Mismatch Cycles*

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Abstract

We document new facts about the cyclicality of worker–occupation mismatch in the US. In downturns, under-qualified workers are more likely to lose their jobs, consistent with the cleansing effect of recessions. Surprisingly, new hires from unemployment are also more mismatched in recessions, and this holds true for over- *and* under-qualification. We build a directed search model, with on-the-job learning about worker skills. Skills are multidimensional and workers select into careers (tasks) based on what they believe to be their comparative advantages. The model explains, simultaneously, the empirical patterns on mismatch and career switching.

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1 Introduction

Over the business cycle, economies face a large amount of reallocation: firms enter and exit, plants are built and destroyed, and workers change jobs and occupations. How do recessions affect resource allocation? In particular, does the mismatch between workers' abilities and the requirements in their occupations increases when jobs are scarce, or is it the opposite? In this paper, we shed light on these questions by documenting new facts on occupational mismatch and switching along the business cycle and constructing a model with information frictions that accounts for the empirical regularities.

Using a direct measure of skill mismatch—the difference between a worker's abilities in different skills and how intensive these skills required by their job—we show that average mismatch in the US economy is procyclical: in recessions, workers' skills are more aligned with job requirements. However, we uncover two important differences depending on the previous employment status. On the one hand, mismatch decreases in recessions for job stayers: they are less under-qualified for their job. On the other hand, mismatch increases in recessions for new hires from unemployment; these workers are both more over-qualified and under-qualified for their job. This evidence suggests that, during recessions, the worst matches are destroyed, consistent with the *cleansing effect* of recessions, but at the same time, highly mismatched jobs are created, consistent with a *sullying effect* of recessions. Besides the evidence on mismatch, we document that new hires from unemployed are more likely to changed occupations in recessions.

To jointly understand these facts, we build a model with three key elements: (i) workers' occupation-specific abilities are unobserved and are learned over time; (ii) the labor market is characterized by directed search protocol; and (iii) there are fixed costs to switch occupation. In this setup, when a match starts, there is a lot of uncertainty about the worker's skills. As long as the worker remains employed in jobs within the same occupation, worker-firm pairs keep learning about the occupation-specific abilities of the worker through noisy signals, and uncertainty decreases over time. If the ability estimate gets close to the job's requirement (perceived mismatch is small), jobs continue; but if the estimate drifts away from the job's requirement, the match efficiently separates.

After a separation, given the ability estimate and the uncertainty surrounding it, workers decide to direct their search to jobs within the same occupation or to pay a cost and switch their occupation. The key assumption is that a worker only learns about her abilities in the skills required by an occupation, thus when a worker switches occupations, it starts learning about new skills. The estimate of occupation-specific ability goes back to its prior and learning must be restarted.

In this setup, we study the impact of an aggregate negative productivity shock. Lower productivity makes mismatch less tolerable, destroying worker-firm matches with high levels of *perceived* mismatch. At the same, a higher fraction of unemployed workers switch occupations endogenously in recessions, and as a consequence, there is a larger mass of jobs that with high uncertainty, generating mistakenly bad matches. This countercyclical information friction reconciles the fact that in recessions, jobs with high perceived mismatch are destroyed, while matches with high unperceived mismatch are created.

Empirical strategy. We study the cyclical behavior of mismatch using a worker-level panel from the 1979 National Longitudinal Study of Youth (NLSY79) between 1979 and 2012. We adapt the index developed in Guvenen, Kuruscu, Tanaka and Wiczer (2018) as a direct measure of skill mismatch.[1] This measure is defined as the difference between a worker's abilities in different skills (e.g. math, verbal) and how intensive these skills required by a job. The larger is this difference, the lower is the quality of a match.

$$\text{Mismatch} = |\text{ worker's abilities - job requirements}|$$

To construct this index, we combine occupational-level data from O*NET with data on workers' employment spells, occupations, and abilities, the latter are obtained from cognitive and non-cognitive tests. Then, we estimate the effect of economic conditions on mismatch by exploiting within-individual variation in mismatch and aggregate unemployment rate across employment spells. Our results show a robust negative association between aggregate unemployment rate and mismatch. This result holds true across industries, occupations, and various measures of economic activity. One advantage of using this mismatch index is that it allows us to isolate the effect of business cycle conditions on the mismatch of ongoing job relationships versus its effect on newly formed relationships. In doing so, we uncover important heterogeneity along previous employment status, as explained earlier. This measure also allows to decompose the mismatch index into positive and negative mismatch, which allows us to capture different cyclical patters for over- and under-qualification.

Related literature Our empirical evidence suggests that during recessions the worst matches are destroyed. The matching model with endogenous separations in Mortensen and Pissarides (1994) can explain the *cleansing effect*: in recessions, reservation match quality increases, low quality matches are destroyed, decreasing average mismatch. However, according to this model, only high-quality matches are formed, meaning that mismatch should also be lower on average for new hires. This goes against our finding that highly mismatched jobs are also created in recessions. This *sullying effect* of recessions may arises in the job-ladder model of Barlevy (2002) or the competition forces in Moscarini (2001). However, none of these mechanisms on their own would give rise to both over- and under-qualification. We contribute by developing a learning model with directed search and switching costs that is able to speak jointly about the empirical regularities.

Our work builds on the idea that firms and workers learn about the quality of the match as it is experienced (Jovanovic, 1979; Pries, 2004; Moscarini, 2005; Borovickova, 2016). A common feature to this literature is that the learning experience about mismatch is the same over the cycle. In our model, learning experiences vary along the cycle as during recessions there is a larger fraction of matches with high uncertainty driven by countercyclical occupational switching. While there are some papers that study the role of uncertainty on labor market flows (Lin, 2014; Leduc and Liu, 2016; Pries, 2016; Schaal, 2017), ours is the first that explores occupational switching as the source of endogenous uncertainty and its effects on labor market outcomes.

[1] Guvenen, Kuruscu, Tanaka and Wiczer (2018) use the index of mismatch to study the impact of match quality on wages and patterns of occupational switching. They find that mismatch decreases wages, but increases the probability of switching occupations. Thus, they argue that this mismatch index can be interpreted as a signal of the lack of job match quality.

2 Mismatch and Occupational Mobility over the Cycle

In this section we document new empirical facts about the cyclical behavior of worker-occupation mismatch and occupational switching.

2.1 Data and variable definitions

Mismatch index To measure the extent to which a worker's skills are aligned with the skills requirements of a job, we use the mismatch index developed by Guvenen *et al.* (2018). Consider that jobs and workers are characterized by J skill dimensions, $j = \{1, .., J\}$. Let $a_{i,j}$ be the measured score of worker i's ability in skill dimension j, and $r_{c_t,j}$ be the measured score of the job requirement in skill dimension j by the occupation held at time t, c_t. At a given point in time, the mismatch between individual i and his occupation c_t is measured as the sum of the absolute value of the difference between the worker's skills and the skill requirements in each dimension:

$$m_{i,c_t} \equiv \sum_{j=1}^{J} \omega_j \, |a_{i,j} - r_{c_t,j}|, \qquad \sum_{j=1}^{J} \omega_j = 1 \tag{1}$$

In the empirical analysis, $a_{i,j}$ corresponds to the the percentile rank of worker i's ability in skill dimension j and $r_{c_t,j}$ percentile rank of the job requirement in skill dimension j. Therefore, m_{i,c_t} ranges between 0 and 100, with 0 indicating a perfect match between a worker's abilities and the job skill requirements, and 100 the highest level of mismatch.[2]

Asymmetric mismatch A worker is said to be mismatched at time t whenever m_{i,c_t} is higher than zero. This may happen either because the worker is under-qualified, i.e. has a level of ability that falls short of the job's skill requirement in a given dimension ($a_{i,j} < r_{c_t,j}$), or because he is over-qualified ($a_{i,j} > r_{c_t,j}$). Given this, m_{i,c_t} can be decomposed into a measure of positive mismatch m^+_{i,c_t}, and a measure of negative mismatch, m^-_{i,c_t}:

$$m^+_{i,c_t} \equiv \sum_{j=1}^{J} \omega_j \max\{a_{i,j} - r_{c_t,j}, 0\} \qquad\qquad m^-_{i,c_t} \equiv \sum_{j=1}^{J} \omega_j \, |\min\{a_{i,j} - r_{c_t,j}, 0\}| \tag{2}$$

Empirical evidence suggests that both cognitive and non-cognitive abilities have important implications for labor market outcomes, namely for wages and occupational choice (see, for example, Heckman, Stixrud and Urzua, 2006; Lindqvist and Vestman, 2011). Therefore, for the empirical analysis, we compute the mismatch index using workers' and jobs' scores in four skills (J=4): verbal, math and

[2]In the empirical analysis, we set equal weights for all dimensions. Guvenen *et al.* (2018) instead use the factor loadings from the first principal component. The results are robust to using different weighting strategies.

technical skills to describe cognitive skills, and a social dimension that captures non-cognitive skills.[3]

Data sources To construct the mismatch index and study its behavior over the cycle, we use a worker-level panel from the NLSY79 between 1979 and 2012 combined with occupational-level data from the O*NET database and aggregate data on unemployment. The NLSY79 is a nationally representative longitudinal survey whose respondents were between the ages of 14-22 when they were first interviewed in 1979 and have been followed through the present. We focus on a sub-sample of males and females from the NLSY79 cross-sectional sample, which includes 2,991 individuals and runs from 1979 and 2012. The complete description of our sample selection criteria is in Appendix A.

Using the Work History Data File, we construct a panel data with monthly frequency reporting information on individuals' labor market history (including wages, occupation and industry for each employment spell), and their scores on the Armed Services Vocational Aptitude Battery (ASVAB) test. These scores are used to measure individual ability in each skill dimension ($a_{i,j}$). Panel A in table B.5 reports the correlation of workers' abilities across skill dimensions. The observed pattern suggests that workers with high abilities in one skill dimension tend to have high ability in the other three, in line with Guvenen *et al.* (2018) and Lise and Postel-Vinay (2016).

In this paper, an occupation is defined by Dorn (2009)'s three-digit occupational classification system, which has the advantage of being consistent over time. Examples are architects, waiters, and lawyers. We compute occupation skill requirements ($r_{c_t,j}$) using O*NET, a database that describes occupations in terms of skill and knowledge requirements.[4] The importance score of 26 out of the 277 descriptors provided by O*NET are transformed into occupation skill requirements ($r_{c_t,j}$) employing Guvenen *et al.* (2018)'s methodology.

To check whether the constructed variables characterize occupations reasonably, Table B.4 presents the percentile rank scores for selected occupations. For instance, economists require the use of the math skill more intensively, whereas lawyers require a higher the use of the verbal skill and elevator installers require mostly technical skills. These scores are consistent with the ones presented by Speer (2017) and Lise and Postel-Vinay (2016). The occupation skill requirements data and the worker-level are merged using three-digit occupational codes. Panel B in Table B.5 shows that workers tend to select themselves into jobs that fit their skill bundles best, however sorting is far from perfect.

Finally, to describe the state of the economy, we use U.S. unemployment rate measured by the civilian unemployment rate at the national level published by the Bureau of Labor Statistics (BLS).

[3] A similar definition of skills has been adopted by several recent papers on the education and labor market effects of different worker abilities (Boehm, 2015; Guvenen *et al.*, 2018; Prada and Urzúa, 2016; Lise and Postel-Vinay, 2016; Speer, 2017). To capture cognitive skills, Guvenen *et al.* (2018) use only the verbal and math dimensions, these are the two components of the Armed Forces Qualifications Test (AFQT), a score that has been extensively used as proxy of cognitive ability in the literature. We add the technical component because Prada and Urzúa (2016) show that is also determinant for labor market outcomes. Our results are robust to using the 3-skill mismatch index.

[4] The O*NET database is the successor to the Dictionary of Occupational Titles, which classified the types of tasks necessary to work in a particular occupation. The O*NET expands upon this, by providing quantitative information on several descriptors that are organized into 9 broad categories: skills, abilities, work activities, work content, experience/education level required, work values, job interests, knowledge and work styles. The scores for each descriptor are built using questionnaires that ask workers to rate their own occupation in terms of a subset of the O*NET descriptors, and a survey of occupation analysts who are asked to rate others descriptors. More information is available at http://www.onetcenter.org.

This is a widely accepted proxy of macroeconomic shocks.[5]. Appendix A contains further details on the construction of the panel and the methodology used to measure abilities and job skill requirements.

2.2 The Cyclical Behavior of Mismatch

To formally examine the dynamics of mismatch over the business cycle, we focus on the set of existing matches at time t, and estimate the following equation:

$$m_{i,c_t} = \beta_0 + \beta_1 U_t + \beta_2 EE'_{i,t} + \beta_3 UE_{i,t} + \beta_4(U_t \cdot EE'_{i,t}) + \beta_5(U_t \cdot UE_{i,t}) + \gamma' x_{i,t} + \delta_i + \delta_y + \delta_m + \varepsilon_{i,t}. \tag{3}$$

where m_{i,c_t} is the mismatch level of worker i in the occupation held at time t, $x_{i,t}$ is a set of individual controls $x_{i,t}$, which includes the region of residence, occupation, industry, and a quadratic polynomial in age; U_t is the aggregate unemployment rate in month m and year y; δ_i, δ_m, and δ_y are individual, monthly and yearly fixed effects, respectively; and $\varepsilon_{i,t}$ is the error term, which includes all unobserved determinants of mismatch for worker i at time t. To allow for a separate new hire effect for workers coming from non-employment and workers making direct job-to-job transitions, we include in our specification the following dummy variables: (i) $UE_{i,t}$, which equals one for workers with an intervening spell of non-employment at t, meaning that the worker was not working at time $t-1$[6] and reported to be employed at time t; and (ii) $EE'_{i,t}$ is a dummy for whether the worker i is making a job-to-job transition at t, which we define to be a situation where the worker was employed at time $t-1$ and t, but with a different employer.[7]

Standard errors are clustered at the individual level to allow for serial correlation.[8] Under the standard exogeneity restrictions, the effect of macroeconomic conditions in month m and year y on the level of mismatch of job-stayers is identified by β_1. If $\beta_1 > 0$, mismatch increases in downturns, i.e. mismatch is countercyclical, consistent with the *sullying effect* of recessions. Otherwise, if $\beta_1 < 0$, mismatch is procyclical, in line with the *cleansing effect* of recessions.

