share of potential matches), there is a greater than 70 percent chance that the worker submits an application based on the signal she observes. Panel F shows the conditional probability that an employed worker applies for a job of productivity z' given that she is currently in a job with productivity z, $1 - \Psi(R(z)|z')$, where $R(z)$ is the lowest signal that a worker currently employed in a productivity z match applies to (see Appendix A.1). For a given productivity z' of the new job, a worker currently employed in a higher z match is less likely to submit an application. Given current productivity z, a worker is more likely to apply for a job the higher its underlying productivity z'.

Panel A of Figure 7 contrasts hours on job search by residual wage quintile in the model with the data.[14] While search is inelastic, the model is consistent with a fairly large decline in the number of hours on job search by current wage in the data. The reason is that workers higher up the job ladder spend less time submitting applications (and I assume that respondents include time filling out applications when asked to report time spent on job search). Panel B plots the mobility-to-application ratio by quintile of residual wage. As workers move up the job ladder, the opportunity cost of applying rises, such that workers require a higher expected success rate to bother to apply. The model overstates somewhat the empirical patterns, but measurement error in wages would bias any pattern toward zero. As these are non-targeted moments, the model does a decent job at matching them.

FIGURE 7. SEARCH AND MOBILITY OUTCOMES BY WAGE QUINTILE, MODEL VS DATA



Note: All panels. By quintile of wage distribution; all data moments are residual controlling for age, gender, race, education and year and wage is that one month earlier. Panel A. Sum of time spent on search and filling out applications, $\int(\tilde{L}(z) + pL(z)a\int(1-\Psi(R(z)|z'))d\Gamma(z'))H(dz,w)$, where $H(z,w)$ is the joint distribution of employment over productivity and wage; see footnote 14 for how $\tilde{L}(z)$ is constructed. Panel B. Share of workers who moved in the past month divided by number of applications submitted in the past 4 weeks. *Source:* Model and SCE 2013–2017.

Table 4 provides a further look at the estimated model. Panel A shows the share of workers, contacts, applicants and hires that is unemployed. The share of unemployed workers is seven percent. Given the high curvature of the search cost, the share of those who learn about a firm's job opening that is unemployed is only modestly higher at nine percent. The unemployed, however, are much more likely to apply, such that they constitute 53 percent of the applications a firm receives. Because the unemployed are less likely to be a good fit for the job, however, roughly 40 percent of hires are unemployed, broadly

[14] The model above excludes a constant in the cost of search, $l^{1+\eta}/(1+\eta)$, because it is not separately identified from the job finding rate, p, without an additional moment. To assess how total hours on job search—the sum of search and time spent on applications—vary over the wage distribution, it is necessary to take a stand on what a unit of search intensity is in the model. To that end, let search effort be $l = \epsilon\tilde{l}$ and set the parameter ϵ such that the model matches the average amount of time individuals spend on job search, 1.33 hours per month. The calibrated value for ϵ implies that 61 percent of the average amount of total time spent searching is spent looking for job opportunities, with the remainder due to filling out applications.

consistent with the available evidence (excluding recalls) (Fujita and Moscarini, 2017).

Panel B shows that the flow value of leisure is 35 percent of average wages, 15 percent of average match output, and 43 percent of the average productivity of viable offered matches. Hence, this is not a low surplus economy. At the same time, the model does not require a very low flow value of leisure to be consistent with empirical residual wage dispersion (Hornstein et al., 2011).

TABLE 4. ADDITIONAL OUTCOMES, MODEL

A. Share unemployed		B. Flow value of leisure		C. Screening of unemployed	
Workers	0.074	To average wage	0.353	Expected return	0.345
Contacts	0.085	To average productivity	0.146	Cost of screening	0.584
Applicants	0.533	To average offered productivity	0.425	Net return relative to flow output	-0.030
Hires	0.394	Labor share	0.765	Breakeven prob. of being empl.	0.137

Note: Panel A. Workers: Unemployment rate; Contacts: Fraction of total potential applicants a job opening contacts who are unemployed; Applicants: Fraction of applicants to a job opening who are unemployed; Hires: Fraction of hires who are unemployed. Panel C. Expected return: Expected return to a firm of screening an applicant who is known to be unemployed. Breakeven prob.: the probability that what looks like an unemployed applicant is in fact employed that makes a firm indifferent between screening the worker and not. *Source:* Model.

Panel C finds that the expected return to screening an applicant who is known to be unemployed is less than the cost of screening the worker. Hence, if a firm could infer an applicant's employment status at no cost, it would want to discard unemployed applicants. At the same time, the net expected flow loss from screening an unemployed applicant relative to flow output is only about three percent. For this reason, if there was a greater than 14 percent chance that an applicant who on initial inspection appeared to be unemployed in fact is employed, the firm would proceed to screen the applicant. The reason why a firm may have a strong preference for employed applicants, yet be close to indifferent between screening an unemployed applicant or not, was highlighted in Proposition 3. Free entry requires that the expected net return to recruiting be zero. At the point when a firm receives an application, however, it has already spent resources c_v. Consequently, screening an applicant is in general a net positive expected value endeavor to the firm. Hence, even though the firm prefers employed applicants, the net return to screening an unemployed applicant is only modestly negative (indeed, as noted in Proposition 3 it could even have been positive). Section 4.4 considers a version of the model in which firms effortlessly learn the unemployment status of some applicants and may discard them. This moderates the impact of shocks but only modestly, due to the forces emphasized in Proposition 3.

4 Persistent Labor Market Fluctuations

I now turn to aggregate dynamics. Motivated by the previous literature, I use the estimated framework to isolate the impact of two types of shocks: separation shocks and productivity shocks (Shimer, 2005).

4.1 Methodology

Solving for the dynamic equilibrium requires tracking the distribution of workers across states—an infinite-dimensional object. Moreover, the distribution enters directly into agents' problem, as opposed to only indirectly through an aggregate statistic such as the interest rate. For this reason, random search models like the current model are notoriously hard to analyze out of steady-state. I make progress by solving a perfect foresight transition experiment. In particular, starting from steady state, agents suddenly realize that either the separation rate, $\delta(t)$, or aggregate productivity, $Z(t)$, will evolve over a transition period so as to match empirical fluctuations in the empirical EU rate or output per worker, respectively. Eventually, however, both return to steady-state. Appendix C.2 presents the dynamic version of the value functions, Appendix C.3 outlines the dynamic laws of motion, Appendix C.4 defines the dynamic equilibrium, and Appendix C.5 discusses the algorithm used to solve the problem. All other parameters are held fixed at their steady-state values. Separation and productivity shocks are assumed to impact all matches, in the latter case by proportionally shifting match productivity by factor $Z(t)$.

The separation shocks may be interpreted as a large negative idiosyncratic shock that renders a match unviable, regardless of its prior productivity. For instance, many models of technological obsolescence have this feature (Aghion and Howitt, 1992; Grossman and Helpman, 1991). Whether these match idiosyncratic shocks are ultimately driven by demand or productivity matters for the interpretation, but not the mechanism. An alternative explanation of the higher EU rate in recessions is that a decline in aggregate productivity results in the endogenous termination of low productivity matches. Under this view, however, one would expect the EU rate to particularly rise at the bottom of the wage distribution in recessions. In contrast, Appendix C.6 documents a proportional increase in the EU rate in recessions at all deciles of the residual wage distribution. The view of recessions adopted here is instead consistent with a literature on uncertainty, which argues that recessions are not so much characterized by modest declines in productivity across all producers, but by a higher incidence of very large negative idiosyncratic shocks impacting a few firms (Bloom et al., 2018; Salgado et al., 2019). Other potential interpretations of the higher separation rate in recessions include tighter financial constraints (Chodorow-Reich, 2014).[15]

4.2 Model versus data

I start by comparing the effect of separation and productivity shocks in the model with the data. My primary focus is the 2007–2015 Great Recession and subsequent recovery, but I briefly highlight that

[15] As I discuss in Appendix A.6, little of the aggregate variation in the EU rate is accounted for by tenure. That is, the higher separation rate in recessions is not primarily accounted for by a flood of newly formed matches with intrinsically high separation rates (Pries, 2004). Rather, the separation rate by tenure rises proportionately during recessions.

similar results hold in earlier recessions.[16] Appendix C.7 contains additional results.

Separation shocks. Figure 8 presents results with respect to separation shocks.[17] The exogenously varying EU rate in panel A—the unique driver of dynamics in this version of the model—spiked by 40 percent at the onset of the recession and gradually reverted back to its pre-recession level. Panel B shows the endogenous UE rate fell by 50 percent. Separation shocks account for 80 percent of the trough in the UE rate. They generate a smaller decline in the JJ rate, as illustrated by panel C, for reasons that I discuss in further detail in Appendix D.1. Panel D highlights this prediction further by plotting the ratio of the JJ to the UE rate, which rose during the Great Recession.[18] The predicted declines in the UE and JJ rates are quite persistent, although not as persistent as in the data. That is, other factors also contribute to the persistent fluctuations observed in the data. Panel E shows that separation shocks account for a large share of the increase in the fraction of hires that come from unemployment during the recession.

Finally, panel F highlights that separation shocks give rise to a strongly negative Beveridge curve, as in the data. This contrasts with the conventional view that separation shocks cannot match this pattern (Shimer, 2005). I reach such a different conclusion because higher unemployment disincentivizes vacancy creation according to the estimated framework, whereas in existing benchmark models it encourages it. Moreover, as in the data, the Beveridge curve shifts out in the recession. The reason is that the increase in the separation rate raises unemployment conditional on vacancies—recall Figure 5.

Productivity shocks. Figure 9 instead considers the impact of productivity shocks. Output per worker in panel A fell at the start of the Great Recession, but recovered fairly quickly (McGrattan and Prescott, 2012). In fact, labor productivity did not fall much during any of the previous three recessions (Hall, 2007). Productivity fluctuations are too small to give rise to any meaningful fluctuations in labor market outcomes.[19] For instance, the UE rate in panel B falls by only a few percent. The reason is that the average hiring firm has a large surplus, even though the flow value of leisure is set such that workers are indifferent between unemployment and working a low productive job. Indeed, the magnitude of residual wage dispersion in the data implies a decent amount of productivity dispersion, making it

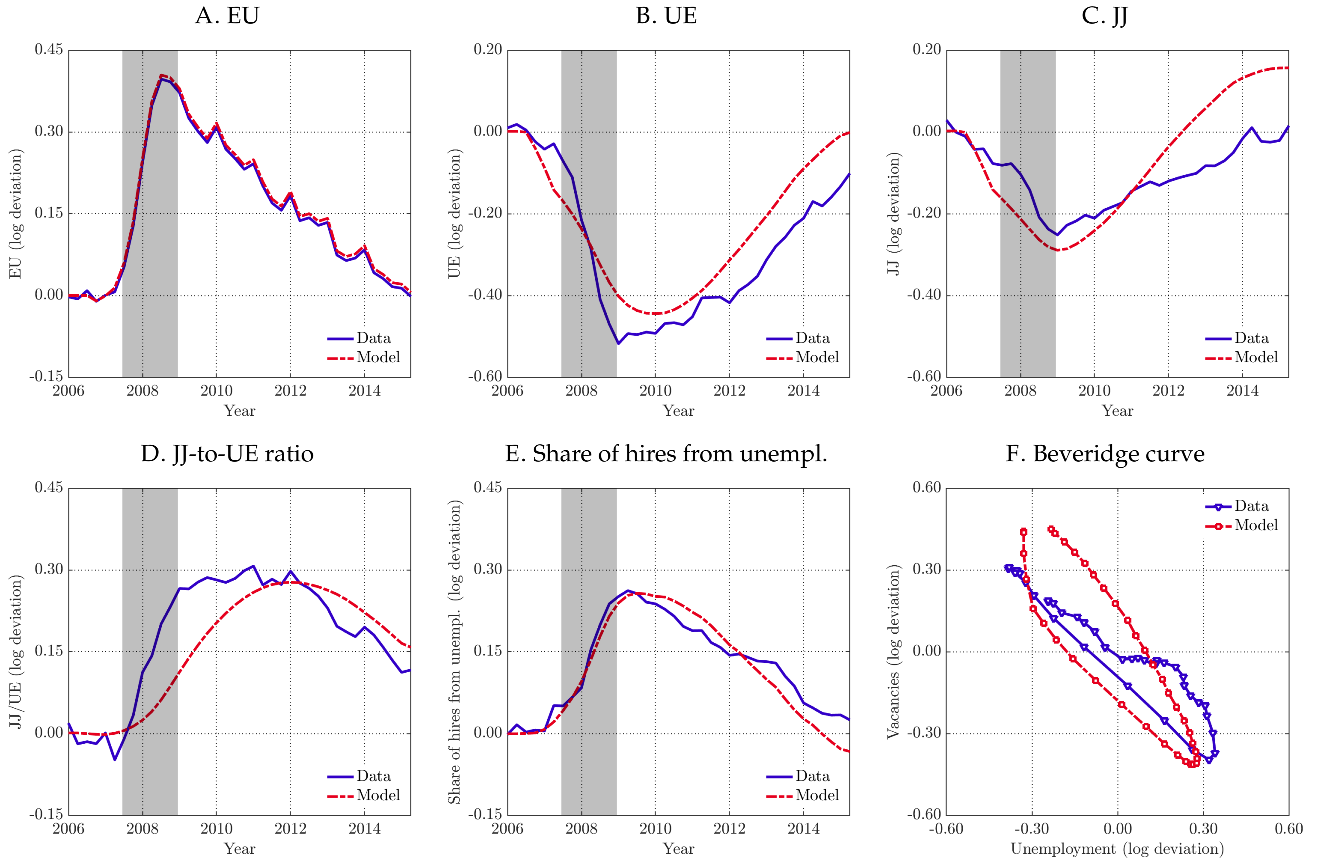
[16] Following Shimer (2005), all empirical moments are quarterly averages of monthly data, in logs, and HP-filtered with smoothing parameter 10^5. The full data set 1976Q1–2020Q2 is used to limit issues associated with the end points. To reduce noise, all graphs plot a three-quarter, centered moving average of the HP-filtered log series, in both the model and data.

[17] While I assess the impact of each shock in isolation, it makes little difference to consider them jointly.

[18] The JJ rate is also less volatile in the 2001 recession, which is the only other recession for which JJ data exist. A similar pattern as in the CPS holds for quits in JOLTS and JJ mobility in the US Census' LEHD data.

[19] Measured productivity in the model falls by somewhat more than the exogenous process I feed in, because the rate at which workers move up the job ladder endogenously declines. Consequently, the employment distribution shifts down the job ladder (Barlevy, 2002). Adjusting for this shift, however, would require the exogenous process for productivity to fall by even less during the recession than the process I currently feed in. Hence, to be conservative I prefer to not make such an adjustment.

FIGURE 8. THE IMPACT OF SEPARATION SHOCKS IN THE GREAT RECESSION, MODEL VS DATA



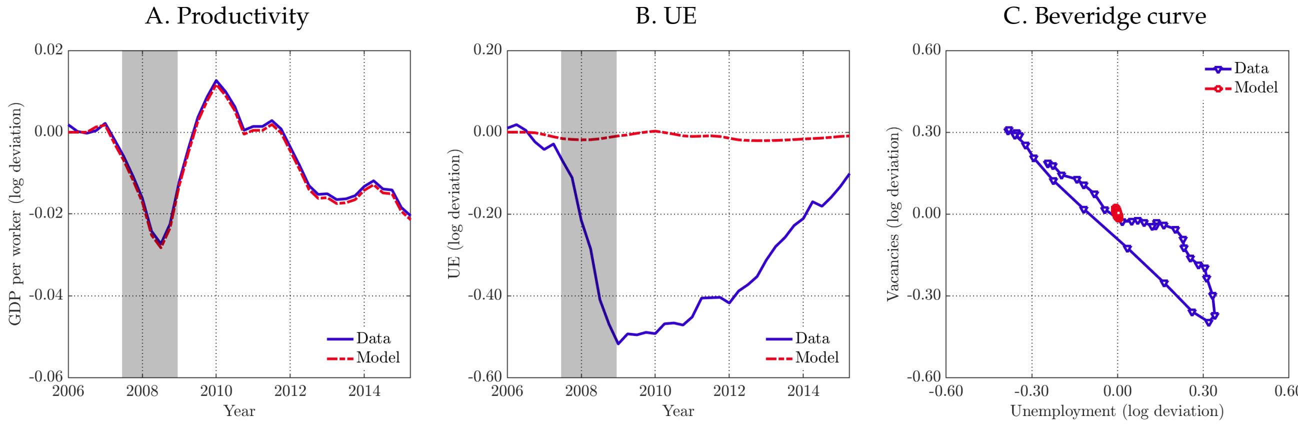
Note: Perfect-foresight impact starting from steady-state in 2007Q2 of fluctuations in the separation rate $\delta(t)$ that match the empirical EU rate between 2007Q3–2015Q4 and then return to steady-state. Quarterly average of monthly data, in logs and HP-filtered with smoothing parameter 10^5 (using the full 1976Q1–2020Q2 sample). Shaded area corresponds to NBER dated recessions. EU: Share of wage employed who are unemployed in the subsequent month. UE: Share of unemployed who are wage employed in the subsequent month. JJ: Share of wage employed who are employed with a different employer relative to last month. Share of hires from unempl.: Hires from unemployment divided by the sum of hires from employment and unemployment. *Source:* Model, CPS and JOLTS.

virtually impossible to infer a low average surplus (Bils et al., 2011). Consequently, productivity shocks generate little volatility and persistence in labor market outcomes (Hagedorn and Manovskii, 2008).

Earlier recessions. Figure 10 conducts the same perfect foresight experiment as above for the three recessions prior to the Great Recession for which CPS micro data are available: the 1980–1982 "Double-Dip" recession, the 1990–1991 "Jobless Recovery" recession, and the 2001 "Dot-Com" recession.[20] In the interest of space, I focus on separation shocks and show only the exogenously varying EU rate and the endogenous UE rate. Similar results as for the Great Recession hold, however, for productivity shocks as well as a broad set of labor market outcomes, and are available on request. Separation shocks account

[20]The micro data from the CPS that I use to construct labor market flows are only available starting in 1976. I have verified that broadly similar results hold in recessions 1948–1976 using aggregate Bureau of Labor Statistics data on unemployment and employment stocks together with the imputation procedure proposed by Shimer (2012). Results are available on request.

FIGURE 9. THE IMPACT OF PRODUCTIVITY SHOCKS IN THE GREAT RECESSION, MODEL VS DATA



Note: Perfect-foresight impact starting from steady-state in 2007Q2 of fluctuations in aggregate productivity $Z(t)$ that match labor productivity between 2007Q3–2015Q4 and then return to steady-state. Quarterly average of monthly data, in logs and HP-filtered with smoothing parameter 10^5 (using the full 1976Q1–2020Q2 sample). Shaded area corresponds to NBER dated recessions. Productivity: Real output per worker. UE: Share of unemployed who are wage employed in the subsequent month. *Source:* Model, CPS and JOLTS.

for a large share of the volatility and persistence of labor market fluctuations over the business cycle.

