Online Appendix to "Mismatch Cycles"

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A Kolmogorov Forward Equations

Let $p_U(\hat{a},\Sigma,z)$ and $p_E(\hat{a},\Sigma,r,z)$ define the job finding rates of unemployed and employed workers as given by (8) and (9).

Active relationships The distribution over active relationships, $\Gamma_t(\hat{a},\Sigma,r)$, is characterized by the following PDE:

$$\dot{\Gamma}_t(\hat{a},\Sigma,r) = \dot{\Gamma}_t^{\text{learn}}(\hat{a},\Sigma,r) + \dot{\Gamma}_t^{\text{ee}}(\hat{a},\Sigma,r) + \dot{\Gamma}_t^{\text{ue}}(\hat{a},\Sigma,r) - \dot{\Gamma}_t^{\text{eu}}(\hat{a},\Sigma,r) - \epsilon\Gamma_t(\hat{a},\Sigma,r). \quad \text{(A.1)}$$

Here, the first term defines distributional dynamics driven by changes in beliefs, given by

$$\dot{\Gamma}_t^{\text{learn}}(\hat{a},\Sigma,r) = \left(\frac{\partial}{\partial\Sigma} + \frac{1}{2}\frac{\partial^2}{\partial\hat{a}^2}\right)\left[\left(\frac{\Sigma}{\sigma}\right)^2\Gamma_t(\hat{a},\Sigma,r)\right].$$

The second term, defines reallocation dynamics due to job-to-job transitions,

$$\dot{\Gamma}_t^{\text{ee}}(\hat{a},\Sigma,r) = -p_E(\hat{a},\Sigma,r,z)\Gamma_t(\hat{a},\Sigma,r) + \sum_{r'\in\mathcal{R}} p_E(\hat{a},\Sigma,r',z)\Gamma_t(\hat{a},\Sigma,r')\cdot\mathbf{1}_{r=r^*(\hat{a},\Sigma,z)},$$

where $\mathbf{1}_C$ denotes the indicator function for a given condition C. The third term, defines the incoming flow of new hires out of unemployment,

$$\dot{\Gamma}_t^{\text{ue}}(\hat{a},\Sigma,r) = p_U(\hat{a},\Sigma,z)\Lambda_t(\hat{a},\Sigma)\cdot\mathbf{1}_{r=r^*(\hat{a},\Sigma,z)}.$$

The fourth term defines separations into unemployment,[1]

$$\dot{\Gamma}_t^{\text{eu}}(\hat{a},\Sigma,r) = \left(\delta + \lim_{\pi\to\infty}\pi\chi^{\text{sep}}(\hat{a},\Sigma,r,z)\right)\Gamma_t(\hat{a},\Sigma,r)$$

where $\chi^{\text{sep}}(\hat{a},\Sigma,r,z)\in\{0,1\}$ is an indicator evaluating to unity when the value of the match becomes negative ($J_t^{\text{act}}(\hat{a},\Sigma,r,z)\leq\mathcal{U}(\hat{a},\Sigma,z)$). Finally, the fifth term defines exogenous career switches.

[1]Note that for the endogenous separations case, the rate of outflows equals ∞ as long as $\Gamma_t(\hat{a},\Sigma,r)\neq 0$ for the corresponding states, implying that the only possible limit is $\Gamma_t(\hat{a},\Sigma,r)=0$ for any states $(\hat{a},\Sigma,r)$ outside the continuation region.

Unemployed Similarly, the distribution over unemployed workers, $\Upsilon_t(\hat{a},\Sigma)$, is characterized by the following PDE:

$$\dot{\Upsilon}_t(\hat{a},\Sigma) = \dot{\Upsilon}^{\text{cs}}_t(\hat{a},\Sigma) + \dot{\Upsilon}^{\text{eu}}_t(\hat{a},\Sigma) - \dot{\Upsilon}^{\text{ue}}_t(\hat{a},\Sigma). \tag{A.2}$$

Here, the first term defines net changes in (current-career) beliefs due to agents switching careers,[2]

$$\begin{aligned}\dot{\Upsilon}^{\text{cs}}_t(\hat{a},\Sigma) = &-\left(\epsilon + \lim_{\pi\to\infty} \pi\chi^{\text{cs}}(\hat{a},\Sigma,z)\right)\Upsilon_t(\hat{a},\Sigma) + \\ &+ \iint \left(\epsilon + \lim_{\pi\to\infty} \pi\chi^{\text{cs}}(\hat{a},\Sigma,z)\right)\Upsilon_t(\hat{a}',\Sigma')\,\mathrm{d}(\hat{a}',\Sigma')\cdot \mathbf{1}_{(\hat{a},\Sigma)=(a_0,S_0)},\end{aligned}$$

where $\chi^{\text{cs}}(\hat{a},\Sigma,z) \in \{0,1\}$ is an indicator evaluating to unity when switching careers is optimal ($U_t(a_0,S_0,z) > U_t(\hat{a},\Sigma,z)$). The second term defines gross inflows into unemployment, including those from exogenous career switches,

$$\dot{\Upsilon}^{\text{eu}}_t(\hat{a},\Sigma) = \int \dot{\Gamma}^{\text{eu}}_t(\hat{a},\Sigma,r)\,\mathrm{d}r + \iiint \epsilon\Gamma_t(\hat{a},\Sigma,r)\,\mathrm{d}(\hat{a}',\Sigma',r)\cdot \mathbf{1}_{(\hat{a},\Sigma)=(a_0,S_0)}.$$

Finally, the third term defines the outflows from unemployment due to workers finding jobs,

$$\dot{\Upsilon}^{\text{ue}}_t(\hat{a},\Sigma) = p_U(\hat{a},\Sigma,z)\Lambda_t(\hat{a},\Sigma).$$

Transmission of aggregate shocks The aggregate productivity state z_t affects the cross-sectional distribution through three channels: (1) its direct impact on job finding rates $p_U(\hat{a},\Sigma,z)$ and $p_E(\hat{a},\Sigma,r,z)$, (2) its direct impact on the separation and career switching thresholds $\chi^{\text{sep}}(\hat{a},\Sigma,r,z)$ and $\chi^{\text{cs}}(\hat{a},\Sigma,z)$, and (3) its direct impact on the desired job rung $r^*(\hat{a},\Sigma,z)$. These direct effects translate into shifts in $\dot{\Gamma}^{\text{ee}}_t$, $\dot{\Gamma}^{\text{eu}}_t$, $\dot{\Gamma}^{\text{ue}}_t$, $\dot{\Upsilon}^{\text{eu}}_t$, $\dot{\Upsilon}^{\text{ue}}_t$ and $\dot{\Upsilon}^{\text{cs}}_t$, which in turn propagate to Γ_t and Υ_t according to (A.1) and (A.2). In particular, an aggregate shock to z_t manifests itself both through a discrete shift in the cross-sectional distributions Γ_t and Υ_t upon impact and by alternating their subsequent evolution $\dot{\Gamma}_t$ and $\dot{\Upsilon}_t$.

For the calibration from Section 3, the direct effects are sizable for p_U, p_E and χ^{sep}, whereas the direct effects on χ^{cs} and r^* are negligible.[3] Specifically, the direct effects on p_U, p_E and

[2]Note that the rate of workers switching careers equals ∞ as long as $\Upsilon_t(\hat{a},\Sigma) \neq 0$ for the corresponding states. The only possible limit is therefore given by $\Upsilon_t(\hat{a},\Sigma) = 0$ for any states $(\hat{a},\Sigma)$ in which workers switch careers. Accordingly, the corresponding switching rates, defining the inflow into (a_0,S_0), equal the inflow into the switching states from employment.