Identification OLS estimation of Equation (3) hinges on a sample of individuals that are employed in month m and year y. Thus, we face an endogeneity problem related to the work decision: if the distribution of the workers' skills changes systematically with the business cycle for other reasons not related to macroeconomic shocks, that could generate a positive (negative) association between economic conditions and mismatch, which would be mistakenly interpreted as match quality being procyclical (countercyclical). To tackle the problem of selection into employment, we exploit within-individual variation in business cycle conditions across months when the individual is reported to be

[5] We also investigate the robustness of the results to alternatives choices such as the difference of the unemployment rate from its Hodrick-Prescott filter, the composite Help-Wanted Index developed by Barnichon (2010), and the Industrial Production Index. Table B.2 reports summary statistics on the main variables used in the empirical analysis

[6] We define a worker to be in non-employment if she reported to be not working, unemployed or out of the labor force.

[7] Transitions from non-employment to employment include *recalls*, workers that return to their previous employer after a jobless spell. For robustness, in Appendix C we also consider different measures of what constitutes a new hire from non-employment.

[8] By clustering the standard errors at the individual level, observations may be correlated within each individual, but must be independent across individuals. However, common shocks such as the business cycles may induce correlation between individuals at a moment in time. The results are robust to the inclusion of standard errors clustered at the month-year level and double clustered at the month-year and individual level instead.

employed. Under the assumption that the selection process across individuals is constant over time, the inclusion of individual fixed effects restores the orthogonality condition violated by the operation of the selection process.

Results We first estimate Equation (3) without the interaction terms. OLS estimates are given in Panel A in Table 1. Column 1 shows a negative relationship between economic conditions and mismatch, i.e mismatch is procyclical. This is consistent with the *cleansing effect* of recessions as suggested by the matching model with endogenous separations in Mortensen and Pissarides (1994). To illustrate the magnitude of the point estimates, an increase in unemployment from the 50^{th} to the 90^{th} percentile is associated with a 1.84% decrease in mismatch. Columns 2 and 3 show that mismatch between workers and jobs diminishes because workers are less under-qualified for the job: for positive mismatch (column 2), the estimated coefficient on the unemployment rate is statistically insignificant, while for negative mismatch (column 3) the coefficient is negative and statistically significant. Table B.6 and B.7 show our results for different combinations of controls, and for mismatch in each skill separately.

Panel B in Table 1 provides points estimates of the coefficients of interest when we separate between job-stayers, job-to-job transitions and new hires from unemployment. Three results stand out. First, mismatch is, on average, larger for new hires from unemployment (column 1 shows that $\beta_3 > \beta_2 > 0$). Second, an increase in unemployment is associated with a decrease in mismatch for job-stayers, but with an increase in mismatch for new hires from unemployment: β_1 remains negative, and the sum $\beta_1 + \beta_5$ is positive and statistically different from zero, as reported in Panel C. Third, columns 2 and 3 show that while the decrease in mismatch for job stayers is only driven by negative mismatch, the increase in mismatch for new hires from unemployment is supported by an increase in both over- and under-qualification.

Interestingly, our results show that for job-to-job transitions mismatch is acyclical, i.e. the sum $\beta_1 + \beta_4$ is not statistically different from zero (Panel C, Table 1). All in all, our findings suggest that even though, on the aggregate, the cleansing effect dominates the sullying effect, both are present in the data. In particular, an increase in the unemployment rate from the 50^{th} to the 90^{th} percentile, is associated with a 1.86% decrease in mismatch for workers in ongoing job relationships, and a 2.56% increase in mismatch for new hires from unemployment. This latter result is in line with the findings from the extensive empirical literature that uses indirect measures of mismatch, such as earnings or job duration, and focus on the flow of new matches to argue that mismatch is countercyclical.

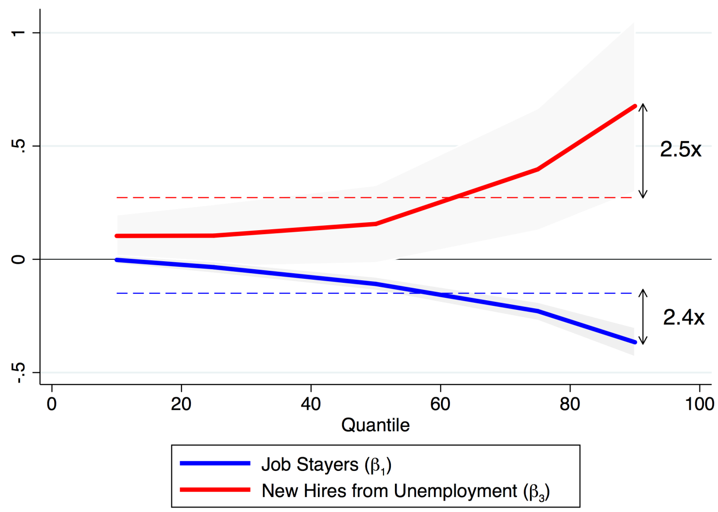
Table 1: MISMATCH AND THE BUSINESS CYCLE

Dependent Variable:	m_{i,c_t}	m^{+}_{i,c_t}	m^{-}_{i,c_t}
	(1)	(2)	(3)
Panel A: No Heterogeneity			
(β_1) Unemployment$_t$	-0.141***	-0.041	-0.099***
	(0.050)	(0.037)	(0.035)
Observations	510788	510788	510788
Adjusted R^2	0.500	0.771	0.763
Panel B: Heterogeneity			
(β_1) Unemployment$_t$	-0.159***	-0.050	-0.109***
	(0.050)	(0.038)	(0.035)
(β_2) EE'$_{i,t}$	0.245*	0.159*	0.086
	(0.133)	(0.096)	(0.096)
(β_3) UE$_{i,t}$	0.414***	0.482***	-0.068
	(0.135)	(0.096)	(0.092)
(β_4) EE'$_{i,t}$ $\times$ Unemployment$_t$	0.146	0.072	0.074
	(0.093)	(0.068)	(0.064)
(β_5) UE$_{i,t}$ $\times$ Unemployment$_t$	0.378***	0.167***	0.212***
	(0.085)	(0.062)	(0.056)
Panel C: Mismatch cyclicality			
($\beta_2 + \beta_4$) EE'$_{i,t}$	-0.013	0.023	-.035
	(0. 099)	(0.075)	(0.070)
($\beta_3 + \beta_5$) UE'$_{i,t}$	0.219**	0.117*	0.102*
	(0. 091)	(0.067)	(0.060)
Observations	510788	510788	510788
Adjusted R^2	0.500	0.771	0.763

Notes: The table reports coefficients from an OLS regression with robust standard errors clustered at the individual level reported in parentheses. Panel A and B report, respectively, estimation results of Equation (3) with and without interactions. Panel C reports statistics for $\beta_1 + \beta_4$ and $\beta_1 + \beta_5$ in Equation (3). All columns include a quadratic polynomial in age, and the following fixed effects: individual, month, year, region, one-digit industry and one-digit occupation. The sample includes all worker-job matches between 1979 and 2012. ***, ** and * represent statistical significance at 1%, 5% and 10% levels, respectively.

Heterogeneity along the mismatch distribution Figure 1 plots the OLS and quantile regression estimation results.[9] The dashed lines correspond to the OLS estimates of the conditional mean effect, the solid lines correspond to the quantile regression estimates for θ ranging from the 10^{th} to the 95^{th} quantile. Our findings suggest that economic conditions affect mainly the upper tail of the mismatch distribution, i.e. workers that are poorly matched. In particular, for job-stayers at the 95^{th} quantile, the correlation between unemployment and mismatch is 2.4 times larger, in absolute value, than the OLS estimate; whereas for workers at the 10^{th} quantile, this correlation is not statistically different from zero.

Figure 1: Quantile and OLS Estimates



Notes: The dashed lines display point estimates based on OLS estimation of Equation (4), the solid lines correspond to the quantile regression estimates for the 10^{th} to the 95^{th} quantile. Source: NLSY79.

Robustness Our results are robust to are robust if we use a different definition of new hires from unemployment to account for short unemployment spells and across different specifications and sample selection criteria, namely, expanding the set of controls (Table C.2), using alternative measures of economic conditions (Table C.3), excluding the period of the Great Recession (Table C.4), restricting the sample to males (Table C.5), and using different methods to compute the mismatch index (Table C.6). Appendix C describes each robustness check in detail and reports the estimation results.

[9] To understand how the relationship between mismatch and economic conditions changes along the distribution of mismatch, we measure the correlation between the unemployment rate and mismatch at different quantiles of the mismatch distribution conditional on the explanatory variables.

$$Q_\theta(m_{i,c_t}|U_t, EE'_{i,t}, UE_{i,t}, x_{i,t}) = \beta_0^\theta + \beta_1^\theta U_t + \beta_2^\theta EE'_{i,t} + \beta_3^\theta UE_{i,t} + \beta_4^\theta U_t \cdot EE'_{i,t} + \beta_5^\theta U_t \cdot UE_{i,t} + \delta^{\theta\prime} x_{i,t} \quad (4)$$

where $\theta \in (0,1)$ and $x_{i,t}$ is a quadratic polynomial in age. Because the OLS estimate of β_1 has a small variation when we exclusion individual, industry and occupation fixed effects, for the purpose of the quantile regression analysis we do not include them.

2.3 Occupational Mobility over the Business Cycle

Now we study the cyclical properties of occupational switching. A career or occupation is defined by skill-mix ("task") of current occupation c_t

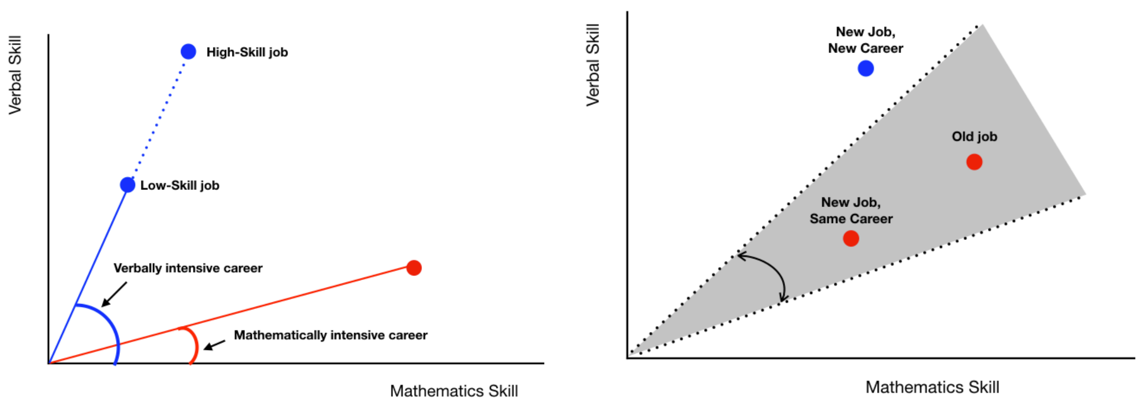
$$\theta_{c_t} = \frac{\mathbf{r}_{c_t} \cdot \mathbf{r}_0}{||\mathbf{r}_{c_t}||||\mathbf{r}_0||} \in [0, \pi/2] \tag{5}$$

We then define career-switches as transitions between sufficiently distant task

$$\Delta\theta_{c_t, c_t+1} \equiv \cos^{-1}\left(\frac{\mathbf{r}_{c_t} \cdot \mathbf{r}_{c_{t+1}}}{||\mathbf{r}_{c_t}||||\mathbf{r}_{c_{t+1}}||}\right) > \bar{\theta} \tag{6}$$

as illustrated in Figure 2. We set $\bar{\theta} = \pi/8$ or $22.5°$. Using this definition, 28% of new hires switch career upon a job switch or after an unemployment spell.

Figure 2: Careers and Career Switching



Using this definition of career switching, we focus on the sample of new hires from unemployment and estimate a linear probability model for the event that a worker hired at time t is observed to be working in a different career from the one in the previous job. The set of controls include mismatch in the previous occupation, age, region, individual and month fixed effects. Robust standard errors are provided, clustered at the individual level to allow for serial correlation. Results in Table 2 show statistically significant evidence for countercyclical occupation switching conditional on being a new hire. These are in line with Kambourov and Manovskii (2008) and Huckfeldt (2016). The former uses the Panel Study of Income Dynamics (PSID) over the period from 1968 to 1997, and using all types of work flows, finds that occupational mobility is countercyclical for young and old workers. The latter uses the Displaced Worker Supplement from the CPS and finds evidence for countercyclical movements of displaced workers across occupations.[10]

[10]In contrast with our findings, Moscarini and Thomsson (2007) and Carrillo-Tudela and Visschers (2014) use, respectively, the CPS and the SIPP, and provide suggestive evidence that occupational mobility is larger in expansions. Note, however, that they do not consider issues of statistical inference. Further, Moscarini and Thomsson (2007) only consider switches among workers who were employed two months in a row, while Carrillo-Tudela and Visschers (2014)'s analysis considers only unemployed job seekers upon reemployment and focus on mobility across broad occupational categories (one-digit level).