4.3 Model versus model—the importance of micro data

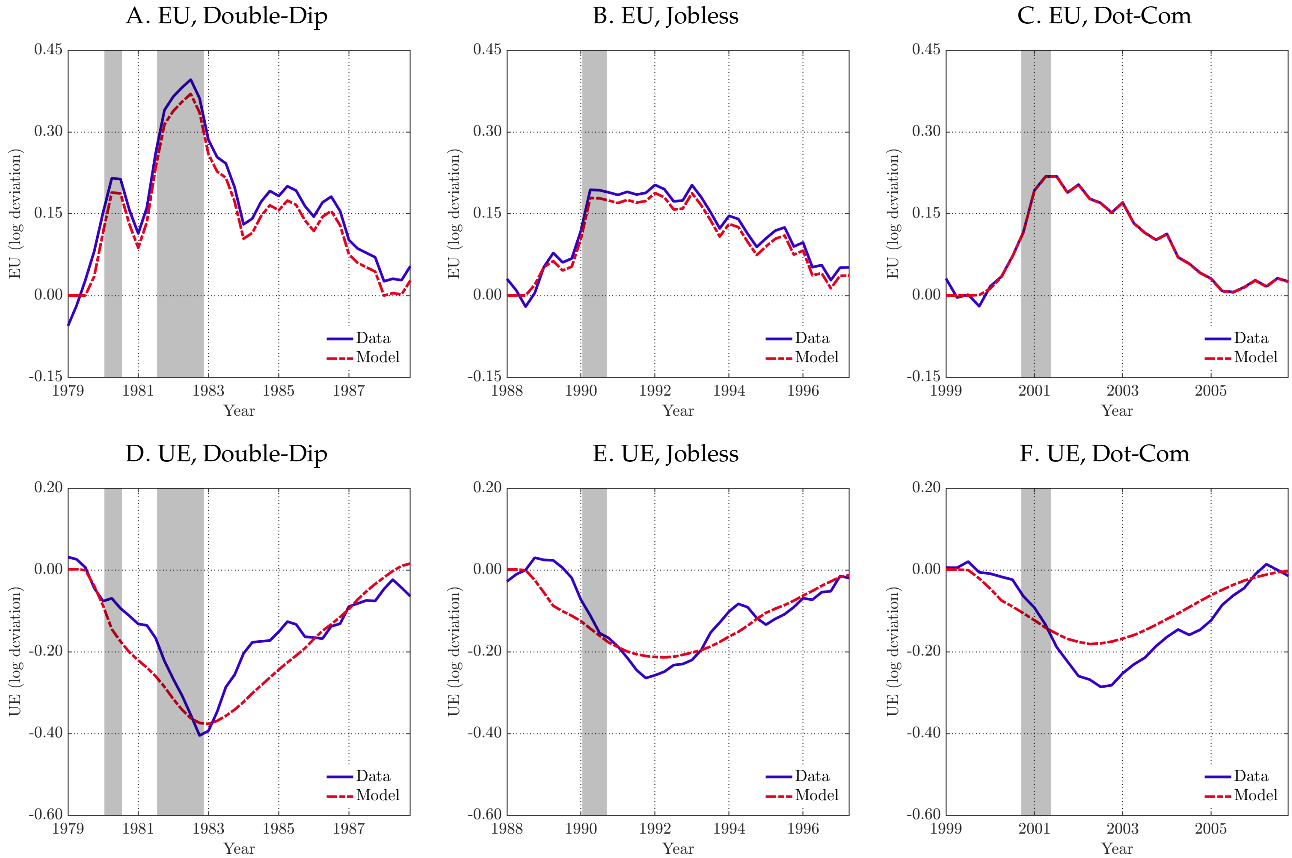
Recall from Figure 1 that the current framework features two additional stages relative to a standard DMP model (extended to feature on-the-job search): an application and a screening stage. To illustrate the importance of modeling both margins, I consider the impact of the same separation shocks as above across several alternative calibrations of the current framework that shut down each of these stages. I focus for now on separation shocks since they show promise in accounting for the behavior of the UE rate in the previous four US recessions, and return to an analysis of other shocks in Section 5.3.

The basic model. The first alternative calibration shuts down both the application and screening stages by setting the cost of applying and the cost of screening to zero, $a = c_s = 0$. I recalibrate the cost of advertising jobs, c_v, such that free entry holds under the same job finding rate p. In this version, workers apply for all jobs they learn of and firms face only advertising costs. With some abuse of terminology since the model allows for JJ mobility, I refer to this as the DMP calibration.

Panel A of Figure 11 shows that the fall in the UE rate in the DMP calibration is a fifth of that in the estimated model in response to the same path for the separation rate. Moreover, the decline is less persistent, such that the UE rate returns to its pre-crisis level already in 2011.

Adding screening. Pissarides (2009) highlights that screening costs amplify shocks. The reason is that

FIGURE 10. THE IMPACT OF SEPARATION SHOCKS IN EARLIER RECESSIONS, MODEL VS DATA

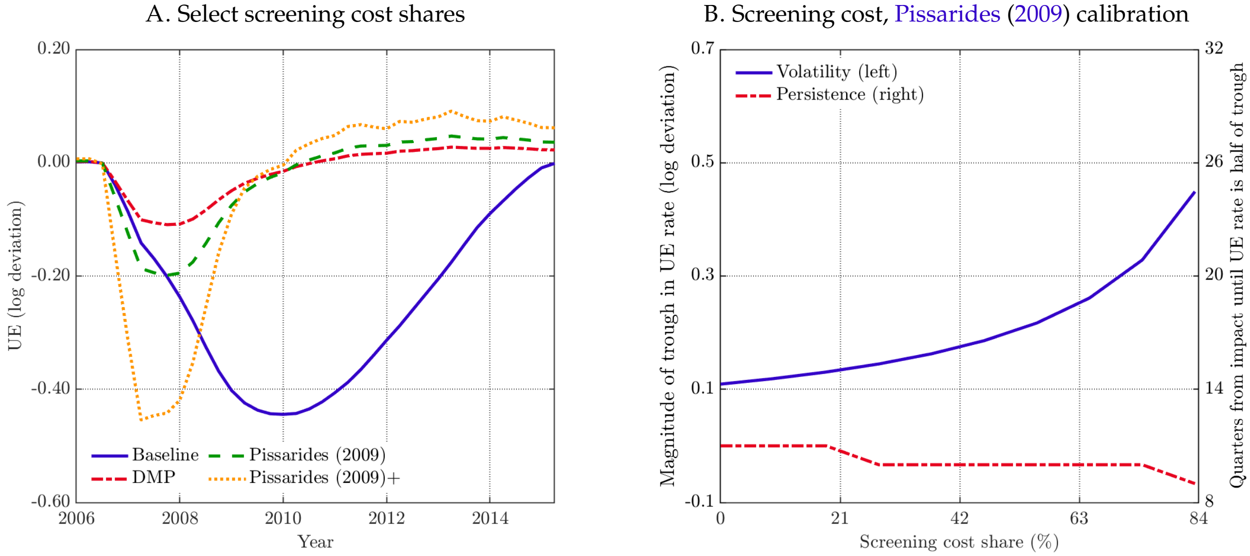


Note: Perfect-foresight impact starting from steady-state in 2007Q2 of fluctuations in the separation rate $\delta(t)$ that match the empirical EU rate over a transition period and then return to steady-state. Quarterly average of monthly data, in logs and HP-filtered with smoothing parameter 10^5 (using the full 1976Q1–2020Q2 sample). Shaded area corresponds to NBER dated recessions. EU: Share of wage employed who are unemployed in the subsequent month. UE: Share of unemployed who are wage employed in the subsequent month. *Source:* Model, CPS.

firms only incur them after meeting a worker, such that they are insulated from congestion in the matching technology. To illustrate this, I set the cost of applying to zero, $a = 0$, such that workers always apply for a job they learn of. This effectively shuts down the application stage, resulting in no selection based on applicants' private information. Firms, however, still have to spend resources on screening after meeting with a worker (but before bargaining with the worker). The cost of advertising and screening, $\{c_v, c_s\}$, are set such that free entry holds under the same job finding rate p and recruiting cost share of screening as in the estimated model. I refer to this as the Pissarides (2009) calibration.

Panel A of Figure 11 shows that the decline in the UE rate is twice as large as in the DMP calibration, consistent with the argument in Pissarides (2009). Indeed, panel B varies the screening cost c_s in the version of the model without an application stage, $a = 0$, illustrating that for a screening cost share of 83 percent, this version of the model can generate the same size of the trough in the UE rate in response

FIGURE 11. THE IMPACT OF SEPARATION SHOCKS ON THE UE RATE ACROSS CALIBRATIONS



Note: Perfect-foresight impact starting from steady-state in 2007Q2 of fluctuations in the separation rate $\delta(t)$ that mimic the EU rate between 2007Q3–2015Q4 and then return to steady-state. Panel A. DMP: No application and screening stage, $a = c_s = 0$. Pissarides (2009): No application stage, $a = 0$, and cost of screening, c_s, recalibrated to match the same cost share of screening as in the estimated model. Pissarides (2009)+: No application stage, $a = 0$, and cost of screening, c_s, recalibrated to match the same trough in the job finding rate as in the estimated model. Panel B. No application stage, $a = 0$, and cost of screening, c_s, recalibrated to match varying cost shares of screening. All panels. The cost of advertising c_v set to match the same job finding rate p as in the estimated model. *Source:* Model.

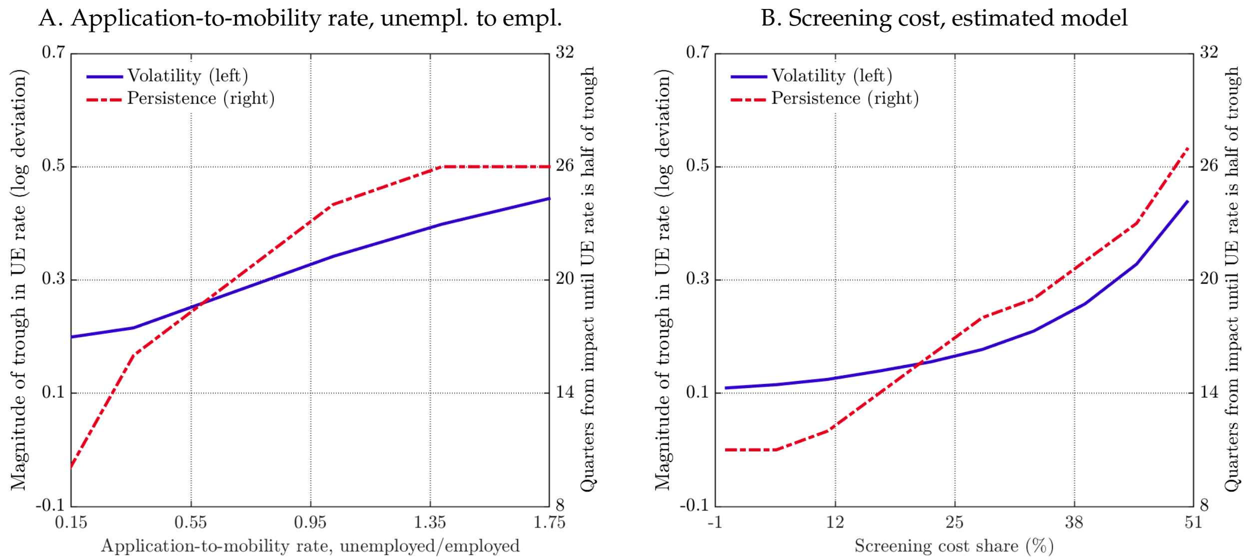
to the same underlying shock as the estimated model.[21] Panel A includes also the resulting path for the UE rate for this high screening cost calibration, which I refer to as the Pissarides (2009)+ calibration. While the version of the model with a screening but without an application stage can generate the same volatility of the UE rate as in the estimated model, it cannot, however, match the persistence of the UE rate. I measure the persistence as the number of quarters since the start of the perfect foresight experiment until the UE rate has closed half of the trough. As the screening cost share rises, the volatility of the resulting UE rate rises, but the persistence of the UE rate *falls*.

Applications and screening. Key to match the empirical persistence of the UE rate is the combination of an application stage and a screening stage. To stress this point further, I consider the impact of lowering the cost of applying, a, while adjusting the cost of advertising and screening, $\{c_v, c_s\}$, to match the same job finding rate p and cost share of screening as in the estimated model. In the limit as $a \to 0$, workers always apply for a job they learn of, such that the ratio of the application-to-mobility

[21]Across all these calibrations, the cost of advertising, c_v, is set such that free entry holds under the same job finding rate as the estimated model. Because workers in these alternative calibrations apply regardless of the signal, whereas in the estimated model they sometimes fail to apply for a job that they would have accepted, the mobility rates are in general higher in the alternative calibrations. In practice, however, the difference in mobility is less than three percent and virtually the same business cycle results hold if I instead adjust also the job finding rate p to target the same UE rate as in the estimated model.

rate of the unemployed to the employed converges to the ratio of the mobility rate of the employed to the unemployed. That is, the model converges to the Pissarides (2009) calibration.

FIGURE 12. HOW THE IMPACT OF SEPARATION SHOCKS ON THE UE RATE VARIES WITH REDUCED-FORM MICRO MOMENTS



Note: Perfect-foresight impact starting from steady-state in 2007Q2 of fluctuations in the separation rate $\delta(t)$ that mimic the EU rate between 2007Q3–2015Q4 and then return to steady-state. Panel A. Different calibrations of the cost of applying, a, to target alternative ratios of the application-to-mobility rate of the unemployed to the employed. Across all alternative calibrations, the cost of advertising and screening, $\{c_v, c_s\}$, are recalibrated to match the same job finding rate p and recruiting cost share of screening. Panel B. Different calibrations of the cost of screening, c_s, to target alternative screening cost shares of recruiting, with the cost of advertising c_v set to match the same job finding rate p as in the estimated model. *Source:* Model.

Panel A of Figure 12 plots the resulting volatility and persistence of the UE rate as a function of the application-to-mobility rate of the unemployed to the employed.[22] In the DMP and Pissarides (2009) calibrations, workers always apply such that the application-to-mobility rate of the unemployed to the employed equals the ratio of the mobility rate of the employed to the unemployed, which is 0.15. In the estimated model, on the other hand, this ratio is 1.75 (as Section 3 notes, the model understates somewhat the empirical ratio, which is two). A lower application-to-mobility rate of the unemployed relative to the employed is associated with a less volatile and less persistent UE rate. Hence, this margin plays a key role in how much shocks are amplified and propagated.

Panel B repeats the exercise in Figure 11B with respect to the screening cost share of recruiting, but this time in the version of the model with an active application stage, $a > 0$. As for the Pissarides (2009) calibration (i.e. $a = 0$), the estimated model (essentially) coincides with the DMP calibration when the screening cost share is zero.[23] The volatility of the UE rate rises with the screening cost share, just as in

[22] I focus on how outcomes vary as a function of this ratio, even though the ratio is a reduced-form equilibrium outcome. Appendix C.8 graphs the same outcomes as a function of the underlying structural parameter, a.

[23] Since the cost of applying remains positive, $a > 0$, and the noise is positive but bounded, $0 < \sigma < \infty$, workers are still

the Pissarides (2009) calibration without an application stage in Figure 11B. In fact, although the version with an application stage ($a > 0$) requires a lower screening cost share to match the same volatility of the UE rate as that without an application stage ($a = 0$), a proportional change in the screening cost share has an almost identical effect on volatility in the two calibrations. The key difference is in the persistence of the UE rate. This rises almost linearly with the screening cost share in the version with an application stage, but falls with the screening cost share without an application stage.

4.4 Robustness

This section presents two extensions of the model that speaks to screening cost heterogeneity and hiring standards. Additionally, Appendix C.1 contains an analysis of the sensitivity of results to the value of workers' bargaining power, finding that results are not particularly sensitive to this parameter. See Appendix C.9 for a sensitivity analysis with respect to the noise in the signal, σ.

Junk applications and screening cost heterogeneity. Central to the findings in this paper is not that firms receive more applications in recessions, but that the composition of applicants shifts toward those who are less selective in their application behavior. Consequently, firms would not want to randomly discard applicants, but selectively discard unviable matches prior to spending any resources screening them. I assume, however, that this is not possible. To assess the sensitivity of my results to this assumption, I extend the model to feature screening cost heterogeneity that is correlated with either the underlying productivity of the match or the employment status of the applicant. In particular, I assume that screening now consists of two stages—an initial cursory assessment and an "interview"—and that the initial assessment reveals with some probability either the employment status of the applicant or the underlying productivity of the match. A firm may choose to not proceed to interview a candidate after the initial assessment. To be extreme, I assume that the initial screening comes at no cost to the firm.

In the first specification, the initial assessment reveals with probability ν the employment status of an applicant. As noted in Section 3.4, my estimates imply that firms would want to discard unemployed applicants. It proceeds to interview those who are revealed to be employed or those for whom it cannot determine their employment status. I calibrate ν to match the ratio of applications-to-interviews of the unemployed to the employed, and find updated costs of advertising and screening, $\{c_v, c_s\}$, such that free entry holds under the same job finding rate p and the same screening cost share as in the estimated

selective in terms of what jobs they apply for but sometimes make a type 1 error. Hence in theory the estimated model does not converge to the DMP model as $c_s \to 0$. In practice, however, the business cycle predictions from this limiting economy with $a > 0$ and the DMP model (which has $a = 0$) are essentially indistinguishable (even though the steady-state differs slightly).

model. Panel A of Table 5 summarizes this calibration—all other parameters are kept fixed and other moments remain (essentially) the same as in the estimated model.[24] The calibrated value of ν implies that firms learn for free the employment status of 36 percent of applicants in the initial screening stage.

Panel A of Figure 13 shows that the impact of separation shocks is less pronounced yet remains substantial. The reason is the logic emphasized in Proposition 3—firms may prefer employed applicants, but still want to proceed to screen also applicants who are known to be unemployed. Although under my estimates firms would like to discard unemployed applicants, as noted in Section 3.4 the net expected loss from screening an unemployed applicant is small. Consequently, allowing firms to discard such applicants prior to spending any resources screening them does not much change the impact of shocks.

In the second specification, the initial assessment reveals that an unviable potential match is so with probability ν_1 and that the match will otherwise not be formed with probability ν_2 (i.e. the potential hire is employed in a more productive match). A firm optimally discards such applicants, and subsequently proceeds to screen remaining applicants at cost c_s. I calibrate ν_1 to match the interview-to-mobility rate of the unemployed and ν_2 to match the interview-to-mobility rate of the employed. Finally, I find updated costs of advertising and screening, $\{c_v, c_s\}$, such that free entry holds under the same job finding rate p and the same screening cost share as in the estimated model. Panel B of Table 5 summarizes the updated parameter values and moments. All other parameters are kept fixed and other moments remain (essentially) the same as in the estimated model.[24]

Panel B shows that the impact of separation shocks is again less pronounced, yet continues to be large. The reason that the effects of separation shocks are large is that the unemployed are less likely to move also per interview in the data relative to the employed (in particular, about $1/1.374 \approx 0.73$ times as likely). In contrast, without the application/interview stage ($a = 0$), the unemployed would be much *more* likely to move per interview (about $1/0.15 \approx 6.7$ times as likely). Note in particular that the empirical patterns remain an order of magnitude off the predictions of the standard model. I also note that if firms had to spend resources on the initial screening, the impact of separation shocks would presumably be somewhere in between the estimated model and these extensions.

Hiring standards. The analysis above follows the standard assumption in the DMP literature of no capacity constraint in production. Consequently, there is no opportunity cost to a firm of filling a job, such that a higher worker finding rate in a recession does not induce a firm to be more selective in hiring. To assess the sensitivity to this assumption, I incorporate long-lasting jobs. To that end, suppose that a

[24]Because I keep the job finding rate p fixed, the resulting UE rate in general changes due to changes in workers' search behavior. As evident in Table 5, in practice changes in search behavior barely affect the UE rate conditional on a fixed p.

firm has to pay a one time cost c_e to set-up a job, a flow cost c_v to advertise an open job, and a cost c_s to screen an applicant (all in terms of the final good). As in the baseline model, when an open job contacts a potential hire, the two draw a match-idiosyncratic productivity z from offer distribution Γ. If an open job hires a worker, it cannot continue to try to recruit for the position. When the match breaks up, the job ceases to exist. Appendix C.10 outlines the value functions in this extended version of the model.