[3]The cyclicality of career-mobility is entirely driven through the distributional shift in Υ_t caused by the shift in the separation threshold χ^{sep}.

χ^{sep} imply strong procyclical fluctuations in the job finding rate from unemployment and the job-to-job mobility rate, and countercyclical fluctuations in the separation rate (reflecting the contraction in the continuation region depicted in Figure 9).[4]

B Examples of General Production Function

This appendix provides two examples of a general production technology $F(z, \boldsymbol{q}, \boldsymbol{a})$ that collapses into (1) when $\boldsymbol{q}_{k,r}$ are orthogonal.

Complementary-skill case Let

$$F(z(t), \boldsymbol{q}_{k,r}, \boldsymbol{a}_i) \equiv \exp\left[z(t) + \sum_{j=1}^{J}\left(\eta q_{k,r,j} - \max\left\{q_{k,r,j} - \frac{q_{k,r,j}a_{i,j}}{\sum_{j=1}^{J} q_{k,r,j}}, 0\right\}\right)\right]. \tag{B.1}$$

Substituting $r = \sum_{j=1}^{J} q_{k,r,j}$ and $w_{k,j} = q_{k,r,j}/(\sum_{j=1}^{J} q_{k,r,j})$, we can rewrite (B.1) in more accessible form

$$\log y_{i,k,r} = z(t) + \sum_{j=1}^{J} w_{k,j}\left(\eta r - \max\{r - a_{i,j}, 0\}\right),$$

which clearly collapses into (1) for an orthogonal weighting scheme; e.g.,[5]

$$\begin{bmatrix}\boldsymbol{w}_1' & \boldsymbol{w}_2' & \cdots & \boldsymbol{w}_K'\end{bmatrix} = \boldsymbol{I}_K.$$

Substitutible-skill case Let

$$F(z(t), \boldsymbol{q}_{k,r}, \boldsymbol{a}_i) \equiv \exp\left[z(t) + \eta\sum_{j=1}^{J} q_{k,r,j} - \max\left\{\sum_{j=1}^{J} q_{k,r,j} - \frac{\sum_{j=1}^{J} q_{k,r,j}a_{i,j}}{\sum_{j=1}^{J} q_{k,r,j}}, 0\right\}\right], \tag{B.2}$$

which can be rewritten more compactly as

$$\log y_{i,k,r} = z(t) + \eta r - \max\left\{r - \sum_{j=1}^{J} w_{k,j}a_{i,j}, 0\right\}.$$

Again, it is easy to verify that $y_{i,k,r}$ collapses into (1) for an orthogonal weighting scheme.

[4] Evaluated at the ergodic distribution, the cyclical differences between expansions and recessions are: 9.5 percentage points (pp.) for the monthly job finding rate from unemployment, 0.4 pp. for the monthly job-to-job mobility rate, and -0.7 pp. for the separation rate.

[5] Here, we tacitly set $K = J$, for ease of exposition. Weighting schemes other than the identity scheme may require a redefinition of skill types, but can equally be reduced to (1) for an appropriate definition of skills as long as $\{\boldsymbol{a}_k\}$ are orthogonal across the adopted career classification $\{k\}$.

Table C.1: Inertia in career mobility

	Recession	Expansion
Unemployed	8.74	8.89
$r = 0$	9.19	9.84
$r = 0.5 \cdot S_0^{1/2}$	7.79	8.37
$r = 1.0 \cdot S_0^{1/2}$	4.91	5.16
$r = 1.5 \cdot S_0^{1/2}$	2.30	2.38
$r = 2.0 \cdot S_0^{1/2}$	0.86	0.89
$r = 2.5 \cdot S_0^{1/2}$	0.26	0.26
$r = 3.0 \cdot S_0^{1/2}$	0.04	0.04

Notes.—The table reports the implicit cost on career mobility induced by mismatch, denominated in monthly average output per worker, $\mathbb{E}[y_{i,t}]/\mathbb{E}[1 - U_t]$.

C Inertia in Career Mobility

As alluded to in the main text, inertia not only marks workers' reallocation across job rungs within careers, but also their career choice. This is because evaluating the prospects of a career takes time due to the information friction and reduces the returns to trying out new careers given the anticipation of mismatch. In what follows, we assess the magnitude of this implicit cost on exploring new careers. We do so by considering a fictitious career-switching problem in which workers can instantaneously churn careers and learn the relevant skill at *infinite speed* subject to an explicit switching cost $\xi_{i,t}$. For any given worker, we then calculate the magnitude of the explicit switching cost $\xi_{i,t}$ that keeps them indifferent between accessing the fictitious churning technology and sticking to their equilibrium career choice. Intuitively, our approach replaces the implicit information friction on career mobility (and the cost of entailing mismatch) by an explicit switching cost $\xi_{i,t}$, which we design so as to impose the same career mobility patterns for all workers.

Specifically, let $X_{i,t}$ denote the current unemployment value $\mathcal{U}(\hat{a}_k, \Sigma_k, z)$ if a worker is currently unemployed, and the joint worker–firm value $J(\hat{a}_k, \Sigma_k, r, z)$ if they are employed. Then the marginal benefit of exploring a new career and learning the relevant skill instantaneously, $(\hat{a}, \Sigma) = (a, 0)$, is given by

$$\tilde{\xi}_{i,t} = \int_{-\infty}^{\infty} \max\left\{\mathcal{U}_t(a, 0) - X_{i,t}, 0\right\} \, \mathrm{d}\Phi\left(\frac{a - a_0}{\sqrt{S_0}}\right).$$

To preempt workers from assessing the churning technology it hence suffices to set $\xi_{i,t} = \tilde{\xi}_{i,t}$. Table C.1 reports the result (denominated in the *economy-wide* average monthly output per worker). The implicit friction is largest for low-skilled workers as they benefit the most from exploring new careers. It ranges from the equivalent of 10 months of output for workers at the bottom rung of the job ladder to about one work day of at the top rung.[6] Averaged across workers and business cycle states, the implicit friction evaluates to the equivalent of 4.75 months of average output per worker.

D Wages Without Commitment by Workers

This appendix details the computation of wages used for the exploration in Section 4. Following Schaal (2017), we adopt the unique wage scheme that induces equilibrium search and job continuation policies to be self-enforcing for workers (without requiring a contractual commitment).

Let w_t denote the wage of worker i at date t, and let W_t define the expected lifetime utility of an employed worker that is delivered by the contracted process for $\{w_t\}$. Notice that the characterization so far only pins down $W_t = x_t$ during hiring but does not determine how the promised hiring utility, x_t, is delivered across states and throughout the duration of the work-relationship. In analogue to (5), the expected utility flow of an active relationship is given by

$$\begin{aligned}\rho W_t^{\text{act}}(\hat{a}_k, \Sigma_k, r, z) = w_{i,t} + \tilde{\Lambda}_t(\hat{a}_k, \Sigma_k, r, z) + \\ + \max_{x,r} \{\kappa p(\theta_t(\omega, z))\,(x - W_t(\hat{a}_k, \Sigma_k, r, z))\} + \\ + \delta\,(\mathcal{U}_t(\hat{a}_k, \Sigma_k, z) - W_t(\hat{a}_k, \Sigma_k, r, z)) + \\ + \epsilon\,(U_t(a_0, S_0, z) - W_t(\hat{a}_k, \Sigma_k, r, z)) + \\ + \lambda_z\,(W_t(\hat{a}_k, \Sigma_k, r, -z) - W_t(\hat{a}_k, \Sigma_k, r, z))\,, \quad \text{(D.1)}\end{aligned}$$

where

$$\tilde{\Lambda}_t(\hat{a}_k, \Sigma_k, r, z) \equiv \left(\frac{\Sigma_k}{\sigma}\right)^2 \left(-\frac{\partial W_t(\hat{a}_k, \Sigma_k, r, z)}{\partial \Sigma_k} + \frac{1}{2}\frac{\partial^2 W_t(\hat{a}_k, \Sigma_k, r, z)}{\partial \hat{a}_k^2}\right)$$

and

$$W_t(\hat{a}_k, \Sigma_k, r, z) = \max\left\{W_t^{\text{act}}(\hat{a}_k, \Sigma_k, r, z), \mathcal{U}_t(\hat{a}_k, \Sigma_k, z)\right\}.$$

Absent contractual commitments, workers' on-the-job search maximizes (D.1) subject to (2).

