Econometrica Supplementary Material

SUPPLEMENT TO "ESTIMATION OF A ROY/SEARCH/COMPENSATING DIFFERENTIAL MODEL OF THE LABOR MARKET": APPENDICES A–C

(*Econometrica*, Vol. 88, No. 3, May 2020, 1031–1069)

CHRISTOPHER TABER
Department of Economics, University of Wisconsin-Madison

RUNE VEJLIN
Department of Economics and Business Economics, Aarhus University and IZA

APPENDIX A: DATA

A.1. *Data Selection*

TABLE A.I presents the full details of the selection criteria. We censor workers after age 55. Workers with missing codes or gaps in codes for highest completed education are disregarded. We censor workers prior to age 19 since the minimum wage in Denmark increases at that age threshold. We define labor market entry to be the month of graduation from the highest completed education recorded.[1] We delete worker histories prior to this date. We disregard workers who are observed in education after the date of highest completed education. For example, if the highest recorded education for a worker is high school, and the individual graduated in 2001 and we later observe the individual in education, say in 2003, then we delete the worker. We also delete workers if they have changing codes for highest completed education, or if they have implausible early labor market entry.

Temporary non-employment (unemployment and non-participation) spells shorter than 13 weeks, where the previous and next establishment ID are the same, are merged into one employment spell. Notice that unemployment and non-participation spells are treated as one type of spell. Short unemployment or non-participation spells between two employment spells shorter than three weeks are allocated to the last of the two employment spells.

We censor workers if they enter self-employment or retirement. We delete workers who have gaps in their spell histories. This could arise if the worker, for some reason, has missing IDA data in a given year because of emigration. We label the states unemployment and non-participation as non-employment.

A.2. *Estimating Labor Market Entry*

We observe graduation times from 1971 and forward. Our sample starts in 1985 which means that we observe some individuals with labor market entry before 1971 (around 1/3 of all workers). We therefore need to approximate the labor market entry year. We use population data (not just those in our sample) graduating in 1971 and 1972 to derive the age distribution at graduation time by sex-education group. This gives us around 70

Christopher Taber: ctaber@ssc.wisc.edu
Rune Vejlin: rvejlin@econ.au.dk

[1]Our information on highest completed education dates back to 1971, which means highest completed education is missing for workers who took an education before 1971. We estimate labor market entry, cf. Section A.2.

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TABLE A.I

OVERVIEW OF DATA CREATION

In Total	Number of Workers	Number of Firms	Number of Spells	Number of Establishments	Fraction Employed
Merged data	5,116,625	455,054	60,914,366	610,130	
Censoring after age 55	4,348,157	446,957	56,090,810	596,777	
Delete workers with all missing educational variables (hffsp)	4,147,463	445,298	54,714,582	594,070	
Delete workers with gaps in educational variables (hffsp)	4,147,463	445,298	54,714,582	594,070	
Delete obs. below age 19	3,967,419	420,223	51,494,700	550,388	
Labor market entry	3,967,419	400,670	43,406,322	517,710	
Delete under education	3,461,332	386,894	37,007,709	496,792	
Changing hffsp codes	3,346,165	385,833	36,778,315	495,453	
Too early labor market entry	3,322,994	385,289	36,540,726	494,727	
Clean for temporary non-employment	3,313,246	384,988	29,495,476	494,275	
Censoring self-employment	3,118,361	368,839	26,920,923	472,219	
Censoring retirement	3,041,336	368,747	26,462,593	472,095	
Delete workers with gaps	2,969,454	365,959	25,630,532	467,983	
Average over yearly cross sections					
Merged data	3,717,692	129,506	3,717,692	167,882	0.60
Censoring after age 55	2,955,775	124,698	2,955,775	161,952	0.68
Delete workers with all missing educational variables (hffsp)	2,894,716	124,084	2,894,716	161,285	0.69
Delete workers with gaps in educational variables (hffsp)	2,894,716	124,084	2,894,716	161,285	0.69
Delete obs. below age 19	2,700,370	116,688	2,700,370	153,681	0.70
Labor market entry	2,375,046	110,346	2,375,046	146,898	0.71
Delete under education	2,143,752	106,593	2,143,752	142,682	0.72
Changing hffsp codes	2,137,499	106,470	2,137,499	142,548	0.72
Too early labor market entry	2,127,965	106,353	2,127,965	142,423	0.72
Clean for temporary non-employment	2,120,247	106,635	2,120,247	142,777	0.72
Censoring self-employment	1,872,217	100,595	1,872,217	136,301	0.78
Censoring retirement	1,763,850	100,568	1,763,850	136,269	0.83
Delete workers with gaps	1,722,319	99,802	1,722,319	135,375	0.83

groups.[2] We now use the sex-education specific graduation age distribution conditional on the fact that we know the individual did not graduate after 1970 to estimate labor market entry. If the minimum age in the estimated distribution implies entry after 1970, we set entry to 1970. This is the case for 1% of the workers for whom we approximate entry.

A.3. *Estimating Experience*

Experience is observed yearly from 1964. We define experience as experience accumulated after labor market entry. Given that we have approximated entry time, we need to approximate experience up to 1970.[3] To do this, we again use those entering the labor market in 1971 and 1972. There are several ways to do this. However, one of the simplest is to calculate the yearly mean experience increase. Assuming that individuals either work full time or not at all, we approximate experience up to 1970 using a binomial distribution, with probability estimated by "sex-education-time since entry" groups. We thus divide workers into four groups based on time since entry. These are 1–5, 6–10, 11–15, and >15 years of age since entry. An example of a group is female kindergarten teachers with one to five years on the labor market.

APPENDIX B: ESTIMATION PROCEDURE

B.1. *Model Simulation*

The model is set up and simulated in continuous time. While discretizing to finite time is sometimes more tractable, we prefer to work with the continuous simulation. The unit of time is a year, but this only matters for the interpretation of the parameters. The data are measured at a weekly frequency. Thus, an implicit assumption is that a weekly frequency is a close enough approximation to continuous time. We think this is reasonable given the transition rates between states in the data. The way the simulation works is the following:

1. We solve for the value functions—detailed in Section B.2.
2. For each person, from the distribution in our sample detailed in Appendix A, we draw the age at which they enter the sampling frame and the age at which they leave the sampling frame.
3. A person enters the labor market non-employed, and using the hazard rate of job arrival rates, we draw the time until they get their first offer.
4. They then decide whether to accept the offer.
5. If they take it, we calculate the wage and then simulate the time until the next event. This is a competing risks model, where we simulate the time until one of three things happen:
   (a) They get an outside offer, in which case they switch to a new job, negotiate a higher wage, or ignore it.
   (b) Human capital evolves and their wage rises.
   (c) They get laid off. At this point, with probability P^*, they receive an offer immediately. If they receive an offer, they decide whether to accept it. If they turn it down or do not draw an outside offer, they become non-employed.
6. We iterate on this simulation until the worker reaches the end of their assigned age sampling frame.

