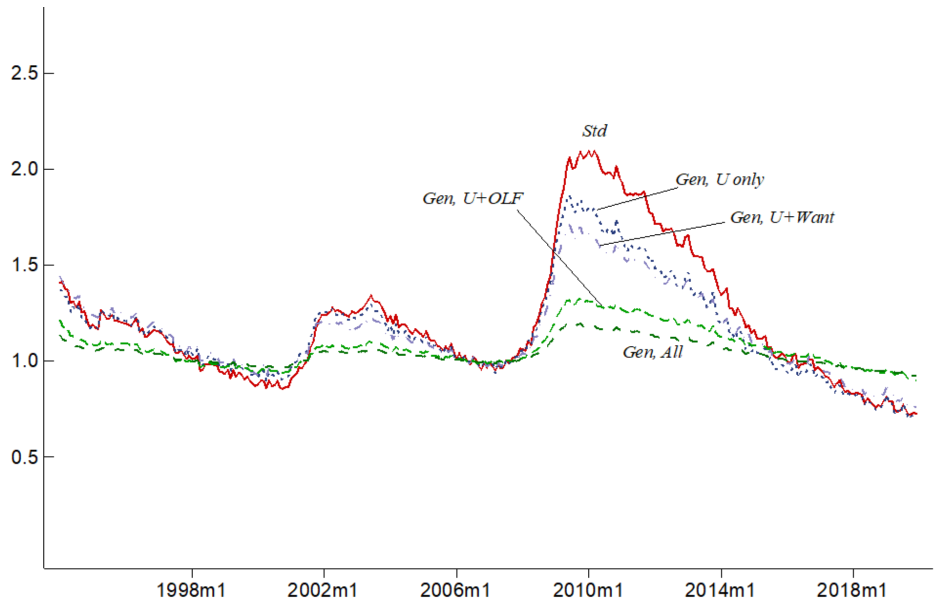
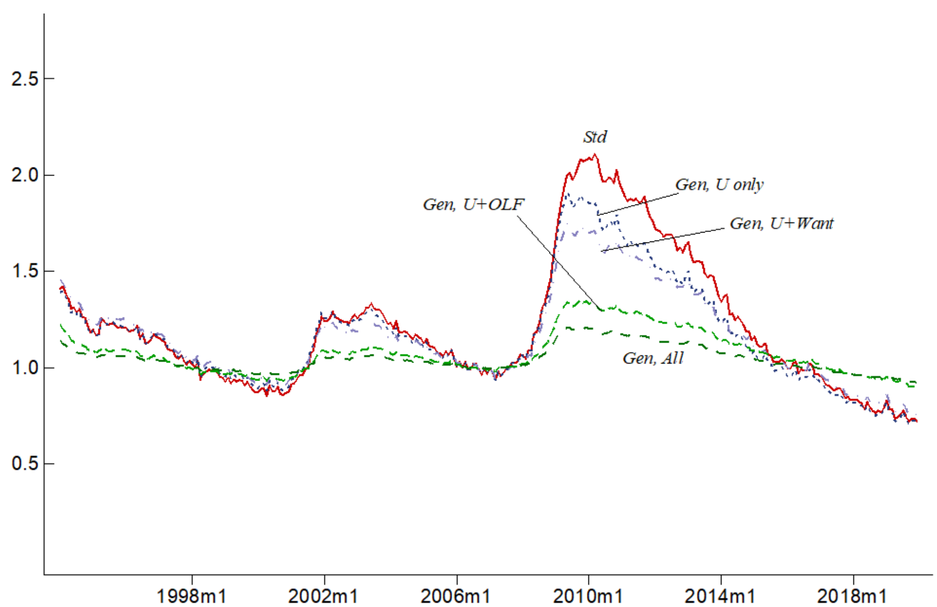
Appendix A. Supplementary Figures

Figure A.1. Standard versus Generalized Measures of Searchers (using direct (raw) measures of relative job-finding rates to construct relative search intensities)



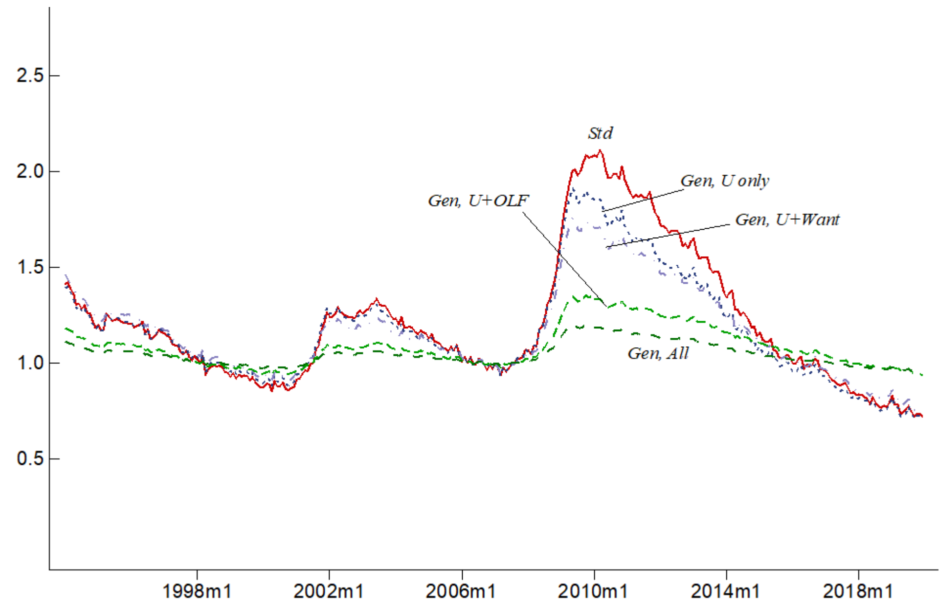
Source: Authors' calculations using Current Population Survey (CPS).
Notes: See notes to Figure 1 in main text. All rates normalized to 1 in 2006.

Figure A.2. Standard versus Generalized Measures of Searchers (using two groups for unemployed – short term and long term unemployed)



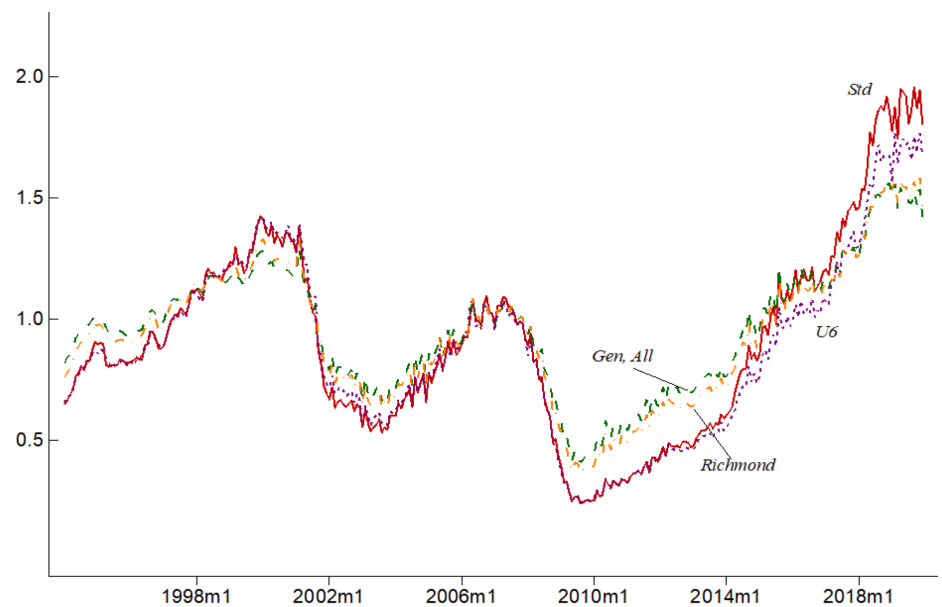
Source: Authors' calculations using CPS.
Notes: See notes to Figure 1 in main text. All rates normalized to 1 in 2006. These results use two groups of effective searchers for Gen, U only; 5 groups for Gen, U + Want; 9 groups for Gen, U + OLF; and 11 groups for Gen, All.