[6] The implicit friction is slightly larger for workers at the bottom job rung than for unemployed workers due to the presence of exogenously laid off workers among the unemployed who have strong incentives to retain their current career.

Rearranging the associated first-order condition, we have

$$\theta = p'^{-1}\left(\frac{c}{J_t(\hat{a}_k, \Sigma_k, r^*, z) - W_t(\hat{a}_k, \Sigma_k, r, z)}\right). \tag{D.2}$$

Comparing (D.2) with (9), we conclude that for search to be self-enforcing, the worker value of the relationship must match the joint value whenever they are actively searching. Accordingly, the unique self-enforcing wage scheme is given by

$$w_{i,t} = e^{z+\eta r}\mathbb{E}_t[e^{-\max\{r-a_k,0\}}] = e^{z+\eta r}\psi(\hat{a}_k - r, \sqrt{\Sigma_k});$$

i.e., workers are compensated their marginal product at each instant of an ongoing work-relationship. Moreover, because $W_t^{\text{act}} = x_t$ must hold at hiring, workers must reimburse firms for their recruitment cost at the instant of hiring, implying a one-time reduction in wages equal to

$$J(\hat{a}_k, \Sigma_k, r, z) - x = c/q\left(\theta(\hat{a}_k, \Sigma_k, r, z)\right).$$

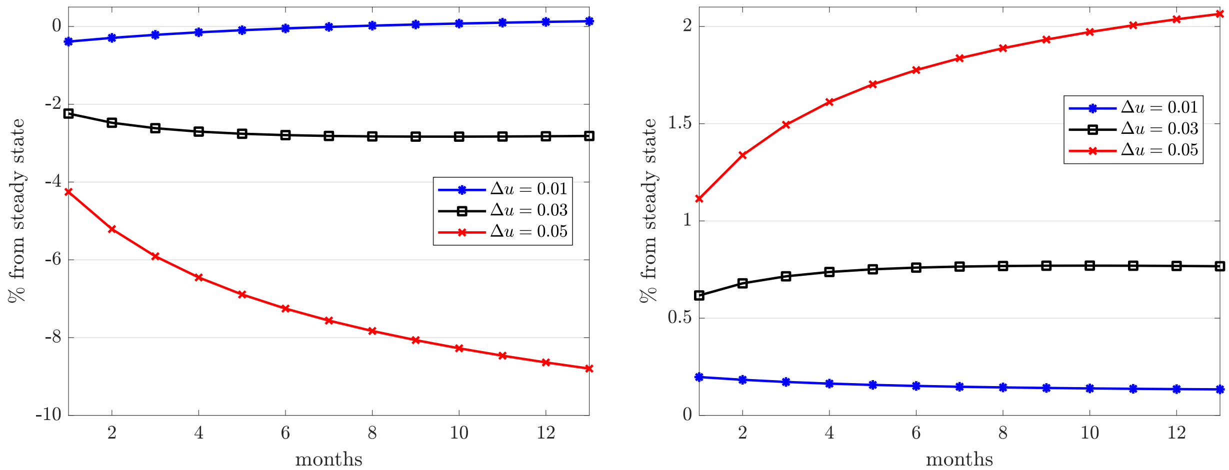
Finally, noticing that the described wage arrangement implies $W_t^{\text{act}} = J_t^{\text{act}}$ at any instant of an ongoing relationship, we conclude that workers' job continuation/separation choices are also aligned with the bilaterally efficient ones observed under commitment.

E Impulse Responses to Aggregate Shocks of Varying Sizes

This appendix compares the dynamic response for mismatch and labor efficiency across aggregate shocks with three different magnitudes. In each case, the economy is initialized at its high productivity state with $z = z_H$. At $t = 0$, the aggregate state switches to $z = z_L$ and stays there for the duration of the response. In this appendix, we consider three different calibrations for z_L, inducing an initial unemployment response (1 month after the realization of the shock) of $\Delta u = 0.01$, 0.03 and 0.05, respectively. To make the three calibrations comparable, we assume that the adverse shock is unanticipated ($\lambda_{z_H} = 0$), so that the varying values for z_L do not change the initial steady state.[7]

Figure E.1 shows the impulse responses for mismatch and labor efficiency. Across the three responses, the decline in mismatch and the increase in labor efficiency are larger the larger the recession. Intuitively, the larger the shock to labor productivity, the larger the shift

[7] The recovery rate λ_{z_L} is kept at its baseline level of 0.0128. The figure shows the response paths conditional on that the aggregate state does not recover throughout the duration of the impulse response.



(a) Mismatch **(b)** Labor efficiency

Figure E.1: Impulse responses to aggregate shocks of varying sizes. *Notes.*—All responses are initialized at the same deterministic steady state, and then exposed to an unexpected shock to z, which respectively induces an initial unemployment response of $\Delta u = 0.01$, 0.03 and 0.05 after 1 month.

in the separation threshold in Figure 9 in the main text, amplifying cleansing and (up to a certain scale) sullying.

Interestingly, there is a dynamic wedge opening up between the three responses: While upon impact they scale roughly proportionately in Δu, the impact on mismatch and labor efficiency one year into the recession is disproportionately increased for the larger shocks. The reason is that once the shock is of a certain scale, further scaling it up will only amplify cleansing but will not induce any additional sullying.[8] This explains why for the smallest shock (where sullying balances cleansing) the impact on mismatch is approximately neutral 12 months into the recession, whereas for the largest shock (where cleansing dominates sullying) mismatch declines to about 8.6 percent below its steady state level after 12 months.

F Measuring Job Requirements, Employment Transitions, and Worker Skills

This appendix details the measurement of job requirements, employment transitions, and worker skills.

[8] Specifically, once the cleansing is sufficiently large to induce the separation of all workers with a "loose career attachment", there will be no additional first order effect on sullying. In Figure 9, this "maximal sullying" point is reached, once the lower separation threshold during recessions shifts above the career-switching threshold. While larger recessions will further shift up the separation threshold, these additional separations will no longer result in career-switches and sullying.

F.1 Job Requirements

Following Guvenen et al. (2020), we measure skill requirements using 26 O*NET descriptors from the Knowledge, Skills and Abilities categories that were identified by the Defense Manpower Data Center (DMDC) to be related to the Armed Services Vocational Aptitude Battery (ASVAB) tests, augmented by six descriptors linked to social skills.[9] As in Guvenen et al. (2020), we link those O*NET descriptors to ASVAB test categories based on the relatedness score provided by DMDC. The verbal skill requirement is then defined as the first principal component of Word Knowledge and Paragraph Comprehension, the math requirement is that of Math Knowledge and Arithmetic Reasoning, and the technical requirement is the first principal component of Electronics Info, General Science, and Mechanical comprehension. For the social dimension, we also collapse the six O*NET descriptors into a single dimension defined by the first principal component. Finally, we normalize all requirements by converting them into percentile ranks based on the distribution of occupations in our NLSY79 sample (see below).