[2] A few workers in the sample cannot be matched using this procedure. In these cases, we aggregate the groups until all can be matched.

[3] To get internal consistency, we thus disregard observed experience prior to 1970.

7. We keep track of the relevant data while the individual is within the sampling frame and use that to construct the auxiliary parameters.

B.2. *Solving for the Value Functions*

When we numerically solve the model, as is standard in finite time models we solve backwards by beginning with the highest level of human capital, $h = H$. We begin by showing how to solve the model at the terminal case and then how to iterate for the lower values.

Solve Model With $h = H$

The key equations are

$$\begin{aligned}
&\big(\rho + \delta_i + \Lambda^e_{ijH}(R)\big)V_{ijH}(R) \\
&\quad = u_{ij}(R\psi_H) + \Bigg(\sum_{\{\ell:V_{ijH}(R)<V_{i\ell H}(\pi_{i\ell})\le V_{ijH}(\pi_{ij})\}} \lambda^e_\ell\big[\beta V_{ijH}(\pi_{ij}) + (1-\beta)V_{i\ell H}(\pi_{i\ell})\big]\Bigg) \\
&\qquad + \Bigg(\sum_{\{\ell:V_{i\ell H}(\pi_{i\ell})<V_{ijH}(\pi_{ij})\}} \lambda^e_\ell\big[\beta V_{i\ell H}(\pi_{i\ell}) + (1-\beta)V_{ijH}(\pi_{ij})\big]\Bigg) + \delta_i V^*_{i0H}, \\
&\big(\rho + \Lambda^n_{i0H}\big)V_{i0H} = u_{i0H} + \sum_{\{\ell:V_{i\ell H}(\pi_{i\ell})>V_{i0H}\}} \lambda^n_j\big[\beta V_{i\ell H}(\pi_{i\ell}) + (1-\beta)V_{i0H}\big], \\
&\qquad V^*_{i0H} = P^* \frac{\displaystyle\sum_{\{\ell:V_{ilh}(\pi_{i\ell})>V_{i0h}\}} \lambda^n_\ell\big[\beta V_{i\ell H}(\pi_{i\ell}) + (1-\beta)V_{i0H}\big]}{\displaystyle\sum_\ell \lambda^n_\ell} + \Bigg(1 - P^*\frac{\Lambda^n_{i0H}}{\sum_\ell \lambda^n_\ell}\Bigg)V_{i0H}.
\end{aligned}$$

Without loss of generality, we order the firm types from lowest to highest in terms of $u_{ij}(\pi_{ij}\psi_H)$. Note that this will also order the value functions $V_{ijH}(\pi_{ij})$. With our functional form:

$$u_{ij}(R\psi_h) = \alpha\log(R) + \alpha\log(\psi_h) + \mu^u_j + v^u_{ij},$$

this ordering will not change with human capital.

First, for all j: define V^*_{ijH} by

$$V^*_{ijH} \equiv V_{ijH}(\pi_{ij}\psi_H) - \frac{\delta V^*_{i0H}}{\rho+\delta}.$$

To solve the model, we start with the most preferred job ($j = J$) (note that we slightly abuse notation, since the ordering is worker-specific):

$$(\rho+\delta)V_{iJH}(\pi_{iJ}) = u_{iJ}(\pi_{iJ}\psi_H) + \delta V_{i0H},$$

so

$$V^*_{iJH} = \frac{u_{iJ}(\pi_{iJ}\psi_H)}{\rho+\delta}.$$

Using algebraic manipulation, we obtain the following equation:

$$V_{ijH}^{*} = V_{ij+1H}^{*} - \frac{u_{ij+1}(\pi_{ij+1}\psi_H) - u_{ij}(\pi_{ij}\psi_H)}{\rho + \delta + \Lambda_{ijH}^{e}(\pi_{ij+1})\beta},$$

which allows us to go backwards from V_{ij+1H}^{*} to V_{ijH}^{*}, and thus solve for all of the V_{ijH}^{*} in closed form.

Next, consider the non-employment equation.

Let ℓ_0 be the lowest utility firm from which the worker would accept a job. First, simplify the equations above and write

$$\left(\rho + \beta\Lambda_{i0H}^{n}\right)V_{i0H} = u_{i0H} + \sum_{j=\ell_0}^{J} \lambda_j^n \beta\left(V_{ijH}^{*} + \frac{\delta V_{i0H}^{*}}{\rho+\delta}\right),$$

$$V_{i0H}^{*} = P^{*}\frac{\sum_{j=\ell_0}^{J}\beta\left(V_{ijH}^{*} + \frac{\delta V_{i0H}^{*}}{\rho+\delta}\right)}{\sum_{\ell}\lambda_\ell^n} + \left(1 - \beta P^{*}\frac{\Lambda_{i0H}^{n}}{\sum_{\ell}\lambda_\ell^n}\right)V_{i0H}.$$

For any ℓ_0, we can solve the algebra for V_{i0H} and V_{i0H}^{*} in terms of the V_{ijH}^{*}, P^{*}, and u_{i0H}. We solve for the value of ℓ_0 that satisfies

$$V_{i\ell_0-1H}(\pi_{i\ell_0-1}\psi_H) < V_{i0H} \leq V_{i\ell_0H}(\pi_{i\ell)}\psi_H).$$

Given this, to see how to calculate rental rates, note that for someone hired out of non-employment to a firm of type j, we solve for the value of R that solves

$$\begin{aligned}
&\left(\rho + \delta_i + \Lambda_{ijh}^{e}(\ell_0)\right)\left[\beta V_{ijH}(\pi_{ij}) + (1-\beta)V_{i0H}\right] \\
&\quad = u_{ij}(R\psi_H) + \left(\sum_{\ell=\ell_0}^{j}\lambda_\ell^e\left[\beta V_{ijH}(\pi_{ij}) + (1-\beta)V_{i\ell H}(\pi_{i\ell})\right]\right) \\
&\qquad + \left(\sum_{\ell=j+1}^{J}\lambda_\ell^e\left[\beta V_{i\ell H}(\pi_{i\ell}) + (1-\beta)V_{ijH}(\pi_{ij})\right]\right) + \delta_i V_{i0H}^{*}.
\end{aligned}$$