Figure A.3. Standard versus Generalized Measures of Searchers (using five groups)



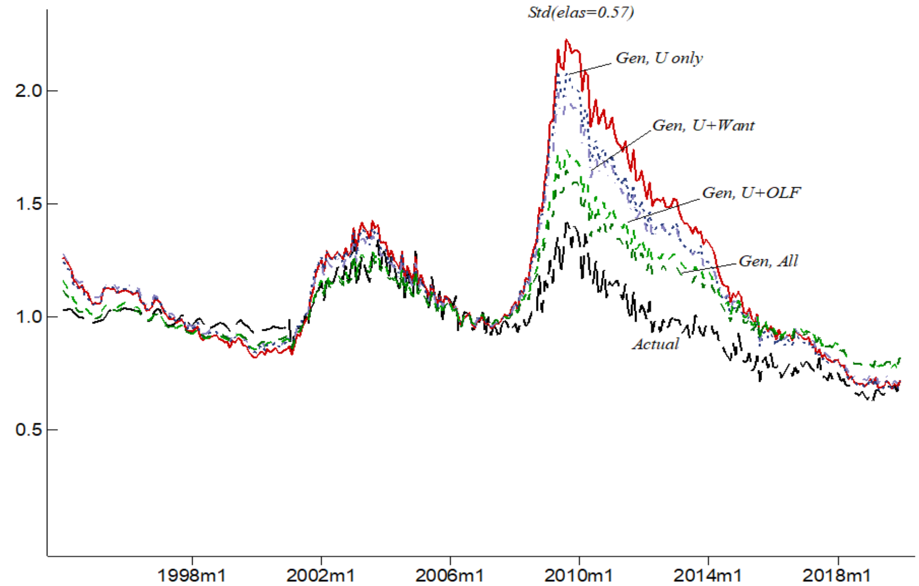
Source: Authors' calculations using CPS.
Notes: See notes to Figure 1. All rates normalized to 1 in 2006. These results use two groups of effective searchers for Gen, U only (short-term and long-term); three groups for Gen, U + Want (adding OLF who want a job); four groups for Gen, U + OLF (adding OLF who don't want a job); and five groups for Gen, All (adding employed).

Figure A.4. Standard, Generalized (Constant Relative Search Intensities, Recruiting Intensity=1), Richmond Fed and U6 Measures of Labor Market Tightness



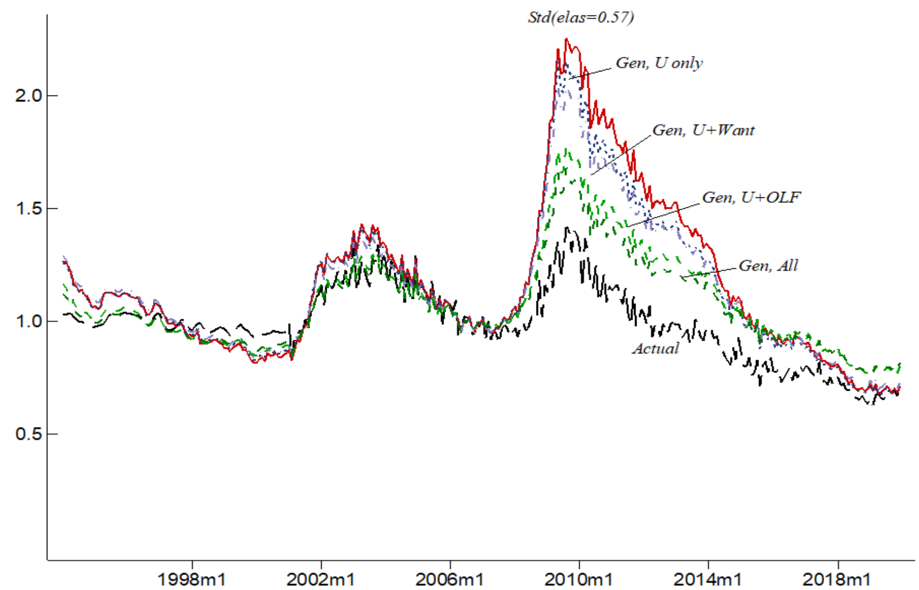
Sources: Authors' calculations using CPS, Job Openings and Labor Turnover Survey (JOLTS) for 2000:M12–2019:M12 and backcast vacancies from Davis, Faberman, and Haltiwanger (2012a) for 1994:M1–2000:M11 (DFH (2012a) vacancies hereafter).
Notes: All rates normalized to 1 in 2006. Std = V/U, Gen, All = V/ES (all twenty- two groups); U6=V/U6 index; Richmond=V/ Richmond Fed NEI.

Figure A.5. Actual vs. Calibrated Job-filling Rates from Matching Function (using direct (raw) measures of job-finding rates to construct relative search intensities)



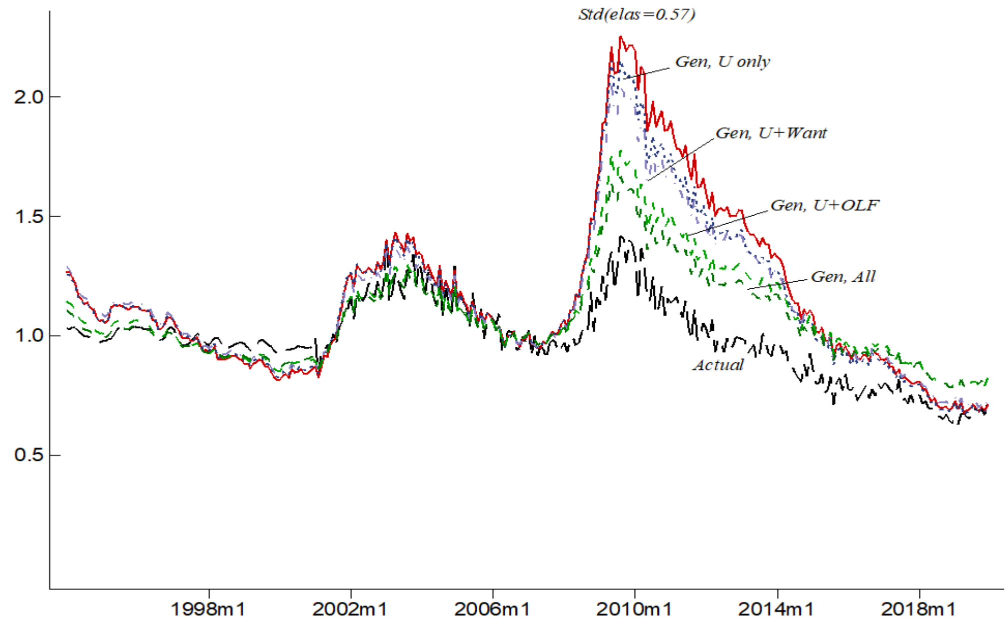
Source: Authors' calculations using CPS, JOLTS, and DFH (2012a) vacancies.
Notes: See notes to Figure 7 in main text. All rates normalized to 1 in 2006. These results use raw job-finding rates rather than demographically adjusted job-finding rates to construct relative search intensities.

Figure A.6. Actual versus Calibrated Job-filling Rates from Matching Function (using two groups for unemployed – short term and long term unemployed)



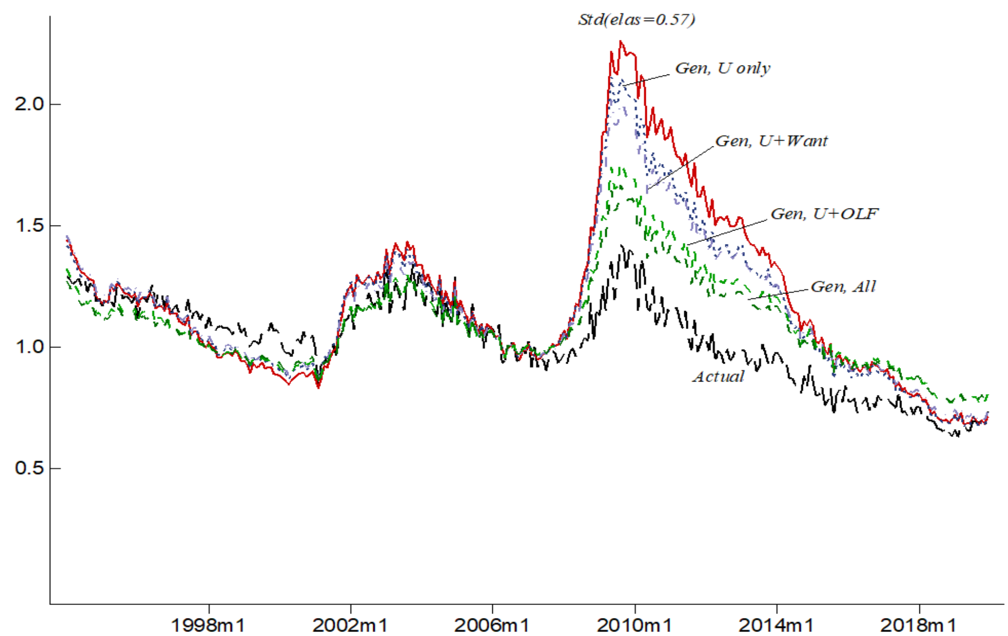
Source: Authors' calculations using CPS, JOLTS, and DFH (2012a) vacancies.
Notes: See notes to Figure 7 in main text. All rates normalized to 1 in 2006. These results use two groups of effective searchers for Gen, U (short-term and long-term); five groups for Gen, U + Want; nine groups for Gen, U + OLF; and eleven groups for Gen, All.