F.2 Employment Transitions

Employment histories We infer employment histories from the NLSY79 Work History Data File, which is a nationally representative panel of workers who are followed from first entry into the labor market. We aggregate the available employment data, which is recorded at a weekly frequency, to a monthly frequency by focusing on the job for which an individual worked the most hours in a given month.

Sample selection As the NLSY79 is well-known and requires little description, we focus in the following on describing the sample selection used in this paper. We focus on the subsample of males and females from the so-called cross-sectional sample, which is designed to represent the non-institutionalized civilian segment of the U.S. in 1979.[10] As is standard in the literature, we drop individuals who were more than two years in the military force, individuals with a weak labor market attachment (spending more than 10 years out of the labor force),

[9]The descriptors used are the following: oral comprehension, written comprehension, deductive reasoning, inductive reasoning, information ordering, mathematical reasoning, number facility, reading comprehension, mathematics skill, science, technology design, equipment selection, installation, operation and control, equipment maintenance, troubleshooting, repairing, computers and electronics, engineering and technology, building and construction, mechanical, mathematics knowledge, physics, chemistry, biology, english language, social perceptiveness, coordination, persuasion, negotiation, instructing, service orientation.

[10]The NLSY79 also contains supplemental samples that oversample ethnic minorities, economically disadvantaged people, and the military, none of which we include in our analysis.

individuals that were already working in 1979, and those that do not have information on the ASVAB test scores.

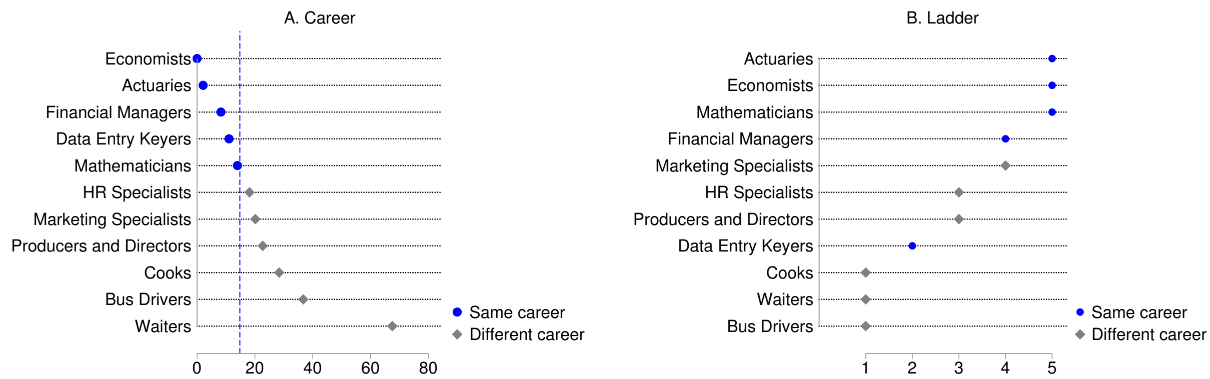
F.3 Worker Skills and Mismatch

Worker skills We measure workers skills using ASVAB test scores available in the NLSY79 (see Appendix F.2 for a description of our subsample). The ASVAB is a general test that measures knowledge and skills in 10 different components that was taken by survey participants when first entering the survey.[11] As in Guvenen et al. (2020), we focus on a subset of seven components (arithmetic reasoning, mathematics knowledge, paragraph comprehension, word knowledge, mechanical comprehension, general science and electronics information) which are linked to math, verbal and technical skills, and are combined using Principal Components Analysis (PCA). For the social dimension, we proceed in the same fashion using the individual scores in two different tests provided by the NLSY79: the Rotter Locus of Control Scale and the Rosenberg Self-Esteem Scale.[12] To adjust for differences in test-taking age, before proceeding with PCA, we normalize the mean and the variance of each test score according to their age-specific values. Then, once we have the raw scores in each skill dimension, we convert these into percentile ranks.

Mismatch We merge the panel of worker-level data with the occupation data using using three-digit Census occupational codes. Note that O*NET uses SOC codes from 2010, which are more detailed than the occupational codes in the NLYS79, based on the three-digit Census occupation codes. Hence several occupations in NLSY79 have more than one score. Using a crosswalk to identify each SOC code with a Census code, we take an unweighted average over all the SOC codes that map to the same code in the census three-digit level occupation classification. We then proceed to construct mismatch as defined in the main body of the paper.

[11]The components are arithmetic reasoning, mathematics knowledge, paragraph comprehension, word knowledge, general science, numerical operations, coding speed, automotive and shop information, mechanical comprehension, and electronics information.

[12]The Rotter Locus of Control Scale measures the degree of control individuals feel they possess over their life, and the Rosenberg Self-Esteem Scale aims at reflecting the degree of approval or disapproval towards oneself. These measures have been commonly used in previous works as measures of non-cognitive skills (Speer, 2017; Lise and Robin, 2017; Guvenen et al., 2020). For more details, see Heckman, Stixrud and Urzua (2006).



(a) By angular distance to Economist

(b) By job rung quintiles

Figure G.1: Examples of occupations inside and outside "Economist" cone. *Notes.*—Blue dots correspond to occupations classified within the same career.

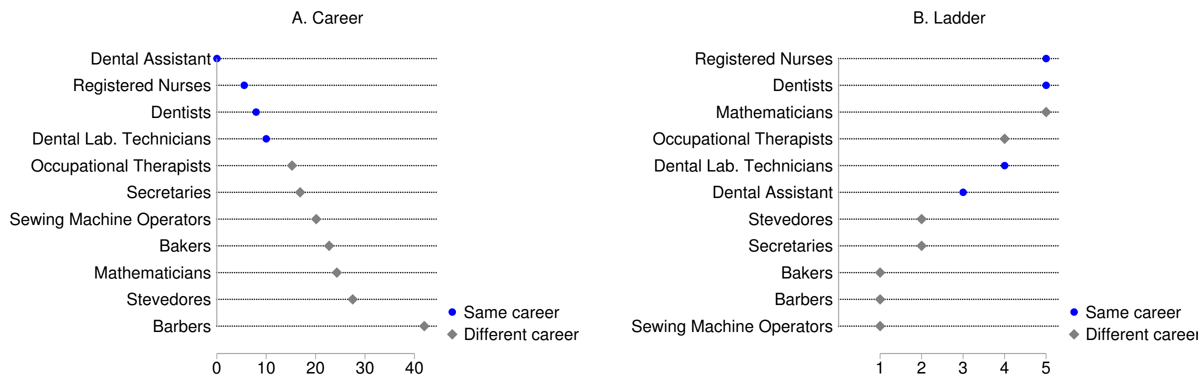
G On Skill-based Definition of Careers

This appendix examines in further detail our skill-based definition of careers. We present examples that illustrate how our definition classifies occupations across different careers; we assess the prevalence of radical vs. gradual career switches; we compare our skill-based measure of career mobility with alternative measures; and finally, we show that the cyclicality of career mobility is primarily driven by job transitions that go through unemployment.

G.1 Illustrative Examples of Career Mobility

We begin presenting two examples of career mobility identified through our angular measure. The first example fixes the requirement vector of the 3-digit occupation $\boldsymbol{q}_1 =$ "Economist" and considers a selection of 3-digit occupational titles with requirement vectors $\boldsymbol{q}_2$. According to our skill-based criterion, these occupations are classified within the same career as an "Economist" if their angular distance $\varphi(\boldsymbol{q}_1, \boldsymbol{q}_2)$ is smaller than the calibrated threshold $\bar{\varphi} = 14.8°$. Figure G.1a plots the angular distances for these occupations relative to an "Economist". By definition, the angular distance from "Economist" to "Economist" is zero. In this example, "Actuaries", "Financial Managers", "Data Entry Keyers" and "Mathematicians and Statisticians" fall inside the "Economist" cone (blue dots) and, hence, transitions from "Economist" to any of these occupations are classified within the same career. In contrast, transitions to occupations that fall outside this cone (gray diamonds), such as "Cooks", are classified as a career switch relative to a "Economist".

