

Measuring Matching Efficiency with Heterogeneous Jobseekers*

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Abstract

Matching efficiency is the productivity of the process for matching would-be workers to available jobs. Measurement of match efficiency follows the same principles as measuring a Hicks-neutral index of productivity of production. We develop a framework for measuring matching productivity when the population of jobseekers is heterogeneous. The efficiency index for each type of jobseeker is the monthly job-finding rate for the type adjusted for the overall tightness of the labor market. We break jobseekers into nine groups—six for unemployed people by source of unemployment, plus jobseekers classified as out of the labor force and two types of people currently holding jobs but looking to make a job-to-job transition. The last three groups account for 78 percent of new hires during normal times. We focus on the period from 2005 through 2012. We find that overall matching efficiency declined over the period, but hardly more than its earlier downward trend. It rose in the year of maximum employment decline, 2009. Matching efficiency declined after 2007 in some types of unemployment, notably permanent job loss, quitting, and new entrants, but rose in others, such as unemployment initiated as a layoff with expectation of recall. Efficiency remained steady during the Great Recession for job-to-job transitions. In its peak year, 2010, unemployment was about one percentage point higher than it would have been if matching efficiency had remained constant.

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Matching efficiency is a key concept in understanding turnover in the labor market. In particular, turnover models imply that a decline in matching efficiency causes a rise in unemployment. Persistent high unemployment has generated concern that the U.S. economy's normal unemployment rate rose from the turmoil of the collapse of the housing market and the subsequent financial crisis. Similar concerns have developed in previous recessions.

The idea has proven useful that matching is a productive process that combines the efforts of jobseekers and of recruiting employers. The matching function—a central feature of the Diamond-Mortensen-Pissarides (DMP) model of unemployment—is a production function with the number of jobseekers and the number of positions open for recruiting taken as inputs and the flow of newly matched worker-employer pairs as the output. Matching efficiency is a multiplicative shifter of the production function, analogous to the Hicks-neutral productivity index in production theory.

The term *mismatch* often appears in discussions of high unemployment. Shocks that cause widespread job loss and leave many workers unmatched with employers will generate mismatch. The role of the matching function is to cure mismatch by using resources—jobseekers' time and employers' recruiting expenditures. Thus mismatch is organic to labor-market models built on matching functions. The presence of high levels of unemployment is not necessarily a sign of a decline in matching efficiency. The appropriate way to proceed is to measure matching efficiency using standard ideas from production theory. If measured efficiency declines, a rising incidence of mismatch is one of a number of potential sources. Proper measurement of matching efficiency is a crucial starting point for understanding the sources of high unemployment.

The Beveridge curve is another way to characterize changes in matching efficiency. A decline in efficiency shifts the curve outward, so vacancies are higher for a given level of unemployment. But the Beveridge curve is a dynamic object—from the beginning, it has been clear that even with constant matching efficiency, the economy makes loops in unemployment-vacancies space rather than moving along a stable curve. For that reason, we focus on matching efficiency in this paper as the more fundamental concept.

Most analysis of the U.S. labor market in the matching-function framework has taken unemployment to be the appropriate measure of jobseeking in the population. Many investigators have been aware that this view is seriously incomplete. In the Current Population Survey (CPS) in 2006, the distribution of hires into new jobs was 22 percent from unemploy-

ment, 42 percent from people not previously in the labor force, and 36 percent from workers in previous jobs who took new jobs without intervening unemployment or time out of the labor force. Job-to-job hiring has long been an important part of DMP modeling, but not in the measurement of matching efficiency. The remarkably large flow into jobs of people who were not previously counted as active searchers in the CPS has received less attention. An important exception is Veracierto (2011), a paper that we build on.

We develop the theory of aggregation of matching functions across diverse groups. The condition for aggregation is a natural one: changes in the success rates for job-seekers should move in proportion to one another. We show that the aggregation condition holds quite well across the six categories of unemployment sources reported in the CPS and for job-to-job transitions. Job-finding rates for people out of the labor force are somewhat less sensitive to overall labor-market conditions, but not enough to have much effect on measured matching efficiency.

Our main finding is that matching efficiency measured consistently with our aggregation theory fell only slightly in recent years, hardly more than would have been expected from the modest downward trend in efficiency. We conclude that the collapse of matching efficiency found by those focusing only on unemployment as a measure of the volume of jobseeking is an artifact of too narrow a definition of the input of jobseeking effort to the matching process.

1 Related Research

Veracierto (2011) introduced the basic idea of including people other than the unemployed in the calculation of matching efficiency. He makes a compelling case that the movements of aggregate unemployment cannot be understood in the DMP framework—especially with respect to the matching function—without considering the role of individuals who are classified as out of the labor market. These people are neither working nor engaging in the specific job-seeking activities in the four weeks prior to the CPS interview that would place them in the category of unemployment. The striking fact is that, after correcting in the standard way for erroneous transitions, the CPS reveals that the number of people classified as out of the labor force in one month who are employed in the next month is always greater than the number moving from unemployment to employment. In normal times, using the obvious notation, the NE flow is almost double the UE flow.

Flinn and Heckman (1983) observe that the natural definition of unemployment is that a non-working individual's transition hazard into employment exceeds a threshold value. By that criterion, it seems likely that a non-trivial fraction of those the CPS classifies as out of the labor force (N) are actually unemployed. The overall NE hazard in normal times is far lower than the UE hazard—5 percent per month compared to 27 percent, so it is clear that the N category in general satisfies the Flinn-Heckman criterion.

The BLS publishes data on broader definitions of unemployment. It is an interesting question but outside the scope of this paper whether a systematic application of the Flinn-Heckman principle might result in a definition of unemployment that captured the great majority of non-workers with high job-finding hazards while excluding those with low hazards. Such a definition would fit the matching function framework nicely.

Veracierto (2011) proposes a simple way around this issue that incorporates those classified as out of the labor force without identifying the individuals with high NE hazards. He uses the ratio of the NE hazard to the UE hazard to weight those classified in N. The resulting figure is interpreted as the effective number of job-seekers in the N category. The total number of job-seekers is the number in U plus the weighted number in N. This figure—interpreted as comprehensive unemployment—is the input to the matching function in a DMP model that takes account of the high incidence of job-seeking in the N category. Veracierto finds (see his figure 36) that matching efficiency was flat before the Great Recession, then declined about 15 percent during the recession.

Our analysis differs from Veracierto's both in the definition of matching efficiency and in the level of disaggregation. Veracierto assumes that unemployed workers and nonparticipants have equal matching efficiency conditional on a given level of search intensity but that nonparticipants have lower search intensity. By contrast, we do not distinguish between matching efficiency and search intensity for a given type of worker and instead estimate an efficiency parameter for each type that combines matching efficiency and search intensity. In addition, our analysis includes job-to-job transitions and further disaggregates workers by their reason for unemployment and by observable characteristics. Our model thus provides a unified treatment of the calculation of aggregate matching efficiency when all people in the economy are potentially job seekers.

Barnichon and Figura (2012) also estimate matching efficiency while allowing heterogeneity across workers in demographics, distinguishing between reasons for unemployment, and

including nonparticipants in the analysis. However, they assume that the matching function applies only to unemployed workers and do not consider job-to-job transitions.

Fujita and Moscarini (2013) study the effect of recalls by unemployed workers' former employers on transition rates and the matching function. They show that if the matching function describes only matches between jobseekers and new employers—not recalls—then matching efficiency is estimated to have declined much more during the Great Recession. Key to their result is that workers on temporary layoffs are not the only ones who experience recalls; about 20 percent of workers who report that they permanently lost their jobs are nonetheless eventually recalled. In our work, we disaggregate workers by their reason for unemployment but do not attempt to distinguish between matches with new employers and recall by the previous employer. Thus, in our specification, a group that is more likely to be recalled will have a higher matching efficiency.