Figure A.7. Actual versus Calibrated Job-filling Rates from Matching Function (using five groups)



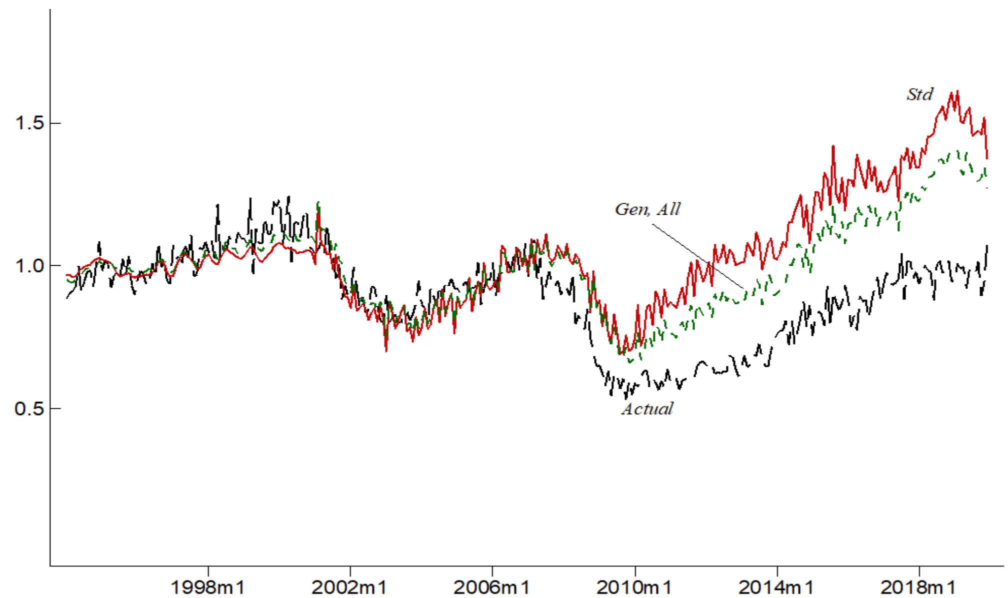
Source: Authors' calculations using CPS, JOLTS, and DFH (2012a) vacancies.
Notes: See notes to Figure 7 in main text. All rates normalized to 1 in 2006. These results use two groups of effective searchers for Gen, U only (short-term and long-term); three groups for Gen, U + Want (adding OLF who want a job); four groups for Gen, U + OLF (adding OLF who don't want a job); and five groups for Gen, All (adding employed).

Figure A.8 Actual versus Calibrated Job-filling Rates from Matching Function with Barnichon (2010) vacancies



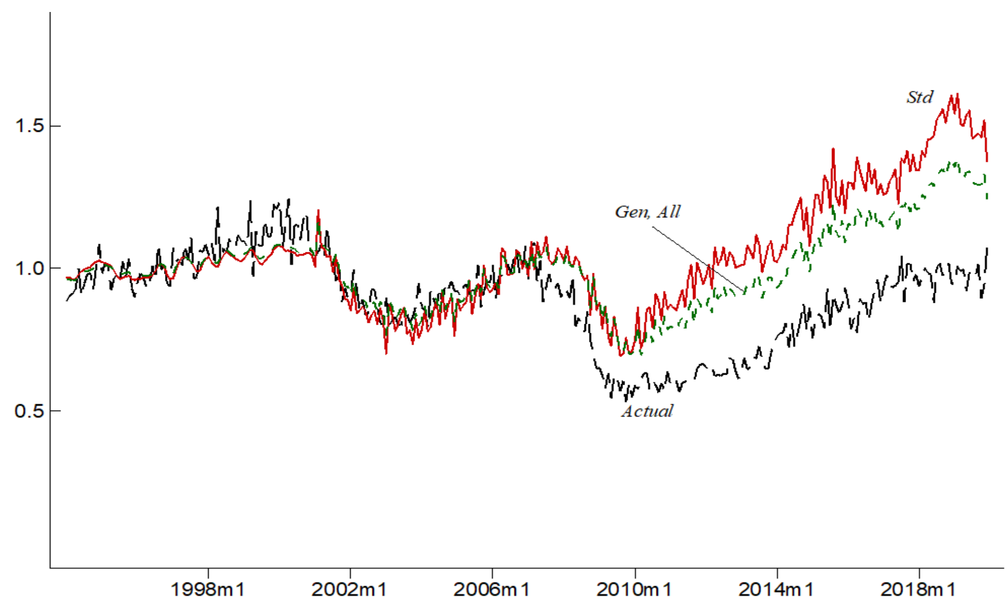
Source: Authors' calculations using CPS, JOLTS, and DFH (2012a) vacancies.
Notes: See notes to Figure 7 in the main text. All rates normalized to 1 in 2006.

Figure A.9. Actual versus Calibrated Job-finding Rates for the Unemployed with Standard and Effective Searchers (using direct (raw) measures of job-finding rates to construct relative search intensities)



Sources: Authors' calculations using CPS, JOLTS, DFH (2012a) vacancies, and BLS Gross Flows.
Notes: See notes to Figure 8 in main text. All rates normalized to 1 in 2006. These results use raw job-finding rates rather than demographically adjusted job-finding rates to construct relative search intensities.

Figure A.10. Actual versus Calibrated Job-finding Rates for the Unemployed with Standard and Effective Searchers (using two unemployment groups – short term and long term unemployed)

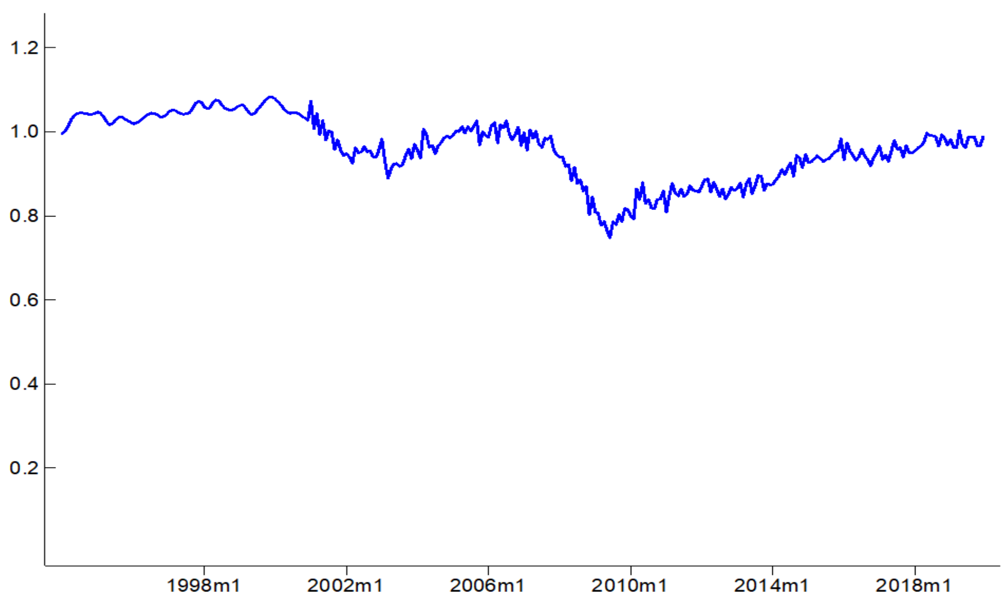


Sources: Authors' calculations using CPS, JOLTS, DFH (2012a) vacancies, and BLS Gross Flows.
Notes: See notes to Figure 8 in main text. All rates normalized to 1 in 2006. Results for Gen, All use two groups among the unemployed (short-term and long-term) plus the same groups among those out of the labor force and employed as in fully generalized measure.

Figure A.11. Actual versus Calibrated Job-finding Rates for the Unemployed with Standard and Effective Searchers (using five groups)

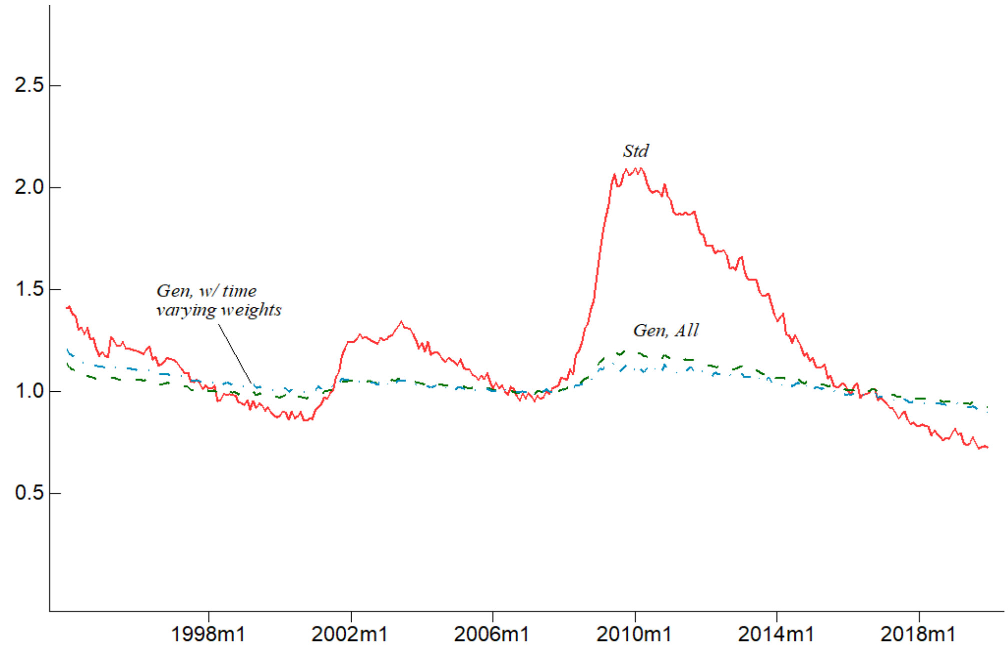
Sources: Authors' calculations using CPS, JOLTS, DFH (2012a) vacancies, and BLS Gross Flows.
Notes: See notes to Figure 8 in main text. All rates normalized to 1 in 2006. These results use five groups for General All (short-term unemployed, long-term unemployed, out of labor force and want a job, out of labor force and don't want a job, employed).