I calibrate the costs of set-up, advertising and screening, $\{c_e, c_v, c_s\}$, such that free entry holds under the same job finding rate p and screening cost share as in the baseline model, with the flow value of leisure b is set such that workers are indifferent between unemployment and employment at the second grid point. One additional moment is required to separate c_e and c_v. As it is difficult to find a good empirical target, I consider the ad hoc target of letting half of the flow cost of opening a job, $c_v + \rho c_e$, be due to the set-up cost, c_e. Panel C of Table 5 summarizes the updated parameter values and moments.[25]

TABLE 5. MODEL EXTENSIONS

	Parameter	Value	Moment	Data	Model
			A. Learn about employment status of applicant		
ν	Probability employment status is revealed	0.361	Application-to-interview, unemp/emp	1.565	1.565
c_v	Cost of advertising	0.005	UE rate	0.151	0.169
c_s	Cost of screening	0.610	Screening share of total cost	0.500	0.504
			B. Learn about productivity of new match		
ν_1	Probability an unviable match is revealed	0.937	Interview-to-mobility rate (unemp)	4.908	4.904
ν_2	Probability a $z' < z$ match is revealed	0.695	Interview-to-mobility rate (emp)	3.571	3.572
c_v	Cost of advertising	0.005	UE rate	0.151	0.169
c_s	Cost of screening	6.639	Screening share of total cost	0.500	0.504
			C. Firm hiring standards		
c_e	Cost of setting up job	0.599	Half of overall flow cost of open job, $c_v + \rho c_e$		
c_v	Cost of advertising	0.002	UE rate	0.151	0.186
c_s	Cost of screening	0.619	Screening share of total cost	0.500	0.503
b	Flow value of leisure	0.259	Indifference at 2nd lowest grid point		

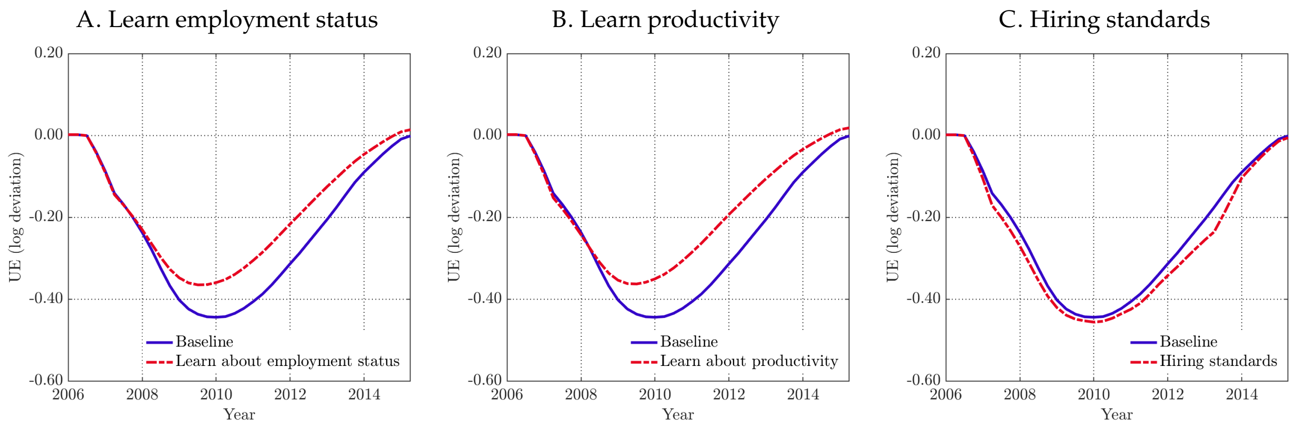
Note: Individuals aged 18–64. When applicable, frequency is monthly. Empirical moments are weighted using the provided survey weights. Empirical application-to-interview and interview-to-mobility rate are based on residual application and mobility patterns controlling for age, gender, education, race and year and evaluated at the sample mean for these covariates. *Source:* Model, CPS and SCE.

Panel C shows that the impact of the same separation shocks in this extension of the model becomes modestly *larger* than in the baseline model. The reason why long-lasting jobs do not moderate the impact of separation shocks is the following. As fewer vacancies are posted in the recession, the rate at which an open job contacts an applicant rises. Without applicant selection, this increases the opportunity cost of filling a job, making firms more selective and raising firms' threat point in wage negotiation. With

[25]Due to changes in workers' search behavior relative to the baseline model, the UE rate conditional on a job finding rate p changes modestly. Nevertheless, given that the changes are small and the business cycle patterns are not sensitive to changing the targeted p, I avoid the added complexity of searching for a new p to match the original UE rate.

applicant selection, on the other hand, the increase in the rate at which an open job contacts an applicant is countered by a worsening in the pool of applicants, which reduces the opportunity cost of filling a job, makes firms less selective and reduces their threat point. Under the estimated values, these two forces close to offset. I also stress that firms in the baseline model receive more applications in a recession per vacancy and per hire. Consequently, in a reduced-form sense, firms do become more selective in hiring in recessions, in the sense that the probability that a given applicant is hired falls.

FIGURE 13. MODEL EXTENSIONS



Note: Perfect-foresight impact starting from steady-state in 2007Q2 of fluctuations in the separation rate $\delta(t)$ that mimic the EU rate between 2007Q3–2015Q4 and then return to steady-state. Panel A. Firm learns for free the employment status of a fraction ν of applicants, and may choose to discard applicants (in equilibrium, unemployed applicants are discarded under the estimated values). Panel B. Firm learns for free the productivity of a fraction ν_1 of unviable matches and a fraction ν_2 of matches that would not otherwise be formed, and discards such applicants. Panel C. Long-lasting jobs with the set-up cost, c_e, and the advertising cost, c_v, such that the flow set-up cost, ρc_e, equals half the overall flow cost of an open job, $c_v + \rho c_e$, and the model matches the same job finding rate p as in the baseline. All panels. Cost of advertising and screening, $\{c_v, c_s\}$, recalibrated to match the job finding rate p and cost of screening share in the estimated model. *Source:* Model.

5 Understanding the persistence of labor market fluctuations

This section turns to a set of counterfactual exercises that lead to two main insights. First, changes in firms' as opposed to workers' behavior account for most of the fall in the UE rate in recessions. Second, changes in labor force composition play a key factor behind firms' lower job creation in recessions.

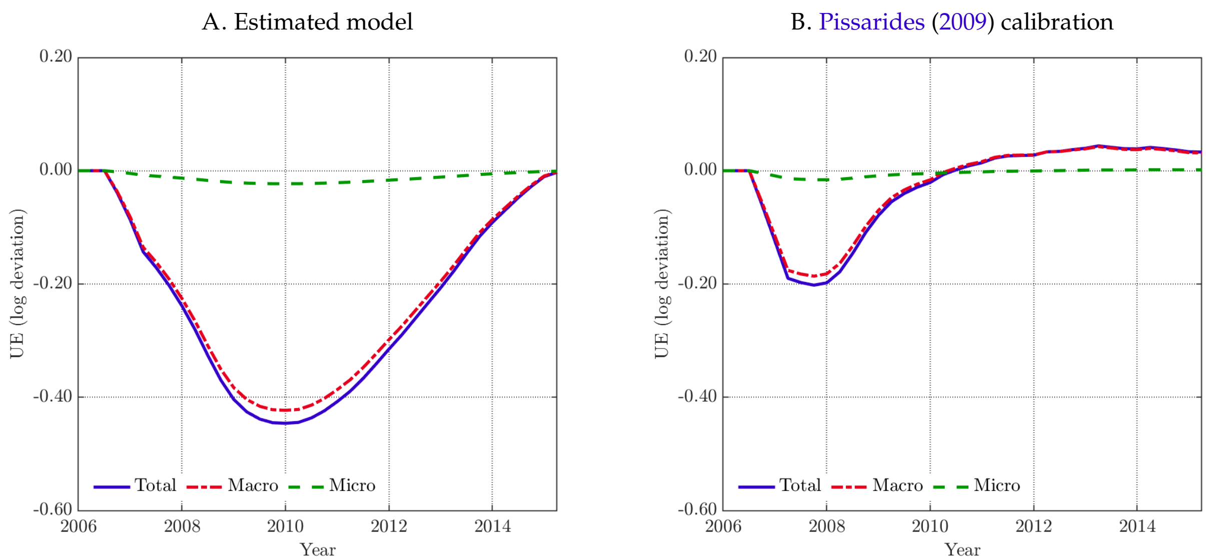
5.1 The fall in the UE rate is due to macro channels

The UE rate is affected by two channels. First, the equilibrium job finding rate per unit of search efficiency, $p(t)$, changes as firms adjust job creation over the cycle. I refer to this as the *macro* channel. Second, changes in how hard workers search for jobs, what jobs they apply for and which ones they accept impact the UE rate through a *micro* channel. That is,

$$UE(t) \quad = \quad \underbrace{p(t)}_{\text{Macro}} \underbrace{l(t) \int_{n(t)}^{\bar{z}} \Big(1 - \Psi(r(t)|z)\Big) d\Gamma(z)}_{\text{Micro}} \tag{7}$$

Figure 14 decomposes the impact of separation shocks on the UE rate according to (7) (see Appendix D.1 for a similar decomposition of the JJ rate). For comparison, I also include the Pissarides (2009) calibration, i.e. the version of the model without an application stage, $a = 0$. Specifically, I let only one of the channels in (7) evolve as in the estimated model, holding the other channel fixed at its steady-state value. Changes in worker search behavior have a small direct, micro effect on the UE rate, both in the estimated model and the Pissarides (2009) calibration. The reason is the high estimated curvature of the cost of searching, η, which implies that search neither varies much with employment status and productivity conditional on time, nor with time conditional on employment status and productivity.

FIGURE 14. DECOMPOSITION OF THE IMPACT OF SEPARATION SHOCKS ON THE UE RATE



Note: Perfect-foresight impact starting from steady-state in 2007Q2 of fluctuations in the separation rate $\delta(t)$ that mimic the EU rate between 2007Q3–2015Q4 and then return to steady-state. Decomposition of UE rate based on (7) into the role of changes in the equilibrium job finding rate $p(t)$ (*macro*) versus changes in workers' probability of moving conditional on learning about a job (*micro*). Panel A. Estimated model. Panel B. Pissarides (2009) calibration with application stage shut down, $a = 0$, and advertising and screening costs, $\{c_v, c_s\}$, recalibrated to match the same job finding rate p and screening cost share as in the estimated model. See text for details. *Source:* Model.

The prediction that worker search, for most practical purposes, is acyclical sets this paper apart from earlier work such as Nagypál (2007), Eeckhout and Lindenlaub (2019) and Faberman et al. (2020), who rely on an elastic and pro-cyclical worker search margin to amplify shocks. It also distinguishes this paper from Moscarini (2001) and Hall (2005b), who argue that changes in what jobs workers apply to play a key role in amplifying shocks. Section 6 provides reduced-form support for these predictions.

5.2 The fall in job creation is driven by composition effects

I now turn to a decomposition of the macro channel along the lines of the analysis in Section 2.2.

Methodology. The dynamic version of the free entry condition for job creation (A.9), rearranged to have the job finding rate $p(t) = y(t)^{\alpha} = q(t)^{\frac{\alpha}{\alpha-1}}$, on the left-hand side, writes

$$
\begin{aligned}
c_v p(t)^{\frac{1-\alpha}{\alpha}} &= \int_{\underline{z}}^{\overline{z}} \Big((1-\beta)(J(z,t)-U(t))^{+} - c_s\Big) \underbrace{\frac{u(t)}{S(t)}}_{\text{Composition}} \underbrace{\Big(1-\Psi(r(t)|z)\Big) l(t)}_{\text{Behavior}} d\Gamma(z) \qquad (8)\\
&+ \int_{\underline{z}}^{\overline{z}} \int_{\underline{z}}^{\overline{z}} \Big((1-\beta)(J(z,t)-J(z',t))^{+} - c_s\Big) \underbrace{\frac{1-u(t)}{S(t)} dG(z',t)}_{\text{Composition}} \underbrace{\Big(1-\Psi(R(z',t)|z)\Big) L(z',t)}_{\text{Behavior}} d\Gamma(z)
\end{aligned}
$$

where the time-varying values of a match, $J(z,t)$, and unemployment $U(t)$, are given by,

$$
\begin{aligned}
(\rho+\kappa)J(z,t) &= z + \underbrace{\delta(t)}_{\text{Direct}} \Big(U(t)-J(z,t)\Big) + \frac{\partial J(z,t)}{\partial t} dt \qquad (9)\\
&+ \frac{\eta z^{-\frac{1}{\eta}}}{1+\eta} \left(\underbrace{p(t)}_{\text{Bargaining}} \int_{\underline{z}}^{\overline{z}} \Big(\beta(J(z',t)-J(z,t))^{+} - az\Big) \Big(1-\Psi(R(z,t)|z')\Big) d\Gamma(z') \right)^{\frac{1+\eta}{\eta}} \\
(\rho+\kappa)U(t) &= b + U'(t)dt + \frac{\eta b^{-\frac{1}{\eta}}}{1+\eta} \left(\underbrace{p(t)}_{\text{Bargaining}} \int_{\underline{z}}^{\overline{z}} \Big(\beta(J(z,t)-U(t))^{+} - ab\Big) \Big(1-\Psi(r(t)|z)\Big) d\Gamma(z) \right)^{\frac{1+\eta}{\eta}}
\end{aligned}
$$

subject to $\lim_{t\to\infty} U(t) = U$, $J(z,t) \geq U(t)$ and $\lim_{t\to\infty} J(z,t) = J(z)$, where I substituted in the optimal choice of search intensity (see Appendix C.2 for details). Equations (8)–(9) highlight four channels through which shocks impact incentives to create jobs: a *direct*, a *bargaining*, a *composition* and a *behavior* effect. The first is due to the direct, partial equilibrium effect of changes in the expected duration of a match—recall the comparative static analysis in Section 2.2. The bargaining effect arises as the job finding rate adjusts in equilibrium (the qualitative analysis in Section 2.2 abstracted from this effect by assuming that $\beta \to 0$). The composition effect results from shifts in the pool of potential hires, which impact firms' incentives to create jobs. Finally, the behavior effect is the consequence of changes in workers' search behavior (Section 2.2 abstracted also from this effect by assuming that $\eta \to \infty$ and $a \to 0$).

To quantify the direct effect, I compute counter-factual value functions (9) under the time-varying separation rate $\delta(t)$, but holding the job finding rate p fixed at its steady-state value. Based on these counter-factual value functions, I compute a counter-factual job finding rate $\tilde{p}(t)$ based on (8) holding composition $\{u, g(z)\}$ and behavior $\{l, L(z), r, R(z)\}$ fixed at their steady-state values. To isolate the role of the bargaining effect, I resolve the value functions (9) under the time-varying equilibrium job finding rate $p(t)$, holding the separation rate δ fixed at its steady-state value. Based on these counter-factual value functions, I compute a counter-factual job finding rate $\tilde{p}(t)$ based on (8) holding other channels fixed. To quantify the composition effect, I compute a counter-factual job finding rate $\tilde{p}(t)$ based on (8) under the equilibrium evolution of labor force composition, but with values and worker behavior fixed at their steady-state values. Finally, the behavior effect results from letting workers' search behavior evolve as in the dynamic equilibrium, while holding values and composition fixed.

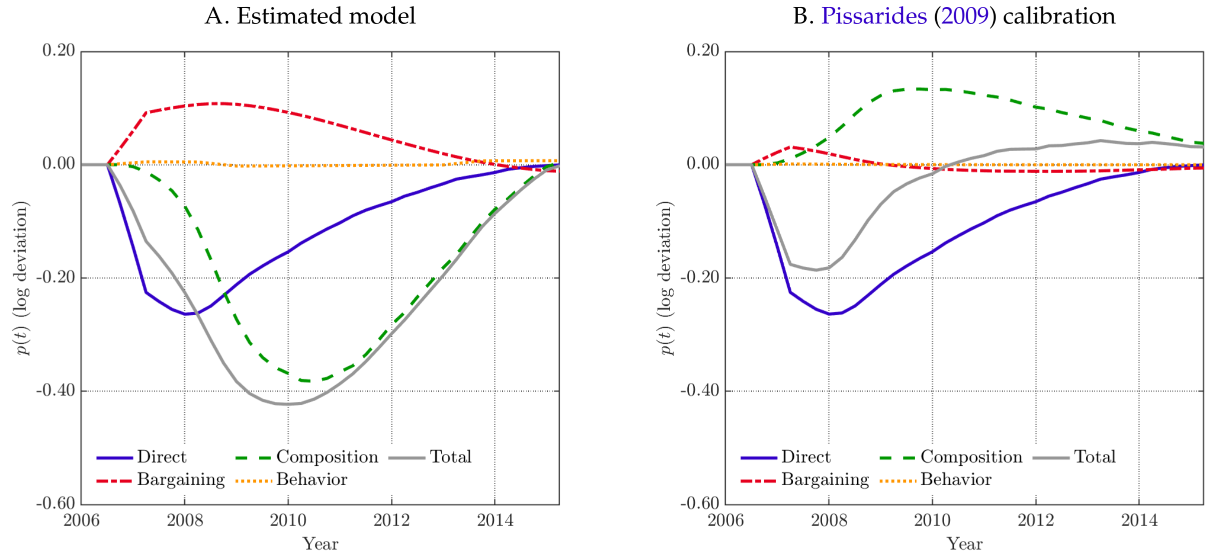
Results. Figure 15 plots the impact of separation shocks on the job finding rate via the channels highlighted in (8)–(9) for the estimated model in panel A. The direct effect accounts for much of the initial fall in job creation, despite the fact that the separation rate initially *falls* given when I start the perfect foresight experiment. The reason is the shorter expected future duration of new jobs, which discourages hiring already on impact.

At the same time, the equilibrium bargaining effect mutes the impact of the direct effect. As the job finding rate falls, it becomes effectively costlier for workers to decline a job offer, because they have to wait longer for another offer to arrive. Consequently, their bargaining position worsens, at the benefit of recruiting firms. Indeed, Hagedorn and Manovskii (2008) advocate for a very low bargaining power of workers β and Hall and Milgrom (2008) abandon Nash bargaining in favor of credible bargaining exactly to mute this powerful offsetting force. A muted bargaining effect, however, is not the reason separation shocks are amplified and in particular propagated in the estimated model (recall that $\beta = 0.5$; see also Appendix C.1 for robustness with respect to β).

Instead, shifts in the pool of potential hires toward the unemployed and down the job ladder serve to significantly amplify the effect of separation shocks through the composition effect (Appendix D.2 shows that the most important channel behind the composition effect is, in turn, the increase in unemployment, as opposed to the shift of employment down the job ladder). Such shifts effectively raise the cost to firms of recruiting, discouraging job creation. Moreover, because changes in composition are slow to materialize, they contribute critically to propagation of shocks. In contrast, the behavior effect is second-order, because worker search and application behavior changes little.

Panel B shows why a model without an application stage does not generate large, persistent declines

FIGURE 15. UNDERSTANDING THE IMPACT OF SEPARATION SHOCKS ON THE JOB FINDING RATE



Note: Perfect-foresight impact starting from steady-state in 2007Q2 of fluctuations in the separation rate $\delta(t)$ that mimic the EU rate between 2007Q3–2015Q4 and then return to steady-state. Decomposition of job finding rate based on (8). See text for details. *Source:* Model.

in the job finding rate in response to a temporary increase in the separation rate. By construction, the direct effect is as large as in the estimated model, while the bargaining effect is weaker since the equilibrium fall in the job finding rate is smaller. The fundamental difference is the composition effect. The build-up in the share of unemployed job applicants *encourages* job creation in benchmark models, because the unemployed are more likely to accept a job offer and the surplus from hiring such workers is larger. Since the composition effect counters the direct effect, separation shocks fail to match the empirical volatility and, in particular, persistence of labor market outcomes. A central prediction of the theory is hence that higher unemployment *discourages* vacancy creation. Appendix D.3 provides time series evidence consistent with this prediction, following Coles and Kelishomi (2018).