To assess movement up and down the job ladder, Figure G.1b plots the same set of



(a) By angular distance to Dental Assistant

(b) By job rung quintiles

Figure G.2: Examples of occupations inside and outside "Dental Assistant" cone. *Notes.*—Blue dots correspond to occupations classified within the same career.

occupational titles according to their position in the job ladder, measured by the corresponding quintile in the job rung distribution. Within the "Economist" cone, "Actuaries"and "Mathematicians and Statisticians" are top-tier occupations (5th quintile) while "Financial Managers" (4th quintile) and "Data Entry Keyers" (2nd quintile) are lower-tier occupations. Changing jobs to any of the latter occupations would entail a movement down the job ladder within the same career.

Figures G.2a and G.2b present a second illustrative example for the occupation $\boldsymbol{q}_1 =$ "Dental Assistant". According to our skill-based definition, if a "Dental Assistant" becomes a "Dental laboratory technician", a "Dentist" or a "registered nurse", this is interpreted as a movement up the job ladder: the skill-mix required by any of those occupations is fairly similar to a "Dental Assistant", but the task complexity is increased. In contrast, if a "Dental Assistant" becomes, say, a "Baker", this is interpreted as a career switch.

G.2 Gradual Career Transitions

Our approach to measuring career mobility identifies large changes in the occupation requirements that occur at distinct points of time. One implication of this approach is that career switches if broken down to a sequence of small steps may not constitute a distinct career switch at any point of time.

In the following, we explore the empirical prevalence of such "gradual" career transitions. To do so, fixing an integer N, we first construct the sample of all N consecutive job transitions in the NLSY79 which do not constitute a career-transition according to our measure. That is, letting $\boldsymbol{Q}_N \equiv \{\boldsymbol{q}_s\}_{s\in\{0,1,\ldots,N\}}$ denote the job requirements of $N+1$ consecutive jobs of a

Table G.1: Gradual job transitions

N	4	5	6	7	8
$\Pr[\varphi(\boldsymbol{q}_0, \boldsymbol{q}_N) < \bar{\varphi}]$	0.82	0.82	0.82	0.82	0.81

Notes.—The table shows the fraction of transition paths for which the final job falls within the cone of the original job; i.e., $\varphi(\boldsymbol{q}_0, \boldsymbol{q}_N) < \bar{\varphi}$.

Table G.2: Cyclicality of career mobility under alternative definitions of a career

	skill-based	1-digit	2-digit	3-digit	1-digit (SOC)	k-means
career mobility	.42	.50	.50	.61	.50	0.45
excess cyclicality	.07	.04	.04	.03	.04	0.04
corr. with skill-based	1.00	.64	.64	.69	.64	0.75

Notes.—First row shows the unconditional career switching propensity (in percent). Second row shows the cyclicality of career mobility, computed as the difference in career mobility in recessions to expansions (in p.p.). Third row shows the correlation of different career mobility measures with our skill-based definition.

given worker, our sample contains the universe of all $\boldsymbol{Q}_N$ such that each individual transition satisfies $\varphi(\boldsymbol{q}_{s-1}, \boldsymbol{q}_s) < \bar{\varphi}$ for all $s \in \{1, 2, \ldots, N\}$. Equipped with this sample, we then re-apply our criterion to the initial and final job, and compute the fraction of samples for which $\varphi(\boldsymbol{q}_0, \boldsymbol{q}_N) < \bar{\varphi}$. Table G.1 reports the results for different values of N. In all cases, we find a moderate prevalence of gradual career transitions of 18–19%. By contrast, for the majority of within-career job sequences the final job falls within the cone of the initial job.

G.3 Comparison With Alternative Definitions of Careers

Here we compare our skill-based measure of career mobility with alternative measures. In particular, we compare it with the following alternative criteria to define careers: 1-digit, 2-digit, or 3-digit occupational codes from Autor and Dorn (2013); 1-digit occupations from the Standard Occupational Classification (SOC); and a classification derived from a k-means algorithm that groups occupations into different careers such that the angular distance to the average skill-requirement in a career is minimized (specifically, we choose the number of clusters to be $k = 6$ that delivers an unconditional career mobility rate of 45%, closely matching the career mobility rate of 42.2% obtained under our skill-based definition). The exercise considers the universe of job transitions and for each transition determines whether or not it is registered as a career transition according to these alternative criteria.

Table G.2 summarizes the comparison. Overall, we see significant differences across these classifications. While all measures are moderately correlated with our baseline measure, with

Table G.3: Cyclicality of career mobility by type of job transition

Transition type	Fraction of all job transitions	Fraction of all career switches	Excess cyclicality
EUE'	.56	.48	.08
EE'	.44	.52	-.01
Total (EUE' + EE')	1.00	1.00	.07

Notes.—Job transitions and career switches by type of job transition. EUE' refers to job transitions that undergo an unemployment spell. EE' refers to direct job-to-job transitions. Excess cyclicality is computed as career switching rate in recessions minus expansions.

correlations ranging from .64 to .75, there are significant differences in the average propensities to switch careers, ranging from .42 to .61. Interestingly, however, despite these differences, all measures imply countercyclical career mobility.

G.4 Cyclicality in Career Mobility By Transition Type

According to our model, the cyclicality of career mobility is intrinsically tied to job transitions through unemployment. We note that this prediction is not driven by our restriction on career transitions.[13] This is because it is precisely the workers that are cleansed from their jobs that cause the increase in career switching during recessions.

To assess this implication of the model, we decompose the empirical cyclicality of career mobility into its cyclicality among transitions through unemployment (EUE') and job-to-job transitions (EE'). Table G.3 shows the decomposition. Consistent with the predictions of the model, the overall cyclicality (+0.07 percentage points in recessions) is exclusively driven by countercyclicality in EUE' transitions (+0.08 percentage points), whereas the propensity to switch careers among EE' transitions is roughly acyclical (-0.01 percentage points).

H On Mismatch Cyclicality

This appendix presents additional empirical results and robustness checks on the cyclicality of mismatch. We show a time series for aggregate mismatch; we examine the cyclical properties of mismatch using alternative business cycle indicators; we assess mismatch cyclicality for

[13] Our model assumes that workers can switch careers exclusively through a spell of unemployment. While in reality, of course, some career switches occur through job-to-job transitions, this assumption is meant to capture that switching careers is more costly and time intensive than other job-to-job transitions. For instance, professional networks are naturally centered around current and past careers, facilitating within-career switches or even giving rise to entirely unsolicited offers. By contrast, career-switching arguably requires a more active search. Our restriction on career-switching captures this, in reduced form, by forcing employed workers to quit their job and search "full time" when seeking a career change.