Figure A.12. Index of Recruiting Intensity Per Vacancy



Source: Index of recruiting intensity from Davis, Faberman, and Haltiwanger (2013).
Notes: Normalized to 1 in 2006.

Figure A.13 Standard versus Generalized Measures of Searchers with time varying search intensities



Sources: Authors' calculations using CPS.
Notes: All measures ratios to population age 16+ normalized to 1 in 2006. Std = Unemployed, General, All = generalized measure, all twenty-two groups with constant relative job search intensities; General, w/time varying weights = generalized measure, all twenty-two groups with time varying relative job search intensities.

Appendix B

B.1 Constructing Relative Job Search Intensities Controlling for Demographics

We use a two-step procedure to construct our relative job search intensity measures. First, we generate estimates of the job-finding rates for each of the 22 groups of searchers that control for changing demographics. Second, we use the resulting job-finding rate series to construct measures of relative job search intensities.

Following Hall and Schulhofer-Wohl (2018) (HSW 2018), we begin by using the CPS microdata to estimate a logit motivated by the following specification:

$$f_{i,t,x} = \frac{\exp(\kappa_{i,t}+x'\beta_i)}{1+\exp(\kappa_{i,t}+x'\beta_i)} \tag{B.1}$$

where $f_{i,t,x}$ is the job-finding rate in period t for an individual in initial status i with the characteristic bundle x. The $\kappa_{i,t}$ are group-specific time effects. As in HSW (2018), the characteristics controlled for in x are age (six age groups), gender, marital status and education (four education groups), along with five more detailed duration-group controls for all of the unemployed groups with 5-26 weeks of unemployment. We estimate this relationship separately for each of the 22 groups using monthly CPS microdata for the period from 1994:1 through 2019:12. All of the estimated job-finding rates we use in our baseline analyses hold demographic composition effects constant based on each group's 2005-2007 characteristics.

To calculate the job-finding rates shown in Table 1, we use our estimates of equation (B.1) which yield predicted monthly values for each cell defined by x, i, and t. We aggregate these estimates using the group-specific 2005-07 distribution across the possible values of x to produce monthly values of job-finding rates for each searcher group i in each period t. Time variation in these job-finding rates is driven by the $\kappa_{i,t}$ estimates from the equation (B.1). For Table 1, we average those monthly values across the 12 months of the year to produce the estimates reported for 2006 and 2010.

For the 2010 estimates, after calculating the monthly values, we make a further adjustment before taking the annual averages. Specifically, we adjust the job-finding rates for employed persons to correct for a problem identified by Fujita, Moscarini, and Postel-Vinay (2019) (FMPV 2019). Beginning in 2007:1, CPS interviewers stopped asking some proxy respondents whether currently employed household members for whom they were reporting were still working for the same employer as in the previous month. As FMPV (2019) show, this change in procedures created a downward bias in the estimated job-finding rates for the employed. FMPV (2019) provide monthly adjustment factors to correct for this bias and we incorporate their adjustment factors throughout our analysis for all months subsequent to 2007:1.[1] We use job-finding rates incorporating the FMPV (2019) adjustment for the estimation of elasticities discussed in the next section.

B.2 Estimating the Matching Function Elasticities

In order to construct the calibrated job-filling and job-finding rates based on the various models discussed in the text, we need an estimate of α, the overall elasticity of hires with respect to effective searchers in the matching function. We have constructed estimates of α, for each model we consider based on an adaptation of the methods developed by HSW (2018). In essence, their approach makes use of estimates of η, the elasticity of the group-specific job-finding rate with respect to vacancy duration, which as shown in the text is isomorphic to α (more specifically, $\alpha=1/(1+\eta)$). In some of our analyses, we use the group-specific elasticities with respect to T_t to construct time-varying relative search intensities, but this is not our baseline case.

For most of the analyses in the main text, we consider simplified specifications based on HSW (2018) to estimate the elasticities of the various job-finding functions. We start with equation (11) from the main text:

[1] The FMPV (2019) adjustment ends in 2018:12. We use the seasonally adjusted value of 2018:12 for all the months in 2019. By this time, the adjustment factor had largely stabilized on a seasonally adjusted basis.

$$\frac{H_{it}}{S_{it}} = f_{it} = \rho_t^{S_i} A_t T_t^{\eta} \tag{B.2}$$

Letting $\rho_t^{S_i} = \gamma_i$ implies the following relationship between the job-finding rate and vacancy duration for any group *i*:

$$f_{it} = \gamma_i A_t (T_t)^{\eta} \tag{B.3}$$

Taking natural logs of (B.3) and adding a time trend, we estimate the following relationship:

$$\log(f_{it}) = \log(\gamma_i) + \eta \log(T_t) + \lambda t + \varepsilon_{it} \tag{B.4}$$

where the unit of observation is a status group *i* in time period *t*, the dependent variable is the predicted average job-finding rate for those in a particular status group and time period based on equation (B.1) and the right hand variables are vacancy duration and the time trend. This is a simplified version of the specification used by HSW (2018, differing from theirs in not allowing for group-specific differences in the elasticity with respect to T_t or for group-specific time trends and also in not allowing for an additional post-2007 time trend. We consider group specific elasticities and time trends as in HSW (2018) below.

The dependent variables for the different versions of equation (B.4) we estimate are available for the full sample period 1994:1 through 2019:12, but the Job Openings and Labor Turnover Survey (JOLTS) data needed to construct T_t are available only beginning in 2000:12. As such, we estimate equation (B.4) using the "gold standard" JOLTS data for the 2000:12 through 2019:12 period.

We estimate (B.4) for several cases. First, we estimate a version of (B.4) with a single group, the unemployed. This is what we refer to as the standard case. Second, we estimate (B.4) for our 22-group specification, using panel estimation with group fixed effects. We also carry out several sensitivity analyses. One is to estimate (B.4) for a single group that corresponds to the U6 population (the unemployed plus the marginally attached plus those working part-time for economic reasons). A second is to estimate (B.4) for the nine groups in the Richmond Fed index, again using panel estimation with group fixed effects. We also estimate the 22-group case using the raw job finding rates as the dependent variable. For the cases with multiple groups (our fully generalized 22-group and the nine-group Richmond Fed index cases), the regression we estimate is weighted, with the weights equal to the population shares of the group in question in the 2006 base period. In all cases, we follow HSW (2018) in instrumenting T_t with Current Establishment Survey (CES) payroll employment. They argue that the primary motivation for this is measurement error in the JOLTS data. The results of our estimation are reported in Table B.1.

Note that we do not use the (B.4) estimates to construct the measures of relative search intensities and in turn effective searchers used in our model projections. Rather, the purpose of (B.4) is to provide the information needed to calibrate the matching function used in those projections. Estimating a version of (B.4) for each specification allows us to assign a value of η and in turn a value of $\alpha = 1/(1+\eta)$ for use in the corresponding matching function.

B.3 Time Varying Relative Search Intensities

In section V, we consider time varying relative search intensities. For this specification, we estimate job-finding functions like HSW (2018)'s equation (7), but with 22 groups. In this more general case, we consider relative search intensities specified as $\rho_t^{S_i} = \gamma_i T_t^{\eta_i}$. This along with (B.2) [equation (11) from the main text] implies a relationship between the job-finding rate and vacancy duration for each group *i*:

$$f_{it} = \gamma_i A_t (T_t)^{\eta+\eta_i} \tag{B.5}$$

Taking natural logs of (B.5) and adding a group-specific time trend, we estimate the following relationship:

$$\log(f_{it}) = \log(\gamma_i) + \tilde{\eta}_i \log(T_t) + \tilde{\lambda}_i t + \varepsilon_{it} \tag{B.6}$$

where the dependent variable is the predicted average job-finding rate across individuals for initial status i in month t based on equation (B.1), the right hand variables are vacancy duration and a time trend, $\tilde{\eta}_i = \eta + \eta_i$ and $\tilde{\lambda}_i = \lambda + \lambda_i$. The difference between (B.6) and (B.4) is that, in (B.6), both the coefficient on T_t and the coefficient on the time trend vary by group. We estimate equation (B.6) using the "gold standard" JOLTS data for the 2000:12 through 2019:12 period. Following HSW (2018), B.6 is estimated as a pooled panel and T_t is instrumented with payroll employment.

