Application Cycles

Niklas Engbom*

February 15, 2019

Click here for most recent version

Abstract

This paper asserts that separation rate shocks are a dominant source of business cycle fluctuations in the vacancy-to-unemployment ratio, overturning conventional wisdom. Motivated by new micro-data, I develop a richer model of the hiring process in which unemployed and employed workers decide what positions to apply for based on an imperfect signal of how good a fit they would be, while firms screen applicants to determine whom to hire. Because the unemployed apply for many positions that they are unlikely to be a good fit for, it is harder for firms to ascertain who is qualified for the job during periods of high unemployment, dampening incentives to create jobs. By highlighting an additional source of congestion in labor markets, I find that separation rate shocks explain two thirds of business cycle volatility in the vacancy-to-unemployment ratio and generate a strong negative Beveridge curve, in line with the data.

Keywords: Unemployment; Labor market frictions; Shimer puzzle

*Federal Reserve Bank of Minneapolis, 90 Hennepin Ave, Minneapolis, MN 55401. Email: niklas.engbom@gmail.com). This is the third chapter of my dissertation. I am extremely grateful to my advisor Richard Rogerson for his continuous support and guidance. I also thank my committee Mark Aguiar, Greg Kaplan and Gianluca Violante, as well as Adrien Bilal, Jan Eeckhout, Federico Huneeus, Gregor Jarosch and Esteban Rossi-Hansberg. The views expressed herein are those of the author and not necessarily those of the Federal Reserve Bank of Minneapolis or the Federal Reserve System.

1 Introduction

A large literature studies the role of productivity shocks in generating cyclical outcomes in frictional labor markets.[1] Although this literature has had significant success, it has identified three issues associated with this approach. First, in order for productivity shocks to explain a significant share of fluctuations in the ratio of vacancies to unemployment—henceforth *the v/u-ratio*—the surplus must be small (Hagedorn and Manovskii, 2008).[2] Second, if as suggested by recent research the flow value of leisure co-varies strongly with productivity, this largely offsets the effect of a small surplus (Chodorow-Reich and Karabarbounis, 2016).[3] Third, the empirical correlation between productivity and the v/u-ratio is far from one—even negative over the past 30 years—suggesting that such shocks do not account for much of the volatility in the v/u-ratio (Hall, 2007).[4]

This paper instead asserts that separation rate shocks are a dominant source of business cycle fluctuations in unemployment and vacancies, overturning conventional wisdom. From an accounting perspective, this is not a particularly bold assertion: Regressing the v/u-ratio on the separation rate in quarterly US data from 1951 to 2017 yields an R-squared of 0.42, versus 0.04 for productivity. Yet conventional wisdom holds that separation rate shocks cannot be a main driver of business cycle fluctuations in unemployment and vacancies, because viewed through the lens of the benchmark Mortensen and Pissarides (1994) model they generate little volatility in these outcomes and a counter-factually positive correlation between the two (Shimer, 2005).

I reconcile data and theory by developing a richer model of the hiring process, embedded in an otherwise standard model. Firms advertise job openings subject to a cost, while workers search for open jobs both as unemployed and employed. When a worker learns about a position, she observes a noisy signal of how good the match would be and decides whether to submit an application. Employers spend resources screening applicants, which reveals the quality of the match and hiring commences if the fit is sufficiently good.

Because the unemployed are eager to find a job, the model predicts that they apply for a larger

[1] See for instance Shimer (2005), Hagedorn and Manovskii (2008), Petrosky-Nadeau and Wasmer (2013), Hall (2005a), Fujita and Ramey (2007), Merz and Yashiv (2007), Hall and Milgrom (2008), Silva and Toledo (2009), Hagedorn and Manovskii (2011), and Mitman and Rabinovich (2014).

[2] In the benchmark Mortensen and Pissarides (1994) model, this boils down to the difference between flow output of the match and the flow value of leisure. Ljungqvist and Sargent (2017) demonstrate how more complicated settings effectively reduce to continuing to require a small "fundamental surplus fraction, an upper bound on the fraction of a job's output that the invisible hand can allocate to vacancy creation."

[3] Additionally, recent micro-evidence in Mas and Pallais (2017) suggests that the flow value of unemployment is about 50 percent of marginal productivity.

[4] See also Barnichon (2010).

number of positions than the employed. But whereas models with endogenous search typically assume that a higher arrival rate of opportunities can be attained without affecting their quality (Christensen et al., 2005), here the unemployed achieve a larger number of applications by also applying for positions that they are less likely to be a good fit for.

This interpretation of the data in turn has important implications for the response of the economy to separation rate shocks. An increase in the separation rate affects firms' incentives to create jobs through two margins: First, it reduces the expected life-time of a match, which discourages vacancy creation. Second, by increasing the unemployment rate, it raises the probability that an applicant is unemployed. Absent the richer hiring process developed in this paper, the second margin encourages vacancy creation, because the unemployed are more likely to accept an offer and have a worse bargaining position. For reasonable parameter values, the two margins largely offset each other such that separation rate shocks explain only a fraction of the empirical volatility and persistence of the v/u-ratio and fail to reproduce the strong negative correlation between unemployment and vacancies in the data. In contrast, in the richer model of the hiring process, higher unemployment is associated with a larger share of applicants who are unlikely to be a good fit for the job. By increasing the cost of hiring during periods of high unemployment, this dampens firms' incentive to create jobs.

The theory highlights two key margins for the quantitative relevance of this channel: First, how indiscriminate the unemployed are in their application behavior relative to the employed; and second, how large costs of screening are relative to the overall cost of hiring for firms. I identify parameters governing the former from newly available data on job search behavior from the *Survey of Consumer Expectations* (SCE). The data indicate large differences in search behavior between the unemployed and employed—the unemployed submit over 11 times as many applications, but are less than three times as likely to receive an offer and get over 20 percent lower residual starting wages (Faberman et al., 2017)—which the model interprets as them applying for many positions that they are unlikely to be a good fit for. In a success of the theory, it explains such large cross-sectional differences in search behavior and outcomes by employment status without resorting to exogenous differences in for instance the rate at which applications are converted to offers or the offer distributions. It also matches as non-targeted outcomes search behavior and mobility as workers climb the job ladder. To inform the second margin, I use recent micro-evidence from Blatter et al. (2012), who exploit detailed firm surveys of the hiring process to document that screening costs constitute roughly half of the overall cost of advertising and screening.

The estimated model implies that separation rate shocks explain two thirds of the empirical volatility in the v/u-ratio during the post-WWII period and give rise to a strong, negative correlation between unemployment and vacancies, in line with the data. In contrast to conventional wisdom, I hence find that separation rate shocks are a main driver of the business cycle dynamics of unemployment and vacancies. I reach such a different conclusion than the literature by highlighting an additional source of congestion in labor markets: Workers base their application decision on private information about the quality of the future match, without taking into account the cost to firms of screening their application. When as suggested by the data the unemployed are particularly indiscriminate in their application behavior, the strength of such negative externalities increases with the unemployment rate, effectively increasing the cost of hiring to firms during periods of high unemployment. This dampens incentives to create jobs, such that a short-lived spike in the separation rate results in a large, persistent decline in the v/u-ratio. In essence, the model encapsulates what online hiring portal HRZone.com describes as:[5]

> *This is another impact of the recession on recruitment—the fact that many organizations are finding it difficult to recruit quality, partly because there are suddenly many more CVs to sift through, from a larger pool of candidates who have been made redundant.*

Understanding the sources of large fluctuations in labor market outcomes is crucial for the design of policy. The seminal result in Shimer (2005) suggests that search frictions alone are not sufficiently large to give rise to substantial cyclical swings in unemployment. Absent other frictions in the labor market, one may be led to conclude that the large, persistent increases in unemployment observed during recessions are primarily due to workers not wanting to work, with limited or no scope for policy to improve outcomes.[6] In contrast, this paper asserts that frictions and externalities intrinsic to the labor market play a first-order role in amplifying shocks, such that business cycle fluctuations in unemployment to a large extent are involuntary. These findings leave significant scope for policy to improve welfare.

Several recent papers revisit the role of shocks other than productivity in driving labor market

[5] `https://www.hrzone.com/talent/acquisition/the-impact-of-the-recession-on-recruitment`.

[6] Although a high flow value of leisure increases amplification (Hagedorn and Manovskii, 2008), it does so by substantially moderating workers' relative desire to work after a negative productivity shock. Since workers barely want to work anyways, the scope for policy to improve welfare remains limited.

dynamics.[7] Hall (2017) shows that under alternating offers bargaining, fluctuations in discount rates may generate substantial volatility in labor market outcomes, while Kehoe et al. (2016) study the role of shocks to financial constraints. Coles and Kelishomi (2018) discard with free entry to argue that the elasticity of entry can be set such that separation rate shocks explain a significant share of the volatility in the v/u-ratio in an environment with both separation rate and productivity shocks, whereas I instead preserve free entry to emphasize endogenous shifts in the cost of recruiting over the business cycle, and I use cross-sectional micro-data to identify the strength of this mechanism. The most related paper to the current is Hall (2005b), who argues 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.[8] Relative to him, I assess how observable shifts in the pool of hires along the unemployed-employed margin amplify separation rate shocks in an environment that incorporates on-the-job search, when as suggested by the micro-data application behavior differs substantially by employment status.[9]

This paper is organized as follows: Section 2 develops a richer model of the hiring process, which Section 3 brings to the data. Section 4 shows that separation rate shocks explain a large share of business cycle fluctuations in unemployment and vacancies, and Section 5 concludes.

2 A Model of Applications and Screening

This section develops a continuous time model of a labor market in which workers are selective in terms of what jobs they apply for and firms pay to advertise jobs and screen applicants. I start

[7] A related literature studies whether the labor market may display multiplicity so that fluctuations are the result of sunspots, going back to the seminal work of Diamond (1982). Sterk (2016) finds that skill losses in unemployment may give rise to multiple steady-states, while Kaplan and Menzio (2016) and Sniekers (2018) argue that demand externalities may give rise to multiplicity. Eeckhout and Lindenlaub (2017) argue that multiplicity may arise because the search decision of employed workers gives rise to a procyclical return to job creation (the current model in contrast emphasizes a countercyclical cost of hiring due to the application decisions of unemployed and employed workers). Relative to these works, I focus on a quantitative assessment of the propagation of separation rate shocks in a richer, micro-founded model of the hiring process rather than a theoretical analysis of multiplicity and sunspots.

[8] Pries (2008) is also related, who combines permanent worker heterogeneity with exogenously given time-varying differences in the separation rate by worker type such that the pool of unemployed shifts towards workers with a higher value of leisure during downturns. In contrast, I propose a micro-founded mechanism that generates endogenous shifts in a pool of ex ante identical applicants over the cycle.

[9] Another related literature studies further the hiring process from the perspective of workers and firms. Faberman et al. (2017) present a partial equilibrium model of application behavior which suggests that the employed are better at converting applications to offers and sample from a better wage offer distribution. Wolthoff (2018) develops a directed search model with an application decision of workers and a screening process of firms, but focuses on equilibrium selection and not the congestion externality in the current paper. Davis and Samaniego de la Parra (2017) document that the advertising phase constitutes only about a fifth of the overall time it takes to fill a vacancy, suggesting in line with the argument in the current paper that screening plays a major role in the hiring process.

with a stationary environment and subsequently introduce aggregate shocks.

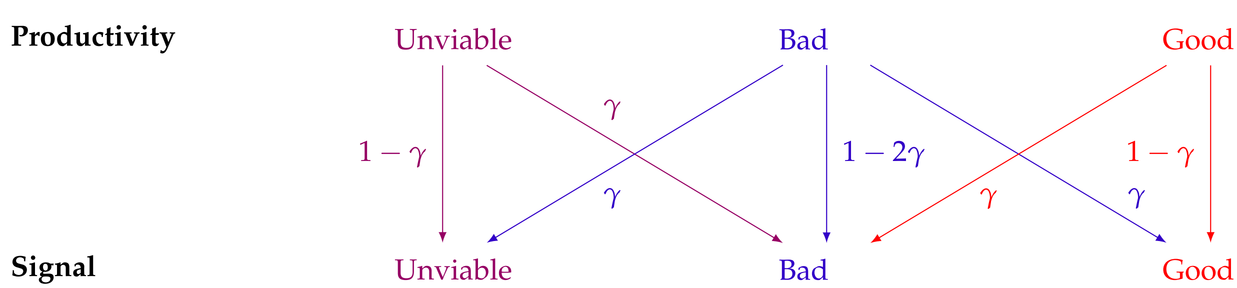
2.1 Environment

The economy is populated by a unit mass of infinitely-lived, risk neutral workers and a positive mass of one-worker firms. All agents discount the future at rate $r > 0$.

