"Measuring Jobfinding Rates and Matching Efficiency with Heterogeneous Jobseekers"

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Online Appendixes

A. Relation between the Standard DMP Matching Setup and the One in this Paper

A1. The standard DMP setup

Start from the matching function:

$$H = \mu P^{\nu} V^{1-\nu}. \tag{A1}$$

Tightness:

$$\theta = \frac{V}{P}. \tag{A2}$$

Job-finding rate:

$$f = \frac{H}{P} = \mu \theta^{1-\nu}. \tag{A3}$$

Job-filling rate:

$$q = \frac{H}{V} = \mu \theta^{-\nu}. \tag{A4}$$

Zero-profit condition:

$$\frac{\kappa}{q} = J. \tag{A5}$$

Vacancies:

$$V = \theta P. \tag{A6}$$

A2. The paper's setup with one type of jobseeker

Tightness (vacancy duration):

$$T = \frac{V}{H}. \tag{A7}$$

Start from the job-finding rate:

$$f = \gamma T^{\eta}. \tag{A8}$$

Matching function:

$$H = \gamma T^{\eta} P; H = \gamma^{1/(1+\eta)} V^{\eta/(1+\eta)} P^{1/(1+\eta)}. \tag{A9}$$

Job-filling rate:

$$\frac{H}{V} = \frac{1}{T}. \tag{A10}$$

Zero-profit condition:

$$\kappa T = J \tag{A11}$$

Vacancies:

$$V = T \cdot H. \tag{A12}$$

A3. Implications of holding T constant as μ changes

Because $T = 1/q$, holding T constant is equivalent to holding q constant. From equation (A4), an increase in μ must be accompanied by in increase in DMP tightness, θ, to hold q constant.

A4. The paper's setup with multiple types of jobseekers

Tightness (vacancy duration):

$$T = \frac{V}{H}. \tag{A13}$$

Start from the job-finding rates:

$$f_i = \gamma_i T^{\eta_i}. \tag{A14}$$

Matching function satisfies:

$$H = \sum_i P_i \gamma_i \left(\frac{V}{H}\right)^{\eta_i}. \tag{A15}$$

Job-filling rate:

$$\frac{H}{V} = \frac{1}{T}. \tag{A16}$$

Zero-profit condition:

$$\kappa T = J. \tag{A17}$$

Vacancies:

$$V = T \cdot H. \tag{A18}$$

The property that the zero-profit condition involves only T is important for our approach to identification.

B. Attrition in the CPS

Table B1 describes our success in matching respondents in different months in the CPS. It shows the weighted percent of observations that were successfully matched to an observation on the same person some month later, conditional on the initial observation being early enough in the CPS sample rotation that a match was theoretically possible. (For example, a match one month later is theoretically possible if the initial observation is not in the outgoing rotation group; a match 15 months later is theoretically possible only if the initial observation is in the incoming rotation group.) The intervals correspond to the spans that we use for estimation. The short-span match rates are quite high; the long-span match rates less so. We calculated the success rates by year. The bottom line of the upper panel shows the standard deviations of the rates across years. They are uniformly small; the success rates were stable over the period from 2001 through 2013.

The table also shows the matching rates that we would obtain if we used the method of Madrian and Lefgren (2000). That method produces a slightly higher match rate than Nekarda's method at a horizon of 1 month because the Madrian and Lefgren 1-month match does not condition on what happens in subsequent months, while Nekarda's 1-month match does. However, the Madrian and Lefgren match rates are lower than the Nekarda match at all horizons longer than 1 month, because at longer horizons Nekarda's method allows some matches that Madrian and Lefgren's method rejects.

Following standard principles of attrition adjustment, we offset the potential bias caused by higher weighting of the respondents who are less likely to drop out. For each date t and span τ, we estimate a fractional logit model (Papke and Wooldridge (1996)) for the probability that an individual observed at t is also observed at $t + \tau$, as a function of the same variables that are on the right-hand side of our logit for jobfinding rates. Let $\hat{p}_{i,t,\tau}$ be the predicted probabilities of

Table B1—Percent of Observations Matched between Months in the Current Population Survey

Number of months separating observations	1	2	3	12	13	14	15
Percent matched, Nekarda method	93.6	91.3	89.3	75.3	74.5	73.5	72.5
Standard deviation across years	0.2	0.3	0.3	1.9	1.9	2.0	2.1
Percent matched, Lefgren-Madrian method	94.7	90.3	86.3	68.8	66.4	64.2	62.1
Standard deviation across years	0.2	0.3	0.5	1.9	1.9	1.9	1.9

remaining in the sample from this model for individual i observed at t, over a span of τ months. To estimate the jobfinding rates over a span of τ months from the logit equation, we weight each observation by $1/\hat{p}_{i,t,\tau}$ times the product of Nekarda's linking weight and the survey weight. Thus observations with a lower probability of remaining in the sample are given higher weight. We re-estimate the weights for each bootstrap sample. We use a fractional logit model because *remaining in the sample* is not a binary event with Nekarda's weights and so cannot be the dependent variable in a conventional logit model.

