Job Specialization and Labor Market Turnover*

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Abstract

I investigate the decline in labor market turnover over recent decades, in particular the fall in job finding and separation rates. I analyze the role of an increase in the specialization of jobs in accounting for this decline. Combining individual level data from NLSY79 with data on skills from the ASVAB and O*NET, I estimate a standard Mincerian wage regression augmented with an empirical measure of mismatch. I find that jobs on average are specialized and that specialization has increased by 15 percentage points since 1995. To quantify the impact of this increasing job specialization on labor market turnover, I build an equilibrium search and matching model with two-sided ex-ante heterogeneity. Workers have different skill endowments and jobs have different skill requirements. The specialization of a job measures the impact of mismatch on match productivity. I show that as jobs become more specialized, my model is able to explain over 50% of the observed decline in labor market turnover. As job specialization increases, well-matched firms and workers choose to remain in their matches longer. This leads to an increase in the proportion of well-matched workers and firms, which in turn results in a decline in labor market turnover.

JEL codes: E24, J63, J64.

Keywords: Turnover, Specialization, Mismatch, Sorting

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1 Introduction

Over the past three decades, there has been a decline in labor market turnover. Measures of turnover such as job finding and separation rates, obtained from worker flow data, or job creation and destruction rates, obtained from firm data, exhibit a secular decline. Figure 1 shows the evolution of separation and job finding rates constructed using monthly CPS data. While the monthly separation rate averaged around 4% during the 1980s, it has declined to around 2% in recent years. The job finding rate also shows a decline over time, from around 44% before 1995 to around 30% in the past decade. I focus on investigating and explaining these observed falls in job finding and separation rates.

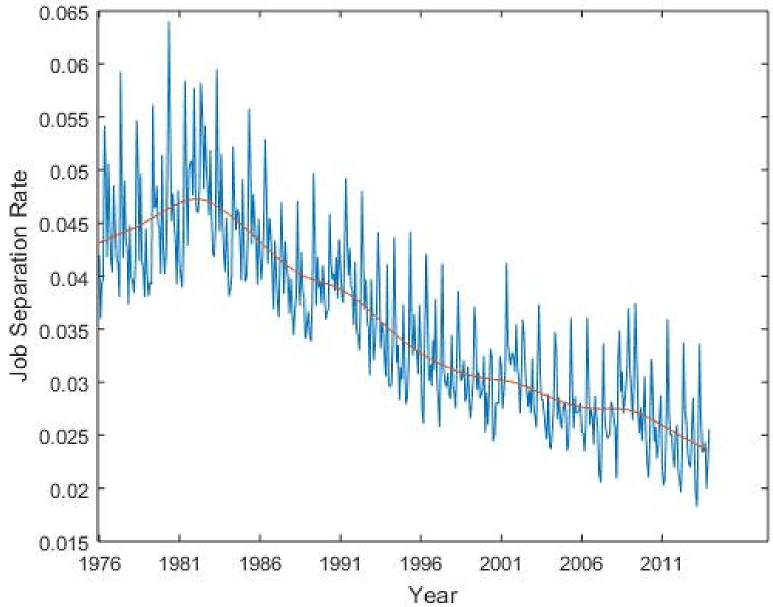
Even though there is a growing empirical literature documenting a secular decline in labor market turnover, there is still no consensus on the underlying economic factors driving it. The fall in labor market turnover could be due to an increase in the costs of making labor market transitions. On the other hand, labor market turnover could be declining because there is less need to make such transitions. We must identify the main forces generating reduced labor market turnover if we are to understand its consequences for the aggregate economy now and in the future. I propose an explanation based on measured increases in job specialization and evaluate its effect on turnover using a calibrated equilibrium search model. In terms of broader effects, the model predicts that this key force behind the observed changes in labor market turnover has had a detrimental impact on aggregate labor productivity and output.

I argue that there has been an increase in the specialization of jobs, and that this has been an important factor explaining the fall in labor market turnover that we see in the data. Job specialization is defined as the impact of mismatch on match productivity, where mismatch is the distance between the skills/ability of a worker and the skill requirements of their job. If there is zero specialization, then any worker of any skill level is suitable for any job, so, mismatch has zero effect on the match productivity. On the other hand, if a job is highly specialized, even a small amount of mismatch can have a large negative impact on match productivity. As job specialization increases, firms are more reluctant to enter into matches with workers ill-suited for the specific skill needs of their jobs. This leads to more skill-compatible matches and reduced labor market turnover, as I will show and explain below.

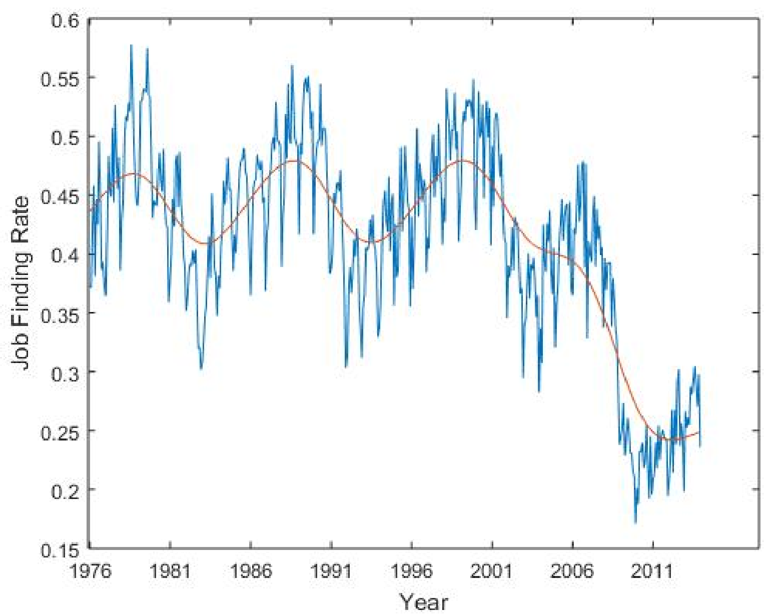
A reasonable estimate of specialization requires an empirical measure of mismatch across the jobs in the economy. I follow the framework of Guvenen et al. (2015) in constructing such a measure. I begin by defining mismatch as the distance between the skills of a worker and the skill requirements of a job in an existing match. Next, I gather data on individual workers and their skill endowments from the National Longitudinal Survey of Youth (NLSY79). NLSY79 sample members take an occupational placement test called Armed Services Vocational Aptitude Battery (ASVAB). The test scores provide detailed measures of each individual's skills along various dimensions. NLSY79 also contains various measures documenting the social skills of a worker. I aggregate selected test scores to construct a skill measure reflecting the verbal, math and social skills of each worker. Next, I obtain data on the skill requirements of jobs from the Occupational Information Network (O*NET) database. This database provides detailed requirements along a large number of skill dimensions for various occupations. As with worker skills, I combine data on multiple skills dimensions to obtain an aggregated measure of verbal, math and social skill requirements for each occupation. Once I have derived the skill endowments of workers and the skill requirements of jobs, I calculate mismatch as the distance between a worker's skill endowment and his job's skill requirement, across all skill dimensions. Finally, I estimate job specialization by using a standard Mincerian wage regression augmented with my empirical measure of mismatch.

I show that jobs on average are specialized, i.e. mismatch has a negative impact on productivity. Moving from the best match (lowest mismatch) to the worst match (highest mismatch) is associated with 38% fall in wages. I also document that job specialization is heterogeneous across occupations, with cognitive occupations having more specialization than manual occupations. Workers of differing educational attainment work in jobs with differing degrees of specialization; more educated workers work in more specialized jobs. Finally, I examine how the specialization of jobs has changed over time and document that specialization, the productivity loss associated with skills mismatch, rose by 15 percentage points between 1980 and 2013. I propose that this increase in the cost of mismatch may have a significant role in explaining the decline in labor market turnover.

Constructing a distribution of employment over mismatch, I analyze how this distribution has changed over time. However, a direct comparison of distributions across time is misleading as the NLSY79 follows the same cohort of individuals. To address this issue, I estimate a linear probability model of employment shares with dummy variables captur-



(a) Separation Rate



(b) Job Finding Rate

Figure 1: Labor Market Turnover

ing both time and age effects. My estimates show that, after controlling for age effects, the employment distribution has shifted towards lower mismatch over time. Workers and jobs sort themselves better in 2013 compared to 1980.

To quantitatively study how increases in job specialization impact labor market turnover, I develop an equilibrium labor search and matching model with two-sided ex-ante heterogeneity. Individual workers are assumed to differ in their skill endowments, while jobs have differing skill requirements, and workers and jobs are located on a unit circle according to their skills. The productivity of a match decreases with mismatch, which is defined to be the distance between the worker (skills) and the firm (skill requirements) in a match. And, I define job specialization in the model as I do in the data. It is the extent to which any given level of mismatch reduces the productivity of the match. Feeding the empirical rise in specialization into my calibrated model, I find that this increase on its own explains more than 50% of the fall in labor market turnover observed in the data.

As jobs become more specialized, workers and firms grow more selective about which matches they enter into. This has two opposing effects on labor market turnover. First, well-matched firms and workers choose to remain in their matches longer, as they know it is more difficult to find an acceptable match in the future. On the other hand, since increased specialization raises the cost of mismatch, ill-suited firms and workers choose to abandon their matches more quickly. To disentangle which effect has a larger impact on aggregate turnover measures, I examine changes in the distribution of employment over mismatch. Since an increase in specialization raises the cost of mismatch, more firms and workers choose to move towards better matches. With increased sorting, a majority of employment faces lower separation rates while a minority faces higher separation rates. This causes a fall in the aggregate separation rate. Further, increased selectivity in match formation reduces the incentive for a firm to post vacancies. This reduces the labor market tightness which in turn causes a decline in the job finding rate.

I also show that the fall in labor market turnover has an adverse effect on aggregate labor productivity. Byrne et al. (2016) documents a 1.75% fall in the growth rate of labor productivity in the 2000s. The empirically measured increase in specialization can explain about 40% of this slowdown in labor productivity. Although increased job specialization causes workers and firms to move to better matches, the resulting fall in mismatch does not fully compensate for the increased productivity costs of mismatch. This causes a fall in aggregate productivity and output. Thus, increased sorting in the labor market need not be productivity enhancing.

