On the Unemployment-Education Gap[*]

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February 14, 2024

Preliminary and incomplete: please do not circulate.

Abstract

College graduates are less likely to be unemployed. While this fact is well known, the reasons for it are not well understood. We document that differences in unemployment by educational attainment, or the unemployment-education gap, narrow over the life-cycle and hypothesize that college graduates enter the labor market with less uncertainty regarding their best occupational fit. A set of supporting facts for this hypothesis are provided, including lower occupational mobility rates and a weaker association between prior experience and the expected duration of a job among college graduates. We then develop a search model with unobserved heterogeneity, learning, and endogenous separations. The model shows that reducing information frictions regarding a worker's ability generates differences in job-finding and separation rates over the life-cycle that are in line with the empirical differences between workers with and without a college degree.

JEL Classification: E24; J24; J62; J64

Keywords: Unemployment; Education; Learning; Occupational Mobility

[*]We thank Ismail Baydur, Carlos Carrillo-Tudela, Chen Liu, Simon Mongey, Serene Tan, Shu Lin Wee, Donghai Zhang, Shengxing Zhang, and participants at the NUS and PHBS brownbag seminars for their insightful comments and questions.

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1 Introduction

College graduates perform better in the labor market than those without a college degree. There are substantial returns to a college degree as measured by wages (Acemoglu and Autor, 2011) and lifetime earnings, where those with a Bachelors degree or above typically earn $1 million more in lifetime income (Abel and Deitz, 2014). College graduates also experience greater employment stability (Cairó and Cajner, 2018) and are less likely to be unemployed. While the difference in unemployment rates between those with a Bachelors degree or above and less than a Bachelors degree, which we refer to as the *unemployment-education gap*, is well documented, there is a fairly small body of research studying its sources. Why is it that college graduates are much less likely to be unemployed? Given that the unemployment rate is one of the most studied indicators in the labor market, differences in unemployment feed into differences in lifetime earnings, and the documented effects of job loss on wages/earnings (Jacobson et al., 1993; Jarosch, 2022) and mental well-being (Krueger and Mueller, 2012), it is surprising that relatively little research exists on the unemployment-education gap.

This paper studies the sources of the unemployment-education gap. We begin by documenting several facts from the Current Population Survey (CPS) and National Longitudinal Survey of Youth 1979 (NLSY79). A key theme behind our analysis is that studying the unemployment-education gap *over the life-cycle* offers important insights into its sources. For example, we document that the unemployment-education gap is decreasing in age. We also find that differences in job-finding and separation rates by educational attainment are decreasing in age. Despite these patterns, even after 30 years in the labor market, significant differences in the unemployment and separation rates remain between college and non-college workers.

Given these facts, it is crucial to focus on the sources of the unemployment-education gap that play a prominent role early in workers' careers. Our hypothesis is the following: college graduates, having spent time in college studying a specific field, acquire information about which career trajectory is their best fit. Hence, college graduates enter the labor market having narrowed down the set of occupations that they would like to work at. How does this lead to a lower unemployment rate? Beginning with the separation rate, college graduates are less likely to realize that an occupation is not a good fit and subsequently separate from their match in favor of sampling a different occupation. Firms anticipate the lower separation risk with a college educated worker and post more vacancies, generating a higher job finding rate. As workers with less than a college degree sample careers and eventually settle into a good fit, their separation risk and unemployment rate decreases, causing the unemployment-education gap to narrow as workers age.

Differences in workers' uncertainty regarding their best occupational fit can also set off a dynamic effect that carries through the life-cycle as college workers are more likely to enter good matches early in their career, which allows for the accumulation of occupation-specific human capital. Our primary goal is to understand the relative contributions of these channels, the initial effect of having a more accurate understanding of their comparative advantage versus the dynamic effect implied by having lower skill mismatch and high on-the-job human capital accumulation, as each source leads to different policy implications. If differences are driven more by initial conditions, policies should focus on improving college education access; if driven more by dynamic effects experienced over working lifetimes, policies should focus on providing insurance against shocks, such as progressive taxation and unemployment insurance.

We then proceed to document a set of facts which offer supporting evidence for the proposition that college graduates enter the labor market with greater certainty about their abilities. First, college graduates switch occupations at a lower rate, and the gap in occupational mobility by education is also decreasing in age. Second, college graduates are not only less likely to switch occupations, but they switch between occupations with more similar requirements than those without a college degree. Third, the expected duration of a job is increasing in the worker's level of prior experience at the beginning of the match, which is consistent with the notion that workers acquire knowledge of their best fit through work experience. Moreover, the relationship between expected match duration and prior experience is stronger for workers with less than a college degree, indicating that less-educated workers rely more on work experience to learn about their best fit. Finally, college graduates form more accurate forecasts regarding their future occupation.

We then take the first steps towards formalizing our hypothesis by developing a directed search model with workers who are ex-ante heterogeneous in their (unobserved) ability, learning, and endogenous separations. Workers and firms match and produce output, which serves as a noisy signal of the worker's ability. The match is destroyed when the worker and firm's beliefs regarding the worker's ability become too low. We present a numerical example showing that this relatively simple environment can generate job-finding and separation probability profiles that are decreasing in age, which is consistent with the data. Moreover, comparative statics show that decreasing the uncertainty of the worker's ability increases both the job-finding and separation probabilities at all ages, but especially early in the life-cycle.

The most closely related paper is Cairó and Cajner (2018), who attribute the lower unemployment rate among college graduates to the fact that college graduates are more likely to work in occupations that require higher levels of specific vocational training, which leads to the formation of match-specific capital and a lower separation rate.[1] While models of match-specific productivity can produce a declining separation rate over the life-cycle (Menzio et al., 2016), they also imply that the separation risk at the beginning of a new match is independent of prior labor market experience, as all unemployed workers are identical. This goes against what we see in the data. In a seminal paper, Topel and Ward (1992) find that the expected duration of a new match is increasing in prior labor market experience. We also reaffirm this finding in the NLSY79 and show that the association between prior experience and expected match duration is stronger among workers with less than a college degree. Moreover, models of match-specific productivity predict that the job-finding rate is constant over the life-cycle, which we show is counterfactual in Section 2.3 and is a feature of the data our simple model is consistent with.

Further, Cairó and Cajner (2018) emphasize that if workers were to switch occupations following a job loss, that any skills acquired through training at their previous job would not be transferrable to their new job. We find, however, that nearly half of unemployed workers do return to the same occupation following an unemployment spell. We also show that, conditional on switching occupations, college graduates transition to occupations with similar skill requirements, which casts some doubt on the notion that the skills acquired through training are not transferrable across occupations (especially for college graduates).[2] To further emphasize this point, we show in Appendix B.15 that an overwhelming majority of respondents in the NLSY79 indicate that at least half of the skills acquired through an employer sponsored training program they recently participated in would either be useful in doing their same job for a different employer or for doing a different job at the same employer. As we outlined above, we propose a mechanism that is consistent with a lower separation rate among college graduates and the fact that the expected dura-

[1] Cairó and Cajner (2018) emphasize that it is the increased training costs associated with hiring a college worker that drives down their job finding rate and why there is little difference in the job finding rate across educational attainment. We find, in the NLSY79, that college graduates are more likely to participate in training/vocational programs in the stages of the life-cycle where they also exhibit a higher job finding probability. See Appendix B.15.

[2] Ma et al. (2023) show that the propensity for workers to engage in "internal" learning/training is decreasing in tenure while the frequency of "external" training/learning has an inverse U-shape in tenure. This also casts doubt on the claim that workers only engage in training early in their tenure at a firm. Moreover, the fact that workers draw upon more external sources for training later in their tenure seems to indicate they may be acquiring skills that are not specifically utilized by their current firm.

tion of a new match is increasing in prior labor market experience. We also propose a mechanism that is consistent with various other features of the data, including the life-cycle patterns involving the job-finding probability, occupational/complex/career mobility, and distance in occupational requirements between occupations in the aforementioned types of transitions.

A second closely related study is Gervais et al. (2016) who document that unemployment is decreasing in age. To explain this fact, they develop a model with multiple occupations where agents enter the labor market uncertain as to which occupation is their best fit. Workers sample occupations and, over time, get closer to finding their best match. As workers become more certain about which occupation is their best fit, they are less likely to separate from their match, which generates a separation and unemployment rate that is decreasing in age.[3] We extend the analysis of Gervais et al. (2016) to study differences in unemployment across levels of educational attainment and over the life-cycle. We propose that college graduates acquire information about their best occupational fit before entering the labor market, rather than relying exclusively on early career job shopping, and discuss the resulting implications for the job finding and separation rates, occupational mobility, and occupational distance in switches.

Papageorgiou (2014) also develops a model whereby workers learn about their occupational comparative advantage through labor market experience. The model can match a host of features of the data, including how occupational mobility declines in age, the experience profile of wages, and within-occupation wage inequality. This paper also finds that the data favors a model of comparative advantage as in Roy (1951) rather than a model of one-dimensional ability. While we also emphasize learning about the best occupational/career fit through experience, we compare workers without a college degree to those with one and emphasize that college graduates do not appear to be relying as much on labor market experience to learn their comparative advantages and study how this translates into differences in job finding rates, separation rates, and unemployment over the life-cycle.

Finally, Sengul (2017) studies the unemployment-education gap and, as in Cairó and Cajner (2018), finds that this is primarily due to the difference in separation rates across education. To explain this finding, the paper proposes that high-skill firms invest more in screening applications from high-skill applicants. The increased screening into high-skill applicants increases the chances that matches turn out to be of high quality and hence leads to a lower chance that the match is destroyed. There is significant overlap between how our analysis could build on Sengul (2017) and Cairó and Cajner (2018) as both papers abstract from life-cycle considerations and focus on differences in match-specific productivity to generate a lower separation rate among college graduates.

The rest of the paper is organized as follows. Section 2 contains our empirical analysis. Section 3 develops a search model with unobserved heterogeneity, learning, and endogenous separations. Section 4 concludes. The appendix contains details to complement the empirical analysis and is referenced throughout the main text.

2 Motivating Evidence

Section 2.1 describes the data. Section 2.2 documents that college-educated male workers experience lower unemployment rates over the course of their working lives compared to those with less than a college degree. Next, Section 2.3 decomposes differences in unemployment across education into differences in

[3] Gorry et al. (2019) also developed a quantitative life cycle model of learning about occupational fit that is consistent with occupational mobility declining in age and quantifies how much workers would be willing to learn their type and transition occupations.

separation and job finding probabilities.

To shed light on the underlying mechanisms behind the unemployment-education gap, Section 2.4 compares occupational and complex mobility across educational attainment and over the life-cycle. Section 2.5 studies changes in occupational requirements in the aforementioned transitions. Section 2.6 documents the relationship between prior experience and expected match duration. Finally, Section 2.7 shows that college graduates forecast their future occupations more accurately, while Section 2.8 summarizes additional evidence and the robustness of the patterns presented throughout this section by controlling for observable characteristics.

2.1 Data

We use three data sources. The first is the Current Population Survey (CPS). It serves as the main source of information about the representative civilian, household-based population in the US and is collected on a monthly basis. We download the monthly CPS files from the Integrated Public Use Micro-data Series (IPUMS) database (Flood et al., 2022) and use the individual identifier, CPSIDP, to link individual records across time to measure mobility. We use technical, demographic, education, and employment variables, which are detailed in Appendix Table A1.

The second primary dataset is the Occupation Information Network (O*NET). The O*NET measures occupational requirements and worker attributes through four survey questionnaires covering skills, knowledge, generalized work activities, and work context. In particular, it characterizes the mix of knowledge, skills, and abilities (KSA) that are commonly used to perform the occupation tasks, and assigns scores to 277 descriptors to indicate their level of importance. We use version 5.0 (published in April 2003) through 24.1 (published in November 2019) of O*NET to measure the skill requirements of occupations in the CPS. As detailed in Appendix Section A.10, we follow Guvenen et al. (2020) in the measurement of occupational skill requirements.

The third dataset is the National Longitudinal Survey of Youth (1979). The NLSY79 tracks the lives of 12,686 individuals born between 1957 and 1964. It covers employment activities that can affect the ability to obtain and perform a job (such as education, training, etc.), as well as other sections on marriage, fertility, household composition, and health. We use the NLSY79 alongside the CPS to examine more features of the data related to unemployment and career mobility over the life-cycle as we can actually track the same individuals over the life-cycle in the NLSY79.[4] We construct a monthly panel of 4,823 male respondents from the NLSY79 that contains information regarding demographics, education, employment status, job characteristics, and test scores. Section B.2 provides details as to how we arrive at this sample.

2.2 Life-cycle Unemployment Rate by Education

We begin by showing the unemployment rate by age and education, computed from the CPS data for the period January 1976 through December 2019.[5] To compute the unemployment in the group of age i and

[4] There are several limitations to the NLSY79 which is why we also use the CPS. First, the sample size is much smaller than the CPS. Second, any results in the NLSY79 could be driven by a cohort effect. For example, we find in our sample that the unemployment rate among workers with a Bachelors degree increases substantially in the later stages of the career. While this could be a robust finding, it is likely driven by the fact that this is around the time that the cohort of workers in the NLSY79 were caught up in the Great Recession.

[5] For our main analysis, we compare workers with a Bachelors degree or above to those who do not. However, college dropouts are common (e.g., Vardishvili (2023)). In Appendix B.13, we identify college dropouts within our NLSY79 sample and compare their outcomes to college graduates. Overall, we find that these patterns follow what we present in the main text in that unemployment, separation, and job mobility rates are decreasing with educational attainment and that college dropouts fall in-between those with no college experience and college graduates in the aforementioned outcomes.