Barlevy (2011) calculates the decline in matching efficiency from the shift in the Beveridge curve, on the assumptions that the separation rate remains unchanged and that unemployment is at its stochastic equilibrium. This analysis depends only on the unemployment rate, not on the number of nonparticipants, job-to-job transitions, or changes in the composition of the unemployed.

Bachmann and Sinning (2012) measure the effects of compositional changes on labor force transition rates without relating these findings to matching efficiency. They find that changes in composition reduce the cyclicity of inflows to unemployment and raise outflows from unemployment early in recessions but reduce outflows later in recessions.

Some papers discuss the decline in matching efficiency, or, equivalently, the outward shift of the Beveridge curve, as the result of a variety of forces. Some, such as Daly, Hobijn, Şahin and Valletta (2012), frame the subject within the more general issue of a possible increase in the natural rate of unemployment. Only part of their discussion relates to changes in matching efficiency. The paper identifies two factors that may have reduced match efficiency since the Great Recession: mismatch and more generous unemployment benefits.

Şahin, Song, Topa and Violante (2012) find that mismatch across industries and occupations accounts for at most one-third of the increase in unemployment during the Great Recession, while geographic mismatch is insignificant. Herz and van Rens (2011) likewise find modest effects of mismatch across industries and very small effects of mismatch across states, while Estevão and Tsounta (2011) find substantial skill mismatches but argue that changes

in migration rates and dispersion in unemployment across states are evidence of geographic mismatch as well. These studies all measure mismatches by the distribution of unemployed workers and jobs across distinct markets defined by locations, industries, or occupations. Estevão and Smith (2013) measure skill mismatches in a different way, by imputing wages for labor force participants based on their observed characteristics; if mismatch is low and unemployment is mainly due to low quality of unemployed workers, unemployed workers will have relatively low imputed wages, while if mismatch is high, unemployed workers will have relatively high imputed wages. Consistent with the papers that look at mismatch across distinct markets, Estevão and Smith (2013) find evidence of an increase in mismatch during the recession.

A large group of papers, including Daly, Hobijn and Valletta (2011), Fujita (2011), Nakajima (2012), and Valletta and Kuang (2010), estimates that extended unemployment benefits raised the unemployment rate by an amount on the order of 1 percentage point. However, Hagedorn, Karahan, Manovskii and Mitman (2013) argue that many of these analyses do not account for the effect of unemployment benefits on firms' incentive to create jobs and that a research design that accounts for such effects finds a much larger impact from unemployment benefits.

Davis, Faberman and Haltiwanger (2013) provide convincing evidence that the matching function involves inputs apart from the stocks of unemployment and vacancies. In the micro data from JOLTS, they show that the job-filling rate for vacancies is dramatically higher in firms that are growing than in firms with constant employment, a contradiction to the hypothesis that only unemployment and vacancies determine hiring rates. They lack any direct measures of the other inputs, but construct an indirect measure from the JOLTS data that eliminates most of the apparent decline in matching efficiency. They do not consider the topic of this paper, the importance of job-seekers who are not counted as unemployed. Their results fit nicely with ours, in the sense that one reasonable interpretation of the variations in matching efficiency that we measure is exactly the combined effect of the omitted inputs to the matching process that they consider.

2 Aggregating Matching Functions

A matching function is a linear homogeneous function $m(X, V)$, increasing and weakly concave in the number of jobseekers X and the number of vacancies V . $H = m(X, V)$ is the flow

of new hires emerging from the matching process. The job-seeking success hazard associated with m is

$$f = \phi\left(\frac{V}{X}\right) = \frac{m(X, V)}{X} = m\left(1, \frac{V}{X}\right). \quad (1)$$

f is the flow rate into new jobs of members of the homogeneous population measured by X .

Now we consider a heterogeneous set of jobseekers drawn from N types. Type i has a matching efficiency parameter μ_i and a parameter ψ_i that indicates what fraction of the population P_i of type i are jobseekers. We define the effective number of jobseekers:

$$X = \sum_i \mu_i \psi_i P_i. \quad (2)$$

We assume that all the job-seekers search in the same market and have the same matching rate except for the efficiency parameter μ_i :

Assumption. Scaled matching hazard function and common pools of vacancies and competing jobseekers:

$$H_i = \mu_i \psi_i \phi\left(\frac{V}{X}\right) P_i. \quad (3)$$

Total hires are $H = \sum_i H_i$. Our basic result is:

Aggregation Theorem: Let m be the matching function corresponding to the jobseeking success hazard function ϕ . Then $H = m(X, V)$.

proof:

$$H = \sum_i H_i = \sum_i \mu_i \psi_i \phi\left(\frac{V}{X}\right) P_i = \phi\left(\frac{V}{X}\right) X = m(X, V). \quad (4)$$

We do not consider the distinction between a contact of a jobseeker and employer and the creation of a job match. The matching function takes account of the fact that many contacts do not result in hires.

Only the product of μ_i and ψ_i appears in these equations, not the two measures separately. There is no prospect of distinguishing changes in matching efficiency from changes in search propensities. From this point forward, we define γ_i as the product $\mu_i \psi_i$. We refer to γ_i as efficiency, but it should be kept in mind that a decline in our measure of efficiency may arise

from a decline in the search propensity of a type rather than a decline in the efficiency of the search of those choosing to search.

2.1 Applying the aggregation principle

Petrongolo and Pissarides (2001) discuss the evidence that the matching function has the Cobb-Douglas form, where the elasticities with respect to X and V are θ and $1 - \theta$:

$$H = X^\theta V^{1-\theta}. \quad (5)$$

The aggregate matching function has no efficiency parameter in our setup—efficiency shows up in the job-finding rates by type and is buried inside the aggregate effective count of jobseekers, X . We solve out X to get

$$\phi\left(\frac{V}{X}\right) = \left(\frac{V}{H}\right)^{\frac{1-\theta}{\theta}}, \quad (6)$$

which leads to

$$f_{i,t} = \gamma_{i,t} \left(\frac{V}{H}\right)^{\frac{1-\theta}{\theta}} = \gamma_{i,t} T_t, \quad (7)$$

where

$$T_t = \left(\frac{V}{H}\right)^{\frac{1-\theta}{\theta}}, \quad (8)$$

our measure of tightness. Finally,

$$\gamma_{i,t} = \frac{f_{i,t}}{T_t}. \quad (9)$$

We discuss the estimation of the elasticity θ in a later section.

3 Specification for Transition Probabilities with Adjustment for Overstatement of Turnover Rates

The job-finding rate $f_{i,t}$ derives from the transition probabilities from a variety of states into the new job state. We let all of the transition probabilities depend on a large vector of observed worker characteristics. The CPS sample is too small to estimate transition rate functions nonparametrically, conditional on each possible combination of characteristics. Instead, we specify the transition probabilities among all the labor market states as multinomial logit functions across the destination state s' conditional on the origin state s .

In our model, individuals occupy one of 9 labor-market states each month. Six of the states refer to unemployment, distinguished by the event leading to unemployment. For

employment, we distinguish a brand-new job from one that an individual held the previous month—the distinction enables us to track job-to-job transitions. We use j to label the state *new job*.

3.1 Multinomial logit specification and adjustment

For each origin state s , we designate a normalization state n_s . For all but the new job state j , the normalization state is the origin state: $n_s = s$. For the new job state, n_j is the existing job state. The probability of transiting from state s to state s' is

$$\hat{\tau}_{t,s,s'}(x_{kt}) = \frac{\exp(\delta_{s,s',t} + \alpha_{s,t}d_{s,s'} + x_{kt}\beta_{s,s'})}{1 + \sum_{s' \in F_s} \exp(\delta_{s,s',t} + \alpha_{s,t}d_{s,s'} + x_{kt}\beta_{s,s'})}. \quad (10)$$

Here $\delta_{s,s',t}$ is a time effect specific to the transition pair s, s' ; $d_{s,s'}$ is a dummy variable taking the value zero if $s' = n_s$ and one otherwise; α_s is a time effect specific to the origin state s alone that lowers the probability of arriving at state n_s ; x_{kt} is a vector of observed variables, some of which vary over time or across individual workers indexed by k ; $\beta_{s,s'}$ is a vector of parameters; and F_s is the set of destination states feasible to reach from origin state s . For the normalization state, the time effects $\delta_{s,n_s,t}$ are taken as zero and the parameters β_{s,n_s} are normalized as a vector of zeros.