This paper contributes to a growing literature engaged in quantifying and understanding the secular decline in labor market turnover. Reductions in measures of turnover based on worker flows data have been documented by many studies including Shimer (2012), Fujita (2015) and Davis et al. (2010). Decker et al. (2014), Decker et al. (2016) and Cairo (2013) provide evidence of a secular downward trend in job flows using data on job creation and destruction. Davis et al. (2010) argue that a fall in the job destruction rate can lead to a decline in unemployment inflows and show that the observed decline in the job destruction rate can account for 28% of the decline in unemployment inflows from 1978 to 2005. Fujita (2015) proposes increased turbulence as a factor driving this fall in turnover. A rise in turbulence is modeled as an increased risk of skills obsolescence during unemployment. As this risk increases, workers are less willing to leave their jobs, so the aggregate separation rate falls. Cairo (2013) argues that increased training requirements for jobs may explain the fall in aggregate job flows. She models training costs as fixed cost and shows that increases in these costs makes firms more reluctant to adjust their employment, resulting in reduced job flows.

I also contribute to the literature of equilibrium search models with heterogeneous workers and firms. I extend the models of Marimon and Zilibotti (1999) and Gautier et al. (2010) by incorporating endogenous separations. Lise et al. (2016) also uses a similar framework to study the role of policy intervention in the labor markets. Although Lise et al. (2016) does not consider time variation in the cost of mismatch or changes in labor market turnover, they find that the cost of mismatch is higher for more skilled workers and this finding is consistent with my empirical results.

The rest of the paper is organized as follows. Section 2 presents the empirical framework and estimates of job specialization. Section 3 describes the model and its equilibrium conditions. Section 4 presents the calibration strategy while the main results of the paper are presented and analyzed in section 5. Section 6 concludes. Supplementary empirical evidence and proofs are provided in the appendix.

2 Empirical Evidence

This section documents the empirical evidence used in this study. I start by constructing a measure of mismatch. I use this measure to show that specialization has increased over time. Finally, I also document that the distribution of employment has shifted to less mismatch over time.

2.1 Data

The data on individual workers are obtained from NLSY79. This data is combined with data on occupational requirements from O*NET as explained below.

2.1.1 NLSY79

NLSY79 is a nationally representative sample of individuals who were between the ages of 14 and 22 years on January 1, 1979. I employ the Employer History Roster of NLSY79 to obtain yearly data on individuals. The employer history roster provides details on all employers for every individual as a single record. The time period considered for the study is 1978 to 2013. This gives up to 36 years of labor market information for the individuals considered. I restrict my analysis to only males in the representative sample. I also consider only individuals who entered the primary labor market after being selected into the sample. I impose this by considering only those individuals who have worked for less than 1,200 hours in 1978. After this selection, I use data on 2,195 individuals and 79,020 total observations in my analysis.

2.1.2 Worker's Skills

One of the reasons to use NLSY79 data is that the individuals in this dataset were administered an occupational placement test called Armed Services Vocational Aptitude Battery, in 1980. This test, administered by U.S. Department of Defense, gives detailed information on worker's skills across multiple dimensions. ASVAB test administered to NLSY individuals had 10 components.[1] Here, following Guvenen et al. (2015), I fo-

[1]The 10 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

cus on 4 components, namely: Word Knowledge, Paragraph Comprehension, Arithmetic Reasoning and Mathematics Knowledge. When the test was administered in 1980, the respondents were of different ages. Since age can have a systematic impact on these test scores, I normalize test scores using age-specific means and variances.

In addition to the verbal and math skill data provided by ASVAB, NLSY79 also provides data on the social skills. I consider the Rotter Locus of Control Scale and Rosenberg Self-Esteem Scale to obtain an estimate of social skills for an individual. The Rotter Locus of Control measures the attitude of respondents towards the role their actions play in determining their life. A lower score indicates that the respondent believes his outcomes are driven by his own actions and not just chance. The Rosenberg Self-Esteem Scale is a measure of one's self-worth. Again, as with the ASVAB scores, these social scores are normalized using age-specific means and variances to remove the impact of age on the scores.

2.1.3 Job's Skill Requirements

The data on skill requirements of different occupations are obtained from the O*NET database. This database put together by the U.S. Department of Labor gives information on knowledge, skills and abilities required to perform around 974 different occupations. For each of these occupations, this database provides a score of importance of 277 different descriptors. From these, I choose 26 descriptors to obtain skill requirements across math and verbal dimensions. I also choose 6 descriptors to capture the social skill requirements in different occupations. Table 1 lists the skills that were chosen. O*NET occupation levels are more detailed than those listed in the NLSY79. Hence, I average the O*NET scores over occupation codes corresponding to NLSY three digit occupation codes.

2.1.4 Skill Dimensions

We now combine the ASVAB and O*NET scores to construct verbal and math dimensions of skill endowments (ASVAB) and skill requirements (O*NET). As a first step, we need to map the 26 categories of O*NET to the 4 ASVAB test components that were chosen earlier. For this purpose, I make use of the crosswalk put together by the Defense Manpower Data Center (DMDC). The DMDC provides a relatedness score for each of the

Verbal and Math Skills	
1. Oral Comprehension	2. Written Comprehension
3. Deductive Reasoning	4. Inductive Reasoning
5. Information Ordering	6. Mathematical Reasoning
7. Number Facility	8. Reading Comprehension
9. Mathematics Skill	10. Science
11. Technology Design	12. Equipment Selection
13. Installation	14. Operation and Control
15. Equipment Maintenance	16. Troubleshooting
17. Repairing	18. Computers and Electronics
19. Engineering and Technology	20. Building and Construction
21. Mechanical	22. Mathematics Knowledge
23. Physics	24. Chemistry
25. Biology	26. English Language
Social Skills	
1. Social Perceptiveness	2. Coordination
3. Persuasion	4. Negotiation
5. Instructing	6. Service Orientation

Table 1: Skills in O*NET

O*NET descriptors to be mapped onto the ASVAB test categories.[2] For each ASVAB test category, we can create an equivalent O*NET requirement by summing the 26 descriptors and weighing them by the relatedness score. At the end of this, we obtain 4 O*NET scores that can be compared with the scores of 4 ASVAB test categories, namely Word Knowledge, Paragraph Comprehension, Arithmetic Reasoning and Mathematics Knowledge.

I standardize each category's standard deviation to 1, and combine these 4 test categories into 2 skill dimensions, namely verbal and math, using Principal Component Analysis (PCA). The verbal score is the first principal component of Word Knowledge and Paragraph Comprehension while the math score is the first principal component of Arithmetic Reasoning and Mathematics Knowledge. Following Lise and Postel-Vinay (2015), I rescale all the four dimensions (verbal worker skills, math worker skills, verbal job requirement, math job requirement) to be in [0,0.5]. [3]

[2]The crosswalk provided by DMDC is available at `http://www.asvabprogram.com/downloads/Technical_Chapter_2010.pdf`

[3]I use a linear transform to achieve this instead of converting the scores into ranks. Linear transform

Moving on to the social dimension, I collapse the six scores from O*NET, after standardizing each score to have a standard deviation of one, into a single social requirement by taking the first principal component. Similarly, on the worker's side, the standardized ASVAB scores (Rotter and Rosenberg) are collapsed into a single social skill score by taking the first principal component. Just like in math and verbal dimensions, social skills and requirements are rescaled to be between 0 and 0.5. We are now able to characterize each worker using his {math, verbal, social} skills and each occupation using its {math, verbal, social} skill requirement.

2.2 Mismatch

I now put together the scores on skill endowments and skill requirements to obtain an estimate of mismatch. Mismatch $x_{i,c}$ is given by the distance measure

$$x_{i,c} = \sum_{j=1}^{n} \left[\omega_j \times |\hat{A}_{i,j} - \hat{r}_{c,j}| \right] \tag{1}$$

where $\hat{A}_{i,j}$ is endowment of worker i in skill dimension j, $\hat{r}_{c,j}$ is requirement of occupation c in skill dimension j and n is the dimension of skills (here 3). The weights give the relative importance of each dimension to mismatch. I use factor loadings of the first component of PCA normalized to 1 as weights which are {verbal,math,social} = {0.438,0.435,0.128}. Thus, mismatch is defined as the distance between a worker's skill endowments and his job's skill requirements across all the skill dimensions.

Figure 2 plots average mismatch over labor market experience. We see a decline in the mismatch, particularly in the first 10 years of work experience, implying that it takes years for workers to find a good match.[4] Incidence of mismatch is also quite heterogeneous in the data. Appendix A provides details of mismatch across different educational attainment, industries and occupations.

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keeps the relative distance within dimensions intact, which is lost when the scores are converted into ranks.

[4]Workers even after taking their ASVAB tests do not choose their ideal jobs immediately because NLSY respondents were not told their exact scores but only given a range in which their score lies. Also, the worker's decision to take up a job might have been influenced by other factors on top of their ASVAB scores. Refer to Guvenen et al. (2015) for a detailed discussion of this issue.

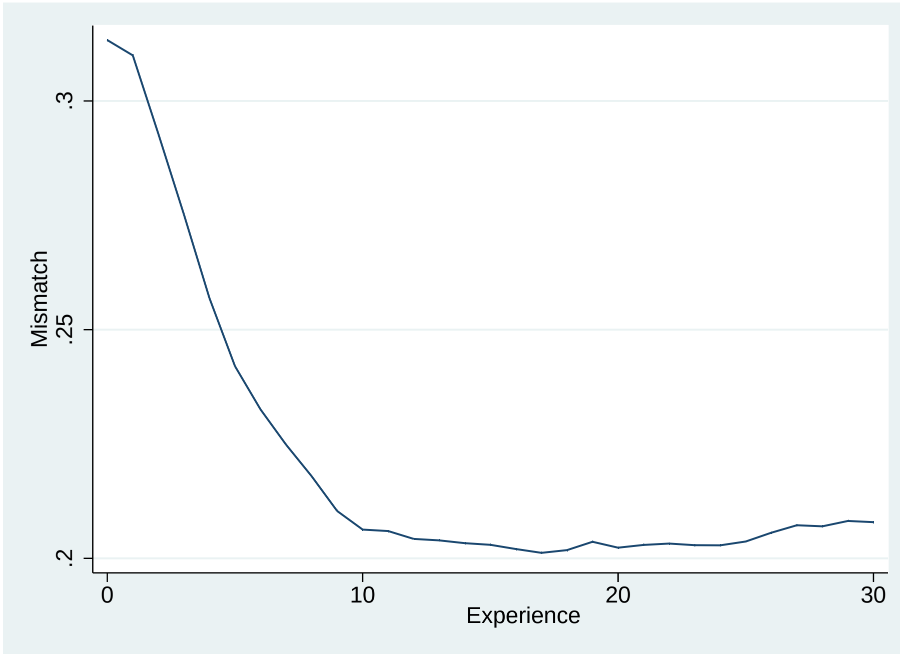


Figure 2: Mismatch over Lifetime

2.3 Job Specialization

The specialization of a job measures the impact of mismatch on the productivity of a match with a worker. For a job with zero specialization, mismatch will have zero impact on productivity. This means any worker of any skill set will be able to perform that job equally well. On the other hand, if a job is highly specialized, mismatch can have a large negative impact on the productivity of a match with a worker. Thus, we can empirically estimate job specialization by regressing match productivity on our measure of mismatch. Since the data on match productivity is not observable, we use individual level real wages from NLSY79 respondents as a proxy for match quality. The estimation of job specialization involves the following regression equation,

$$lnw_{i,c,t} = Z'_{i,t}\chi + \phi x_{i,c,t} + \alpha_2 T_{i,c,t} + \alpha_3 E_{i,t} + \epsilon_{i,c,t} \tag{2}$$

This is a standard Mincerian wage regression augmented by our empirical measure of mismatch. Here $w_{i,c,t}$ is the wage earned by worker i, working in occupation c at time t. $Z_{i,t}$ refers to the vector of observables of worker i at time t, $x_{i,c,t}$ is the mismatch that worker i faces being employed in occupation c at time t, $T_{i,c,t}$ is the occupational tenure of worker i in occupation c at time t and $E_{i,t}$ is the labor market experience of the worker i. The parameter ϕ is our estimate of job specialization as it measures the impact of mismatch on wages. While performing the regression, I also include average skill endowment of each worker and average skill requirement of each occupation to control for the fixed effects along with demographic information.