Table 1: Average Unemployment Rate

Age	20-24	25-34	35-44	45-54	55-64
Overall					
Average (%)	11.05	6.12	4.54	4.23	4.21
Normalized	2.61	1.45	1.07	1.00	1.00
By education					
Less than College (%)	11.58	7.46	5.61	5.05	4.77
Bachelors (%)	6.93	3.00	2.53	2.82	3.49
Above Bachelors (%)	6.08	2.32	1.73	1.94	2.37
Differences					
Less than College - Bachelors (PP)	4.65	4.45	3.08	2.23	1.27
Less than College - Above Bachelors (PP)	5.50	5.14	3.88	3.10	2.39

Notes: Data from the IPUMS-CPS, 1976:1-2019:12. In the last panel, PP references to percentage points.

education attainment j, first, we restrict to males in the labor force.[6] Next, we count the population of unemployed and employed workers using the final basic weights, denoted by $N(U_{ij})$ and $N(E_{ij})$ respectively. In particular, unemployed workers are defined as individuals whose employment status is (i) unemployment, (ii) unemployed, experienced worker or (iii) unemployed, new worker. Employed workers refer to those individuals whose employment status is (i) at work, or (ii) has a job, but not at work last week.[7] The unemployment rate of age i and education attainment j is given by

$$u_{ij} = \frac{N(U_{ij})}{N(U_{ij}) + N(E_{ij})}. \tag{1}$$

Table 1 presents the unemployment rate by education and age. The upper panel reports the average unemployment rate for different age groups, and it is evident that the unemployment rate decreases monotonically with age, which is in line with the findings of Gervais et al. (2016). The second panel shows that unemployment is decreasing in education at each age.[8] The third panel displays the differences in unemployment between those with less than a college degree and those with a Bachelors degree and above. The main takeaway from this panel is that the unemployment-education gap is decreasing over the life-cycle.

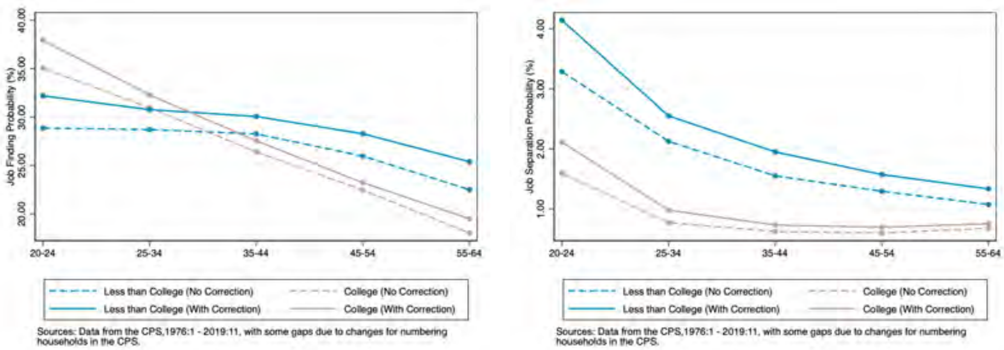
2.3 Job Finding and Separation Probabilities

To look deeper into what is driving the unemployment-education gap, we compute the job finding and separation probabilities for each education group over the life-cycle. The idea here is if we have a labor market where workers are either unemployed or employed, and find jobs at rate f and transition from

[6]We restrict to males to make our findings in the CPS more comparable to our analysis which utilizes the NLSY79, where we also restrict to males. Our main findings are unchanged if we include females in the sample.

[7]This case comprises those who did not work the previous week but acknowledged having a job or business from which they were temporarily absent due to reasons such as illness, vacation, bad weather, or labor disputes.

[8]Throughout the analysis, we use "Bachelors" and "college degree" interchangeably. That is, workers with a college degree are those with a Bachelors degree. Workers with less (more) than a college degree have less (more) than a Bachelors.



(a) Job Finding Probability

(b) Job Separation Probability

Figure 1: Job-Finding and Separation Probabilities over the Life-Cycle

employment to unemployment at rate s, then the steady-state unemployment rate is

$$u = \frac{s}{s+f}. \tag{2}$$

From equation (2), either a lower job finding rate or a higher job separation rate can result in a higher unemployment rate. We now proceed to investigate which rate contributes more to the unemployment-education gap at each stage of the life-cycle.

As a first step, we compute the transition probabilities directly.[9] We start with the longitudinal labor market flows at individual-level from 1976:1 through 2019:11, with identified employment status (unemployed, employed, or not in the labor force) in the current and subsequent period.[10] Next, we count the number of transitions that occurred in period t in the group of age i and education j using the longitudinal weights.[11] Let $N(EU)_t^{ij}$ ($N(UE)_t^{ij}$) denote the number of transitions from employment (unemployment) to unemployment (employment) in group ij during period t. Next, we count the size of each labor force status in period t using the longitudinal weights, where $N(U)_t^{ij}$ ($N(E)_t^{ij}$) denotes the population of unemployed (employed) workers in the group of age i and education j in period t. Finally, the average transition probability in each age-education group is given by the weighted average of transition probabilities across all periods:

$$JFP^{ij} = \sum_t \omega_t^{ij} \frac{N(UE)_t^{ij}}{N(U)_t^{ij}} \times 100, \qquad JSP^{ij} = \sum_t \omega_t^{ij} \frac{N(EU)_t^{ij}}{N(E)_t^{ij}} \times 100, \tag{3}$$

where JFP^{ij} (JSP^{ij}) denotes the job finding (job-separation) probability and the weight ω_t^{ij} represents the share of observations at period t in a specific group of age i and education j.

The dashed lines in Figure 1 present the resulting the transition probabilities, while the solid lines correct for time aggregation bias as in Shimer (2012).[12] First, both the job finding and separation probabilities

[9] An alternative approach to indirectly compute the job finding and separation rates in an approach that follows Shimer (2005) and Elsby et al. (2009). Doing so gives the same conclusions presented in this section. See Appendix A.5.

[10] The panel data is constructed by linking individual histories across samples through the unique identifier *CPSIDP*, and we have confirmed the matching quality by checking the consistency of key demographic variables such as race and gender, and dropped inconsistent observations.

[11] There are thirteen gaps in the data set due to missing linkage weights for the following periods: 1976:12, 1977:1, 1977:4, 1977:6-11, 1985:6, 1985:9, 1995:5, and 1995:8. The reason behind this is that the observations during these periods cannot be linked to the samples from the following calendar month in the IPUMS-CPS data.

[12] More details can be found in Appendix A.4.

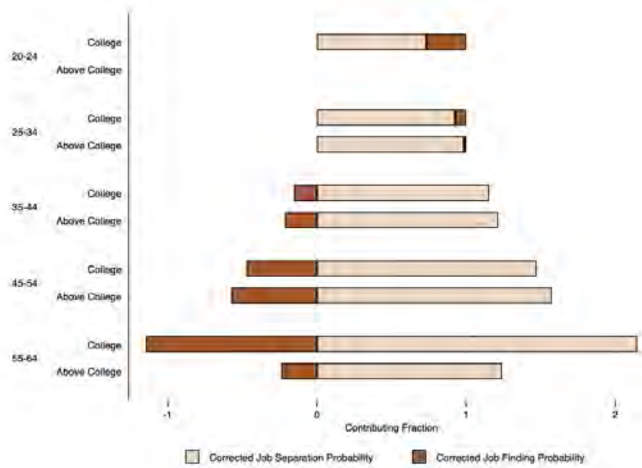


Figure 2: Decomposition of Unemployment Rate Differences

decline with age. Second, those with a college degree have a higher job finding probability during the early career stages, but it drops sharply in age to the point where, at the end of the life-cycle, workers with less than a college degree have a higher job finding probability. Third, workers with at least a college degree consistently exhibit a lower separation rate than the less educated workers. Notably, college graduates experience a separation rate that is at least 50% lower than the less educated counterparts during prime ages. These results suggest that a large portion of the unemployment-education gap throughout the life-cycle is driven by differences in the separation rate.[13]

To further explore the role of job finding or separation probabilities in contributing to unemployment-education gap over the life cycle, we use the simple decomposition exercise outlined in Pissarides (2009) to decompose the unemployment-education gap at each age bin into two sources: (i) differences in job finding probabilities and (ii) differences in job separation probabilities. As demonstrated in Figure 2, differences in job separation probabilities (shadowed in light brown) contribute to a larger proportion of unemployment rate differences at each age bin.[14] However, differences in the job finding probability contribute a non-trivial amount, nearly 30%, to the unemployment-education gap in the 20-24 age bin.

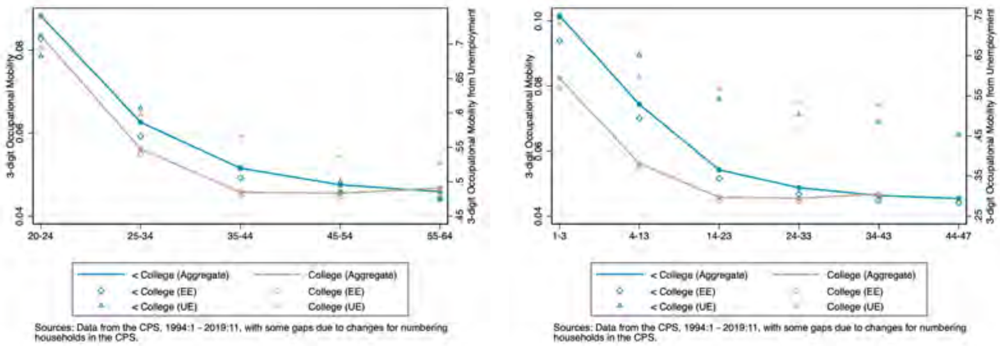
2.4 Occupational and Complex Mobility

We begin exploring the possible mechanisms underlying the age-profile of transition rates by investigating occupational mobility between education groups. First, we directly measure life-cycle occupational mobility for male workers aged 20 to 64, drawing upon data from the monthly CPS files, which encompasses the period from January 1994 to December 2019.[15] For workers whose types are characterized by age i and

[13] We show in Appendix B.14, using data from the NLSY79, that the unemployment-education gap and difference in separation probabilities between levels of educational attainment do not appear to be driven by a small group of workers with less than a college degree who exhibit an abnormally large number of separations from employment to unemployment. While excluding such workers certainly shifts the separation probability profile among workers with less than a college degree down, there is still a sizeable gap in both the unemployment rate and separation probability that narrows over the life-cycle.

[14] Appendix Section A.3 provides a detailed description of the computation process, as well as decomposition results by using alternative transition probabilities: (i) uncorrected job finding/separation probabilities, (ii) job finding/separation rates, and (iii) moving average job finding/separation rates. The first age bin has been omitted for individuals in the education group with education beyond college, assuming that those with education beyond college typically enter the labor market at the age of 24 or older.

[15] Measurements of occupational mobility are prone to measurement error. Appendix A.8 shows that our main takeaways are the same after applying the correction proposed by Moscarini and Thomsson (2007).



(a) Age

(b) Potential Experience

Figure 3: Uncorrected Occupational Mobility

education attainment j, this approach enables us to separately compute occupational mobility for job-to-job (EE) transitions and transitions from unemployment (UE). For EE transitions, we restrict our attention to observations with known occupations across two consecutive months. Next we calculate the proportion of transitions that are accompanied by an occupational switch that is defined by a change in 3-digit CPS1990 occupation codes in the two consecutive months. For occupation switches with unemployment as an intermediate phase, we first identify the occupations before and immediately following the unemployment spell, and then compute the fraction of occupational switches present among employment observations interceded by unemployment.[16] We arrive at aggregate occupational mobility by computing the weighted average of occupational mobility across different transition types, with the weight corresponding to the share of the respective transition type. Appendix A.7 shows that the patterns presented in this section are robust to computing occupational mobility rates at the 1- and 2-digit levels.

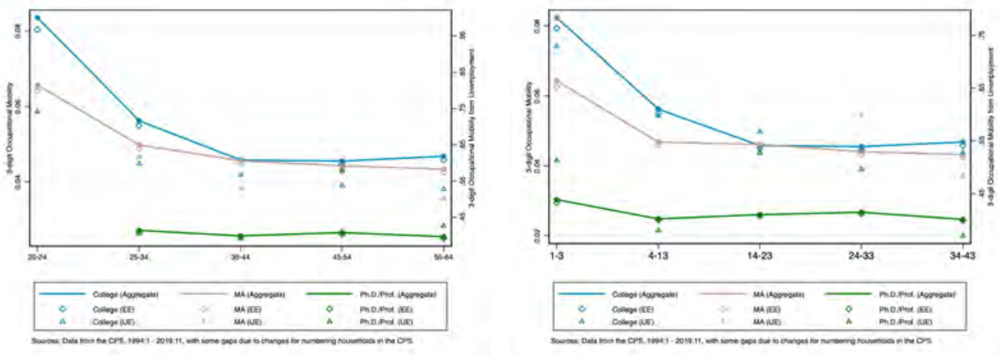
Figure 3 presents the occupational mobility rates by age and education. The diamonds (triangles) represent the original occupational mobility among EE (UE) transitions, while the solid line is the weighted average of occupational mobility through either EE or UE transitions. There are two primary findings. First, occupational mobility rates are decreasing in age. Second, less-educated workers tend to change occupations more frequently than their well-educated counterparts at each age, especially in EE transitions.

One complicating factor in the interpretation of Figure 3(a) is that educational attainment affects the timing of labor market entry, potentially leading to biases in early-stage mobility measurements for college workers. To address this concern, we further investigate the patterns of occupational mobility along presumed years of potential experience where we assume college graduates enter the labor market at the modal age of 22, while those with less than a college degree do so at the modal age of 18.[17] Figure 3(b) illustrates occupational mobility throughout career stages for each education group. Relative to Figure 3(a), while the broader pattern is unchanged, we can see that the gap in occupational mobility rates is larger when comparing across years of potential experience. To further demonstrate the relationship between education and occupational mobility, Figure 4 shows that possessing an advanced degree (Masters/Ph.D./Professional) is associated with even lower occupational mobility rates across both age and potential experience.

A stricter criterion to identify large changes in one's career incorporates considerations about employer

[16] To identify occupation switches through unemployment, we need to restrict to observations that were unemployed at t but employed at $t+1$, and with known occupational records both before unemployment (period $t-1$ or $t-2$), and after unemployment (period $t+1$).