We include the effect captured by $\alpha_{s,t}$ because the transition data from the Current Population Survey contain biases that overstate turnover, so that observed transition probabilities $\hat{\tau}_{t,s,s'}(x_{kt})$ differ from true transition probabilities, which we denote $\tau_{t,s,s'}(x_{kt})$. Abowd and Zellner (1985) described the problem and proposed adjustments to aggregate flow data. Their adjustments do not apply to econometric models estimated from data on individuals, except to the extent that they rewrite the data for obviously spurious reported transitions. So far as we know, our approach is the first to consider a solution at the individual level that fully reconciles transition probabilities to the observed changes in the distribution of the population from month to month. Our model hypothesizes that reporting errors tend to lower the probability of remaining in the previously reported state and raise the probabilities for other states correspondingly. These errors arise from random mis-classification of respondents.

The time effects in equation (10) are not identified. The model

$$\hat{\tau}_{t,s,s'}(x_{kt}) = \frac{\exp(\lambda_{s,s',t} + x_{kt}\beta_{s,s'})}{1 + \sum_{s' \in F_s} \exp(\lambda_{s,s',t} + x_{kt}\beta_{s,s'})}. \quad (11)$$

is identified, with the normalization $\lambda_{s,n_s,t} = 0$. Further, it is in the canonical form that standard logit software requires. Estimation of equation (11) on the transition data yields estimates of

$$\lambda_{s,s',t} = \delta_{s,s',t} + \alpha_{s,t}d_{s,s'}. \quad (12)$$

After estimation, we solve the transition equations,

$$\sum_s \sum_x \pi_{st}(x) \tau_{t,s,s'}(x) = \pi_{s',t+1}, \quad s' = 1, \dots, 9, \quad (13)$$

for $\alpha_{s,t}$ for each t . The true transition probabilities are those that would obtain if $\alpha_{s,t} = 0$:

$$\tau_{t,s,s'}(x_{kt}) = \frac{\exp(\delta_{s,s',t} + x_{kt}\beta_{s,s'})}{1 + \sum_{s' \in F_s} \exp(\delta_{s,s',t} + x_{kt}\beta_{s,s'})} = \frac{\exp(\lambda_{s,s',t} - \alpha_{s,t}d_{s,s'} + x_{kt}\beta_{s,s'})}{1 + \sum_{s' \in F_s} \exp(\lambda_{s,s',t} - \alpha_{s,t}d_{s,s'} + x_{kt}\beta_{s,s'})}. \quad (14)$$

Here $\lambda_{s,s',t}$ is the estimate from the logit estimation, π_{st} is the fraction of respondents in month t who are in state s , and $\pi_{st}(x)$ is the fraction of respondents in month t who are in state s and have covariates x . The transition equations form a nonlinear system in $\alpha_{s,t}$ of dimension equal to the number of states. By writing equation (13) in terms of fractions rather than counts of respondents, we automatically account for population growth.

Our correction for reporting errors is only a first-order correction. It forces the transition rates to match the observed marginal distribution of labor market states s but not the joint distribution of s and observables x . Thus, although the corrected transition rates between two dates t and $t+1$ will be consistent with the marginal distribution of s at both t and $t+1$, the corrected transition rates need not be consistent with the joint distribution of s and x at $t+1$. This in turn implies that the product of the corrected transition rates between t and $t+1$ and the rates between $t+1$ and $t+2$ need not be consistent with the marginal distributions of s at t and $t+2$.

The relation between the estimated retention probabilities $\hat{\tau}_{t,s,n_s}$ and the adjusted probabilities τ_{t,s,n_s} is fairly simple:

$$\hat{\tau}_{t,s,n_s}(x_{kt}) = \frac{1}{1 + \sum_{s' \in F_s} \exp(\lambda_{s,s',t} + x_{kt}\beta_{s,s'})} \quad (15)$$

and

$$\tau_{t,s,n_s}(x_{kt}) = \frac{1}{1 + \exp(-\alpha) \sum_{s' \in F_s} \exp(\lambda_{s,s',t} + x_{kt}\beta_{s,s'})}, \quad (16)$$

so the ratio of the adjusted retention probability to the estimated probability is

$$\frac{\tau}{\hat{\tau}} = \frac{1}{\hat{\tau} + \exp(-\alpha)(1 - \hat{\tau})}. \quad (17)$$

<i>Estimated retention probability</i>	α							
	0.00	0.2	0.4	0.6	0.8	1	1.2	1.4
0.2	1.00	1.17	1.36	1.56	1.79	2.02	2.27	2.52
0.4	1.00	1.12	1.25	1.37	1.49	1.61	1.72	1.82
0.6	1.00	1.08	1.15	1.22	1.28	1.34	1.39	1.43
0.8	1.00	1.04	1.07	1.10	1.12	1.14	1.16	1.18
1.0	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00

Table 1: Ratio of Adjusted to Estimated Value of the Retention Probability

Table 1 shows the ratio of adjusted to estimated probabilities for a variety of values of the estimated probability and the adjustment coefficient α .

4 Data and Adjustments

We use data from the monthly CPS for the years 2001 through 2012. The CPS divides the civilian noninstitutional population, ages 16 and older, into people who are employed, unemployed, and not in the labor force. Employed people are those who worked for pay or profit during the reference week, were temporarily absent from work for reasons such as vacation, illness, weather, or industrial dispute, or did at least 15 hours of unpaid work in a family-owned business. People who are not employed are classified as unemployed if they are currently available for work and either have actively looked for work during the previous four weeks or expect to be recalled from a temporary layoff. All other people who are not employed are classified as not in the labor force. We further divide the employed people according to how long they have had their jobs and the unemployed people according to the reasons they became unemployed. Thus, the 9 labor-market states we derive from the CPS are:

- Not in labor force: People who did not satisfy the CPS definition of either employed or unemployed.
- New job: Employed people who either were not employed in the previous month or were employed by a different employer for their main job in the previous month.
- Existing job: Employed people who were employed by the same employer for their main job in the previous month.

- On layoff: Unemployed people who report being on layoff.
- Lost job permanently: Unemployed people, not on layoff, who report that they were working or left military service immediately before they began looking for work, and that they lost their last jobs.
- Temporary job ended: Unemployed people, not on layoff, who report that they were working or left military service immediately before they began looking for work, and that their last jobs were temporary jobs that ended.
- Quit: Unemployed people, not on layoff, who report that they were working or left military service immediately before they began looking for work, and that they quit their last jobs.
- New entrant: Unemployed people who have never worked.
- Re-entrant: Unemployed people who were not working or in military service immediately before they began looking for work but who have worked at some time in the past.

We match respondents across months using the method of Madrian and Lefgren (2000) and remove high-frequency, likely spurious transitions between unemployment and non-participation following Elsby, Hobijn and Şahin (2013). Specifically, if a respondent is out of the labor force, unemployed, and out of the labor force in three consecutive months, we recode the middle month to out of the labor force. If the respondent is unemployed in the first and third months and out of the labor force in the middle month, we recode the middle month to unemployed with the same reason for unemployment as the first month. Among respondents who remain unemployed, we remove spurious changes in the reason for unemployment by insisting that the reason must remain the same as that given in the first interview of the unemployment spell, except that we allow transitions between temporary layoff status and permanent job loss because a worker could be temporarily laid off and later learn that the job loss had become permanent. The distinction between employed workers in new and existing jobs is possible only for workers who were also interviewed in the previous month. Hence, to compute the stocks of workers in new and existing jobs, we use a logit model to impute a job duration for workers whose duration is unknown based on the share of each duration among workers whose duration is known, conditional on observables.