Table 2: Occupational Switch and the Business Cycle

	Occ. Switch		Distance	
	(1)	(2)	(3)	(4)
Unemployment_t	0.008^{**}	0.007^{**}	0.005^{**}	0.005^{*}
	(0.004)	(0.004)	(0.003)	(0.003)
Prev. Mismath		0.001^{***}		0.001^{***}
		(0.000)		(0.000)
Observations	10901	10901	10901	10901
Adjusted R^2	0.115	0.117	0.139	0.142

Notes: The table reports coefficients with robust standard errors clustered at the individual level reported in parentheses. The dependent variable is the probability of occupational switching. Controls include mismatch in the previous occupation, age, region, individual and month fixed effects. The sample includes all new hires from unemployment between 1980 and 2012. ***, ** and * represent statistical significance at 1%, 5% and 10% levels, respectively.

Taking stock We have presented a set of new empirical facts about the cyclical behavior of worker-occupation mismatch, and occupational switching for the unemployed.

Fact 1: Mismatch is procyclical for workers in ongoing job relationships, acyclical for workers making job-to-job transitions, and countercyclical for new hires from unemployment.

Fact 2: For job stayers, the decrease in mismatch is driven by negative mismatch, while for new hires from unemployment both positive and negative mismatch support the increase in mismatch as the unemployment rate increases.

Fact 3: Occupational switching for the unemployed increases in recessions. In the next section, we develop a theoretical framework that speaks to these facts jointly.

3 A Model of Mismatch Cycles

We develop a model of the labour market with aggregate shocks and endogenous occupational switching that gives rise to the cleansing and sullying effects.

3.1 Environment

Time is continuous and the future is discounted by all agents at a rate ρ. There is a continuum of risk-neutral workers and potential firms.

Workers. Each worker $i \in [0,1]$ is endowed with a vector of time-invariant worker-specific abilities in the different skills $\{a_i(k) : k \in [0,1]\}$, where each ability $a_i(k) \sim \mathcal{N}(0, S_0)$ is *iid* across skills and across workers. Abilities are not observed by either the worker or the employer, but the distribution of types is public information. We normalize the unconditional mean to zero.

Firms. Each firm j is characterized by two indices (k_j, r_j), where k_j defines the skill-type used in production (the occupation) and r represents the skill requirement or how intensively it uses the skill. We assume that requirements r_j are publicly observed. Since occupations are characterized by a particular skill k, we use the terms occupations and skills indistinctively.

Output and aggregate productivity. A firm-worker pair in a particular occupation with ability a and requirement r, produces flow output

$$dy = (z + \eta r - \max\{r - a, 0\})\, dt, \quad \eta \in (0, 1), \tag{7}$$

where z is observable aggregate productivity and $\eta \in (0, 1)$ is a parameter that controls the asymmetry at which skill requirements affects output: higher skill-requirement r increases potential output, but less than what mismatch hurts it. When a worker is overqualified ($r < a$), output evolves as $dy/dt = z + \eta r$, and is increasing in the firm's requirement. In contrast, when a worker is underqualified ($r > a$), output becomes $dy/dt = z + a - (1 - \eta)r$, and is decreasing in the requirement. Aggregate productivity z follows a Poisson process that can take two values, $z_t \in \{z_1, z_2\}$, with switching intensities λ_1 and λ_2; we normalize $z_1 \leq z_2$ and identify the first state with a recession.

Separations. Separations are of two types: exogenous at rate δ or endogenous. Upon a break, workers fall into unemployment and firms into posting vacancies. Following Menzio and Shi (2011), we assume that the underlying contract space is complete, so that separations are bilaterally efficient, in other words, separation is determined by the joint surplus of a relationship.

Learning worker's abilities. Recall that abilities are unobserved, but requirements are observed. We assume that partners in a match learn about the worker's abilities while producing exclusively from a noisy signal[11]

$$ds_t = a_i(k_j)dt + \sigma dW_t, \qquad W_t \sim Wiener. \tag{8}$$

Following Jovanovic (1979), agents make inferences about abilities in a Bayesian way by optimally weighing new information from signals against old information from prior estimates. This is a passive learning technology in the sense that firms process the information that is available to them, but they cannot take any action to change the quality of the signals. Let $\mathcal{I}_t = \sigma\{s_r, r \leq t\}$ denote the sigma-algebra generated by the history of signals. Let $\hat{a}_t \equiv \mathbb{E}[a|\mathcal{I}_t]$ be the best estimate (in a mean-squared error sense) of the worker's abilities and let $\Sigma_t \equiv \mathbb{E}[(a_t - \hat{a}_t)^2|\mathcal{I}_t]$ be the corresponding uncertainty.

[11] In this specification, agents do not use output for inference. Alternatively, we could specify transitory shocks to output that impede learning. However, this alternative only complicates the analysis without adding insights. Either we would need to deal with non-linear learning issues (if the noise is outside the max-operator), or would need to carry around an additional state variable (if the noise is inside the max-operator).

Proposition 1 shows that the posterior distribution of abilities is Gaussian $a_t|\mathcal{I}_t \sim \mathcal{N}(\hat{a}_t, \Sigma_t)$ and characterizes the evolution of the first and second moments.

Proposition 1 **(Filtering.).** *The posterior distribution of abilities is Gaussian* $a_t|\mathcal{I}_t \sim \mathcal{N}(\hat{a}_t, \Sigma_t)$ *where the first two moments evolve as follows:*

$$d\hat{a}_t = \frac{\Sigma_t}{\sigma} d\hat{W}_t \tag{9}$$

$$d\Sigma_t = -\left(\frac{\Sigma_t}{\sigma}\right)^2 dt \tag{10}$$

Under the information set of the firm-worker pair $\mathcal{I}_t$*, the filtered process or news, given by* $d\hat{W}_t = \frac{1}{\sigma}(a_t - \hat{a}_t)\,dt + dW_t$*, is a standard Brownian motion.*

According to Proposition 1, the estimate $\hat{a}_t$ follows a Brownian motion with time-varying uncertainty Σ_t that decreases with tenure. Due to Bayesian updating, when uncertainty is high, estimates optimally put more weight on signals instead of the prior. In that case, while learning is faster, there is more noise into the estimation. Thus estimates are more volatile with high uncertainty. This result will be key for generating decreasing hazard rates of separation. Using the filtering equations, we can compute expected output flow as

$$\mathbb{E}[dy]/dt = z + \eta r - \mathbb{E}\max\{r - a, 0\} = z + \eta r - \sqrt{\Sigma}\left[\nu\Phi(\nu) + \phi(\nu)\right] \tag{11}$$

where we define *expected under-qualification* as $\nu \equiv (r - \hat{a})/\sqrt{\Sigma}$, and Φ and ϕ denote the CDF and the PDF of a Gaussian variable, respectively.[12]

3.2 Labor markets

Labor markets are characterized by directed search across occupations and random matching within an occupation. Occupation submarkets are indexed by $\omega \equiv (k, r, x, \hat{a}_k, \Sigma_k)$ where x denotes the promised utility to the worker, $\hat{a}_k = \mathbb{E}[a_i(k)|\mathcal{I}]$ is first moment of the beliefs about workers abilities, and $\Sigma_k = \mathbb{V}[a_i(k)|\mathcal{I}]$ is the second moment of beliefs, our notion of uncertainty. To enter a submarket, firms create vacancies at a flow cost c, which is the same across markets. Free entry at each submarket determines endogenously the number of entrant firms per submarket, hence θ_ω is pinned down.

Matching within occupations. Within a submarket ω, we consider a random matching environment in which firms and workers meet through a standard CRS matching function $M(u_\omega, v_\omega)$ which converts unemployed workers u_ω and vacancies v_ω into matches. Let $\theta_\omega \equiv v_\omega/u_\omega$ be the market tightness in submarket ω. Conditional on θ_ω, workers are matched with a vacancy at rate $p(\theta_\omega) = M(1, \theta_\omega)$ and vacancies are matched with a worker at rate $q(\theta_\omega) = p(\theta_\omega)/\theta_\omega$. Matching in a submarket w pins down promised utility x. In equilibrium, submarkets are fully characterized by the tightness function $\theta_t(\omega) \equiv \theta(\omega, \psi)$. A key assumption is that firms in different occupations do not congest each other in the matching process of a particular occupation.

[12] For any $x \sim \mathcal{N}(\mu_x, \sigma_x^2)$ we have $\mathbb{E}[\max\{x, 0\}] = \mu_x\left\{1 - \Phi\left(-\frac{\mu_x}{\sigma_x}\right)\right\} + \sigma_x\phi\left(-\frac{\mu_x}{\sigma_x}\right) = \mu_x\Phi\left(\frac{\mu_x}{\sigma_x}\right) + \sigma_x\phi\left(\frac{\mu_x}{\sigma_x}\right)$.

Unemployed workers and occupation switches. While unemployed, workers receive home production flow utility b and search for jobs in a directed way. Unemployed workers choose if they apply to jobs within the same occupation k as they previously held, in which case they may consider submarkets indexed by their type $(\hat{a}_k, \Sigma_k)$. In this case, their only choice is the requirement and the promised utility. Since there is no learning during unemployment, upon a new match, the worker type starts at the same value at which it leaves unemployment.

Alternative, unemployed workers may decide to which occupations. To switch career paths, workers bear a switching cost ξ, which allows them to search for jobs in a random new career path k'. Note that since k lays in a continuum, $k' \neq k$, which means that upon switching the worker type resets to the unconditional prior (a_0, Σ_0).[13] To keep the model stationary, we also introduce a small exogenous risk of career switching ϵ which occurs at the moment of separation.

Aggregate state. The aggregate state in this economy consists of a triple $\psi \equiv (z, \Gamma, \Lambda)$, where z is aggregate productivity, Γ is the probability distribution over active relationships $(\hat{a}, \Sigma, r)$ and Λ is the distribution over the unemployed $(\hat{a}, \Sigma)$.

3.3 Value functions and optimal policies

For notation simplicity, we index value functions with time t, to express their dependence on the aggregate state, for example, $V_t(\cdot) \equiv V(\cdot, \psi)$.

Value of unemployment. The value of being unemployed *conditional* on searching within occupation k, denoted by $U_t^k(\hat{a}, \Sigma)$, is given by:

$$\rho U_t^k(\hat{a}, \Sigma) \;=\; b + \max_{x,r} \; p(\theta) \left(x - U_t^k(\hat{a}, \Sigma) \right) \tag{12}$$

subject to $\theta = \theta_t(\omega)$, where the choice of requirement r also includes the possibility of no search $(p(\theta) = 0)$ which implies $U_t^k = b/\rho$. Then, the overall value of being unemployed, defined by $\mathcal{U}_t^k(\hat{a}, \Sigma)$, is the maximum between retaining the current path k or switching to a new occupation k':

$$\mathcal{U}_t^k(\hat{a}, \Sigma) \;= \max \left\{ U_t^k(\hat{a}, \Sigma), -\xi + U_t^{k'}(a_0, S_0) \right\} \tag{13}$$

For convenience, we define the indicator $\chi_t(\hat{a}, \Sigma)$ which is equal to one if the choice is to switch career and zero otherwise. This choice determines an ability thresholds a^s, such that below it the worker decides to pay the cost and switch and occupation. This threshold is depicted as the black solid line in Figure 4.

Value of a vacancy. Let $V_t^k(\omega)$ be the value of a vacancy in a particular submarket ω and let $J_t^k(\hat{a}, \Sigma, r)$ be the joint value of a firm-worker relationship. Then the value of opening a vacancy is

[13] We confirm numerically that workers do not find it optimal to return to an occupation that has been abandoned in the past.

given by:

$$\rho V_t^k(\omega) = -c + q(\theta)\mathbb{E}[J_t^k(\hat{a}, \Sigma, r) - x - V_t^k(\omega)] \tag{14}$$

where $\theta = \theta_t(\omega)$. By free entry, the utility of creating a vacancy is equal to zero $V_t^k(\omega) = 0$ in each submarket, implying that $c = q(\theta)\left\{J_t^k(\hat{a}, \Sigma, r) - x\right\}$. This expression pins down the promised utility delivered to the worker as of function of market tightness θ:

$$x = J_t^k(\hat{a}, \Sigma, r) - c/q(\theta). \tag{15}$$

By properties of the matching function, x is increasing in tightness (workers are paid more if they apply to markets with low finding probabilities). Proposition 17 derives the optimal submarket choice (θ^*, r^*).