2.3.1 Baseline

log wage	Coefficients
Mismatch	-0.3809^{***}
Skill	0.6188^{***}
Requirement	0.3432^{***}
Skill*Tenure	0.0004^{***}
Requirement*Tenure	0.0003^{***}

*** refers to $p < 0.01$. Regression also includes labor market experience, occupational tenure, demographics and dummies for 1-digit industry and occupation.

Table 2: Job Specialization: Baseline

Table 2 presents the major results of this regression analysis. The important finding is, jobs on average are specialized, or equivalently, mismatch is costly. The regression shows that moving from the best match (lowest mismatch) to the worst match (highest mismatch) is associated with 38% fall in wages.[5] We also find that the workers with higher skill endowments earn more on average. Similarly, occupations with higher skill requirements pay more on average. One additional finding is, the tenure effect is higher for workers with higher skills or jobs with higher skill requirements. The regression also confirms other well-known results, the details of which are relegated to the appendix. Some of these findings are, workers with more education earn higher wages, wages follow

[5] The wage effect may appear to be low, but this effect is within an industry and occupation group.

an increasing and concave profile with labor market experience and job tenure.

2.3.2 Cross-sectional Properties

We now look at the behavior of job specialization across different occupation categories. Following Acemoglu and Autor (2011), I classify occupations into Cognitive vs. Manual and Non-Routine vs. Routine.

Jobs	Specialization
Cognitive	-0.4022^{***}
Manual	-0.2811^{***}

Table 3: Cognitive vs. Manual

Jobs	Specialization
Non-Routine	-0.3813^{***}
Routine	-0.2893^{***}

Table 4: Non-Routine vs. Routine

Tables 3 and 4 provides the estimates of specialization across different occupation categories. These estimates reinforce our earlier understanding, namely, cognitive jobs are more specialized compared to manual jobs and non-routine jobs are more specialized than routine jobs.

I now look at the specialization of jobs held by workers with different educational attainment. Table 5 gives the estimates across different worker groups.

Workers	Specialization
High school graduate	-0.1155^{***}
College dropout	-0.1971^{***}
College graduate	-0.7292^{***}
More than college	-1.3921^{***}

Table 5: Job Specialization: Education

Workers who are not college graduates perform jobs with very low specialization. And unsurprisingly, college graduates are associated with jobs that are highly specialized. This result provides an interesting perspective on the skill-biased technology debate extended by Acemoglu and Autor (2011), David and Dorn (2013) and others. The estimates in table 5 indicate that jobs performed by workers with low education have the least specialization and hence can be replaced or automated with minimal loss in productivity. Specialization of jobs performed by workers could be an important measure in assessing the impact of technological change on employment.

2.3.3 Time Variation

The primary interest of this empirical exercise is to document how my measure of job specialization has changed over time. To investigate this, I use a dummy variable approach by splitting the sample into two halves, namely pre- and post-1995. The time-varying estimates are given in table 6

Period	Specialization
$Pre - 1995$	-0.2857^{***}
$Post - 1995$	-0.4380^{***}

Table 6: Job Specialization: Pre and Post 1995

Table 6 shows that my estimate of job specialization has increased by 15 percentage points. The wage loss associated with a given level of mismatch has increased after 1995.

Even though the benchmark results show job specialization pre- and post-1995, the increase in job specialization can be found even if we split our sample across different decades. Table 7 shows the estimates of specialization across decades.

Period	Specialization
$1980 - 1989$	-0.2524^{***}
$1990 - 2000$	-0.3325^{***}
$2001 - 2013$	-0.4506^{***}

Table 7: Job Specialization: Across Decades

Since our sample consists of the same individuals over time, the increased specialization we find might be due to workers getting older and not due to changes in the cost of mismatch of an average worker. It could be the case that workers move to jobs with higher specialization as they get older and my regression results capture this change. In order to address this concern, I estimate changes in specialization only for workers who have not changed jobs over the period 1990-2013. By concentrating on these workers, I can test for the systematic effect of an aging sample on job specialization.

Period	Specialization
$1990 - 2000$	-0.4334^{***}
$2001 - 2013$	-0.5151^{***}

Table 8: Job Specialization: No Occupational Change

Table 8 shows the estimates of job specialization for workers who have not changed jobs across the entire time period of 1990-2013. Even if we consider only those workers who have not moved to a different job over time, specialization of jobs has increased from -0.4334 in the decade of 1990-2000 to -0.5151 in the past decade. Thus, the increased job specialization we found reflects an actual increase in cost of mismatch for an average worker, and not just because of workers moving to more specialized jobs as they get older. Below, I construct a distribution of employment over mismatch and further control for age by addressing the cohort effects.

2.4 Employment Distribution

The regression analysis has shown that the mismatch is costly. We now analyze how the employment is distributed over mismatch and how this distribution has changed over time. Since we have a measure of mismatch for each employed individual across years, we can construct the distribution of employment each year by calculating the share of employment belonging to different values of mismatch. Figures 3 and 4 shows the constructed distribution in the year 1980 and 2013 respectively. We see that the share of employment is declining with mismatch. This goes along with our earlier finding that mismatch is costly, and as a result, there are more matches with lower levels of mismatch.

The previous analysis found that the cost of mismatch has increased over time. We now examine how the distribution of employment over mismatch has evolved during a similar time period. But, direct comparison of distribution across time would be misleading in our case. This is because NLSY79 follows the same cohort of individuals over time.

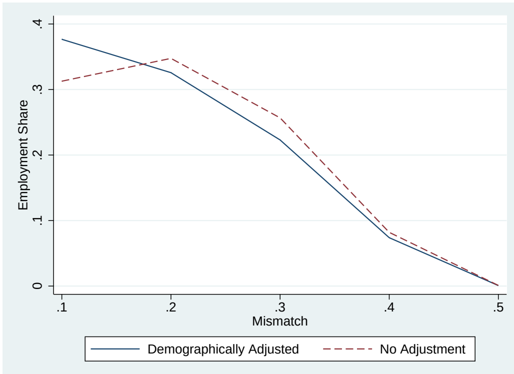


Figure 3: Employment Distribution: 1980

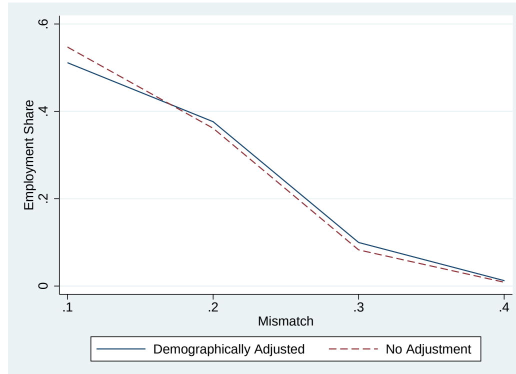


Figure 4: Employment Distribution: 2013

Thus, as we move ahead in time, the average labor market experience of our sample also increases. As workers spend more time in the labor market, they might learn more about their skills or learn about various job opportunities and hence move to a job which is the closest match to their skills.[6] Thus an aging sample of workers can mechanically lead to a shift in the employment distribution towards lower mismatch.[7] We call this *cohort effect*. Thus, we need to isolate and filter out the *cohort effects* in order to extract the actual *time effects* of the employment distribution.

In order to control for the cohort effect, I estimate a linear probability model for the employment shares in the individual level data of NLSY79. To estimate the share of employment having mismatch in the interval $[x_0, x_1]$, my dependent variable takes the value of 1 if a match has a mismatch $x \in [x_0, x_1]$ and 0 otherwise. The independent variables include year dummies to capture time effects and demographic controls (dummies that distinguish between young (16-24), middle-aged (25-54) and old (55-) workers) to capture the cohort effects on the employment share. Using the estimated regression, the time effects can be isolated by fixing the demographic controls at their sample means. A detailed description of this empirical analysis is present in Appendix B.

Figures 3 and 4 show the distribution of employment in 1980 and 2013 respectively. The dotted lines show the original distribution constructed from the NLSY79 data and we

[6]The literature of learning models deals with workers who learn about their own skills, the match quality or other attributes of jobs over the time of experience. Some of the papers who explore these topics include Jovanovic (1979), Sanders (2014) and others.