Similarly, for a worker hired at j, with an outside offer from k, with $k < j$, we solve for the value of R for which

$$\begin{aligned}
&\left(\rho + \delta_i + \Lambda_{ijh}^{e}(k+1)\right)\left[\beta V_{ijH}(\pi_{ij}) + (1-\beta)V_{ikH}(\pi_{ik})\right] \\
&\quad = u_{ij}(R\psi_H) + \left(\sum_{\ell=k+1}^{j}\lambda_\ell^e\left[\beta V_{ijH}(\pi_{ij}) + (1-\beta)V_{i\ell H}(\pi_{i\ell})\right]\right) \\
&\qquad + \left(\sum_{\ell=j+1}^{J}\lambda_\ell^e\left[\beta V_{i\ell H}(\pi_{i\ell}) + (1-\beta)V_{ijH}(\pi_{ij})\right]\right) + \delta_i V_{i0H}^{*}.
\end{aligned}$$

With log utility, this is straightforward.

Solve Model for $h < H$

This does not significantly alter the solution method. As discussed in general, there may be parameter values such that one may choose to quit and choose non-employment when human capital goes up. To simplify the computation, we do not check this condition every time we solve the model, but after estimating the model, verify that it is not an issue. In this section, we ignore this possibility. We again present the key equations, noting that only the first equation changes in a substantial way:

$$\begin{aligned}
&\big(\rho + \delta_i + \lambda_h + \Lambda^e_{ijh}(R)\big)V_{ijh}(R) \\
&\quad = u_{ij}(R\psi_h) + \left(\sum_{\{\ell: V_{ijh}(R) < V_{i\ell h}(\pi_{i\ell}) \le V_{ijh}(\pi_{ij})\}} \lambda^e_\ell\big[\beta V_{ijh}(\pi_{ij}) + (1-\beta)V_{i\ell h}(\pi_{i\ell})\big]\right) \\
&\qquad + \left(\sum_{\{\ell: V_{i\ell h}(\pi_{i\ell}) < V_{ijh}(\pi_{ij}))\}} \lambda^e_\ell\big[\beta V_{i\ell h}(\pi_{i\ell}) + (1-\beta)V_{ijh}(\pi_{ij})\big]\right) + \lambda_h V_{ijh+1}(R) + \delta_i V^*_{i0h}, \\
&\big(\rho + \Lambda^n_{i0h}\big)V_{i0h} = u_{i0h} + \sum_{\{\ell: V_{i\ell h}(\pi_{i\ell}) > V_{i0h}\}} \lambda^n_j\big[\beta V_{i\ell h}(\pi_{i\ell}) + (1-\beta)V_{i0h}\big], \\
&\qquad V^*_{i0h} = P^* \frac{\displaystyle\sum_{\{\ell: V_{ilh}(\pi_{i\ell}) > V_{i0h}\}} \lambda^n_\ell\big[\beta V_{i\ell h}(\pi_{i\ell}) + (1-\beta)V_{i0h}\big]}{\displaystyle\sum_\ell \lambda^n_\ell} \\
&\qquad\qquad + \left(1 - P^* \frac{\Lambda^n_{i0h}}{\displaystyle\sum_\ell \lambda^n_\ell}\right)V_{i0h}.
\end{aligned}$$

We again order the firm types from lowest to highest, now in terms of $u_{ij}(\pi_{ij}\psi_h) + \lambda_h V_{ijh+1}(\pi_{ij})$. Note that this will also order the $V_{ij}(\pi_{ij})$. Once again, with log utility, this ordering will not change with human capital.

We again define V^*_{ijh} implicitly by

$$V^*_{ijh} = V_{ijh}(\pi_{ij}\psi_h) - \frac{\delta V^*_{i0h}}{\rho + \delta}.$$

We can show that

$$V^*_{iJh} = \frac{u_{iJ}(\pi_{iJ}\psi_h) + \lambda_h V_{iJh+1}(\pi_{iJ})}{\rho + \delta},$$

and

$$V^*_{ijh} = V^*_{ij+1h} - \frac{u_{ij+1}(\pi_{ij+1}\psi_H) - u_{ij}(\pi_{ij}\psi_H) + \lambda_h\big[V_{ij+1h+1}(\pi_{ij+1}) - V_{ij+1h+1}(\pi_{ij})\big]}{\rho + \delta + \Lambda^e_{ijh}(\pi_{ij+1})\beta}.$$

The non-employment condition is analogous to the above case (just with h rather than H), and we can solve the model in the same way.

Given this, to see how to calculate rental rates, note that for someone hired out of non-employment to a firm of type j, we solve for the value of R that solves

$$\begin{aligned}&\big(\rho+\delta_i+\Lambda^e_{ijh}(\ell_0)\big)\big[\beta V_{ijH}(\pi_{ij})+(1-\beta)V_{i0H}\big]\\&\quad=u_{ij}(R\psi_H)+\left(\sum_{\ell=\ell_0}^{j}\lambda^e_\ell\big[\beta V_{ijH}(\pi_{ij})+(1-\beta)V_{i\ell H}(\pi_{i\ell})\big]\right)\\&\qquad+\left(\sum_{\ell=j+1}^{J}\lambda^e_\ell\big[\beta V_{i\ell H}(\pi_{i\ell})+(1-\beta)V_{ijH}(\pi_{ij})\big]\right)+\lambda_h V_{ijh+1}(R)+\delta_i V^*_{i0H}.\end{aligned}$$

Similarly, for a worker hired at j, with an outside offer from k, with $k<j$, we solve for the value of R for which

$$\begin{aligned}&\big(\rho+\delta_i+\Lambda^e_{ijh}(k+1)\big)\big[\beta V_{ijH}(\pi_{ij})+(1-\beta)V_{ikH}(\pi_{ik})\big]\\&\quad=u_{ij}(R\psi_H)+\left(\sum_{\ell=k+1}^{j}\lambda^e_\ell\big[\beta V_{ijH}(\pi_{ij})+(1-\beta)V_{i\ell H}(\pi_{i\ell})\big]\right)\\&\qquad+\left(\sum_{\ell=j+1}^{J}\lambda^e_\ell\big[\beta V_{i\ell H}(\pi_{i\ell})+(1-\beta)V_{ijH}(\pi_{ij})\big]\right)+\lambda_h V_{ijh+1}(R)+\delta_i V^*_{i0H}.\end{aligned}$$