Workers. At any point in time, a worker may be unemployed, in a bad p_b productivity match (mismatched) or in a good p_g productivity match (well-matched). A worker enjoys flow value b as unemployed and wage w as employed. I discuss how wages are set momentarily. Unemployed and mismatched workers search for jobs, in the latter case with relative efficiency ϕ. I assume that well-matched workers do not search, since their return to searching is zero. Frictions prevent workers from immediately learning about all open positions. Denote by f (ϕf) the endogenous Poisson arrival rate of information about open positions for unemployed (mismatched) workers.

A potential match between a worker and firm can be unviable, bad or good. When a worker learns about an open position, she observes a signal $\sigma(p)$ of the productivity of the potential match. Specifically, I assume that an unviable match sends a bad signal with probability γ and an unviable signal with complementary probability, a good match sends a bad signal with probability γ and a good signal with complementary probability, and a bad match sends an unviable or good signal each with probability γ and a bad signal with probability $1 - 2\gamma$. Figure 1 illustrates the structure of signals. Based on the signal, the worker decides whether to apply, which costs c_a.

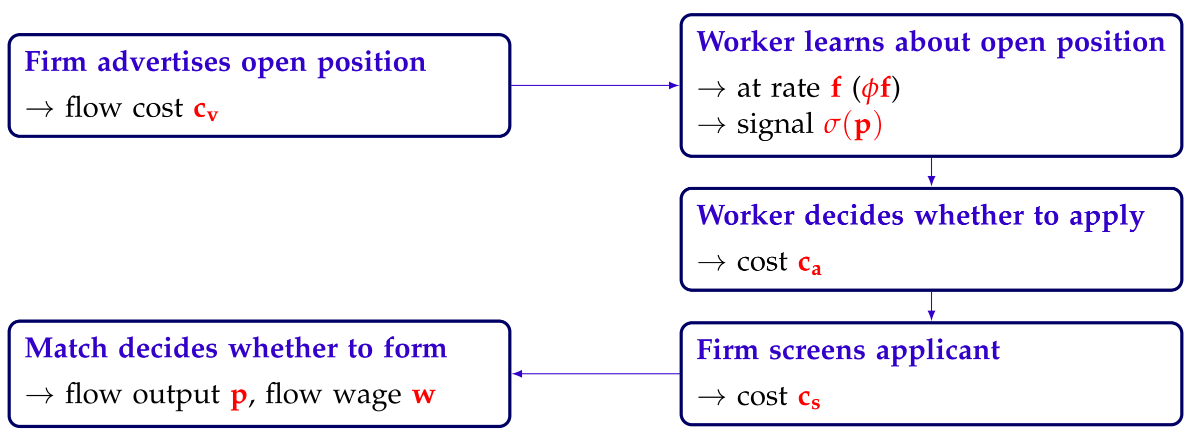
FIGURE 1. STRUCTURE OF SIGNALS



Firms. Firms produce a single good using only labor and a constant returns to scale technology. Because of constant returns, I can analyze matches in isolation. A match between a firm and a worker is characterized by its idiosyncratic productivity p, drawn at the time of initial contact between the firm and the worker. I need not take a stand on what exactly p represents—it may reflect physical productivity, idiosyncratic demand for the match's product, a worker's pleasure of being in a particular workplace, commuting time, etc. Denote by π_i the probability that productivity is $i = \{u, b, g\}$. The productivity of an unviable match is so low that it is not worth forming it. Productivity remains fixed except that it becomes unviable at Poisson rate s.

To hire workers, a firm advertises job openings at flow cost c_v. For instance, many job boards charge a fee. Subsequently, it screens the applications it receives at cost c_s. For instance, it has to read through applicants' material and interview potential hires. The risks associated with an unviable match are assumed to be so large that a firm always screens applicants.[10] Screening reveals the productivity of the match. The match is formed if there are bilateral gains from trade, production commences and wages are paid. Figure 2 illustrates the timing of the model.

FIGURE 2. TIMING OF EVENTS



Wage setting. Workers and firms bargain over the surplus of the match following the offer matching framework of Cahuc et al. (2006) with worker bargaining power β.

Matching. Denote by u the unemployment rate, by e_b the mass of mismatched workers, by $e = u + \phi e_b$ the efficiency mass of searching workers, and by v the mass of open positions. The flow of meetings $m(v, e)$ is given by a constant returns to scale matching function, which is increasing and strictly concave in both arguments. Constant returns imply that the rate at which the unemployed

[10]For instance, online recruiting site CareerBuilder reports that 41 percent of companies say that a bad hire in the last year has cost them at least \$25k while 25 percent say it has cost them at least \$50k.

learn about positions, $f = m(v,e)/e = m(\theta,1)$, and the rate at which open positions contact potential applicants, $q = m(v,e)/v = f/\theta$, are only functions of labor market tightness, $\theta = v/e$.[11]

2.2 Stationary equilibrium

To simplify, I assume that application costs are small, $c_a \to 0$. From personal experience this seems reasonable—the cost of submitting one more application via EconJobMarket is close to zero. Second, following Lise and Robin (2017) I assume that workers' bargaining power is low, $\beta \to 0$, which substantially simplifies the dynamic analysis. I require, however, that these limits go to zero in such a way that workers apply for any position that in expectation improves productivity.[12] As a low worker bargaining power and the resulting weak endogenous wage cyclicality are known to amplify the response of the economy to shocks in the benchmark Mortensen and Pissarides (1994) model, I note that on-the-job search in the current model result in pro-cyclical wages even with a zero bargaining power. In fact, Appendix C shows that separation rate shocks in the model give rise to wage dynamics that match well the data. Furthermore, absent screening costs, separation rate shocks continue to give rise to tiny fluctuations in labor market outcomes also under a zero worker bargaining power, mirroring arguments in Mortensen and Nagypal (2007) and Ljungqvist and Sargent (2017) that the key factor governing amplification is not wage stickiness per se.

Under these assumptions, the surplus value of a mismatch, S_b, and of a good match, S_g, are

$$S_i = \frac{p_i - b}{r+s}, \quad i = \{b, g\} \tag{1}$$

The unemployed apply for all positions and mismatched workers for those that send good or bad signals, where the bargaining protocol ensures that application decisions are bilaterally optimal.

The expected value of an open position to a firm, J, solves

$$J = q\left[\frac{u}{e}\left(\pi_b S_b + \pi_g S_g - c_s\right) + \frac{\phi e_b}{e}\left(\gamma\pi_u + (1-\gamma)\pi_b + \pi_g\right)\left(\frac{\pi_g\left(S_g - S_b\right)}{\gamma\pi_u + (1-\gamma)\pi_b + \pi_g} - c_s\right)\right] \tag{2}$$

An open job contacts a potential applicant at Poisson rate q. The worker is unemployed with prob-

[11] I refer to the measure that can be observed in the data—the ratio of vacancies to unemployment—as the v/u-ratio to distinguish it from the theoretical concept of tightness, v/e.

[12] Specifically, this requires that in the limit, $\lim \frac{c_a}{\beta} < \min\left\{\frac{\gamma\pi_g}{\gamma\pi_u + (1-2\gamma)\pi_b + \gamma\pi_g}\frac{p_g - p_b}{r+s}, \frac{\gamma\pi_b}{(1-\gamma)\pi_u + \gamma\pi_b}\frac{p_b - b}{r+s}\right\}$.

ability u/e, in which case she always applies for the job. The firm screens the worker, productivity is revealed and the match is formed if productivity is bad or good. With probability $\phi e_b/e$ 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.[13]

A *stationary equilibrium* with vacancy creation consists of surplus functions $\{S_b, S_g\}$, a mass of vacancies v, and a distribution $\{u, e_b, e_g\}$ such that (a) the surplus functions solve the problem of matches; (b) free entry holds; and (c) the distribution is given by its law of motion and is stationary.

Beveridge Curve. A standard law of motion implies that the stationary unemployment rate is $u = s/\Big(s + f(\pi_b + \pi_g)\Big)$ while the mass of mismatched workers is $e_b = f\pi_b s/\Big((s + \phi f \pi_g)(s + f(\pi_b + \pi_g))\Big)$. Hence, the ratio of unemployed searchers to total searchers is

$$\frac{u}{e} = \frac{s + \pi_g \, \phi \, f(\theta)}{s + \Big(\pi_b + \pi_g\Big) \, \phi \, f(\theta)} \tag{3}$$

This is the first equilibrium condition, an augmented *Beveridge Curve* that relates the share of unemployed searchers to market tightness θ. The share of unemployed searchers falls in tightness,

$$\frac{\partial \log \frac{u}{e}}{\partial \log \theta} = -X\,\eta, \qquad X = \frac{s\,\pi_b\,\phi\,f(\theta)}{\Big(s + \pi_g\,\phi\,f(\theta)\Big)\Big(s + (\pi_b + \pi_g)\,\phi\,f(\theta)\Big)} > 0$$

where $\eta = f'(\theta)\theta/f(\theta) \in (0,1)$ is the elasticity of the job finding rate with respect to vacancies.

Job Creation. In an equilibrium with positive job creation, firms advertise job openings until the expected gains from doing so are exhausted. Equating the value of opening a job (2) with the cost of advertising a job, the second key equilibrium condition is a *Job Creation* condition that relates the cost of contacting a potential applicant to the expected return from doing so,

$$\Big(r + s\Big)\,c_v\,\frac{\theta}{f(\theta)} = \pi_g\Big(p_g - p_b\Big) - C_1 + \frac{u}{e}\Big[\Big(\pi_b + \pi_g\Big)\Big(p_b - b\Big) - C_2\Big] \tag{4}$$

where $C_1 = (r+s)c_s\Big(\gamma\pi_u + (1-\gamma)\pi_b + \pi_g\Big)$ and $C_2 = (r+s)c_s\Big((1-\gamma)\,\pi_u + \gamma\pi_b\Big)$.

The left hand side of (4) equals the flow equivalent expected cost of contacting one potential

[13] Note that it is never optimal for a firm to post a vacancy not intending to screen applicants, since no new information has been revealed to the firm between these two decisions.

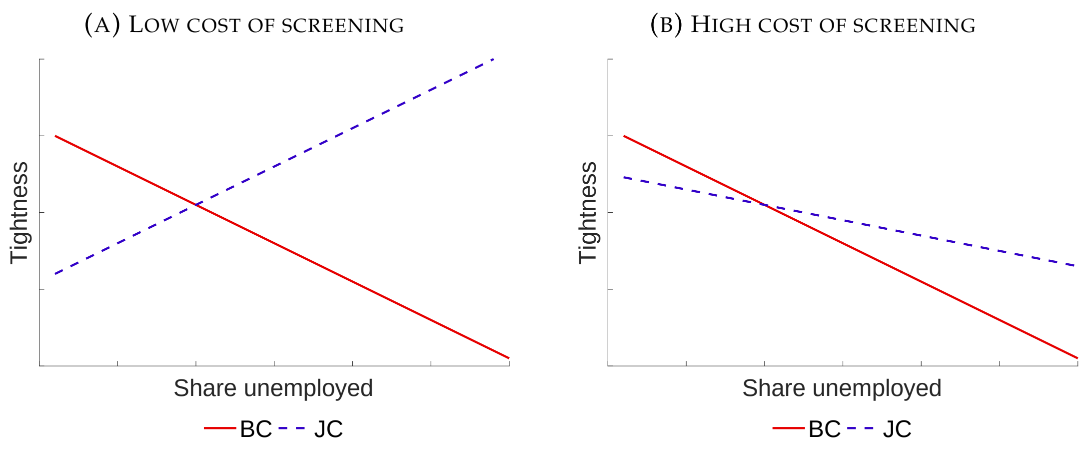
applicant, while the right hand side reflects the expected flow return to contacting a potential applicant. The firm gets $\pi_g(p_g - p_b)$ from forming good matches but has to pay cost C_1 associated with screening applicants for the position. Whenever the firm contacts an unemployed worker, it gets a premium $(\pi_b + \pi_g)(p_b - b)$ 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 unemployed workers.