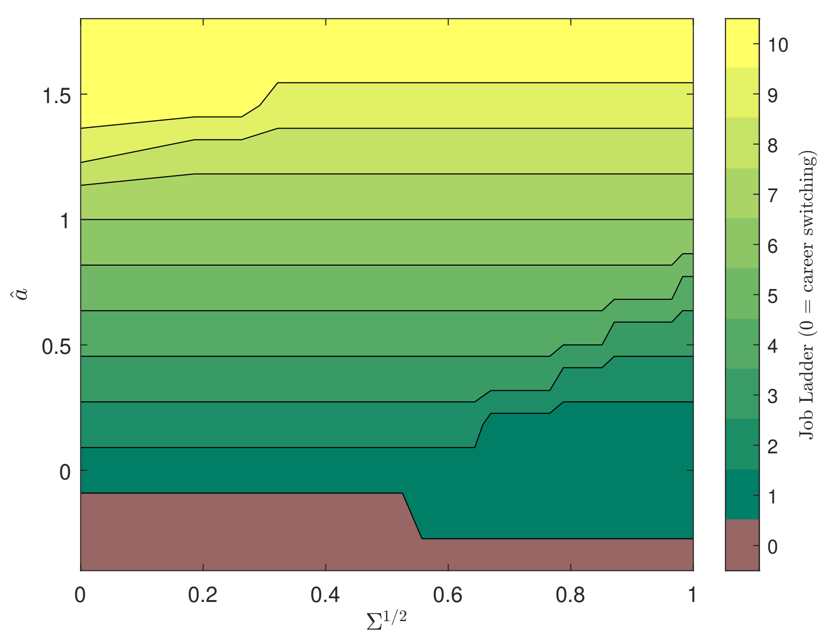
Proposition 2 (**Equilibrium submarket choice**)**.** *Assuming a Cobb-Douglas matching function, the optimal choices for market tightness and requirements are:*

$$\theta^*(\hat{a}, \Sigma, r) = \left[\frac{J_t^k(\hat{a}, \Sigma, r) - U_t^k(\hat{a}, \Sigma)}{(1-\alpha)c}\right]^{1/\alpha}, \tag{16}$$

$$r^*(\hat{a}, \Sigma) = \arg\max_r \; J_t^k(\hat{a}, \Sigma, r). \tag{17}$$

Figure 3 plots the optimal requirement choice r^* for each level of uncertainty Σ and expected ability $\hat{a}$, depicting a job ladder.

Figure 3: Optimal job requirement choice



Notes: The figure plots the job ladder in terms of the optimal requirement choice r^* for each level of uncertainty Σ and expected ability $\hat{a}$.

As an illustration, the following example derives analytically the requirement choice assuming that it only maximize flow payoffs.

Example: Static requirement choice. From (3), expected flow output is given by

$$\mathbb{E}[dy/dt] \quad = \quad z + \eta r - \sqrt{\Sigma}\left[\nu \Phi\left(\nu\right) + \phi\left(\nu\right)\right], \qquad \nu = (r - \hat{a})/\sqrt{\Sigma}.$$

The FOC with respect to r is given by[14]

$$\frac{\partial \mathbb{E}[dy/dt]}{\partial r} \quad = \quad \eta - \sqrt{\Sigma}\left[\frac{\Phi\left(\nu\right)}{\sqrt{\Sigma}} + \nu\frac{\phi\left(\nu\right)}{\sqrt{\Sigma}} + \frac{\phi'\left(\nu\right)}{\sqrt{\Sigma}}\right] = \eta - \Phi\left(\nu\right) = 0$$

where we have used that $\phi'\left(\nu\right) = -\nu\phi\left(\nu\right)$ for a standard Normal density. Thus the FOC reads $\Phi(\nu) = \eta$ which implies that workers will err on the side of being under-qualified: $\nu = \Phi^{-1}(\eta) > 0$. Finally, rearranging the FOC, we get that the requirement choice that maximizes flow profits is

$$r^* = \hat{a} + \Phi^{-1}(\eta)\sqrt{\Sigma} \tag{18}$$

For $\eta < 1/2$, returns to over-qualification are small relative to the risk of under-qualification, inducing workers to choose low-requirement jobs $r^* < \hat{a}$; while for $\eta > 1/2$, returns to over-qualification are large, so workers instead prefer to err on the upside, choosing high-requirement jobs $r^* > \hat{a}$. Uncertainty Σ amplifies the strength of these biases.

Joint value of a relationship. Consider the joint value of a continuing relationship $J_t^k(\hat{a}, \Sigma, r, z)$ (here we make explicit its dependence on z). It consists of the output flow plus the continuation value for the firm and the worker, during all the periods in which it is active. Let τ denote the stopping time or date in which the relationship finishes. Then, the joint value is given by:

$$J_t^k(\hat{a}, \Sigma, r, z) \quad = \quad \max_{\tau} \mathbb{E}\left[\int_t^{\tau} e^{-(\rho+\delta)t} dy + e^{-(\rho+\delta)\tau}\; U_\tau^k(\hat{a}_\tau, \Sigma_\tau)\Big|\mathcal{I}_t\right], \tag{19}$$

where dy is defined in (7) and the beliefs evolve following (9) and (10). Here we have used the fact that upon break, the firm's continuation value (posting vacancies) is zero due to free entry.

This inaction problem is non-standard because it is four-dimensional. Following Baley and Blanco (2019), in order to provide sufficient conditions of optimality, we impose the Hamilton-Jacobi-Bellman equation, the value matching condition, and the standard smooth pasting condition for the four states $(\hat{a}, \Sigma, r, z)$. Proposition 3 formalizes this.

[14]The second order condition for maximization is satisfied, as $\frac{\partial^2 \mathbb{E}[dy/dt]}{\partial r^2} = -\frac{\phi(\nu)}{\sqrt{\Sigma}} < 0$.

Proposition 3. ***[HJB Equation, Value Matching and Smooth Pasting]*** *τ is the optimal separation time if:*

1. *For an active relationship, the optimal value satistifies the HJB equation:*

$$\rho J_t^k(\hat{a},\Sigma,r,z) = \underbrace{z+\eta r-\sqrt{\Sigma}\left[\nu\Phi(\nu)+\phi(\nu)\right]}_{\text{expected output}} \underbrace{-\left(\frac{\Sigma}{\sigma}\right)^2\frac{\partial J_t^k}{\partial\Sigma}+\frac{1}{2}\left(\frac{\Sigma}{\sigma}\right)^2\frac{\partial^2 J_t^k}{\partial\hat{a}^2}}_{\text{learning}}$$
$$+\underbrace{\lambda_{z'|z}\left[J_t^k(\hat{a},\Sigma,r,z')-J_t^k(\hat{a},\Sigma,r,z)\right]}_{\text{aggregate shocks}}$$
$$+\underbrace{\delta\left[\epsilon U_t^k(a_0,S_0)+(1-\epsilon)U_t^k(\hat{a},\Sigma)-J_t^k(\hat{a},\Sigma,r,z)\right]}_{\text{exog. separations}}, \quad (20)$$

where $\nu=(r-\hat{a})/\sqrt{\Sigma}$ is expected under-qualification.

2. *At the border of the inaction region, it satisfies*

$$J_t^k(\hat{a},\Sigma,r,z)=\epsilon U_t^k(a_0,S_0)+(1-\epsilon)U_t^k(\hat{a},\Sigma) \quad (21)$$

which sets the value of separating equal to the value of not separating:

3. *At the border of the inaction region, it satisfies the smooth pasting conditions for $\underline{a}$ and $\overline{a}$*

$$J_\mu(\hat{a},\Sigma,r,z)=J_\Sigma(\hat{a},\Sigma,r,z)=J_z(\hat{a},\Sigma,r,z)=0 \quad (22)$$

Proposition 4 (Continuation thresholds for employed)**.** *The choice to continue a relationship takes the form of a time-dependent continuation region:*

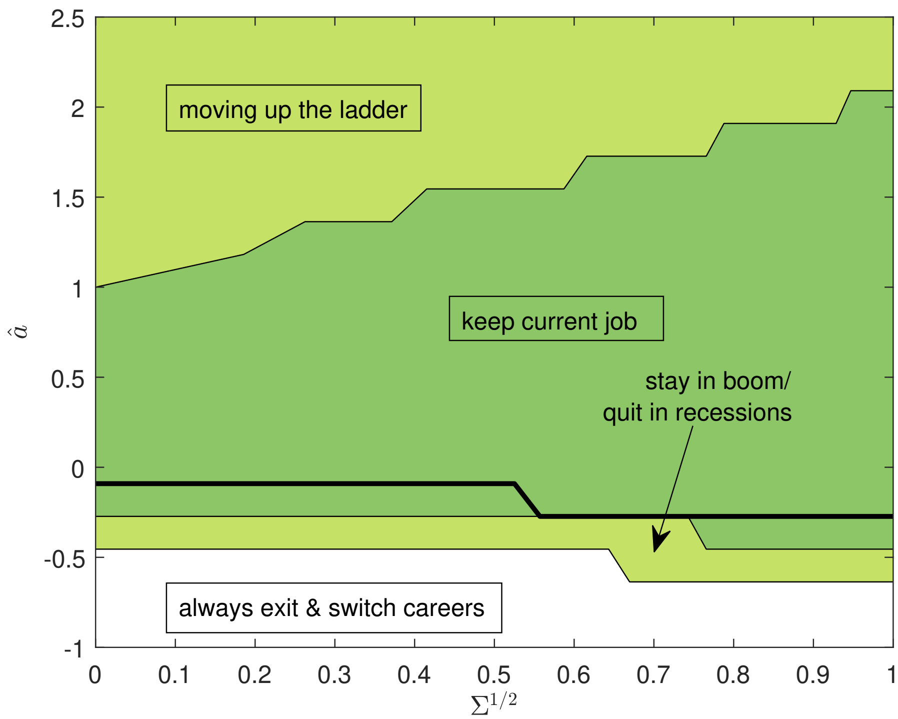
$$\mathcal{C}_t^*=\{(\hat{a},\Sigma,r,z): J_t^k(\hat{a},\Sigma,r,z)>\epsilon U_t^k(a_0,S_0)+(1-\epsilon)U_t^k(\hat{a},\Sigma)\} \quad (23)$$

which defines two thresholds for the ability estimate $\underline{a}(\Sigma,r,z)$ and $\overline{a}(\Sigma,r,z)$ such that the relationship continues as long as $\underline{a}<\hat{a}<\overline{a}$.

Note that, as in Baley and Blanco (2019), inaction regions refer to mismatch estimates and not the true mismatch. As a result, there are relationships that are destroyed because they are perceived to be highly mismatched, when the true mismatch is actually low. This feature is key to account for evidence showing that, conditional on mismatch, younger relationships and relationships starting in bad times are more likely to break.

Let us discuss some properties of the continuation region. First, fix aggregate productivity z_t and skill requirement, then *uncertainty widens the inaction region.* This feature captures the well known option value effect in Dixit (1991): due to high uncertainty, firms and workers are more tolerant to higher mismatch levels and delay any adjustment. As a result of uncertainty dynamics, the option value is time varying and the inaction region is time dependent. In particular, for a given worker-firm pair, uncertainty decreases over time so the inaction region shrinks with match tenure. Now,

Figure 4: Continuation Thresholds over the Cycle



Notes: The graph pictures the inaction thresholds $\underline{a}, \overline{a}$ when the aggregate productivity z is high (red) or low (blue). The requirement level is fixed at the average requirement.

fix instead the level of uncertainty Σ, then *aggregate productivity widens the inaction region.* When aggregate productivity z increases, the ability estimate $\hat{a}$ that makes the worker and the firm indifferent between breaking the match or continuing is higher, hence the inaction region widens for all levels of uncertainty Σ.

Block recursivity Inspecting the different value functions $J, U, \mathcal{U}, V$ we see that none of them depends on the aggregate state ψ other than through aggregate productivity z. Hence, there exists a block-recursive equilibrium in which none of the value functions depend on the distributions Γ and Λ. Therefore, from now on, the notation with subscript t denotes exclusively the dependence on the aggregate productivity z.

3.4 Distributions

Now we characterize the dynamics of distribution over active relationships $\Gamma_t(\hat{a}, \Sigma, r)$ and the distribution over the unemployed $\Lambda_t(\hat{a}, \Sigma)$. To keep the notation simple, we suppress the dependence on the aggregate shock z from the distributions and use instead the time subscript.