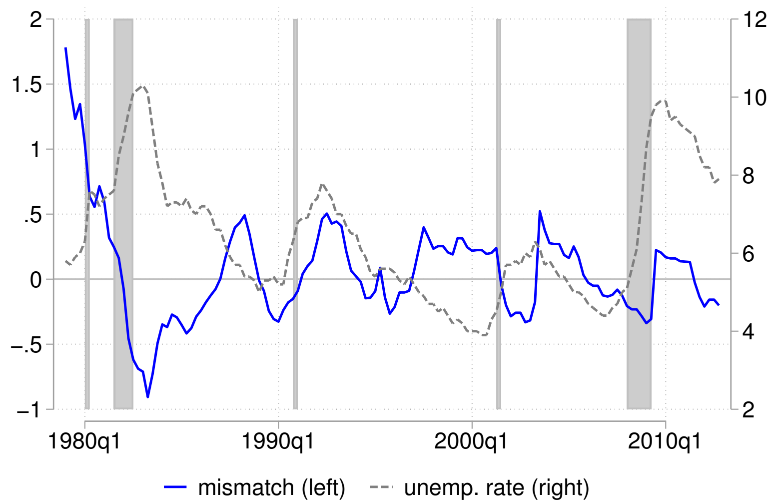


Figure H.1: Time series of aggregate mismatch and the unemployment rate. *Notes.*—The figure shows time series of residualized mismatch (left scale, controlled by the baseline regression controls) and the unemployment rate (right scale, in percentage points). Shaded regions correspond to NBER-defined recessions.

job-to-job movers; we present a robustness check using the two cohorts of the NLSY data; and finally, we show the cyclical properties of mismatch for each of the four underlying skill dimensions (math, verbal, technical and social skills).

H.1 Aggregate mismatch cyclicality

Figure H.1 plots time series of aggregate mismatch and the unemployment rate. To construct the aggregate mismatch series (left scale), we residualize mismatch with respect to the controls from the baseline regression (12), and then compute a symmetric 2-quarter moving average to smooth the series from seasonal fluctuations.

By construction, the mismatch series is centered around zero. For most of the sample period, we observe a negative correlation between mismatch and the unemployment rate, with two notable exceptions: the period around the 1990-1991 recession, and the years prior to the Great Recession where both series are declining.

For comparison, the shaded regions indicate NBER-defined recessions. Both the unemployment rate and mismatch are lagging the NBER-defined recessions. We further explore this in Appendix H.2.

H.2 Alternative cyclical indicators

Our baseline recession indicator defines recessions as times when the unemployment rate exceeds its long-term average of about 6.5%. Using an unemployment-defined cyclical indicator is natural for our purpose because, by definition, fluctuations in mismatch are tied to job flows, especially in and out of unemployment.

Here, we examine the cyclical properties of mismatch using alternative business cycle indicators: (A) unemployment rate, (B) HP-filtered unemployment rate, (C) NBER recession indicator (applied to all months within a quarter), and (D) 4-quarter lag of the NBER recession indicator. We repeat the main regression for mismatch cyclicality in (12) using these four alternative measure of the business cycle.

Table H.1 presents the results. In Panels A and B we use unemployment-related indicators and confirm our baseline results: total mismatch is procyclical; the procyclicality of total mismatch is primarily driven by underqualified workers being laid-off in recessions; and new hires from unemployment have countercyclical fluctuations in mismatch.

Next, we examine mismatch cyclicality using the NBER-defined indicators. When using the contemporaneous NBER indicator (Panel C) we obtain insignificant coefficients. In contrast, when using the lagged NBER indicator (Panel D) the coefficients are highly significant and comparable in size to our baseline results. These results are explained by the lag in unemployment compared to the NBER recession indicator as visible in Figure H.1.[14] As argued above, this matters, because fluctuations in mismatch are intrinsically tied to job flows, explaining why it is the lagged NBER indicator that is significantly correlated with mismatch.

In summary, we conclude that mismatch contemporaneously correlates with unemployment measures, while it correlates with the lagged NBER indicator.

H.3 HP-filtered Mismatch

Our baseline regression controls for time- and age-trends by controlling for 5-yearly fixed effects and a polynomial in workers age. Here we explore an alternative, in which we explicitly extract the business cycle component in mismatch. To do so, we first aggregate mismatch across workers in order to isolate an aggregate time trend using a standard HP-filter with $\lambda = 129,600$ (based on the monthly frequency adjustment advocated by Ravn and Uhlig, 2002). We then subtract this trend from the cross-sectional panel data used in our estimation framework. Table H.2 reports the results from this exercise. The results closely resemble the

[14]The contemporaneous correlation between the unemployment rate and the NBER indicator is 0.12, while

Table H.1: Cyclicality of mismatch in the data: Alternative cyclical indicators

Dependent variable ($\times$100):	$m_{i,t}$ (1)	$m^{+}_{i,t}$ (2)	$m^{-}_{i,t}$ (3)
Panel A: Unemp. rate			
Job stayers ($\beta_1 + \beta_2$)	-0.167^{***}	-0.047	-0.120^{***}
	(0.056)	(0.041)	(0.038)
New hires ($\beta_1 + \beta_3$)	0.247^{**}	0.140^{*}	0.107^{*}
	(0.100)	(0.072)	(0.065)
Total cyclicality	-0.147^{***}	-0.037	-0.110^{***}
	(0.055)	(0.041)	(0.037)
Panel B: Unemp. rate deviations			
Job stayers ($\beta_1 + \beta_2$)	-0.123	-0.013	-0.110^{**}
	(0.084)	(0.064)	(0.054)
New hires ($\beta_1 + \beta_3$)	0.371	0.172	0.198
	(0.239)	(0.178)	(0.149)
Total cyclicality	-0.091	-0.006	-0.084
	(0.082)	(0.063)	(0.053)
Panel C: NBER			
Job stayers ($\beta_1 + \beta_2$)	-0.075	-0.060	-0.015
	(0.112)	(0.083)	(0.075)
New hires ($\beta_1 + \beta_3$)	-0.124	-0.287	0.162
	(0.332)	(0.244)	(0.198)
Total cyclicality	-0.075	-0.064	-0.011
	(0.109)	(0.081)	(0.072)
Panel D: NBER lagged			
Job stayers ($\beta_1 + \beta_2$)	-0.198^{**}	-0.065	-0.133^{**}
	(0.090)	(0.067)	(0.059)
New hires ($\beta_1 + \beta_3$)	1.061^{***}	0.695^{***}	0.366^{*}
	(0.329)	(0.249)	(0.204)
Total cyclicality	-0.150^{*}	-0.046	-0.104^{*}
	(0.090)	(0.066)	(0.059)

Notes.—Standard errors clustered at the worker level are in parenthesis. Asterisks, *, **, ***, indicate coefficients that are significantly different from 0 at the 10%, 5%, 1% level, respectively. Dependent variables are multiplied by 100 (so mismatch ranges from 0 to 100). Panel A and B include yearly fixed effects.

Table H.2: Cyclicality of mismatch in the data: HP-filtered mismatch

Dependent variable (×100):	$m_{i,t}$ (1)	$m^+_{i,t}$ (2)	$m^-_{i,t}$ (3)
Job stayers ($\beta_1 + \beta_2$)	-0.329^{**}	-0.107	-0.222^{*}
	(0.145)	(0.124)	(0.119)
New hires ($\beta_1 + \beta_3$)	0.975^{***}	1.059^{***}	-0.084
	(0.300)	(0.273)	(0.214)
Total cyclicality	-0.260^{*}	-0.026	-0.234^{**}
	(0.146)	(0.124)	(0.118)

Notes.—Standard errors clustered at the worker level are in parenthesis. Asterisks, *, **, ***, indicate coefficients that are significantly different from 0 at the 10%, 5%, 1% level, respectively. Dependent variables are multiplied by 100 (so mismatch ranges from 0 to 100).