Table B.2 presents the estimates of $\tilde{\eta}_i$ and $\tilde{\lambda}_i$ based on equation (B.6). The estimated elasticity of the job-finding rate with respect to vacancy duration is positive for all groups, but there is considerable cross-group variation. All groups exhibit a declining trend in job-finding rates, but again there is considerable cross-group variation.

We use the estimates in Table B.2 to construct our measures of time-varying search intensities. To use these estimates, however, we must extract the idiosyncratic components η_i and γ_i, as the common components of the elasticity with respect to vacancy duration and the time trend (η and λ) can be expected to capture factors in addition to variation in search intensities. The time-varying versions of the $\rho_t^{S_i}$'s that we estimate incorporate only the idiosyncratic components of these effects (the η_i and the λ_i). These are assumed to have mean zero on a base-period-population-weighted basis. Our most general estimate of job search intensity for the members of group i is thus $\rho_t^{S_i} = \gamma_i T_t^{\eta_i} e^{\lambda_i t}$.

We implement the time-varying measure of search intensity as follows. First, we use the estimates of average 2006 job-finding rates reported in Table 1 to generate our measures of γ_i. We normalize the reported job-finding rates so that, for the recently laid off unemployed, $\gamma_i = 1$ on average over the 12 months of 2006. The values of γ_i for all of the other groups then are defined based on the ratio of their 2006 average job-finding rate to that for the recently laid off unemployed. We use the estimated elasticities with respect to vacancy duration shown in Table B.2 to construct our measures of η_i . The elasticities reported in Table B.2 are estimates of $\tilde{\eta}_i$; based on those values, we compute $\eta_i = \tilde{\eta}_i - \eta$ where η is the (base period) population weighted average of the estimates from Table B.2. We treat the idiosyncratic trend component λ_i in an analogous fashion. For the time-varying search intensity measures, all of the $T_t^{\eta_i}$ and $e^{\lambda_i t}$ are normalized to equal 1.0 on average over the 12 months of 2006.

The base-period population-weighted estimate of η is 0.75 which is the same as the estimate that emerges from Table B.1 for the common elasticity case. This estimate of the population-weighted elasticity is used in section V as the matching elasticity for calibrating the job-finding and job-filling rates based on the generalized model. As with the results in section IV, this yields an aggregate matching elasticity of 0.57.

Figure A.13 shows the standard measure of searchers—the unemployed—together with the two versions of our generalized searcher measure, one constructed using fixed relative search intensities and the second constructing using time-varying relative search intensities as just described. All three measures shown in the figure are ratios of searchers to the population age 16 and older normalized to equal 1.0 in 2006. The standard measure is much more cyclical than either generalized measure.

The generalized measure that allows for time-varying relative search intensities is slightly less countercyclical than the baseline measure. In part, this reflects the fact that, in contractions, the unemployed are a rising share of effective searchers, but the relative search intensity of key groups, such as the long-term unemployed, is declining.

In the main text, we focus primarily on measures based on time-invariant relative job search intensities. The time-invariant relative job search intensities are transparent and readily interpretable. Further, using the time invariant relative search intensities avoids any risk of unfairly advantaging the generalized matching function relative to the standard matching function for tracking time series variation in actual job-filling and job-finding rates. The fact that even the measure based on time-varying relative job search intensities as proxied by time variation in job-finding rates uses only the idiosyncratic portion of that variation means that such concerns should be largely obviated in any case. Figure A.13 suggests that the variation in relative job search intensities identified by our approach is not great, though as already discussed there may be common variation in job search intensities it simply cannot capture.

B.4 Functional forms of Generalized Job-finding and Filling Rates with Time Varying Recruiting Intensity and Relative Job Search Intensities

In section V, we consider more general versions of the job-finding and job-filling rate specifications. For job filling, when adding just recruiting intensity, equation (10) in the main text becomes:

$$\frac{H_t}{V_t} = \mu_t \left(\frac{U_t}{V_t}\right)^{\alpha} [(\frac{H_t}{E_t})^{\phi}]^{(1-\alpha)} [\frac{\sum_i \gamma_i S_{it}}{U_t}]^{\alpha} \tag{B.7}$$

Also adding time variation in search intensities yields:

$$\frac{H_t}{V_t} = \mu_t \left(\frac{U_t}{V_t}\right)^{\alpha} [(\frac{H_t}{E_t})^{\phi}]^{(1-\alpha)} [\frac{\sum_i \gamma_i T_t^{\tilde{\eta}_i - \eta} e^{\tilde{\lambda}_i - \lambda} S_{it}}{U_t}]^{\alpha} \tag{B.8}$$

In our analysis, ϕ = 0.82, the estimate from DFH (2013) based on cross-sectional micro data. Note also that only the idiosyncratic variation in the relative search intensities contributes to the generalized measure of labor market tightness. The analogous specification for job-finding rates with time varying recruiting intensity but fixed relative search intensities is given by:

$$\frac{H_{ut}}{U_t} = \frac{H_{ut}}{S_{ut}} = \mu_t^{1+\eta} (\frac{H_t}{E_t})^{\phi\eta} (V_t / H_t)^{\eta} \sum_{i \in u} (\gamma_i S_{it} / S_{ut}) \tag{B.9}$$

Also adding time variation in search intensities yields:

$$\frac{H_{ut}}{U_t} = \frac{H_{ut}}{S_{ut}} = \mu_t^{1+\eta} (\frac{H_t}{E_t})^{\phi\eta} (V_t / H_t)^{\eta} \frac{\sum_{i \in u} \gamma_i T_t^{\tilde{\eta}_i - \eta} e^{\tilde{\lambda}_i - \lambda} S_{it}}{U_t} \tag{B.10}$$

B.5 Estimates of Intercepts and Slopes of Beveridge Curves

Table B.3 presents estimates of the intercept and the slope of the Beveridge curve obtained from a descriptive regression of vacancies on unemployment using the data plotted in Figure 4 (shown in the top row) and from a descriptive regression of vacancies on effective searchers using the data plotted in Figure 5 (shown in the fifth row). In addition to the estimates using the fully generalized measures of effective searchers, Table B.3 also reports the results of several intermediate generalized Beveridge curve equations, all using effective vacancies but varying the construction of effective searchers. The effective searcher measure used in the first of these intermediate equations differs from the standard equation only in allowing for heterogeneity among the unemployed; the next adds those out of the labor force who want a job; and the third adds the remaining people who are out of the labor force. Consistent with Figure 4, the slope of the standard Beveridge curve is well below one in absolute value, reflecting the much greater proportional variation in unemployment than in job openings. In contrast, consistent with Figure 5, the slope of the descriptive regression using the fully generalized measure is much larger than one in absolute value, reflecting the much greater proportional variation in effective vacancies than in effective searchers. Not surprisingly, the slope coefficients estimated using the intermediate versions of effective searchers lie between these two extremes.

Also included in Table B.3 are coefficient estimates for descriptive Beveridge curve equations using the alternative measures underlying the U6 and Richmond Fed indexes as effective searchers. The standard measure of vacancies is used in all cases. The slope of the Beveridge curve using the U6 measure is similar to that for the standard unemployment measure. The slope using the Richmond Fed index lies between that for the standard and the fully generalized measures, similar to that for our measures with intermediate versions of effective searchers.

B.6 Interpretation of Calibration vs. Regression Analysis of Alternative Models

Our calibration exercise is designed to assess how well each of a set of models—matching functions with a given elasticity and set of arguments (different versions of effective searchers and effective vacancies)—tracks the job-filling rate and the job-hiring rate from unemployment. Intuitively, a model will perform better in this calibration exercise when its calibrated values not only are more correlated with the actual movement in the outcome of interest but also when the amplitude of its predictions is closer to that of the actual outcome.

This is a very different exercise than regressing an actual outcome on one or more model calibrated measures and looking at the model fit. This latter approach lacks the theoretical justification that underlies our calibration approach. Regressing actual outcomes on model-calibrated outcomes not only introduces an arbitrary additively-separable constant but also permits an arbitrary slope coefficient that deviates from the specified functional form of the matching function. Both the constant and slope of any such regression are difficult to interpret in the context of the specified functional forms of the standard and generalized models.

It is especially unclear what one would make of a regression of actual outcomes on multiple calibrated outcomes simultaneously. Because the calibrated job-filling rates for the standard and the general model are highly correlated, there is no particular reason to think that regressing the actual on both the standard model and general model calibrated job-filling rates should yield a zero coefficient on the former and a coefficient of 1.0 on the latter. Nor is it clear that examining the goodness of fit of such a regression will be informative.