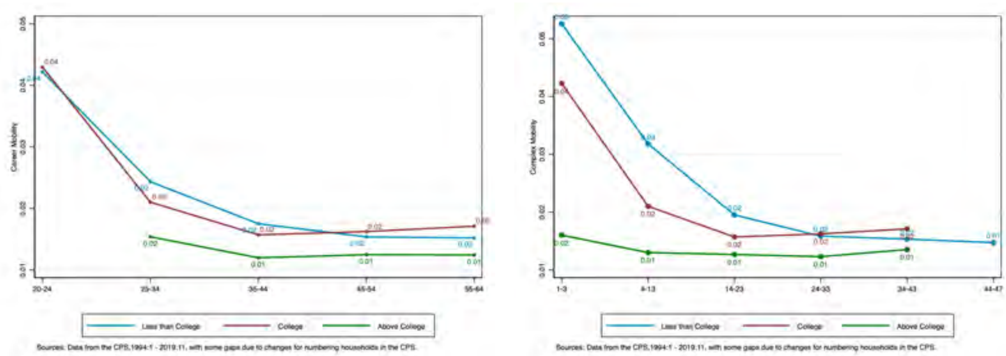
[17] A comprehensive crosswalk between education and potential experience is available in Appendix Table A4.



(a) Age (b) Potential Experience

Figure 4: Uncorrected Occupational Mobility Across Specific College Degrees

and industry switches, commonly known as a "complex transition" following Neal (1999), Pavan (2011), and Wee (2013). Specifically, it is defined as the occurrence of a 3-digit occupational change adjusted for suspicious transitions (see Appendix A.8), a 3-digit industry change, and an employer change. Although the definition is lucid, its accuracy may be subject to measurement errors due to missing answers to the "EMPSAME" question in the CPS, which asks whether the respondent worked for the same employer as the previous month.[18] Specifically, we observe a 32% blank response rate to "EMPSAME" out of the corrected occupational transitions, which is significantly higher than that in occupational stayers (5.37%). Therefore, discarding all of these observations with blank answers carries a significant risk of biasing the estimates of complex mobility. To address this issue, we adopt the approach proposed by Moscarini and Thomsson (2007) and assign a probability that a blank answer actually corresponded with a change in employer. This correction is detailed in Appendix A.9.



(a) Age (b) Potential Experience

Figure 5: Complex Mobility

Figure 5 shows the dynamics of complex mobility across age and potential experience. Notably, the analysis indicates a downward trend in complex mobility as workers age. Moreover, individuals with higher levels of education exhibit lower propensities to go through complex changes, relative to their less-

[18]A blank answer includes the following cases: Blank (Missing in the raw data), Don't know (97), Refusal (96) and Not in the universe (99).

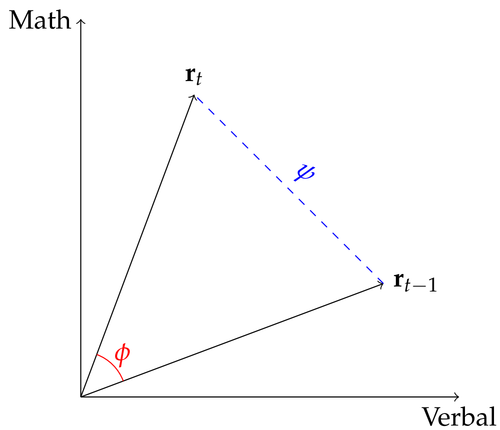


Figure 6: Comparison of Euclidean and Angular Distance

educated counterparts. Collectively, these results are consistent with the pattern observed in the separation and occupational mobility rates.

2.5 Occupational Distance

To this point, we have shown that individuals with more education experience lower separation rates, occupational mobility, and complex mobility rates. This is consistent with our hypothesis that college educated individuals experience lower mobility rates because they have more information about which occupations and careers are their best fit. Another implication of this hypothesis would be that, conditional on going through an occupation or complex change, college graduates would transition between similar occupations whereas those with less than a college degree may be prone to taking more significant changes in their career trajectory when switching occupations. We examine this in the data by comparing occupational requirements in occupation and complex switches.

To quantify the distance between occupations, we adopt a two-step approach. First, we measure the verbal, math, and social skill requirements for each occupation as in Guvenen et al. (2020).[19] To capture skills used in lower-wage occupations, we apply the methodology of Autor and Dorn (2013) in measuring an occupation's routine and manual task intensity. After measuring occupational requirements, we proceed to compute the distance between two jobs before and after a transition. The first distance measure, the Euclidean distance, between two occupations at time $t-1$ and t, $\psi(\mathbf{r}_{t-1}, \mathbf{r}_t)$, is

$$\psi(\mathbf{r}_{t-1}, \mathbf{r}_t) = \sqrt{\sum_k (\mathbf{r}_{t-1,k} - \mathbf{r}_{t,k})^2}, \tag{4}$$

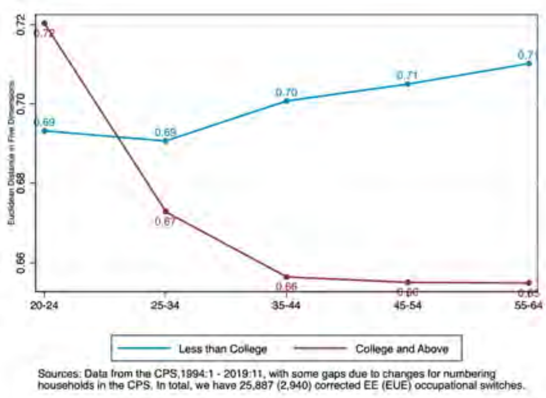
where $\mathbf{r}_{t,k}$ is the occupation at period t's requirement in aptitude $k \in \{\text{verbal, math, social, manual, routine}\}$. Alternatively, we can measure the angular distance, which captures the occupational difference of requirement composition between these two occupations. Specifically, let $\phi\colon \mathbb{R}^5 \times \mathbb{R}^5 \to [0, \pi/2]$. The angular distance between two vectors $\mathbf{r}_{t-1}$ and $\mathbf{r}_t$ is

$$\phi(\mathbf{r}_{t-1}, \mathbf{r}_t) = \cos^{-1}\left(\frac{\mathbf{r}_{t-1} \cdot \mathbf{r}_t'}{\|\mathbf{r}_{t-1}\| \|\mathbf{r}_t\|}\right). \tag{5}$$

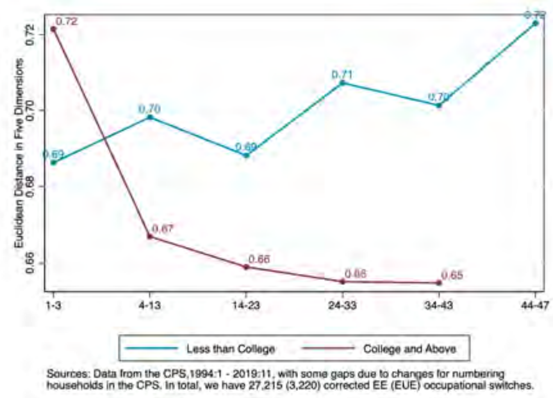
[19]See Appendix A.10 for a detailed explanation of measuring skill requirements.

Figure 6 provides a graphical comparison of the two types of occupational distance measures, using a simplified scheme in which each occupation is represented by two dimensions of skills (verbal, math). The Euclidean distance accounts for differences in both the composition and the magnitude of occupational requirements. In contrast, the angular distance quantifies the similarity in the composition of these occupational requirements.

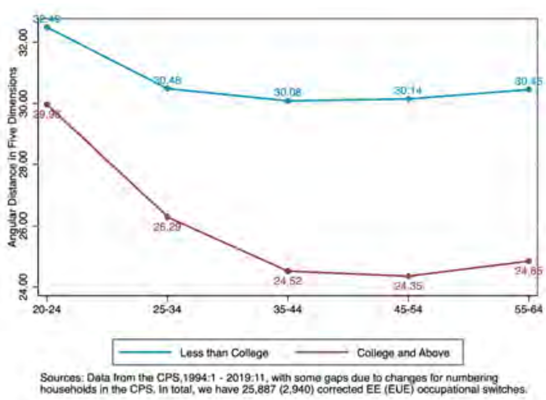
Figure 7 analyzes the occupational distance of workers undergoing (corrected) occupational transitions, disaggregated by education, age, and years of potential experience. Specifically, the upper (bottom) panel depicts the average Euclidean (angular) occupational distance over either age or years of potential experience.



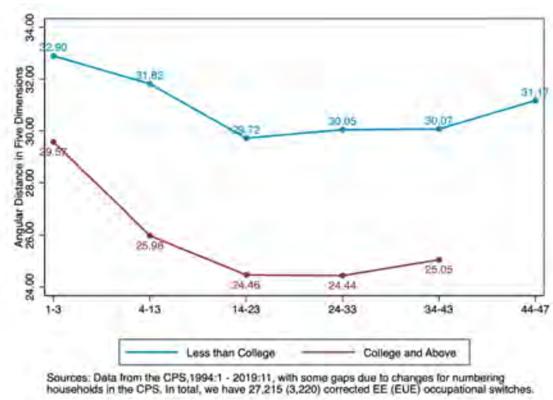
(a) Age (Euclidean)



(b) Potential Experience (Euclidean)



(c) Age (Angular)

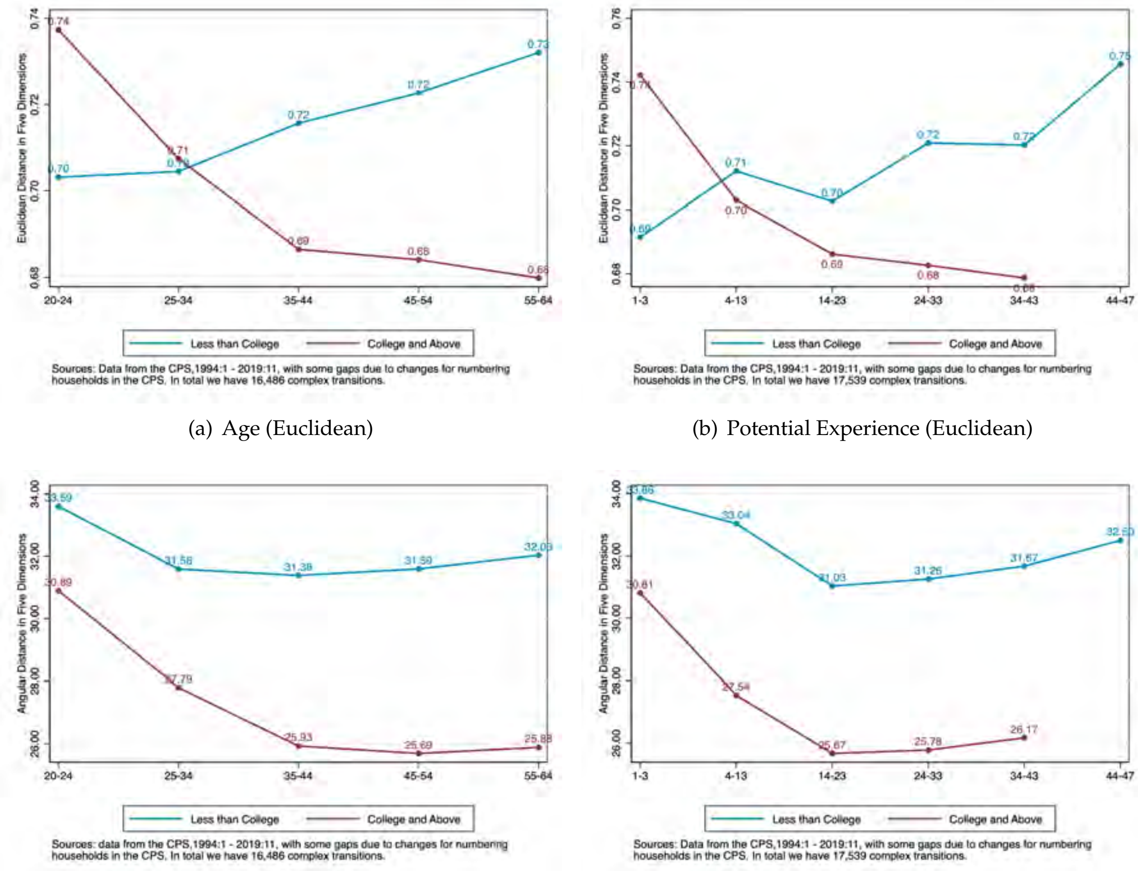


(d) Potential Experience (Angular)

Figure 7: Occupational Distance in Occupation Transitions

The main finding in Figure 7 is that the average distance of occupational requirements during occupation switches is consistently lower for college graduates across most of the life-cycle. From panels (c) and (d), we see that the average angular distance in occupation switches remains lower throughout the life-cycle for those with a college degree. This shows that not only do college graduates switch occupations at a lower rate, but when they do switch occupations, they tend to transition into occupations with a similar requirement composition as their previous occupation. Figure 8 paints a similar picture if we restrict our attention to the occupational distance in complex switches.

An intriguing observation from the Euclidean distance comparisons in Figure 7 and 8 is that during



(a) Age (Euclidean)

(b) Potential Experience (Euclidean)

(c) Age (Angular)

(d) Potential Experience (Angular)

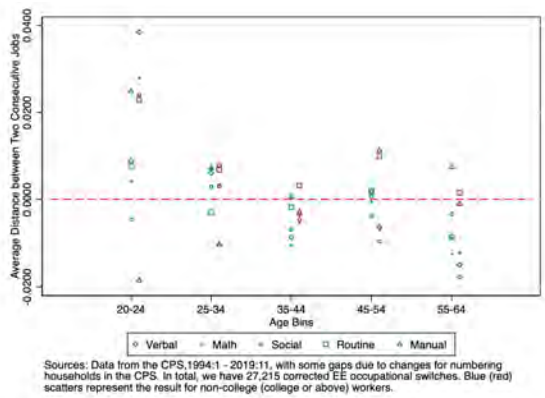
Figure 8: Occupational Distance in Complex Transitions

the initial stages of their careers (at 20-24 years old or 1-3 years of potential experience), the Euclidean distance of workers with a college degree in either occupation or complex transitions is higher compared to their counterparts without a college degree. Appendix Tables A6 and A8 show that once we control for observable characteristics, there is no statistically significant difference in the Euclidean distance for college-educated workers in complex or occupation transitions.