Recall the time-varying choices of career switching $\chi_t^*(\hat{a}, \Sigma)$ from (13), market tightness $\theta_t^*(\hat{a}, \Sigma, r)$ from (16), market requirement $r_t^*(\hat{a}, \Sigma)$ from (17), and the continuation region $\mathcal{C}_t^*$ from (23). Then, the distributional dynamics are characterized by the following system of PDEs:

$$\dot{\Gamma}_t(\hat{a}, \Sigma, r) = \dot{\Phi}_t^{\text{act}}(\hat{a}, \Sigma, r) + \dot{\Phi}_t^{\text{in}}(\hat{a}, \Sigma, r) - \dot{\Phi}_t^{\text{out}}(\hat{a}, \Sigma, r) \tag{24}$$

$$\dot{\Lambda}_t(\hat{a}, \Sigma) \quad = \quad \dot{\Phi}_t^{\text{cs}}(\hat{a}, \Sigma) \;-\; \int \dot{\Phi}_t^{\text{in}}(\hat{a}, \Sigma) dr \;+\; \begin{cases} \epsilon \iiint \dot{\Phi}_t^{\text{out}}(\hat{a}, \Sigma, r) d(\hat{a}, \Sigma, r) & \text{if } (\hat{a}, \Sigma) = (a_0, S_0) \\ (1-\epsilon) \int \dot{\Phi}_t^{\text{out}}(\hat{a}, \Sigma, r) dr & \text{otherwise} \end{cases} \tag{25}$$

The distribution of workers in active relationships $\dot{\Phi}_t^{\text{act}}$ changes due to the evolution of beliefs:

$$\dot{\Phi}_t^{\text{act}}(\hat{a}, \Sigma, r) = \frac{2\Sigma_t}{\sigma_s} \Gamma_t(\hat{a}, \Sigma, r) + \left(\frac{\Sigma_t}{\sigma_s}\right)^2 \frac{\partial \Gamma_t(\hat{a}, \Sigma, r)}{\partial \Sigma} + \frac{1}{2} \left(\frac{\Sigma_t}{\sigma_s}\right)^2 \frac{\partial^2 \Gamma_t(\hat{a}, \Sigma, r)}{\partial \hat{a}^2}. \tag{26}$$

The distribution of new workers that flow into employment $\dot{\Phi}_t^{\text{in}}$ depends on the finding probability of the particular labor submarket from where they are coming $p(\theta(\hat{a}, \Sigma, r))$ as follows:

$$\dot{\Phi}_t^{\text{in}}(\hat{a}, \Sigma, r) = \begin{cases} \Lambda_t(\hat{a}, \Sigma) p(\theta^*(\hat{a}, \Sigma, r)) & \text{if } r = r_t^*(\hat{a}, \Sigma) \\ 0 & \text{otherwise} \end{cases} \tag{27}$$

The distribution of workers that go into unemployment $\dot{\Phi}_t^{\text{out}}$ depends on both exogenous (at rate δ) and endogenous separations

$$\dot{\Phi}_t^{\text{out}}(\hat{a}, \Sigma, r) = \delta \Gamma_t(\hat{a}, \Sigma, r) + (1-\delta) \Gamma_t(\hat{a}, \Sigma, r) \mathbf{1}_{\{(\hat{a}, \Sigma, r) \notin \mathcal{C}_t^*\}}. \tag{28}$$

where $\mathbf{1}$ is the Dirac-δ function that takes value of infinite at the boundary of the continuation region.[15] Finally, the distribution of unemployed workers that switch careers $\dot{\Phi}_t^{\text{cs}}$ considers the nets flows, this is the inflow into the career which enter at the prior, and the outflow from the career:

$$\dot{\Phi}_t^{\text{cs}}(\hat{a},\Sigma) = \begin{cases} \iint \mathbf{1}_{\{\chi_t(\hat{a},\Sigma)=1\}}\ \Lambda_t(\hat{a},\Sigma)\ d(\hat{a},\Sigma) & \text{if } (\hat{a},\Sigma) = (a_0,\Sigma_0) \\ -\mathbf{1}_{\{\chi_t(\hat{a},\Sigma)=1\}}\ \Lambda_t(\hat{a},\Sigma) & \text{otherwise} \end{cases} \tag{29}$$

where again $\mathbf{1}$ is the Dirac-δ function that takes value of infinite at the boundary of the switching region.

3.5 Equilibrium

A *block recursive equilibrium* consists of worker choices for career switching χ_t^*, market tightness θ_t^*, market requirement r_t^*, continuation region $\mathcal{C}_t^*$; value functions $U, J, \mathcal{U}$, and distributions $\dot{\Gamma}_t, \dot{\Lambda}_t$, such that:

1. Choices maximize expected utility
2. The distributions are consistent

4 Quantifying mismatch

In this section, we calibrate and quantify the mismatch model to assess the performance of the model.

IN PROGRESS.

[15] Note that Γ_t goes to zero at the boundary, so that its product with the Dirac-δ is essentially the mass of agents being redirected from employment into unemployment due to endogenous separations.

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A Proofs

Proof. Of Proposition 1 (Filtering).

□

Proof. Of Proposition 2 (Equilibrium submarket choice). Substituting promised utility from (15) into the value of unemployment conditional on a career path k in (12), we reexpress the worker's submarket choice in terms of tightness and requirements:

$$\max_{\theta_t, r_t} \left\{ p(\theta_t) \left(J_t^k(\hat{a}, \Sigma, r) - c\theta_t / p(\theta_t) - U_t^k(\hat{a}, \Sigma) \right) \right\}$$

The FOC with respect to θ yields

$$p'(\theta_t)^{-1} = \frac{J_t^k(\hat{a}, \Sigma, r) - U_t^k(\hat{a}, \Sigma)}{c}. \tag{30}$$

Assuming a Cobb-Douglas matching function, the finding probability is $p(\theta) = \theta^{1-\alpha}$, which implies

$$\theta^*(\hat{a}, \Sigma, r) = \left[\frac{J_t^k(\hat{a}, \Sigma, r) - U_t^k(\hat{a}, \Sigma)}{(1-\alpha)c} \right]^{1/\alpha}. \tag{31}$$

And the FOC with respect to r_t implies that the optimal choice maximizes the joint surplus:

$$r^*(\hat{a}, \Sigma) = \arg\max J_t^k(\hat{a}, \Sigma, r). \tag{32}$$

□

Mismatch Cycles

Isaac Baley, Ana Figueiredo and Robert Ulbricht

Data Appendix

A Data Appendix

Sample selection The NLSY79 is a nationally representative longitudinal survey of 12,696 individuals who were between 14 and 22 years when they were first interviewed in 1979. We focus on a sub-sample of males and females from the cross-sectional sample, meaning that we drop the military samples and exclude oversamples of special demographic/racial groups from the NLSY79. The cross-sectional sample of the NLSY79 has 6,111 respondents and was designed to represent the non-institutionalized civilian segment of people living in the United States in 1979 with ages 14-22 as of December 31, 1978.[16] As standard in the literature, we further drop individuals who were more than two years in the military force, individuals who displayed weak labor market attachment, i.e. individuals spent more than 10 years out of the labor force, individuals that were already working in 1979, and those that do not have information on the Armed Services Vocational Aptitude Battery (ASVAB) test scores. Our final sample is composed of 2,991 individuals. Descriptive statistics for the sample are reported in Panel A of Table A.1.

Worker's employment history The NLSY79 interviewed individuals on an annual basis in the years from 1979 to 1993, and on a biannual basis for the period 1994-2012. Information on labor force status is recorded at a weekly frequency throughout the sample period, even in the later period where interviews were at biannual frequency. To construct a monthly panel for our main analysis, we use the NLSY79's Work History Data file. This file is a week-by-week record of the working history for each respondent, which contains information about weekly labor status and hours worked. While an individual may hold more than one job, we focus on the primary job at a given month, which is defined as the one for which an individual worked the most hours in a given month. For each primary job, we retain information on the hourly wage, occupation and industry codes. Before merging occupation and industry information with the employment panel, we clean occupational and industry titles following **?**'s approach: to each job, we assign the occupation and industry code that is most often observed during the employment spell. In the NLSY79, occupation titles are described by the three-digit Census occupation code. Because this classification system changed over time[17], before cleaning we converted all the occupational codes across the years into the *occ1990dd* occupation system developed by Dorn (2009), which has the advantage of being time-consistent.[18] Wages correspond to the hourly wage, which include tips, overtime and bonuses, are measured in 2000 dollars (we use the consumer price index from the BLS to deflate wages).

[16] The NLSY consists of three sub-samples: *(i)* a cross-sectional sample; *(ii)* a supplemental sample designed to oversample civilian Hispanic, black, and economically disadvantaged non-black/non-Hispanic youths; and *(iii)* a military sample designed to represent the youths enlisted in the active military forces as of September 30, 1978. We restrict our sample to members of the representative cross-sectional sample because many members of supplemental and military samples were dropped from the NLSY

[17] Until 2000, NLSY79 reports occupation codes in the Census 1970 three-digit occupation code. After this year, occupation codes are reported in the Census 2000 three-digit occupation code.

[18] The crosswalk files between the Census classification codes and the *occ1990dd* occupation aggregates created by Autor and Dorn (2013) can be found at `http://www.ddorn.net/data`.

Worker's employment transitions We identify a *job-to-job* transition when the primary job for an individual at month t is different from the one reported in the previous month, and a *non-employment to employment* transition if the worker was unemployed in month $t-1$ (i.e. reported to be not working, unemployed or out of the labor force) and employed in month t, meaning that she reported a job.[19] Additionally, we define a worker making an occupational switch when the occupation at month t is different from the one in the last reported job. Panel B in Table A.1 reports descriptive statistics about employer and occupational mobility. We observe that, from 1979 and 2012, individuals change employer, on average, 13.69 times (including job-to-job and non-employment to employment transitions), out of which 7 they also change occupation. Annual occupational mobility in our sample is 21.49% compared with 15.79% reported in **?** and 18.48% reported in Kambourov and Manovskii (2008) who use the Panel Study of Income Dynamics (PSID) for the period 1968-1997.

Worker's abilities In addition to an individual's labor market history, the NLSY79 has information on the ASVAB test scores, which was taken by individuals between ages 14 and 24. The ASVAB is a general test that measures knowledge and skills in 10 different components.[20] We focus on a subset of six components (arithmetic reasoning, mathematics knowledge, paragraph comprehension, word knowledge, mechanical comprehension, general science and electronics information) which are linked to the 3 skill counterparts considered in the empirical analysis: math, verbal and technical. To measure individuals' skills in each dimension, $a_{i,j}$, we follow **?**'s approach: the ASVAB categories are reduced into the 3 skill dimensions using Principal Component 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.[21] 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. Also, once we have the raw scores in each skill dimension, we convert them into percentile rank scores, $a_{i,j}$ in Equation (1).[22]

Job skill requirements To obtain measures of the skill requirements in each occupation, $r_{c_t,j}$, we use the O*NET database, that collects that on a list of 277 descriptors, with the ratings of importance level and relevance, for 974 different occupations. As in **?**, we use 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 each ASVAB category; and other six descriptors to describe

[19]The NLSY79 provides a mapping that links jobs across consecutive interviews, which allows us to build employment spells for each job reported by the respondent.

[20]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.

[21]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 studies as measures of non-cognitive skills Speer (2017); Lise and Postel-Vinay (2016); **?**. For more details, see Heckman *et al.* (2006).

[22]Because the raw scores that result from PCA do not have any meaning, we transform them into percentile rank scores, as in **?**. This allows us to have a clear interpretation of the scores and compare two different scores. The percentile rank is the percentage of scores that fall below a given score. For example, if an individual's raw score in *math* is transformed into a percentile rank score of 50, it means that the individual is better than 50% of the sample in *math*.

the social dimension.[23] Following **?**'s methodology, for each occupation, we build a score comparable to each ASVAB category, and then we collapse the seven ASVAB categories analogues into the 3 skill dimensions (verbal, math and technical) by applying PCA. For the social dimension, we also collapse the six O*NET descriptors into a single dimension by taking the first principal component. Finally, we rescale the scores by converting them into percentile rank scores, $r_{c_t,j}$ in Equation 1.[24] Panel B in Table B.2 reports summary statistics of the measures of job skill requirements. To check whether the constructed variables characterize occupations reasonably, we report the mean percentile rank score of each main occupation category of the *occ1990dd* occupation system from Dorn (2009) in Table B.3. *Managerial occupations* require more verbal and math skills than *Repair occupations*, which have a higher requirement of the technical skill. As expected, within each broad category there is a large variation in job skill requirements as shown in table B.4. For instance, economists require the use of the math skill more intensively, whereas lawyers, within the same broad category, require a higher the use of the verbal skill but use the technical skill less intensively.

Merge Once we have the percentile rank scores in each skill dimension on the occupation and worker-side, 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 2000, 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.

Upon merging, we are ready to compute mismatch (m_{i,c_t}), positive mismatch (m^+_{i,c_t}) and negative mismatch (m^-_{i,c_t}).

[23]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.

[24]We use O*NET 21.1, which was released in November 2016. Because our panel data starts in 1979, one might be concerned that the computed scores do not reflect the change in the requirements of which occupation over time. We computed the job skill requirements for the first version of O*NET, and the correlation between these and the scores we use in the main analysis is around 0.80, which mitigates these concerns.

Table A.1: Descriptive Statistics of the Sample

The table reports descriptive statistics of the sample used in the empirical analysis, which is a sub-sample of 2,991 individuals from the cross-sectional sample of the NLSY79 and runs over the period from 1979 and 2012. *Job mobility* is defined as the fraction of individuals who start a new job in a given month, including *job-to-job* and *non-employment to employment* transitions. *Occupational mobility* is defined as the fraction of individuals who switch occupations in a given month. Source: NLSY79 and author's calculations.

	Mean	Std. Dev	p10	p90
Panel A: Sample characteristics				
Female (% of total)	48.51			
Male (% of total)	51.49			
African-American (% of total)	11.27			
Hispanic (% of total)	7.15			
Age at interview	33.70	10.03	20.00	47.00
Panel B: Work history				
# Job Transitions per individual	13.69	7.62	5.00	24.00
# Occupation Transitions per individual	7.28	4.77	2.00	14.00
Job mobility (per month, % of total)	3.24	2.66	0.85	7.07
Occupation mobility (per month, % of total)	1.78	1.50	0.50	3.91
Job tenure (months)	14	21	1	35
Occupation tenure (months)	39	65	2	120
Unemp. duration (months)	7	11	1	17

B Additional Tables and Figures

Table B.2: Summary Statistics

The table reports summary statistics for the main variables used in the empirical analysis. Panel A presents the statistics for the measure of worker's abilities in the different skills dimensions, $a_{i,j}$. The sample includes respondents in the NLSY79 dataset that satisfy the selection criteria in Appendix A. Panel B reports the statistics for the measures of job skill requirements, $r_{c,j}$, at the three-digit occupational code level constructed by Dorn (2009). Panel C presents the statistics for the job mismatch measures. *Mismatch$_t$* is defined as $m_{i,c_t} \equiv \sum_{j=1}^{J} \omega_j \, |a_{i,j} - r_{c_t,j}|$; *Positive mismatch$_t$* as $m^+_{i,c_t} \equiv \sum_{j=1}^{4} \omega_j \max\{a_{i,j} - r_{c_t,j}, 0\}$; and *Negative mismatch$_t$* as $m^-_{i,c_t} \equiv \sum_{j=1}^{4} \omega_j \, |\min\{a_{i,j} - r_{c_t,j}, 0\}|$. The sample consists of unique occupations observed in NLSY79 with occupational characteristics in O*NET. Panel D reports summary statistics of the business cycle indicators. *Unemployment Rate$_t$* is the monthly unemployment rate at the national level published by BLS. *Vacancies Index$_t$* is the Composite Help-Wanted index developed by Barnichon (2010) which captures the behavior of total - print and online - help-wanted advertising, a proxy for the number of job openings at a given point in time. *Industrial Production$_t$* is the monthly industrial production index. Source: NLSY79, O*NET, BLS and author's calculations.