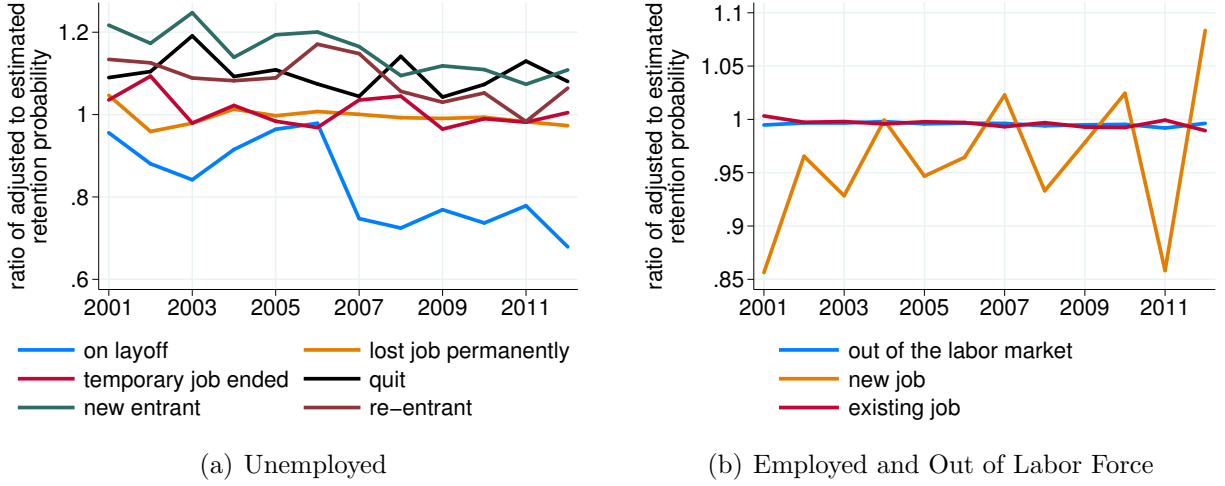


Figure 1: Ratio of adjusted to estimated retention probabilities

Source: Authors' calculations from Current Population Survey microdata. Annual averages of monthly data.

The variables describing personal characteristics, denoted $x_{k,t}$, are dummy variables for

- female
- married
- six age groups (16–24, 25–34, 35–44, 45–54, 55–64, and 65-plus)
- four education groups (less than high school, high school graduate, some college but less than a bachelor's degree, and bachelor's or higher degree)
- seven unemployment duration groups, for transitions from unemployment only (1–4 weeks, 5–8 weeks, 9–13 weeks, 14–17 weeks, 18–21 weeks, 22–26 weeks, and 27 or more weeks)

Figure 1(a) and Figure 1(b) show the adjustment factors derived from our multinomial logit model for the retention probability for individuals in each labor-market state. We calculate the ratio of the adjusted retention probability $\tau_{t,s,n_s}(x_{k,t})$ to the observed retention probability $\hat{\tau}_{t,s,n_s}(x_{k,t})$ for each value of $x_{k,t}$, then compute the weighted average of this ratio over the distribution of $x_{k,t}$ at each date. Among the unemployed on layoff, the model adjusts the retention probability downward by around 10 percent prior to the Great Recession and 20 percent after. Based on reported transitions, movements out of the on-layoff state are

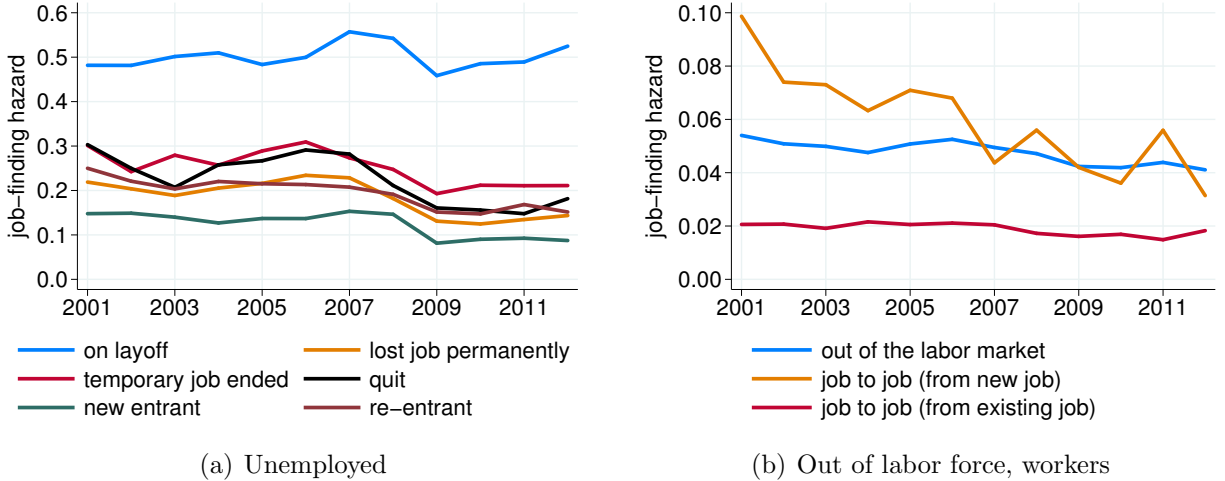


Figure 2: Job-finding hazards

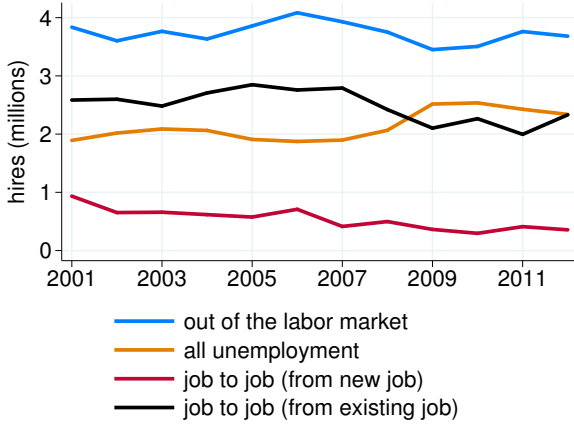
Source: Authors' calculations from Current Population Survey microdata. Annual averages of monthly data.

smaller than is consistent with the stability of the fraction of the population in that state. A model without the adjustment would overstate the fraction of the population on layoff.

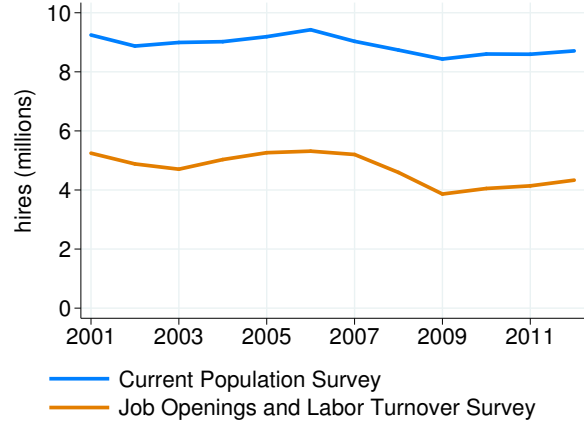
The adjustments to the retention probability for permanent job losers and those whose temporary jobs ended are quite small. The adjustments are upward for the retention probabilities for those who quit their jobs or previously were not in the labor force (entrants and re-entrants). Figure 1(b) shows that the adjustments for the retention probabilities for those out of the labor force and for those holding existing jobs are quite small. The adjustments for those holding new jobs tend to be about five percent downward, but are variable from year to year. In the remainder of the paper, all of the transition probabilities we report are adjusted as shown in these figures.

Figure 2(a) shows the job-finding rates (transition rates into the new job state) for the six categories of unemployment, starting in 2001. Most show the same pattern, falling during the recession of 2001, rising to a peak in 2006 or 2007, dropping sharply in the Great Recession, and then remaining at depressed levels through 2012. The rate for workers on layoff is exceptional in two ways—it is around twice as high as in any of the other unemployment categories, and it recovers more than any of the other rates between 2009 and 2012, to somewhat above its average level over the entire period.