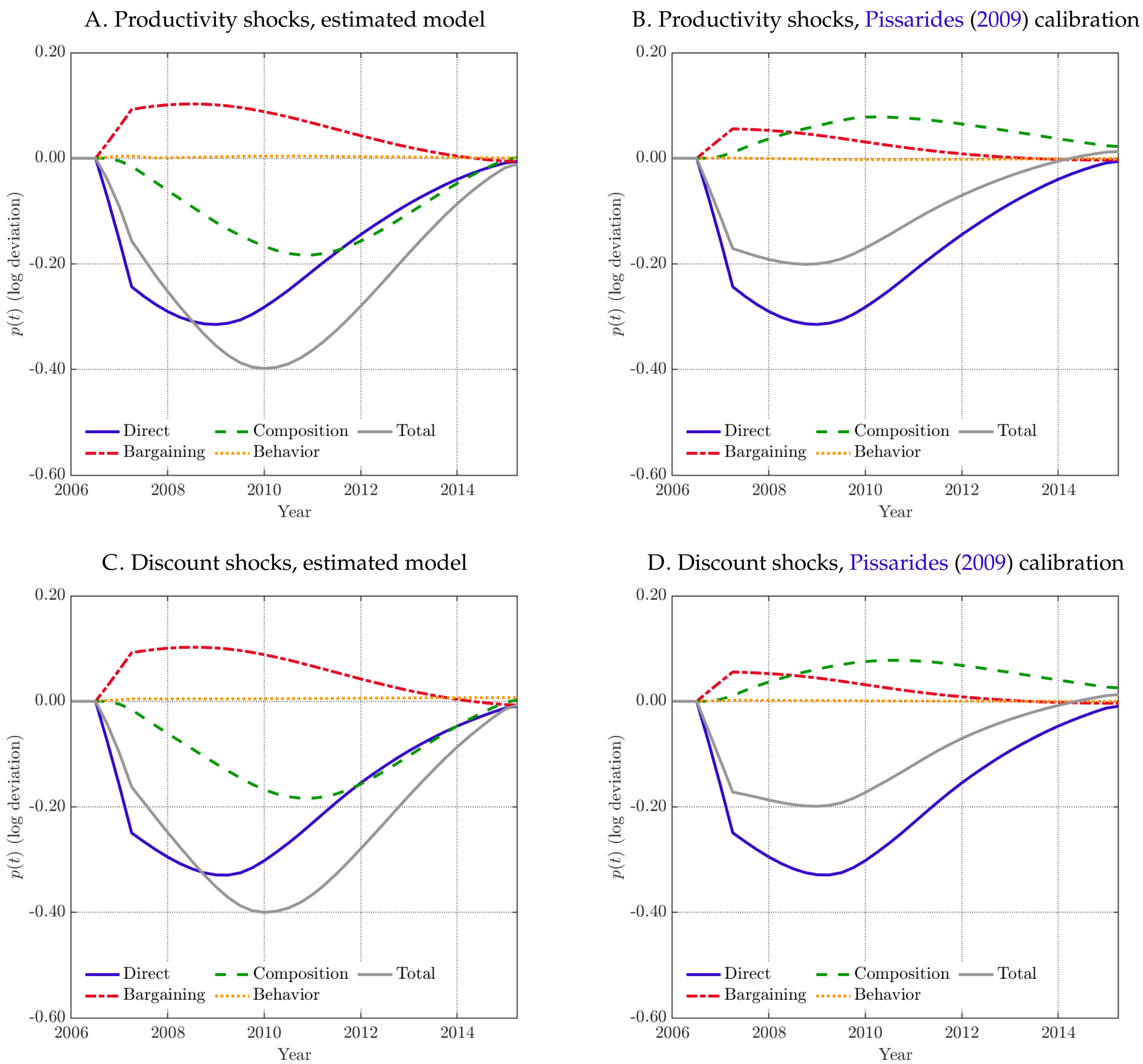
Recall from the qualitative, comparative statics analysis in Section 2.2 that a change in the separation rate impacts the equilibrium by shifting both the JC curve (2) and the Beveridge curve (5). Appendix D.4 quantifies the role of these two channels, finding an important role played by both channels.

5.3 Propagation of other shocks

Most of the analysis so far has focused on separation shocks, because they showed promise in accounting for the path of the UE rate during the past four US recessions. Nevertheless, the mechanism emphasized here would also propagate other shocks, including productivity and discount shocks. In particular, the direct impact of such shocks in (9) would be different—they would impact the flow value of the match

$z(t)$ or the discount rate $\rho(t)$, respectively, instead of the separation rate $\delta(t)$—but the equilibrium forces would be similar. To highlight this point, I feed in a path for aggregate productivity, $Z(t)$, or the discount rate, $\rho(t)$, such that the path for the job finding rate is the same as under the separation shocks analyzed above. Appendix 5.3 shows that this requires a fall in aggregate productivity is 23 percent, i.e. an order of magnitude larger than in the data, while the discount rate must rise from five to 12 percent.

FIGURE 16. UNDERSTANDING THE IMPACT OF OTHER SHOCKS ON THE JOB FINDING RATE



Note: Perfect-foresight impact starting from steady-state in 2007Q2 of fluctuations in aggregate productivity, $Z(t)$, or the discount rate, $\rho(t)$, that generate the same path for the job finding rate $p(t)$ as under the separation shocks considered above between 2007Q3–2015Q4 and then return to steady-state. Aggregate productivity $Z(t)$ shifts the productivity of all matches, new and old, proportionally. Decomposition of job finding rate based on (8); see text for details. *Source:* Model.

Figure 16 shows that these two alternative sources of shocks require a larger direct effect to generate the same equilibrium fall in the job finding rate as separation shocks. In an accounting sense, this is because the composition effect is weaker, whereas the bargaining and behavior effects are of the same size. Separation shocks impact the expected discounted flow value of a match *and* the rate at which workers separate to unemployment, whereas productivity and discount shocks only affect the expected discounted flow value (the separation rate may, of course, still change endogenously in response). This second channel—higher unemployment due to a higher inflow rate—is why the previous literature has preferred productivity or discount shocks over separation shocks, because *ceteris paribus* higher unemployment encourages job creation in benchmark models. In contrast, here this force discourages job creation by raising the cost of recruiting. Consequently, the predictions of the estimated model differ more from those of existing theories under separation shocks. Nevertheless, the impact of productivity and discount shocks remains larger and in particular more persistent relative to previous models.

6 Reduced-form support

In this last section of the paper, I turn to reduced-form support for two salient predictions of the theory: pro-cyclical search is not a key factor amplifying shocks, while a counter-cyclical cost of recruiting is.

6.1 Data and methodology

Long time series of rich data on worker search behavior and firm recruiting outcomes are not available, so I instead exploit spatial covariation between these outcomes and the unemployment rate based on three data sources. First, I construct the state-year unemployment rate from the CPS. Second, I compute the number of applications submitted and the number of hours spent on job search in a month by all workers as well as for the unemployed only at the state-year level in 2013–2017 based on the SCE. Third, I calculate applications received per vacancy, hours spend on recruiting per vacancy and the time to fill a vacancy at the city-year level in the 1980–1982 EOPP (I discuss the EOPP in some more detail in Appendix B.2). To provide a comparison with the model, I also conduct the same perfect foresight transition experiment as above, but for a set of artificial localities characterized by differential paths for the separation rate $\delta(t)$ constructed so as to replicate the experiences of US states over this period.

6.2 Results

Worker search outcomes. Panel A of Table 6 projects the number of applications a worker submitted or the number of hours she spent on job search in the past month on the local unemployment rate, either among all workers or only the unemployed (measured one month earlier). All variables are in logs, and hence the point estimate may be interpreted as an elasticity. In my baseline specification, I do not include any covariates, but I have verified that the same conclusion holds if I instead use residual worker search outcomes and the residual unemployment rate controlling flexibly for age, education, gender and race, as well as if I instead use only the cyclical HP-filtered component of the local unemployment rate.

The point estimates indicate that search intensity is counter-cyclical, consistent with findings in Mukoyama et al. (2018) based on time use surveys, although none is statistically significant at conventional levels. Higher unemployment is associated with workers submitting more applications and spending more hours on job search. According to the model, separation shocks account for a large share of these patterns, including the fact that hours on job search and number of applications are counter-cyclical among all workers, but pro-cyclical among the unemployed. The reason is that as the job finding rate falls, workers have a lower chance of finding a job to apply to and hence spend fewer hours applying. At the same time, labor force composition shifts toward unemployment and down the job ladder, raising the average probability that a worker applies for a job conditional on learning about it. The second force is so strong that aggregate search intensity is counter-cyclical. This offsetting effect, however, is not active among the unemployed, who hence unambiguously spend less time applying for jobs.

Firm recruiting outcomes. Panel B regresses the number of applications firms receive per vacancy, hours spent on recruiting per vacancy, and the duration of a vacancy on the local unemployment rate.[26] All variables are in logs, so the point estimates are elasticities. Higher unemployment is associated with firms receiving more applications, spending more hours on recruiting, and filling vacancies faster. Because applications per vacancy and hours spent on recruiting per vacancy rise more than vacancy duration falls, applications per hire and time per hire rise with the unemployment rate. According to the model, separation shocks account for a large share of these reduced-form empirical patterns.

Subject to the usual caveats associated with applying a cross-sectional estimate to aggregate time trends, Figure 17 contrasts the implied fluctuations in firms' recruiting outcomes based on the point estimates in Table 6 during the Great Recession with the predictions of the model. In the spirit of the quote at the beginning of this paper, firms get inundated in applications in recessions, as illustrated by panel A. Indeed, the fact that the structural estimates and the reduced form variation line up so well is quite remarkable, given that they exploit very different sources of variation. Firms spend more time on

[26]One possible concern is that if some locations have worse recruiting practices, that may show up as more time spent on recruiting *and* higher unemployment. In robustness exercises (available on request), I find similar results exploiting only the cyclical component of the local unemployment rate. To the extent that such differences in recruiting practices are time-invariant, these findings suggests that such omitted variables are not driving these empirical patterns.

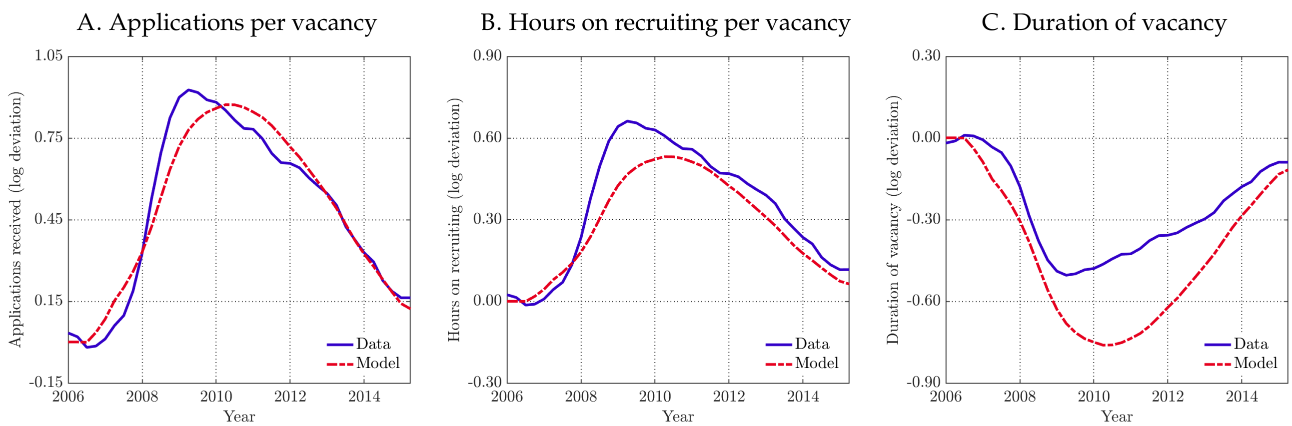
TABLE 6. WORKER & FIRM SEARCH OUTCOMES, DATA VS MODEL

	A. Worker search outcomes				B. Firm search outcomes		
	Hours	Hours (U)	# Apps.	# Apps. (U)	Applications	Hours	Duration
Data	0.009	-0.235	0.503	-0.221	1.306***	0.933***	-0.710**
	(0.343)	(0.259)	(0.307)	(0.388)	(0.389)	(0.197)	(0.270)
Model	0.126	-0.483	0.353	-0.612	1.337	0.770	-1.160

Note: Regression of the log of the locality-year level outcome on the log state-year unemployment rate plus a constant, with standard errors in parenthesis (clustered by locality). Panel A. All individuals aged 18–64; (U) refers to only unemployed individuals (based on status one month prior to survey). Level of variation is state-year. Model based outcomes are from a perfect-foresight experiment for 50 "states" starting from steady-state in 2007Q3 of fluctuations in the separation rate, $\delta(t)$, constructed so as to replicate the experiences of US states over the 2007Q3–2015Q4 period and then return to steady-state, using only years 2013–2015 to align with the data. Panel B. Level of variation is city-year. Model based outcomes are from a perfect-foresight experiment for 28 "cities" starting from steady-state in 1980Q1 of fluctuations in the separation rate, $\delta(t)$, constructed so as to replicate the experiences of US states over the 1980Q1–1988Q4 period and then return to steady-state, using only years 1980–1982 to align with the data. All panels. * significant at 10%; ** significant at 5%. *Source:* Model, CPS, EOPP and SCE 1980–2017.

recruiting in panel B, while filling vacancies faster in panel C. In fact, the model implies that separation shocks overstate the fall in vacancy durations in the data, suggesting that additional forces serve to slow down recruiting in recessions. Plausible factors include difficulty quickly scaling up hiring, as captured by convex recruiting costs (Fujita and Ramey, 2007).

FIGURE 17. FIRMS' RECRUITING ENVIRONMENT, MODEL



Note: Model is based on perfect-foresight impact starting from steady-state in 2007Q2 of fluctuations in the separation rate $\delta(t)$ that mimic the EU rate between 2007Q3–2015Q4 and then return to steady-state. Data are based on the estimated cross-sectional elasticities in Panel B of Table 6 times the log deviation in aggregate unemployment. *Source:* Model, CPS, EOPP and SCE 1980–2017.

7 Conclusion

Recent micro evidence on how workers search for jobs is shown to have critical implications for the macroeconomic propagation of labor market shocks. Because the unemployed apply for more jobs that they are unlikely to be a good fit for, it becomes harder for firms to assert who is a good fit for the job during periods of high unemployment. By dissuading job creation, a short-lived adverse shock has a persistent negative impact on job finding. Reduced-form evidence supports the prediction that firms receive more applications and spend more time on hiring when unemployment is high.

My findings shed new light on the sources of large, persistent fluctuations in labor market outcomes. In particular, I find an important role for separation shocks in accounting for the behavior of the job finding rate in recessions. This finding is consistent with an earlier literature that viewed recessions as periods of increased reallocation of labor across sectors or firms, driven by greater dispersion in idiosyncratic demand (Lilien, 1982). For instance, the construction sector contracted in the Great Recession, necessitating the reallocation of workers to other sectors. It is also consistent with recent evidence of greater idiosyncratic volatility in recessions (Bloom et al., 2018), in particular a higher incidence of negative idiosyncratic firm-level shocks (Salgado et al., 2019).

The findings in this paper suggest that firms may want to charge applicants a fee in order to discourage workers from applying for jobs that they think they would be unlikely to be a good fit for. It would be interesting to understand why such fees are rarely observed in the real world, with worker risk aversion, financial market incompleteness and equity considerations being some plausible factors. For instance, firms may worry that such fees would particularly discourage poor but suitable candidates from applying. Other potential reasons include the fact that scam firms would have an incentive to charge fees but never hire, such that no worker would be willing to apply to a job that required a fee. It would also be interesting to assess the implications of worker search behavior for secular labor market trends. In particular, a secular decline in the cost of applying for jobs—for instance due to increasing use of Internet-based job search—may, perhaps counter-intuitively, have *reduced* labor market dynamics.

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Online Appendix—Not for Publication

A Model

This section presents details on the model in Section 2.

A.1 Value functions

Denote by U the value of unemployment and by $J(z)$ the value of a match between a worker and a firm with productivity z. A well-known feature of this class of models is that the equilibrium is bilaterally optimal, so it is sufficient to consider the problem of an unemployed worker and a match to solve for the allocation (Engbom, 2020). Hence, in the interest of space I present recursions for workers' value and discuss further how wages are determined in Appendix A.4.

The value of unemployment solves the Hamilton-Jacobi-Bellman equation (HJB),

$$(\rho+\kappa)U = b+\max_{l}\left\{lp\int_{\underline{x}}^{\overline{x}}\max\left\{\beta\int_{\underline{z}}^{\overline{z}}\max\left\{J(z)-U,0\right\}d\Omega(z|x)-ab,0\right\}d\Phi(x)-\frac{bl^{1+\eta}}{1+\eta}\right\} \tag{A.1}$$

where κ is the permanent exit rate introduced in Section 3. An unemployed worker enjoys flow value of leisure b and choses the rate pl at which she learns about job openings. If she becomes aware of an opening, she observes a signal x of the underlying productivity of the match z distributed according to $\Phi(x)$. Based on the signal, she has to decide whether to spend ab applying for the job. The firm screens her application,[27] match productivity is revealed, the match is formed if it provides positive surplus, and the worker gets a share β of the surplus.

As in McCall (1970), an unemployed worker prefers work over unemployment in any match with productivity greater than some reservation threshold n, implicitly defined by $U = J(n)$. I assume that a higher signal x is associated with a higher underlying productivity z, in a first-order stochastic sense, $\partial\Omega(z|x)/\partial x < 0$. Because the value of a match is increasing in productivity, the optimal application decision of the unemployed is characterized by a reservation rule r,[28]

$$ab = \beta\int_{\underline{z}}^{\overline{z}}\Big(J(z)-U\Big)^{+}d\Omega(z|r) \tag{A.2}$$

where $(x)^{+} = \max\{x,0\}$. The application reservation threshold r is such that the cost of applying, ab, equals the expected return to applying, consisting of a share β of the surplus from a match. The worker applies if the signal is sufficiently good, $x \geq r$, and does not apply otherwise.

[27] Notice that a firm has not received any additional information between the advertising and screening phase. Hence, if it finds it worthwhile to advertise a job, it also finds it worthwhile to screen the applications it receives for the job.

[28] Assuming that $J'(z) > 0$, an integration by parts of the right hand side of (A.2) implies that

$$\int_{n}^{\overline{z}}\Big(J(z)-U\Big)d\Omega(z|x) = -\Big[\Big(1-\Omega(z|x)\Big)\Big(J(z)-U\Big)\Big]_{z=n}^{\overline{z}}+\int_{n}^{\overline{z}}\Big(1-\Omega(z|x)\Big)J'(z)dz = \int_{n}^{\overline{z}}\Big(1-\Omega(z|x)\Big)J'(z)dz$$

since $\lim_{z\to\overline{z}}\Omega(z|x) = 1$ and $J(n) = U$. Hence, the derivative of the right hand side of (A.2) with respect to the signal equals $-\int_{n}^{\overline{z}}\frac{\partial\Omega(z|x)}{\partial x}J'(z)dz$, which is positive since by assumption $J'(z) > 0$ and $\partial\Omega(z|x)/\partial x < 0$.

Using the optimal reservation rule and Bayes' rule, the optimal search intensity l is given by

$$l = \left(\frac{p}{b}\int_{\underline{z}}^{\overline{z}}\left(\beta(J(z)-U)^{+}-ab\right)\left(1-\Psi(r|z)\right)d\Gamma(z)\right)^{\frac{1}{\eta}} \tag{A.3}$$

The searching worker learns about an open job at rate p and sample a potential productivity z from the offer distribution $\Gamma(z)$. She observes a signal $x|z \sim \Psi(x|z)$ that depends on the underlying productivity. If the signal is good enough, $x \geq r$, she concludes that it is worthwhile spending time a (with opportunity cost ab) applying for the job. The conditional probability that she applies is hence $1-\Psi(r|z)$. The firm screens her application, the match is formed if $z \geq n$, and the worker gets a share β of the surplus.