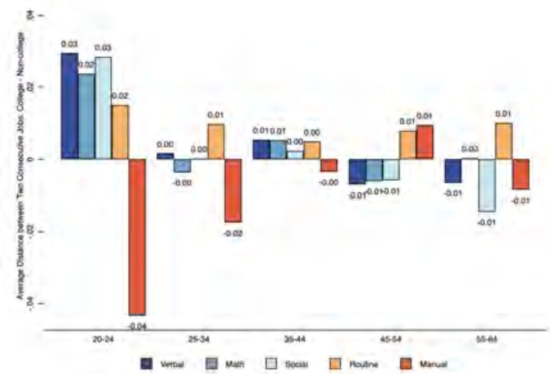
To examine why workers with a college degree exhibit little difference in the Euclidean distance but with consistently lower angular distance compared to their counterparts with less than a college degree, we calculate the average occupational distance along each aptitude at each age and years of potential experience bin across different education levels. To do this, we first calculate the average occupational distance in transitions for workers with age i and education level j along each aptitude k, denoted by $\bar{\zeta}_{ij,k}$:

$$\bar{\zeta}_{ij,k} = \frac{\sum_{m=1}^{M_{ij}} \Delta r_{ij,k}^{m}}{M_{ij}}, \tag{6}$$

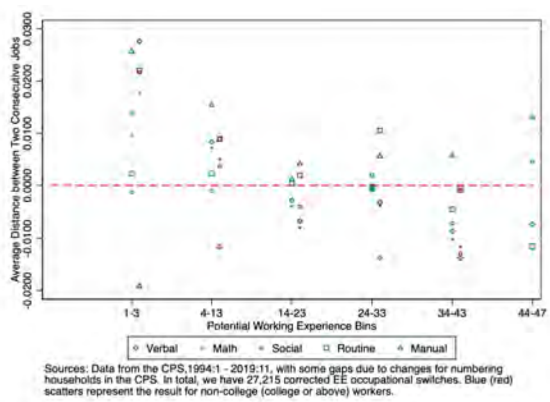
where $\Delta r_{ij,k}^{m}$ is the requirement distance in dimension k for each transition occurring among workers with age i and education level j and M_{ij} is the total transitions among workers with age i and education level j. We can then obtain the average occupational distance for each subgroup by taking the unweighted average



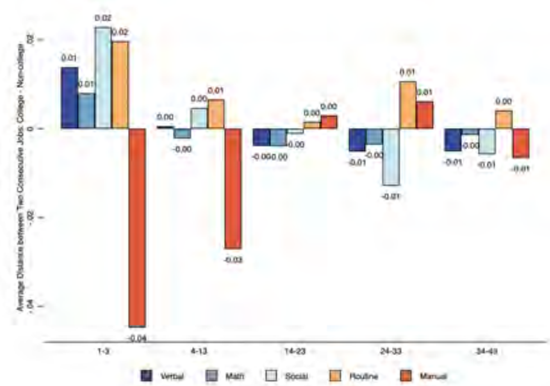
(a) Age



(b) Age, College - Non-college



(c) Potential Experience



(d) Potential Experience, College - Non-college

Figure 9: Average Occupational Distance in Corrected Occupation Transitions

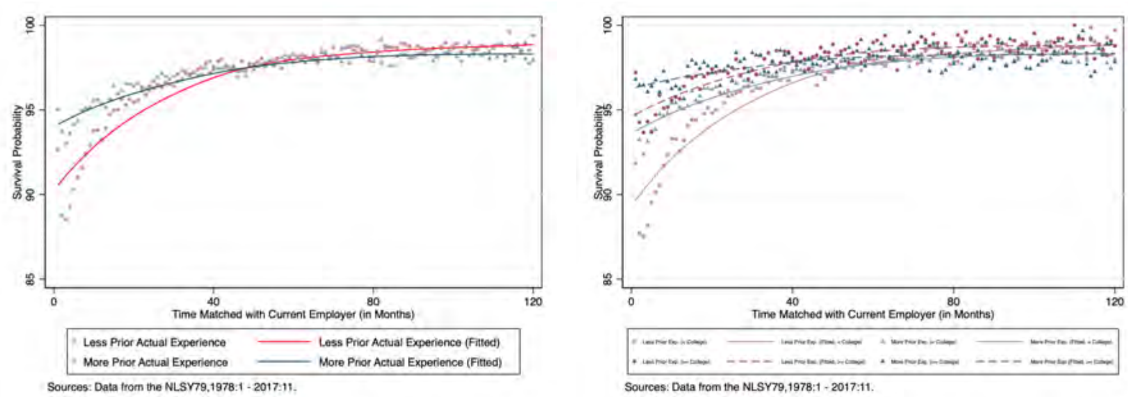
across requirement dimensions, which is given by $\bar{\zeta}ij = (1/5)\sum_{k\in\{v,m,s,ma,ro\}}\bar{\zeta}_{ij,k}$. This computation allows us to compare the average occupational distance in transitions experienced by workers possessing different educational attainment at different career stages, thereby elucidating the underlying factors that give rise to discrepancy in Euclidean and angular distances.

Figure 9 presents the average occupational distance in corrected occupation transitions across different dimensions, comparing various life stages and educational groups. Panels (a) and (c) show the mean occupational distance for two successive jobs along each dimension, while the blue (red) markers are for non-college (college) workers. Panels (b) and (d) detail the differences in mean occupational distance between college-educated workers and those without a college degree across each requirement category. The key finding here is that in the initial stages of a worker's career, individuals with a college education tend to shift to occupations with higher requirements in all dimensions, except for manual tasks. For a more detailed comparison within other transitions types, see Appendix A.10.3. The takeaway from this exercise is that college workers who are early in their career gravitate towards jobs that not only align with their previous job's requirements but also necessitate a greater degree of capabilities across all dimensions. This is why the angular distance is lower among college graduates, while the Euclidean distance does not exhibit the same pattern early in the career.

2.6 Experience and Match Duration

This section leverages the NLSY79 data to demonstrate the relationship between accumulated prior experience and the survival probability of a match. To compute the survival probability of a match, we simply calculate the fraction of matches that survive between months t and $t+1$. To identify matches that survive between periods, it is vital to know the worker's employer ID when they are employed. To address this issue, we drop the 116 respondents with an incomplete employer ID record from our baseline NLSY79 sample (see Appendix B.2 for a description of the sample construction), leaving 4,697 respondents.

As a first step, we group workers into two groups based on their level of accumulated experience at the beginning of a new employment spell. The first group, experienced workers, are those who enter the new match with more than 76 months of actual working experience. The second group, inexperienced, are workers who begin a new match with less than 77 months of actual working experience. The threshold used to split the sample, 76 months of actual working experience, is simply the median number of months of actual working experience at the formation of new matches in our sample.



(a) All Workers

(b) By Education

Figure 10: Prior Experience and Match Survival

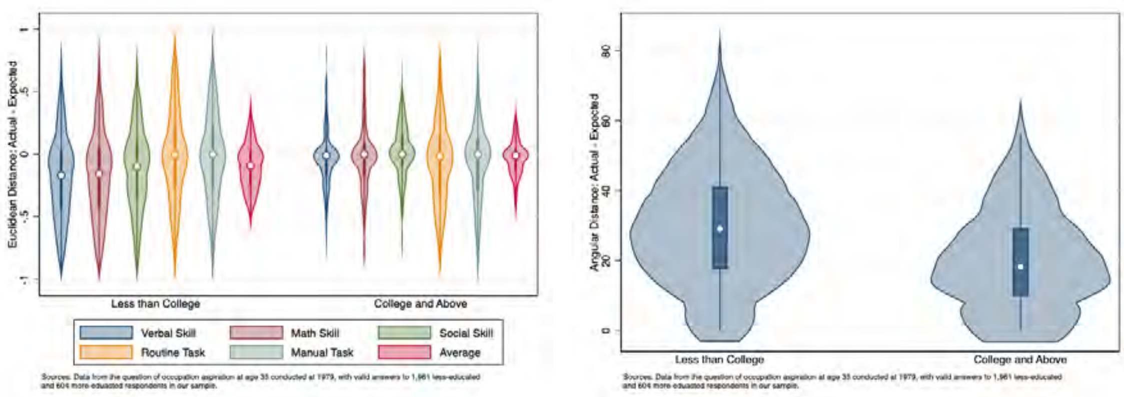
Figure 10 presents the fraction of matches that survive between months t and $t+1$ as a function of the number of months matched with the current employer across the first 10 years, or 120 months, of the match. From panel (a), we can see that the survival probability is increasing in the match duration, with the steepest increase in the survival probability occurring early in the match. We can also see that, early in the match, workers who enter the match with more prior experience exhibit a higher survival probability. This finding echoes Topel and Ward (1992), who found that the expected match duration is increasing in the worker's prior experience. Panel (b) shows that the association between prior experience and survival probability appears to be much stronger among workers with less than a college degree. We can see this by observing the difference in the fitted survival probabilities between workers with more and less prior experience. For workers with less than a college degree, the survival probability shifts up by much more than for workers with a college degree. This is consistent with our proposition that workers with less than a college degree learn more about their comparative advantages from actual labor market experience than workers with a college degree. As a robustness exercise, we estimate a logit model to control for observable characteristics and confirm that more prior experience is associated with a higher survival probability and that this effect is weaker for workers with a college degree. See Appendix B.12 for more details.

2.7 Expectations about Future Occupation

Until this point, we have provided evidence that is consistent with the notion that college graduates enter the labor market with better knowledge of their comparative advantages. In this section, we provide more direct evidence on this by comparing the accuracy of workers' expectations regarding their future occupation across educational attainment. In particular, respondents in the NLSY79 were asked the following question in their 1979 interview: "What kind of work would you like to be doing when you are 35 years old?". Of the 4,823 respondents in our sample, 2,565 respondents listed an expected future occupation, of which 604 obtained a Bachelors degree or above. Accordingly, the forecast error in terms of either euclidean ($\overline{FCE}_i^{Euc}$) or angular distance ($\overline{FCE}_i^{Ang}$) between their actual and expected occupations at age 35 can be expressed as: [20]

$$\overline{FCE}_i^{Euc} = \frac{\sum_{j\in\{v,m,s,ro,ma\}} |s_j - \hat{s}_j|}{5}, \qquad \overline{FCE}_i^{Ang} = \cos^{-1}\left(\frac{\mathbf{s}\cdot\hat{\mathbf{s}}}{|\mathbf{s}|\cdot|\hat{\mathbf{s}}|}\right),$$

where s_j ($\hat{s}_j$) denotes the realized (expected) occupation's measurement in attribute j at age 35.



(a) Euclidean Distance

(b) Angular Distance

Figure 11: Distributions of Skill Distance between Actual and Expected Occupation at Age 35

Figure 11 displays the distribution of forecast errors. The main takeaway from this figure is that college workers form more accurate forecasts regarding their future occupation. This can be seen in two different ways. First, the distribution of occupational distances among college graduates has more mass around 0. In particular, 15% of workers with a college degree's actual and expected occupation had the same average occupational requirement, as opposed to 6% of workers with less than a college degree. Second, the average forecast error measured by angular distance for college workers is 19.86, which is about two-thirds of that for non-college workers (28.65). Table 2 confirms what we can see from the graphs. In particular, the mean and variance in occupational distance between actual and expected job at age 35 are significantly lower among college graduates.

[20]If a respondent worked in multiple occupations at age 35, we compute the average skill requirements across the jobs worked during that year.

Table 2: Mean and Variance of Occupational Distance Between Actual and Expected Age 35 Occupation

	Verbal	Math	Social	Routine	Manual	Average
Less than College	-0.15 (0.13)	-0.14 (0.13)	-0.10 (0.12)	-0.00 (0.14)	-0.02 (0.14)	-0.09 (0.04)
College and Above	-0.04 (0.07)	-0.03 (0.09)	0.01 (0.06)	-0.06 (0.12)	-0.07 (0.11)	-0.04 (0.02)

Notes: Data from NLSY79. Each cell displays the mean and variance (in parentheses) in distance between the required skills (or task intensities) of the actual and expected occupation at age 35. Let $\mu_{c,j}$ ($\mu_{n,j}$) denote the absolute value of the mean occupational distance among respondents with (less than) a college degree along the aptitude $j \in \{\text{verbal}, \text{math}, \text{social}, \text{routine}, \text{manual}, \text{average}\}$. We test the null hypothesis that $\mu_{c,j} = \mu_{n,j}$ against the alternative $\mu_{c,j} < \mu_{n,j}$ and reject the null hypothesis at a significance level less than 0.01 across each for $j \in \{\text{verbal}, \text{math}, \text{social}, \text{average}\}$.

2.8 Robustness and Additional Evidence

This section summarizes additional empirical exercises to complement the analysis presented throughout Section 2. First, college graduates also switch careers at a lower rate, where a career switch is when a worker switches to an occupation with sufficiently different skill requirements. Appendix A.11 contains the details on career mobility. Second, average skill mismatch, as measured by Guvenen et al. (2020), is lower among college graduates throughout the life-cycle. This suggests that college graduates find better matches, as measured by skill mismatch, from the beginning of their career. Appendix B.8 presents the analysis of skill mismatch by age and educational attainment. Third, we compare the average dispersion in skill requirements by educational attainment. The intuition here is that if a worker is more certain of their ability, they would have a higher willingness to work in a job with a relatively imbalanced set of skill requirements. This can be juxtaposed with workers who are uncertain of their skills, who may be more inclined to take jobs with balanced skill requirements. Under our proposed mechanism, college graduates would then work in jobs with a higher dispersion in skill requirements. Appendix B.9 shows that this in the case in the NLSY79.