The derivative of tightness with respect to the share of unemployed job seekers is,

$$\frac{\partial \log \theta}{\partial \log \left(\frac{u}{e}\right)} = \frac{\Upsilon}{1-\eta}, \qquad \Upsilon = \frac{\frac{u}{e}\left[\left(\pi_b + \pi_g\right)\left(p_b - b\right) - C_2\right]}{\pi_g\left(p_g - p_b\right) - C_1 + \frac{u}{e}\left[\left(\pi_b + \pi_g\right)\left(p_b - b\right) - C_2\right]}$$

Since $\eta \in (0,1)$, a higher share of unemployed job seekers incentivizes firms to enter if $(\pi_b + \pi_g)(p_b - b) - C_2 > 0$. In this case, the additional profits due to the unemployed being more likely to accept an offer and having a worse bargaining position outweigh the cost of screening additional applicants. This ensures a unique stationary equilibrium with positive job creation.[14] If this does not hold, tightness falls in the share 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, such that the additional cost from such applications outweighs the benefit from receiving them. Figure 3 illustrates these cases.

FIGURE 3. EQUILIBRIUM DETERMINATION



There is some question as to whether firms can easily infer the employment status of an appli-

[14]Existence of a stationary equilibrium with positive job creation also requires that $\pi_g\left(\frac{p_g - b}{r+s}\right) + \pi_b\left(\frac{p_b - b}{r+s}\right) > c_s$.

cant prior to screening the application and based on this discard it. Data from online recruiting firm GetHired.com indicate that 43 percent of applicants misrepresent themselves on their resume, suggesting that quickly inferring the employment status of an applicant may not be all that easy. In any case, the fact that the value of recruiting falls in the share of unemployed job seekers does not in general imply that a firm may not want to proceed to screen an applicant who is known to be unemployed. That is, the value of recruiting falls in the share of unemployed job seekers if

$$\Big(\pi_b + \pi_g\Big)\frac{p_b - b}{r+s} < c_s\Big((1-\gamma)\pi_u + \gamma\pi_b\Big) \tag{5}$$

whereas a firm wants to proceed to screen an applicant who is known to be unemployed if

$$\pi_b\frac{p_b - b}{r+s} + \pi_g\frac{p_g - b}{r+s} > c_s \tag{6}$$

In general, (5) is not inconsistent with (6). In fact, under my baseline estimates, both (5) and (6) hold: A firm prefers as many employed applicants as possible, but having already paid the advertising cost it would proceed to screen an applicant who is known to be unemployed.

2.3 Comparative statics

In response to a permanent increase in the separation rate, the Beveridge Curve (3) shifts to the right from BC to BC′, as illustrated by Figure 4. The increase in the separation rate also discourages job creation by reducing the expected duration of a match, shifting the Job Creation curve (4) down from JC to JC′. The left panel illustrates these shifts for the case without costs of screening. Permanent shifts in the separation rate may induce either a positive or negative correlation between the steady-state share of unemployed job seekers and tightness, depending on the relative strengths of these two shifts. Quantitatively, I find that the model without screening costs at most is consistent with a weak negative correlation between unemployment and vacancies, in contrast to the strong negative correlation in the data. The right hand panel illustrates the impact of a permanent increase in the separation rate under high screening costs. This unambiguously reduces tightness, resulting in a negative correlation between tightness and the share of unemployed job seekers, and a larger effect on unemployment than the case without screening costs.

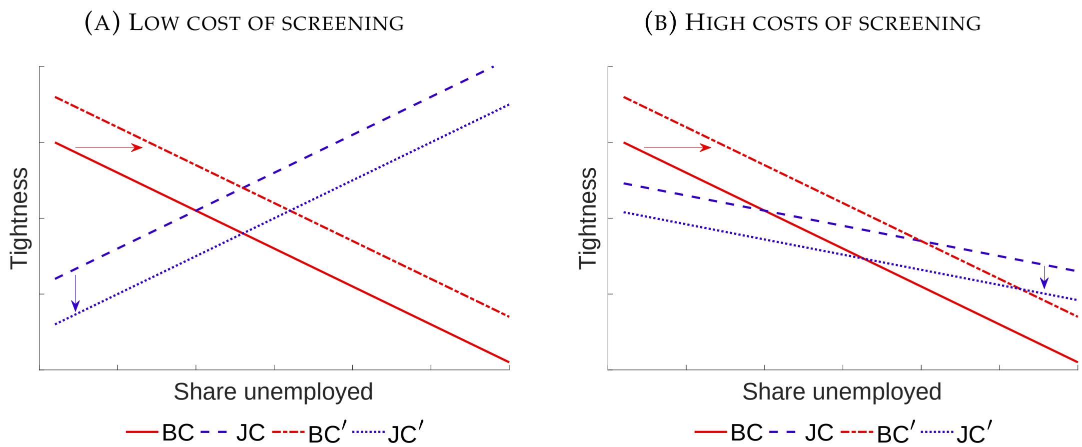
To formalize this intuition, denote by $y = \pi_g p_g + \frac{u}{e}\Big(\pi_b + \pi_g\Big)p_b$ the expected output of a match, by $B = \pi_g p_b + \frac{u}{e}\Big(\pi_b + \pi_g\Big)b$ the expected outside value of a recruit, and by $C = C_1 +$

$\frac{u}{e}C_2$ the effective flow cost of screening. Differentiating the Job Creation decision (4), substituting for the elasticity of the share of unemployed job seekers with respect to the separation rate and rearranging, the elasticity of tightness with respect to the separation rate is,

$$\frac{\partial \log \theta}{\partial \log s} = -\frac{1}{1-\eta\,(1-XY)}\left[\frac{s}{s+r}\,\frac{y-B}{y-B-C}-XY\right] \tag{7}$$

Appendix B decomposes the elasticity of tightness with respect to the separation rate based on equation (7) and the estimated parameter values in Section 3.

FIGURE 4. IMPACT OF A PERMANENT CHANGE IN THE SEPARATION RATE



2.4 Wages

To identify all parameters of the model, I also require wage data. To this end, denote by $W_b(w)$ the surplus value to a mismatched worker when paid wage w and by $W_g(w)$ that to a well-matched worker when paid wage w. Imposing the Cahuc et al. (2006) bargaining protocol, they solve

$$\begin{aligned} rW_b(w) &= w-b+\phi f\left(\pi_b(1-\gamma)+\pi_g\right)\left(S_b-W_b(w)\right)-sW_b(w) \\ rW_g(w) &= w-b-sW_g(w) \end{aligned}$$

Solving the worker's value functions, the starting wage of an unemployed worker in a bad match is $w_b(u)=b-\phi f\left(\pi_b(1-\gamma)+\pi_g\right)\frac{p_b-b}{r+s}$ and that in a good match is $w_g(u)=b$. The wage for someone who gets an outside offer is $w_b(b)=p_b$ and $w_g(b)=p_b$, regardless of whether she switches or not. Hence, the difference in starting wages of the unemployed and employed is

$$w_{ue} = \frac{\pi_b}{\pi_b + \pi_g} \log\left(b - \phi f\left(\pi_b(1-\gamma) + \pi_g\right) \frac{p_b - b}{r+s}\right) + \frac{\pi_g}{\pi_b + \pi_g} \log(b) - \log(p_b) \tag{8}$$

The replacement rate relative to average productivity is

$$reprate = \frac{b\Big(1-u\Big)}{e_b p_b \ + \ \Big(1 - e_b - u\Big) p_g} \tag{9}$$

Finally, the labor share equals

$$labshare = \frac{1}{1-u}\left[\frac{m_b(u)w_b(u) + m_b(b)w_b(b)}{p_b} + \frac{m_g(u)w_g(u) + m_g(b)w_g(b)}{p_g}\right] \tag{10}$$

where the share of workers in different productivity matches by renegotiation benchmark is

$$m_b(u) = \frac{f\pi_b}{s + \phi f((1-\gamma)\pi_b + \pi_g)} u, \qquad m_b(b) = \frac{\phi f(1-\gamma)\pi_b}{s + f\phi\pi_g} m_b(u)$$

$$m_g(u) = \frac{f\pi_g}{s} u, \qquad m_g(b) = \frac{\phi f \pi_g}{s}(m_b(u) + m_b(b))$$

3 Bringing the Model to the Data

This section estimates parameters governing the hiring process and shows that the model matches key patterns of worker application behavior and mobility in the cross-section. I externally calibrate the discount rate r to equal a five percent annual real interest rate. One of b, p_b and p_g can be normalized, so I normalize by setting $p_b = 1$. Since the starting wage of job-to-job (JJ) movers equals $w_{jj} = p_b$, I normalize empirical wage measures by the residual starting wage of JJ movers.

3.1 Data

I use the SCE from 2013 to 2016 to reproduce some of the facts documented by Faberman et al. (2017); see these authors for greater details about the survey. The survey is administered to roughly 1,300 people annually and asks whether the respondent searched for a job in the past month, how many applications she submitted, current and past wages, demographics, etc.

I focus on male workers aged 18–64 who are either employed or unemployed. The definition of unemployment is somewhat broader than the BLS definition, because I include anyone who reports that she searched in the past month regardless of whether she wants a job. I drop those who are self-employed, or in the case of the unemployed those whose last job was self-employment. The final sample consists of 1,405 observations, 62 of which were unemployed at the start of the prior month. Application rates, mobility rates and starting wages are residual after controlling flexibly for age, eduction and calendar year, and are normalized to the group of 35–44 year olds.

Table 1 summarizes search outcomes during the subsequent month by employment status at the beginning of the month. The unemployed are three times as likely to look for work and submit over 11 times as many applications as the employed. They receive less than three times as many offers, but are more likely to accept an offer such that their mobility rate is seven times as high.[15] Finally, they earn 23 log points lower residual starting wages than JJ movers.

TABLE 1. JOB SEARCH AND OUTCOMES BY EMPLOYMENT STATUS

Status last month	#obs	Looked	Applications	Offers	Mobility	Wage
Unemployed	62	0.82	10.65	0.55	0.25	-0.231
Employed	1343	0.27	0.94	0.21	0.036	0
Relative		*3.07*	*11.28*	*2.69*	*6.98*	*-0.231*

Note: SCE 2013–2016. Residual measures controlling for five age groups, four education groups and calendar year. Education and year coefficients are restricted to sum to zero. Search measures are normalized to the group of 35–44 year olds. Weighted with the appropriate survey weights.

3.2 Worker-level parameters

I target for the separation rate s an estimate of the employment-to-unemployment (EU) mobility rate. I estimate the equilibrium contact rate f as a parameter and later use it as an input to estimate the parameters governing firm behavior. With high-frequency data, it would be straightforward to estimate f as the fraction of unemployed workers that submit an application in a short time interval. Unfortunately, only monthly data are available, leading to concerns about time aggregation bias.[16] Given relatively low monthly mobility rates, I abstract from such bias in my baseline specification to estimate the application rate of unemployed workers as the average number of applications submitted during a month by workers who are unemployed at the beginning of the

[15]The mobility rates are somewhat higher than the corresponding numbers from the Current Population Survey (CPS). In my estimation, I adjust the rates to match the CPS following Faberman et al. (2017).