The value of a match is given by the HJB equation,

$$\begin{aligned}(\rho+\kappa)J(z) &= z+\delta(U-J(z)) \\ &+ \max_{l}\left\{lp\int_{\underline{x}}^{\overline{x}}\max\left\{\beta\int_{\underline{z}}^{\overline{z}}(J(z')-J(z))^{+}d\Omega(z|x)-az,0\right\}d\Phi(x)-\frac{zl^{1+\eta}}{1+\eta}\right\}\end{aligned} \tag{A.4}$$

A match produces z and separates at rate δ, in which case the worker becomes unemployed and the firm gets value zero. It optimally choses the arrival rate of job opportunities, pl. If the worker encounters a job opening, she observes a signal x distributed according to $\Phi(x)$ and submits an application at cost az if the signal is sufficiently good. The new firm screens her application, match productivity is revealed, the match is formed if it provides positive surplus, and the worker gets a share β of the differential surplus.[29]

A worker employed in a match with productivity z moves to another employer z' whenever $z' \geq z$. As for the unemployed, the application decision of the employed is also characterized by a reservation threshold: apply for the job if and only if the signal of fit is sufficiently good, $x \geq R(z)$, given by,

$$az = \beta\int_{\underline{z}}^{\overline{z}}\left(J(z')-J(z)\right)^{+}d\Omega(z'|R(z)) \tag{A.5}$$

The optimal search intensity of the employed, $L(z)$, is given by the first-order condition,

$$L(z) = \left(\frac{p}{z}\int_{\underline{z}}^{\overline{z}}\left(\beta(J(z')-J(z))^{+}-az\right)\left(1-\Psi(R(z)|z')\right)d\Gamma(z')\right)^{\frac{1}{\eta}} \tag{A.6}$$

following the same logic as that behind (A.3). Notice again the assumption that incumbent matches can contract on the worker's application and search behavior, which greatly simplifies the problem.

A.2 Stationary law of motion

The distribution of employment, $g(z)$, satisfies for $z \geq n$ the Kolmogorov forward equation (KFE),

$$\begin{aligned}0 &= -\left(\kappa+\delta+L(z)p\int_{z}^{\overline{z}}\left(1-\Psi(R(z)|z')\right)d\Gamma(z')\right)g(z) \\ &+ \gamma(z)p\left(\left(1-\Psi(r|z)\right)\frac{lu}{1-u}+\int_{n}^{z}L(z')(1-\Psi(R(z')|z))dG(z')\right)\end{aligned} \tag{A.7}$$

[29] When a worker moves to a new employer, the value of the previous match is lost but the worker gets compensated by the full value of the old match plus a share β of the differential surplus between the two matches. From the joint perspective of the old match, it gains a share β of the differential surplus when the worker moves to a new employer.

where the unemployment rate, u, is given by

$$0 = -\left(\kappa + pl\int_{n}^{\overline{z}}\Big(1-\Psi(r|z)\Big)d\Gamma(z)\right)u + (1-u)\delta + \kappa \tag{A.8}$$

Workers in equation (A.7) leave matches with productivity z either because they permanently exit at rate κ, separate to unemployment at rate δ, or find a new better job. The latter is a function of how hard they search, $L(z)$, the equilibrium contact rate p, the offer distribution $\gamma(z)$, and the probability that they submit an application depending on the signal, $\psi(R(z)|z')$. There is an inflow of workers into matches of productivity z from unemployment and employment that depends on the offer density at z, $\gamma(z)$, the contact rate p, search intensity, $\{l, L(z)\}$, the application reservation threshold, $\{r, R(z)\}$, and the distribution of unemployed and employed workers, $\{u, g(z)\}$.

A.3 Free entry and equilibrium

Given a stationary distribution for the composition of the labor force $\{u, g(z)\}$ defined by (A.7)–(A.8), free entry requires that entrepreneurs advertise jobs until the cost of doing so, c_v, equals the expected return,

$$\begin{aligned} c_v \;=\;& \underbrace{q\,\frac{ul}{S}\int_{\underline{z}}^{\overline{z}}\Big((1-\beta)(J(z)-U)\mathbb{1}_{z\geq n} - c_s\Big)\Big(1-\Psi(r|z)\Big)d\Gamma(z)}_{\text{Expected return from meeting unemployed worker}} \\ &+ \underbrace{q\,\frac{1-u}{S}\int_{\underline{z}}^{\overline{z}}\int_{\underline{z}}^{\overline{z}}\Big((1-\beta)(J(z)-J(z'))\mathbb{1}_{z\geq z'} - c_s\Big)\Big(1-\Psi(R(z')|z)\Big)d\Gamma(z)L(z')dG(z')}_{\text{Expected return from meeting employed worker}} \end{aligned} \tag{A.9}$$

A vacancy contacts a potential hire at worker finding rate q and draws a productivity of the potential match from offer distribution $\Gamma(z)$. The potential hire is randomly drawn from the search efficiency weighted pool of workers, and makes an optimal decision whether to apply based on the signal she observes of fit. If the firm receives an application, it pays the screening cost, match productivity is revealed, the match is formed if it provides positive surplus, and the firm gets a share $1-\beta$ of the value.

Definition 1. *A stationary search equilibrium consists of value functions, $\{U, J(z), W(z,w)\}$; a reservation threshold, $\underline{z}$; search policies, $\{l, L(z)\}$; application reservation thresholds, $\{r, R(z)\}$; wage policies, $\{w_u(z), w(z,z')\}$; finding rates and vacancies, $\{p, q, V\}$; and a distribution of workers $\{u, g(z)\}$ such that*

1. *The value functions, search policies and application reservation thresholds solve the problem of the unemployed (A.1) and the match (A.4);*
2. *The value function of workers and wage policies are consistent with the splitting rule, (A.10)–(A.11);*
3. *The finding rates are consistent with the search intensity of workers and the number of vacancies;*
4. *The distribution of workers are consistent with the law of motion (A.7)–(A.8);*
5. *The number of vacancies is consistent with free entry (A.9).*

A.4 Value of worker

Let $W(z,w)$ be the value to a worker of being employed in a match with productivity z when paid wage w under optimal policy rules $R(z)$ and $L(z)$. It satisfies the HJB,

$$\begin{aligned}(\rho+\kappa)W(z,w) &= w+\delta\Big(U-W(z,w)\Big) \\ &+ pL(z)\int^{z}\Big(J(z')+\beta(J(z)-J(z'))-W(z,w)\Big)^{+}\Big(1-\Psi(R(z)|z')\Big)d\Gamma(z') \\ &+ pL(z)\int_{z}\Big(J(z)+\beta(J(z')-J(z))-W(z,w)\Big)\Big(1-\Psi(R(z)|z')\Big)d\Gamma(z')\end{aligned} \tag{A.10}$$

As noted above, the worker's search intensity, $L(z)$, and application threshold, $R(z)$, are assumed to be contractable between the incumbent firm and worker. Notice also that the worker is assumed to search on the job at the cost of forgone production, such that the cost is explicitly born by the firm (but implicitly shared with the worker through a lower wage).

Based on the value function of the worker, two policies characterize wages. The wage of an unemployed worker who meets a firm with productivity z is given by $w_u(z)$. The wage of a worker currently employed in a match with productivity z who successfully meets a potential alternative employer $z' \geq z$ is given by $w(z,z')$. These wage policies are defined by

$$W(z,w_u(z)) = U+\beta\Big(J(z)-U\Big), \qquad W(z',w(z,z')) = J(z)+\beta\Big(J(z')-J(z)\Big) \tag{A.11}$$

A.5 Proofs

Proposition 1 An unemployed worker applies for a job given signal x if and only if the cost of applying is less than the expected return to applying conditional on the signal x, i.e. if

$$\frac{a}{\beta}b < \int_{\underline{z}}^{\overline{z}}\Big(J(z)-U\Big)^{+}d\Omega(z|x) \tag{A.12}$$

When the signal is unviable, x_u, the right hand side of (A.12) is strictly positive since

$$\begin{aligned}\int_{\underline{z}}^{\overline{z}}\Big(J(z)-U\Big)^{+}d\Omega(z|x_u) &= \underbrace{\frac{(1-\psi)\gamma_u}{(1-\psi)\gamma_u+\psi\gamma_b}\times 0}_{\text{productivity is unviable}}+\underbrace{\frac{\psi\gamma_b}{(1-\psi)\gamma_u+\psi\gamma_b}\Big(J(z_b)-U\Big)}_{\text{productivity is bad}} \\ &= \frac{\psi\gamma_b}{(1-\psi)\gamma_u+\psi\gamma_b}M_b > 0\end{aligned}$$

Since $\lim \frac{a}{\beta}=0$, an unemployed worker applies for the job regardless of the signal (it is straightforward to show that the right hand side of (A.12) is strictly positive when the signal is bad or good).

A mismatched worker ($z=z_b$) applies for a job given signal x if and only if the cost of applying is less than the expected return to applying conditional on the signal x, i.e. if and only if

$$\frac{a}{\beta}z < \int_{\underline{z}}^{\overline{z}}\Big(J(z')-J(z)\Big)^{+}d\Omega(z'|x) \tag{A.13}$$

When the signal is unviable, x_u, the right hand side of (A.13) is identically zero since

$$\int_{\underline{z}}^{\overline{z}} \Big(J(z') - J(z)\Big)^+ d\Omega(z'|x_u) \;=\; \underbrace{\frac{(1-\psi)\gamma_u}{(1-\psi)\gamma_u + \psi\gamma_b}}_{\text{productivity is unviable}} \times 0 + \underbrace{\frac{\psi\gamma_b}{(1-\psi)\gamma_u + \psi\gamma_b}\Big(J(z_b) - J(z_b)\Big)}_{\text{productivity is bad}} \;=\; 0$$

Hence, a mismatched worker will not apply for a job that sends a bad signal. When the signal is bad, x_b, the right hand side of (A.13) is strictly positive, since

$$\begin{aligned}\int_{\underline{z}}^{\overline{z}} \Big(J(z') - J(z)\Big)^+ d\Omega(z'|x_u) \;&=\; \underbrace{\frac{\psi\gamma_u}{\psi\gamma_u + (1-2\psi)\gamma_b + \psi\gamma_g}}_{\text{productivity is unviable}} \times 0 + \underbrace{\frac{(1-2\psi)\gamma_b}{\psi\gamma_u + (1-2\psi)\gamma_b + \psi\gamma_g} \times 0}_{\text{productivity is bad}} \\ &+ \underbrace{\frac{\psi\gamma_g}{\psi\gamma_u + (1-2\psi)\gamma_b + \psi\gamma_g}\Big(J(z_g) - J(z_b)\Big)}_{\text{productivity is good}} \;>\; 0\end{aligned}$$

Hence, a mismatched worker will apply for a job that sends a bad signal (it is straightforward to show that the right hand side of (A.13) is strictly positive when the signal is good).

A well-matched worker ($z = z_g$) applies for a job given signal x if and only if the cost of applying is less than the expected return to applying conditional on the signal x. Since a well-matched worker cannot improve her productivity, she never applies for a job (this follows from the assumption that the incumbent firm and worker can contract on search and application behavior, such that the worker does not exert costly search for the sole benefit of reshuffling rents between her and her current employer).

The optimal search intensity of an unemployed worker (A.3) is

$$l \;=\; \beta^{\frac{1}{\eta}} \left(\frac{p}{b} \int_{\underline{z}}^{\overline{z}} \Big((J(z) - U)^+ - \frac{a}{\beta} b \Big) \Big(1 - \Psi(r|z) \Big) d\Gamma(z) \right)^{\frac{1}{\eta}} \tag{A.14}$$

Since $\lim \frac{a}{\beta} = 0$, the term in the brackets limits to something strictly positive, which raised to something that limits to zero equals one. Since $\lim \beta^{\frac{1}{\eta}} = \lim (\eta\beta)^{\frac{1}{\eta}} \eta^{-\frac{1}{\eta}}$ and by assumption $\lim \eta\beta = 1$, it follows that $\lim \beta^{\frac{1}{\eta}} = 1$. Consequently, the optimal search intensity of the unemployed is one. A similar logic establishes that the optimal search intensity of a mismatched worker is also one. Finally, a well-matched worker has a zero return to search, and hence does not search.

Substituting these optimal policies into the value of unemployment (A.1) and the value of a match (A.4),

$$\begin{aligned}(\rho + \kappa)U \;&=\; b \\ (\rho + \kappa)J(z) \;&=\; z + \delta(U - J(z)) \\ J(z) - U \;&=\; \frac{z - b}{\rho + \delta}\end{aligned}$$

for $z = \{z_b, z_g\}$.

Proposition 2 The derivative of tightness with respect to the ratio of unemployed job seekers is,

$$\frac{\partial \log y}{\partial \log\left(\frac{u}{g_b}\right)} = \frac{Y}{1-\xi}, \qquad Y = \frac{\frac{u}{g_b}\left(\left(\gamma_b+\gamma_g\right)\left(z_b-b\right)-C_2\right)}{\gamma_g\left(z_g-z_b\right)-C_1+\frac{u}{g_b}\left(\left(\gamma_b+\gamma_g\right)\left(z_b-b\right)-C_2\right)} \tag{A.15}$$

where $\xi = p'(y)y/p(y) \in (0,1)$ is the elasticity of the job finding rate with respect to tightness. Hence, a higher ratio of unemployed job seekers incentivizes firms to enter if

$$\underbrace{(\gamma_b+\gamma_g)\frac{z_b-b}{\rho+\delta}}_{\text{Excess return from screening unemployed}} \quad > \quad \underbrace{c_s\Big((1-\psi)\gamma_u+\psi\gamma_b\Big)}_{\text{Excess cost from screening unemployed}}$$

Proposition 3 A firm prefers to screen an unemployed applicant if the expected return to doing so exceeds the cost,

$$\underbrace{\gamma_b\frac{z_b-b}{\rho+\delta}+\gamma_g\frac{z_g-b}{\rho+\delta}}_{\text{Return from screening unemployed}} \quad > \quad c_s \quad \iff \quad \gamma_g\frac{z_g-z_b}{\rho+\delta}+(\gamma_b+\gamma_g)\frac{z_b-b}{\rho+\delta} \quad > \quad c_s$$

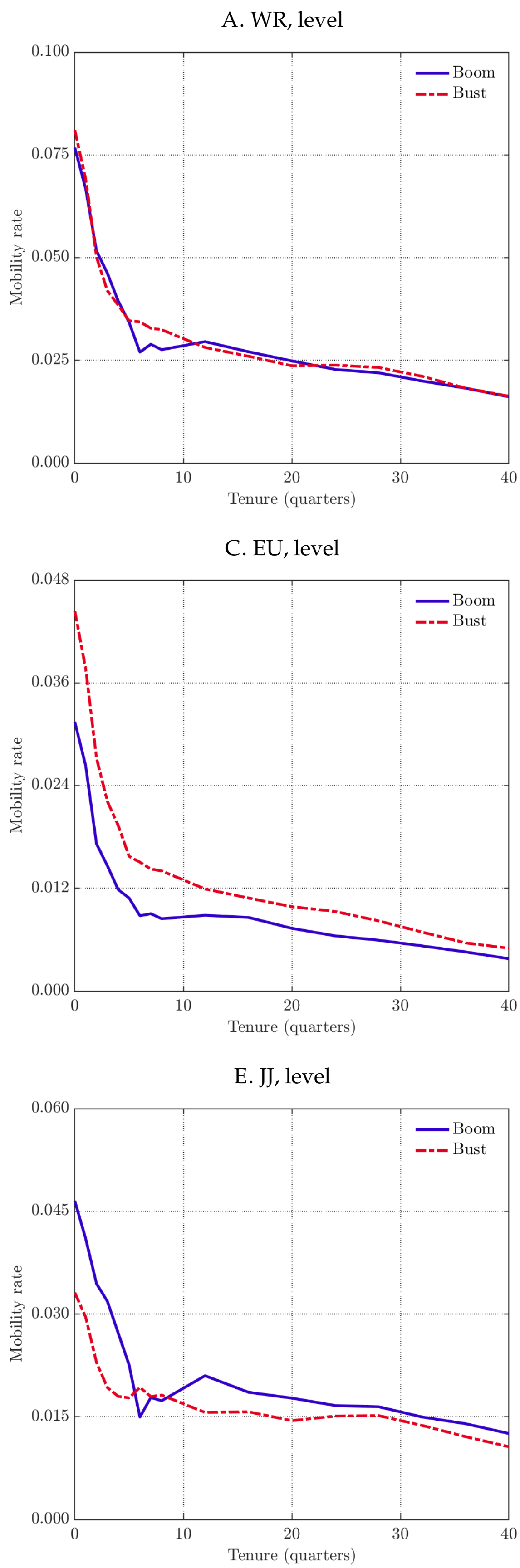
Combining this with condition (3) gives the expression in the paper.

A.6 Mobility by tenure

This subsection shows that mobility by tenure changes proportionately during recessions. To this end, I merge the 1983–2018 CPS tenure supplements with the basic monthly CPS data, measuring tenure as the number of quarters a worker has been with her current employer. I first residualize the mobility rates by regressing a worker's probability of making an EU or JJ move in the current month on tenure-date fixed effects, controlling for age, gender, education and race. Subsequently, I collapse the estimated tenure-date fixed effects to the tenure-date level, take the logs of the estimates, and regress this on flexible tenure effects and their interaction with the log unemployment rate, controlling for a linear time trend to account for secular trends. I use the estimated coefficients to predict mobility rates at each tenure associated with a one standard deviation lower or higher unemployment rate (roughly 50 percent lower or higher unemployment), which I label as "Boom" and "Bust," respectively.

Figure A.1 plots the resulting residual worker mobility by tenure according to three measures—overall worker mobility (EU+JJ), EU mobility and JJ mobility—in either logs or levels. Note that the "Boom" and "Bust" designations refer to the state of the unemployment rate at the time of the survey, not at the time a match was formed. Five observations stand out. First, as is well known, all forms of worker mobility decline with tenure. Second, the sum of the monthly EU and JJ mobility rates is close to acyclical. Third, the acyclicality of the overall worker mobility rate is due to almost fully offsetting movements in the EU and JJ mobility rates—the EU rate rises during recessions by an equal amount as the JJ falls at all tenure levels. Fourth, because the EU and JJ rates are similar in levels at all tenure levels, the offsetting movements over the business cycle also serve to generate a close to acyclical log worker mobility rate. Fifth, the EU and JJ mobility rates by tenure move close to proportionally up or down over the business cycle. In particular, there is little evidence that matches formed during recessions would be of higher quality in the sense that they last longer in a relative sense. I stress that this statement should be interpreted in a matching sense, according to which an "overqualified" worker is a *worse* match.

FIGURE A.1. MOBILITY BY TENURE IN BOOMS AND BUSTS, DATA



Note: Data: Individuals aged 18–64. EU rate: Share of wage employed who are unemployed in the subsequent month. JJ rate: Share of wage employed who are employed at a different employer relative to last month. WR rate: Sum of EU and JJ rates. *Source:* CPS 1983–2018.

B Estimation

This section provides details on the data and estimation in Section 3.