As for the robustness of the findings presented throughout Section 2, the patterns presented from the CPS generally hold in the NLSY79. In particular, Section B.3 presents the life-cycle unemployment patterns, Section B.4 the life-cycle job finding and separation probabilities, Section B.6 the occupation and complex switching probabilities, and Section B.7 shows the average distance in occupational requirements in transitions and career mobility rates. Finally, almost all the relationships between having a college degree and the various outcomes of interest are robust to controlling for standard observable characteristics. See Appendix A.12 for the CPS and Appendix for NLSY79 analyses, respectively.

3 Simple Model with Information Frictions

In this section, we write a model with unobserved heterogeneity among workers and learning to study how a reduction in the uncertainty regarding a worker's underlying ability affects both the job finding and separation probabilities over the lifecycle. Section 3.1 introduces the environment, Section 3.2 characterizes the equilibrium, and Section 3.3 presents a numerical example.

3.1 Environment

Time, Agents, and Preferences Time is discrete and goes on forever. At period $t = 0$, there is a unit measure of workers and a large measure of homogenous firms. Workers are endowed with an indivisible unit of labor. All agents are risk neutral and share the discount factor $\beta \in (0, 1)$. Each firm corresponds to one job that either filled or vacant.

Workers are ex-ante heterogeneous in their ability. The ability of a type-i worker is denoted by a_i. Upon entering the labor market, a worker's ability is drawn from a normal distribution where $a_i \sim \mathcal{N}(\bar{\mu}_a, \sigma_a^2)$. A worker's ability is fixed and unobservable. That is, neither a worker nor the firm know an individual worker's ability. However, the distribution of abilities is public information.

Technology Firms operate a technology that maps one unit of labor from a type-i worker into z_i units of output where $z_i = a_i + \varepsilon$, ε is an i.i.d. productivity shock, and $\varepsilon \sim \mathcal{N}(0, \sigma_\varepsilon^2)$. While the distribution of the productivity shock is public information, neither firms nor workers observe the value of ε. Match output, z_i, is observable. Thus, workers and firms use the noisy signal, z_i, to update their beliefs regarding the worker's ability. This will be explained in greater detail below.

The Labor Market The labor market is organized in a continuum of submarkets indexed by $\omega = (\mu, y, x)$. In submarket ω, firms search for workers with expected ability μ, experience y, and offer workers contracts worth x in lifetime utility. A worker's experience level is given by $y \in \mathbb{W}$ and evolves as follows. A worker with experience y who is employed and produces in a period enters the following period with experience $y' = y + 1$. A worker with experience y who does not produce in the current period enters the next period with experience y.

Timing Each period is divided into five stages: learning, separation, search/matching, production, and entry/exit. We proceed to fill in the details of each stage.

Stage 1: Learning Consider a worker who entered the previous production stage employed and with experience y. Moreover, denote the mean and variance of the prior distribution regarding the worker's ability by μ_a and $\sigma_{a,y}^2$, respectively. Having observed output z_i, the worker and firm update their beliefs regarding the worker's ability in a Bayesian manner. Given that the noisy signal and underlying ability are both normally distributed, the posterior distribution is given by $\mathcal{N}(\mu_a', \sigma_{a,y'}^2)$ where

$$\mu_a' = \frac{\sigma_{a,y}^2 z_i + \sigma_\varepsilon^2 \mu_a}{\sigma_{a,y}^2 + \sigma_\varepsilon^2}, \tag{7}$$

$$\sigma_{a,y'}^2 = \frac{\sigma_a^2 \sigma_\varepsilon^2}{y' \sigma_a^2 + \sigma_\varepsilon^2}. \tag{8}$$

From equation (7), the worker and firm place more weight on the noisy signal if the prior beliefs are imprecise (i.e., $\sigma_{a,y}^2$ is large). Alternatively, the worker and firm place more weight on their prior belief if the distribution of match productivity shocks, ε, is noisy. Equation (8) shows that a worker's experience, y, is a sufficient statistic for the variance of the posterior distribution and that the worker and firm's beliefs will become more precise as the worker accumulates more experience. It is for this reason that we only keep track of the worker's experience as a state variable, instead of the variance, when we introduce the value functions in Section 3.2. Finally, workers who entered the previous production stage unemployed, with experience y, and prior beliefs summarized by the distribution $\mathcal{N}(\mu_a, \sigma^2_{a,y})$ do not update their beliefs.

Stage 2: Separation At the separation stage, a match between a worker with experience y and expected ability μ_a and a firm destroy the match with probability $d \in [\delta, 1]$. The separation probability is specified by the employment contract and the lower bound δ represents separations which occur due to exogenous reasons. A worker who loses their job in the separation stage must wait one period before they can search for another job.

Stage 3: Search and Matching In the search and matching stage, firms first decide whether to create a vacancy and, if so, which submarket to post it in. Workers choose which submarket to search in. Firms incur a cost $k > 0$ to open and maintain a vacancy for one period. Workers who begin the period unemployed search with probability one. There is no search on the job.

Workers and firms who search in the same market are brought together by a constant returns to scale matching technology. Let $v(\omega)$ denote the measure of vacancies in submarket ω and $u_i(\omega)$ the measure of unemployed workers with expected ability μ_i searching in submarket ω. The number of matches in a submarket ω is given by the matching function $F(u(\omega), v(\omega))$ where $u(\omega) = \int u_i(\omega)di$ is the total measure of unemployed workers searching in submarket ω. Define $\theta(\omega) = v(\omega)/u(\omega)$ as tightness in submarket ω. The probability that a worker matches with a vacancy is given by $p(\theta(\omega)) = F/u(\omega)$ where $p : \mathbb{R}_+ \to [0, 1]$ is twice continuously differentiable, strictly increasing, strictly concave, $p(0) = 0$, and $p(\infty) = 1$. The probability that a vacancy matches with a worker is given by $q(\theta(\omega)) = F/v(\omega)$ where $q : \mathbb{R}_+ \to [0, 1]$ is twice continuously differentiable, strictly decreasing, strictly convex, $q(0) = 1$, and $q(\infty) = 0$.

Stage 4: Production In the production stage, unemployed workers produce b units of output. Matches between a type-i worker and a firm draw a productivity shock ε and produce $z_i = a_i + \varepsilon$ units of output.

Stage 5: Entry and Exit In the entry/exit stage, a fraction λ of workers exit the economy. At the same time, a measure λ of workers enter the economy, draw their ability a_i, and begin their career unemployed with experience $y = 0$.

Contractual Environment The contract space is complete, giving rise to bilaterally efficient employment contracts. Therefore, employment contracts offered by the firm will maximize the joint surplus of the match.

3.2 Equilibrium

We focus on stationary equilibria. Moreover, following Menzio and Shi (2011), it is straightforward to show that the equilibrium is block-recursive. Therefore, in what follows, we abstract from including the aggregate state, which describes the distribution of workers across states of employment and unemployment, as an argument in the value functions.

Consider an unemployed worker with expected ability μ_a and experience y at the production stage. In the current period, they produce output b, remain in the economy between periods with probability $1 - \lambda$, and search in the next period's search and matching stage. If they search in submarket $\omega = (\mu_a, y, x)$, they find a job with probability $p(\theta(\mu_a, y, x))$ and their continuation value is x, the value of the employment contract. If they don't find a job, their continuation value is the value of unemployment, $V_u(\mu_a, y)$. The value of unemployment, $V_u(\mu_a, y)$, satisfies:

$$V_u(\mu_a, y) = b + \beta(1-\lambda)\{V_u(\mu_a, y) + R(x, V_u(\mu_a, y))\}, \tag{9}$$

where

$$R(x, V_u(\mu_a, y)) = \max_x p(\theta(\mu_a, y, x))(x - V_u(\mu_a, y)). \tag{10}$$

Now consider a match between a firm and a worker with expected ability μ_a, experience y, and who produce z units of output in the current production stage. The sum of the firm's profits and worker's utility in the current period are equal to the match output, z. After producing, the worker's experience level is $y' = y + 1$. With probability $1 - \lambda$, the worker does not exit the labor market. In the following learning stage, the firm and worker, having observed output z, update their beliefs regarding the worker's ability according to equations (7) and (8). In the separation stage, the match is destroyed with probability $d \in [\delta, 1]$. If the match is destroyed, the worker receives the value of unemployment, $V_u(\mu_a', y')$ while the firm's continuation value is zero. With probability $1 - d$, the match is not destroyed. In this case, the sum of the worker's utility and firm's profits are given by the expected value of the match in the following production stage, $\mathbb{E}V_e(\mu_a', y', z')$, where expectations are taken with respect to the posterior distribution of beliefs. It follows that $V_e(\mu_a, y, z)$ satisfies:

$$V_e(\mu_a, y, z) = z + \beta(1-\lambda) \max_{d\in[\delta,1]} \{dV_u(\mu_a', y') + (1-d)\mathbb{E}V_e(\mu_a', y', z')\}. \tag{11}$$

In any submarket visited by a positive number of workers, tightness is consistent with the firm's incentives to create vacancies if and only if

$$k \geq q(\theta(\mu_a, y, x))\{\mathbb{E}V_e(\mu_a, y, z) - x\}, \tag{12}$$

and $\theta(\mu_a, y, x) \geq 0$ with complementary slackness. We restrict attention to equilibria in which $\theta(\mu_a, y, x)$ satisfies the complementary slackness condition in every submarket, even those that are not visited by workers.

We now turn to characterizing the solution to the separation problem. From (11), we have $d \in [\delta, 1]$ determined by the inequality $\mathbb{E}V_e(\mu_a', y', z') \lesseqgtr V_u(\mu_a', y')$. If $\mathbb{E}V_e(\mu_a', y', z') > V_u(\mu_a', y')$, the value of continuing the match is greater than the value of destroying it, giving $d = \delta$. If $\mathbb{E}V_e(\mu_a', y', z') \leq V_u(\mu_a', y')$, the value of destroying the match is greater than the value of maintaining it and hence, $d = 1$.

Proceeding to the submarket choice among unemployed workers, we can substitute the firm's free entry-condition into (10) to reduce the worker's submarket choice to:

$$\max_\theta -k\theta + p(\theta)[\mathbb{E}V_e(\mu_a, y, z) - V_u(\mu_a, y)]. \tag{13}$$

From (13), the first order condition is given by

$$k \geq p'(\theta)[\mathbb{E}V_e(\mu_a, y, z) - V_u(\mu_a, y)], \tag{14}$$

with $\theta \geq 0$ with complementary slackness. From (14), we can see that θ is increasing in the expected match surplus, $\mathbb{E}V_e(\mu_a, y, z) - V_u(\mu_a, y)$. Moreover, $\theta = 0$ solves (13) if

$$\mathbb{E}V_e(\mu_a, y, z) - V_u(\mu_a, y) < \frac{k}{p'(0)}. \tag{15}$$

Thus, workers with an expected ability and experience level such that the expected value of a match relative to the value of unemployment is low enough, they only search in submarkets where there are no vacancies, $\theta = 0$, face a job finding probability $p(\theta) = 0$, and remain unemployed until they exit the labor market. Recall that if $\mathbb{E}V_e(\mu_a, y, z) - V_u(\mu_a, y) < 0$, then $d = 1$. Therefore, if a worker has an expected ability, μ_a, and experience level, y, that leads to an endogenous separation ($d = 1$), these workers will both have their job endogenously destroyed and remain unemployed until exiting the labor market.

3.3 Numerical Example

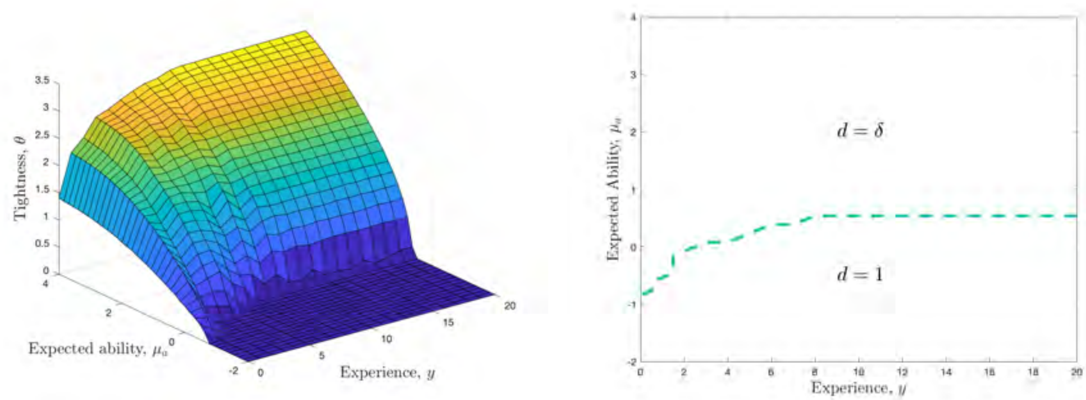
This section presents a numerical example of the preceding environment to (i) display the policy functions and (ii) demonstrate the effect of a reduction in uncertainty regarding workers' underlying productivity on the job finding and separation profiles over the life-cycle. The matching function is $F(u, v) = uv/[u + v]$, which guarantees $p(\theta) \in [0, 1]$ and $q(\theta) \in [0, 1]$. Table 3 presents the parameter values used in the numerical example.

Table 3: Parameter Values

	Definition	Value
β	Discount factor	0.996
λ	Entry/exit probability	0.008
δ	Exogenous separation probability	0.02
b	Utility while unemployed	0.60
k	Vacancy cost	0.30
$\bar{\mu}_a^2$	Mean of ability distribution	1
σ_a^2	Variance of ability distribution	1
σ_ε^2	Variance of match-specific productivity	1

As a first step, Figure 12 displays the policy functions for tightness and the separation probability in the experience, y, and expected ability, μ_a, space. Panel (a) shows that tightness is generally increasing in both expected ability and experience. However, increasing a worker's experience level while holding their expected ability fixed can cause tightness to decrease, as increasing y is akin to reducing the variance of the prior distribution. If firms know with greater precision that a worker is of a low ability, then they may be less willing to post vacancies in submarkets for such workers. On the other hand, a reduction in the variance of the prior also means that a match is less likely to end in an endogenous separation. This induces firms to post more vacancies and hence, explains why the effect of experience on tightness can be non-monotone. Panel (a) also displays a region where tightness is equal to zero. It is in this region where (15) is satisfied.