An analogy to the production function literature may be helpful. In that literature, much attention has been paid to assessing whether some of the cyclical fluctuations in the measured Solow residual is accounted for by variation in factor utilization not measured in the standard approach. Evaluation of this hypothesis has proceeded along the lines of our analysis – that is, by comparing the variation in the Solow residual under the standard and utilization-adjusted functional forms. In computing these residuals, one needs to be careful about the measurement of inputs, the measurement of utilization rates for the case with variable utilization rates and the calculation of the key output elasticities needed for the production function. Similar to our case, little would be learned from estimating the relationship between output and the calibrated estimates from two separate production functions on the right-hand side of a regression equation.

References

Fujita, Shigeru, Guiseppe Moscarini, and Fabien Postel-Vinay. 2019. "Measuring Employer-to-Employer Reallocation," unpublished working paper.

Hall, Robert and Sam Schulhofer-Wohl. 2018. "Measuring Job-finding rates and Matching Efficiency with Heterogeneous Job-Seekers," *American Economic Journal: Macroeconomics*, 10(1): 1-32.

Table B1: Cyclical And Trend Variation in the Job Finding Rate – Common Elasticities

	Elasticity with Respect To Vacancy Dur	Trend in Efficiency
Unemployed Pooled	1.04	-0.24
	(0.05)	(0.02)
22 groups (with fixed effects)	0.75	-0.20
	(0.04)	(0.01)
U6 pooled	1.10	-0.28
	(0.05)	(0.02)
Richmond Fed (with fixed effects)	0.67	-0.20
	(0.04)	(0.01)
Raw JFR (with fixed effects)	0.78	-0.22
	(0.04)	(0.01)

*Notes:*Trend coefficients are multiplied by 100. For the 22 group and Richmond Fed estimation it is a panel estimation (9 groups) with fixed effects for each group. Also, these panel based group estimation use population weights of the groups for the base period 2006.

Table B2: Cyclical And Trend Variation in the Job Finding Rate – Heterogeneous Elasticities

	Elasticity with Respect To Vacancy Dur	Trend in Efficiency
Unemployed: Recently Left Job	0.96	-0.27
Unemployed: Recently Permanently Laid Off	1.13	-0.24
Unemployed: Recently Temporarily Laid Off	0.23	-0.02
Unemployed: Temp. Job Recently Ended	0.51	-0.16
Unemployed: Recently Newly Entered	1.98	-0.53
Unemployed: Recently Re-Entered	1.15	-0.29
Unemployed: Left Job Months Ago	0.92	-0.27
Unemployed: Permanently Laid Off Months Ago	1.26	-0.27
Unemployed: Temporarily Laid Off for Months	0.52	-0.09
Unemployed: Temp. Job Ended Months Ago	0.94	-0.20
Unemployed: Newly Entered Months Ago	1.76	-0.47
Unemployed: Re-Entered Months Ago	1.22	-0.31
Unemployed: Long-Term Unemployed	1.55	-0.39
Want Job: Discouraged	1.11	-0.25
Want Job: Looked Last 12 Months	1.37	-0.32
Want Job: Other	0.74	-0.21
Not in Labor Force: In School	1.11	-0.42
Not in Labor Force: Retired	0.29	-0.07
Not in Labor Force: Disabled	0.91	-0.25
Not in Labor Force: Other	0.82	-0.26
Employed: Involuntary Part-Time	1.20	-0.37
Employed: Not Involuntary Part-Time	0.78	-0.20

Notes: The recently unemployed groups refer to those who have been unemployed for 0-4 weeks. Unemployed Months Ago refers to those who have been unemployed for 5-26 weeks. Long-Term Unemployed refers to those who have been unemployed for 27 weeks or more, Trend coefficients are multiplied by 100. $p<0.01$ for all reported coefficients (except for trend coefficient on recently temporary layoffs which is not statistically significant from zero).

Table B3: Slopes and Intercepts for Alternative Beveridge Curves: Constant Relative Search Intensities, Recruiting Intensity=1

	Intercept	Slope
Standard	1.66 (0.02)	-0.56 (0.02)
General, Unemployed Only	1.86 (0.02)	-0.76 (0.03)
General, Unemployed+Want Job	1.97 (0.04)	-0.86 (0.03)
General, Unemployed + OLF	2.91 (0.07)	-1.80 (0.06)
General, All	4.13 (0.10)	-3.02 (0.10)
U6	1.61 (0.03)	-0.50 (0.02)
Richmond Fed Index	2.82 (0.06)	-1.72 (0.06)

Notes: Standard=Unemployed; General, All=All effective searchers; General,Unemployed+OLF=Effective searchers excluding employed; General, Unemployed+Want Job=Effective searchers with unemployed + want a job; General, Unemployed=Effective searchers with unemployed only. All s normalized to one in 2006. Reported are intercept and slope of regression of vacancy on searcher . Standard errors in parentheses.

C. **Data Appendix**

C.1 Construction and Use of linked Current Population Survey (CPS) data files

We construct the job-finding rates used in our analysis from linked Current Population Survey (CPS) data files. The following variables were used to link individual records from month *t* to the record for the same person in month *t+1*:

Household identifier (concatenation of HRHHID and HRHHID2)
Person line number (PULINENO)
State (GESTFIPS)
Race (PTDTRACE)
Sex (PESEX)
Age (PEAGE)
Month in sample (HRMIS)

Given the sample rotation pattern in the CPS, the records for individuals in month-in-sample (MIS) 1-3 or 5-7 in month *t* can be matched to records for the same people in month *t+1*. A person in MIS 1 in month *t* would be in MIS 2 in month *t+1*, a person in MIS 2 in month *t* would be in MIS 3 in month *t+1*, and so on. Individuals in MIS 4 are not interviewed again until MIS 5, which occurs 8 months later, so the month-to-month change in their job status is not observed; the month-to-month change in job status also is not observed for individuals in MIS 8.

Everyone in our linked data file is assigned to a month *t* job searcher group. The 22 job searcher groups are as listed below and shown in Table 1:

Unemployed: Recently Left Job
Unemployed: Recently Permanently Laid Off
Unemployed: Recently Temporarily Laid Off
Unemployed: Temp. Job Recently Ended
Unemployed: Recently Newly Entered
Unemployed: Recently Re-Entered
Unemployed: Left Job Months Ago
Unemployed: Permanently Laid Off Months Ago
Unemployed: Temporarily Laid Off for Months
Unemployed: Temp. Job Ended Months Ago
Unemployed: Newly Entered Months Ago
Unemployed: Re-Entered Months Ago
Unemployed: Long-Term Unemployed
Want Job: Discouraged

Want Job: Looked Last 12 Months
Want Job: Other
Not in Labor Force: In School
Not in Labor Force: Retired
Not in Labor Force: Disabled
Not in Labor Force: Other
Employed: Involuntary Part-Time
Employed: Not Involuntary Part-Time

The first six groups are unemployed individuals who have been unemployed less than 5 weeks; the next six groups are unemployed individuals who have been unemployed 5 to 26 weeks; and the thirteenth group is individuals who have been unemployed 27 weeks or longer. The three groups labeled "Want Job" are individuals who are out of the labor force but say they would like to be working; the four "Not in Labor Force" groups are people who are out of the labor force and do not say they would like to be working. The final two groups distinguish people involuntarily working part-time from other employed people.

The basic CPS labor force status variable is PEMLR, which categorizes individuals as employed (PEMLR=1,2), unemployed (PEMLR=3,4) or out of the labor force (PEMLR=5, 6 7). Individuals who were unemployed or out of the labor force in month t and employed in month $t+1$ are counted as having found a job. For the employed, we use the variable PUIODP1 to identify individuals who changed jobs between month t and month $t+1$.

The effective searcher measures use the relative job-finding rates described in appendix B along with the estimates of each of the groups in the working age population from the CPS. For all of these estimates, we used PWSSWGT, the CPS final weight, to construct the necessary aggregates. PWCMPWGT, the CPS composite weight constructed to produce estimates that are consistent with published Bureau of Labor Statistics data, is not available from 1994 through 1997. For the period from 1998 through 2019, however, our results were unaffected by the choice between PWSSWGT and PWCMPWGT. We have verified that our estimates of the number of people in each group are very close to published BLS estimates. For these and all series we create, we follow the seasonal adjustment methods used by the BLS. That is, we use the Census X-12 seasonal adjustment routine set to the multiplicative X-11 method with auto trend filters and the auto seasonal filter (both the X-12 defaults).

C.2 Effective vacancy series

Our baseline estimates use the number of job openings as the effective vacancy series (that is we set recruiting intensity equal to one). For the period from 2000:12 through 2019:12, job openings are the seasonally adjusted job openings series from the Job Openings and Labor Turnover Survey (JOLTS). In our baseline estimates, job vacancy estimates for the period from 1994:1 through 2000:11 are based on the projection methods of Davis, Faberman and Haltiwanger (2012). Using data for 2001 to 2011, they find a tight relationship between establishment-level growth rates in Business Employment Dynamics (BED) data and establishment-level measures of hires, separations, quits, layoffs and vacancies in the JOLTS. These relationships vary over the cycle and DFH (2012) estimate a specification that relates the JOLTS outcomes at the establishment-level to the establishment-level employment growth rate bin as well as a series of cyclical controls (see equation (7) of DFH (2012)). Using the resulting estimates, they backcast the JOLTS aggregate measures using the micro BED data from 1990 to 2000 and the cyclical variables from their model.[2] The backcast series are seasonally adjusted. We splice in the backcast vacancy series so the value in the overlap month 2000:12 is the same as in the actual JOLTS data.