Reweighting to account for attrition did not change the estimated jobfinding rates appreciably. This finding is unsurprising because the variables in the attrition model are also controls in the model for jobfinding rates. In essence, the attrition weights account only for potential misspecification of the functional form of the jobfinding rate equation.

C. Estimates of Aggregate Matching Efficiency for Alternative Specifications

Table C1 shows our basic results for three alternative specifications. The left panel shows the detrended index of matching efficiency measured over short spans and the right panel the index for long spans, excluding job-to-job, as in Figure 7. It includes the years 2001 through 2003, years affected by the 2001 tech crash, and 2008, years affected by the financial crisis. The left column in each panel repeats the index from the body of this paper. The next column is similar in all respects except that no demographic effects are swept out. The third column is similar to the base except that the elasticity of the jobfinding rate with respect to tightness is constrained to be the same for every initial status group. This corresponds to the assumption that the matching function is Cobb-Douglas in a weighted sum of jobseekers. The right-most column is based on estimates of the base specification, but uses only data for 2001 through 2007, the years prior to the crisis.

Table C1—Detrended Indexes of Matching Efficiency for Alternative Specifications

	Short spans				Long spans			
Year	*Base*	*No demo-graphics*	*Common elasticity*	*Pre-crisis*	*Base*	*No demo-graphics*	*Common elasticity*	*Pre-crisis*
2001	1.000	1.000	0.040	1.000	1.000	1.000	1.000	1.000
2002	1.033	1.035	1.076	0.923	1.028	1.034	1.029	0.972
2003	1.030	1.032	1.083	0.875	1.068	1.089	1.068	0.989
2008	1.005	1.005	1.022		1.020	1.015	1.020	
2009	1.039	1.037	1.133		1.044	1.046	1.043	
2010	1.026	1.029	1.086		1.029	1.051	1.029	
Standard deviation	0.024	0.024	0.040	0.029	0.023	0.027	0.023	0.020

Note: The standard deviation includes the omitted years 2004-2007 and 2011-2013

In all cases, the results conform to the overall conclusion of the paper, that a fixed-weight index shows that matching efficiency departed from its trend only slightly. The standard deviations of the alternative indexes of matching efficiency, shown at the foot of the table, are greater than the preferred base specification, shown at the left of each panel, but are still quite small. By contrast, the standard deviation of the detrended version of the matching efficiency index in Figure 8, based on a single type of unemployment, is vastly higher, at 0.155.

D. Recruiting Intensity

D1. Davis-Faberman-Haltiwanger's Estimates of Vacancy Duration and Recruiting Intensity

Davis, Faberman and Haltiwanger (2013) derive an adjustment to the JOLTS measure of vacancy duration to account for time aggregation, and a second adjustment for recruiting intensity. Table D1 shows, in a format similar to Table C1, our measure of matching efficiency with trend, using T with the time-aggregation adjustment alone, and T with the product of the time-aggregation adjustment and the recruiting-efficiency adjustment. Adding the time-aggregation adjustment by itself has almost no effect on the index of matching efficiency. The adjustment for recruiting intensity eliminates some of the downward trend in both indexes, but does not affect the overall conclusion of the paper.

Table D1—Indexes of Matching Efficiency, with Trends, Including Adjustments from Davis and Co-Authors

	Short spans, with trend			Long spans, with trend		
Year	*Base*	*With time aggre-gation*	*With time aggregation and intensity*	*Base*	*With time aggre-gation*	*With time aggregation and intensity*
2001	1.000	1.000	1.000	1.000	1.000	1.000
2002	1.006	1.011	1.004	1.000	1.004	0.999
2003	0.978	0.984	0.980	1.012	1.020	1.007
2008	0.833	0.835	0.869	0.843	0.845	0.893
2009	0.833	0.837	0.869	0.833	0.842	0.882
2010	0.796	0.804	0.832	0.795	0.803	0.849
2013	0.743	0.751	0.786	0.743	0.753	0.807