B.1 Algorithm

I solve the problem numerically on a discretized grid for productivity with n grid points in three steps using an implicit method. Note first that the value of unemployment can be written as

$$\begin{aligned}
\rho U &= b - \frac{\eta}{1+\eta} lpab \int_{\underline{z}}^{\overline{z}} \Big(1 - \Psi(r_u|z')\Big)\gamma(z')dz' \\
&+ \frac{\eta}{1+\eta} lp\beta \int_{\underline{z}}^{\overline{z}} \Big(1 - \Psi(r_u|z')\Big)\gamma(z')\mathbb{1}_{J(z')\geq U}\Big(J(z') - U\Big)dz' - \kappa U \\
&= \mathbf{f}_u + \Big(\mathbf{T}_u + \mathbf{D}_u + \mathbf{K}_u\Big)\mathbf{V}
\end{aligned}$$

where $\mathbf{f}_u$ is the net flow value in unemployment under optimal policies (a scalar), $\mathbf{T}_u$ is an 1-by-$n+1$ optimal transition vector from unemployment under optimal policies, $\mathbf{D}_u$ is an 1-by-$n+1$ vector of zeros, and $\mathbf{K}_u$ is an 1-by-$n+1$ exogenous exit vector. Similarly, the value of employment can be written as

$$\begin{aligned}
\rho J(z) &= z - \frac{\eta}{1+\eta} L(z)paz \int_{\underline{z}}^{\overline{z}} \Big(1 - \Psi(r(z)|z')\Big)\gamma(z')dz' \\
&+ \frac{\eta}{1+\eta} L(z)p\beta \int_{\underline{z}}^{\overline{z}} \Big(1 - \Psi(r(z)|z')\Big)\gamma(z')\mathbb{1}_{z'\geq z}\Big(J(z') - J(z)\Big)dz' - \delta(J(z) - U) - \kappa J(z) \\
&= \mathbf{f}_e + \Big(\mathbf{T}_e + \mathbf{D}_e + \mathbf{K}_e\Big)\mathbf{V}
\end{aligned}$$

where $\mathbf{f}_e$ is the n-by-1 vector of net flow output under the optimal policies, $\mathbf{T}_e$ is an n-by-$n+1$ optimal transition matrix from employment under optimal policies, $\mathbf{D}_e$ is an n-by-$n+1$ exogenous transition matrix into unemployment, and $\mathbf{K}_e$ is an n-by-$n+1$ permanent exit matrix. Combining the equations for unemployment and employment, the value recursion can be written in matrix form as

$$\rho\mathbf{V} = \mathbf{f} + \mathbf{A}\mathbf{V}, \quad \text{where } \mathbf{f} = \begin{bmatrix} \mathbf{f}_u \\ \mathbf{f}_e \end{bmatrix}, \ \mathbf{A} = \left(\underbrace{\begin{bmatrix} \mathbf{T}_u \\ \mathbf{T}_e \end{bmatrix}}_{\mathbf{T}} + \underbrace{\begin{bmatrix} \mathbf{D}_u \\ \mathbf{D}_e \end{bmatrix}}_{\mathbf{D}} + \underbrace{\begin{bmatrix} \mathbf{K}_u \\ \mathbf{K}_e \end{bmatrix}}_{\mathbf{K}} \right), \ \mathbf{V} = \begin{bmatrix} U \\ \mathbf{J} \end{bmatrix}$$

To solve a stationary version of the model, I iterate over three steps. I start by guessing an initial $n+1$-by-1 vector $\mathbf{V}_0$. Then for each iteration $i \geq 0$

1. Find the $n+1$-by-1 reservation vector $\mathbf{r}_i$ and $n+1$-by-1 search vector $\mathbf{s}_i$;

2. Construct the optimal transition matrix $\mathbf{A}_i$ and flow output $\mathbf{f}_i$;

3. Update the value functions according to

$$\mathbf{V}_{i+1} \quad = \quad ((\rho + \Delta)\mathbb{I}_{n+1} - \mathbf{A}_i) \setminus (\mathbf{f}_i + \Delta \mathbf{V}_i)$$

where Δ is a (generally small) step-size parameter and $\mathbb{I}_{n+1}$ is the $n+1$-by-$n+1$ identity matrix. If $\mathbf{V}_{i+1}$ is sufficiently close to $\mathbf{V}_i$, stop; otherwise return to 1.

Having obtained optimal decision rules, I can ex post solve in one step for the invariant distribution of employment over the job ladder from,

$$\mathbf{g} \quad = \quad -\hat{\mathbf{A}}^T \setminus \begin{bmatrix} \kappa \\ \mathbf{0}_{n\times 1} \end{bmatrix}$$

where $\mathbf{0}_{n\times 1}$ is a vector of zeros of length n-by-1 and $\hat{\mathbf{A}} = \hat{\mathbf{T}} + \mathbf{D} + \mathbf{K}$ is an augmented version of the converged mobility matrix based on,

$$\hat{\mathbf{T}}_u \quad = \quad lp \int_{\underline{z}}^{\overline{z}} \Big(1 - \Psi(r_u|z')\Big) \gamma(z') \mathbb{1}_{J(z') \geq U} dz'$$

$$\hat{\mathbf{T}}_e \quad = \quad L(z)p \int_{\underline{z}}^{\overline{z}} \Big(1 - \Psi(r(z)|z')\Big) \gamma(z') \mathbb{1}_{z' \geq z} dz'$$

This algorithm is generally very fast as it avoids a general equilibrium loop. This is possible because although the job finding rate p is truly an equilibrium object, it can be treated a parameter during estimation. Ex post, the flow cost of a vacancy—a free parameter—can be set such that p is consistent with optimal behavior of firms based on

$$S \quad = \quad lu + (1-u) \int_{\underline{z}}^{\overline{z}} L(z) dG(z), \qquad V \quad = \quad p^{\frac{1}{\theta}} S, \qquad q \quad = \quad \left(\frac{V}{S}\right)^{\theta - 1}$$

and the free entry condition (A.9).

As the allocation can be determined without alluding to wages, I solve for wages in a last step after having solved for the allocation. In fact, since I do not target any moments related to wages in estimation, there is no need to solve for wages during estimation.

B.2 Data details

The SCE survey is annual, cross-sectional and currently available for 2013–2017. While the survey was designed to be representative, non-response necessitates the use of survey weights, which I employ throughout my analysis. It asks workers about current employment status, earnings, standard demographic variables, and a rich set of questions about job search in the past four weeks, including whether the respondent looked for a job, how many applications she sent, whether she received any job offers, and whether she accepted a job. It asks these questions both of those currently employed and non-employed. The survey also records information on the current and previous employment spell, including start and end dates, sector, occupation, pay, hours, etc.

The EOPP. While 40 years old, the EOPP provides the best available data on firm recruiting outcomes in the US. The survey asks firms retrospective questions regarding recruiting at the time of their last hire (which could have taken place several years prior to the survey), including how many applications they received, how many hours they spent on recruiting, and how long it took to fill the vacancy. It focuses on 28 cities, which I link to the local unemployment rate in the year of the last hire from the CPS. As the historical CPS micro data do not contain rich geographic identifiers, I use the state-level unemployment rate. Moreover, the CPS only identifies all states starting in 1978 and very few firms made their last hire in 1982, so I focus on the 1978–1981 period for which over 96 percent of observations refer to.

B.3 Variable definitions

A worker is employed if she is currently working for pay. She is unemployed if she either does not have a job but searched for one in the past four weeks and is available to start, or is on layoff (regardless of whether she searches or not). Note that following Faberman et al. (2020), the definition of employment status differs slightly from the standard BLS definition, as it includes also those who search for a job but say they do not want one. To align the retrospective job search questions with the theory, I construct a measure of employment status one month prior to the survey and compute all search outcomes relative to employment status one month earlier. I discuss further below how I impute employment status one month earlier. A worker makes an EU (UE) transition if she was employed (unemployed) one month prior to the survey, but is unemployed (employed) at the time of the survey. She makes a JJ transition if she was employed one month prior to the survey and is employed at the time of the survey, but with at most one month of tenure with her current employer.

To be consistent with the theory, I compute all search outcomes by employment status one month earlier. I infer employment status one month earlier using an algorithm that extends that in Faberman et al. (2020). In particular, I use the following sequential approach:

1. Worker received a job offer in the past month
   - 1.1 She was employed at the time of the offer $\implies$ she was employed one month ago
   - 1.2 She was not employed at the time of the offer:
     - i. Year is 2013
       - A. She is currently employed or unemployed $\implies$ she was unemployed one month ago
       - B. She is currently NILF $\implies$ she was NILF one month ago
     - ii. Year is not 2013
       - A. She was looking for a job at the time of the offer or she is currently on layoff $\implies$ she was unemployed one month ago
       - B. She was not looking for a job at the time of the offer and she is not currently on layoff $\implies$ she was NILF one month ago
2. Worker did not receive a job offer in the past month
   - 2.1 She is currently employed
     - i. She has more than 1 month of tenure $\implies$ she was employed one month ago
     - ii. She has one 1 month of tenure or less
       - A. Her activity prior to her current employment was not non-employment $\implies$ she was employed one month ago

B. The time between her current job and previous job was less than 2 weeks $\implies$ she was employed one month ago
C. Her activity prior to her current employment was non-employment, she previously had a job, she had at least 2 weeks between employment spells and she has been looking for work for at least 30 days $\implies$ she was unemployed one month ago
D. Her activity prior to her current employment was non-employment, she previously had a job, she had at least 2 weeks between employment spells and she has been looking for work for less than 30 days $\implies$ she was NILF one month ago
E. Her activity prior to her current employment was non-employment, she never had a job before, and she has been looking for work for at least 30 days $\implies$ she was unemployed one month ago
F. Her activity prior to her current employment was non-employment, she never had a job before, and she has been looking for work for less than 30 days $\implies$ she was NILF one month ago

2.2 She is currently unemployed
- i. She is on layoff
  - A. Less than 4 weeks $\implies$ she was employed one month ago
  - B. At least 4 weeks $\implies$ she was unemployed one month ago
- ii. She is not on layoff
  - A. Length of current non-employment spell is less than one month $\implies$ she was employed one month ago
  - B. Length of current non-employment spell is at least one month and has been looking for work for at least 30 days $\implies$ she was unemployed one month ago
  - C. Length of current non-employment spell is at least one month and she has been looking for work for less than 30 days $\implies$ she was NILF one month ago

2.3 She is currently NILF
- i. Length of current non-employment spell is less than one month $\implies$ she was employed one month ago
- ii. Length of current non-employment spell is at least one month
  - A. She has been looking for work for at least 30 days $\implies$ she was unemployed one month ago
  - B. She has been looking for work for less than 30 days $\implies$ she was NILF one month ago

B.4 Comparison with CPS

Table B.1 provides a comparison with labor market stocks and flows in the CPS for the overlapping 2013–2017 period. As noted by Faberman et al. (2020), the SCE overstates somewhat the labor force participation rate, wage employment rate and unemployment rate relative to the CPS. It understates the EU rate and the UE rate, bringing it more in line with panel data sets such as the Panel Study of Income Dynamics and the Survey of Income and Program Participation (Engbom, 2020). This is consistent with the well-known fact that the CPS overstates gross worker flows due to measurement error in employment status (Abowd and Zellner, 1985; Poterba and Summers, 1986). The JJ rate is somewhat higher in the SCE than the raw number in the CPS.

TABLE B.1. SUMMARY STATISTICS RELATIVE TO THE CPS

	LF particip.	Empl. rate	Unempl. rate	EU rate	UE rate	JJ rate
SCE	0.818	0.676	0.073	0.006	0.155	0.022
CPS	0.754	0.647	0.060	0.011	0.229	0.018

Note: Individuals aged 18–64. LF particip.: Sum of wage employed, self employed and unemployed divided by population; Empl. rate: Wage employed divided by population; Unempl. rate: Unemployed divided by sum of unemployed and wage employed; EU rate: Share of wage employed in previous month who are unemployed in current month; UE rate: Share of unemployed in previous month who are wage employed in current month; JJ rate: Share of wage employed in previous month who are wage employed at a different employer in current month. All panels and moments: Weighted using provided survey weights. *Source:* CPS and SCE 2013–2017.

C Persistent Labor Market Fluctuations

This section provides additional details on the dynamic model in Section 4.

C.1 Workers' bargaining power

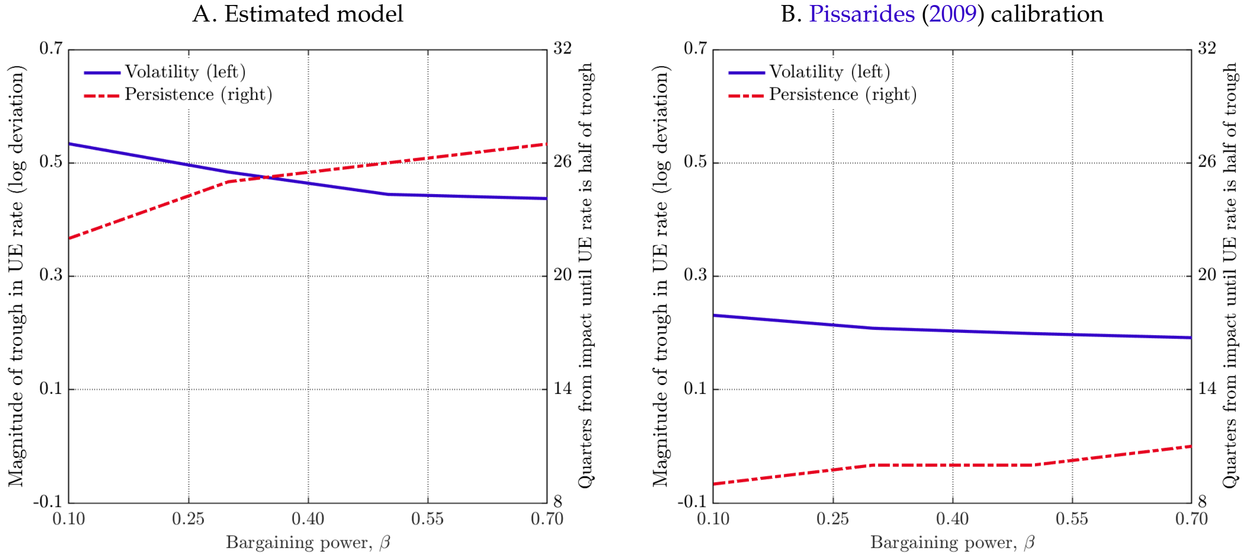
This paper emphasizes an inefficiency in the application stage, since workers do not fully internalize the cost (and benefit) of submitting an application. That is, the model is in general inefficient. That being said, I preset the bargaining power of workers to the elasticity of the matching function with respect to vacancies, $\beta = \theta$, alluding to a Hosios (1990) condition although no such condition is known to hold here. Is a violation of the Hosios (1990) condition why I reach such different findings relative to the earlier literature? To illustrate that this does not appear to be why I find such persistent effects of shocks, I consider a range of alternative values for β ranging from 0.1 to 0.7.[30] I recalibrate the cost of advertising jobs and screening applicants to be consistent with free entry under the same job finding rate p and screening cost share of total hiring costs as the estimated model.

Panel A of Figure C.1 shows that the volatility of the UE rate falls and the persistence rises in β. The fact that a low β is associated with a more volatile UE rate is well-known (Mortensen and Nagypal, 2007; Hagedorn and Manovskii, 2008). The reason is that it isolates the wage from movements in tightness. Quantitatively, however, changes in β has a modest impact on the volatility and persistence of the UE rate, which consistently remain much larger than in the Pissarides (2009) calibration in panel B.

It would be very interesting to contrast the business cycle behavior of the decentralized economy with that chosen by a social planner subject to the same technological constraints. Solving the planner's problem over the transition path, however, is beyond the available numerical techniques. The reason is that although workers and firms in the decentralized equilibrium need to forecast the evolution of the entire distribution of employment over the job ladder, they do not think that their decisions impact this evolution. A social planner, on the other hand, recognizes that her decisions impact the evolution of this distribution. Consequently, her problem is to make a sequence of choices so as to *control the evolution of the entire distribution* of employment. Computationally, this is a very demanding problem to solve. For this reason, I focus on a positive analysis in this paper, and leave a normative analysis to future work.

[30]While workers fully internalize the impact of their application decision when $\beta = 1$, firms would not create any jobs for such a high value of β. Similarly, if $\beta = 0$, workers would never bother to search and apply for jobs.

FIGURE C.1. ROBUSTNESS TO WORKERS' BARGAINING POWER



Note: Perfect-foresight impact starting from steady-state in 2007Q2 of fluctuations in the separation rate $\delta(t)$ that mimic the EU rate between 2007Q3–2015Q4 and then return to steady-state. Impact of varying workers' bargaining power β. Panel A. Estimated model with cost of advertising and screening, $\{c_v, c_s\}$, recalibrated to match the same job finding rate p and screening cost share of recruiting as in the estimated model. Panel B. Pissarides (2009) calibration with application stage shut down, $a = 0$, and advertising and screening costs, $\{c_v, c_s\}$, recalibrated to match the same job finding rate p and screening cost share as in the estimated model. *Source:* Model.

C.2 Dynamic value functions

The time-varying value a match, $J(z,t)$, and unemployment, $U(t)$, solve the HJB equations,

$$\begin{aligned}(\rho+\kappa)J(z,t) &= z + \delta(t)(U(t) - J(z,t)) + \frac{\partial J(z,t)}{\partial t}dt \\ &+ \max_l \left\{ lp(t) \int_{\underline{x}}^{\overline{x}} \max\left\{ \beta \int_{\underline{z}}^{\overline{z}} \max\left\{ J(z',t) - J(z,t), 0 \right\} d\Omega(z|x) - az, 0 \right\} d\Phi(x) - \frac{zl^{1+\eta}}{1+\eta} \right\}\end{aligned} \tag{C.1}$$

$$\begin{aligned}(\rho+\kappa)U(t) &= b + U'(t)dt \\ &+ \max_l \left\{ lp(t) \int_{\underline{x}}^{\overline{x}} \max\left\{ \beta \int_{\underline{z}}^{\overline{z}} \max\left\{ J(z,t) - U(t), 0 \right\} d\Omega(z|x) - ab, 0 \right\} d\Phi(x) - \frac{bl^{1+\eta}}{1+\eta} \right\}\end{aligned} \tag{C.2}$$

subject to the boundary conditions $J(z,t) \geq U(t)$, $\lim_{t\to\infty} J(z,t) = J(z)$ for all z and $\lim_{t\to\infty} U(t) = U$.[31] The optimal search and application policies are

$$
\begin{aligned}
L(z,t) &= \left(\frac{p(t)}{z}\int_{\underline{z}}^{\overline{z}}\Big(\beta(J(z',t)-J(z,t))^{+}-az\Big)\Big(1-\Psi(R(z,t)|z')\Big)d\Gamma(z')\right)^{\frac{1}{\eta}} && \text{(C.3)}\\
l(t) &= \left(\frac{p(t)}{b}\int_{\underline{z}}^{\overline{z}}\Big(\beta(J(z,t)-U(t))^{+}-ab\Big)\Big(1-\Psi(r(t)|z)\Big)d\Gamma(z)\right)^{\frac{1}{\eta}}\\
az &= \beta\int_{\underline{z}}^{\overline{z}}\Big(J(z',t)-J(z,t)\Big)^{+}d\Omega(z'|R(z,t)), \qquad ab \;=\; \beta\int_{\underline{z}}^{\overline{z}}\Big(J(z,t)-U(t)\Big)^{+}d\Omega(z|r(t))
\end{aligned}
$$

Substituting optimal search intensity into the value of a match (C.1) and unemployment (C.2) gives (9). In addition, the optimal reservation threshold $n(t)$ is implicitly defined by,

$$
U(t) = J\Big(n(t),t\Big) \qquad \text{(C.4)}
$$

The dynamic value of a worker who is paid wage w in match z at time t, $W(z,w,t)$, solves

$$
\begin{aligned}
(\rho+\kappa)W(z,w,t) &= w+\delta(t)\Big(U(t)-W(z,w,t)\Big) && \text{(C.5)}\\
&+ p(t)L(z,t)\int^{z}\Big(J(z',t)+\beta(J(z,t)-J(z',t))-W(z,w,t)\Big)^{+}\Big(1-\Psi(R(z,t)|z')\Big)d\Gamma(z')\\
&+ p(t)L(z,t)\int_{z}\Big(J(z,t)+\beta(J(z',t)-J(z,t))-W(z,w,t)\Big)\Big(1-\Psi(R(z,t)|z')\Big)d\Gamma(z')
\end{aligned}
$$

subject to the boundary conditions $W(w,z,t) \geq U(t)$, $W(w,z,t) \leq J(z,t)$ and $\lim_{t\to\infty} W(w,z,t) = W(w,z)$ for all w and z. In cases where either the worker would like to separate to unemployment under the going wage, $W(w,z,t) < U(t)$, or the firm terminate the match, $W(w,z,t) < J(z,t)$, I allow for renegotiation of the wage such that the party that has a credible threat to leave the match is left indifferent between exercising the threat and remaining in the match under the updated wage.