This is more complicated than in the previous case because, when solving, we need to worry about $V_{ijh+1}(R)$ in addition to $u_{ij}(R\psi_H)$. With log utility, this is straightforward since the expression is linear. If

$$u_{ij}(R\psi_h)=\alpha\log(R)+\alpha\log(\psi_h)+\mu^u_j+v^u_{ij},$$

then one can show

$$V_{ijh}(R)=A_h\log(R)+B_h,$$

where

$$\begin{aligned}A_H&=\frac{\alpha}{\rho+\delta_i+\Lambda^e_{ijH}(R)},\\B_H&=\frac{\alpha\log(\psi_H)+\mu^u_j+v^u_{ij}+\left(\sum_{\{\ell:V_{ijH}(R)<V_{i\ell H}(\pi_{i\ell})\le V_{ijH}(\pi_{ij})\}}\lambda^e_\ell\big[\beta V_{ijH}(\pi_{ij})+(1-\beta)V_{i\ell H}(\pi_{i\ell})\big]\right)}{\rho+\delta_i+\Lambda^e_{ijH}(R)}\\&\quad+\frac{\left(\sum_{\{\ell:V_{i\ell H}(\pi_{i\ell})<V_{ijH}(\pi_{ij}))\}}\lambda^e_\ell\big[\beta V_{i\ell H}(\pi_{i\ell})+(1-\beta)V_{ijH}(\pi_{ij})\big]\right)+\delta_i V^*_{i0H}}{\rho+\delta_i+\Lambda^e_{ijH}(R)},\\A_h&=\frac{\alpha+\lambda_h A_{h+1}}{\rho+\delta_i+\lambda_h+\Lambda^e_{ijh}(R)},\end{aligned}$$

$$B_h = \frac{\alpha \log(\psi_h) + \mu_j^u + \upsilon_{ij}^u + \left(\sum_{\{\ell: V_{ijh}(R) < V_{i\ell h}(\pi_{i\ell}) \leq V_{ijh}(\pi_{ij})\}} \lambda_\ell^e \left[\beta V_{ijh}(\pi_{ij}) + (1-\beta) V_{i\ell h}(\pi_{i\ell}) \right] \right)}{\rho + \delta_i + \lambda_h + \Lambda_{ijh}^e(R)}$$
$$+ \frac{\left(\sum_{\{\ell: V_{i\ell h}(\pi_{i\ell}) < V_{ijh}(\pi_{ij}))\}} \lambda_\ell^e \left[\beta V_{i\ell h}(\pi_{i\ell}) + (1-\beta) V_{ijh}(\pi_{ij}) \right] \right) + \lambda_h B_{h+1} + \delta_i V_{i0h}^*}{\rho + \delta_i + \lambda_h + \Lambda_{ijh}^e(R)}.$$

APPENDIX C: AUXILIARY MODEL

C.1. *Notation*

Let us define the variables used from the data. Let

- $i = 1, \dots, N$ index individuals,
- $\ell = 1, \dots, L_i$ index employment spells, that is, a spell of consistent employment with no non-employment in between,
- $j = 1, \dots, J_{i\ell}$ index a job spell that occurs within employment spell ℓ for individual i,
- $t = 1, \dots, T_{i\ell j}$ index the set of wage observations on job spell $i\ell j$,
- $f_{i\ell j}$ the establishment associated with this job spell,
- $D_{i\ell j}$ the duration that the worker worked on job spell $i\ell j$,
- $w_{i\ell jt}$ the tth log wage observation at job $i\ell j$,
- $E_{i\ell jt}$ the tth experience observation at job $i\ell j$,
- $TE_{i\ell jt}$ the tth tenure observation at job $i\ell j$, which is set to 0 on the first November cross section in job $i\ell j$, and from that, it increases with $E_{i\ell jt}$,[4]
- $k = 1, \dots, K_i$ the number of non-employment spells for individual i,
- D_{ik}^n the duration of non-employment spell ik.

We assume that there is a large number of people in the economy, but a finite number of J job types. Our econometric specification differs from the identification section in the paper in that we do not explicitly observe the type of establishment. Instead, we infer the type of establishment by using data from coworkers.[5]

Given these variables from the data, we now define intermediate variables, which we will use in the actual auxiliary parameters. First, we define intermediate variables related to transitions. As argued previously, we use the revealed preference of a job-to-job transition to indicate preference for a job. With this in mind, we define:

$$S_{i\ell j} \equiv \begin{cases} 1 & \text{if spell } i\ell j \text{ starts with a job-to-job transition and does not end with one,} \\ -1 & \text{if spell } i\ell j \text{ ends with a job-to-job transition and does not start with one,} \\ 0 & \text{otherwise.} \end{cases}$$

Thus, $S_{i\ell j} = 1$ indicates that the worker has shown a preference for the job, in the sense that the worker likely voluntarily initially chose it over another one but did not voluntarily choose another job when the employment relationship ended. Similarly, $S_{i\ell j} = -1$

[4]We have tried to define tenure in different ways, such as counting years instead of real experience and also by approximating tenure at the first November cross section. It does not affect the later results. At most, the later auxiliary parameters change by 2%.

[5]We could use coworkers to estimate the posterior type probabilities for each establishment, but this is not central to anything we do.

indicates that the worker did not particularly like the job, in the sense that they only entered when they had no other job offers and then left for another job. Since it is part of an auxiliary model, it does not need to be a perfect measure of preference, just correlated with preference.

Note that if the spell is left-censored, we assume that it starts from non-employment. Likewise, if the job is right-censored, we assume that it ends in job destruction. $S_{i\ell j}$ should sum to zero for each individual when summing up jobs but not when summing up establishments. $S_{i\ell j}$ thus measures whether the worker has revealed a preference for working in establishment $f_{i\ell j}$. There could potentially be many different ways to construct a function related to revealed preferences. The above function only puts weight on the least preferred job (the first job in an employment spell) and the most preferred job (the last job in an employment spell) and assigns equal weight to the jobs in between. We prefer this functional form due to its simplicity.