D2. Implications of the Findings about Recruiting Intensity of Gavazza and Co-Authors

Gavazza, Mongey and Violante (2016) conclude that, to a fair approximation, recruiting intensity satisfies their equation (29):

$$\log \Phi = -\alpha \frac{\gamma_2}{\gamma_1 + \gamma_2} \log q = \pi \log T, \tag{D1}$$

and the value of the elasticity is $\pi = 0.40$, from the values of the parameters reported in their Table 2. If the matching function is written with endogenous recruiting intensity that enters the matching function in vacancy-augmenting form, as in their equation (2), it is

$$H = \sum_i \phi_i \left(\frac{\Phi V}{H} \right) P_i = \sum_i \gamma_i T^{\pi} T^{\tilde{\eta}_i}. \tag{D2}$$

Thus we can partition our estimated elasticities η_i into lower values $\tilde{\eta}_i = \eta_i - \pi$ that isolate the effect from tightness itself and the common effect of endogenous recruiting intensity, π. The addition of endogenous recruiting effort requires no modification in our estimation. It only contributes this decomposition of our findings.

E. Mismatch Effects in the Duration of Vacancies, T

Our estimation equation (7) involves a concave log transform of T, so there is an issue of using the aggregate value when there is dispersion across units—T

is potentially subject to mismatch bias. To understand this issue, we studied the industry-level data on hires and job openings published for JOLTS, across 4 geographic units and 25 industries. We hypothesize that the ratio of openings to hires—the vacancy duration T—has three components: (1) an aggregate tightness measure, as used in our work, (2) a unit-specific component, reflecting the deviation of tightness in the unit from the aggregate measure, and (3) measurement error, occurring because JOLTS is a fairly small survey and from other random sources unrelated to tightness.

We believe that that the unit-specific component is moderately persistent, mainly because both aggregate vacancy duration and its counterpart in the geographic and industry units are persistent. On the other hand, the measurement errors are likely to be transitory. We begin our investigation by studying the autocovariance functions of the disaggregated data stated as deviations from the aggregate series for T_t. If the measurement errors were white noise and the unit-specific tightness process quite persistent, the functions would spike at zero—the only lag value where the measurement error would contribute—then drop immediately to a gradually declining value starting at a log of one month. In fact, the autocovariance functions resemble those of a fairly non-persistent autoregressive process, with no special spike at zero lag. There is no highly persistent component.

To capture this finding more rigorously, we estimate the following equation:

$$\log T_{i,t} = \lambda_i + \bar{T}_t + \rho_\ell \log T_{i,t-\ell} + \iota_{i,t}. \tag{E1}$$

Here λ_i is a level effect for industry i, $\bar{T}_t$ is a time effect, ρ_ℓ measures the predictive power of the observation ℓ months earlier, and $\iota_{i,t}$ is the residual. The coefficient ρ_ℓ declines with the length of the lag, ℓ—it is analogous to the autocovariance in this panel setting.

Table E1 shows estimates of the prediction coefficient.

Table E1—Estimates for the Forecasting Power of Lagged Vacancy Duration at Selected Lags

Lag, months	12	18	24
Coefficient	0.226	0.087	0.036
Standard error	(0.015)	(0.015)	(0.015)

F. Technical Issues in Computing Jobfinding Rates in Small Cells

In a small number of cases where all respondents who started in status i in month t were employed at $t+\tau$ or where none of them were, we take the predicted jobfinding rate to be 1 or 0.

The rare event of a sample size of zero within a status-month-span cell occurred once in the CPS data. No individuals who are new entrants to the labor force in February 2008 were present for a full 15-month time span. As a result, we cannot estimate the time effect in $\kappa_{i,t,\tau}$ in equation (6) for that initial status, date, and time span. Instead, we impute the 15-month jobfinding rates for new entrants in February 2008 based on the jobfinding rates in adjacent months and years. Specifically, we impute

$$f_{i,\text{Feb 2008},15} = \frac{1}{2}\left(\frac{f_{i,\text{Feb 2007},15}}{f_{i,\text{Jan 2007},15}+f_{i,\text{Mar 2007},15}} + \frac{f_{i,\text{Feb 2009},15}}{f_{i,\text{Jan 2009},15}+f_{i,\text{Mar 2009},15}}\right) \times \left(f_{i,\text{Jan 2008},15} + f_{i,\text{Mar 2008},15}\right),$$

where $i =$ *recently entered labor force*. We apply a similar procedure in the bootstrapped jobfinding rates when a particular bootstrap sample has no observations for a given initial status, date, and time span.