Figure 2(b) shows the job-finding rates for people who are out of the labor force. Their rates move in the same pattern as those for the unemployed, but with less amplitude, pre-



(a) New hires by source



(b) Total new hires from CPS and JOLTS

Figure 3: New hires

Source: Authors' calculations from Current Population Survey microdata and Job Openings and Labor Turnover Survey. Annual averages of monthly data.

sumably because many of the people in that category are committed to non-work activities and thus unresponsive to cyclical changes in the labor market. The figure also shows job-changing rates for workers. Most of the job-changing flow originates from existing jobs (those with more than one month of tenure). The job-changing rate for workers in existing jobs is quite stable, with a slight decline in 2009 and a return to the 2007 level in 2012. The job-changing rate for workers in the new job category, with only a month of tenure, declined substantially over the period. There is no obvious decline apart from trend in the Great Recession.

Figure 3(a) shows the number of people starting new jobs each month, the product of the job-finding hazard and the corresponding population. We do not calculate this number directly from the number of CPS respondents reporting that they are in new jobs because new and existing jobs cannot be distinguished for respondents who have just entered the sample. The largest of the three flows is from out of the labor force into employment. This flow is procyclical; it fell substantially in 2009 but returned to normal by 2012. The second largest flow in most years is from existing jobs to new jobs. That flow is also procyclical. It fell substantially in 2009 and remained far below normal in 2012. There is also a downward trend in the flow of workers from one new job to another. In most years, the flow from unemployment to employment is smaller than the flow from nonparticipation to employment

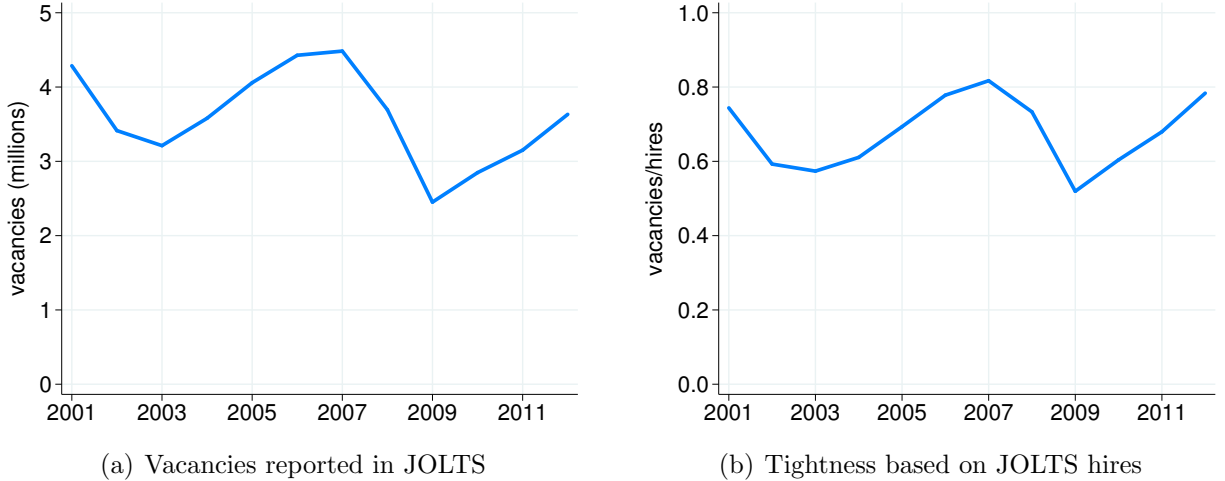


Figure 4: Vacancies and tightness

Source: Authors' calculations from Job Openings and Labor Turnover Survey. Annual averages of monthly data.

or the job-to-job flow. The UE flow is strongly countercyclical. It remained high through 2012.

Figure 3(b) shows the number of new hires from the CPS survey of households and from the Job Openings and Labor Turnover Survey of employers, JOLTS. The CPS and JOLTS surveys vary similarly over time, but the level of hires is substantially higher in the CPS. The reasons for the discrepancy may include: (1) JOLTS does not include hires at new establishments or self-employment, as discussed by Davis, Faberman, Haltiwanger and Rucker (2010), and (2) the CPS may capture more of the mobility between jobs that last only days or a few weeks.

Figure 4(a) shows the number of job openings (vacancies) from JOLTS. Figure 4(b) shows labor-market tightness (the ratio of vacancies to hires raised to the power $(1 - \theta)/\theta = 1.5$, based on the value of $\theta = 0.40$ that we estimate in the next section) using the JOLTS measures of hires and vacancies. We do not use the CPS measure of hires to construct tightness because the CPS survey covers a larger universe of jobs than the JOLTS sample that we must rely on for vacancies. We use the data in Figure 4(b) as our measure of labor-market tightness when we measure matching efficiency.

5 Estimating the Elasticity of the Matching Function

The job-finding rate is

$$\left(\frac{V}{H}\right)^{\frac{1-\theta}{\theta}}. \quad (18)$$

To estimate the elasticity, we form an index,

$$Z_t = \sum_i f_i P_{i,t}, \quad (19)$$

where f_i is the observed job-finding rate of type i , averaged during some base period, and $P_{i,t}$ is, as before, the number of people of type i in month t .

The estimating equation is

$$\log H_t - \log V_t = k + \theta(\log Z_t - \log V_t) + \epsilon_t. \quad (20)$$

Here k is a constant that accounts for the fact that Z_t is an index that is proportional to the job-seeker aggregate X_t but has a constant of proportionality different from one. Our identifying assumption is that the disturbance in the matching function, ϵ_t , is orthogonal to $\log Z_t - \log V_t$. The disturbance might not be orthogonal to $\log V_t$ or $\log Z_t$, but its effect is likely to move the two variables in the same direction, in which case the difference is unchanged. Accordingly, we estimate the equation by time-series regression, taking account of the serial correlation of ϵ_t .

5.1 Results

Table 2 shows estimates of the elasticity of the matching function based on equation (20). We use data on hires and vacancies from JOLTS and use average job-finding rates by labor market status from 2005 through 2007 to construct the job-seeking index Z_t . We use the Newey and West (1987) estimator of the sampling distribution and select a lag length according to the method of Newey and West (1994). The first column estimates the equation over all months for which data are available—December 2000 to March 2013, with some exceptions when the structure of the CPS data changed in ways that prevent matching respondents across months—and finds an elasticity of 0.23. The second column uses the six years before the recession and finds an elasticity of 0.40. In our counterfactual simulations, we use the elasticity of 0.40 as a benchmark. Our identifying assumption may have broken down in 2008 and later years. In a later section, we consider the robustness of our results with respect to the matching function elasticity.

	$\log (H_t/V_t)$	
	(1)	(2)
$\log (Z_t/V_t)$	0.229 (0.055)	0.395 (0.051)
Constant	-1.549 (0.435)	-2.806 (0.398)
Observations	146	82
<i>R</i> -squared	0.18	0.26
Newey-West optimal lags	15	19
Sample	full	2001–2007

Table 2: Estimates of the elasticity of the matching function

Newey-West standard errors with optimal lag in parentheses. Samples: full sample includes monthly data from December 2000 to March 2013, except for January 2003 and May 2004; 2001–2007 sample includes monthly data from January 2001 to December 2007, except for January 2003 and May 2004. Source: Authors' calculations from Current Population Survey microdata and Job Openings and Labor Turnover Survey.