Table H.3: Cyclicality of mismatch among job-to-job transitions in the data

Dependent variable (×100):	$m_{i,t}$ (1)	$m^+_{i,t}$ (2)	$m^-_{i,t}$ (3)
Job-to-job transitions (β_1)	0.265	0.442^{**}	-0.177
	(0.293)	(0.215)	(0.200)

Notes.—Standard errors clustered at the worker level are in parenthesis. Asterisks, *, **, ***, indicate coefficients that are significantly different from 0 at the 10%, 5%, 1% level, respectively. Dependent variables are multiplied by 100 (so mismatch ranges from 0 to 100).

baseline case. Mismatch among job stayers is countercyclical, largely due to countercyclicality in underqualification, whereas mismatch among new hires is procyclical, largely due to procylicality in overqualification. The main differences are that the procyclicality among new hires is now even more pronounced and that underqualification among new hires is now mildly countercyclical as opposed to mildly procyclical (in either case, it is statistically insignificant in our limited sample).

H.4 Job-to-Job Transitions

Our model has sharp predictions for mismatch cyclicality among job stayers and new hires from unemployment, which are corroborated in the data and reported in the main body in Table 4. Here we supplement the analysis with empirical observations of mismatch cyclicality for job-to-job movers. Table H.3 shows the impact of a recession on mismatch among job-to-job movers, as captured by β_1 in specification (12). We obtain significant countercyclical fluctuations in positive mismatch. This observation is consistent with procyclical upgrading of match quality driven by job-to-job transitions, as examined by Gertler, Huckfeldt and Trigari

the cross-autocorrelation between the unemployment rate and the lagged NBER indicator is 0.5.

Table H.4: Cyclicality of mismatch in the data: NLSY79 and NLSY97

Dependent variable (×100):	$m_{i,t}$ (1)	$m^{+}_{i,t}$ (2)	$m^{-}_{i,t}$ (3)
Job stayers ($\beta_1 + \beta_2$)	-0.272^{**}	-0.013	-0.259^{***}
	(0.114)	(0.080)	(0.076)
New hires ($\beta_1 + \beta_3$)	0.542^{**}	0.491^{***}	0.051
	(0.234)	(0.168)	(0.144)
Total cyclicality	-0.242^{**}	0.010	-0.252^{***}
	(0.113)	(0.080)	(0.075)

Notes.—Standard errors clustered at the worker level are in parenthesis. Asterisks, *, **, ***, indicate coefficients that are significantly different from 0 at the 10%, 5%, 1% level, respectively. Dependent variables are multiplied by 100 (so mismatch ranges from 0 to 100).

(2020). While we see a significant increase in overqualification during recessions, we do not see a significant impact on underqualification or total mismatch among job-to-job movers.

H.5 Two cohorts: NLSY79 and NLSY97

For our baseline estimates, we only use data from the NLSY 1979 cohort. The reason is that the 1997 cohort does not contain data on the Rotter Locus of Control Scale and the Rosenberg Self-Esteem Scale, which we use to construct a measure of social ability and which is found to be a key predictor of labor market outcomes by Guvenen et al. (2020) and Lise and Postel-Vinay (2020). Here, we replicate the mismatch cyclicality results extending the data to include the 1997 cohort. Due to the lack of data needed to measure social ability in the 1997 survey, mismatch now only comprises math, verbal, and technical skills. Table H.4 presents the results which are analogue to those in Table 4 in the main text. Overall, the coefficients are very similar across both samples. We conclude that our results are robust to including one or two cohorts.

H.6 By Skill Dimension

In the main text, we assess the cyclicality of a mismatch index, defined in (10), which aggregates mismatch across four skill dimensions using market weights. Here, we examine the cyclical properties of mismatch for each skill dimension: math, verbal, technical and social. We do so by running the same empirical specification as in (12) but separately by skill. Table H.5 is the analog to Table 4 in the main text. As before, we report the cyclicality of total, positive, and negative mismatch, and report coefficients separately for job stayers, new hires from unemployment, and the totality of workers.

Table H.5: Cyclicality of mismatch in the data: By skill dimension

Dependent variable (×100):	$m_{i,t}$ (1)	$m^{+}_{i,t}$ (2)	$m^{-}_{i,t}$ (3)
Panel A: Math			
Job stayers ($\beta_1 + \beta_2$)	-0.379^{***}	-0.030	-0.349^{***}
	(0.164)	(0.113)	(0.107)
New hires ($\beta_1 + \beta_3$)	0.693^{*}	0.535^{**}	0.159
	(0.376)	(0.260)	(0.231)
Total cyclicality	-0.334^{**}	-0.002	-0.332^{***}
	(0.163)	(0.113)	(0.106)
Panel B: Verbal			
Job stayers ($\beta_1 + \beta_2$)	-0.298^{*}	0.013	-0.311^{***}
	(0.160)	(0.107)	(0.102)
New hires ($\beta_1 + \beta_3$)	0.986^{***}	0.741^{***}	0.245
	(0.366)	(0.244)	(0.224)
Total cyclicality	-0.235	0.052	-0.288^{***}
	(0.159)	(0.107)	(0.102)
Panel C: Technical			
Job stayers ($\beta_1 + \beta_2$)	-0.273	0.028	-0.301^{***}
	(0.167)	(0.123)	(0.107)
New hires ($\beta_1 + \beta_3$)	0.006	0.089	-0.083
	(0.367)	(0.268)	(0.237)
Total cyclicality	-0.247	0.044	-0.290^{***}
	(0.166)	(0.122)	(0.107)
Panel D: Social			
Job stayers ($\beta_1 + \beta_2$)	-0.044	0.152	-0.196^{*}
	(0.160)	(0.107)	(0.114)
New hires ($\beta_1 + \beta_3$)	0.551	0.413^{*}	0.138
	(0.372)	(0.250)	(0.247)
Total cyclicality	-0.012	0.167	-0.179
	(0.159)	(0.107)	(0.113)

Notes.—Standard errors clustered at the worker level are in parenthesis. Asterisks, *, **, ***, indicate coefficients that are significantly different from 0 at the 10%, 5%, 1% level, respectively. Dependent variables are multiplied by 100 (so mismatch ranges from 0 to 100).

Overall, mismatch cyclicality by skill dimension has the same cyclical properties as total mismatch. For each skill dimensions, we consistently obtain procyclical mismatch among job stayers (first row of each panel), that is, mismatch decreases for job stayers in recessions and the decline is entirely driven by layoffs of underqualified workers (those with negative mismatch, column 3). Additionally, we obtain countercyclical mismatch among new hires from unemployment (second row of each panel), in this case driven by more overqualified workers finding jobs in recessions than in expansions (those with positive mismatch, column 2). Finally, total mismatch is procyclical (third row of each panel), as before. While all skill dimensions show similar cyclical properties, math and verbal skills are the ones with the highest statistical significance.

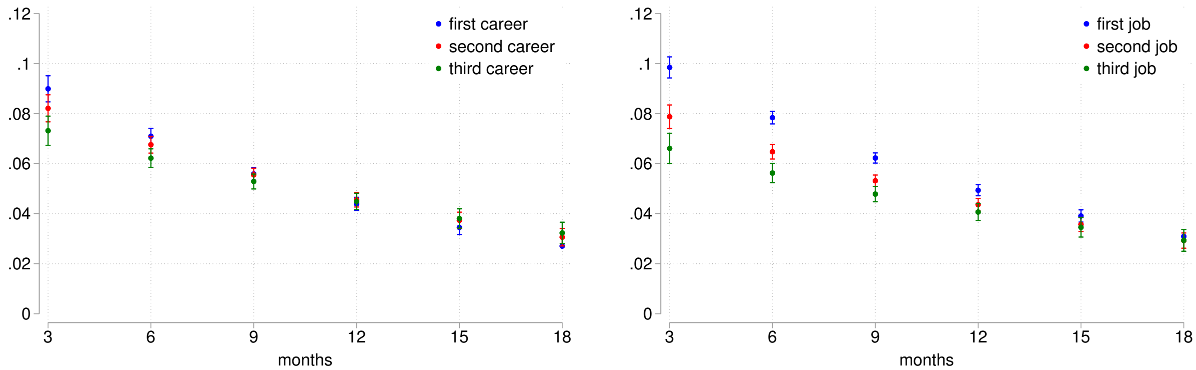
I Across-career vs. Within-career Experiences

This appendix provides further suggestive evidence on the assumptions, mechanisms, and implications of our learning model. Our model assumes that learning is geared towards workers' ability in their *current* career. Moreover, for simplicity, we further assume that ability is uncorrelated across careers (but have noted that this assumption is not essential). Using the NLSY data, we present various pieces of evidence that validate these assumptions and, furthermore, corroborate key implications of the model on the difference between career switches and job transitions within a career.