Panel (b) displays the solution to the separation choice in the experience and expected ability space. We can see a region where the worker has a low expected ability where $d = 1$, i.e., if an employed worker's expected ability and experience level were to drift in this region, their job would be endogenously destroyed. We can also see that this region closely corresponds to the region in panel (a) where $\theta = 0$, as workers whose jobs are endogenously destroyed will only enter submarkets with $\theta = 0$. Panel (b) also shows that workers with a higher expected ability require a higher level of experience to have their job destroyed. This is because a worker with a higher expected ability with low experience has a relatively imprecise prior when compared to a worker with the same expected ability but a higher level of experience. In the former case, there is still enough of a chance that the worker's true ability is above the current expected value and hence, it is worth maintaining the match. In the later case, the worker and firm are more certain that the worker is of a low ability and are more willing to destroy the match.



(a) Tightness

(b) Separation Probability

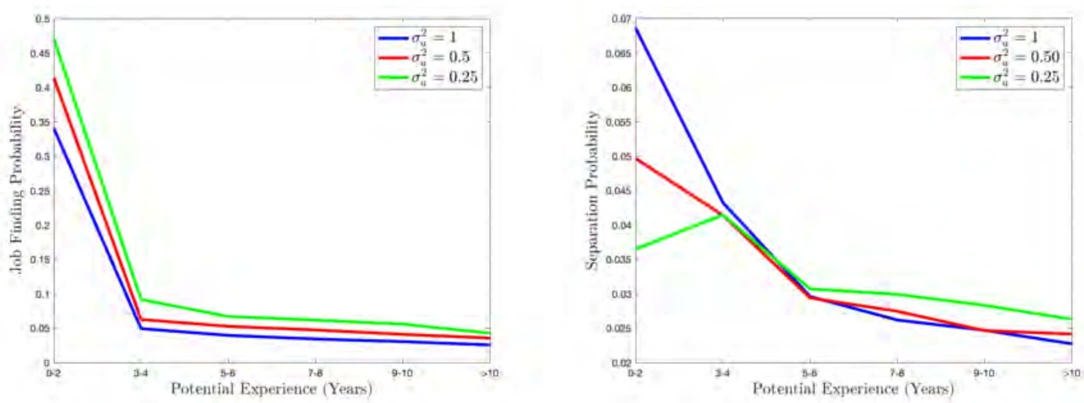
Figure 12: Policy Functions

We proceed to study the effect of reducing the uncertainty regarding workers' abilities on the job finding and separation probabilities over the life-cycle. To do so, we simulate the employment histories for nearly 10,000 workers and construct job finding and separation probabilities across bins of potential experience. Figure 13 presents the results. Beginning with panel (a), the job finding probability is decreasing in potential experience. This is because workers who are primarily unemployed in the later stages of their career are those who have an expected ability and experience level where $\theta = 0$, and hence do not exit unemployment. The average job finding probability is high at the beginning of workers' careers because all workers start out with an expected ability of $\mu_a = \bar{\mu}_a$. Over time, the low ability worker's true type is revealed and many lose their jobs. Over time, the composition of unemployed workers becomes primarily composed of the low ability workers who have a job finding probability equal to zero, and hence, the average job finding probability declines with potential experience. Notice that this declining job finding probability profile is, qualitatively, aligned with what we see in the data (e.g., Figure 1).[21] Moreover, the model of match-specific productivity in the last section would predict a job finding probability that is flat over the life-cycle, as all unemployed workers are the same.

Panel (a) also shows the effect of reducing σ_a^2, the variance of the distribution of abilities among workers, which represents a reduction in the uncertainty regarding a worker's ability. Reducing σ_a^2 causes the job finding profile to shift up at each level of potential experience. This occurs because a reduction in un-

[21] Gorry (2016) develops a model that can generate a decreasing age profile in the job finding probability. In his model, workers learn how to better distinguish good from bad matches by accumulating experience. Thus, workers with more experience can identify and reject bad job offers, and hence, accept few offers.

certainty means that firms face a lower separation risk and post more vacancies, which leads to a higher job finding probability. This also ties back to panel (a) of Figure 12 where we showed that tightness is generally increasing in a worker's experience level and the associated reduction in uncertainty.



(a) Job Finding Probability

(b) Separation Probability

Figure 13: Job Finding and Separation Probabilities

Proceeding to panel (b) of Figure 13, we see that the separation probability is generally decreasing in potential experience. The intuition is similar to panel (a). Initially, all workers begin with the same expected ability. As workers and firms begin to observe match output, low ability workers' types begin to be revealed. Eventually, workers enter a region of expected ability and experience where their match is destroyed. It is at this point where these workers enter unemployment and remain so until exiting the labor market. Over time, the pool of employed workers shifts towards those who, given their expected ability and experience level, will never have their job destroyed endogenously. If those workers, for exogenous reasons, do lose their job, then they will enter submarkets with a high level of tightness (as shown in Figure 12) and quickly find a job.

As a final exercise in this numerical example, panel (b) shows the effect of reducing σ_a^2 on the separation probability. First, we see that reducing σ_a^2 from 1 to 0.5 generally reduces the average separation probability, especially at the earlier stages of the career. The intuition for this is the following: with a lower value of σ_a^2, workers with a low expected ability are less likely to form matches to begin with, and hence, do not have the opportunity to learn with greater precision that they are a low ability type and have their job destroyed in the process. Another way to say this is that reducing σ_a^2 causes fewer matches to be created that are bound to be destroyed later on. Panel (b) also reveals that reducing σ_a^2 can have more nuanced effects on the average separation probability over potential experience. When $\sigma_a^2 = 0.25$,the average separation probability increases between the 0-2 and 3-4 years of potential experience bins. This is because a lower value of σ_a^2 causes workers and firms to be less responsive in updating their beliefs to a noisy signal. In this case, when $\sigma_a^2 = 0.25$, workers and firms are quite slow in updating their prior beliefs upon receiving negative signals regarding the worker's ability. Thus, with a slower learning process, it takes longer for those matches to arrive at a point where the match is endogenously destroyed. In this example, the separation probability peaks during the 3-4 years of potential experience bin and declines thereafter.

3.4 Comparison with Match-Specific Productivity Shocks

The results in Section 3.3 show that a directed search model with information frictions and learning can generate decreasing job finding and separation probabilities over the life-cycle. Moreover, a reduction in information frictions can qualitatively generate the differences in both the job finding and separation probabilities by educational attainment that are observed in the data.

An alternative approach to generate the unemployment-education gap would be to develop an environment with workers who differ in their education and productivity, match-specific productivity that is learned with a delay, and endogenous separations. Appendix C.1 presents such an environment and shows that highly educated workers experience both a higher job-finding probability and a lower separation probability. We interpret this finding to mean that there is a role for match surplus heterogeneity in generating the unemployment-education gap. However, there are several predictions from this model that are at odds with the data.

The first is that average match-specific productivity is lower among highly educated workers. Guvenen et al. (2020) proposed looking into the black-box of match-specific productivity by directly measuring skill-mismatch between the worker's skills and the skill requirements of their occupation. In Section B.8, we showed that skill mismatch is decreasing in the worker's educational attainment, which would indicate that highly educated workers have, on average, a higher match-specific productivity.

Second, this environment, as with any that relies exclusively on match-specific productivity to generate endogenous separations, predicts that the expected duration of a match is independent of the worker's prior experience. However, this "resetting" property is counterfactual. Topel and Ward (1992) find that the separation probability is decreasing in a worker's experience. In Section 2.6, we also documented this pattern in the NLSY79 data.

Third, the model with match-specific productivity predicts that the worker's job-finding probability is independent of their prior experience. This is again due to the resetting property and generates a job-finding probability that is constant over the life-cycle. This goes against what see in the data, as Figure 1 shows that the job-finding probability decreases with age.

4 Conclusions and Next Steps

This paper aims to better understand the sources of the unemployment-education gap. The mechanism at the heart of our analysis is that college educated workers enter the labor market with more certainty about their ability and best occupational/career fit. We have argued that examining the unemployment-education gap over the life-cycle offers important insights into its sources, and have provided several supporting facts for the proposed mechanism. As a first step towards formalizing the mechanism, we developed a directed search model with information frictions and learning. This simple environment can qualitatively match several features of the data. Next steps include extending the model of Section 3 to allow for competing mechanisms and to speak to more features of the data (e.g., occupational mobility).

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Appendix

A Empirical Appendix (CPS)

A.1 CPS Variables

Table A1: IPUMS-CPS Variables

Variable	Variable Label	Interpretation
Panel A: Technical Variables		
YEAR	Survey year	From 1976 to 2018
MONTH	Survey month	From Jan to December
CPSID	An unique identifier	A 14-digit numeric variable that uniquely identifies households across CPS samples
MISH	Month in sample, household level	The number of survey round from 1 to 8
WTFINL	Final basic weight	The final person-level weight used in analyses of basic monthly data
LNKFW1MWT	Longitudinal weight for linking adjacent months of the CPS	A 14-digit numeric variable with four implied decimals
Panel B: Demographic Variables		
AGE	Age	Each person's age at last birthday, 1976-2022
RACE	Racial Categories	Regroup into 3 broad categories: white (1), black/negro (2) and others (3)
MARST	Marital status	Regroup into 3 broad categories: married (including married, spouse present, and married, spouse absent) and single (including separated, divorced, windowed, never married/single, widowed or divorced), NIU (Non-marriageable age), 1976-2022
STATEFIP	State (FIPS code)	Identify the household's state of residence, where 99 state not identified. 1976-2022
NCHILD	Number of own children in household	The number of own children (of any age or marital status, could be stepchildren, adopted children as well as biological children) residing with each individual, top-coded at 9 children, 1976-2022
CHILDBEARING	Child bearing	No children (0) and at least one child (1) in the household unit, 1976-2022

EDUC	Educational attainment	A combination of HIGRADE (pre-1992, highest grade of school/year of college) and EDUC99 (post-1992, highest degree/diploma attained)
Panel C: Employment Variables		
POPSTAT	Population status	Indicates if the person is an adult civilian, in the armed forces, or a child
LABORFORCE	Labor force status	A dichotomous variable indicating if the respondent is in the labor force during the preceding week
EMPSTAT	Employment status	Indicates whether persons were part of the labor force–working or seeking work–and, if so, whether they were currently unemployed
OCC1990	Occupation, 1990 basis	A modified 1990 Census Bureau occupational classification scheme, yielding 389 categories
IND1990	Industry, 1990 basis	A consistent industry codes for IPUMS-CPS since 1968, comprising 245 groups
SAMEEMP	Still working for same employer	It indicates if the respondent was employed by the same employer and the same job he/she reported working as his/her main job in the previous month's survey, 1994-2002
SAMEACT	Still have the same work activities	It indicates if the respondent's usual work activities or duties have changed during the previous month, 1994-2022
UHLKB1	Look for work last 4 weeks	It indicates if a respondent search for work during last 4 weeks, 1994-2022
CLASSWKR	Class of worker	It indicates if a respondent was self-employed, was an employee in private industry or the public sector, was in the armed forces, or worked without pay in a family business or farm, 1976–2022

Notes: For the employed, occupational and industrial information applies to the job held in the reference week, while for the unemployed, that are classified according to their last job, if any.

A.2 Education Categories

The CPS question regarding educational attainment underwent a modification by the US Census Bureau in January 1992. Prior to 1992, the question inquired about the highest grade attended and completed (years of education). However, after that point, the question focused on the highest degree obtained. As a result, we classify educational categories using different thresholds based on either years of education or degree attainment, as demonstrated in the third column in the Table A2. Specifically:

(i) The category "Less than College" now includes individuals who have completed up to three years of college in the old question or have obtained an associate's degree or completed an academic program in the new question.

(ii) The category "College" encompasses those who have completed four years of college in the old question or have obtained a bachelor's degree in the new question.

(iii) The category "Above College" now includes individuals who have completed at least five or more years of college in the old question or have obtained a master's degree, professional school degree, or doctorate degree in the new question.