6 Measuring matching efficiency

Matching efficiency at date t , for a worker with characteristics $x_{k,t}$, who is in labor market state s , is

$$\gamma_{st}(x_{k,t}) = \frac{\tau_{t,s,j}(x_{k,t})}{T_t}. \quad (21)$$

We calculate aggregate efficiency, holding the joint distribution of characteristics and labor market states fixed at some baseline distribution $\bar{F}(s, x)$, as

$$\bar{\gamma}_t = \int_{s,x} \frac{\tau_{t,s,j}(x_{k,t})}{T_t} d\bar{F}(s, x). \quad (22)$$

This calculation uses the estimated probabilities τ we compute from the logit model with adjustment for reporting errors.

We calculate indexes of matching efficiency for each of the nine labor-market states. Each is the job-finding hazard from Figure 2(a) and Figure 2(b) adjusted for market tightness by dividing by the JOLTS index of tightness in Figure 4(b). We state them as indexes by setting the average value in the years 2005 through 2007 to one. Figures 5(a) to 5(i) show the resulting indexes. From 2007 to 2009, matching efficiency rose for employed people and those not in the labor force. Efficiency fell from 2007 to 2009 for new entrants and those who quit or permanently lost their jobs but rose for laid-off workers, people who re-entered

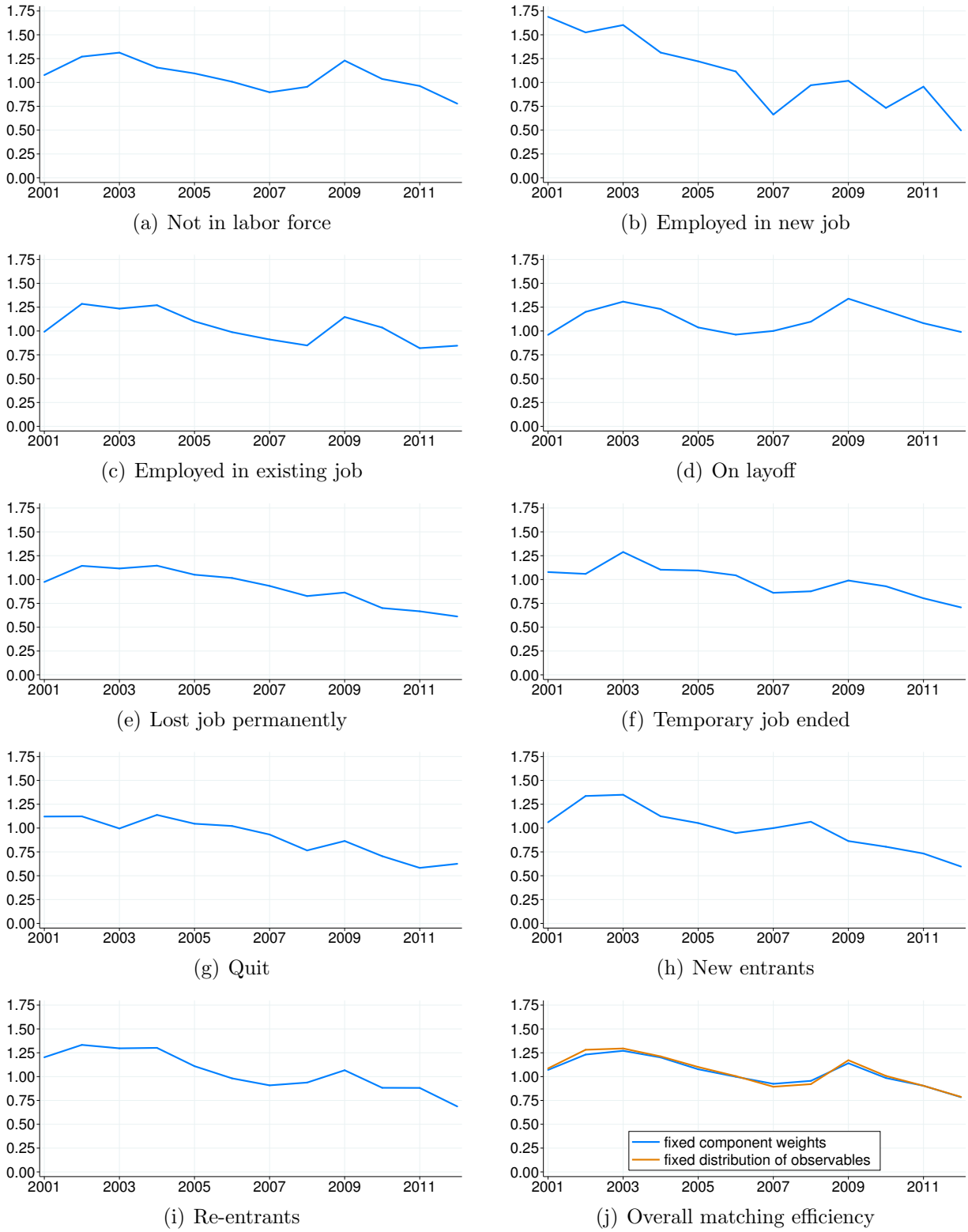


Figure 5: Indexes of matching efficiency

Source: Authors' calculations from Current Population Survey microdata and Job Openings and Labor Turnover Survey. Annual averages of monthly data.

the labor force, and workers whose temporary jobs ended. From 2009 to 2012, efficiency fell for all types. There is a striking decline in the matching efficiency of people in new jobs over the 12-year period, and especially before 2007; however, matching efficiency for this group reflects the probability of finding a new job — which implies, among other things, not remaining in the same job — and so the decline in this group’s efficiency may reflect an increased rate of remaining in the same job for more than one month.

Figure 5(j) shows two indexes of overall matching efficiency. One is a weighted average of the nine components in figures 5(a) to 5(i), using weights representing the relative importance of the components in X over the average in the pre-slump period 2005 through 2007. (We have also calculated a similar index using weights from the slump, 2008 through 2012; it is virtually identical.) The other is a weighted average holding the distribution of worker characteristics fixed at the average distribution in 2005 to 2007, based on the formula in equation (22) and our multinomial logit estimates. The characteristics we control for are sex, marital status, six age categories, four education categories, and eight categories of unemployment duration. The index holding worker characteristics fixed follows almost the same path as the fixed-weights average of the components in figures 5(a) to 5(i), which shows that once we control for the distribution of workers across labor market states, changes in the distribution of other observables have little effect on measured efficiency. The estimated indexes show that matching efficiency rose slightly from 2007 to 2009 and has gradually declined since then.

Table 3 compares the recent trend in matching efficiency with the pre-recession trend by estimating the following regression on the annual estimates of matching efficiency:

$$\bar{\gamma}_t = \omega_0 + \omega_1 t + \omega_2 recession_t + \omega_3 recession_t \times (t - 2008) + \omega_4 slump_t + \omega_5 slump_t \times (t - 2010) + \epsilon_t, \quad (23)$$

where $recession_t$ is an indicator for the years 2008 and 2009, and $slump_t$ is an indicator for the years 2010, 2011, and 2012. Because we have only 12 annual observations of matching efficiency, our tests have little power. Still, we find a statistically unambiguous overall downward trend throughout the period starting in 2001. We cannot reject the hypothesis that the post-recession trend is the same as the pre-recession trend (that is, $\omega_5 = 0$). There is some evidence that the post-recession decline rate is higher than the pre-recession rate. However, we start the analysis in 2001, and matching efficiency actually rose from 2001 to 2002. If we instead started the analysis in 2002, we would find a steeper pre-recession trend

	matching efficiency	
	(1)	(2)
year	-0.039 (0.018)	-0.047 (0.020)
recession	0.001 (0.126)	-0.015 (0.140)
recession $\times$ (year-2008)	0.224 (0.138)	0.298 (0.152)
slump	0.116 (0.145)	0.168 (0.161)
slump $\times$ (year-2010)	-0.061 (0.071)	-0.063 (0.078)
constant	79.58 (36.51)	95.88 (40.42)
Observations	12	12
<i>R</i> -squared	0.76	0.77
Fixed component weights?	Y	N
Fixed distribution of observables?	N	Y

Table 3: Tests for trend breaks in matching efficiency

Annual data. Source: Authors' calculations from Current Population Survey microdata and Job Openings and Labor Turnover Survey.

and correspondingly less difference between the pre- and post-recession patterns. It appears that almost all of the widely remarked decline in matching efficiency is not a special effect of the Great Recession, but a trend that has persisted since 2001. The graphs for the nine individual categories confirm this impression fairly uniformly.