	Observations	Mean	Std. Dev	Min.	Max.
Panel A: Worker's abilities					
Pctl. rank of the verbal skill	2991	49.81	28.43	1	100
Pctl. rank of the math skill	2991	50.15	28.76	1	100
Pctl. rank of the mechanical skill	2991	50.36	28.87	1	100
Pctl. rank of the social skill	2991	49.95	28.86	1	100
Panel B: Job Skill Requirements					
Pctl. rank of the verbal skill	324	50.47	28.92	1	100
Pctl. rank of the match skill	324	50.46	28.92	1	100
Pctl. rank of the technical skill	324	50.37	28.96	1	100
Pctl. rank of the social skill	324	50.44	28.94	1	100
Panel C: Job Match Quality					
Mismatch$_t$	850377	27.27	14.22	1.25	91.25
Positive mismatch$_t$	850377	12.86	15.08	0.00	91.25
Negative mismatch$_t$	850377	14.41	14.89	0.00	82.00
Panel D: Business Cycle Indicators					
Unemployment Rate$_t$	408	0.06	0.02	0.04	0.11
Vacancies Index$_t$	408	2.75	0.44	1.70	3.90
Industrial Production$_t$	408	77.17	18.40	48.47	105.33

Table B.3: Mean Percentile Scores of Job Skill Requirements for Broad Occupation Classes

The table reports the mean percentile rank scores, $r_{c_t,j}$, along the four skill dimensions considered in the empirical analysis for the main occupation categories of *occ1990dd* occupation system from Dorn (2009). Source: O*NET, ASVAB and author's calculations.

Broad Occupational Titles	Mean Percentile Rank Score			
	Verbal	Social	Math	Technical
Managerial and Professional Specialty Occupations	83.33	77.63	77.53	36.83
Technical, Sales, and Administrative Support Occupations	58.27	54.07	56.00	28.64
Service Occupations	39.24	57.53	27.71	38.35
Farming, Forestry, and Fishing Occupations	28.50	37.00	36.50	53.83
Precision Production, Craft, and Repair Occupations	31.78	33.75	42.63	82.16
F. Operators, Fabricators, and Laborers	21.31	21.64	26.05	66.45

Table B.4: Percentile Scores of Job Skill Requirements for Selected Occupations

The table reports the percentile rank scores, $r_{c_t,j}$, along the four skill dimensions considered in the empirical analysis for selected three-digit occupations in the O*NET dataset. Source: O*NET, ASVAB and author's calculations.

Occupation	Percentile rank score			
	Verbal	Social	Math	Technical
Agents and Business Managers of Artists, Performers, and Athletes	93	99	64	3
Economists	91	65	96	10
Elevator Installers and Repairers	52	45	53	100
Helpers–Installation, Maintenance, and Repair Workers	30	29	16	92
Lawyers	100	89	72	6
Painting Workers	4	14	9	62
Tour and Travel Guides	51	73	31	18
Waiters	71	29	7	13

Table B.5: Correlation between Worker's Abilities and Job Skill Requirements

The table reports the correlation pattern between the percentile rank scores of worker's abilities, $a_{i,j}$, and the percentile scores of job skill requirements, $r_{c_t,j}$, across 4 skill dimensions: verbal, math, technical and social. The values in bold capture the sorting pattern between worker's abilities and job skill requirements. In Panel A, correlations are computed using the sample of individuals in the sample. The correlations in Panel B are computed using the individual-month observations in the sample. Source: NLSY79, O*NET and author's calculations.

	$q(a_{i,v})$	$q(a_{i,m})$	$q(a_{i,t})$	$q(a_{i,s})$
Panel A: Worker's abilities				
$a_{i,v}$	1	0.785	0.728	0.319
$a_{i,m}$	0.785	1	0.760	0.317
$a_{i,t})$	0.728	0.760	1	0.295
$a_{i,s}$	0.319	0.317	0.295	1
Panel B: Job Skill Requirements				
$r_{c_t,v}$	0.315	0.362	0.316	0.189
$r_{c_t,m}$	0.271	0.338	0.313	0.168
$r_{c_t,t}$	0.114	0.198	0.277	0.0951
$r_{c_t,s}$	0.311	0.299	0.181	0.179

Table B.6: Mismatch and the Business Cycle: Total Mismatch

The table reports coefficients from an OLS regression with robust standard errors clustered at the individual level reported in parentheses. In columns 1-4, the dependent variable is total mismatch, m_{i,c_t} (Equation 1). In columns 5-8, the dependent variable is the level of mismatch in each skill dimension: math (m^m_{i,c_t}), verbal (m^v_{i,c_t}), technical (m^t_{i,c_t}) and social (m^s_{i,c_t}). The mismatch measure in skill j is defined as $m^j_{i,c_t} \equiv |a_{i,j} - r_{c_t,j}|$, where $a_{i,j}$ is the worker i's ability in skill j and $r_{c_t,j}$ the job requirements of skill j. All columns include a quadratic polynomial in age. The sample includes all worker-job matches between 1979 and 2012. ***, ** and * represent statistical significance at 1%, 5% and 10% levels, respectively.

Dependent Variable:	m_{i,c_t}				m^m_{i,c_t}	m^v_{i,c_t}	m^t_{i,c_t}	m^s_{i,c_t}
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Unemployment$_t$	-0.137^{***}	-0.144^{***}	-0.141^{***}	-0.134^{**}	-0.202^{***}	-0.097	-0.230^{***}	-0.034
	(0.050)	(0.050)	(0.050)	(0.052)	(0.071)	(0.071)	(0.067)	(0.071)
Observations	520141	510788	510788	510788	510788	510788	510788	510788
Adjusted R^2	0.488	0.494	0.500		0.498	0.501	0.547	0.604
Individual FE	Y	Y	Y	N	Y	Y	Y	Y
Region FE	Y	Y	Y	Y	Y	Y	Y	Y
Industrial FE	Y	Y	Y	Y	Y	Y	Y	Y
Occupation FE	N	N	Y	Y	Y	Y	Y	Y

Table B.7: Mismatch and the Business Cycle: Positive and Negative Mismatch

The table reports coefficients with robust standard errors clustered at the individual level reported in parentheses. Panel A and B replicate columns 3-8 of table B.6 using as the dependent variable the measures of positive and negative mismatch (Equation 2), respectively. All columns include a quadratic polynomial in age, and the following fixed effects: individual, month, year, region, one-digit industry and one-digit occupation. The sample includes all worker-job matches between 1979 and 2012. ***, ** and * represent statistical significance at 1%, 5% and 10% levels, respectively.

Dependent Variable:	m_{i,c_t}		m^m_{i,c_t}	m^v_{i,c_t}	m^t_{i,c_t}	m^s_{i,c_t}
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Positive Mismatch						
Unemployment$_t$	-0.041	-0.015	-0.058	-0.026	-0.085^{*}	0.004
	(0.037)	(0.053)	(0.049)	(0.048)	(0.051)	(0.045)
Observations	510788	510788	510788	510788	510788	510788
Adjusted R^2	0.771		0.752	0.780	0.773	0.765
Panel B: Negative Mismatch						
Unemployment$_t$	-0.099^{***}	-0.118^{***}	-0.143^{***}	-0.071	-0.146^{***}	-0.037
	(0.035)	(0.041)	(0.045)	(0.044)	(0.043)	(0.052)
Observations	510788	510788	510788	510788	510788	510788
Adjusted R^2	0.763		0.747	0.771	0.740	0.812

Table B.8: Mismatch and the Business Cycle: Heterogeneous Effects

The table reports coefficients with robust standard errors clustered at the individual level reported in parentheses. In column 1, the dependent variable is total mismatch, m_{i,c_t} (Equation 1). In columns 2-5, the dependent variable is the level of mismatch in each skill dimension: math (m^m_{i,c_t}), verbal (m^v_{i,c_t}), technical (m^t_{i,c_t}) and social (m^s_{i,c_t}). The mismatch measure in skill j is defined as $m^j_{i,c_t} \equiv |a_{i,j} - r_{c_t,j}|$, where $a_{i,j}$ is the worker i's ability in skill j and $r_{c_t,j}$ the job requirements of skill j. All columns include a quadratic polynomial in age, and the following fixed effects: individual, month, year, region, one-digit industry and one-digit occupation. The sample includes all worker-job matches between 1979 and 2012. ***, ** and * represent statistical significance at 1%, 5% and 10% levels, respectively.

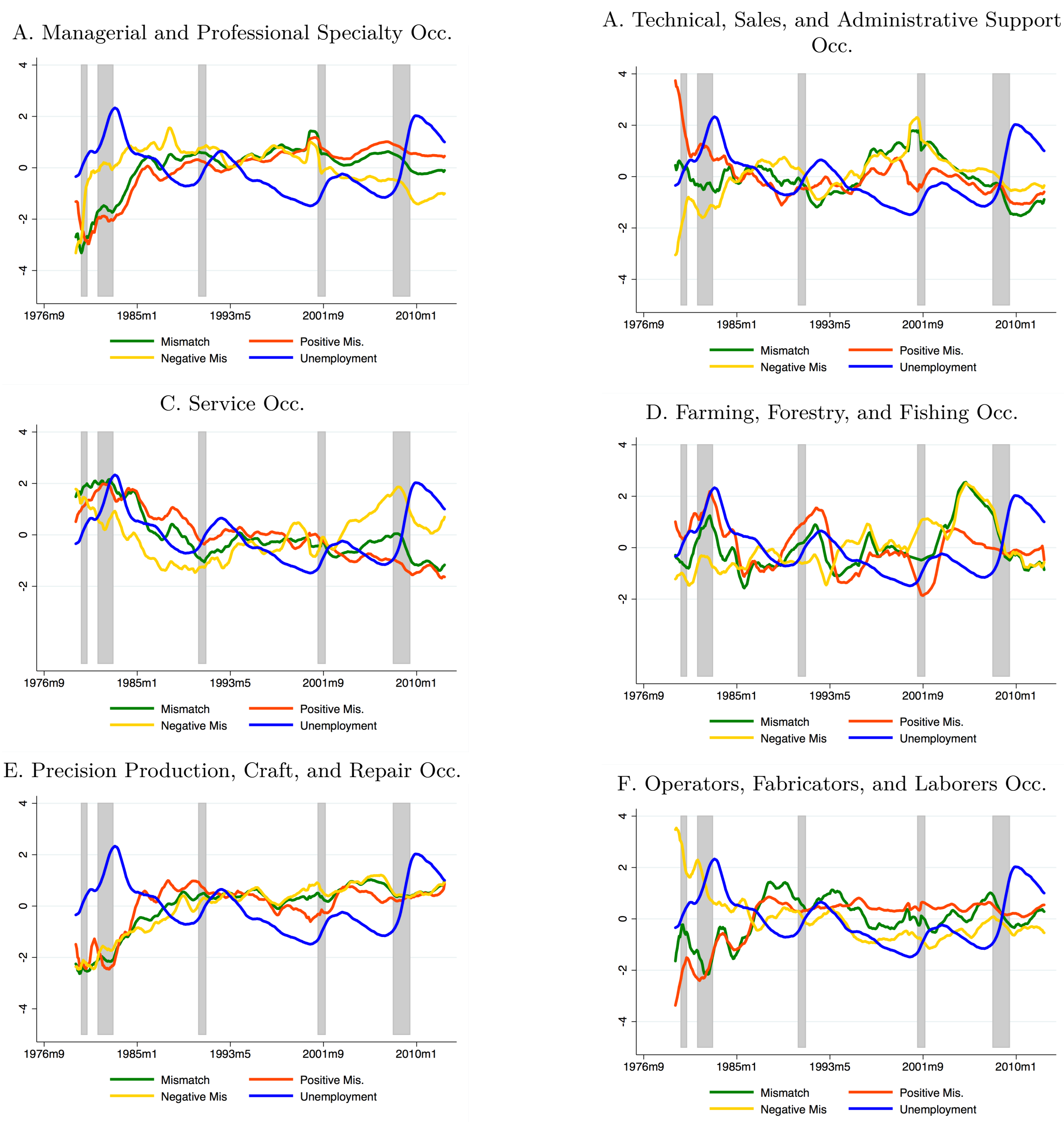
Dependent Variable:	m_{i,c_t}	m^m_{i,c_t}	m^v_{i,c_t}	m^t_{i,c_t}	m^s_{i,c_t}
	(1)	(2)	(3)	(4)	(5)
Unemployment$_t$	-0.159^{***}	-0.222^{***}	-0.123^{*}	-0.242^{***}	-0.048
	(0.050)	(0.071)	(0.072)	(0.068)	(0.071)
EE'$_{i,t}$ × Unemployment$_t$	0.146	0.044	0.165	0.174	0.203
	(0.093)	(0.132)	(0.135)	(0.127)	(0.132)
UE$_{i,t}$ × Unemployment$_t$	0.378^{***}	0.486^{***}	0.566^{***}	0.202^{*}	0.260^{**}
	(0.085)	(0.120)	(0.119)	(0.114)	(0.124)
Observations	510788	510788	510788	510788	510788
Adjusted R^2	0.500	0.498	0.501	0.547	0.604

Table B.9: The Direction of Switch and the Business Cycle

The table reports coefficients from the proportional hazard model with robust standard errors clustered at the individual level reported in parentheses. The dependent variable is the probability that the worker-job pair ends given that it lasted until τ. *Unemployment*$_{\tau_0}$ corresponds to the aggregate unemployment rate at the start if the match, and *Unemployment*$_{\tau}$ measures current aggregate unemployment rat. UE is a dummy variable that equals one if the worker was hired out of unemployment, and *Switcher* equals one if conditional on starting a new job the worker changed occupation. All columns include the following controls: quadratic polynomial in age, current wage, education, race, gender, one-digit industry, one-digit occupation. The sample includes all worker-job matches between 1980 and 2012. * ***, ** and * represent statistical significance at 1%, 5% and 10% levels, respectively.