We now define

$$\widetilde{S}_{i\ell j} \equiv S_{i\ell j} - \frac{\sum_{\ell^*=1}^{L_i} \sum_{j^*=1}^{J_{i\ell^*}} S_{i\ell^* j^*} 1[\ell^* \neq \ell \vee j^* \neq j]}{\left(\sum_{\ell^*=1}^{L_i} J_{i\ell^*}\right) - 1}.$$

Again, $\widetilde{S}_{i\ell j}$ should sum to zero for each individual when summing up jobs but not when summing up establishments.

As mentioned above, the other complicated aspect of identification is that we use coworkers as a proxy for job types. In particular, we use coworkers to estimate the covariance of workers' preferences over jobs, so we define

$$\widetilde{S}_{-i\ell j} = \frac{\sum_{i^*=1}^{N} \sum_{\ell^*=1}^{L_{\iota^*}} \sum_{j^*=1}^{J_{i^*\ell^* j^*}} \widetilde{S}_{i^*\ell^* j^*} 1[i^* \neq i, f_{i^*\ell^* j^*} = f_{i\ell j}]}{\sum_{i^*=1}^{N} \sum_{\ell^*=1}^{L_{\iota^*}} \sum_{j^*=1}^{J_{i^*\ell^* j^*}} 1[i^* \neq i, f_{i^*\ell^* j^*} = f_{i\ell j}]},$$

where $1[\cdot]$ is an indicator function. In other words, $\widetilde{S}_{-i\ell j}$ is just the average value of $S_{i^*\ell^* j^*}$ for people who work at firm $f_{i\ell j}$, excluding individual i.

Finally, we create

$$\widetilde{r}_{-i\ell j} \equiv \widetilde{S}_{-i\ell j} - \frac{1}{\sum_{\ell^*=1}^{L_i} J_{i\ell^*} - 1} \sum_{\ell^*=1}^{L_i} \sum_{j^*=1}^{J_{i\ell^*}} \widetilde{S}_{-i\ell^* j^*} 1[\ell^* \neq \ell \vee j^* \neq j].$$

Thus, while $\widetilde{S}_{i\ell j}$ measures individual i's preference for a job, $\widetilde{r}_{-i\ell j}$ measures how much coworkers of individual i in job $f_{i\ell j}$ like it.

We also need some analogous intermediate variables regarding wages. First, define $\overline{w_i}$ as the mean worker log wage over the individual's working life

$$\overline{w}_i = \frac{\sum_{\ell=1}^{L_i}\sum_{j=1}^{J_{i\ell}}\sum_{t=1}^{T_{i\ell j}} w_{i\ell jt}}{\sum_{\ell=1}^{L_i}\sum_{j=1}^{J_{i\ell}} T_{i\ell j}}.$$

For the jobs where we observe a wage, we also define the average job wage

$$\overline{w}_{i\ell j} = \frac{1}{T_{i\ell j}}\sum_{t=1}^{T_{i\ell j}} w_{i\ell jt}.$$

For the jobs where we observe at least one wage, define

$$\widetilde{w}_{i\ell j} \equiv \overline{w}_{i\ell j} - \frac{\sum_{\ell^*=1}^{L_i}\sum_{j^*=1}^{J_{i\ell^*}} \overline{w}_{i^*\ell^* j^*}}{\sum_{\ell^*=1}^{L_i}\sum_{j^*=1}^{J_{i\ell^*}} 1[T_{i\ell^* j^*} > 0]}.$$

$\widetilde{w}_{i\ell j}$ has the nice feature that it will sum to zero across jobs for each individual.

When we look at coworkers, for the same reason as for $\widetilde{r}_{-i\ell j}$, it is sometimes necessary to take the individual out of the calculation, so define

$$\widetilde{w}_{-i\ell j} \equiv \frac{\sum_{i^*=1}^{N}\sum_{\ell^*=1}^{L_{\iota^*}}\sum_{j^*=1}^{J_{i^*\ell^* j^*}} \widetilde{w}_{i^*\ell^* j^*} 1\big[i^* \neq i, f_{i^*\ell^* j^*} = f_{i\ell j}\big]}{\sum_{i^*=1}^{N}\sum_{\ell^*=1}^{L_{\iota^*}}\sum_{j^*=1}^{J_{i^*\ell^* j^*}} 1\big[i^* \neq i, f_{i^*\ell^* j^*} = f_{i\ell j}\big]}.$$

$\widetilde{w}_{-i\ell j}$ measures the average value of $\widetilde{w}_{i^*\ell^* j^*}$ over jobs at establishment $f_{i^*\ell^* j^*}$, taking out the contribution from individual i.

C.2. *Auxiliary Parameters*

Using the definitions of the intermediate variables, we now define the auxiliary parameters used in the estimation. In general, note that many of the auxiliary parameters are calculated over different samples, since not all variables are defined for each job spell.

For expositional reasons, we divide the parameters into two groups: those that are primarily important for turnover, and those that are primarily important for wages. There are eight parameters that are important for turnover: μ_δ, σ_δ^2, λ^e, λ^n, σ_n, f_u, P^*, and γ_θ.

We first discuss the auxiliary parameters chosen to identify these variables:

- Level and variance of job destruction rate, μ_δ, σ_δ^2: This is the rate at which people enter non-employment. We identify the mean and variance by using the average duration of employment spells:

$$\overline{L} = \frac{\displaystyle\sum_{i=1}^{N} \frac{\displaystyle\sum_{\ell=1}^{L_i}\left(\sum_{j=1}^{J_{i\ell}} D_{i\ell j}\right)}{L_i}}{\displaystyle\sum_{i=1}^{N} 1[L_i > 0]},$$

and the variance

$$\frac{\displaystyle\sum_{i=1}^{N}\left(\frac{\displaystyle\sum_{\ell=1}^{L_i}\left(\sum_{j=1}^{J_{i\ell}} D_{i\ell j}\right)}{L_i} - \overline{L}\right)^2}{\displaystyle\sum_{i=1}^{N} 1[L_i > 0]}.$$

• Arrival rate of outside offers from employment, λ^e: This will be important for determining how long someone stays on a job before moving to the next job. We use the average length of time on a job:[6]

$$\overline{J} = \frac{\displaystyle\sum_{i=1}^{N} \frac{\displaystyle\sum_{\ell=1}^{L_i}\left(\sum_{j=1}^{J_{i\ell}-1} D_{i\ell j}\right)}{\displaystyle\sum_{\ell=1}^{L_i} J_{i\ell} - 1}}{\displaystyle\sum_{i=1}^{N} 1\left[\sum_{\ell=1}^{L_i} J_{i\ell} - 1 > 0\right]}.$$

• Arrival rate of jobs from non-employment, λ^n: Similarly to the previous one, this will be important for the rate at which people enter employment from non-employment. We use the average length of non-employment spells:

$$\overline{K} = \frac{\displaystyle\sum_{i=1}^{N} \frac{\displaystyle\sum_{k=1}^{K_i} D^n_{ik}}{K_i}}{\displaystyle\sum_{i=1}^{N} 1[K_i > 0]}.$$

[6]The distinction between this one and the first is that this one is the length of time working for a particular employer, while the first is the length of time between non-employment spells. Thus, the first one includes more than one job if the movement was through a job-to-job transition.