7 Counterfactual Analysis of Labor Market Outcomes

One use we make of the multinomial logit results is to calculate counterfactual outcomes with altered job-finding rates. According to equation (7), we can calculate the counterfactual job-finding rates that would have occurred at any date t if market tightness had been fixed at some pre-recession level $\bar{T}$ by multiplying the observed job-finding rates by $\bar{T}/T_t$. We can also calculate the counterfactual unemployment rate at any date t by simulating workers' labor market outcomes with the counterfactual job-finding rates. Such counterfactuals tell us how changes in the efficiency of each type i would have affected labor market stocks and flows, holding market tightness fixed.

As above, let j be the state *new job*. We create a model in which the job-finding rates $\tau_{t,s,j}(x_{k,t})$ are increased by multiplying by a function of time, e^{z_t} . The model boosts the logit score of destination state f by the factor $e^{\tilde{z}_{s,t}(x)}$. This factor satisfies

$$e^{z_t} \tau_{t,s,j}(x) = \frac{\exp(\tilde{z}_{s,t}(x) + \delta_{s,j,t} + x\beta_{s,j})}{1 + \sum_{s' \in F_s} \mathbb{I}(s' = j) \exp(\tilde{z}_{s,t}(x) + \delta_{s,s',t} + x\beta_{s,s'})}. \quad (24)$$

Here $\mathbb{I}$ is an indicator function taking the value 1 if its argument is true and zero if false. We choose the base state to be remaining in an unemployment state or out of the labor force when those are the origin states and choose *existing job* when the origin state is *new job*. Equation (24) is linear in $\exp(\tilde{z}_{s,t}(x))$. We solve for it in each job-seeking origin state and for each observed value of $x_{k,t}$. The effect of boosting the job-finding probability is to reduce the transition probabilities to other states in accord with the logit specification.

With the counterfactual job-finding rates in hand, we simulate counterfactual employment and unemployment rates as follows. We start with the observed distribution of CPS respondents across labor market states s and observables x in a particular month t_0 . Then, for each subsequent month t , we draw the worker's labor market state s_t from a multinomial distribution with probabilities $\tau_{t-1,s_{t-1},s_t}(x_{k,t-1})$. We also update the elements of x that correspond to unemployment duration but do not update other elements of x .

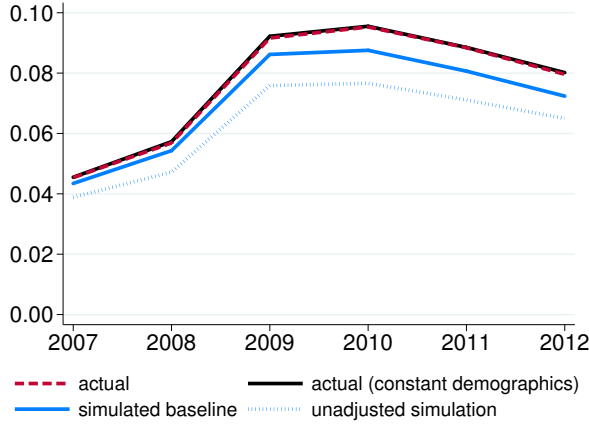
7.1 Counterfactual calculations with constant labor-market tightness

Figure 6(a) and Figure 6(b) test whether our baseline simulations match the observed behavior of the unemployment rate and the employment-population ratio, respectively. We start the simulations with the observed distribution of workers in December 2006. For workers in the initial population whose job duration or unemployment duration is unknown, we impute duration from logit models.

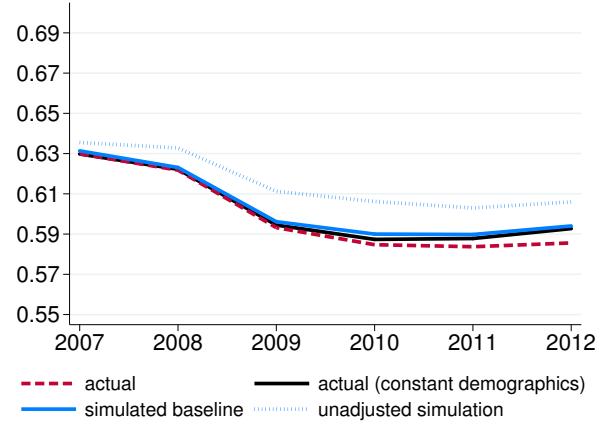
The figures show the observed rates, the observed rates adjusted to hold demographics constant at their distribution in December 2006, the rates in a baseline simulation that uses the observed time series for market tightness T , and the rates in an unadjusted simulation that does not account for the reporting-error parameters $\alpha_{s,t}$. The figures exhibit the means across 100 simulations; the standard error of the mean from the 100 simulations is 0.007 to 0.018 percentage points, depending on the date and the specification.

The baseline simulation performs well. It almost exactly matches the employment-population ratio holding demographics constant (which is appropriate because our simulation does not include changes in the distribution of demographics) and comes close to matching the path of the unemployment rate. The adjustment for reporting errors is crucial to this result: The unadjusted simulation badly understates the unemployment rate and overstates the employment-population ratio. Despite the adjustment, gaps remain between the baseline simulation and the actual data because, as discussed above, our correction for reporting errors forces the transition rates to match the observed marginal distribution of labor market states s but not the joint distribution of s and observables x . We conjecture that matching the joint distribution of s and x could be particularly important for matching the stock of unemployment because x includes dummy variables for unemployment duration, which can also be subject to reporting errors. We are continuing to investigate how to adjust for this problem.

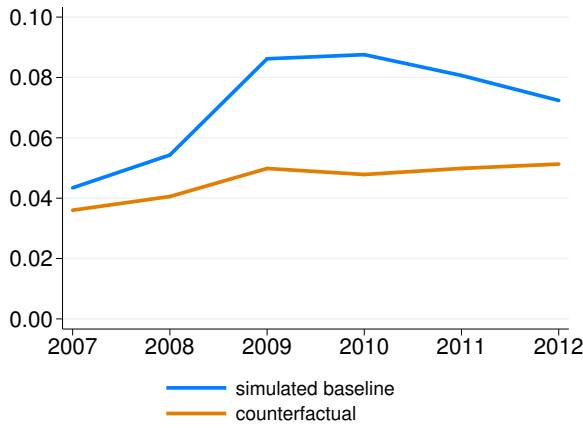
Figure 6(c) compares the baseline unemployment rate with the unemployment rate in a counterfactual simulation that holds T fixed at its December 2006 value and sets the matching elasticity θ at its estimated value of 0.40. In the baseline, annual average unemployment peaks in 2010 at 4.4 percentage points above its value in 2007, and by 2012, unemployment is still 2.9 percentage points above the 2007 average. The counterfactual shows that if T had been fixed at its December 2006 value, annual average unemployment would have risen



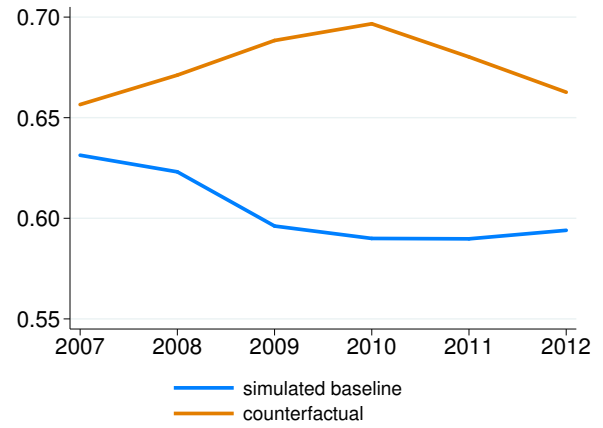
(a) Simulated vs. actual unemployment rate