As a sensitivity check, we also constructed an alternate set of estimates using job openings for the period from 1994:1 through 2000:11 projected using the methodology described by Barnichon (2010). The Barnichon job vacancy index makes use of data on help wanted advertising to proxy for the trend in vacancies. Over time, help wanted advertising has shifted from newspapers to online

[2] DFH (2012) mostly focus on the backcast hires and separations series in their analysis. Their methodology for backcasting is the same across all JOLTS measures.

platforms, so that tracking the volume of either independently is not sufficient to gauge the post-1995 change in help wanted advertising. Barnichon constructs a composite index of job openings that assumes this shift began in 1995 and that online advertising has accounted for an increasing share of help advertising over time. Barnichon kindly provided us with a spreadsheet containing values of his index for the pre-2001 period in units corresponding to the number of job openings estimated in the JOLTS from 2000:12 forward.

In addition to the baseline estimates with effective vacancies defined simply as the number of job openings, we also use the results of Davis, Faberman and Haltiwanger (2013) (DFH 2013) to construct an effective vacancy series that adjusts for changes in recruiting intensity. In a cross-sectional analysis of JOLTS microdata, DFH 2013 estimate an elasticity of the job-filling rate with respect to the gross hiring rate of 0.82. They interpret this finding in terms of recruiting intensity. Under the hypothesis that recruiting intensity varies with gross hires over time in the same way that it does in the cross section, this relationship can be used to construct an index of changes in recruiting intensity over time. That is the index we use in our analysis. The index of recruiting intensity is reported in Figure A.12.

DFH (2013) conduct a number of robustness checks on this indirect measure of recruiting intensity. In the cross section, they find that the elasticity of the job-filling rate with respect to gross hiring is 0.80 using variation across industries, size classes and turnover quintiles. In the macro data, they estimate a generalized Beveridge Curve relating the log of unemployment to the log of the effective vacancy rate using the specification that log recruiting intensity is log linear in gross hires. The latter implies a regression that relates the log of the unemployment rate to log vacancies and log gross hires. The fit of this generalized Beveridge Curve is substantially better than the fit of the standard Beveridge curve. Moreover, the estimated elasticity of recruiting intensity with respect to gross hires is 0.836 – very close to the estimate from the micro cross sectional data.

C.3 *Job-Filling and Job-Finding Rates*

The actual job-filling rate in our calibrated exercises is measured as the ratio of hires to vacancies from JOLTS (inclusive of the backcast series from DFH (2012)). The actual job-finding rate of the unemployed in our calibrated exercises is measured as the ratio of the gross flows from unemployment to employed divided by the stock of the unemployed from the published BLS Gross Flows data.

C.4 Normalization

For all of the figures shown in the paper and accompanying appendices, as well as in all of the calculations that involve the matching function, effective vacancies are normalized so that they average 1.0 in 2006. In other words, we normalize each effective vacancy series by dividing the values by average effective vacancies across the 12 months of 2006.

References

Barnichon, Regis. 2010. "Building a Composite Help-Wanted Index," *Economics Letters*, 109, 175-178.

Davis, Steven J., R. Jason Faberman, and John C. Haltiwanger. 2012. "Labor Market Flows in the Cross section and Over Time," *Journal of Monetary Economics*, 59: 1-18.

Davis, Steven J., R. Jason Faberman, and John C. Haltiwanger. 2013. "The Establishment-Level Behavior of Vacancies and Hiring," *Quarterly Journal of Economics*, 128(2): 581-622.

Appendix D. Response to Justin Wolfers' written comments

This appendix provides a response to Justin Wolfers' post-conference written comments, which are distinct from his oral comments at the conference. In his post-conference written comments, Wolfers investigates whether the within-sample forecast of the job-filling rate using our general measure of labor market tightness (V/ES, where V is job vacancies and ES is effective searchers) improves on a forecast using the standard measure of labor market tightness (V/U, where U is unemployment). This exercise is quite distinct in its approach and objectives from the analysis reported in our paper.

Our analysis focuses on the performance of the matching function in accounting for key labor market outcomes. The matching function is the cornerstone of much of modern macro-labor economics. An important puzzle, however, has been why the standard matching function does not do a better job of capturing observed variation in job filling and job finding rates. We find that a generalized matching function based on the ratio of vacancies to effective searchers significantly outperforms the standard matching function in predicting these outcomes. In making this evaluation, we employ estimates of the matching function elasticity α based on the instrumental variables (IV) estimation approach developed by Hall and Schulhofer-Wohl (2018). An important advantage of this approach is that it yields plausibly consistent estimates. The values we estimate for α vary depending on the specific measure of labor market tightness we are analyzing, but all are well within the range of estimates found elsewhere in the matching function literature. Wolfers denotes our IV estimates of this key elasticity as "imposed" while his OLS based estimates of this elasticity are his "preferred" estimates, but OLS estimates of the matching function are well-known to be inherently biased and, as discussed below, the estimate he obtains for the standard model is well outside the consensus range in the existing literature for this parameter's value.

Even taking Wolfers' OLS approach at face value, his analysis and inferences have a number of limitations. First, his evaluation of the performance of the OLS estimates in forecasting the job filling rate makes use of the same data sample to produce the estimates and then assess how well predictions based on the estimates fit the data. For evaluating forecast performance, it is instructive to investigate out-of-sample implications. We have redone Wolfers' exercise but using out-of-sample data to evaluate the estimates obtained. Specifically, we estimate the OLS relationship using data from 1994:1-2007:12 and then evaluate the model's out-of-sample performance using the same metrics that Wolfers applies in his comments. For this restricted sample, the OLS estimates of α are 0.33 (0.014) using the standard measure of labor market tightness and 0.52 (0.016) using our generalized measure. This compares to Wolfers' estimates of 0.25 and 0.44 for the full sample and to our IV estimates of 0.49 and 0.57, in each case for the standard and generalized models, respectively. Whereas our IV estimates are in the middle of the range in the existing literature for the value of α, Wolfers' OLS estimate of 0.25 for the full sample and our OLS estimate of 0.33 for the pre-2008 sample are very low relative to those extant estimates.

Figure D.1 shows the analog to Wolfers' Figure 3 using the estimates of α (and μ) obtained from models fit with data for 1994:1-2007:12. Like Wolfers in his Figure 3, we normalize the series in Figure D.1 to have an average value of one in 2006. It is apparent that, even using Wolfers' approach, the out-of-sample forecast for the post-Great Recession period using the general measure outperforms the forecast using the standard measure. For the out-of-sample period 2008:1 to 2019:12, the RMSE using the general measure is about 80 percent of that using the standard measure, a smaller improvement than when using our estimates but a significant improvement nonetheless.

Even more important, when using Wolfers' preferred OLS estimates of α, the standard measure performs very poorly with regard to accounting for the observed variation in the job finding rate among the unemployed. Figure D.2 uses Wolfers' OLS full sample estimates of α (and μ)

together with equations (14) and (15) from the main text to evaluate how well the predicted job finding rate among the unemployed matches the actual rate (note that this requires using the relationship $\alpha = 1/(1+\eta)$). This figure is analogous to our Figure 8 but with Wolfers' preferred OLS estimates substituted for our IV estimates. Using these estimates, the generalized labor market tightness measure does much better than the standard measure for tracking the job finding rate among the unemployed, even more so than when our IV estimates are used. Based on the analysis in Figure 8 and panel C of Table 3 in the paper, our IV estimates imply that the RMSE for the generalized model is 0.67 times that of the standard model. Using Wolfers' preferred estimates, this ratio drops to just 0.33. Put differently, using Wolfers' preferred elasticity estimates, the RMSE in the predicted job finding rate among the unemployed using the standard labor market tightness measure is three times as large as that using our generalized measure.

It is also of interest to consider an out-of-sample forecasting exercise for the predicted job finding rate among the unemployed. For this purpose, we use the same estimated coefficients based on the 1994:1-2007:12 sample that were employed for Figure D.1. The results are shown in Figure D.3, which is the analogue to Figure D.2 but using the elasticity estimates based on the pre-2008 data. Using these estimates, the generalized measure again does much better than the standard measure for tracking the job finding rate among the unemployed. The ratio of the RMSE for the 2008:1-2019:12 period using the generalized model to the RMSE for the same period using the standard model is 0.40. The improvement is slightly less than when using Wolfer's preferred estimates based on the full sample. Recall from Figure D.1, however, that when using an out-of-sample analysis for the *job-filling* rate, the generalized model outperforms the standardized model to a greater extent than when using Wolfer's preferred estimates.