These wage policies $w_u(z)$ and $w(z,z',t)$ are given by

$$
W(z,w_u(z,t),t) = U(t)+\beta\Big(J(z,t)-U(t)\Big), \quad W(z',w(z,z',t),t) = J(z,t)+\beta\Big(J(z',t)-J(z,t)\Big) \qquad \text{(C.6)}
$$

[31] Note that the problem of a match is now a stopping time problem, as a worker may prefer to be employed in some match $\hat{z}$ at time t, but not in match $\hat{z}$ at some other time t'. While I allow for endogenous separations, it turns out that in the discretized approximation of the model, fluctuations in the reservation threshold $\underline{z}(t)$ are not large enough to switch across grid points.

C.3 Dynamic evolution of labor market

The evolution of the composition of the labor force in the dynamic equilibrium is given by

$$\begin{aligned}
\frac{\partial g(z,t)}{\partial t} &= -\left(\kappa + \delta(t) + L(z,t)p(t)\int_{z}^{\overline{z}} \Big(1 - \Psi(R(z,t)|z')\Big) d\Gamma(z')\right) g(z,t) \qquad \text{(C.7)} \\
&+ \gamma(z)p(t)\left(\Big(1 - \Psi(r(t)|z)\Big)\frac{l(t)u(t)}{1-u(t)} + \int_{n(t)}^{z} L(z',t)(1 - \Psi(R(z',t)|z))dG(z',t)\right) \\
u'(t) &= -\left(\kappa + p(t)l(t)\int_{n(t)}^{\overline{z}} \Big(1 - \Psi(r(t)|z)\Big) d\Gamma(z)\right) u(t) + (1-u(t))\delta(t) + \kappa
\end{aligned}$$

subject to $g(z,0) = g(z)$ for all z and $u(0) = u$.[32]

C.4 Dynamic equilibrium

Definition 2. *A dynamic search equilibrium consists of value functions, $\{U(t), J(z,t), W(z,w,t)\}$; a reservation threshold, $n(t)$; search policies, $\{l(t), L(z,t)\}$; application reservation thresholds, $\{r(t), R(z,t)\}$; wage policies, $\{w_u(z,t), w(z,z',t)\}$; finding rates and aggregate vacancies, $\{p(t), q(t), V(t)\}$; and a distribution of workers $\{u(t), g(z,t)\}$ such that*

1. *The value functions, search policies and application reservation thresholds solve the problem of the match and unemployed worker* (C.1)–(C.2)*;*
2. *The value function of workers and wage policies are consistent with the splitting rule,* (C.5)–(C.6)*;*
3. *The finding rates are consistent with the implied aggregate search intensity of workers and the aggregate number of vacancies;*
4. *The distribution of workers evolves according to the law of motion* (C.7)*;*
5. *The aggregate number of vacancies is consistent with free entry* (8)*.*

C.5 Dynamic algorithm

The dynamic version of the model is more involved to solve than the stationary version, as it requires solving for the entire path for the distribution of workers over the job ladder. Nevertheless, the advantages of working in continuous time make it feasible to solve the problem without resorting to approximation techniques such as, for instance, parameterizing the distributions. I solve the problem using what is essentially a large-dimensional shooting algorithm, iterating backward and forward in time until the value functions and distributions have converged.

I start by expanding the state-space to also include time by constructing a discretized grid for time up to some large T and by guessing an $n+1$-by-T matrix of values, $\mathbf{V}_0$, over this grid (a reasonable first guess is a replicated version of the stationary solution). I also compute an $n+1$-by-$n+1$-by-T optimal transition matrix $\mathbf{T}_0$ consistent with the value functions. Then for each iteration $i \geq 0$,

[32] Technically, there is also a boundary condition $g(n(t),t) = 0$ for all t and a corresponding inflow to unemployment. This reflects the possibility that a match that is viable at time t may not be so at time $t + \Delta$, in which case I allow for endogenous separations. In the numerical approximation, however, the movement in values is too small to induce a change in the reservation productivity across grid points. Hence, to simplify the notation I do not include this term in (C.7).

1. Going forward in time, given optimal mobility $\mathbf{T}_i$, update the vector of job finding rates $\mathbf{p}_{i+1}$ such that free entry holds at any point in time. Update the distribution of workers $\mathbf{g}_{i+1}$ to be consistent with optimal mobility $\mathbf{T}_i$ and the job finding rate $\mathbf{p}_{i+1}$;

2. Going backward in time, given a vector of job finding rates $\mathbf{p}_{i+1}$, solve the time-dependent problem of the match and the unemployed to obtain updated optimal mobility $\mathbf{T}_{i+1}$. If this transition matrix is sufficiently close to that in iteration i, stop; otherwise return to 1.

Solving the dynamic model takes significantly longer time than the static model. For this reason, I use the static model in estimation, as it requires solving the model a large number of times.

C.6 Mobility by residual wage

This subsection shows that mobility by residual wages changes proportionately during recessions. To this end, I merge the 1978–2019 CPS ASEC files with the basic monthly CPS data, measuring the hourly wage as total annual labor income divided by total annual hours worked. I first compute residual wages by regressing log hourly wages on age, education, gender, race, education, occupation and industry dummies, fully flexibly by year. I drop individuals earning less than a quarter of the federal minimum wage in 2019 ($7.25/4). Subsequently, I bin individuals into wage deciles based on their residual wage. Second, I residualize mobility rates by regressing a worker's probability of making an EU move in the current month on wage decile-year fixed effects, controlling for age, gender, education and race. Subsequently, I collapse the estimated wage decile-year fixed effects to the wage decile-year level, take the logs of the estimates, and regress this on flexible wage decile effects and their interaction with the log unemployment rate, controlling for a linear time trend to account for secular trends. I use the estimated coefficients to predict mobility rates at each wage decile associated with a one standard deviation lower or higher unemployment rate (roughly 50 percent lower or higher unemployment), which I label as "Boom" and "Bust," respectively.

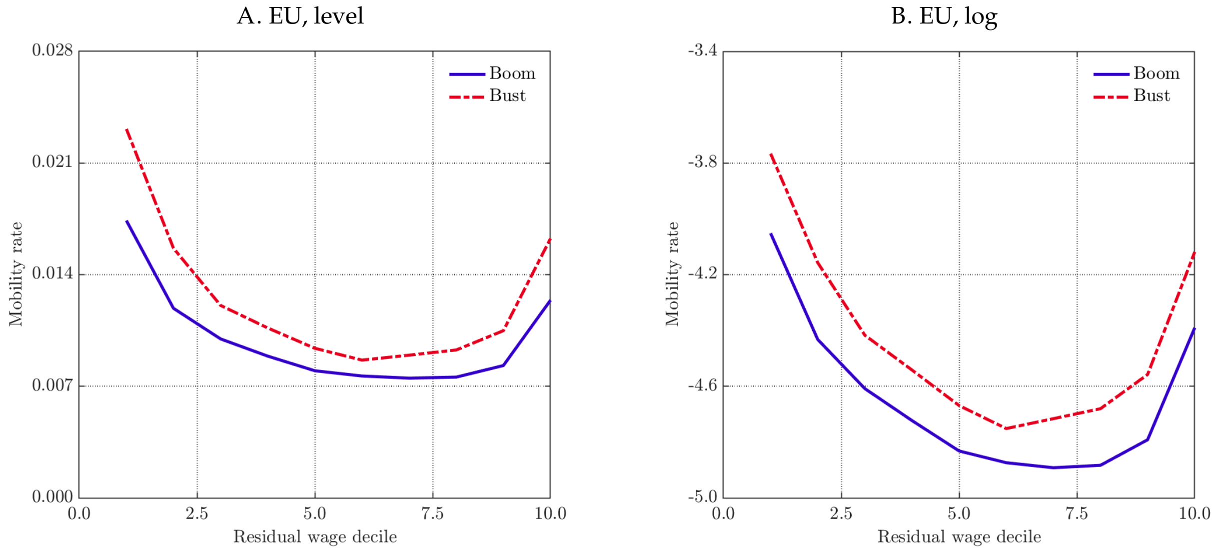
Figure C.2 plots the resulting residual EU mobility rate by wage decile in either logs or levels. Two observations stand out. First, the EU rate falls with the residual wage. Second, the EU rate by residual wage decile moves close to proportionally up or down over the business cycle. In particular, there is little evidence that matches at the bottom of the ladder are more likely to break up in recessions.

C.7 Additional results

Figure C.3 plots additional labor market outcomes during the Great Recession in response to separation shocks. Panel A shows the number of unemployed. Following Shimer (2005) I plot the HP-filtered log stock of unemployment, but the path for the HP-filtered log unemployment *rate* is essentially identical. Separation shocks account for a large share of the volatility and persistence of the share of unemployed. In fact, they account for a larger share of the evolution of unemployment than the UE rate. The likely reason is that the model abstracts from flows in and out of non-participation. While the discrepancy between the empirical unemployment rate and that which would be predicted based on a two-state model and EU/UE flows is not that large—motivating my decision to abstract from modeling non-participation in order to focus on the key novelty in this paper—it would nevertheless be interesting to incorporate also non-participation in future work.

Panel B shows that separation shocks overstate the volatility of vacancies. Vacancies, however, are known to be measured imperfectly in the data, which may account for the discrepancy. Panel C plots that the ratio of vacancies to unemployed (I refer to this as the V/U ratio to differentiate it from the

FIGURE C.2. MOBILITY BY WAGE DECILE IN BOOMS AND BUSTS, DATA



Note: Individuals aged 16+. EU rate: Share of wage employed who are unemployed in the subsequent month; residual controlling for age, gender, education and race. Residual wage decile: Residual log hourly wage controlling for age, education, gender, race, education, occupation and industry dummies, fully flexibly by year. Boom (Bust) refers to a period of one standard deviation lower (higher) aggregate unemployment rate. *Source:* CPS 1978–2019.

theoretical concept of tightness, V/S). Separation shocks account for a large share of the decline and persistence.

C.8 From micro to macro—structural parameters

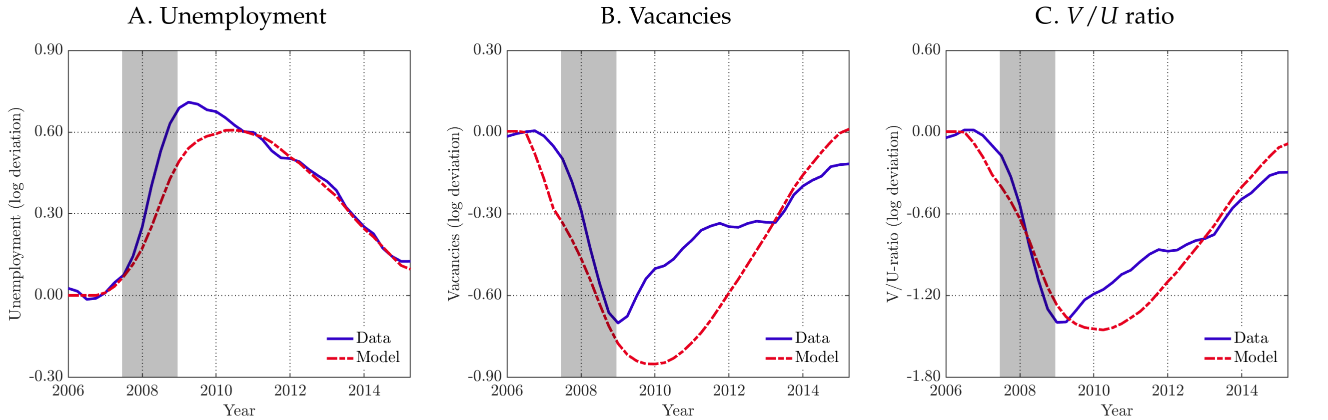
Figure C.4 plots how the business cycle properties of the model vary with the underlying structural parameters, a and c_s, instead of the reduced form equilibrium moments shown in Figure 12.

C.9 The noise in the signal, σ, and business cycle dynamics

An alternative way to attain essentially the same result as in Section 4.3 with respect to varying the cost of applying, a, is to instead vary the noise in the signal, σ. A more noisy signal relative to its estimated value serves to raise the application-to-mobility rate of workers. Moreover, because the employed are more selective in the estimated model—i.e. their application-to-mobility rate is lower—a higher σ particularly raises their application-to-mobility rate. Indeed, in the limit $\sigma \to \infty$, workers always apply such that the ratio of the application-to-mobility rates of the unemployed to the employed converges to the ratio of the mobility rate of the employed to the unemployed, i.e. the model converges to the Pissarides (2009) model. Across all calibrations, the cost of advertising and screening, $\{c_v, c_s\}$, are set to match the same job finding rate p and cost share of screening as in the benchmark.[33]

[33] *Ceteris paribus*, greater noise in the signal reduces workers' search intensity and it impacts the chance that a worker fails to apply to a job that she would have accepted. Because search is so inelastic and the cost of applying so low, these two margins are second-order. In particular, across all counterfactuals the realized mobility rates deviate by at most three percent relative to the benchmark in steady-state, and their cyclical properties are virtually unaffected by adjusting the job finding rate p to target the same job finding rate as in the estimated model. Hence for simplicity, I opt to not recalibrate the job finding rate p.

FIGURE C.3. THE IMPACT OF SEPARATION SHOCKS IN THE GREAT RECESSION, MODEL VS DATA



Note: Perfect-foresight impact starting from steady-state in 2007Q2 of fluctuations in the separation rate $\delta(t)$ that match the empirical EU rate between 2007Q3–2015Q4 and then return to steady-state. Quarterly average of monthly data, in logs and HP-filtered with smoothing parameter 10^5 (using the full 1976Q1–2020Q2 sample). Shaded area corresponds to NBER dated recessions. V/U ratio: Vacancies divided by unemployed. *Source:* Model, CPS and JOLTS.

C.10 Value functions with long-lasting jobs

In the extended model with long-lasting jobs, the steady-state value of an open job to a firm, C, is

$$\begin{aligned} \rho C &= -c_v + q\frac{ul}{S}\int_{\underline{z}}^{\overline{z}} \Big((1-\beta)(J(z)-U-C)^+ - c_s\Big)\Big(1-\Psi(r|z)\Big)d\Gamma(z) \qquad \text{(C.8)} \\ &+ q\frac{1-u}{S}\int_{\underline{z}}^{\overline{z}}\int_{\underline{z}}^{\overline{z}} \Big((1-\beta)(J(z)-J(z')-C)^+ - c_s\Big)\Big(1-\Psi(R(z')|z)\Big)d\Gamma(z)L(z')dG(z') \end{aligned}$$

where the updated values of a match, $J(z)$, and unemployment, U, are

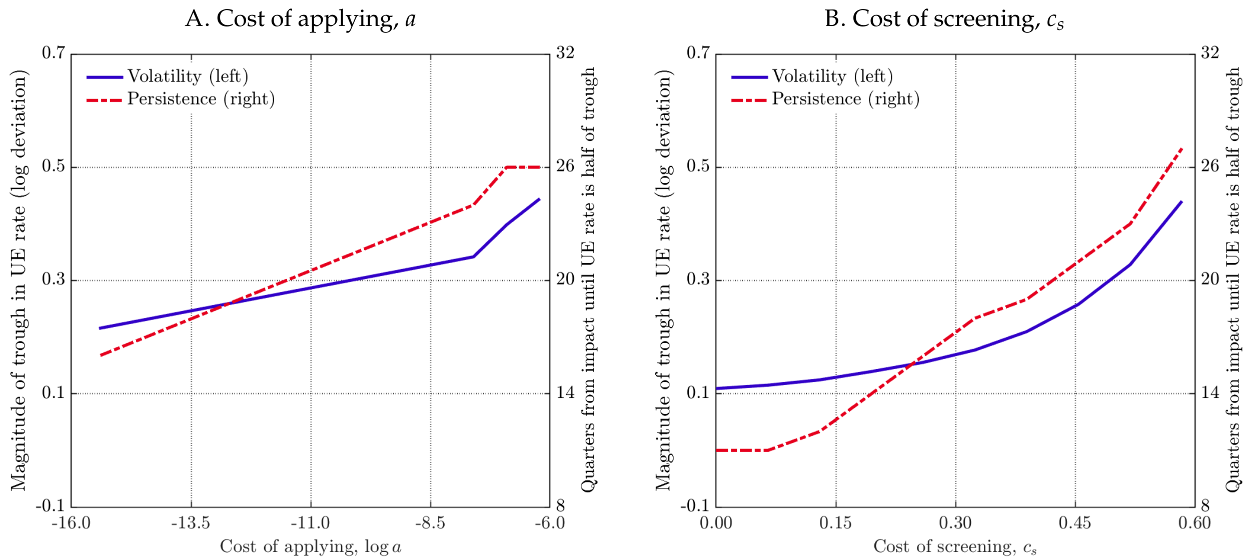
$$\begin{aligned} (\rho+\kappa)U &= b + \frac{\eta b^{-\frac{1}{\eta}}}{1+\eta}\left(p\int_{\underline{z}}^{\overline{z}} \Big(\beta(J(z)-U-C)^+ - ab\Big)\Big(1-\Psi(r|z)\Big)d\Gamma(z)\right)^{\frac{1+\eta}{\eta}} \\ (\rho+\kappa)J(z) &= z + \delta\Big(U - J(z)\Big) \\ &+ \frac{\eta z^{-\frac{1}{\eta}}}{1+\eta}\left(p\int_{\underline{z}}^{\overline{z}} \Big(\beta(J(z')-J(z)-C)^+ - az\Big)\Big(1-\Psi(R(z)|z')\Big)d\Gamma(z')\right)^{\frac{1+\eta}{\eta}} \end{aligned}$$

The dynamic value functions are straight-forward extensions of the static value functions. Free entry requires that $C = c_e$ in steady-state as well as during any time over the transition.

D Understanding the persistence of labor market fluctuations

This section presents details on the counterfactual exercises in Section 5.

FIGURE C.4. HOW THE IMPACT OF SEPARATION SHOCKS ON THE UE RATE VARIES WITH THE COST OF APPLYING AND SCREENING



Note: Perfect-foresight impact starting from steady-state in 2007Q2 of fluctuations in the separation rate $\delta(t)$ that mimic the EU rate between 2007Q3–2015Q4 and then return to steady-state. Panel A. Different calibrations of the cost of applying, a, to target alternative ratios of the application-to-mobility rate of the unemployed to the employed. Panel B. Different calibrations of the cost of screening, c_s, to target alternative screening cost shares of recruiting. All panels. Across all alternative calibrations, the cost of advertising and screening, $\{c_v, c_s\}$, are recalibrated to match the same job finding rate p and recruiting cost share of screening. *Source:* Model.