- Variance in preferences for non-work, σ^2_{nu}: The way we have parameterized this, it will be related to the variance of non-employment spells:

$$\frac{\displaystyle\sum_{i=1}^{N}\left(\frac{\displaystyle\sum_{k=1}^{K_i} D^n_{ik}}{K_i} - \overline{K}\right)^2}{\displaystyle\sum_{i=1}^{N} 1[K_i > 0]}.$$

- Variation in non-pecuniary benefits at the establishment level, f_u: This parameter picks up whether there is a great deal of commonality across workers in the preferences for particular establishments. We use the covariance between coworkers' preference for the job, as measured through job-to-job transitions:

$$\operatorname{cov}(\widetilde{r}_{-i\ell j}, \widetilde{S}_{i\ell j}).$$

- Probability of immediate offer after job destruction, P^*: This will be important, because it depends on what fraction of job-to-job transitions are voluntary. We have direct evidence on this from the survey data. We select those from the survey who are in our data and who made a job-to-job transition between the job asked about in the interview and the time of the interview. We then calculate the fraction that reports that employment terminated on their employer's initiative. Formally, we match on

$$\frac{\displaystyle\sum_{i=1}^{N} \begin{array}{l} 1[\mathit{Survey}_{1995,i} = 1 \wedge J_{1990,i} = 1 \wedge S_{1995,1990,i} = 1 \wedge R_{1995,i} = 1] \\ \quad + 1[\mathit{Survey}_{2000,i} = 1 \wedge J_{1995,i} = 1 \wedge S_{2000,1995,i} = 1 \wedge R_{2000,i} = 1] \end{array}}{\displaystyle\sum_{i=1}^{N} \begin{array}{l} 1[\mathit{Survey}_{1995,i} = 1 \wedge J_{1990,i} = 1 \wedge S_{1995,1990,i} = 1] \\ \quad + 1[\mathit{Survey}_{2000,i} = 1 \wedge J_{1995,i} = 1 \wedge S_{2000,1995,i} = 1] \end{array}},$$

where $\mathit{Survey}_{x,i}$ is an indicator variable for being in the survey in year x; $J_{y,i}$ is an indicator variable for being in a job in November year x; $S_{x,y,i}$ is an indicator for having a November cross-section job in year y ending in a job-to-job transition before year x; and $R_{y,i}$ is an indicator for having reported in year x that the employment terminated on the employer's initiative.

- Importance of ability in preferences for non-employment, γ_θ: This is important for how the duration varies with general ability θ. We use the covariance between the length of a non-employment spell and average wages in the data (for people that ever work):

$$\frac{\displaystyle\sum_{i=1}^{N}\sum_{k=1}^{K_i} D^n_{ik}\overline{w_i}}{\displaystyle\sum_{i=1}^{N} K_i} - \left(\frac{\displaystyle\sum_{i=1}^{N}\sum_{k=1}^{K_i} D^n_{ik}}{\displaystyle\sum_{i=1}^{N} K_i}\right)\left(\frac{\displaystyle\sum_{i=1}^{N}\sum_{k=1}^{K_i} \overline{w_i}}{\displaystyle\sum_{i=1}^{N} K_i}\right).$$

These were the eight auxiliary parameters used to identify the structural turnover parameters. For wages, we have 10 parameters: E_θ, σ^2_θ, σ^2_ξ, $\sigma^2_{\upsilon p}$, $f_{u,p}$, f_p, α, β, b_1, b_2.

We use the following auxiliary parameters:

- Mean level of general ability, E_θ: Since all other variables are mean zero, this will be important for getting the overall wage in the economy, so we use the average log wage across all time periods:

$$\overline{w} \equiv \frac{\sum_{i=1}^{N}\sum_{\ell=1}^{L_i}\sum_{j=1}^{J_{i\ell}}\sum_{t=1}^{T_{i\ell j}} w_{i\ell jt}}{\sum_{i=1}^{N}\sum_{\ell=1}^{L_i}\sum_{j=1}^{J_{i\ell}} T_{i\ell j}}.$$

- The variance of general ability, the variance of measurement error, and the variance of the comparative advantage piece: σ_θ^2, σ_ξ^2, $\sigma_{v^p}^2$: Since these parameters will be important for variance at different levels, we decompose the overall variance into three components: within job spell, between job spell/within worker, and between worker. We think that σ_ξ will be important for the first; σ_{v^p} will be important for the second; and σ_θ will be important for the third:

$$\begin{aligned}
\frac{\sum_{i=1}^{N}\sum_{\ell=1}^{L_i}\sum_{j=1}^{J_{i\ell}}\sum_{t=1}^{T_{i\ell j}} (w_{it} - \overline{w})^2}{\sum_{i=1}^{N}\sum_{\ell=1}^{L_i}\sum_{j=1}^{J_{i\ell}} T_{i\ell j}} &= \frac{\sum_{i=1}^{N}\sum_{\ell=1}^{L_i}\sum_{j=1}^{J_{i\ell}}\sum_{t=1}^{T_{i\ell j}} (w_{i\ell jt} - \overline{w}_{i\ell j})^2}{\sum_{i=1}^{N}\sum_{\ell=1}^{L_i}\sum_{j=1}^{J_{i\ell}} T_{i\ell j}} \\
&\quad + \frac{\sum_{i=1}^{N}\sum_{\ell=1}^{L_i}\sum_{j=1}^{J_{i\ell}}\sum_{t=1}^{T_{i\ell j}} (\overline{w}_v - \overline{w}_i)^2}{\sum_{i=1}^{N}\sum_{\ell=1}^{L_i}\sum_{j=1}^{J_{i\ell}} T_{i\ell j}} \\
&\quad + \frac{\sum_{i=1}^{N}\sum_{\ell=1}^{L_i}\sum_{j=1}^{J_{i\ell}}\sum_{t=1}^{T_{i\ell j}} (\overline{w}_i - \overline{w})^2}{\sum_{i=1}^{N}\sum_{\ell=1}^{L_i}\sum_{j=1}^{J_{i\ell}} T_{i\ell j}}.
\end{aligned}$$