These findings relate to the statement in section V.B of the main text of our paper that "the relatively poor performance of the standard model cannot be rescued with an alternative estimate of the matching function elasticity." Especially during the post-2007 period, lowering the matching function elasticity α to improve the tracking of the job filling rate based on the standard measure of labor market tightness yields a significant *worsening* of the ability to track the job finding rate among the unemployed.

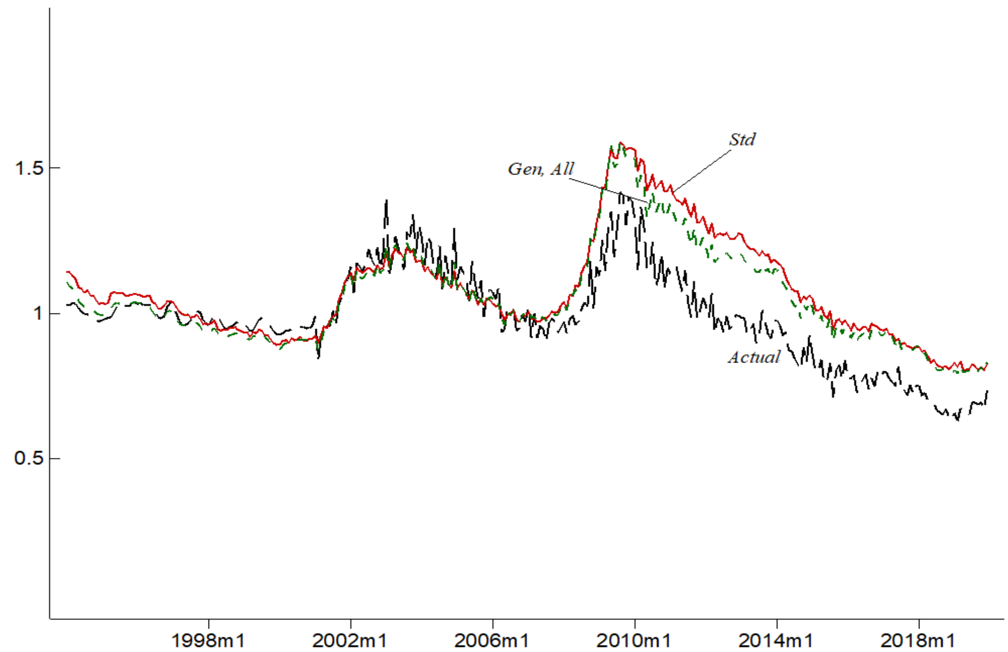
Wolfers' comments seem to suggest that it would be of interest to estimate yet another set of OLS elasticities using the job finding rate of the unemployed as the outcome measure and then conduct an independent forecasting evaluation based on those results. To do this, however, would be essentially to abandon the matching function. The matching function implies cross-equation restrictions on the parameters that govern the relationships of the job filling rate and the job finding rate to measures of labor market tightness. Whatever approach one takes to estimate the elasticities, these cross-equation restrictions need to be taken into account. Both in the main text and in this appendix, our analysis imposes this internal consistency, whereas the approach Wolfers seems to be suggesting would violate it.

In sum, we view both the evidence reported in the paper and the new evidence based on Wolfers' OLS approach described in this appendix as providing strong support for our claim that the generalized matching function meaningfully outperforms the standard matching function.

Reference

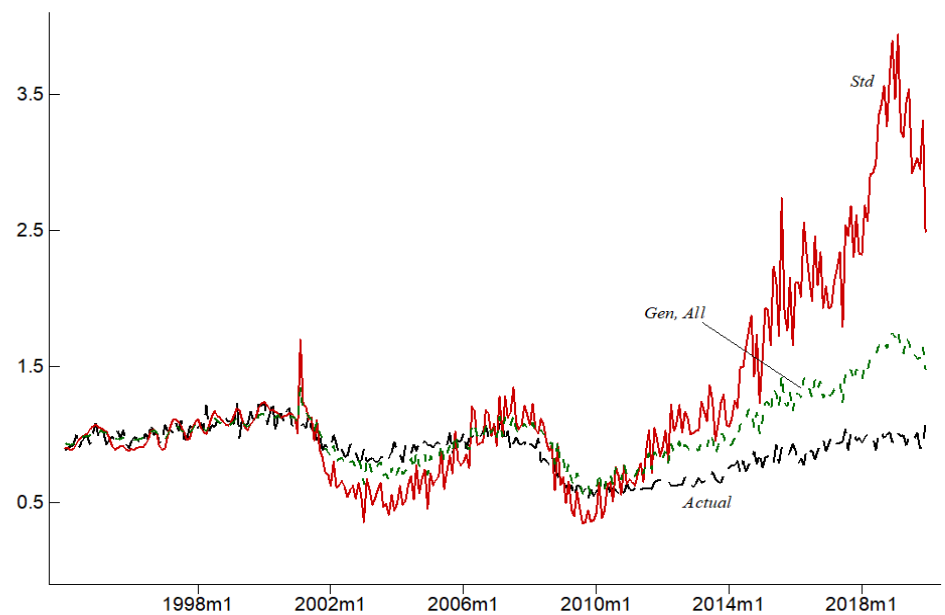
Hall, Robert and Sam Schulhofer-Wohl. 2018. "Measuring Job-finding rates and Matching Efficiency with Heterogeneous Job-Seekers," *American Economic Journal: Macroeconomics*, 10(1): 1-32.

Figure D.1. Predicting the Job-Filling Rate Based on Estimated OLS Matching Function Coefficients for Sample 1994:1-2007:12



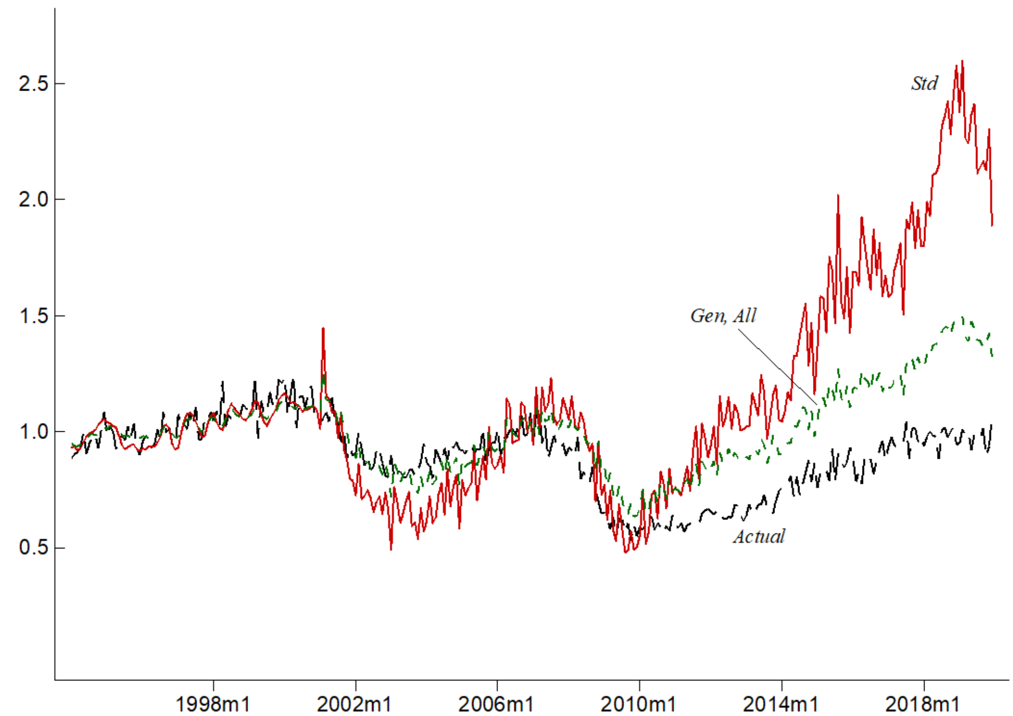
Source: Authors' calculations using CPS, JOLTS, and DFH (2012a) vacancies.
Notes: Job filling rate is H/V. Predicted from Standard uses V/U. Predicted from General, All uses V/ES (all twenty- two groups). All normalized to 1.0 in 2006.

Figure D.2. Predicting the Job-Finding Rate for the Unemployed Based on Wolfers' Preferred OLS Matching Function Coefficients



Sources: Authors' calculations using CPS, JOLTS, DFH (2012a) vacancies, and BLS Gross Flows.
Notes: All rates normalized to 1 in 2006. Job finding rate for unemployed is H_{ut} / U_t. Predicted from Std uses V/U. Predicted from Gen, All uses V/ES (all twenty- two groups).

Figure D.3. Predicting the Job-Finding Rate for the Unemployed Based on Estimated OLS Matching Function Coefficients for Sample 1994:1-2007:12



Sources: Authors' calculations using CPS, JOLTS, DFH (2012a) vacancies, and BLS Gross Flows.
Notes: All rates normalized to 1 in 2006. Job finding rate for unemployed is H_{ut} / U_t. Predicted from Std uses V/U. Predicted from Gen, All uses V/ES (all twenty- two groups).