[7]The average mismatch decreases with the labor market experience as seen from figure 2

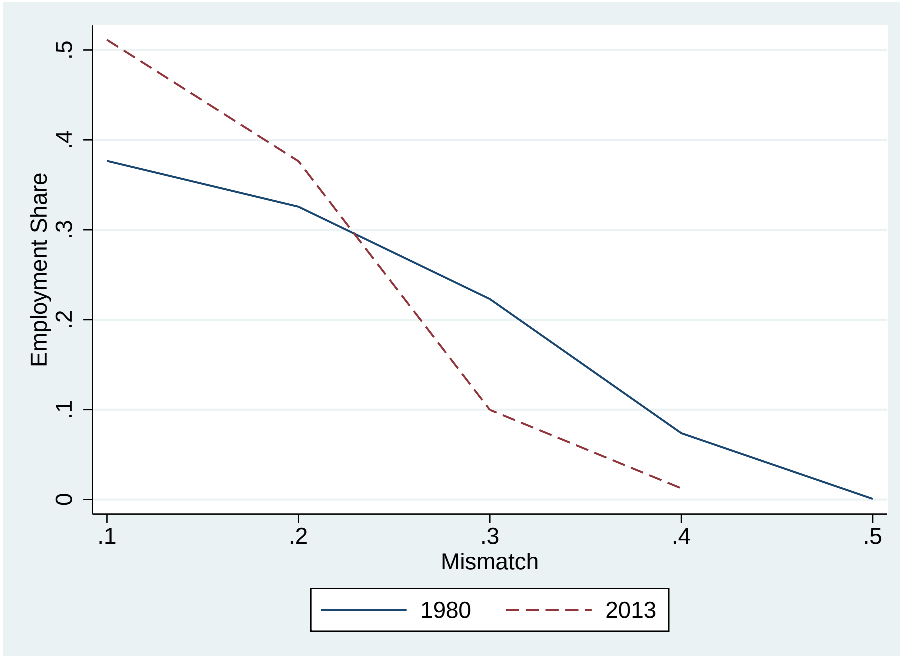


Figure 5: Employment Distribution: 1980 vs. 2013

see that the distribution has shifted towards lower mismatch in 2013. As discussed before, this shift could be a combination of both cohort and time effects. The solid lines show the distribution after removing the cohort effects. As seen from the figure 5, the distribution has shifted towards the lower mismatch even after filtering out the cohort effects. This shows that the workers and jobs sort themselves better in 2013 compared to 1980. Again, controlling for these cohort effects allows me to study the effect of specialization across matches while eliminating the effect of increased sorting resulting from an older sample of workers in the NLY79.

2.5 Job Specialization and Labor Market Turnover

In this section, I provide microeconomic evidence of changes in labor market turnover and job specialization. I show that the labor market turnover has declined over time for workers across different educational attainment. I also show that the specialization of jobs performed by workers having different education has increased over time. This may be a preliminary evidence supporting my hypothesis: increases in job specialization have caused a decline in labor market turnover. At the same time, it is important to note that the evidence presented here demonstrates a mere association between job specialization and labor market turnover and does not prove causality.

Classification	Δf	Δs	$\Delta \phi$
Aggregate	-14.41	-32.06	15.23
High school graduate	-13.95	-21.36	7.18
College dropout	-14.48	-23.95	38.11
College graduate	-11.96	-19.05	63.29
More than college	-8.46	-12.12	19.55

[1] f is job finding rate, s is separation rate, ϕ is my estimate of specialization.

[2] Δf and Δs is percent change while $\Delta \phi$ is percentage point change pre and post 1995.

Table 9: Job Specialization and Labor Market Turnover

The measures of labor market turnover, namely the separation rate and job finding rate are constructed from CPS microdata. More precisely, I follow Shimer (2012) and compute separation and job finding rates using time-series data on employment, unemployment and short-term unemployment (unemployment with duration less than 5 weeks). Figure 1 shows the evolution of labor market turnover from 1976 till 2013. There has been a steady decline in the separation rate from the early 1980s while the decline in the job finding rate is less apparent. The aggregate separation rate averages around 0.0284 post 1995 compared to 0.0418 before 1995. Similarly, the job finding rate averages around 0.4407 compared to 0.3772 before 1995. The separation rate has declined by 32% while the job finding rate has declined by 14% post 1995.

We now decompose this decline in turnover across different education groups and how it is related to changes in job specialization. As can be seen from table 9, both job finding and separation rates have declined across all education groups. Figures showing the evolution of labor market turnover across education can be found in appendix A. More importantly, job specialization has increased across all education groups. Thus, the increase in job specialization is associated with a decline in labor market turnover but need not have caused it. In the next section, we show that increases in job specialization do indeed cause a decline in labor market turnover.

3 The Model

This section presents a search and matching model with ex-ante heterogeneous workers and jobs distributed over a unit circle. I extend Marimon and Zilibotti (1999) and Gautier et al. (2010) by incorporating endogenous separations.

3.1 Environment

The economy consists of ex-ante heterogeneous workers and jobs. Workers having different skill endowments and jobs having different skill requirements are uniformly distributed over a circle of unit length. There is a unit measure of workers in total. At a given instant, a worker can be employed or unemployed. We do not allow for on-the-job search, and hence employed workers have to go through unemployment before changing jobs. Let the total measure of firms located on the circle be M. At each instant, the firm can either post a vacancy or it is matched with a worker and involved in production. Unmatched firms need to pay a cost to post vacancy. Existing matches face idiosyncratic productivity shocks $\epsilon \in [0, \bar{\epsilon}]$ that arrive at the rate λ from a distribution F(.).

3.2 Match Productivity

The productivity of a match decreases with the distance between the worker and firm in the match. Let a worker be located at $w \in [0, 2\pi]$ and a firm at $f \in [0, 2\pi]$ on the circle.[8] The productivity of this match depends on $\widehat{f,w} \in [0, \frac{1}{2}]$, the arc-length (distance) between worker and firm. Let $\eta(\widehat{f,w})$ denote the productivity of the match. We can interpret $\widehat{f,w}$ as the measure of mismatch in our model framework and accordingly, $\eta(\widehat{f,w})$ is the mismatch function. The mismatch function that we will use in our quantitative exercise is

$$\eta(\widehat{f,w}) = 1 - \gamma \widehat{f,w} \tag{3}$$

[8] In the model environment, location is synonymous with skills. A worker at location w is equivalent to a worker with skill w. Similarly, a firm at location f is same as a job with skill requirement f.

where γ measures job specialization. Just as in the empirical framework, γ measures the importance of mismatch to match productivity. When γ takes a value of zero, mismatch has zero effect on productivity and hence there is no job specialization. A higher value of γ signifies a larger (negative) impact of mismatch on productivity and hence greater job specialization. Thus, our specification of productivity is consistent with our empirical counterpart.

3.3 Labor Market Matching

Workers and firms are involved in random search and hence any unemployed worker can meet and be interviewed by any vacant firm with equal probability. Let $v : [0, 2\pi] \to \mathrm{R}^+$ denote the density of vacancies at location f and $u : [0, 2\pi] \to [0, 1]$ denote the density of unemployed at location w. The matching function $m : \mathrm{R}^+ \times [0, 1] \to \mathrm{R}^+$ gives the flow of interviews between a firm located at f and a worker located at w. As is standard, $m(v(f), u(w))$ is increasing in both $v(f)$ and $u(w)$, and is constant returns to scale. Let $q(f, w) = m(v(f), u(w))/v(f)$ be the probability that a firm at f meets a worker from w and $\theta(f, w) = v(f)/u(w)$ gives the labor market tightness. Since mismatch is costly in our environment ($\gamma > 0$), only a fraction of these meetings materialize into productive job matches and this fraction is determined in the equilibrium.

3.4 Continuation Values

In this subsection, I present the recursive formulation of the dynamic problem faced by the firms and the workers. Let $V(f)$ denote the value of a vacant firm at the location f.

$$rV(f) = -c + \frac{1}{2\pi} \int_{f}^{f+2\pi} q(f, \tau)\ max\{J^0(f, \tau), V(f)\} d\tau \tag{4}$$

where r is the interest rate. A vacant firm at location f upon paying a cost c to post a vacancy, meets a worker from location τ with probability $q(f, \tau)$. Upon meeting, the vacant firm must decide whether to accept the match, earning the value J^0 or continue to remain vacant. We assume there is a free entry of vacancies. This will drive down the value of a vacant firm to zero in equilibrium.

$$V(f) = 0, \forall f \in [0, 2\pi] \tag{5}$$

The continuation value of an unemployed worker is given by U.

$$rU(w) = b + \frac{1}{2\pi}\int_{w}^{w+2\pi} \theta(\tau, w)q(\tau, w)\ [max\{W^0(\tau, w), U(w)\} - U(w)]d\tau \qquad (6)$$

where b determines the flow value of an unemployed worker, which could include the unemployment insurance, home production or value of leisure. The unemployed worker at location w meets a firm from f with a probability $\theta(\tau, w)q(\tau, w)$, and has to decide whether to accept a job match and earn a value of W^0 or continue to remain unemployed.

We now move onto the continuation values during the period of match creation. The value the firm receives at the period of match formation is given by

$$rJ^0(f, w) = \eta(f, w)\bar{\epsilon} - \omega_0(f, w) + \lambda\int_0^{\bar{\epsilon}}[max\{J(f, w, z), V(f)\} - J^0(f, w)]dF(z) \qquad (7)$$

The output of a match is given by the product of mismatch component η and the idiosyncratic productivity ϵ. Following other models with endogenous job separation like Mortensen and Pissarides (1994), Mortensen and Pissarides (1999) and Fujita and Ramey (2012), new matches are formed at the frontier of the idiosyncratic productivity $\bar{\epsilon}$.[9] After the starting period, idiosyncratic productivity changes with probability λ and the new productivity value is drawn from the distribution $F(.)$. ω_0 is the wage paid to the worker at the period of match creation; wage determination is explained later. Similarly, the continuation value of the worker at the starting period is given by

$$rW^0(f, w) = \omega_0(f, w) + \lambda\int_0^{\bar{\epsilon}}[max\{W(f, w, z), U(w)\} - W^0(f, w)]dF(z) \qquad (8)$$

The worker at the starting period receives a wage ω_0 and has to decide whether to continue with the match, earning a value of W or become unemployed earning a value of U. Finally, I list the continuation values of firms and workers involved in incumbent matches. The only difference is, now the matches need not be at the highest idiosyncratic productivity level.

$$rJ(f, w.\epsilon) = \eta(f, w)\epsilon - \omega(f, w, \epsilon) + \lambda\int_0^{\bar{\epsilon}}[max\{J(f, w, z), V(f)\} - J(f, w, \epsilon)]dF(z) \quad (9)$$

[9] The assumption that all new matches start at the highest idiosyncratic productivity level simplifies the analysis, as all the meetings with sufficiently low mismatch gets converted into productive matches.