Table A2: Imputation of Years of Potential Experiences

Category	Refined Category	CPS Education	Presumed Pot. Exp.
Less than College	Less than College	< 4 years of college (110)	$Age - 18$
College	College	4 years of college (110) Bachelor's degree (111)	$Age - 22$
Above College	Master	5+ years of college (120)	$Age - 23$
		5 years of college (121)	$Age - 23$
		6+ years of college (122)	$Age - 24$
		Master degree (123)	$Age - 24$
	Professional school and Doctorate Degree	Professional school degree (124) Doctorate degree (125)	$Age - 28$

A.3 Decomposition of the Unemployment Rate Differences

A.3.1 Computation Approach

To investigate the determinants of the differences in life-cycle unemployment rates between workers with different education levels, we employ the method by Pissarides (2009) to decompose the observed unemployment differences between education levels at each age bins into differences in job separation and finding probabilities. Specifically, we focus on a simple two-state models, with workers moving between employment (E) and unemployment (U). The difference in unemployment rate for a particular age group (i) and educational level (j) over a given period (t), denoted by $\Delta u_{ij,t}$, is defined as:

$$\Delta u_{ij,t} = s_{ij,t}(1 - u_{ij,t}) - f_{ij,t}u_{ij,t},$$

where $s_{ij,t}$ and $f_{ij,t}$ represent the job separation and finding probabilities, respectively, for the specific age i and education group j at time t. If the two flow rates remain constant at s and f for a sufficiently long time, the unemployment rate will eventually converge to

$$u_{ij} = \frac{s_{ij}}{s_{ij} + f_{ij}}. \tag{A.16}$$

By taking first differences of Equation (A.16) between education levels j and j', we can obtain the decomposition equation:

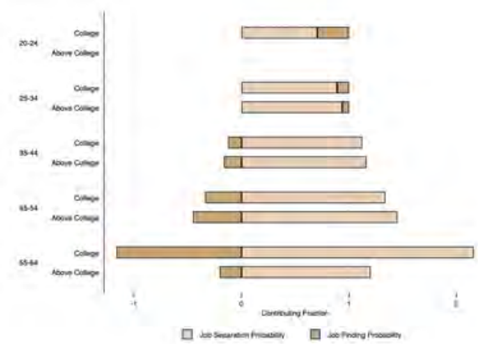
$$\Delta u_i = u_{ij} - u_{ij'} = (1 - u_{ij})u_{ij'}\frac{(s_{ij} - s_{ij'})}{s_{ij'}} - u_{ij}(1 - u_{ij'})\frac{(f_{ij} - f_{ij'})}{f_{ij'}}.$$

This equation demonstrates that the differences in unemployment rates between education levels can be decomposed into flow-in and flow-out rates. By rearranging this equation, we can compute the contribution of each flow rate to the difference in unemployment between education levels j and j':

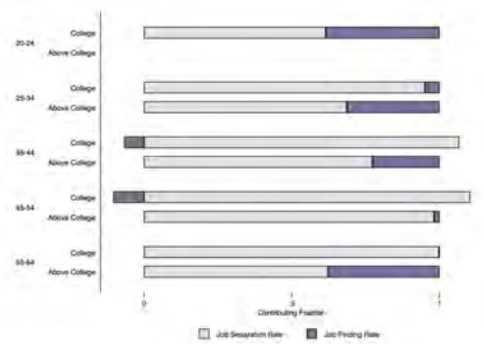
$$1 = \underbrace{\frac{(1 - u_{ij})u_{ij'}\frac{(s_{ij} - s_{ij'})}{s_{ij'}}}{\Delta u_i}}_{\text{Fraction Explained by Diff. in JSP}} + \underbrace{\frac{-u_{ij}(1 - u_{ij'})\frac{(f_{ij} - f_{ij'})}{f_{ij'}}}{\Delta u_i}}_{\text{Fraction Explained by Diff. in JFP}}. \tag{A.17}$$

A.3.2 Decomposition Results (Supplementary)

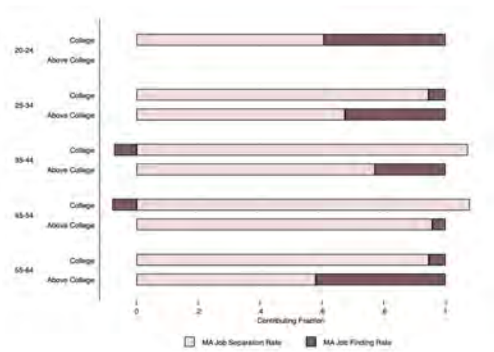
In addition to the job finding and separation rates with correction for time aggregation, there are additional measures of flow rates, that includes: (i) uncorrected job finding/separation probabilities; (ii) job finding/separation rates; and (iii) moving average job finding/separation rates. To ensure the robustness of our decomposition results, Figure A1 presents the explanatory fractions for the observed differences in unemployment rates between education levels by employing each of the alternative measures of flow rates. Consistent with the decomposition results obtained using the corrected job finding and separation probabilities, we find that the differences in job separation rates between workers with less than a college degree and those with a college degree or above primarily explain the observed differences in unemployment rates between these two groups.



(a) Uncorrected JF/JS Probabilities



(b) JF/JS Rates



(c) Moving Average JF/JS Rates

Figure A1: Decomposition of Unemployment Differences

A.4 Transition Probabilities with Correction for Time Aggregate Bias

Start with employment status of individuals who belongs to age cohort i and education group j in consecutive months from January 1976 through November 2019 , we construct time-series for the gross flow of workers ($F(XY)_t$) between unemployment (U), employment (E), inactivity (I) and with missing record (M), denoted by $F(XY)_t = \frac{N(XY)_t}{\sum_{Z\in\{U,E,I,M\}} N(XZ)_t}$, where $N(XY)_t$ represents the number of workers who transition from X to Y in period t. Based on that, we can compute the original monthly transition probability between different labor force status by $n(AB)_t = \frac{F(AB)_t}{\sum_{M\in\{U,E,I\}} F(AM)_t}$, where $A, B \in \{U, E, I\}$. In particular, n is a 3 matrix that governs the full month transition probability between labor force status.

To correct for the seasonal nature of transition probability, we seasonally adjust the time-series using a ratio-to-moving average (RMA) technique. The specifies are as follow. First, we calculate the moving average (MA) by taking the weighted average of the prior six months and the six months lagged around the targeted month. Then. we generate a ratio for each month at each year by dividing the flow value by the moving average (MA). Next, we compute the average ratio for each month by taking the average across different years. After that, we compute the ratio between the average ratio in each month with the base ratio, where the base ratio is the mean of the average ratio in 1998. Finally, we can obtain the seasonally adjusted transition probability by dividing the raw value by the ratio from the previous step.

With the seasonally-adjusted time-series transition probabilities. i.e., $\tilde{n}_t$, in hand, we proceed to derive out the instantaneous transition rate matrix λ_t by $\lambda_t = P_t \times \tilde{u}_t \times P_t$, where $\tilde{u}_t$ and P_t are the log value of the eigenvalues and associated eigenvectors of $\tilde{n}_t$.

Next, we can construct the unbiased full month transition probability between labor force states A and B for subgroup with age cohort i and education attainment j as $\Lambda_t^{ij}(AB) = 1 - exp(-\lambda_t^{ij}(AB))$, that is interpreted as the probability that a worker who starts the period in state A transitions to state B during the month conditional on not experiencing a transition to state C. Lastly, we compute the average transition probabilities with correction of time aggregation bias for each subgroup of age i and education attainment j by taking the mean value of $\Lambda_t^{ij}(AB)$ across different periods.

A.5 Job Finding and Job Separation Rates

Following Shimer (2005) and Elsby et al. (2009), the unemployment outflow (f_t) and inflow rates (s_t) for each cohort of age i and education j from the law of motion for unemployment:

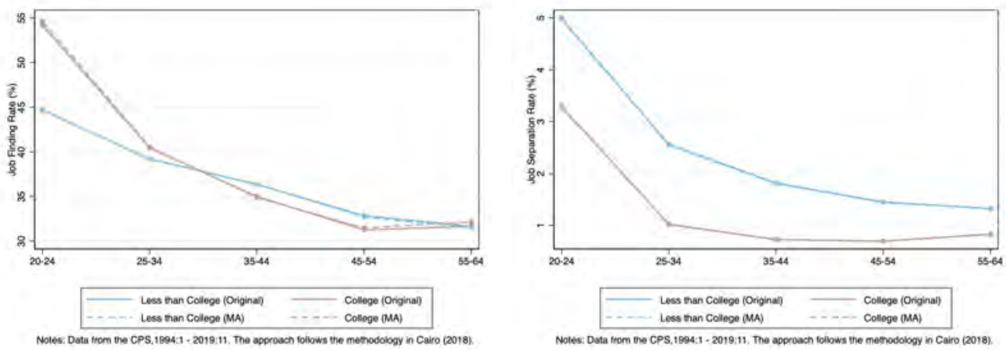
$$u_{t+1} = (1 - F_t)u_t + u^s_{t+1} \qquad \Rightarrow \qquad F_t = 1 - \frac{u_{t+1} - u^s_{t+1}}{u_t}, \tag{A.18}$$

where F_t is the monthly outflow probability. Equation (A.18) states that the number of unemployed workers at month $t+1$, u_{t+1}, is equal to the number of unemployed workers at month t who did not find a job with probability $(1 - F_t)$, plus the number of short-term unemployed workers who are unemployed at month $t+1$, but employed at month t, denoted by u^s_{t+1}. Therefore, the outflow rate f_t can be derived from $f_t = -\log(1 - F_t)$.

To compute the inflow rate, s_t, we start from the law of motion for the evolution of the unemployment rate:

$$\dot{u} = \overbrace{s_t(l_t - u_t)}^{inflow} - \overbrace{u_t f_t}^{outflow} = -(s_t + f_t)(u_t - u^*), \tag{A.19}$$

where u^* is the steady state unemployment and l_t is the size of the labor force. The second equality comes



(a) Job Finding Rate

(b) Job Separation Rate

Figure A2: Original and 12-month Moving Average Transition Rate

from the labor market equilibrium condition $s_t e_t^* = u^* f_t$. By solving (A.19) and assuming s_t, f_t and l_t are constant between surveys, we can infer s_t from

$$u_{t+1} = \frac{(1 - e^{(-s_t - f_t)})s_{t+1}}{f_{t+1} + s_{t+1}} l_t + u_t e^{(-s_t - f_t)}. \tag{A.20}$$

By following this method, we obtain measures of the inflow and outflow rates for each month from January 1994 to December 2019. Observations prior to 1994 were discarded because the unemployment duration variable is only available in IPUMS-CPS starting from 1994. To compute the inflow and outflow rates, we first compute the unemployment rate for each group by $u_t^{ij} = \frac{U_t^{ij}}{U_t^{ij} + E_t^{ij}}$, where U_t^{ij} (E_t^{ij}) is the unemployed (employed) population at month t among workers in the age bin i and with education attainment j. In the same manner, we calculate the short-term unemployment rate for each group, where short-term unemployment is defined as a duration of less than 5 weeks and is denoted by $u_{t,s}^{ij}$. Next, we can readily infer the hazard rates at month t from equations (A.18) and (A.20). Finally, we take 12-month moving average of these monthly series to obtain a smoother series.

Figure A2 presents the outflow and inflow rates with and without 12-month moving average. The age profile patterns of the transition rates are similar to those seen in the transition probabilities shown in Figure 1, although the values of the measured transition rates are higher. It's noteworthy that the outflow rate of the college group is lower than that of the less-educated group starting from age 35, but the inflow rate of the college group is consistently lower than those with less than a college degree. It is also worth noting that applying the same decomposition exercise to these transition rates does not change our conclusion that the separation rate drives the majority of the differences in unemployment between education groups over the life-cycle. However, the job finding rate contributes 39% to differences in unemployment between ages 20-24. See Appendix Section A.3.

A.6 Aggregate Job Finding and Separation Rates

Table A3: Aggregate Job Finding and Separation Rates/Probabilities by Educational Attainment

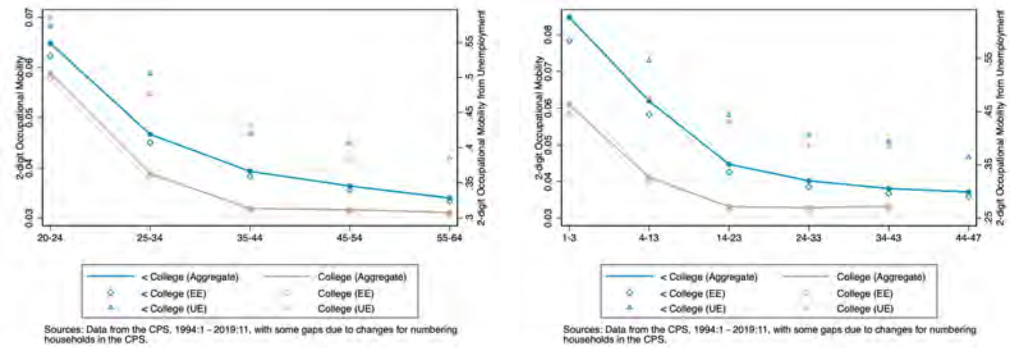
	Less than Bachelors	Bachelors	Above Bachelors
Probability (uncorrected for time-aggregation bias)			
Job Finding (%)	27.59	27.17	24.84
Separation (%)	1.94	0.73	0.46
Probability (corrected for time-aggregation bias)			
Job Finding (%)	30.16	29.11	26.07
Separation (%)	2.26	0.90	0.54
Rates			
Job Finding (%)	39.16	33.34	30.21
Separation (%)	2.46	0.91	0.56
Rates (moving average)			
Job Finding (%)	39.09	33.43	30.12
Separation (%)	2.47	0.91	0.56

Notes: Data from the IPUMS-CPS, 1976:1-2019:12.

A.7 Uncorrected Occupational Mobility

Table A4: Crosswalk between Age and Years of Potential Experience

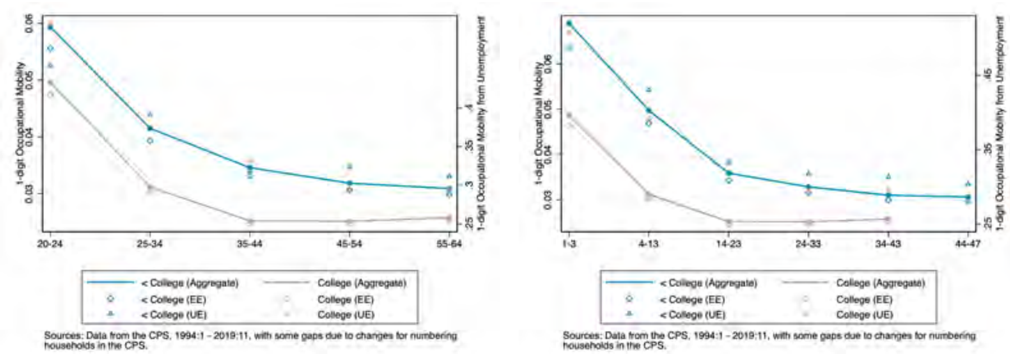
		Years of Potential Experience					
		1-3	4-13	14-23	24-33	34-43	44-47
Age	Less than bachelor	18-20	21-30	31-40	41-50	51-60	61-64
	Bachelor	22-24	25-34	35-44	45-54	55-64	-
	MA	24-26	27-36	37-46	47-56	57-64	-
	PhD/Prof	28-30	31-40	41-50	51-60	61-64	-