- Importance of establishment for productivity, f_p: Here we use the covariance of coworkers' log wages relative to the wages these workers have received at other firms:

$$\operatorname{cov}(\widetilde{w}_{i\ell j}, \widetilde{w}_{-i\ell j}).$$

- Correlation between establishment productivity and establishment non-pecuniary aspects, $f_{u,p}$. Here we use the covariance between workers' wages at the firm and the coworkers' preferences for the firm:

$$\operatorname{cov}(\widetilde{r}_{-i\ell j}, \widetilde{w}_{i\ell j}).$$

- Importance of wages as a component of utility, α: To identify this, we use the fraction of wage losses that occur at job-to-job transitions:

$$\Pr(\overline{w}_{i\ell j+1} < \overline{w}_{i\ell j}) = \frac{\sum_{i=1}^{N}\sum_{\ell=1}^{L_i}\sum_{j=2}^{J_{i\ell}} 1[\overline{w}_{i\ell j} < \overline{w}_{i\ell j-1}]}{\sum_{i=1}^{N}\sum_{\ell=1}^{L_i}(J_{i\ell}-1)}.$$

The idea behind this is that the more important wages are as a determinant of job preferences, the less often we will see wage losses at job-to-job transitions.

- Bargaining parameter and human capital production parameters, β, b_1, b_2: Estimation of these parameters is quite subtle, and distinguishing between them is difficult. Choosing which auxiliary parameters to use was not straightforward, and we explored many options, ultimately deciding the following approach was intuitively better and more robust than the alternatives. In our model, β essentially picks up the importance of the bargaining process as a determinant of wages (smaller values of β imply that it is more common). Thus, β can be identified by measuring the importance of tenure. We estimate the following regression using those observations with no left-censored tenure (meaning job spells where we do not observe the beginning of the spell):

$$w_{i\ell jt} = \beta_{i\ell j} + \beta_1 E_{i\ell jt} + \beta_2 E_{i\ell jt}^2 + \beta_3 TE_{i\ell jt}^2 + \epsilon_{i\ell jt},$$

where $\beta_{i\ell j}$ is a job-spell fixed effect. We match on the estimates of β_1, β_2, and β_3. Note that since $\beta_{i\ell j}$ is a job-spell fixed effect, as pointed out by Altonji and Shakotko (1987), Topel (1991), and others, experience and tenure are perfectly correlated within a spell. As a result, we cannot identify the coefficient on tenure directly. Instead, we use the coefficient on tenure squared to pick up the importance of bargaining. Intuitively, this works because the rate at which people switch jobs is identified from other auxiliary parameters, so for any level of bargaining power, we know the rate at which that bargaining power should decline. The squared term should pick up both the magnitude of the tenured effect and the rate at which it stops increasing, and since other components of the model pick up the rate, the magnitude of this parameter should identify the magnitude of the bargaining effect.

C.3. *Standard Errors*

Standard errors for the paper are computed using the formula in Gourieroux, Monfort, and Renault (1993), which is the standard formula for standard errors. For that, the covariance matrix for the auxiliary parameters is needed. We obtain this by bootstrapping. More specifically, in each bootstrap repetition we draw N (N is the sample size) individuals with replacement from the data. We relabel the worker IDs. In each bootstrap, we use the individual's contributions to form the auxiliary parameters from the data and thus do not recalculate, for example, the coworker contributions. For example, the auxiliary parameter that we use to primarily pin down f_p is $\text{cov}(\widetilde{w}_{i\ell j}, \widetilde{w}_{-i\ell j})$. When we draw worker i and relabel the worker ID to i', we can recalculate $\widetilde{w}_{i'\ell j}$, and we will get exactly $\widetilde{w}_{i\ell j}$. Recalculating variables that only depend on within-worker variation is not problematic. However, recalculating variables that depend on variation across coworkers is problematic, since in each bootstrap, a worker might end up working with copies of themselves, which would generate a bias in the auxiliary parameters. Given that, we have opted not to recalculate these. This implies that when we draw individual i in a bootstrap, we will reuse the original values of both $\widetilde{w}_{i\ell j}$ (which does not matter) and $\widetilde{w}_{-i\ell j}$ (which matters). However, not recalculating all the variables is not optimal as it will bias the variance towards zero. Since we have population-wide data with many individuals, we view this as a minor problem. After having done 500 bootstrap repetitions, we calculate the covariance matrix of the estimated auxiliary parameters.

Recall that our objective function is the sum of the squared deviation between the simulated model and the data weighted by the inverse of the absolute value of the estimated parameters. The weighting matrix and the covariance matrix are used together with the numerical derivatives to calculate the standard errors.

C.4. *Alternative Auxiliary Model*

Here we present the auxiliary parameters used in the alternative model estimated in Section 9.

Turnover Rates

In the baseline estimation, we used durations in all the auxiliary parameters. We now propose using hazards to identify the structural parameters determining turnover rates (λ^e, λ^n, σ_ν^2, μ_δ, σ_δ^2 and γ_θ):

- λ^e: We will replace the average job duration with the average hazard rate out of a job. We use only jobs that end in a job-to-job transition in order to be similar to the auxiliary parameter that we are replacing:

$$\frac{\sum_{i=1}^{N}\sum_{\ell=1}^{L_i}(J_{i\ell}-1)}{\sum_{i=1}^{N}\sum_{\ell=1}^{L_i}\sum_{j=1}^{J_{i\ell}-1} D_{i\ell j}}.$$

- λ^n: Instead of the duration of non-employment spells, we will use the average hazard rate out of non-employment:

$$\frac{\sum_{i=1}^{N} K_i - CU_{iK_i}}{\sum_{i=1}^{N}\sum_{k=1}^{Ki} D^n_{ik}}.$$