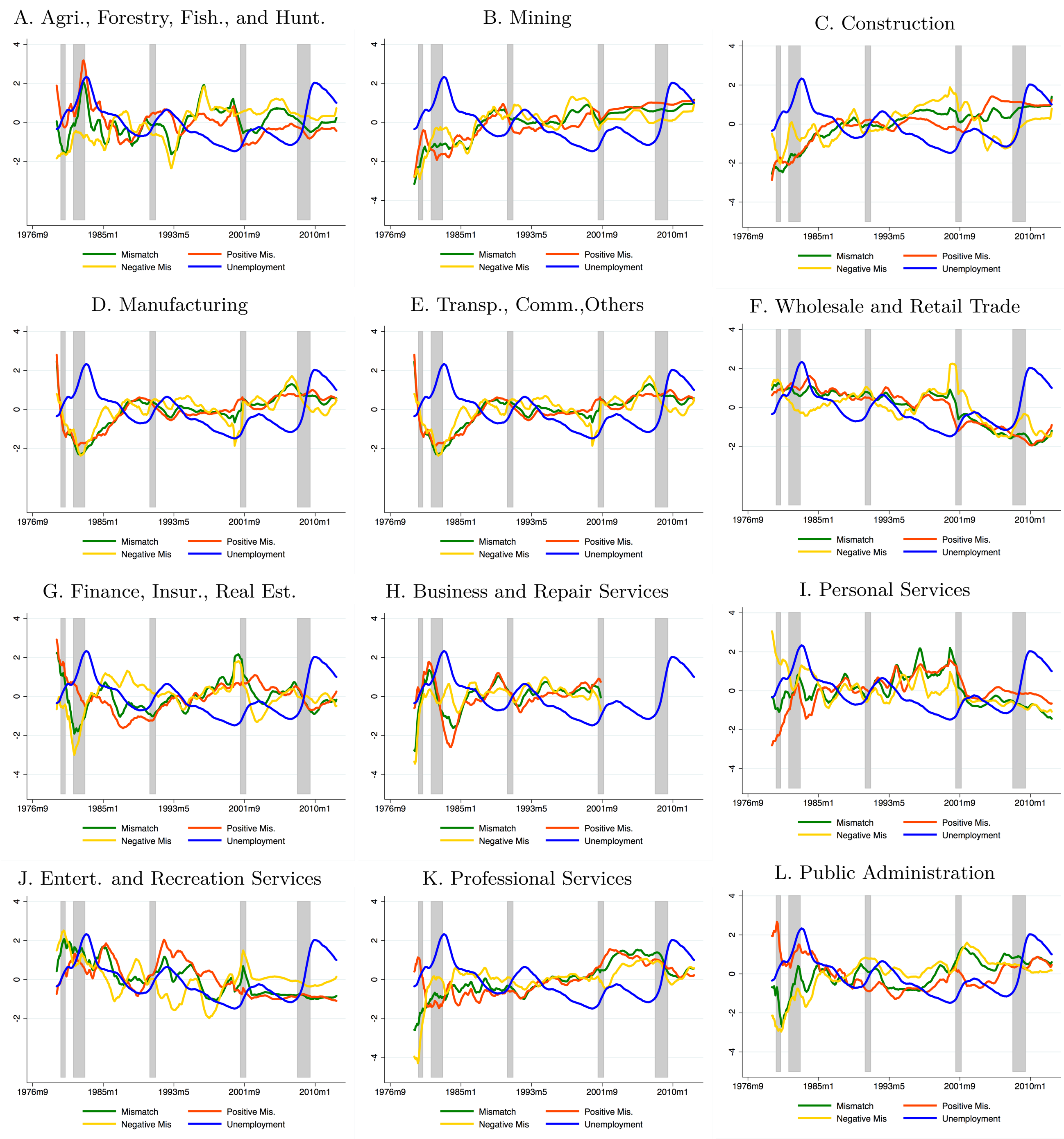
Dependent Variable: Hazard Rate of Separation					
	(1)	(2)	(3)	(4)	(5)
Unemployment$_{\tau_0}$	0.0236***	0.0234***	0.0228***	0.0222***	0.0193***
	(0.0062)	(0.0063)	(0.0063)	(0.0063)	(0.0064)
Unemployment$_{\tau}$	-0.0666***	-0.0659***	-0.0951***	-0.0958***	-0.0945***
	(0.0058)	(0.0059)	(0.0099)	(0.0098)	(0.0102)
Mismatch$_{\mathrm{i}}$		0.0039***	-0.0030	-0.0030*	-0.0032*
		(0.0005)	(0.0018)	(0.0018)	(0.0019)
Unemployment$_{\tau}$ $\times$ Mismatch$_{\mathrm{i}}$			0.0010***	0.0010***	0.0011***
			(0.0003)	(0.0003)	(0.0003)
UE_i				0.1139***	0.0540**
				(0.0143)	(0.0252)
UE_i $\times$ Switcher$_{\mathrm{i}}$					0.0989***
					(0.0306)
Observations	596372	592792	592792	592792	574862

Figure B.1: Mismatch by Occupation and Unemployment



Notes: Data are shown in standard deviations. *Unemployment* is the monthly unemployment rate at the national level.*Mismatch* is average mismatch M_t in equation **??**. *Positive Mis.* and *Negative Mis.* are, respectively, average positive and negative mismatch as defined in section 2.1 and constructed the same way as M_t. Shaded areas correspond to NBER recessions.

Figure B.2: Mismatch by Industry and Unemployment



Notes: Data are shown in standard deviations. *Unemployment* is the monthly unemployment rate at the national level.*Mismatch* is average mismatch M_t in equation **??**. *Positive Mis.* and *Negative Mis.* are, respectively, average positive and negative mismatch as defined in section 2.1 and constructed the same way as M_t. Shaded areas correspond to NBER recessions.

Table B.10: Correlation of Mismatch by Occupation and Unemployment

	M_t	M_t^+	M_t^-
Managerial and Professional Specialty Occ.	-0.583	-0.521	-0.293
Technical, Sales, and Administrative Support Occ.	-0.672	0.0293	-0.670
Service Occ.	0.242	0.179	0.120
Farming, Forestry, and Fishing Occ.	-0.259	0.359	-0.575
Precision Production, Craft, and Repair Occ.	-0.421	-0.308	-0.441
Operators, Fabricators, and Laborers Occ.	-0.401	-0.442	0.329

Notes: This table reports the correlation between the unemployment rate and the average of total, positive and negative mismatch for each occupation category.

Table B.11: Correlation of Mismatch by Industry and Unemployment

	M_t	M_t^+	M_t^-
Agriculture, Forestry, Fishing, and Hunting	-0.168	0.325	-0.460
Mining	-0.355	-0.327	-0.293
Construction	-0.344	-0.228	-0.322
Manufacturing	-0.435	-0.388	-0.414
Transportation, Communications, and Others	-0.420	-0.182	-0.464
Wholesale and Retail Trade	-0.0860	0.0427	-0.324
Finance, Insurance and Real Estate	-0.526	-0.241	-0.352
Business and Repair Services	-0.442	-0.570	-0.0195
Personal Services	-0.441	-0.461	0.00653
Entertainment and Recreation Services	0.309	0.226	0.154
Professional and Related Services	-0.364	-0.350	-0.189
Public Administration	-0.0946	0.503	-0.406

Notes: This table reports the correlation between the unemployment rate and the average of total, positive and negative mismatch for each industry category.

C Robustness Checks

In this section, we show that our empirical findings about the dynamics of mismatch over the cycle are robust to different specifications, sample selection criteria and methods to measure mismatch.

New hires from non-employment In the baseline case presented in Table 1 we used the broadest definition of new hires from non-employment: , independent of how long the unemployment spell, all workers who did not reported a job at $t-1$ (i.e reported to be not working, unemployed or out of the labor force) and are working at time t were considered to be new hires from unemployment. This definition includes *recalls*, i.e workers that return to their previous employer after a jobless spell. However, new hires from unemployment with short jobless spells may be in fact be job-changers taking a short break between jobs. To address this issue, we recode workers with jobless spells equal or smaller than 1, 2 and 3 months as workers making job-to-job transitions. Note that, in this case, those workers that return to their previous employer within 1, 2 and 3 months are recoded as job stayers. Table C.1 shows that our results are robust to these different definitions.

Controls We investigate whether the results are robust to introducing additional controls, namely we add one lag of the unemployment rate, U_{t-1}. Table C.2 shows that expanding the set of controls with the unemployment rate in the previous month has little effect on the estimates.

Alternative measures of economic conditions We replicate the estimation of Equation (3) and (**??**) using three additional measures of business cycle conditions at the national level: *(i)* composite Help-Wanted Index developed by Barnichon (2010), that captures the number of job openings, an important alternative indicator of labor market conditions; *(ii)* the Industrial Production Index; and *(iii)* the deviations from the Hodrick-Prescott filtered unemployment rate. As shown in Panel A of Table C.3, an increase in vacancy postings, i.e. an improvement in economic conditions, is associated with (*i*) an increase in mismatch between worker's abilities and job skill requirements (column 1), (*ii*) an increase in under-qualifications (columns 5, respectively). We also find important heterogeneity along previous employment status: for job stayers, mismatch decreases when vacancies increase; but for new hires from unemployment, mismatch increases; and for new hires from employment, mismatch does not change (column 2). We find the same the same pattern when using the industrial production index (Panel B of table C.3). Thus, we conclude that the main results are robust to using alternative state variables.

Great Recession The sample used in the empirical analysis covers the period between 2008 and 2014, which includes the period of the Great Recession. According to the National Bureau of Economic Research, the Great Recession began in December 2007 and ended in June 2009. We re-estimate Equation (3) and (**??**) restricting the sample to the years before this period, 1979-2006, and find that the results are robust to the Great Recession (Table C.4): the sign of the estimated coefficients is the same as the ones in Table 1 and their magnitude is relatively unchanged.

Only Males So far, we have focused on sub-sample of males and females from the cross-sectional sample of the NLSY79. However, most of the studies on match quality and wage cyclicality restrict the sample to males on the grounds that it is a more homogeneous group, and also because of the sharp transitional dynamics of female participation in the past decades. For comparability, Table C.5 provides OLS estimates of Equation (3) and (**??**) using a sample restricted to males, and shows that our findings remain unchanged.

Alternative empirical measures of mismatch In the empirical analysis, we measured mismatch as an unweighted average of the mismatch along 4 skill dimensions (math, verbal, social and technical) and that uses factor analysis to identifythe set of underlying factors used to compute the skill scores. Table C.2 shows that our findings are robust to four different versions the mismatch index: (*i*) a mismatch index with only 3 skill dimensions (math, verbal and social), as in **?**, (ii) a mismatch index that is a weighted average of the mismatch along 3 skills, in which I use the same weights as in **?**: (verbal, math,social) = (0.43, 0.43, 0.12), (*iii*) a mismatch index that follows Speer (2017)'s methodology in the computation of the worker's abilities and the job skill requirements[25], and (*iv*) a mismatch measure in terms of mean squared deviation between worker's abilities and job skill requirements: $m_{i,c_t} \equiv \left(\sum_{j=1}^{J} (a_{i,j} - r_{c_t,j})^2 / J \right)^{0.5}$.

[25] Speer (2017)'s methodology differs in two dimensions. First, instead of collapsing the several categories into 3 skill dimensions using PCA, he computes the score of each skill asthe mean score across the different components of the test. Given this, the math score is the mean of the mathematics knowledge and arithmetic reasoning tests, verbal the mean of word knowledge and paragraph comprehension and the technical score is the mean of general science and electronics information. Second, while **?** run PCA on the whole set of O*NET descriptors, and do not rely on an priori judgment of which descriptors are measures of skills, Speer (2017) chooses a subset of O*NET descriptors for each skill, and takes the mean as the score for the job skill requirement in each skill dimension.

Table C.1: Mismatch and the Business Cycle: New hires from unemployment

The table reports coefficients from an OLS regression with robust standard errors clustered at the individual level reported in parentheses. In columns 1-2, the dependent variable is mismatch, m_{i,c_t}, in columns 3-4 is positive mismatch, m^+_{i,c_t}, and in columns 5-6 is negative mismatch, m^-_{i,c_t}. $EE'_{i,t}$ is a dummy for whether individual i is a new hire from employment and $UE_{i,t}$ is a dummy for whether individual i is a new hire from unemployment. All columns include a quadratic polynomial in age, and the following fixed effects: individual, month, year, region, one-digit industry and one-digit occupation. The sample includes all worker-job matches between 1979 and 2012. ***, ** and * represent statistical significance at 1%, 5% and 10% levels, respectively.