As before, the productive firm earns output net of wages paid and has to decide whether to continue with the match earning a value of J or dissolve the match and become vacant. The worker's continuation value is given by

$$rW(f,w,\epsilon) = \omega(f,w,\epsilon) + \lambda \int_0^{\bar{\epsilon}} [max\{W(f,w,z), U(w)\} - W(f,w,\epsilon)] dF(z) \tag{10}$$

3.5 Wage Determination

The surplus generated from a successful match is shared between the worker and firm using Nash bargaining. Wages of a worker having bargaining power β satisfy the equation

$$(1-\beta)[W(f,w,\epsilon) - U(w)] = \beta J(f,w,\epsilon) \tag{11}$$

Substituting the value functions, the wage received by a matched worker is given by

$$\omega(f,w,\epsilon) = \beta \left[\eta(\widehat{f,w})\epsilon + \frac{1}{2\pi} \int_w^{w+2\pi} \theta(\tau,w) q(\tau,w) J^0(\tau,w) d\tau \right] + (1-\beta)b \tag{12}$$

and the starting wage is given by

$$\omega_0(f,w) = \beta \left[\eta(\widehat{f,w})\bar{\epsilon} + \frac{1}{2\pi} \int_w^{w+2\pi} \theta(\tau,w) q(\tau,w) J^0(\tau,w) d\tau \right] + (1-\beta)b \tag{13}$$

3.6 Equilibrium

Following Marimon and Zilibotti (1999), Gautier et al. (2006) and Gautier et al. (2010), we concentrate on symmetric equilibrium where both unemployment and vacancies are uniformly distributed over the circle. The following proposition proves that it is an equilibrium in our environment.

Proposition 1. *Given a free entry of vacancies, an uniform distribution of unemployment and vacancies, i.e.* $u(w) = u \ \forall w \in [0, 2\pi]$ *and* $v(f) = v \ \forall f \in [0, 2\pi]$ *is an equilibrium.*

Proof. In Appendix.

The intuition is, given that unemployment has a uniform distribution, vacancies must be distributed uniformly. Otherwise, in a location with relatively many vacancies, the outside option of being unemployed (and hence wages) will be higher. This reduces the value of vacancies at such locations which in turn violates the free entry condition. Similarly, given that vacancies are uniformly distributed, unemployment also must be distributed uniformly. If not, a firm can profitably deviate and post a vacancy in a location having more unemployment, again violating the free entry condition.

The major implication of this proposition is that market tightness θ no does not depend on the location of the match i.e. $\theta(f, w) = \theta$, $\forall f$,$w \in [0, 2\pi]$. As a result, continuation values depend only on the distance of the match i.e. $x \equiv \widehat{f, w}$ and not on the location of workers or firms. Under a uniform distribution of unemployment and vacancies, we can simplify the continuation values as follows. The continuation value of a vacant firm is given by

$$rV = -c + 2q(\theta) \int_0^{\bar{x}} J^0(\tau)d\tau \tag{14}$$

while that of an unemployed worker is

$$rU = b + 2\theta q(\theta) \int_0^{\bar{x}} [W^0(\tau) - U]d\tau \tag{15}$$

Here, $\bar{x}$ denotes the cut-off distance between a worker and a firm. If the distance is greater than $\bar{x}$, workers and firms choose to walk away during the interview without forming a match.

Continuation values during the time of the match can be reformulated as

$$rJ^0(x) = \eta(x)\bar{\epsilon} - \omega_0(x) + \lambda \int_0^{\bar{\epsilon}} [max\{J(x, z), V\} - J^0(x)]dF(z) \tag{16}$$

while that of the worker is

$$rW^0(x) = \omega_0(x) + \lambda \int_0^{\bar{\epsilon}} [max\{W(x, z), U\} - W^0(x)]dF(z) \tag{17}$$

Finally, the continuation value of a firm involved in an existing match is given by

$$rJ(x, \epsilon) = \eta(x)\epsilon - \omega(x, \epsilon) + \lambda \int_0^{\bar{\epsilon}} [max\{J(x, z), V\} - J(x, \epsilon)]dF(z) \tag{18}$$

while that of the worker is

$$rW(x, \epsilon) = \omega(x, \epsilon) + \lambda \int_0^{\bar{\epsilon}} [max\{W(x, z), U\} - W(x, \epsilon)]dF(z) \tag{19}$$

The equilibrium wages in the starting period simplifies to

$$\omega_0(x) = \beta[\eta(x)\bar{\epsilon} + c\theta] + (1 - \beta)b \tag{20}$$

and continuing wages are given by

$$\omega(x, \epsilon) = \beta[\eta(x)\epsilon + c\theta] + (1 - \beta)b \tag{21}$$

3.7 Model Solution

Equilibrium of this model is characterized by $\{\theta, \bar{x}, \epsilon^*(x)\}$ where θ denotes market tightness (independent of f and w), $\bar{x}$ denotes the cutoff distance and $\epsilon^*(x)$ gives the cut-off productivity. If the distance is greater than $\bar{x}$, workers and firms choose to walk away from their interview without forming a match. If the idiosyncratic productivity of a match with mismatch x is below $\epsilon^*(x)$, firms and workers mutually choose to separate from the existing match. We use the free entry condition and the definition of cutoffs to solve for the equilibrium objects.

- *Free Entry Condition*

  With a free entry of vacancies, the value of a vacant firm is zero in equilibrium.

$$rV = 0 \tag{22}$$

  Using the definition of continuation values and wages, we get the following equation,

$$c = \frac{2q(\theta)(1-\beta)}{r+\lambda}\left[\bar{\epsilon}\bar{x}\bar{\eta}(\bar{x}) - b\bar{x} - \frac{\beta c\theta\bar{x}}{1-\beta} + \frac{\lambda}{r+\lambda}\int_0^{\bar{x}}\int_{\epsilon^*(\tau)}^{\bar{\epsilon}} \eta(\tau)(z-\epsilon^*(\tau))dF(z)d\tau\right] \tag{23}$$

- *Cutoff Distance*

  The cutoff distance $\bar{x}$ gives the level of mismatch at which the meeting firm and worker are indifferent between forming the match and walking away empty handed.

$$W^0(\bar{x}) - U = J^0(\bar{x}) = 0 \tag{24}$$

  Substituting the continuation values, we get

$$\bar{\epsilon} + \frac{\lambda}{r+\lambda}\int_{\epsilon^*(\bar{x})}^{\bar{\epsilon}}(z-\epsilon^*(\bar{x}))dF(z) = \frac{b}{\eta(\bar{x})} + \frac{\beta c\theta}{(1-\beta)\eta(\bar{x})} \tag{25}$$

- *Cutoff Productivity*

  Cutoff productivity $\epsilon^*(x)$ leaves an incumbent match with mismatch level x indifferent between continuing to stay together and ending the match.

$$W(x,\epsilon^*(x)) - U = J(x,\epsilon^*(x)) = 0 \tag{26}$$

  Substituting continuation values, we have

$$\epsilon^*(x) + \frac{\lambda}{r+\lambda}\int_{\epsilon^*(x)}^{\bar{\epsilon}}(z-\epsilon^*(x))dF(z) = \frac{b}{\eta(x)} + \frac{\beta c\theta}{(1-\beta)\eta(x)} \tag{27}$$

The derivations of these equilibrium conditions can be found in the appendix. Equations (23),(25) and (27) constitute the equilibrium equations of the model. We solve them simultaneously for $\{\theta, \bar{x}, \epsilon^*(x)\}$.

3.8 Labor Market Flows

In this section, I present equations governing the labor market flows. Even though we don't need to obtain the employment distribution to solve the model, these distributions are needed to calculate labor market turnover, the primary objective of this paper. Let $e_x(\epsilon)$ represent the distribution (CDF) of employment with mismatch x. The total employment having a mismatch level of x is $e_x(\bar{\epsilon})$. Aggregate employment e is obtained by integrating over all possible mismatch values,

$$e = 2\int_0^{\bar{x}} e_x(\bar{\epsilon})dx \tag{28}$$

Since there is a unit measure of workers in total, aggregate unemployment u is

$$u = 1 - e \tag{29}$$

We now detail the flow equations of employment at each level of mismatch level x.

$$\text{Inflow into unemployment from } x = \lambda F(\epsilon^*(x))e_x(\bar{\epsilon}) \tag{30}$$

The measure of workers who transition from being employed with mismatch x to unemployment is the fraction of total employment with mismatch x who receives a productivity realization lower than their cutoff productivity $\epsilon^*(x)$.

$$\text{Outflow from unemployment to } x = \theta q(\theta)u \tag{31}$$

The probability of an unemployed worker finding a job with mismatch x is fairly standard. Since we consider an equilibrium with a uniform distribution of vacancies and unemployment, market tightness θ and hence the job finding probability $\theta q(\theta)$ does not depend on the location of job creation.

In the steady state, the inflows into unemployment should be equal to the outflow from unemployment at each mismatch level x. Equating the flow equations gives us an expression for the total employment at each x.

$$e_x(\bar{\epsilon}) = \frac{\theta q(\theta)\left[1 - 2\displaystyle\int_0^{\bar{x}} e_x(\bar{\epsilon})dx\right]}{\lambda F(\epsilon^*(x))} \tag{32}$$

Once we have the total employment for each mismatch level, we can retrieve the distribution of employment over the space of $\{x, \epsilon\}$ as follows.

$$e_x(\epsilon) = \begin{cases} 0 & \text{if } \epsilon < \epsilon^*(x) \\ [F(\epsilon) - F(\epsilon^*(x))]e_x(\bar{\epsilon}) & \text{if } \epsilon^*(x) \leq \epsilon < \bar{\epsilon} \\ \frac{\theta q(\theta)[1-2\int_0^{\bar{x}} e_x(\bar{\epsilon})dx]}{\lambda F(\epsilon^*(x))} & \text{if } \epsilon = \bar{\epsilon} \end{cases}$$

Employment for each mismatch level x exists in the interval $[\epsilon^*(x), \bar{\epsilon}]$. The above equation for distribution is obtained by equating the flows in and out of employment at each value of x and ϵ. Finally, we can derive the aggregate separation rate (s), one of the measures of the labor market turnover. It is defined as total job separations across all mismatch levels as a fraction of aggregate employment.

$$s = \frac{\lambda \int_0^{\bar{x}} F(\epsilon^*(x))e_x(\bar{\epsilon})dx}{\int_0^{\bar{x}} e_x(\bar{\epsilon})dx} \tag{33}$$

Job finding rate is defined as the total outflows from unemployment to employment over the circle as a fraction of aggregate unemployment.

$$f = 2\bar{x}\theta q(\theta) \tag{34}$$

4 Calibration

I calibrate the model to quantitatively assess the impact of an increase in job specialization on labor market turnover. In total, there are 10 parameters to calibrate. Three parameters are chosen exogenously outside the model while the remaining seven parameters are selected so that the model can match various moments from the data.

Table 10 gives the values of the parameters that are chosen externally without solving the model. The model is calibrated at a monthly frequency. The interest rate r is set to 0.004 to obtain an annual interest rate of 4.8%. The matching function is assumed to be Cobb-Douglas of the form $m = \mu u^{\alpha} v^{1-\alpha}$. The elasticity of matching function α is chosen to be 0.5 following the evidence reported in Petrongolo and Pissarides (2001). Following

Parameter	Definition	Value
r	Interest rate	0.004
β	Worker's bargaining power	0.5
α	Elasticity of matching function	0.5

Table 10: Externally Chosen Parameters

most of the literature like Pissarides (2009), worker's bargaining power β is set equal to the elasticity of matching function.