[16]Specifically, some unemployed in the beginning of the month find a job during the month, causing them to reduce the number of applications they send.

month. Robustness exercises suggest that time aggregation is a second-order issue.[17]

The application rate of mismatched workers is $f(\gamma\pi_u + (1-\gamma)\pi_b + \pi_g)$, but equating this with the average number of applications submitted during a month by workers who are employed at the beginning of the month is again subject to the same time aggregation concerns as above.[18] Since monthly EU and JJ mobility rates are low, I again abstract from such time aggregation bias to write the overall application rate of employed workers as,

$$\text{\# applications}_t|E_t = \frac{e_b}{1-u}\phi f\left(\pi_g + \pi_b(1-\gamma) + \pi_u\gamma\right) = \frac{\pi_b s\phi f\left(\pi_g + \pi_b(1-\gamma) + \pi_u\gamma\right)}{\left(\pi_b + \pi_g\right)\left(s + \phi f\pi_g\right)} \tag{11}$$

Since the unemployed apply for any position and accept bad and good matches, the probability that a worker unemployed at the start of the month remains so throughout the month equals,

$$Prob(\text{no transition}|U_t) = e^{-f\left(\pi_b+\pi_g\right)} \tag{12}$$

A mismatched worker remains with the same employer for a month with probability $\exp(-s - \phi f((1-\gamma)\pi_b/2 + \pi_g))$, where I assume that she switches half of the time when she meets another bad match. Although somewhat arbitrary, this most closely approximates the continuous productivity case in which a worker never meets a match with the same productivity as she is currently in. A well-matched worker remains with the same employer with probability $\exp(-s)$. Hence the probability that an employed worker remains with the same employer throughout a month is,

$$\begin{aligned} Prob(\text{no transition}|E_t) &= \frac{e_b}{e_b+e_g}e^{-s-\phi f\left(\frac{(1-\gamma)\pi_b}{2}+\pi_g\right)} + \frac{e_g}{e_b+e_g}e^{-s} \\ &= \left[\frac{\pi_b s e^{-\phi f\left(\frac{(1-\gamma)\pi_b}{2}+\pi_g\right)} + \pi_b\phi f\pi_g + \pi_g(s+\phi f\pi_g)}{\left(\pi_b+\pi_g\right)\left(s+\phi f\pi_g\right)}\right]e^{-s} \end{aligned} \tag{13}$$

Given that s and f are determined, the system (11)–(13) together with starting wages (8), the replacement rate (9) and the labor share (10) constitute six equations in the remaining six parameters governing worker behavior, $\{\pi_b, \pi_g, \phi, \gamma, b, p_g\}$. I invert this system.

[17] It is complicated to derive a closed form expression for the expected number of applications submitted during a month by workers unemployed in the beginning of the month. I have instead approximated the application rates using a weekly model, which suggests little difference to my baseline estimates using a monthly model.

[18] As for the unemployed, some mismatched workers find a good job during the month and stop applying for jobs while others lose their job and start applying for more jobs.

Parameter values. I target a monthly EU mobility rate of 1.6 percent, which is the average over the 1994–2016 period in the matched CPS micro data for male, private sector workers aged 18–64.[19] I adjust the JJ mobility rate in the SCE to equal a 2.7 percent monthly rate, and I adjust the unemployment-to-employment (UE) mobility rate down by the same factor to 18.8 percent. The implied unemployment rate is 7.2 percent, which given that it is a somewhat broader measure than the BLS definition is in the right ballpark. I make this adjustment following Faberman et al. (2017) to bring the SCE closer to the CPS, but it turns out to have no significant effect on any of the main results in this paper.[20] In addition to the moments on application rates, mobility and starting wages by employment status, I target a replacement rate of 60 percent of average productivity and a labor share of 68 percent. The former is the midpoint of the 71 percent estimated by Hall and Milgrom (2008) and the 49 percent in Mas and Pallais (2017). Table 2 summarizes the targeted moments and the model's ability to replicate them. I stress that the model successfully matches these moments without requiring the unemployed to exogenously differ in their ability to convert applications to jobs or sample from a different offer distribution.

TABLE 2. MODEL FIT

	# Appl. (U)	# Appl. (E)	EU	UE	JJ	Starting wage	Labor share	Repl. rate
Data	10.65	0.94	0.016	0.188	0.027	-0.231	0.68	0.60
Model	10.65	0.94	0.016	0.188	0.027	-0.231	0.68	0.60

Note: # applications by employment status, starting wage of unemployed and UE and JJ mobility rates from the SCE 2013–2016, the latter two adjusted following Faberman et al. (2017) to better match the levels in the CPS. EU mobility rate from the CPS 1994–2016. Empirical # applications, mobility rates and starting wage are residual after controlling for age, education and calendar year; # applications and mobility rates are normalized to the group of 35–44 year olds and for the average education level. See text for further details.

[19] This is lower than what the aggregate BLS data and the methodology in Shimer (2005) suggest. The reason for the discrepancy between the matched micro data and the aggregate data remains an unresolved question, but may be due to well-known issues with classification error in employment status (Abowd and Zellner, 1985; Poterba and Summers, 1986) and recall (Fujita and Moscarini, 2017). Fortunately, results are not sensitive to the exact value for s.

[20] The targeted JJ mobility rate is somewhat higher than the average over the 1994–2016 period in the CPS, which is 2.5 percent per month for male private sector workers aged 18–64. The JJ mobility rate, however, has been trending down secularly since 1994, suggesting that the average over the post-war period may be somewhat higher than 2.5 percent. The average UE mobility rate is 27 percent per month over the 1978–2016 period in the CPS, with little secular trend. As noted above, this is likely inflated by classification error and recall. Furthermore, the broader measure of unemployment in the SCE includes some people who the CPS classifies as not in the labor force, with a much lower transition rate. The average BLS unemployment rate for male workers from 1951 to 2017 is 5.8 percent. Faberman et al. (2017) show that the broader definition of unemployment in the SCE includes about 15 percent of those not in the labor force under the BLS definition. Given an average non-participation rate of men 18–64 of a little over 10 percent, this gives an unemployment rate of about 7.3 percent. In an earlier version I found very similar results without making the Faberman et al. (2017) adjustment.

Table 3 presents the estimated structural and auxiliary parameters, expressed as daily rates since Section 4 will simulate a dynamic version of the economy at a daily frequency. Only two percent of potential matches are viable and it is eight times as likely to be low productive relative to high productive. There is significant noise in the signal of match quality and mismatched workers search with 71 percent of the intensity of unemployed workers. In the estimated economy, 43 percent of employed workers are mismatched, implying that the unemployed search a little over three times as much as the average employed worker. Accidentally, this is close to the empirical difference in the fraction of people looking actively for jobs in Table 1. The estimated flow value of unemployment equals 97 percent of output in low productivity matches, while good matches are estimated to be twice as productive as bad matches. Although the difference is big, the implied variance of log labor productivity is 0.13, which is lower than typical estimates of the dispersion in value added per worker or TFP across firms (see for instance Decker et al., 2017). In addition, p may be interpreted as also encompassing personal utility derived from the job etc. In any case, a lower value for p_g amplifies the effect of shocks and hence a high value is conservative.

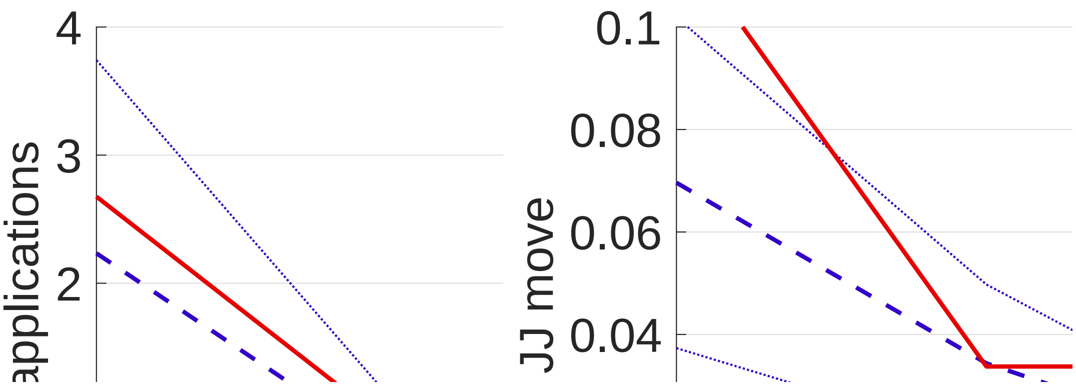
TABLE 3. WORKER PARAMETER VALUES (DAILY FREQUENCY)

	Description	Value
s	Separation rate	0.0005
f	Arrival rate	0.3550
π_b	Probability of bad match	0.0175
π_g	Probability of good match	0.0021
ϕ	Relative search intensity	0.7051
γ	Noise in signal	0.2798
b	Flow value of leisure	0.9668
p_g	Productivity of good match	2.0784

Validation. As a worker climbs the job ladder, she submits fewer applications and is less likely to make a move. The left panel of Figure 5 plots the number of applications submitted during the month by rank in the job ladder in the data in dashed blue and in the model in solid red. The job ladder in the data is quartile of the residual wage distribution at the beginning of the month. In the model, the first group is workers in low productivity matches with unemployment as renegotiation benchmark (11 percent of employed workers), while the other groups are the average across those who have climbed the ladder, either in productivity or renegotiation sense.[21] The right panel plots the probability of a JJ move. Both statistics are substantially below that of unemployed workers, even at the bottom of the distribution, and they fall significantly as workers climb the job ladder. I conclude that the model matches well the data in this untargeted dimension.

FIGURE 5. SEARCH OUTCOMES BY RANK IN LADDER

(A) # APPLICATIONS (B) MOBILITY RATE



Note: Empirical rates are residual controlling for age, education and calendar year from the SCE 2013–2016. Number of applications and probability of JJ move during the month by rank in residual wage distribution at the beginning of the month. Data is quartile of residual wage distribution. First group in model is mismatched workers with unemployment as renegotiation benchmark, other groups are everyone further up the ladder.

3.3 Firm-level parameters

It remains to determine the parameters governing firm behavior: matching efficiency, χ; the cost of advertising job openings, c_v; the cost of screening, c_s; and the elasticity of the matching function, α. I first discuss how the first three parameters are identified off cross-sectional information on hiring behavior of firms, taking as given an estimate of the elasticity of the matching function, α.

A vacancy contacts a potential applicant at rate $q = \chi^{1/\alpha} f^{1-1/\alpha}$ and the probability that she submits an application is $\frac{u}{e} + \frac{\phi e_b}{e}\left(\gamma\pi_u + (1-\gamma)\pi_b + \pi_g\right)$. Based on an empirical estimate of the number of applicants per vacancy, I set matching efficiency to,

$$\chi = f^{1-\alpha}\left[\left(\#\,\text{applicants}\right)\Big/\left(\frac{u}{e} + \frac{\phi e_b}{e}\left(\gamma\pi_u + (1-\gamma)\pi_b + \pi_g\right)\right)\right]^{\alpha} \tag{14}$$

[21]Mapping the model to the data in terms of the wage ladder is not entirely straightforward. Mismatched workers with unemployment as renegotiation benchmark earn the lowest wage in the model (11 percent of workers), while well-matched workers with unemployment as renegotiation benchmark earn the second lowest wage (another 11 percent). The latter group neither submits applications nor moves since decisions are bilaterally optimal and the match is at the top of the productivity ladder. Remaining workers earn wage p_b regardless of whether they are mismatched or well-matched, but those who are mismatched continue to submit applications and move. This zigsacky pattern of search in the wage dimension motivates my decision to group everyone else into "those who have climbed the ladder."

The average cost to screen per vacancy equals,

$$\text{Cost of screening} \;=\; q\,c_s\left(\left(\gamma\pi_u + (1-\gamma)\pi_b + \pi_g\right) \;+\; \frac{u}{u+\phi e_b}\left((1-\gamma)\pi_u + \gamma\pi_b\right)\right) \tag{15}$$

The cost parameters, c_v and c_s, are hence identified from two conditions: (1) the ratio of the total cost of screening (15) as a fraction of the total cost of hiring (the sum of the total cost of screening (15) and the cost of advertising c_v), and (2) that free entry holds.

Davis and Samaniego de la Parra (2017) find that a vacancy on average receives 8.6 applications, which I use to estimate matching efficiency based on equation (14).[22] Table 4 reproduces data from Blatter et al. (2012), who use detailed Swiss data to document that screening costs equal 48 percent of the total cost of advertising, screening and external placement agencies. As it is not immediately clear how to treat the cost of external placement agencies, excluding such costs the share accounted for by screening rises to 57.6 percent. These statistics are for firms with 100+ employees, whereas the employment-*unweighted* average screening cost across all firms is 57 percent or 64.6 percent excluding the cost of external placement agencies. As most hiring takes place at firms with 100+ employees and it is unclear whether the cost of external placement agencies should be included in the cost of screening, I target for my baseline parameterization a relative cost of screening of 52.8 percent of the total cost of hiring, constructed as the average of the share including and excluding the cost of external placement agencies.

TABLE 4. BREAKDOWN OF COSTS OF HIRING

	Advertising	Screening	External advisors
All firms	31.3%	57.0%	11.7%
100+ employees	35.4%	48.0%	16.6%

Source: Blatter et al. (2012) based on Swiss administrative data 1998–2004. Advertising includes the cost of newspaper advertisements, requests from employment agencies, internal job advertisements, etc.; Screening includes the cost of preparing the interview, conducting the interview, reflection time, administrative effort, etc.; External advisors are "costs for services of external placement agencies."