	1 month			2 months			3 months		
	$m_{i,t}$	$m^+_{i,t}$	$m^-_{i,t}$	$m_{i,t}$	$m^+_{i,t}$	$m^-_{i,t}$	$m_{i,t}$	$m^+_{i,t}$	$m^-_{i,t}$
Unemployment$_t$	-0.159***	-0.050	-0.109***	-0.158***	-0.049	-0.109***	-0.158***	-0.049	-0.109***
	(0.050)	(0.038)	(0.035)	(0.050)	(0.038)	(0.035)	(0.050)	(0.038)	(0.035)
$EE'_{i,t}$ × Unemployment$_t$	0.153*	0.078	0.075	0.165**	0.092	0.073	0.188**	0.093	0.096*
	(0.086)	(0.063)	(0.058)	(0.081)	(0.059)	(0.055)	(0.078)	(0.057)	(0.053)
$UE_{i,t}$ × Unemployment$_t$	0.442***	0.195***	0.247***	0.467***	0.188**	0.279***	0.483***	0.209**	0.275***
	(0.097)	(0.070)	(0.064)	(0.109)	(0.078)	(0.072)	(0.121)	(0.087)	(0.079)
Observations	510788	510788	510788	510788	510788	510788	510788	510788	510788
Adjusted R^2	0.500	0.771	0.763	0.500	0.771	0.763	0.500	0.771	0.763

Table C.2: Mismatch and the Business Cycle: Lagged Unemployment

The table reports coefficients from an OLS regression with robust standard errors clustered at the individual level reported in parentheses. In columns 1-2, the dependent variable is mismatch, m_{i,c_t}, in columns 3-4 is positive mismatch, m^+_{i,c_t}, and in columns 5-6 is negative mismatch, m^-_{i,c_t}. $EE'_{i,t}$ is a dummy for whether individual i is a new hire from employment and $UE_{i,t}$ is a dummy for whether individual i is a new hire from unemployment. All columns include a quadratic polynomial in age, and the following fixed effects: individual, month, year, region, one-digit industry and one-digit occupation. The sample includes all worker-job matches between 1979 and 2012. ***, ** and * represent statistical significance at 1%, 5% and 10% levels, respectively.

Dependent Variable:	m_{i,c_t}		m^+_{i,c_t}		m^-_{i,c_t}	
	(1)	(2)	(3)	(4)	(5)	(6)
Unemployment$_t$	-0.175^{***}	-0.194^{***}	-0.050	-0.060	-0.125^{***}	-0.135^{***}
	(0.062)	(0.063)	(0.047)	(0.048)	(0.040)	(0.041)
Unemployment$_{t-1}$	0.042	0.042	0.011	0.012	0.031	0.030
	(0.072)	(0.072)	(0.055)	(0.055)	(0.047)	(0.047)
EE'$_{i,t}$ × Unemployment$_t$		0.146		0.072		0.074
		(0.093)		(0.068)		(0.064)
UE$_{i,t}$ × Unemployment$_t$		0.378^{***}		0.167^{***}		0.212^{***}
		(0.085)		(0.062)		(0.056)
Observations	510788	510788	510788	510788	510788	510788
Adjusted R^2	0.500	0.500	0.771	0.771	0.763	0.763

Table C.3: Mismatch and the Business Cycle: Alternative Indicators

The table reports coefficients from an OLS regression with robust standard errors clustered at the individual level reported in parentheses. In columns 1-2, the dependent variable is mismatch, m_{i,c_t}, in columns 3-4 is positive mismatch, m^+_{i,c_t}, and in columns 5-6 is negative mismatch, m^-_{i,c_t}. Panel A uses as the business cycle indicator the Composite Help-Wanted index developed by Barnichon (2010) and Panel B uses the industrial production index. $EE'_{i,t}$ is a dummy for whether individual i is a new hire from employment and $UE_{i,t}$ is a dummy for whether individual i is a new hire from unemployment. All columns include a quadratic polynomial in age, and the following fixed effects: individual, month, year, region, one-digit industry and one-digit occupation. The sample includes all worker-job matches between 1979 and 2012. ***, ** and * represent statistical significance at 1%, 5% and 10% levels, respectively.

Dependent Variable:	m_{i,c_t}		m^+_{i,c_t}		m^-_{i,c_t}	
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Vacancies						
Vacancies$_t$	0.241**	0.276**	0.056	0.075	0.186**	0.201**
	(0.112)	(0.113)	(0.082)	(0.082)	(0.081)	(0.082)
EE'$_{i,t}$ × Vacancies$_t$		−0.297		−0.044		−0.253
		(0.290)		(0.216)		(0.201)
UE$_{i,t}$ × Vacancies$_t$		−0.969***		−0.595***		−0.374**
		(0.284)		(0.210)		(0.180)
Observations	510788	510788	510788	510788	510788	510788
Adjusted R^2	0.500	0.500	0.771	0.771	0.763	0.763
Panel B: Industrial Production						
Industrial Prod$_t$	0.034***	0.034***	0.014*	0.014*	0.019**	0.020**
	(0.012)	(0.012)	(0.009)	(0.009)	(0.009)	(0.009)
EE'$_{i,t}$, × Industrial Prod$_t$		−0.001		−0.001		0.001
		(0.010)		(0.007)		(0.007)
UE$_{i,t}$, × Industrial Prod$_t$		−0.022**		−0.001		−0.020***
		(0.009)		(0.006)		(0.006)
Adjusted R^2	0.500	0.500	0.771	0.771	0.763	0.763
Observations	510788	510788	510788	510788	510788	510788
Panel C: Unemployment (HP-filtered)						
Unemployment$_t$	−0.111**	−0.135**	−0.019	−0.031	−0.092**	−0.104***
	(0.052)	(0.053)	(0.040)	(0.040)	(0.036)	(0.037)
EE'$_{i,t}$ × Unemployment$_t$		0.214*		0.045		0.168*
		(0.127)		(0.095)		(0.086)
UE$_{i,t}$ × Unemployment$_t$		0.481***		0.264***		0.217***
		(0.114)		(0.085)		(0.073)
Adjusted R^2	0.500	0.500	0.771	0.771	0.763	0.763
Observations	510788	510788	510788	510788	510788	510788

Table C.4: Mismatch and the Business Cycle: Great Recession

The table reports coefficients from an OLS regression with robust standard errors clustered at the individual level reported in parentheses. In columns 1-2, the dependent variable is mismatch, m_{i,c_t}, in columns 3-4 is positive mismatch, m^+_{i,c_t}, and in columns 5-6 is negative mismatch, m^-_{i,c_t}. $EE'_{i,t}$ is a dummy for whether individual i is a new hire from employment and $UE_{i,t}$ is a dummy for whether individual i is a new hire from unemployment. All columns include a quadratic polynomial in age, and the following fixed effects: individual, month, year, region, one-digit industry and one-digit occupation. The sample includes all worker-job matches between 1979 and 2006. ***, ** and * represent statistical significance at 1%, 5% and 10% levels, respectively.

Dependent Variable:	m_{i,c_t}		m^+_{i,c_t}		m^-_{i,c_t}	
	(1)	(2)	(3)	(4)	(5)	(6)
Unemployment_t	-0.147^{**}	-0.169^{***}	-0.030	-0.040	-0.117^{***}	-0.129^{***}
	(0.061)	(0.062)	(0.047)	(0.048)	(0.042)	(0.042)
$\text{EE'}_{i,t} \times \text{Unemployment}_t$		0.121		0.065		0.056
		(0.095)		(0.070)		(0.065)
$\text{UE}_{i,t} \times \text{Unemployment}_t$		0.374^{***}		0.157^{**}		0.217^{***}
		(0.088)		(0.064)		(0.058)
Observations	457246	457246	457246	457246	457246	457246
Adjusted R^2	0.505	0.505	0.778	0.778	0.764	0.764

Table C.5: Mismatch and the Business Cycle: Only Males

The table reports coefficients from an OLS regression with robust standard errors clustered at the individual level reported in parentheses. In columns 1-2, the dependent variable is mismatch, m_{i,c_t}, in columns 3-4 is positive mismatch, m^+_{i,c_t}, and in columns 5-6 is negative mismatch, m^-_{i,c_t}. $EE'_{i,t}$ is a dummy for whether individual i is a new hire from employment and $UE_{i,t}$ is a dummy for whether individual i is a new hire from unemployment. All columns include a quadratic polynomial in age, and the following fixed effects: individual, month, year, one-digit industry and one-digit occupation. The sample includes all worker-job matches between 1979 and 2012 for males. ***, ** and * represent statistical significance at 1%, 5% and 10% levels, respectively.

Dependent Variable:	m_{i,c_t}		m^+_{i,c_t}		m^-_{i,c_t}	
	(1)	(2)	(3)	(4)	(5)	(6)
Unemployment_t	-0.221^{***}	-0.243^{***}	-0.088	-0.096^{*}	-0.134^{**}	-0.147^{***}
	(0.075)	(0.076)	(0.055)	(0.056)	(0.052)	(0.053)
$\text{EE'}_{i,t} \times \text{Unemployment}_t$		0.249^{*}		0.131		0.118
		(0.131)		(0.097)		(0.087)
$\text{UE}_{i,t} \times \text{Unemployment}_t$		0.396^{***}		0.120		0.275^{***}
		(0.127)		(0.092)		(0.082)
		(0.203)		(0.146)		(0.131)
Observations	266459	266459	266459	266459	266459	266459
Adjusted R^2	0.487	0.488	0.766	0.766	0.760	0.760

Table C.6: Mismatch and the Business Cycle: Alternative Mismatch Measures

The table reports coefficients from an OLS regression with robust standard errors clustered at the individual level reported in parentheses. In columns 1-2, the dependent variable is mismatch, m_{i,c_t}, in columns 3-4 is positive mismatch, m^+_{i,c_t}, and in columns 5-6 is negative mismatch, m^-_{i,c_t}. Panel A uses a version version of the mismatch index with only 3 skill dimensions (math, verbal and social). In Panel B, each skill has a different weight in the computation of the mismatch index. The weights are the ones used in **?**: (verbal, math, social) = (0.43, 0.43, 0.12). Panel C uses a mismatch index computed as in Speer (2017). Panel D uses a mismatch measure in terms of mean squared deviation between worker's abilities and job skill requirements: $m_{i,c_t} \equiv \left(\sum_{j=1}^{J} (a_{i,j} - r_{c_t,j})^2 / J \right)^{0.5}$. $EE'_{i,t}$ is a dummy for whether individual i is a new hire from employment and $UE_{i,t}$ is a dummy for whether individual i is a new hire from unemployment. All columns include a quadratic polynomial in age, and the following fixed effects: individual, month, year, one-digit industry and one-digit occupation. The sample includes all worker-job matches between 1979 and 2012. ***, ** and * represent statistical significance at 1%, 5% and 10% levels, respectively.

Dependent Variable:	m_{i,c_t}		m^+_{i,c_t}		m^-_{i,c_t}	
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Guvenen et al. (2015), unweighted						
Unemployment$_t$	-0.110^{**}	-0.130^{**}	-0.027	-0.036	-0.083^{**}	-0.094^{***}
	(0.050)	(0.051)	(0.036)	(0.036)	(0.036)	(0.036)
EE'$_{i,t}$ × Unemployment$_t$		0.136		0.063		0.073
		(0.093)		(0.065)		(0.065)
UE$_{i,t}$ × Unemployment$_t$		0.433^{***}		0.201^{***}		0.232^{***}
		(0.086)		(0.060)		(0.058)
Adjusted R^2	0.510	0.511	0.770	0.770	0.779	0.779
Panel B: Guvenen et al. (2015), weighted						
Unemployment$_t$	-0.132^{**}	-0.154^{***}	-0.036	-0.047	-0.097^{**}	-0.047
	(0.057)	(0.058)	(0.040)	(0.041)	(0.038)	(0.041)
EE'$_{i,t}$ × Unemployment$_t$		0.114		0.053		0.053
		(0.107)		(0.073)		(0.073)
UE$_{i,t}$ × Unemployment$_t$		0.483^{***}		0.236^{***}		0.236^{***}
		(0.097)		(0.066)		(0.066)
Adjusted R^2	0.485	0.485	0.768	0.768	0.762	0.768
Panel C: Speer (2017)						
Unemployment$_t$	-0.158^{***}	-0.175^{***}	-0.072^{*}	-0.084^{**}	-0.085^{***}	-0.094^{***}
	(0.043)	(0.043)	(0.038)	(0.038)	(0.027)	(0.028)
EE'$_{i,t}$ × Unemployment$_t$		0.089		0.086		0.041
		(0.083)		(0.070)		(0.052)
UE$_{i,t}$ × Unemployment$_t$		0.375^{***}		0.236^{***}		0.187^{***}
		(0.075)		(0.064)		(0.045)
Adjusted R^2	0.517	0.517	0.781	0.781	0.848	0.848
Panel D: Alternative measure						
Unemployment$_t$	-0.137^{***}	-0.157^{***}	-0.048	-0.057	-0.090^{**}	-0.099^{**}
	(0.050)	(0.051)	(0.040)	(0.040)	(0.039)	(0.040)
EE'$_{i,t}$ × Unemployment$_t$		0.177^{*}		0.071		0.066
		(0.092)		(0.074)		(0.069)
UE$_{i,t}$ × Unemployment$_t$		0.394^{***}		0.181^{***}		0.200^{***}
		(0.086)		(0.065)		(0.062)
Adjusted R^2	0.519	0.519	0.785	0.785	0.772	0.772
Observations	510788	510788	510788	510788	510788	510788