Parameter	Definition	Value	Target
c	Vacancy posting cost	0.8106	Market tightness (θ)
b	Value of leisure	0.6460	60% of aggregate output
μ	Efficiency of matching function	0.6583	Job finding rate (f)
λ	Frequency of shocks	0.0996	Separation rate (s)
σ_ϵ	Std. dev. of shocks	0.3891	Emp. share at $x = 0.1$
$\bar{\epsilon}$	Maximum shock realization	1.6033	Maximum mismatch ($\bar{x}$)
γ	Importance of mismatch	0.5135	Job specialization (ϕ)

Table 11: Calibration Targets

Table 11 details the strategy followed to calibrate the rest of the parameters of the model. We choose the parameters by minimizing the distance between model generated moments and their corresponding data counterparts. The moments we match correspond to the initial steady state of the economy. Vacancy posting cost c is chosen to match the average labor market tightness θ from the data. Following Pissarides (2009), θ is chosen to be 0.72.[10] The flow value of unemployment b is set to 60% of the aggregate output which is closer the values used by Hall and Milgrom (2008) and Fujita and Ramey (2012). This is between the values chosen by Shimer (2005) and Hagedorn and Manovskii (2008).[11] The

[10] Hagedorn and Manovskii (2008) also calibrate vacancy posting cost by targeting the labor market tightness θ. They use a value of 0.634 for θ which is close to the one used by Pissarides (2009).

[11] Shimer (2005) calibrates the value of b to be 40% of the aggregate output while Hagedorn and Manovskii (2008)'s calibration implies b to be 95.5% of aggregate output. Hall and Milgrom (2008) reconciles both the strategies and calibrates b to be 71% of the aggregate output.

efficiency parameter of the matching function μ is set to target the aggregate job finding rate corresponding to the initial steady state. The target job finding rate is chosen to be 0.44 consistent with evidence from the CPS microdata over the period 1976-1995.

The idiosyncratic shock process follows a truncated lognormal distribution and has 3 parameters to be calibrated. The frequency of arrival of idiosyncratic productivity shocks λ is chosen to match the aggregate separation rate in the initial steady state. The target separation rate is set to 4.2%, consistent with the CPS evidence over the period of 1976-1995. The standard deviation of the idiosyncratic productivity realization, σ_ϵ, is selected to match the employment share of the low mismatch level of 0.1 in the year 1980. The upper support of productivity realizations $\bar{\epsilon}$ is chosen to match the maximum mismatch present in the year 1980.

Finally, the parameter governing the importance of mismatch γ is calibrated by matching the job specialization (ϕ) obtained from the regression (2) over the period of 1980-1995 with the model counterpart given by the coefficient δ in the following regression

$$log\omega(x,\epsilon) = \alpha + \delta x + \tau\epsilon + e \tag{35}$$

with $x \leq \bar{x}$ and $\epsilon \geq \epsilon^*(x)$.
ω is the equilibrium wage earned by the worker in a job with mismatch x and facing an idiosyncratic productivity realization of ϵ.

Target	Data	Model	Source
Market tightness (θ)	0.72	0.80	Pissarides (2009)
Job finding prob. (f)	0.4407	0.4425	CPS (1980-1995)
Separation rate (s)	0.0418	0.0426	CPS (1980-1995)
Emp share at $x = 0.1$	0.3767	0.3479	NLSY (1980)
Maximum mismatch ($\bar{x}$)	0.4	0.3758	NLSY (1980)
Job specialization (ϕ)	-0.2857	-0.2849	NLSY (1980-1995)

Table 12: Matching the Targets

Table 12 shows the performance of the model in matching the chosen targets. Overall, the model does a very good job in generating moments that are close to their data counterparts. Table 11 gives the resulting parameter values chosen to match the targets considered. Before moving on to the main quantitative experiment of the paper, I first check the model's performance in matching the distribution of employment over mismatch in the initial steady state.

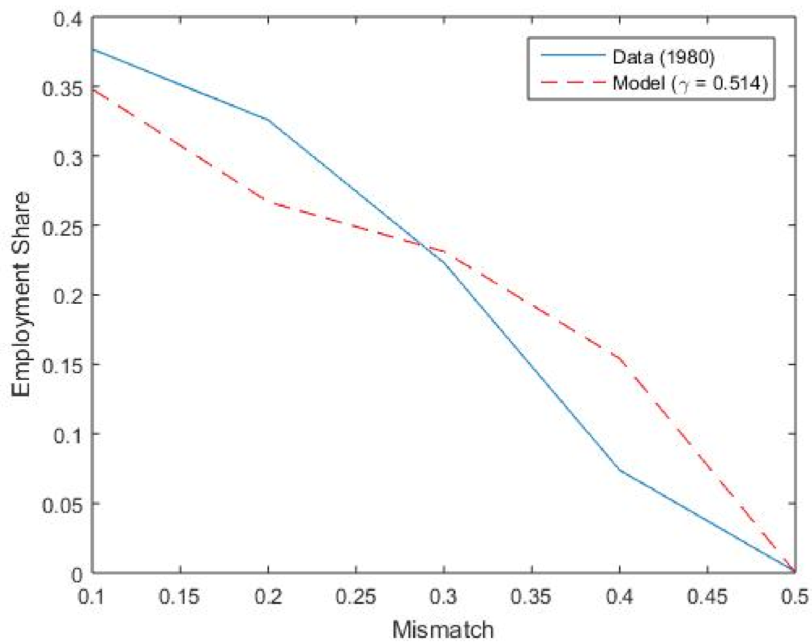


Figure 6: Employment Distribution: Model vs. Data

Figure 6 compares the model generated employment distribution with its counterpart from data in the year 1980. The model is able to capture the declining employment share over mismatch and this is an implication of mismatch being costly in our model environment.

5 Results

We now turn to the main question of the paper, how does an increase in job specialization affect labor market turnover? To answer this question, we increase job specialization in our model environment by raising the mismatch parameter γ, disciplining its rise by matching the increase in job specialization in the data. Table 13 gives the value of γ corresponding to the new steady state and the corresponding regression coefficients.

γ	Data	Model	Source
0.5135	-0.2857	-0.2849	NLSY (1980-1995)
0.773	-0.4380	-0.4380	NLSY (1996-2013)

[1] Data and model moments are the regression coefficients of log wages on mismatch.

Table 13: Increase in Specialization

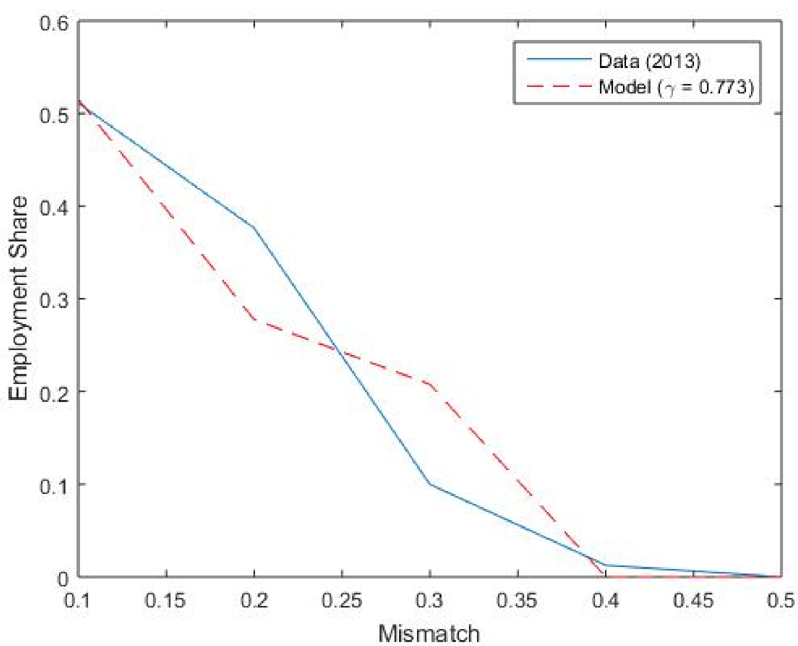
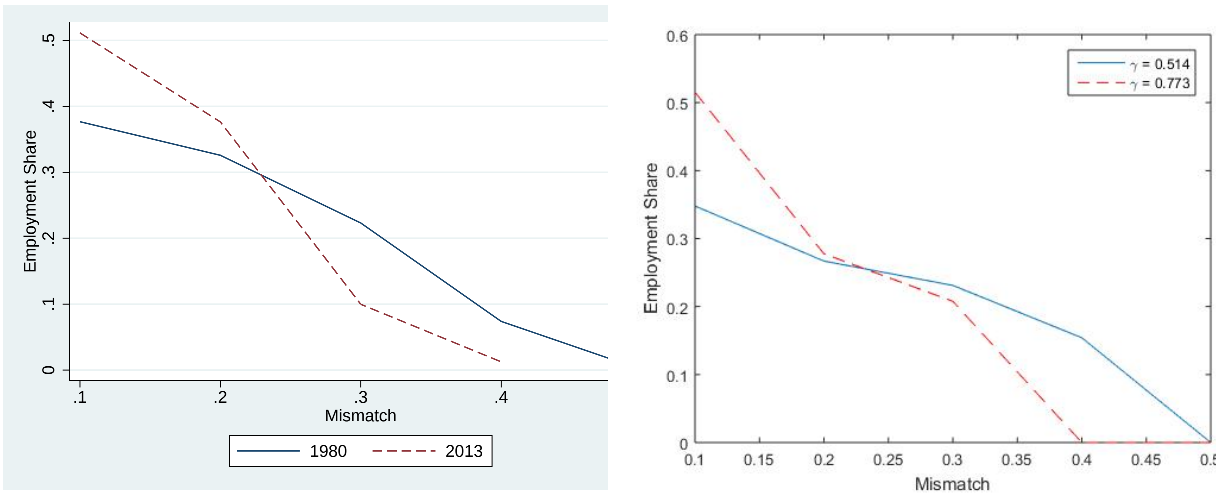


Figure 7: Employment Distribution: Model vs. Data



(a) Data

(b) Model

Figure 8: Employment Distribution

5.1 Employment Distribution

Figure 7 shows the distribution generated by the model in the new steady state and the corresponding distribution from data in the year 2013. The new steady state of the model captures well the shift of the distribution of employment towards lower levels of mismatch found in the data. Figure 8 shows the evolution of the employment distribution in the data and its counterpart generated by my model. Even though a number of recent papers like Song et al. (2015), Card et al. (2013) and Håkanson et al. (2015) document increased sorting among workers, there is still no consensus on the underlying economic phenomena driving this change. My model shows that an increase in the specialization of jobs is an important contributor for the observed rise in sorting found in the data. Investigating this job specialization channel further could be a fruitful area of research.