- σ_ν^2: Instead of the variance of non-employment spells, we propose using the fraction that never experiences a job-to-non-employment transition conditional on having employment at some point:

$$\frac{\sum_{i=1}^{N} 1[CE_{i1J_{i1}}=1]}{\sum_{i=1}^{N} 1[L_i>0]}.$$

- μ_δ, σ_δ^2: Previously, we used the mean and variance of employment durations. We propose replacing these with the average hazard rate out of employment and the fraction that is always non-employed:

$$\frac{\sum_{i=1}^{N} L_i - CE_{iL_iJ_{iL_i}}}{\sum_{i=1}^{N}\sum_{\ell=1}^{L_i}\left(\sum_{j=1}^{J_{i\ell}} D_{i\ell j}\right)},$$

$$\frac{\sum_{i=1}^{N} 1[L_i = 0]}{N}.$$

- γ_θ: We suggest re-weighting the covariance by non-employment spells rather than by person. That is, we use

$$\operatorname{cov}\bigl(D_{ik}^n, \overline{w_i}\bigr).$$

Firm Parameters

We use other auxiliary parameters to identify the firm parameters (f_p, f_u, and $f_{u,p}$). First, we propose an alternative way to measure coworkers' value of a job, which can be used instead of $\widetilde{r}_{-i\ell j}$.

For this, we define the number of job-to-job separations, s_{-i}^q, and the number of job-to-job hires, h_{-i}^q, for each establishment, q. Since we want to use this to estimate the correlation between person i's preferences and their coworkers', we exclude individual i from this calculation:

$$s_{-i}^q = \sum_{i^*=1}^{N}\sum_{\ell=1}^{L}\sum_{j=1}^{J_{i\ell j}-1} 1\bigl[q = f_{i^*\ell j}, i \neq i^*\bigr],$$

$$h_{-i}^q = \sum_{i^*=1}^{N}\sum_{\ell=1}^{L}\sum_{j=2}^{J_{i\ell j}} 1\bigl[q = f_{i^*\ell j}, i \neq i^*\bigr].$$

From this, define

$$h_{-i\ell j} \equiv \frac{h_{-i}^{f_{i\ell j}}}{h_{-i}^{f_{i\ell j}} + s_{-i}^{f_{i\ell j}}}.$$

Thus, $h_{-i\ell j}$ is a measure of the degree to which individual i's coworkers at establishment $f_{i\ell j}$ like working there, expressed by looking at job-to-job transition patterns. Since our goal is to construct a covariance, we construct a residualized version of $h_{-i\ell j}$ by subtracting the mean value of $h_{-i\ell j}$ across jobs for individual i:

$$\widetilde{h}_{-i\ell j} \equiv \frac{h_{-i}^{f_{i\ell j}}}{h_{-i}^{f_{i\ell j}} + s_{-i}^{f_{i\ell j}}} - \frac{1}{\sum_{\ell^*=1}^{L_i} J_{i\ell^*}} \sum_{\ell^*=1}^{L_i}\sum_{k=1}^{J_{i\ell}} \frac{h_{-i}^{f_{i\ell^* k}}}{h_{-i}^{f_{i\ell^* k}} + s_{-i}^{f_{i\ell^* k}}}.$$

Note that this does not include employment spells where the employee is employed by firm $f_{i\ell j}$ in the first job spell.

We propose replacing $\widetilde{r}_{-i\ell j}$ with $\widetilde{h}_{-i\ell j}$, such that we now use

$$\operatorname{cov}(\widetilde{h}_{-i\ell j}, \widetilde{S}_{i\ell j})$$

instead of

$$\operatorname{cov}(\widetilde{r}_{-i\ell j}, \widetilde{S}_{i\ell j}).$$

In the data, we estimate the AKM model, $w_{i\ell jt} = x_{i\ell jt}\beta + \theta_i + \phi_{f(i\ell jt)}$, where $x_{i\ell jt}$ contains real experience, real experience squared, real experience cubed, and year dummies.[7] All are interacted with educational groups.[8] Let $f(i\ell jt)$ be the establishment at time t in job spell $i\ell j$. Form employment weighted quartiles of $\hat{\phi}_{f(i\ell jt)}$, and calculate the mean change in $\overline{w_{i\ell j}}$ from time $t-1$ to t for all observations where $f(i\ell jt) \neq f(i\ell jt+1)$ and where $\hat{\phi}_{f(i\ell jt)}$ is in the first (fourth) quartile, and $\hat{\phi}_{f(i\ell jt+1)}$ is in the fourth (first) quartile. We then construct the expected value of mean wages on jobs as people make job-to-job transitions from a job in one quartile of the establishment affects distribution to another. We propose using two auxiliary parameters. First, $E(\Delta\overline{w_{i\ell j}} \mid Q1 \rightarrow Q4)$, which is the average change in wages for the job after the move minus the value for the job before the move. Second, we match on the ratio $E(\Delta\overline{w_{i\ell j}} \mid Q4 \rightarrow Q1)/E(\Delta\overline{w_{i\ell j}} \mid Q1 \rightarrow Q4)$ (where -1 would represent perfect symmetry).

Our model does not account for firm size, so we are not able to precisely mimic the data with the model regarding these two auxiliary parameters. In the data, we use the fixed effects to determine the quartile, while in the simulated version, we use the fact that we know the quartiles ourselves from the parameter values, so we determine them in this way. While this is not perfect, we think it is a reasonable way to see if the model is able to replicate the basic facts in the data.

Notice that the ranking of establishments in the data will be noisy due to the inconsistency of the fixed effects estimated in the AKM model. This will bias the auxiliary parameter towards perfect symmetry. This is not the case in the simulated data, since we know the ranking and thus we will have a harder time to fit these statistics.

Bargaining Power and Weight on Wages

We follow Altonji and Shakotko (1987) and estimate the following regression using those observations with no left-censored tenure (meaning job spells where we do not observe the beginning of the spell):

$$w_{i\ell jt} = \beta_0 + \beta_1 E_{i\ell jt} + \beta_2 E_{i\ell jt}^2 + \beta_3 TE_{i\ell jt} + \epsilon_{i\ell jt},$$

where we instrument $TE_{i\ell get}$ by the deviation from the match mean. We then match on β_1, β_2, and β_3. Finally, instead of using the fraction experiencing a wage drop at job-to-job transitions to identify α, we use the average wage increase at job-to-job transitions.

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Co-editor Liran Einav handled this manuscript.

Manuscript received 31 May, 2016; final version accepted 2 December, 2019; available online 22 January, 2020.