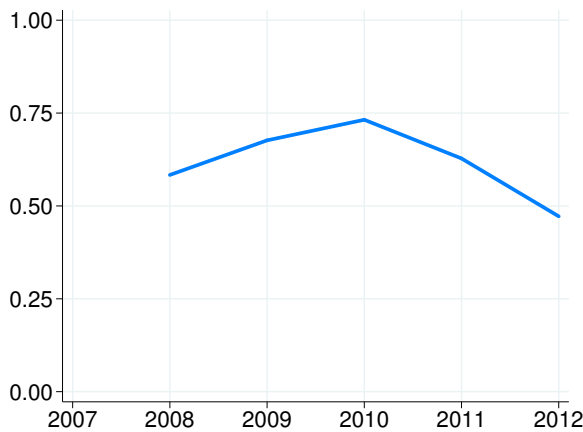
(b) Simulated vs. actual employment-population ratio



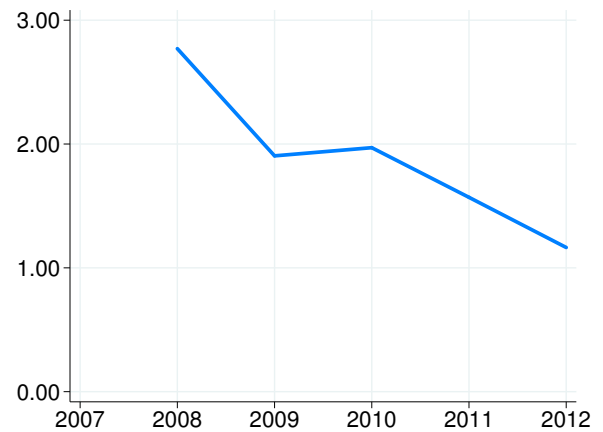
(c) Counterfactual unemployment rate



(d) Counterfactual employment-population ratio



(e) Fraction of rise in unemployment explained by T



(f) Fraction of fall in employment explained by T

Figure 6: Results of counterfactual simulations

Source: Authors' calculations from Current Population Survey microdata and Job Openings and Labor Turnover Survey. Annual averages of monthly data. Simulated baseline and counterfactual results are means from 100 simulations. Counterfactual sets $\theta = 0.40$.

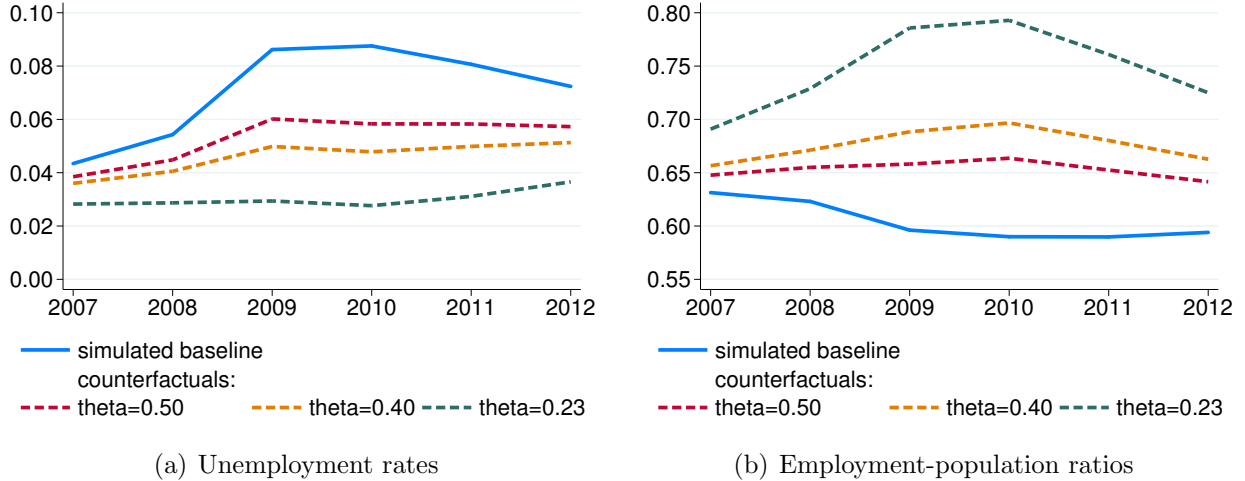


Figure 7: Robustness of simulations to alternative values of θ

Source: Authors' calculations from Current Population Survey microdata and Job Openings and Labor Turnover Survey. Annual averages of monthly data. Simulated baseline and counterfactual results are means from 100 simulations.

only 1.5 percentage points above the 2007 rate. In the counterfactual, the lower unemployment rate is accompanied by a substantial rise and then fall in the employment-population ratio, shown in Figure 6(d); in 2010, the counterfactual employment-population ratio is 10 percentage points above that in the baseline simulation.

In Figures 6(e) and 6(f), we calculate the fraction of the increase in unemployment and the decrease in employment compared with the 2007 average that can be explained by the change in T . We find that the fraction of unemployment that T explains is hump-shaped: In the worst year, 2010, tightness explains nearly three-fourths of the rise in unemployment, but by 2012, T explains only half of the rise in unemployment. We also find that tightness explains much more than 100 percent of the fall in the employment-population ratio.

In our model, changes in matching efficiency explain whatever part of the rise in unemployment is not explained by T . Thus, the fraction of the excess unemployment relative to 2007 that is explained by decreases in matching efficiency is U-shaped. Low matching efficiency explains 40 percent of the excess unemployment early in the recession, slightly more than one-fourth of the excess unemployment in 2010, but—as the downward trend in matching efficiency continues—half of the excess unemployment by 2012.

8 Robustness

Figure 7 shows how the simulation results depend on the matching elasticity θ . In addition to our baseline of $\theta = 0.40$, we consider a parametrization with equal elasticities for jobseekers and vacancies ($\theta = 0.5$), and a parametrization corresponding to the value of $\theta = 0.23$ that we estimated in Table 2 using the hires data from 2000 to 2013. Lower values of θ imply that T explains a larger share of the increase in unemployment; indeed, if we assume $\theta = 0.23$, T explains all of the rise in unemployment. However, lower values of θ also predict larger increases in the employment-population ratio, and if $\theta = 0.23$, this increase is implausibly large.

We calculate the effect of matching efficiency on unemployment in this paper as a residual, the change in unemployment that is not explained by T . In future work, we plan to also calculate the effect of matching efficiency directly, by constructing counterfactual logit coefficients that hold the matching efficiency index constant and simulating the unemployment rate with these counterfactual coefficients. The direct calculation can potentially differ from the residual calculation because of nonlinearities in the model.

9 Conclusion

Many authors have demonstrated a decline in labor-market matching efficiency during the Great Recession and ensuing slump. With the exception of Veracierto’s pioneering work, research has made the assumption that the measure of job-seeking volume is the stock of unemployed workers. But the Current Population Survey shows that only about a quarter of newly filled jobs involves hires of the unemployed. The remaining three quarters come from out of the labor market or from job-to-job transitions. We develop a consistent approach to aggregation over heterogeneous categories of job-seekers, with a separate measure of matching efficiency for each category and a related measure of aggregate matching efficiency.

Our concept of matching efficiency combines the propensity of the members of a category of potential job-seekers to engage in active search with the per-period effectiveness of those active searchers. Absent direct measures of search effort, as in Krueger and Mueller (2011), we cannot break the two factors apart.

We confirm that matching efficiency has declined in some categories of unemployment, including permanent job loss, a category that rose substantially as a fraction of total unem-

ployment in the Great Recession. Most of the decline is the continuation of a trend that has existed since 2001 and possibly earlier. Because such a large fraction of hiring occurs out of pools of job-seekers other than the unemployed, one important implication is that the decline in matching efficiency among the unemployed drove up the unemployment rate, but the labor market still generated large volumes of job-finding among groups not counted as unemployed.

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