It remains to determine the elasticity of the matching function, α. Based on a variety of estimates, many of which are summarized in Petrongolo and Pissarides (2001), Mortensen and Nagypal (2007) conclude that 0.4 is an appropriate value for this elasticity. This, however, is in models

[22] I calculate this based on their 7.7 million vacancies and 65.9 million applications.

that abstract from on-the-job search, whereas reliable estimates that allow for on-the-job search are hard to come by. To estimate this parameter, I rely on the structure of the model and Simulated Method of Moments. I fix an α, estimate the remaining parameters based on the discussion above, and simulate the dynamic version of the economy presented in Section 4. In the simulated data, I regress the UE mobility rate on the ratio of vacancies to unemployment, where both series are in logs and HP-filtered with smoothing parameter 10^5. I adjust the structural parameter α to minimize the distance between the estimated elasticity and 0.4. Key indicators of the reliability of this procedure are whether the estimated elasticity is monotonic in the underlying structural parameter and whether the minimum distance increases quickly as the structural parameter deviates from the estimated value, both of which I find are satisfied. This indicates that the estimated structural parameter α is well identified by the reduced form elasticity.

Table 5 summarizes the estimated parameters governing hiring. The cost of advertising a vacancy and screening an applicant equal 26 and 3.1 percent of quarterly output, respectively. Adding these up, the total cost of advertising and screening for a vacancy equals half of quarterly output, which is necessary to reconcile the targeted profit share with free entry. For comparison, Blatter et al. (2012) document that the total cost of hiring a worker—including costs associated with training new workers—may equal up to 1.3 times quarterly wages.[23] The chance that this process results in a hire is only 10 percent, which is required to match the estimated number of applications received per vacancy together with the large difference between the number of applications submitted and mobility rates. Finally, the estimated elasticity of the matching function is 0.675, i.e. higher than the reduced form, empirical estimate abstracting from on-the-job search would suggest. This is in line with arguments in Petrongolo and Pissarides (2001) that abstracting from employed job searchers will lead to an underestimate of the true matching elasticity.

TABLE 5. FIRM PARAMETER VALUES

	Description	Value
χ	Matching efficiency	6.015
c_v	Cost of advertising position	38.423
c_s	Cost of screening applicant	4.468
α	Elasticity of job finding rate w.r.t. tightness	0.675

[23] Data from GetHired.com similarly suggest that the costs of advertising a job opening, pre-screening candidates, preparing for interviews, interviewing and wrapping up can be as high as $19k.

4 The Role of Frictions in Amplifying Shocks

This section considers a dynamic version of the economy in response to separation rate shocks. I follow Shimer (2005) to assume that such shocks evolve according to a first-order Markov process in continuous time: At Poisson rate λ the aggregate state gets updated from s to s', with support such that mismatch is always preferable to unemployment. The surplus functions solve

$$rS_b(s) \;=\; p_b - b \;-\; sS_b(s) \;+\; \lambda \mathbb{E}_s\Big(S_b(s') - S_b(s)\Big) \tag{16}$$

$$rS_g(s) \;=\; p_g - b \;-\; sS_g(s) \;+\; \lambda \mathbb{E}_s\Big(S_g(s') - S_g(s)\Big) \tag{17}$$

The value functions (16)–(17) do not contain the expected evolution of the distribution of employment and hence it is easy to solve for them out of steady state (Lise and Robin, 2017). Effectively, the zero bargaining power of workers renders the surplus entirely backward-looking. Given a solution to the surplus functions, the dynamic economy is characterized by the system

$$\dot{u}(t) \;=\; s(t)\Big(1-u(t)\Big) \;-\; f\Big(\theta(t)\Big)\,(\pi_g + \pi_b)\,u(t) \tag{18}$$

$$\dot{e}_b(t) \;=\; -\Big[\phi f\Big(\theta(t)\Big)\pi_g \;+\; s(t)\Big]\,e_b(t) \;+\; f\Big(\theta(t)\Big)\pi_b u(t) \tag{19}$$

$$\frac{c_v\theta(t)}{f\Big(\theta(t)\Big)} \;=\; \pi_g\left[S_g\Big(s(t)\Big) - S_b\Big(s(t)\Big)\right] - \tilde{C}_1 + \frac{u(t)}{u(t)+\phi e_b(t)}\left[\Big(\pi_b+\pi_g\Big)S_b(s(t)) - \tilde{C}_2\right] \tag{20}$$

where $\tilde{C}_1 = c_s(\gamma\pi_u + (1-\gamma)\pi_b + \pi_g)$ and $\tilde{C}_2 = c_s((1-\gamma)\pi_u + \gamma\pi_b)$. Starting from an initial condition $\{u(0), e_b(0)\}$, the system (18)–(20) characterizes the dynamic economy $\{u(t), e_b(t), \theta(t)\}$ in response to a sequence of shocks $s(t)$. I approximate the model at a daily frequency and assume that the Markov process is the discrete time equivalent of an AR(1) process with mean reversion ρ and intensity of shocks σ. I simulate the model 1,000 times starting from the stationary equilibrium, each time drawing a new sequence of aggregate shocks and discarding the initial 1,000 observations. I aggregate the data to a quarterly frequency and report average statistics across the simulations based on HP-filtered data using 268 quarters with smoothing parameter 10^5.

4.1 Volatility and persistence of the v/u-ratio

Table 6 compares the predicted impact of separation rate shocks in the model with the data. Panel A summarizes the data, which are an updated version of Shimer (2005) including an additional

14 years of data at the end of the sample period.[24] Vacancies are 25 percent more volatile than unemployment and vary substantially more than the separation rate. Furthermore, unemployment and vacancies are strongly negatively correlated, resulting in a highly volatile v/u-ratio.[25]

Panel B shows that absent screening costs, separation rate shocks cannot replicate these patterns. Although the standard deviation of unemployment is non-trivial at 35 percent of its empirical counterpart, this is almost entirely driven by the separation rate. In contrast, the standard deviation of vacancies equals just over 10 percent of the empirical volatility, while the standard deviation of the v/u-ratio and the job finding rate are less than 20 percent of their empirical counterparts. Furthermore, the issue stressed by Shimer (2005) for the benchmark Mortensen and Pissarides (1994) model is evident also here: separation rate shocks result in at most a weakly negative correlation between unemployment and vacancies, in contrast to the data.

Panel C shows that separation rate shocks explain a large share of the empirical volatility of labor market outcomes in the estimated model. Relative to the model without screening costs, the unemployment rate is more than twice as volatile and more persistent; vacancies and the job finding rate are over five times as volatile and substantially more persistent; and all endogenous outcomes are less correlated with the separation rate, indicating that the model generates significant internal propagation of separation rate shocks (although they remain more correlated with the separation rate than in the data). Productivity fluctuates endogenously in the model with a standard deviation of 0.012 versus 0.02 in the data and with correlations with the other endogenous and exogenous variables that are generally of the right sign. Hence as in Barlevy (2002), recessions are "sullying," because laid-off workers initially return in low productivity matches. Most importantly, separation rate shocks explain two-thirds of the overall empirical volatility in the v/u-ratio and all of the empirical variability in the v/u-ratio that can be projected on the separation rate, which equals $\rho_{s,v/u}\sigma_s = 0.651 \times 0.438 = 0.285$. They also generate a strong negative correlation between vacancies and unemployment, in line with the data. Appendix A contains robustness exercises under different relative importance of the costs of screening.

To further illustrate the dynamic impact of a separation rate shock, Figure 6 plots the impulse response of unemployment and the v/u-ratio to a one standard deviation impulse to the separa-

[24]Specifically, following Shimer (2005) I use data on the stock of unemployed, short-term unemployed and employed from the BLS to estimate labor market flows. Vacancies come from the help-wanted index spliced with JOLTS data for the later years. All series are seasonally adjusted and HP-filtered with smoothing parameter 10^5.

[25]I refer to the vacancy-to-unemployment ratio as the *v/u-ratio* as distinct from the theoretical concept of tightness.

tion rate.[26] Short-lived shocks result in persistent responses of the v/u-ratio and unemployment, both in the data and model. Shocks in the model match well the empirical pattern.

TABLE 6. DYNAMICS IN RESPONSE TO SEPARATION RATE SHOCKS

PANEL A: DATA

		u	v	v/u	f	p	s
Standard deviation		0.208	0.250	0.438	0.142	0.020	0.074
Autocorrelation		0.954	0.953	0.956	0.934	0.899	0.747
	u	1	-0.856	-0.946	-0.955	-0.281	0.657
	v		1	0.973	0.859	0.143	-0.617
	v/u			1	0.930	0.209	-0.651
Correlation matrix	f				1	0.242	-0.518
	p					1	-0.462
	s						1

PANEL B: WITHOUT COST OF SCREENING

		u	v	v/u	f	p	s
Standard deviation		0.074	0.030	0.087	0.023	0.006	0.074
Autocorrelation		0.917	0.593	0.870	0.663	0.982	0.747
	u	1	-0.264	-0.942	-0.758	-0.469	0.837
	v		1	0.573	0.764	-0.475	-0.712
	v/u			1	0.911	0.234	-0.961
Correlation matrix	f				1	0.168	-0.988
	p					1	-0.193
	s						1

PANEL C: ESTIMATED COST OF SCREENING

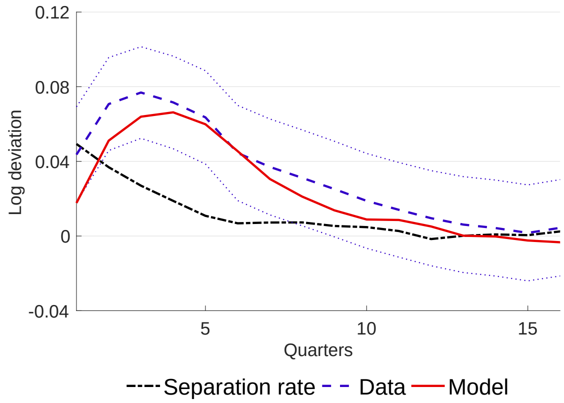
		u	v	v/u	f	p	s
Standard deviation		0.154	0.153	0.293	0.119	0.012	0.074
Autocorrelation		0.941	0.866	0.918	0.888	0.983	0.747
	u	1	-0.812	-0.952	-0.918	-0.476	0.767
	v		1	0.952	0.969	-0.015	-0.928
	v/u			1	0.991	0.243	-0.890
Correlation matrix	f				1	0.227	-0.935
	p					1	-0.169
	s						1

Note: Data from the BLS, the Conference Board's Help Wanted Index and JOLTS, 1951Q1–2017Q4. HP-filtered with smoothing parameter 10^5.

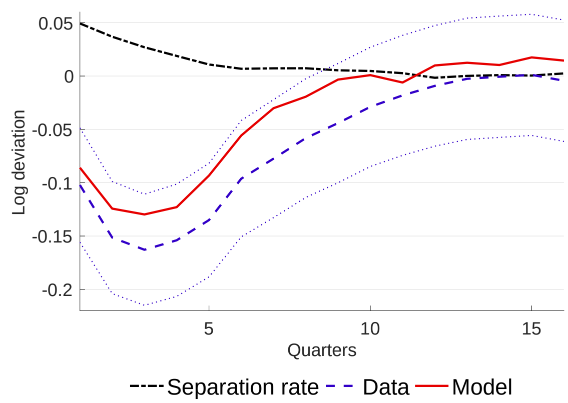
[26] I construct this by regressing the unemployment rate or v/u-ratio at time $T + t$ on the innovation to the separation rate at time T, controlling for the innovation to productivity at time T.