5.2 Labor Market Turnover

Table 14 summarizes the main result of the paper. The top panel of the table presents the data moments while the bottom panel gives the model counterpart. The high turnover economy corresponds to the initial steady state of our model with low job specialization. Here, γ is chosen to be 0.5135 to match the estimates of job specialization found in the initial period of 1980 to 1995. My model matches the moments in the high turnover

	High Turnover	Low Turnover
Data	*CPS (1980-1995)*	*CPS (1996-2013)*
f	0.4407	0.3
s	0.0418	0.0284
$\bar{x}$	0.4	0.37
u	0.7	0.6
Model	$\gamma = 0.5135$	$\gamma = 0.773$
f	0.4425	0.33
s	0.0426	0.0345
$\bar{x}$	0.3758	0.2922
u	0.0888	0.0956

[1] f is the job finding rate, s is the separation rate, $\bar{x}$ is the maximum (cutoff) mismatch and u is the unemployment rate.

[2] Data moments f, s and u are constructed from CPS microdata and are averaged over the time period considered while $\bar{x}$ corresponds to maximum mismatch in year 1980 and 2013 respectively.

Table 14: Increase in Job Specialization

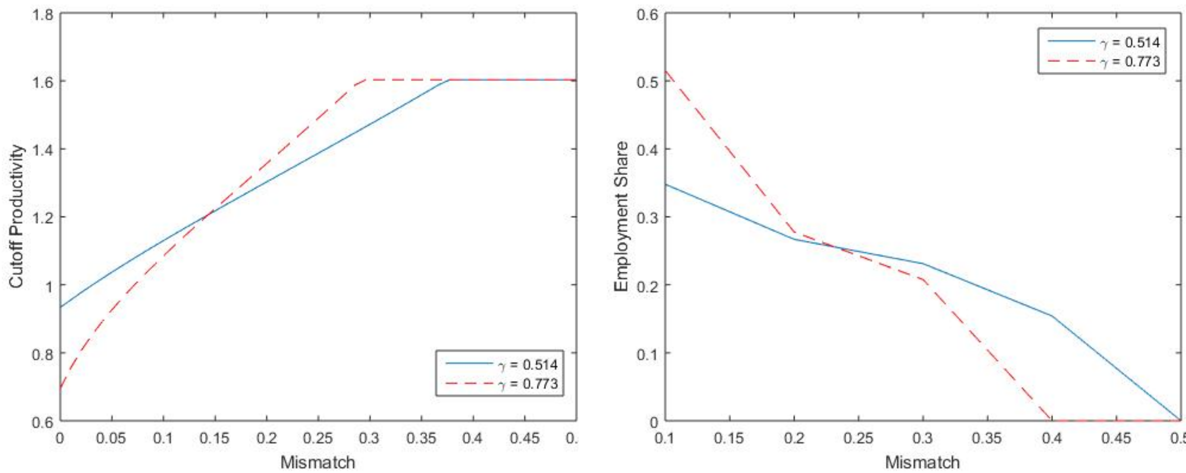
economy well. The unemployment rate at the initial steady state is 8.8% which is higher than what we find in the data. The model generated cutoff distance $\bar{x}$ is 0.38 which is close to its data value in the year 1980. This means, not all meetings are converted to productive matches. Even at the highest idiosyncratic productivity realization, a worker is suitable to work at only about 80% of the available jobs.

We next discuss the results for the low turnover economy obtained by setting the specialization parameter γ to a higher value of 0.773. The productivity cost associated with mismatch has increased in the new steady state. This causes a decline in labor market turnover. The job finding rate (f) falls from 0.4425 to 0.33 while the separation rate s declines from 0.0426 to 0.0345. There is a slight increase in the unemployment rate in the new steady state. Increased job specialization also causes the cutoff mismatch $\bar{x}$, threshold, to fall from 0.3758 to 0.2922. Now a worker is suitable to work only at about 60% of the available jobs down from about 80% in the initial steady state. The same holds for a firm with respect to finding a suitable worker. This decline in cutoff mismatch is an important channel causing the observed decline in labor market turnover. With $\bar{x}$ declining, both firms and workers are more selective in accepting a match that is not an exact match for them. Thus, with increased specialization, both vacant firms and unemployed workers are forced to be matched in a narrower region of the labor market compared to earlier times.

5.3 Separation Rate

There is a decline in the separation rate because increased job specialization reduces the substitutability between worker's skills for firms. Hence, well matched workers and firms are more reluctant to let go of each other compared to before. As the jobs have become more specialized, well matched firms and workers realize that once separated from their existing match, it is more difficult to get a better match in the future. Hence, the cutoff productivity and the separation rate for good matches fall. Figure 9a shows the schedule of cutoff productivity as a function of mismatch at both steady states. As can be seen from the dashed line in the figure, with increased job specialization, the cutoff productivity of good matches has decreased in turn leading to a fall in the separation rate for those matches.

But on the other hand, with an increase in specialization, the cost of mismatch has



(a) Cutoff Productivity

(b) Employment Share

Figure 9: Mechanism

increased, making bad matches even more difficult to sustain at lower levels of productivity. This causes the cutoff productivity of bad matches to increase, leading to an increase in the separation rate for those matches. As seen from figure 9a, the cutoff productivity schedule pivots up for the bad matches. Hence, both firms and workers involved in bad matches are more ready to separate now compared to before.

In order to disentangle which effect has the bigger impact, we look at the employment share at different levels of mismatch. Figure 9b shows the distribution of employment over mismatch at both low and high job specialization. Since an increase in specialization increases the cost of mismatch, more firms and workers move towards better matches. As seen from figure 9b, at the initial steady state, around 35% of the firms and workers were with their best matches. With increased job specialization, almost 52% of the firms and workers have found their best match. Thus, increased specialization forces the firms and workers to sort themselves into better matches. With increased sorting, a majority of the employment is faced with lower separation rate while a minority faces higher separation rate. This leads to a fall in the aggregate separation rate as seen from table 14.

5.4 Job Finding Rate

Unlike the separation rate, every unemployed person faces the same job finding rate f and this job finding rate is affected by movements in labor market tightness θ and the cutoff mismatch $\bar{x}$. To understand the mechanism behind the decline in the job finding rate, we need to understand the dynamics of vacancy creation and cutoff mismatch. Since with increased specialization it is even more difficult for a firm to find the right worker, the measure of vacancies falls from 0.0711 to 0.0704. This causes labor market tightness θ to fall from 0.8 to 0.7360. Since the cost of mismatch has increased in our new steady state, the cutoff mismatch $\bar{x}$ also falls from 0.3758 to 0.2922. The combined reduction in labor market tightness and cutoff mismatch causes the job finding rate to fall from 0.44 to 0.33. In the data, the job finding rate has declined from around 0.44 before 1995 to around 0.3 in the past decade. Thus, the increase in job specialization can explain almost all of the observed decline in the job finding rate.

5.5 Aggregate Labor Productivity

Finally, we investigate the impact of a decline in turnover on aggregate labor productivity. The increase in job specialization makes aggregate labor productivity fall by 24% in my steady state analysis. If we interpret the period of study to be 35 years, then on average, the productivity growth falls by 0.78% yearly. Byrne et al. (2016) documents a 1.75% fall in the growth rate of labor productivity in the 2000s. An increase in job specialization can explain about 40% of the observed slowdown in labor productivity. Even though increased specialization causes the workers and firms to move to better matches (resulting in lower mismatch), the cost of mismatch has increased over time and this has a negative impact on labor productivity. This exercise shows that increased sorting in the labor market need not be productivity enhancing and careful research needs to be conducted to identify the determinants of labor market sorting.

6 Conclusion

I argue that specialization of jobs has increased over time and this has led to a fall in labor market turnover. Job specialization is defined as the impact of mismatch on match productivity, where mismatch is the distance between the skills and abilities of a worker and the skill requirements of their job. I provide an estimate of job specialization using individual level data from NLSY79 and show that specialization has increased by 15 percentage points post 1995. I then formulate an equilibrium labor search model with ex-ante heterogeneous workers and jobs and show that the increase in job specialization causes a fall in labor market turnover. When jobs are less specialized, both firms and workers are willing to sustain higher levels of mismatch on average. As jobs become more specialized, both vacant firms and unemployed workers are forced to form matches in a narrower skill region. This forces already existing good matches to last longer, and bad matches to be destroyed faster. Since the employment share of good matches increases compared to bad matches, overall turnover falls in the economy. The calibrated version of my model shows that this mechanism can explain more than 50% of the observed decline in the labor market turnover.

I estimate the distribution of employment over mismatch and its evolution over time. The estimated distribution shows that more employment has shifted towards lower mismatch and the cutoff level for mismatch has fallen over time. Consequently, the increase in job specialization provides an explanation for the increased sorting seen in the labor market. I also find that the decline in turnover has had an adverse impact on productivity growth. Even though the increased specialization has reduced mismatch on average, the resulting fall in mismatch does not fully compensate for the increased productivity costs of mismatch.