I.1 Evidence from Job Separation Hazards

In the model, we make the simplifying assumption that skills are independent *across* careers. This assumption implies that the separation hazard should be independent of the number of careers previously held by a worker. Figure I.1a shows that this is indeed the case in the data. It plots the job separation hazard conditional on the number of careers held. Corroborating the independence assumption, there are no significant differences between the separation hazards for the first, second, and third career.

In contrast, the model implies that learning *within* careers is a relevant factor and thus one would expect that job separation hazards would depend on prior work experience *within* that same career. Figure I.1b confirms this prediction by plotting the job separation hazard conditional on the number of jobs held by a worker within the same career. We observe that the separation hazard for the first job in a career is significantly larger than for subsequent jobs in the same career; moreover, the separation hazard declines at a steeper rate for the first job in a career, consistent with uncertainty being highest at the beginning of a career.



(a) By number of careers previously held

(b) By number of jobs within same career

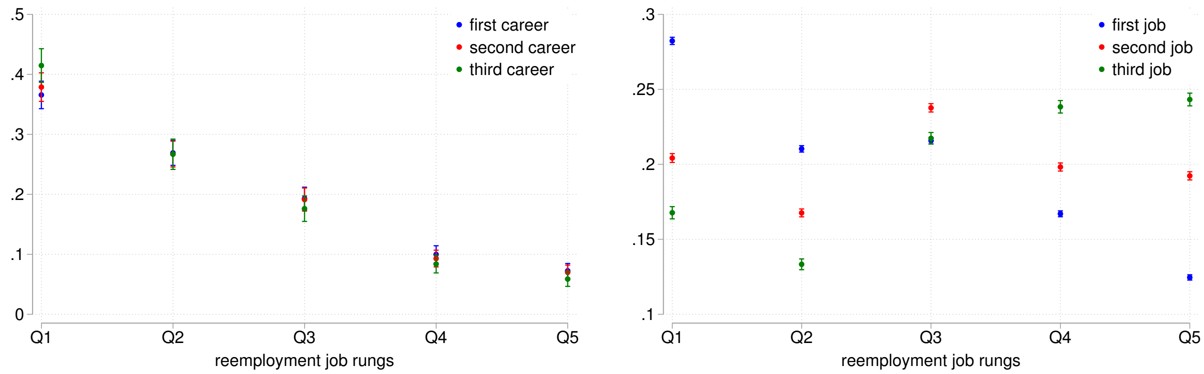
Figure I.1: Job separation hazards by number of careers (panel a) and for subsequent jobs within the same career (panel b). *Notes.*—Separation hazards include EU and EE' transitions and assume a linear baseline hazard. Error bars indicate 95% confidence intervals. All moments are residualized with respect to race, gender, education, region of residence, a quadratic polynomial in age, and month and 5-year fixed effects.

I.2 Evidence from Distributions of Reemployment Job Rungs

Next, we use the distribution of reemployment job rungs to provide additional indirect evidence. As with the separation hazards, uncorrelated learning across careers implies that the distribution of reemployment job rungs should be independent of the number of careers. This is indeed confirmed in Figure I.2a, where we observe that the likelihood to start at any job rung is independent of the number of careers previously held.

In particular, regardless of the number of careers held before, upon a career switch a worker is always more likely to start at the bottom of the job ladder, consistent with the predictions of the model. Figure I.3 further substantiates this finding, showing that the tendency of workers to start at the bottom job rung after career-switches holds *independently of their job rung in the previous career*. This fact supports our prediction that career switches entail restarting learning about untried skills and thus workers optimally aim for jobs at the bottom of the new job ladder.

Regarding *within* career transitions, Figure I.2b shows that the distribution of reemployment job rungs within a career is affected by the number of previously held jobs, consistent with learning within careers. This distribution is initially skewed towards the lowest job rung and becomes increasingly skewed towards the highest job rung as career tenure increases. These observations are consistent with the predictions of the model: Short-tenure workers are more likely to start at the bottom of the job ladder while long-tenure workers are more likely to get reemployed at higher rungs as explored in Section 4.



(a) By number of careers previously held **(b)** By number of jobs within same career

Figure I.2: Distribution of reemployment job rungs. *Notes.*—Error bars indicate 95% confidence intervals. Include EU and EE' transitions. All moments are residualized with respect to race, gender, education, region of residence, a quadratic polynomial in age, and month and 5-year fixed effects.

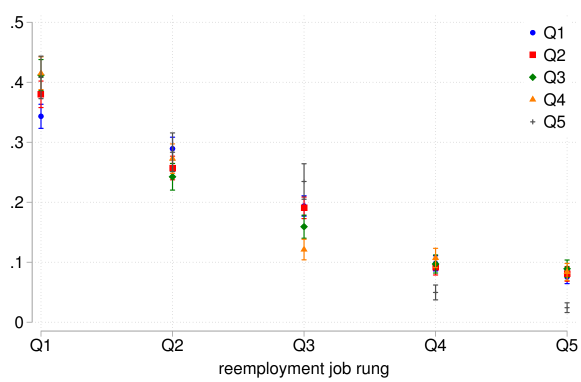


Figure I.3: Reemployment job rungs for career switchers, conditional on previous position in the job ladder (by rung quintiles). *Notes.*—Error bars indicate 95% confidence intervals. Transitions include EUE' and EE' transitions. All moments are residualized with respect to age, gender, race, education, region, industry, and 5-year fixed effects

Table I.1: Empirical distribution of mismatch across job rungs

Quintile of $r_{i,t}$	$m_{i,t}$	$m^{+}_{i,t}$	$m^{-}_{i,t}$
Q1	2.01	7.78	−5.77
Q2	−0.72	2.09	−2.80
Q3	−0.96	−1.47	0.52
Q4	−1.55	−4.28	2.73
Q5	0.73	−6.07	6.81

Notes.—Mismatch is residualized with respect to region, a quadratic polynomial in age, and individual, month and 5-yearly fixed effects.

I.3 Evidence from the Distribution of Mismatch Across Job Rungs

Finally, our model predicts that, with the exception of the highest job rung, mismatch is declining in job rungs. Moreover, the decline is driven by a decline in overqualification, whereas underqualification becomes relatively more important at higher job rungs (c.f. Figure 6b). To explore this prediction, we use the generalized model introduced in Section 3.1 to assign a task complexity $r_{i,t}$ to each job. We then compute the average mismatch (residualized with respect to region, a quadratic polynomial in age, and individual, month and 5-yearly fixed effects) for each quintile of the task complexity distribution. Table I.1 reports the results. Consistent with the model, total mismatch is declining across job rungs with the exception of the highest job rung, and the decline is driven by overqualification.

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