FIGURE 6. IMPULSE RESPONSES TO A SEPARATION RATE SHOCK

(A) UNEMPLOYMENT



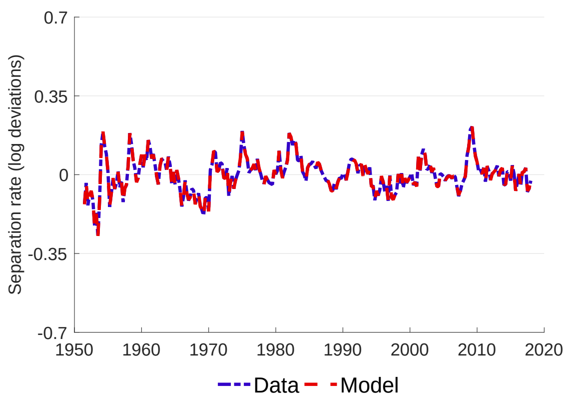
(B) V/U-RATIO



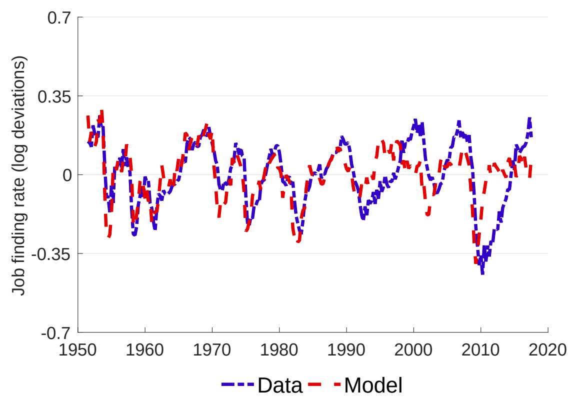
Note: Data from the BLS, the Conference Board's Help Wanted Index and JOLTS, 1951Q1–2017Q4. HP-filtered with smoothing parameter 10^5*. Impulse responses to a one-standard deviation pulse to the separation rate controlling for the contemporaneous impulse to productivity. Dotted blue lines are 95% confidence interval.*

FIGURE 7. SIMULATED SERIES, 1951Q1–2017Q4

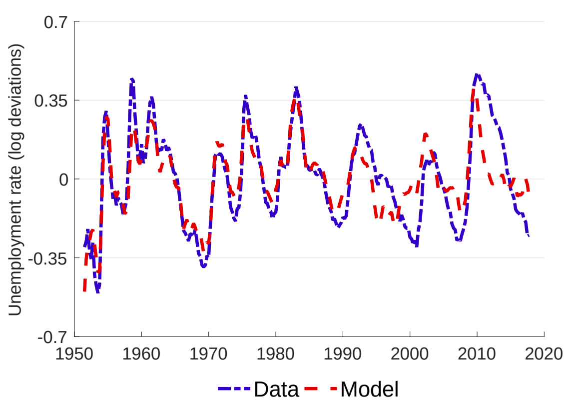
(A) SEPARATION RATE



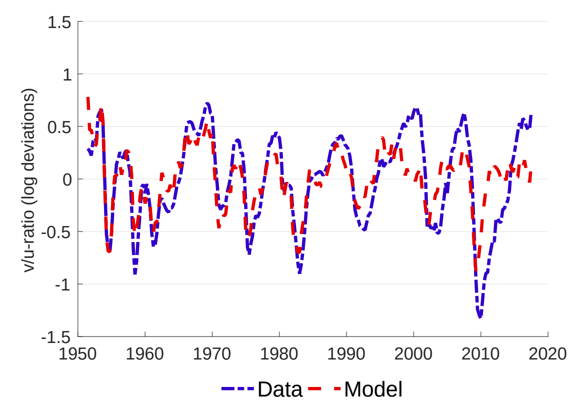
(B) JOB FINDING RATE



(C) UNEMPLOYMENT RATE



(D) V/U-RATIO



Note: Data from the BLS, the Conference Board's Help Wanted Index and JOLTS, 1951Q1–2017Q4. HP-filtered with smoothing parameter 10^5*.*

Figure 7 compares job finding rate, unemployment rate and labor market tightness in the model with the same series in the data in response to a sequence of separation rate shocks that mimic the actual data in the US over the 1951Q1–2017Q4 period. Separation rate shocks in the model capture well the empirical series, particularly up to the 1980s.

Table 7 highlights that amplification in the model is not driven by a counterfactually rigid wage.[27] Under the estimated screening costs, separation rate shocks generate a standard deviation of average wages over the business cycle that equals 70 percent of its empirical counterpart, with an elasticity with respect to unemployment that is somewhat *more negative* than in the data.

TABLE 7. WAGE CYCLICALITY

	(1) St.d.	(2) AR(1)	(3) $\eta(wage, u)$	(4) $\eta(wage, p)$
Data	0.018	0.911	-0.037	0.590
Model	0.013	0.947	-0.084	0.554

Note: Data from the BLS, 1951Q1–2017Q4. Wage is the labor share times average value added per worker. $\eta(x, y)$ denotes the elasticity of x with respect to y. All variables are seasonally adjusted, in logs and HP-filtered with smoothing parameter 10^5.

4.2 Shifts in the composition of hires

The model highlights that shifts in the composition of applicants along the unemployed-employed margin are an important component of the amplification of separation rate shocks. To assess whether separation rate shocks replicate changes in the composition of hires over the business cycle in the data, I compute the number of employed hires as the JJ mobility hazard times one minus the unemployment rate, $jj_t(1 - u_t)$, and the number of unemployed hires as the UE hazard rate times the unemployment rate, $ue_t u_t$, using CPS data from 1994Q1 to 2017Q4.[28] I compute the share of employed hires, take the log of this and HP-filter it with smoothing parameter 10^5. Table 8 reports that its standard deviation is 0.063 in the data versus 0.057 in the model, highlighting that separation rate shocks in the model give rise to shifts in the composition of the pool of hires over the business cycle that is of the same magnitude as in the data.

[27] Appendix C discusses how I solve for wages in the dynamic economy.

[28] It is only possible to construct a JJ hazard series starting with the introduction of dependent interviewing techniques at the time of the 1994 redesign of the CPS.

TABLE 8. SHARE OF EMPLOYED HIRES

	(1) St.d.	(2) AR(1)	(3) $\rho(hires_e, u)$	(4) $\rho(hires_e, eu)$	(5) $\rho(hires_e, v/u)$
Data	0.063	0.823	-0.877	-0.404	0.857
Model	0.057	0.936	-0.969	-0.782	0.982

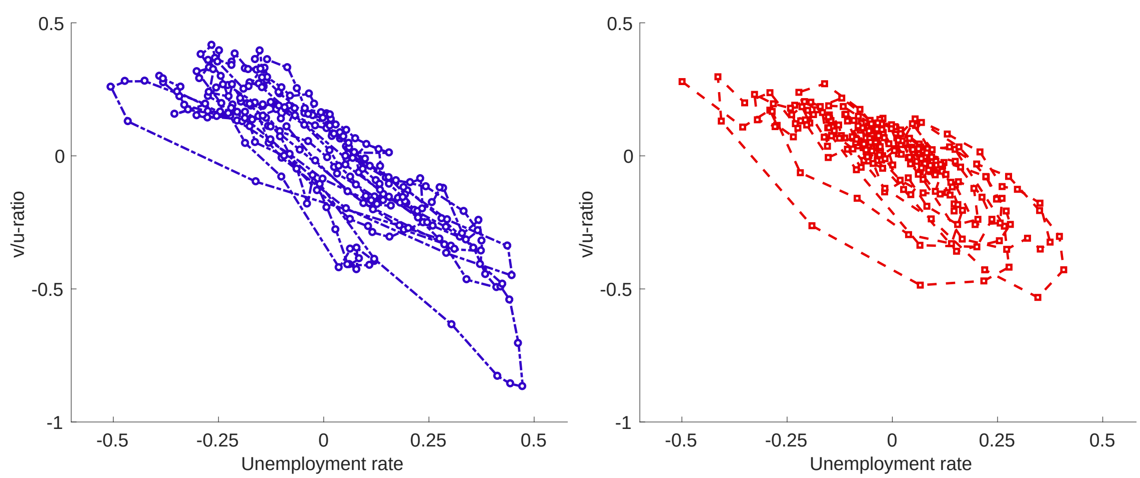
Note: Data from the CPS, 1994Q1–2017Q4. Employed hires equals the JJ hazard rate times one minus the unemployment rate, unemployed hires equals the UE hazard rate times the unemployment rate. All variables are in logs and HP-filtered with smoothing parameter 10^5.

4.3 Beveridge cycles

Figure 8 shows that separation rate shocks explain well the empirical Beveridge curve, including its counter-clockwise cycles documented by Sniekers (2018). The increase in the separation rate at the start of the recession reduces job creation, generating a steep increase in the unemployment rate. As the economy recovers, the share of mismatched applicants rises, since most people out of unemployment start as mismatched. The higher share of mismatched applicants encourages job creation conditional on unemployment, pushing out the Beveridge curve.

FIGURE 8. BEVERIDGE CURVE

(A) DATA (B) MODEL



Note: Data from the BLS, the Conference Board's Help Wanted Index and JOLTS, 1951Q1–2017Q4. HP-filtered with smoothing parameter 10^5.

4.4 Pro-cyclical matching efficiency

Separation rate shocks also induce what appears to be a pro-cyclical matching efficiency, for a similar reason as above. Specifically, I define the reduced-form matching efficiency as the residual from the actual number of hires and what would be predicted based on a Cobb-Douglas matching function that combines unemployment and vacancies (using the reduced form elasticity of the matching function), $\hat{\chi} = hires_t / \left(u_t^{0.4} v_t^{0.6}\right)$. Separation rate shocks explain two-thirds of the empirical fluctuations in matching efficiency, as illustrated by Table 9.

TABLE 9. MATCHING EFFICIENCY

	(1) St.d.	(2) AR(1)	(3) $\rho(\hat{\chi}, u)$	(4) $\rho(\hat{\chi}, eu)$	(5) $\rho(\hat{\chi}, v/u)$
Data	0.151	0.968	-0.983	-0.435	0.915
Model	0.097	0.924	-0.958	-0.875	0.999

Note: Data from the BLS and JOLTS, 2001Q1–2017Q4. Matching efficiency is inferred as $\hat{\chi} = hires_t / \left(u_t^{0.4} v_t^{0.6}\right)$. $\rho(x, y)$ denotes the contemporaneous correlation between x and y. Logs and HP-filtered with smoothing parameter 10^5.

4.5 Dependence of the v/u-ratio on unemployment

To assess whether separation rate shocks explain the empirical relationship between the v/u-ratio, productivity, the separation rate and the unemployment rate, I regress following Coles and Kelishomi (2018) the v/u-ratio on productivity, the separation rate and the unemployment rate,

$$\log\left(\frac{v_t}{u_t}\right) = \beta_0 + \beta_1 \log p_t + \beta_2 \log eu_t + \beta_3 \log u_{t-1} + \varepsilon_t$$

All variables are HP-filtered and I use the lagged unemployment rate to avoid simultaneity issues.

Table 10 presents results. In the data, the v/u-ratio is negatively related to current productivity, conditional on the separation rate and lagged unemployment, although only weakly statistically significant. Separation rate shocks in the model qualitatively matches this, but the point estimate is much larger.[29] More importantly, the v/u-ratio is strongly negatively correlated with the separation rate, with a slightly more negative point estimate in the model. Finally, controlling for productivity and the separation rate, the v/u-ratio is negatively correlated with the unemployment rate. As noted by Coles and Kelishomi (2018), this is at odds with the benchmark Mortensen and Pissarides (1994) model without on-the-job search, where the v/u-ratio is independent of the

[29] The standard deviation of productivity in the model, however, is only 60 percent of its empirical counterpart, suggesting a role also for underlying true productivity shocks. Such shocks would presumably make the estimated coefficient less negative.

unemployment rate. With on-the-job search and the richer model of the hiring process, separation rate shocks match closely the empirical relationship.

TABLE 10. DEPENDENCE OF THE V/U-RATIO ON UNEMPLOYMENT

	(1) $\log p_t$	(2) $\log eu_t$	(3) $\log u_{t-1}$	(4) N	(5) R^2
Data	-0.977*	-1.922***	-1.528***	267	0.834
	(0.589)	(0.250)	(0.074)		
Model	-7.430***	-2.302***	-1.284***	267	0.985
	(0.240)	(0.058)	(0.027)		

Note: Data from the BLS, the Conference Board's Help Wanted Index and JOLTS, 1951Q1–2017Q4. Estimates from regression of the v/u-ratio on productivity, the separation rate and the lagged unemployment rate. All variables are HP-filtered with smoothing parameter 10^5. *Robust standard errors in parenthesis. *statistically significant at 10%; ** 5%; ***at 1%.*

4.6 A counter-cyclical cost of hiring

Finally, key to the results in this paper is a mechanism that generates a counter-cyclical cost of hiring. To highlight this further, I can rewrite the free entry condition (20) in terms of the total cost of hiring, $C\left(\theta(t), \frac{u(t)}{e(t)}\right) = c_v + \chi\theta(t)^{\alpha-1}\left(\tilde{C}_1 + \frac{u(t)}{e(t)}\tilde{C}_2\right)$,

$$C\left(\theta(t), \frac{u(t)}{e(t)}\right) = \chi\theta(t)^{\alpha-1}\left(\pi_g\left[S_g\Big(s(t)\Big) - S_b\Big(s(t)\Big)\right] + \frac{u(t)}{e(t)}\Big(\pi_b + \pi_g\Big)S_b(s(t))\right) \tag{21}$$

The right-hand side of (21) consists of standard terms in on-the-job search models capturing the return to vacancy creation. In contrast to a standard model, however, the cost of hiring on the left-hand side depends on labor market tightness and the share of unemployed job seekers.