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A Supplementary Empirical Evidence

Education	Mismatch
Less than high school	0.228
High school	0.206
Some college	0.243
College	0.225
More than college	0.214

Table 15: Mismatch Across Education

Industry	Mismatch
Agriculture, Forestry, Fishing, and Hunting	0.245
Mining	0.187
Construction	0.187
Manufacturing	0.204
Transportation, Communications, Public Utilities	0.201
Wholesale and Retail Trade	0.256
Finance, Insurance and Real Estate	0.233
Business and Repair Services	0.209
Personal Services	0.313
Entertainment and Recreation Services	0.287
Professional and Related Services	0.207
Public Administration	0.222

Table 16: Mismatch Across Industries

Occupation	Mismatch
Managerial	0.168
Professional Specialty	0.197
Technical, Sales and Administrative Support	0.248
Service	0.332
Farming, Forestry and Fishing	0.228
Precision Production, Craft and Repair	0.187
Operators, Fabricators and Laborers	0.217

Table 17: Mismatch Across Occupations

Education	Full Sample	Pre 1995	Post 1995	% Change
Aggregate	0.0355	0.0418	0.0284	-32.0574
High school graduate	0.0583	0.0646	0.0513	-20.5882
Less than college	0.0296	0.0334	0.0254	-23.9521
College graduate	0.0153	0.0168	0.0136	-19.0476
More than college	0.0093	0.0099	0.0087	-12.1212

Table 18: Separation rate by education

Education	Full Sample	Pre 1995	Post 1995	% Change
Aggregate	0.4106	0.4407	0.3772	-14.4089
High school graduate	0.4169	0.4462	0.3843	-13.8727
Less than college	0.4233	0.4545	0.3887	-14.4774
College graduate	0.3713	0.3937	0.3466	-11.9634
More than college	0.3324	0.3463	0.317	-8.4609

Table 19: Job finding rate by education

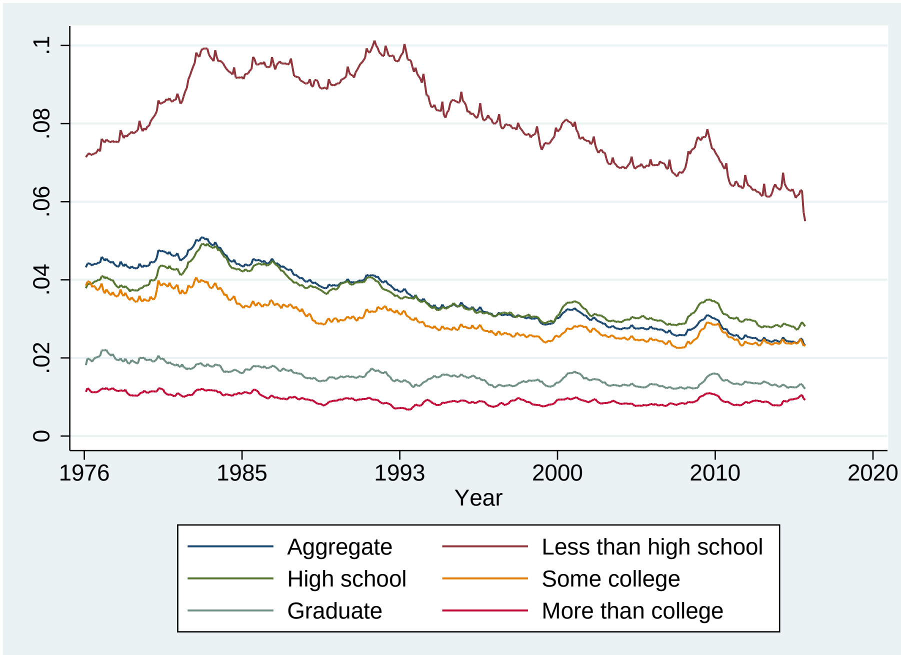

Figure 10: Separation rate by education

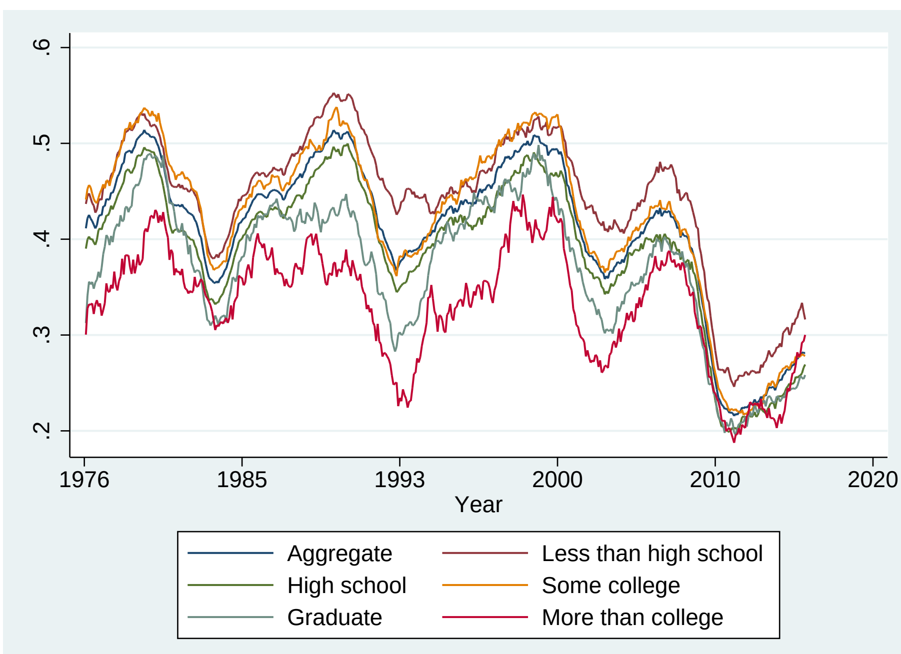

Figure 11: Job finding rate by education

Education	Full Sample	Pre 1995	Post 1995	pp. change
Aggregate	-0.3809	-0.2857	-0.438	15.23
High school graduate	-0.2320	-0.1795	-0.2513	7.18
Less than college	-0.1972	0	-0.427	42.7
College graduate	-0.7292	-0.3671	-1	63.29
More than college	-1.3921	-1.253	-1.4485	19.55

[1] Regression coefficient is insignificant for less than college workers pre 1995.

[2] pp. change refers to percentage point change.

Table 20: Job specialization by education

B The Construction of An Employment Distribution

This section describes the construction of an employment distribution across years and the filtering of cohort effects from the time effects. Mismatch x is set to a grid $[0, x_1, x_2, ..., x_{N-1}, 0.5]$. Let e_{1t} be the share of employment with mismatch $x \in [0, x_1]$ at time t. I use a linear probability model to obtain this employment share from the individual level data of NLSY79.

Let y^1_{it} take a value of 1 if a worker i has a job with mismatch $x \in [0, x_1]$ at time t and 0 otherwise. Let D_t denote the time dummies taking value of 1 at time t and 0 on other dates. The employment share can be obtained using the following regression.

$$y^1_{it} = \alpha_1 + \sum_{t=2}^{T} \alpha_t D_t + \epsilon_{it} \tag{36}$$

The employment share with mismatch $x \in [0, x_1]$ at time t is given by

$$e_{1t} = \alpha_1 + \alpha_t \ \forall t \tag{37}$$

$\{e_{1t}\}_{t=1}^{T}$ gives the evolution of employment share with mismatch $x \in [0, x_1]$ over time. The time evolution of the entire distribution can be found by repeating this process for all grid points.

As argued in the main text, it would be misleading to compare this distribution across time since *we have not controlled for the cohort effects*. This is because as workers spend more time in the labor market, they might learn more about their skills or learn about various job opportunities and hence move to a job which is the closest match to their skills. Thus an aging sample of workers can mechanically lead to a shift in the employment distribution towards lower mismatch. To control for this cohort effect, we introduce dummy variables that take values of 1 or 0 across different age groups. Let $\{A_{jt}\}_{j=1}^{J}$ be the dummies across J different age groups. To control for the cohort effect, I estimate the following linear probability model

$$y_{it}^{1} = \alpha_1 + \sum_{t=2}^{T} \alpha_t D_t + \sum_{j=2}^{J} \beta_j A_{jt} + \epsilon_{it} \tag{38}$$

We can filter out the cohort effect by replacing the age dummies with their sample means as follows:

$$\widehat{e}_{1t} = \alpha_1 + \alpha_t + \sum_{j=2}^{J} \beta_j \overline{A}_j \ \forall t \tag{39}$$

$\{\widehat{e}_{1t}\}_{t=1}^{T}$ gives the evolution of employment share with mismatch $x \in [0, x_1]$ after controlling for the aging of cohort over time. As before, we can repeat this analysis for all the grid points of mismatch x to find how the employment distribution evolves over time.

C Proofs and Derivations

C.1 Proof of Proposition 1

Assumption: There is free entry of vacancies. In equilibrium, $V(f) = 0 \ \forall f \in [0, 2\pi]$

We need to prove $u(w) = u \Leftrightarrow v(f) = v \ \forall w, f \in [0, 2\pi]$.

$(\Rightarrow)$ $u(w) = u \Rightarrow v(f) = v \ \forall f, w \in [0, 2\pi]$.

Proof. Suppose $v(f') > v(f)$ for some f and f'. This implies $\theta(f') > \theta(f)$ and hence $q(f') < q(f)$. Thus $V(f') < V(f)$ which violates the free entry condition.

$(\Leftarrow)$ $v(f) = v \Rightarrow u(w) = u \ \forall f, w \in [0, 2\pi]$.

Proof. Suppose $u(w') > u(w)$ for some w and w'. This implies $\theta(w') < \theta(w)$ and hence $q(w') > q(w)$. Thus it is profitable for the firm at w to deviate and create a vacancy at w' as $V(w') > V(w)$ violating the free entry condition.

Thus under free entry of vacancies, $u(w) = u \Leftrightarrow v(f) = v \ \forall w, f \in [0, 2\pi]$ $\blacksquare$.

C.2 Derivation of Equilibrium Conditions

The equilibrium conditions consists of free entry condition, definition of cutoff skill distance and the definition of cutoff productivity.

Free entry condition gives

$$\begin{aligned} c = \frac{2q(\theta)(1-\beta)}{r+\lambda}\left[\int_0^{\bar{x}} \eta(x)\bar{\epsilon}dx - b\bar{x} - \frac{\beta c\theta\bar{x}}{1-\beta}\right] \\ + \frac{2q(\theta)\lambda}{r+\lambda}\int_0^{\bar{x}}\int_{\epsilon^*(\tau)}^{\bar{\epsilon}} J(\tau,z)dF(z)d\tau \end{aligned} \tag{40}$$

The definition of cutoff distance is

$$(1-\beta)\left[\eta(\bar{x})\bar{\epsilon} - b\right] - \beta c\theta + \lambda\int_{\epsilon^*(\bar{x})}^{\bar{\epsilon}} J(\bar{x},z)dF(z) = 0 \tag{41}$$

Cutoff productivity satisfies

$$(1-\beta)\left[\eta(x)\epsilon^*(x) - b\right] - \beta c\theta + \lambda\int_{\epsilon^*(x)}^{\bar{\epsilon}} J(x,z)dF(z) = 0 \tag{42}$$

We can combine the definition of $J(x,\epsilon)$ with the definition of cutoff productivity to get a simplified solution for J in terms of cutoff productivity as

$$J(x,\epsilon) = \frac{(1-\beta)\eta(x)}{r+\lambda}\left[\epsilon - \epsilon^*(x)\right] \tag{43}$$

Plugging back this equation for J back into the original equilibrium equations give us the final equilibrium conditions to solve for $\theta, \bar{x}$ and $\epsilon^*(x)$.