D.1 Micro and macro channels for the JJ rate

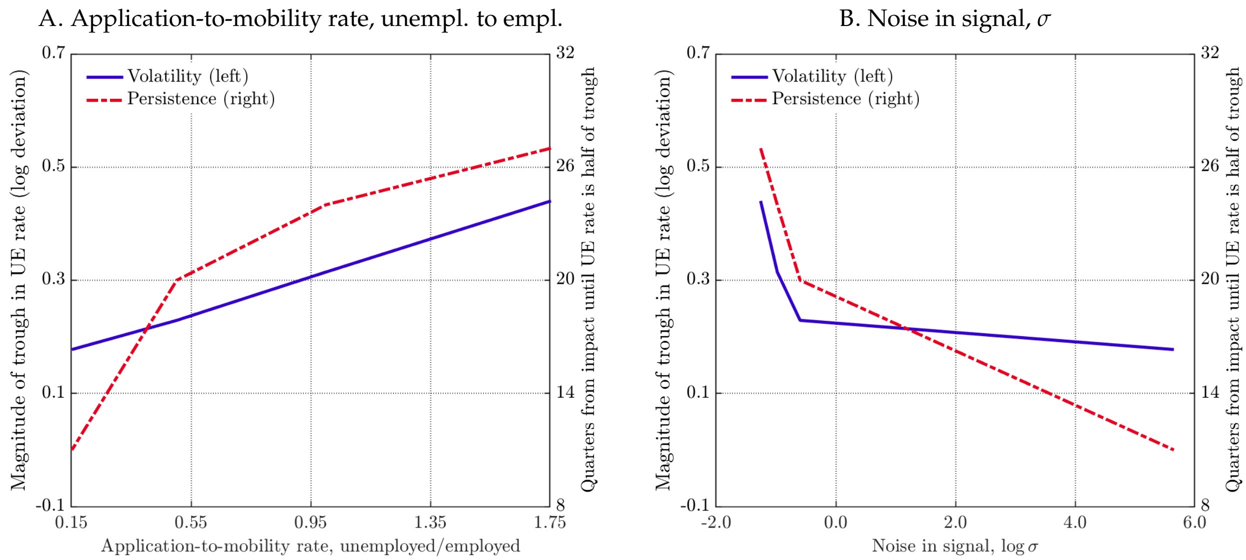
The JJ rate can be decomposed into three channels

$$JJ(t) = \underbrace{p(t)}_{\text{Macro}} \int_{\underline{z}}^{\overline{z}} \underbrace{L(z,t) \int_{z}^{\overline{z}} \Big(1 - \Psi(R(z,t)|z')\Big) d\Gamma(z')}_{\text{Micro}} \underbrace{dG(z,t)}_{\text{Job ladder}} \tag{D.1}$$

First, the equilibrium job finding rate per unit of search efficiency, $p(t)$, changes as firms' incentives to create jobs fluctuate over the business cycle. I refer to this as the *macro* channel. Second, changes in how hard workers search for jobs, what jobs they apply for and which job offers they accept conditional on their place in the job ladder impact the JJ rate through a *micro* channel. Finally, the JJ rate is affected by a *job ladder* channel, as employed workers position in the job ladder changes over the business cycle. In particular, the employment distribution shifts down the job ladder in the recession, and workers further down the job ladder are more likely to search for, apply for, and accept a job.

Figure D.1 shows that changes in worker search behavior have a small direct, micro effect on the JJ rate, in both the estimated model and the Pissarides (2009) calibration. The reason is the high estimated curvature of the cost of searching, η, which implies that search neither varies much with employment status and productivity conditional on time, nor with time conditional on employment status and productivity. In contrast, shifts in the pool of employed down the job ladder serve to counter the impact of a decline in the job finding rate on the realized JJ rate. For this reason, the JJ rate falls by less than the UE rate in the recession, consistent with the data.

FIGURE C.5. HOW THE IMPACT OF SEPARATION SHOCKS ON THE UE RATE VARIES WITH THE NOISE IN THE SIGNAL



Note: Perfect-foresight impact starting from steady-state in 2007Q2 of fluctuations in the separation rate $\delta(t)$ that mimic the EU rate between 2007Q3–2015Q4 and then return to steady-state. Different calibrations of the noise in the signal, σ, to target alternative ratios of the application-to-mobility rate of the unemployed to the employed. The cost of advertising and screening, $\{c_v, c_s\}$, are recalibrated to match the same job finding rate p and recruiting cost share of screening. *Source:* Model.

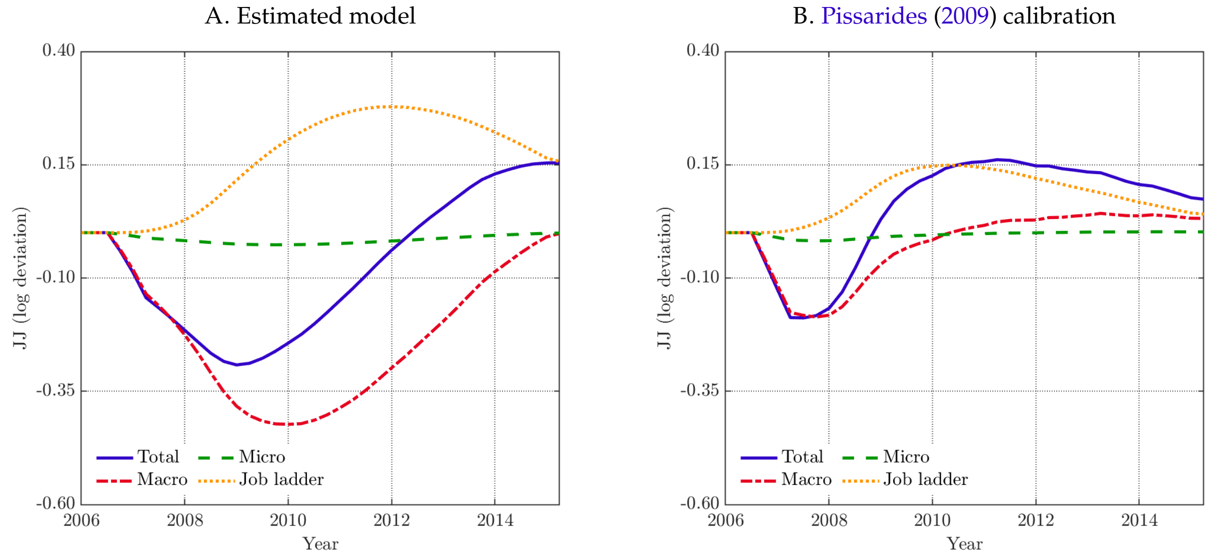
D.2 Decomposition of composition effect

Figure D.2 decomposes the composition effect in (8) into the role of shifts toward unemployment—the *unemployment* channel—versus shifts of employment down the job ladder—the *job ladder* channel. I construct the former by shifting only the share of unemployed as in the estimated model, holding everything else fixed (including the distribution of employment over the job ladder). I construct the latter by shifting only the distribution of employment over the job ladder as in the estimated model, holding everything else fixed (including the share of unemployed). The shift of potential hires toward the unemployed is the quantitatively most important factor behind the composition effect in (8).

D.3 Time series support

A central prediction of the theory is hence that, *ceteris paribus*, higher unemployment *discourages* vacancy creation, instead of encourages it as in existing frameworks. Table D.1 provides empirical support for the prediction of the current model by regressing the job finding rate, vacancies and tightness on the separation rate and one quarter lagged unemployment, with or without controls for labor productivity, following Coles and Kelishomi (2018). Consistent with the predictions of the theory, both the EU rate and the unemployed rate are negatively correlated with the job finding rate, vacancy rate and tightness.

FIGURE D.1. DECOMPOSITION OF THE JJ RATE



Note: Perfect-foresight impact starting from steady-state in 2007Q2 of fluctuations in the separation rate $\delta(t)$ that mimic the EU rate between 2007Q3–2015Q4 and then return to steady-state. Decomposition of JJ rate based on (D.1). Micro: Impact of changing only worker search behavior as in the estimated model, holding all other factors fixed at steady state. Macro: Impact of changing only equilibrium job finding rate $p(t)$ as in the estimated model, holding all other factors fixed at steady state. Job ladder: Impact of changing only distribution of employed workers over the job ladder $G(z,t)$ as in the estimated model, holding all other factors fixed at steady state. Panel A. Estimated model. Panel B. Estimated model with application stage shut down, $a = 0$, and cost of advertising, c_v, and screening, c_s, recalibrated to match the same job finding rate p and screening cost share as in the baseline model. *Source:* Model.

TABLE D.1. REGRESSION OF VACANCY CREATION ON SEPARATION RATE AND UNEMPLOYMENT

	A. UE rate			B. Vacancies			C. Tightness		
	Data	Data	Model	Data	Data	Model	Data	Data	Model
EU rate	-0.362	-0.382	-0.669	-0.739	-0.820	-1.344	-1.107	-1.225	-1.685
Unemployment	-0.548	-0.532	-0.313	-0.472	-0.408	-0.565	-1.304	-1.212	-1.407
GDP per worker	no	yes	no	no	yes	no	no	yes	no

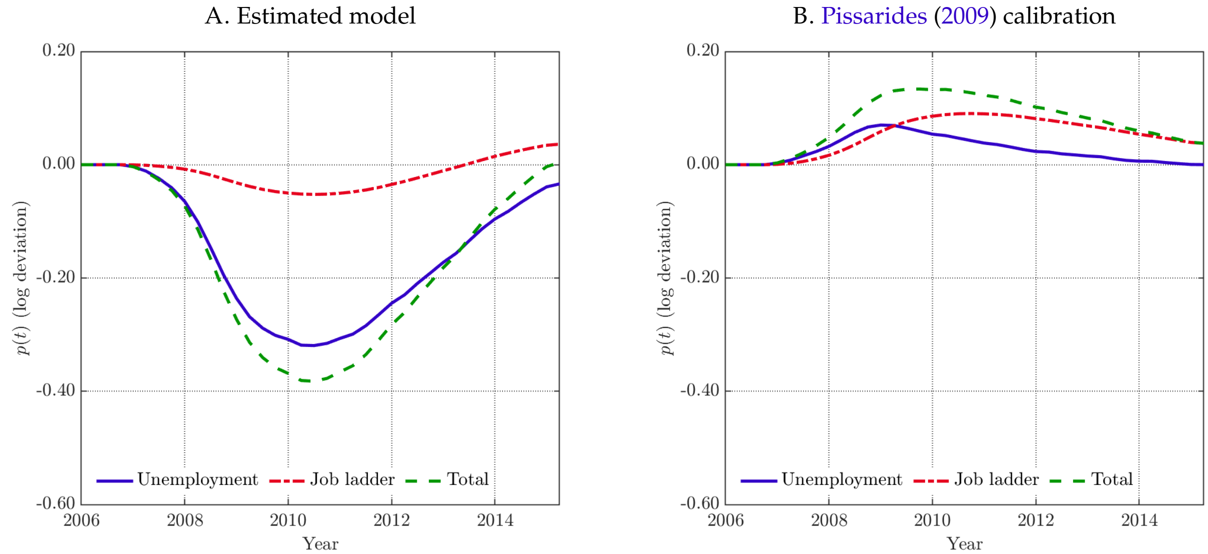
Note: Linear regression of measures of job creation on contemporaneous EU rate and one-quarter lagged unemployment for 2007Q2–2015Q4. One quarter lagged unemployment is used to mitigate simultaneity issues. EU rate: Share of wage employed who are unemployed in subsequent month. Unemployed: Total number of unemployed. UE rate: Share of unemployed who are wage employed in subsequent month. Vacancies: total job openings. Tightness: Vacancies divided by stock of unemployed. Model: Perfect-foresight impact starting from steady-state in 2007Q2 of fluctuations in the separation rate $\delta(t)$ that match the empirical EU rate between 2007Q3–2015Q4 and then return to steady-state. Data: Quarterly average of monthly data, in logs and detrended using an HP-filter with smoothing parameter 10^5 on the full 1978Q1–2020Q2 sample. *Source:* Model, Conference Board, CPS, and JOLTS.

D.4 An alternative decomposition

An alternative way to decompose the large effects of separation shocks is based on the observation that the separation rate $\delta(t)$ directly shows up in the system of equations determining the equilibrium in two places, as highlighted by Section 2.2. First, it shows up in the value of a match (9), which I refer to as the *HJB* channel. Second, it directly enters the evolution of the composition of the labor force (C.7). I refer to this channel as the *KFE* channel.

Several considerations make it useful to assess the relative importance of these channels. For instance,

FIGURE D.2. UNDERSTANDING THE COMPOSITION EFFECT



Note: Perfect-foresight impact starting from steady-state in 2007Q2 of fluctuations in the separation rate $\delta(t)$ that mimic the EU rate between 2007Q3–2015Q4 and then return to steady-state. Decomposition of composition effect in (8) into the role of shifts in the unemployment rate versus shifts in the composition of employment over the job ladder. Unemployment: Equilibrium job finding rate $\tilde{p}(t)$ consistent with (8) under the time path for unemployment $u(t)$ in the estimated model, holding everything else fixed. Job ladder: Equilibrium job finding rate $\tilde{p}(t)$ consistent with (8) under the time path for the distribution of employment over the job ladder $G(z,t)$ in the estimated model, holding everything else fixed. Panel A. Estimated model. Panel B. Estimated model with application stage shut down, $a = 0$, and cost of advertising, c_v, and screening, c_s, recalibrated to match the same job finding rate p and screening cost share as in the baseline model. See text for details. *Source:* Model.

if the higher separation rate in recessions does not apply to new jobs, the HJB channel is not operative (Appendix A.6 finds, however, that the EU rate rises proportionately at all tenures in recessions, at odds with this interpretation). Conversely, other factors such as productivity shocks may discourage firms from creating jobs without having a direct impact on the separation rate. That is, the KFE channel may not be operative in response to such shocks, yet such shocks may still be amplified through the mechanism emphasized here as the job finding rate falls and the unemployment rate rises.

To isolate the HJB channel, I let the separation rate $\delta(t)$ in the value of a match (9) change, but counter-factually assume that it remains fixed at its steady-state value in the evolution for employment and unemployment (C.7). I resolve the equilibrium system (8), (9) and (C.7) under this counter-factual assumption. To quantify the KFE effect, I let the separation rate $\delta(t)$ change in the evolution for employment and unemployment (C.7), but counter-factually assume that it remains fixed in the value of a match (9). I again resolve the system (8), (9) and (C.7) under this counter-factual assumption.

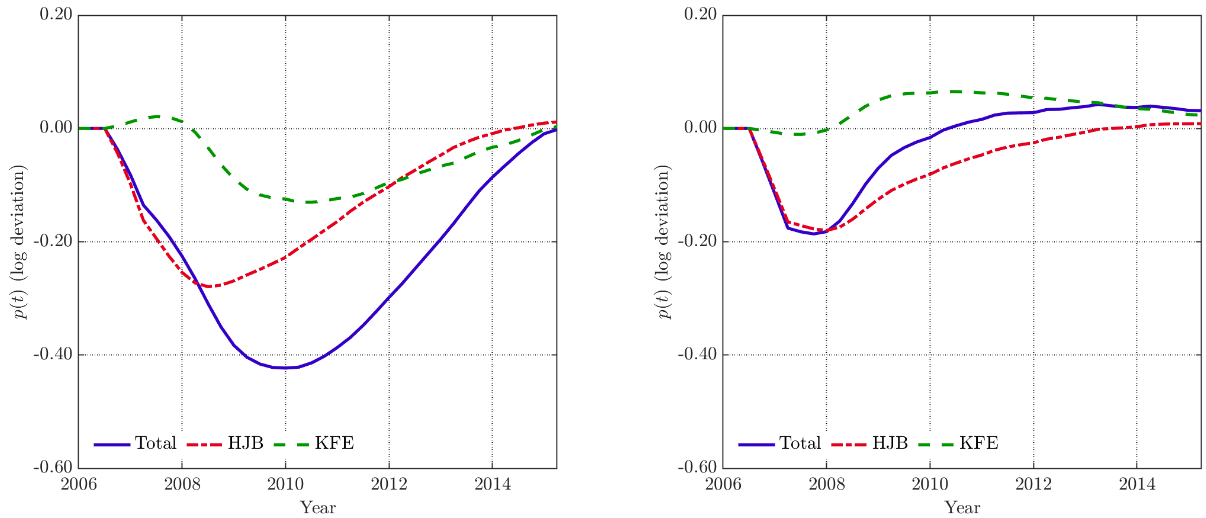
Figure D.3 finds that the HJB channel is the most important channel through which a change in the separation rate impacts the job finding rate. This is particularly true on impact, due to the forward-looking nature of job creation. The higher separation rate discourages job creation, which raises the unemployment rate and shifts workers down the job ladder. Such compositional shifts further discourage job creation by raising the cost of the recruiting. The KFE channel is quantitatively smaller, yet contributes importantly to propagation. As workers lose their jobs faster, the pool of hires shifts toward the unemployed, in turn discouraging job creation by raising the cost of recruiting.

At the same time, the KFE channel is the most important source of differences in predictions between the estimated model in panel A and the Pissarides (2009) model in panel B. As more workers become laid off, job creation is discouraged in the estimated model. In contrast, in benchmark models, this channel would encourage job creation.

FIGURE D.3. UNDERSTANDING THE IMPACT ON THE JOB FINDING RATE

A. Estimated model

B. Pissarides (2009) calibration

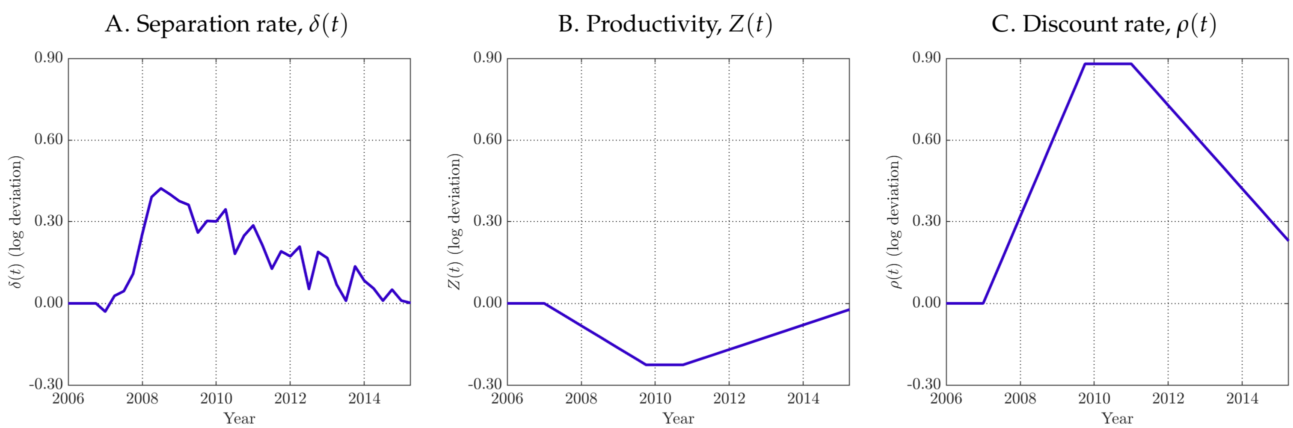


Note: Perfect-foresight impact starting from steady-state in 2007Q2 of fluctuations in the separation rate $\delta(t)$ that mimic the EU rate between 2007Q3–2015Q4 and then return to steady-state. HJB: Job finding rate consistent with the equilibrium system (8), (9) and (C.7) under the counter-factual assumption that $\delta(t) \equiv \delta$ in the evolution of labor force composition (C.7). KFE: Job finding rate consistent with the equilibrium system (8), (9) and (C.7) under the counter-factual assumption that $\delta(t) \equiv \delta$ in the value function (9). Panel A. Estimated model. Panel B. Estimated model with application stage shut down, $a = 0$, and cost of advertising, c_v, and screening, c_s, recalibrated to match the same job finding rate p and screening cost share as in the baseline model. See text for details. *Source:* Model.

D.5 Other shocks

Figure D.4 illustrates the required paths for aggregate productivity and the discount rate that generates the same fall in the job finding rate as under the separation shocks.

FIGURE D.4. MAGNITUDE OF EXOGENOUS SHOCKS, LOG DEVIATION



Note: Exogenous change in separation rate, $\delta(t)$, aggregate productivity, $Z(t)$, and discount rate, $\rho(t)$, required to generate the same path for the job finding rate $p(t)$, in log deviations. Aggregate productivity $Z(t)$ shifts the productivity of all matches, new and old, proportionally. *Source:* Model.