Holding fixed the share of unemployed job seekers, the derivative of the cost $C\left(\theta(t), \frac{u(t)}{e(t)}\right)$ with respect to tightness is,

$$\frac{\partial \log C\left(\theta, \frac{u}{e}\right)}{\partial \log \theta} = -\Big(1-\alpha\Big)\frac{\text{Cost of screening}}{c_v + \text{Cost of screening}}$$

where the cost of screening is the total cost of screening for the applications received by a vacancy in equation (15). Under the estimated values, a one percent increase in tightness reduces the cost of hiring by 0.159 percent, holding fixed the share of unemployed job seekers.

Differentiating the cost $C\left(\theta(t), \frac{u(t)}{e(t)}\right)$ with respect to the share of unemployed job seekers holding tightness fixed,

$$\frac{\partial \log C\left(\theta, \frac{u}{e}\right)}{\partial \log \frac{u}{e}} = \frac{q \frac{u}{e} \tilde{C}_2}{c_v + \text{Cost of screening}}$$

Under the estimated parameter values, a one percent increase in the share of unemployed job seekers increases the cost of hiring by 0.175 percent, holding fixed tightness.[30]

This analysis suggests that to a first-order approximation, an appropriate specification for the cost of hiring in a model which abstracts from a micro-founded hiring process would be,

$$\tilde{C}\left(\theta(t), \frac{u(t)}{e(t)}\right) \quad = \quad c - 0.159 \log \theta(t) \ + \ 0.175 \log\left(\frac{u(t)}{e(t)}\right)$$

where the constant c is set such that the model matches some desired moment in steady-state—typically the job finding rate—and free entry holds.

5 Conclusion

This paper asserts that separation rate shocks are a main driver of the business cycle behavior of unemployment and vacancies, in contrast to conventional wisdom. I develop a micro-founded, richer description of the hiring process, and embed it into an otherwise standard matching model. The theory highlights an additional source of congestion in the labor market: By applying for jobs that they are unlikely to be a good fit for, the unemployed exert a negative externality on firms, who have to pay to screen these applications. As a consequence, the cost of hiring endogenously increases during periods of high unemployment. I estimate key parameters using new data on worker search behavior and outcomes, and find that separation rate shocks explain two thirds of the empirical volatility in labor market tightness and generate a strong negative correlation between unemployment and vacancies, in line with the data. My findings highlight that a better micro-level apprehension of the process that brings workers and firms together has important implications for our understanding of business cycle fluctuations in labor market outcomes.

The insights in this paper have broader implications. For instance, if additional search effort is associated with marginally worse opportunities and bad applications exert a negative externality on employers, countercyclical search intensity may amplify rather than dampen unemployment

[30] The true relationship is not log-linear: the elasticity of the cost of hiring with respect to tightness (the share of unemployed job seekers) is larger in absolute terms the higher (lower) is the share of unemployed job seekers (tightness). In other words, the marginal effect of a change in tightness or the share of unemployed job seekers on the cost of hiring is greater when the economy is in a recession.

fluctuations as in Mukoyama et al. (2018). Similarly, requiring as several countries do that the unemployed exert sufficient search effort to qualify for unemployment benefits may slow rather than fasten the recovery of unemployment after a negative shock, if it prods unemployed workers to apply for many jobs that they are unlikely to be well-suited for. Furthermore, to the extent that the Internet has reduced the cost of applying for jobs, this may counterintuitively explain a decline in labor market fluidity over the past decades. Finally, with respect to a key inspiration for this paper—the job market for academic economists—my findings may advocate for instituting a cap on the number of applications a candidate may submit or pricing applications in order to induce applicants to internalize the externality they exert on committees by applying for jobs they know they are very unlikely to take.

References

Abowd, John M. and Arnold Zellner, "Estimating gross labor-force flows," *Journal of Business & Economic Statistics*, 1985, *3* (3), 254–283.

Barlevy, Gadi, "The Sullying Effect of Recessions," *Review of Economic Studies*, 2002, *69* (1), 65–96.

Barnichon, Regis, "Productivity and Unemployment over the Business Cycle," *Journal of Monetary Economics*, 2010, *57* (8), 1013–1025.

Blatter, Marc, Samuel Muehlemann, and Samuel Schenker, "The costs of hiring skilled workers," *European Economic Review*, 2012, *56* (1), 20–35.

Cahuc, Pierre, Fabien Postel-Vinay, and Jean-Marc Robin, "Wage Bargaining with On-the-Job Search: Theory and Evidence," 2006.

Chodorow-Reich, Gabriel and Loukas Karabarbounis, "The Cyclicality of the Opportunity Cost of Employment," *Journal of Political Economy*, 2016, *124* (6), 1563–1618.

Christensen, Bent Jesper, Rasmus Lentz, Dale T. Mortensen, George R. Neumann, and Axel Werwatz, "On-the-Job Search and the Wage Distribution," *Journal of Labor Economics*, 2005, *23* (1), 31–58.

Coles, Melvyn G and Ali Moghaddasi Kelishomi, "Do Job Destruction Shocks Matter in the Theory of Unemployment?," *American Economic Journal: Macroeconomics*, 2018, (forthcoming).

Davis, Steven J and Brenda Samaniego de la Parra, "Application Flows," 2017.

Decker, Ryan A, John Haltiwanger, Ron S Jarmin, and Javier Miranda, "Changing Business Dynamism and Productivity: Shocks vs. Responsiveness," 2017.

Diamond, Peter A., "Aggregate Demand Management in Search Equilibrium," *Journal of Political Economy*, 1982, *90* (5), 881–894.

Eeckhout, Jan and Ilse Lindenlaub, "Unemployment Cycles," 2017.

Faberman, R. Jason, Andreas Mueller, Aysegul Sahin, and Giorgio Topa, "Job Search Behavior among the Employed and Non-Employed," 2017.

Fujita, Shigeru and Garey Ramey, "Job Matching and Propagation," *Journal of Economic Dynamics and Control*, 2007, *31* (11), 3671–3698.

— **and Giuseppe Moscarini**, "Recall and Unemployment," *American Economic Review*, 2017, *102* (7), 3875–3916.

Hagedorn, Marcus and Iourii Manovskii, "The Cyclical Behavior of Equilibrium Unemployment and Vacancies Revisited," *American Economic Review*, 2008, *98* (4), 1692–1706.

— **and** — , "Productivity and the Labor Market: Comovement over the Business Cycle," *International Economic Review*, 2011, *52* (3), 603–619.

Hall, Robert E., "Employment fluctuations with equilibrium wage stickiness," *American Economic Review*, 2005, *95* (1), 50–65.

Hall, Robert E, "The Amplification of Unemployment Fluctuations through Self-Selection," 2005.

— , "How Much Do We Understand about the Modern Recession?," *Brookings Papers on Economic Activity*, 2007, *2*, 13–30.

Hall, Robert E., "High Discounts and High Unemployment," *American Economic Review*, 2017, *107* (2), 305–330.

— **and Paul R. Milgrom**, "The limited influence of unemployment on the wage bargain," *American Economic Review*, 2008, *98* (4), 1653–1674.

Kaplan, Greg and Guido Menzio, "Shopping Externalities and Self-Fulfilling Unemployment Fluctuations," *Journal of Political Economy*, 2016, *124* (3), 771–825.

Kehoe, Patrick, Virgiliu Midrigan, and Elena Pastorino, "Debt Constraints and Employment," 2016.

Lise, Jeremy and Jean Marc Robin, "The macrodynamics of sorting between workers and firms," *American Economic Review*, 2017, *107* (4), 1104–1135.

Ljungqvist, Lars and Thomas J. Sargent, "The fundamental surplus," *American Economic Review*, 2017, *107* (9), 2630–2665.

Mas, Alexandre and Amanda Pallais, "Labor Supply and the Value of Non-Work Time: Experimental Estimates from the Field," 2017.

Merz, Monica and Eran Yashiv, "Labor and the Market Value of the Firm," *American Economic Review*, 2007, *97* (4), 1419–1431.

Mitman, Kurt and Stanislav Rabinovich, "Do Unemployment Benefit Extensions Explain the Emergence of Jobless Recoveries?," 2014.

Mortensen, D. T. and C. A. Pissarides, "Job Creation and Job Destruction in the Theory of Unemployment," *The Review of Economic Studies*, 1994, *61* (3), 397–415.

Mortensen, Dale T. and Eva Nagypal, "More on unemployment and vacancy fluctuations," *Review of Economic Dynamics*, 2007, *10* (3), 327–347.

Mukoyama, Toshihiko, Christina Patterson, and Aysegul Sahin, "Job Search Behavior over the Business Cycle," *American Economic Journal: Macroeconomics*, 2018, *10* (689), 190–215.

Petrongolo, Barbara and Christopher A. Pissarides, "Looking into the Black Box : A Survey of the Matching Function," *Journal of Economic Literature,*, 2001, *39* (2), 390–431.

Petrosky-Nadeau, Nicolas and Etienne Wasmer, "The Cyclical Volatility of Labor Markets under Frictional Financial Markets," *American Economic Journal: Macroeconomics*, 2013, *5* (51), 193–221.

Poterba, James M and Lawrence H Summers, "Reporting Errors and Labor Market Dynamics," *Econometrica*, 1986, *54* (6), 1319–1338.

Pries, Michael J., "Worker heterogeneity and labor market volatility in matching models," *Review of Economic Dynamics*, 2008, *11* (3), 664–678.

Shimer, Robert, "The Cyclical Behavior of Equilibrium and Vacancies Unemployment," *American Economic Review*, 2005, *95* (1), 25–49.

Silva, Jose Ignacio and Manuel Toledo, "Labor Turnover Costs And The Cyclical Behavior Of Vacancies And Unemployment," *Macroeconomic Dynamics*, 2009, *13* (S1), 76–96.

Sniekers, Florian, "Persistence and Volatility of Beveridge Cycles," *International Economic Review*, 2018, *59* (2).

Sterk, Vincent, "The Dark Corners of the Labor Market," 2016.

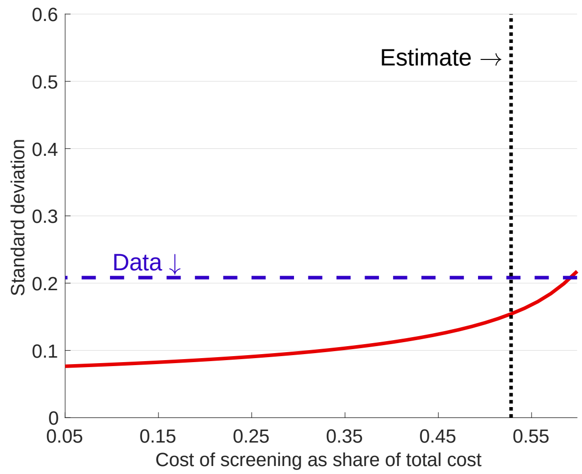
Wolthoff, Ronald, "Applications and Interviews: Firms' Recruiting Decisions in a Frictional Labour Market," *The Review of Economic Studies*, 2018, *85* (2), 1314–1351.

A Appendix: Robustness

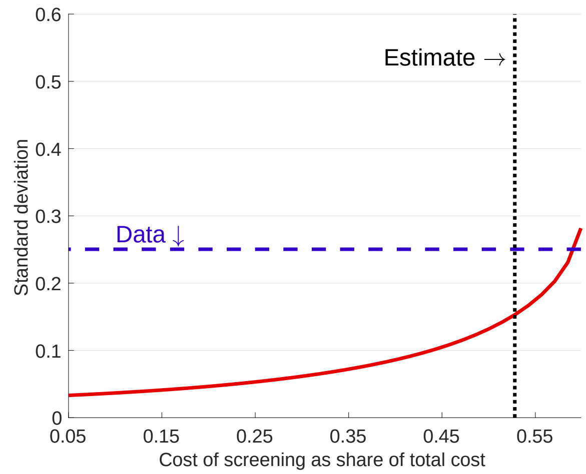
To further highlight the sensitivity of results to different costs of screening, I reestimate the model for costs of screening ranging from zero to the maximum 57 percent value considered above. Figure 9 graphs the volatility of unemployment and tightness, their autocorrelation, and their contemporaneous correlation with the separation rate as a function of the relative importance of the cost of screening. As evidenced from the top two panels, as the cost of screening increases separation rate shocks explain more and more of the volatility of unemployment and vacancies and get closer and closer to the relative volatility of these two series. The middle panels show that unemployment and vacancies become increasingly persistent as the cost of screening rises, with a particularly pronounced increase in the latter. The bottom left panel shows that separation rate shock give rise to an increasingly negative correlation between vacancies and unemployment as the cost of screening rises. Finally, the bottom right panel shows that the correlation between the unemployment rate and the exogenous driving force, the separation rate, weakens as costs of screening grow, highlighting that the model predicts increasing internal propagation of shocks as costs of screening increase.

FIGURE 9. VOLATILITY AND AUTOCORRELATION OF UNEMPLOYMENT AND VACANCIES AND CONTEMPORANEOUS CORRELATION WITH SEPARATION RATE BY COST OF SCREENING

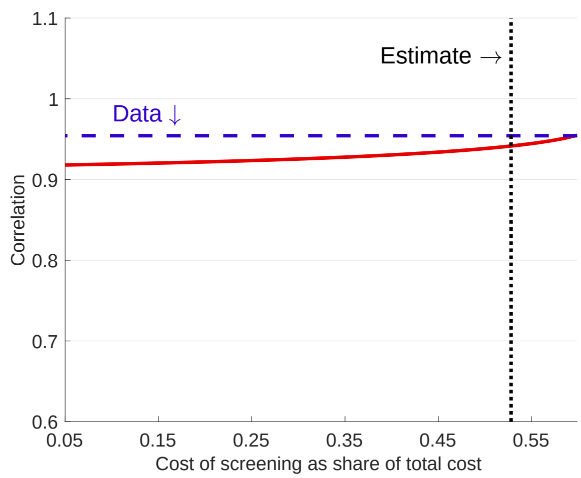
(A) STANDARD DEVIATION OF UNEMPLOYMENT



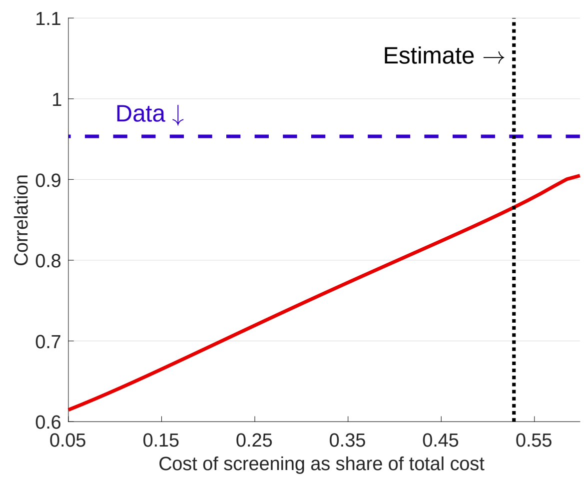
(B) STANDARD DEVIATION OF VACANCIES



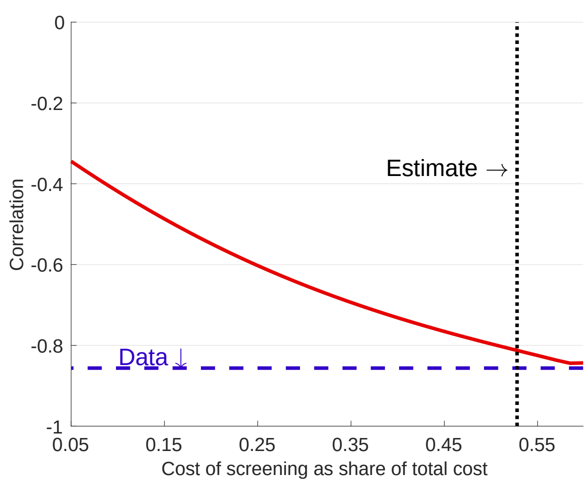
(C) AUTOCORRELATION OF UNEMPLOYMENT



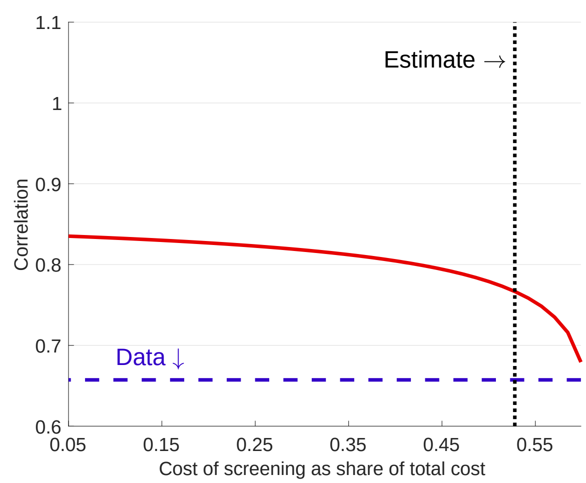
(D) AUTOCORRELATION OF VACANCIES



(E) CORRELATION VACANCIES-UNEMPLOYMENT RATE



(F) CORRELATION UNEMPLOYMENT-SEPARATION RATE



B Appendix: Sources of amplification

To better understand the sources of amplification of separation rate shocks, recall from equation (7) that the elasticity of tightness with respect to a permanent change in the separation rate equals,

$$\frac{\partial \log \theta}{\partial \log s} = -\underbrace{\frac{1}{1-\eta\left(1-XY\right)}}_{\textbf{(1)}}\left[\underbrace{\frac{s}{s+r}}_{\textbf{(2)}}\underbrace{\frac{y-B}{y-B-C}}_{\textbf{(3)}} - \underbrace{XY}_{\textbf{(4)}}\right] \tag{22}$$

Table 11 decomposes the elasticity based on equation (22). The first row shows the benchmark Mortensen and Pissarides (1994) model (see for instance Shimer, 2005, for a derivation) when the estimated elasticity of the matching function equals its reduced form value of 0.4. With a zero bargaining power for workers, the elasticity is larger than what Shimer (2005) found, but still small. The second row adds on the job search but not the richer model of hiring (i.e. it assumes $c_s = 0$). The higher estimated elasticity with on-the-job search raises the first term (1) such that the overall elasticity increases to 2.3. The final row shows the effect of the richer model of hiring. Feedback from the labor market, reflected in the first and fourth terms, increases the elasticity by a factor of almost 1.5, while the third term rises by a factor of 2.1. The overall elasticity is seven.[31]

TABLE 11. DECOMPOSITION OF ELASTICITY OF TIGHTNESS W.R.T. SEPARATION RATE

	(1)	(2)	(3)	(4)	(2)-(4)	**Total**
Mortensen and Pissarides (1994)	1.67	*0.80*	*1*	*0*	0.80	**1.33**
OJS & no cost of screening	2.94	*0.80*	*1*	*0.02*	0.78	**2.29**
Full model	3.88	*0.80*	*2.12*	*-0.10*	1.80	**6.98**

Note: Decomposition of the elasticity of tightness w.r.t. a permanent change in the separation rate based on equation (22). Mortensen and Pissarides (1994): Based on elasticity $\eta = 0.4$; OJS & no cost of screening: Estimated model with $c_s = 0$; Full model: Estimated model with screening costs.

[31] An elasticity of seven would suggest a volatility of tightness of 0.52, i.e. significantly larger than the 0.29 reported by Table 6. Note, however, that the elasticity (22) is for true labor market tightness while Table 6 reports the volatility of the v/u-ratio, and the elasticity (22) is w.r.t. a permanent shock while Table 6 uses a less persistent shock process.

C Appendix: Dynamics of wages

In the dynamic economy, the surplus values of workers are given by

$$\begin{aligned}
rW_b(w;s,u,e_b) &= w - b + \phi f\Big(\theta(s,u,e_b)\Big)\Big(\pi_b(1-\gamma)+\pi_g\Big)\Big(S_b(s) - W_b(w;s,u,e_b)\Big) \\
&- sW_b(w;s,u,e_b) + \lambda\mathbb{E}_s\Big(W_b(w;s',u,e_b) - W_b(w;s,u,e_b)\Big) \\
&+ \frac{\partial W_b(w;s,u,e_b)}{\partial u}\dot{u}(s,u,e_b) + \frac{\partial W_b(w;s,u,e_b)}{\partial e_b}\dot{e_b}(s,u,e_b) \\
rW_g(w;s) &= w - b - sW_g(w;s) + \lambda\mathbb{E}_s\Big(W_g(w;s') - W_g(w;s)\Big)
\end{aligned}$$

where tightness is given by $\theta(s,u,e_b)$,

$$\frac{c_v\theta(s,u,e_b)}{f\Big(\theta(s,u,e_b)\Big)} = \pi_g\left[S_g\Big(s\Big) - S_b\Big(s\Big)\right] - \tilde{C}_1 + \frac{u(s,u,e_b)}{u(s,u,e_b)+\phi e_b(s,u,e_b)}\left[\Big(\pi_b+\pi_g\Big)S_b(s) - \tilde{C}_2\right]$$

and the endogenous states evolve according to $\dot{u}(s,u,e_b)$ and $\dot{e}_b(s,u,e_b)$,

$$\begin{aligned}
\dot{u}(s,u,e_b) &= s\Big(1-u(s,u,e_b)\Big) \; - \; f\Big(\theta(s,u,e_b)\Big)\left(\pi_g+\pi_b\right)u(s,u,e_b) \\
\dot{e}_b(s,u,e_b) &= -\left[\phi f\Big(\theta(s,u,e_b)\Big)\pi_g \; + \; s\right]e_b(s,u,e_b) \; + \; f\Big(\theta(s,u,e_b)\Big)\pi_b u(s,u,e_b)
\end{aligned}$$

I can solve for the surplus functions on a grid for w, s, u and e_b based on the above system. Given a solution, I define the wage policies as

$$\begin{aligned}
W_b\Big(w_{b,u}(s,u,e_b);s,u,e_b\Big) &= 0 \\
W_b\Big(w_{b,b}(s,u,e_b);s,u,e_b\Big) &= S_b(s) \\
W_g\Big(w_{g,u}(s);s\Big) &= 0 \\
W_g\Big(w_{g,b}(s);s\Big) &= S_b(s)
\end{aligned}$$

The inflow of workers into a particular state is

$$
\begin{aligned}
m^I_{b,u}(t) &= f(t)\pi_b u(t) \\
m^I_{b,b}(t) &= \phi f(t)(1-\gamma)\pi_b m_{b,u}(t) \\
m^I_{g,u}(t) &= f(t)\pi_g u(t) \\
m^I_{g,b}(t) &= \phi f(t)\pi_g \Big(m_{b,u}(t) + m_{b,b}(t)\Big)
\end{aligned}
$$

while the outflow is

$$
\begin{aligned}
m^U_{b,u}(t) &= \Big(s(t) + \phi f(t)\Big((1-\gamma)\pi_b + \pi_g\Big)\Big)\, m_{b,u}(t) \\
m^U_{b,b}(t) &= \Big(s(t) + \phi f(t)\Big(\pi_b + \pi_g\Big)\Big)\, m_{b,b}(t) \\
m^U_{g,u}(t) &= s(t) m_{g,u}(t) \\
m^U_{g,b}(t) &= s(t) m_{g,b}(t)
\end{aligned}
$$

In the discrete-time daily approximation of the model, the average wage in a particular sub-group, $\bar{w}_{x,y}(t)$, evolves according to

$$
\bar{w}_{x,y}(t+1) = \frac{\Big(m_{x,y}(t) - m^U_{x,y}(t)\Big)\bar{w}_{x,y}(t) + m^I_{x,y}(t) w_{x,y}(t+1)}{m_{x,y}(t+1)}
$$