(a) Age

(b) Potential Experience

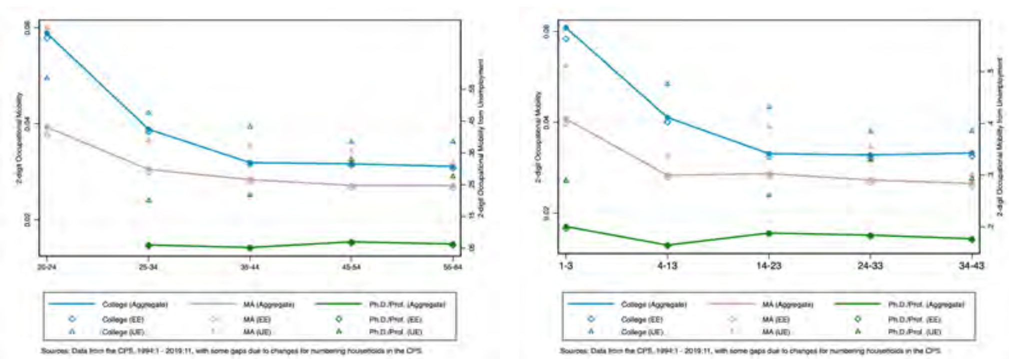
Figure A3: Uncorrected Occupational Mobility at 2-digit Occupation Codes



(a) Age

(b) Potential Experience

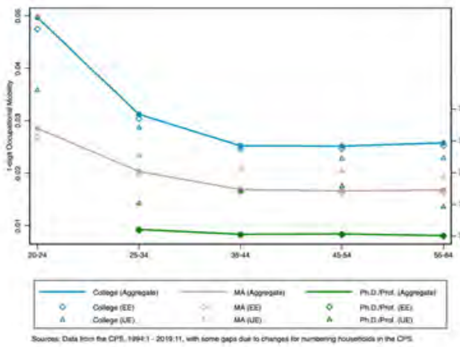
Figure A4: Uncorrected Occupational Mobility at 1-digit Occupation Codes



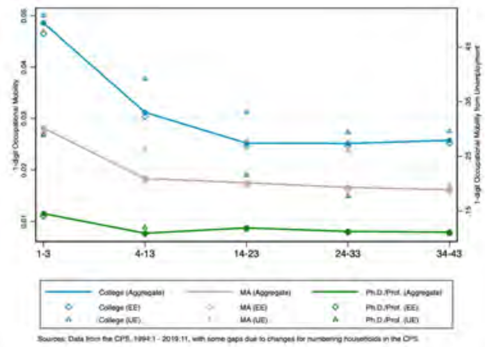
(a) Age

(b) Potential Experience

Figure A5: Uncorrected Occupational Mobility at 2-digit Occupation Codes



(a) Age



(b) Potential Experience

Figure A6: Uncorrected Occupational Mobility at 1-digit Occupation Codes

A.8 Corrected Occupational Mobility

Although the comparison of occupational mobility patterns is evident, occupational records in survey data are prone to measurement error. To mitigate this concern, we apply the methodology proposed by Moscarini and Thomsson (2007) to ascertain genuine EE occupational transitions by relying on the dependent questions that appeared in the CPS starting in 1994.[22] This process encompasses three stages: first, flagging transitions susceptible to measurement error in occupational codes; second, subjecting these dubious transitions to the $ANY3$ filter; and finally, passing the remaining suspicious transitions through the *Flag* filter. Despite the complexity of this procedure, it is a standard approach in addressing measurement error is occupational mobility, and thus we delegate a more comprehensive overview of the process to Appendix Section A.8.1. Overall, Figures A8-A9 show that after applying this correction, occupational mobility rates decrease with age and potential experience. Notably, workers with higher levels of education are less likely to undergo occupational switches.

A.8.1 Detailed Correction Process

First, we constrain our analysis to individuals possessing complete data for the first four consecutive survey months, aged between 18 and 64, and with available data from January 1994 through November 2019.[23] To address the potential miscoding problem after 1994, we identify an EE transition as suspicious if either of the following two events holds true: (i) a blank response to the "same employer?" question in the subsequent period $t+1$; (ii) a blank answer to the "same activity?" question in the subsequent month $t+1$.[24] The

[22]It is worth noting that a significant overhaul of the interviewing technique occurred in 1994 by introducing a battery of so-called dependent coding questions, sometimes referred to as “dependent interviewing”. The dependent questions include at least "same usual activity as previous month?" and "same employer as previous month?," among others. This measure substantially improves the accuracy of transition records through cross-checking based on dependent coding. In particular, the same occupation as the previous month was automatically assigned if the respondent indicated being employed in the same job as the previous month.

[23]Our rationale for limiting the analysis to the first four consecutive months is twofold: first, the longitudinal structure is indispensable because for verifying whether suspicious transitions can pass the filter in the following correction process, each single transition is inspected under the magnifying lens of a “global” view of that worker’s employment history over four consecutive months, including one month before and one after the two months spanned by the transition; second, CPS interviewers track housing units rather than individuals or families, leading to potential attrition due to temporary absence, migration, or mortality. To minimize sample selection bias resulting from attrition, we concentrate on the first four months of the sample. In this sample, observations for ages 18 to 20 will be used for calculating occupational mobility over years of potential experience for workers with less than a college degree.

[24]This step differs slightly from Moscarini and Thomsson (2007) as we lack the variables "CHDUTY" and "SAMEJOB" for sample periods. Instead, we employ "SAMEEMP" to capture the same information as "SAMEJOB" and use "SAMEACT" to encompass the content of the "CHDUTY" and "SAMEACT" questions. Moreover, "blank" includes all values other than yes or no.

identification process is depicted in Figure A7.

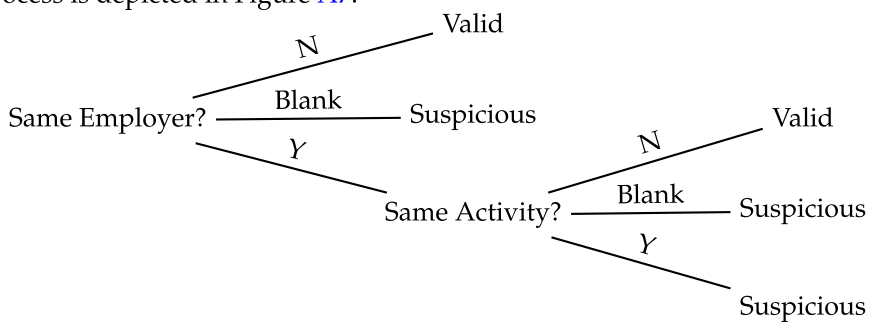
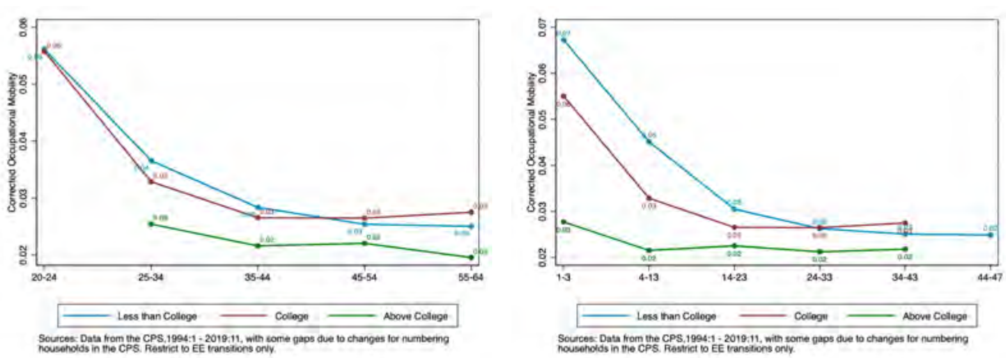


Figure A7: Identification Process for Suspicious Transitions

Next, we pass the suspicious transitions through the first filter – $ANY3$ Filter. The underlying idea is that if certain key factors undergo changes during two consecutive months coinciding with a shift in the Occupational Classification codes (OCC), the OCC code alteration signifies genuine occupational mobility. Three particular variables are pertinent to this method: (i) change of class of worker (private firm, federal, state or local government, or self-employed, . . .) at $t+1$; (ii) change of three-digit industry codes at $t+1$; (iii) look for work in past four weeks, labelled as active search, at time $t+1$. We regard any occupational change meeting all three criteria simultaneously as fake: no change in industry, no change in the class of worker, and no active job search in the last four weeks. Conversely, if the suspicious transition involves a change in worker class or industry code in period $t+1$, or active job search in period t, it remains in the suspicious group and undergoes further validation in the next filter.

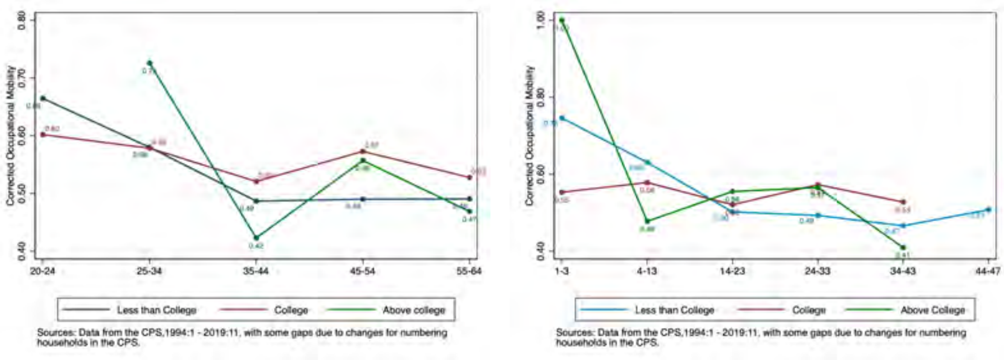
The second filter is to detect fake genuine transitions by utilizing the limited but valuable longitudinal component of the monthly CPS. Our strategy for refining mobility data is premised on the idea that certain occupational sequences are more likely to be fake if they are uncommon or infrequently observed among all transitions. For those suspicious transitions (from employment) survived from ANY3 Filter, we classify the patterns "AABN," "ABCN," "NABN," "NABA," and "ABAN" as fake transitions, where N denotes the unemployed, while A and B denote different employed occupations. Note that the selected format of fake transitions are consistent with Moscarini and Thomsson (2007).



(a) Age

(b) Potential Experience

Figure A8: Corrected Occupational Mobility for EE Transitions



(a) Age (b) Potential Experience

Figure A9: Corrected Occupational Mobility for UE Transitions

A.9 Correction for Employer Switches

Following Moscarini and Thomsson (2007), we compute the probability that a blank answer to the "EMPSAME" question actually corresponded with a change in employer. We compute that probability, δ, for the full sample, each age-education group (δ^{ij}), and each age-potential experience group $k(\delta^{ik})$. In particular, we allocate blank answers to "EMPSAME" to Yes and No based on their proportionate frequency in the corrected occupational mobility measure.[25] Formally, the adjustment parameters are computed as follows:

$$\delta = \frac{\Pr(\text{OCCMOB} \mid \text{No}) - \Pr(\text{OCCMOB} \mid \text{Yes})}{\Pr(\text{OCCMOB} \mid \text{No}) + \Pr(\text{OCCMOB} \mid \text{Yes})}, \tag{A.21}$$

where *No* and *Yes* represent the number of responses to the "SAMEJOB" question indicating whether an individual has stayed with the same employer or switched employers and $OCCMOB$ represents the number of observations of occupational switches. The value of δ quantifies the extent to which blank responses to the question on same employer ("EMPSAME") are likely to reflect a change in employer status. An equivalent interpretation is that it captures the likelihood that an individual who has changed occupations also changed employers, even if they report a blank answer to the "EMPSAME" question. After applying this correction to our sample, we find an average job-to-job transition rate of 3.23%, which closely aligns with the 3.2% computed by Moscarini and Thomsson (2007).

A.10 Skill Distance

A.10.1 Skill Measurement

To measure the distance in skill requirements between occupations, we start by measuring the occupation's requirement along three different skill dimensions. Specifically, each occupation is characterized by a three-dimensional vector $(r_{verbal}, r_{math}, r_{social})$ where r_{verbal} measures the occupation's verbal skill requirement, r_{math} measures the math/quantitative skill requirement, and r_{social} captures the social skill requirement.

To measure verbal and mathematical skill requirements, we strictly follow the methodology used by Guvenen et al. (2020). The first step is to construct four scores for each occupation in CPS sample. The scores

[25] If Blanks are a random sample of the population for job mobility purposes, then their occupational mobility rate should be the weighted average of those of the Yes and No, as such the overall job mobility rate should not change. The closer the occupational mobility rate of the Blank to that of the No, the higher the adjusted career mobility should be.

Table A5: List of Descriptors

Panel A: Verbal and Math Skills	
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
Panel B: Social Skills	
Social Perceptiveness	Coordination
Persuasion	Negotiation
Instructing	Service Orientation

are: (i) word knowledge, (ii) paragraph comprehension, (iii) arithmetic reasoning, and (iv) mathematics knowledge. To construct these scores, we first select 26 O*NET descriptors that are chosen by the Defense Manpower Data Center (DMDC) and are listed in the top part of Table A5. In the raw data, these descriptors range in value from 0 to 5. We re-scale their values in each year to fall between 0 and 1 and then take the average value for each descriptor from O*NET oldest version 5.0 (published in April 2003) through version 24.0 (published in August 2019).[26] It is noteworthy that skill information for five occupations, namely *Other Telecom Operators, Gardeners and Groundskeepers, Other Precision and Craft Workers, Other Woodworking Machine Operators, and Misc. Textile Machine Operators*, is not available in the O*NET dataset. To address this issue,we infer their skill information by using the most similar occupations that are adjacent in the occupational code lists. The manipulation would have a negligible impact on the overall accuracy of our computations, as the number of observations for these five occupations account for only 0.8% of the entire sample. Finally, we construct a weighted average in each of the four skill categories using the weights matrix provided by the DMDC. For example, to construct the word knowledge score in occupation o, $S_{o,wk}$, we compute

$$S_{o,wk} = \sum_{i=1}^{26} s_{o,i} * \omega_{wk,i}, \tag{A.22}$$

where $s_{o,i}$ is descriptor i's average value between 2003 and 2019 for occupation o and $\omega_{wk,i}$ is the weight given to descriptor i in the category of word knowledge.

[26]Our analysis excludes data from O*NET versions prior to version 4.0, which were published before June 2002. This decision was based on the fact that these earlier versions relied on data provided by occupational analysts, which is substantially different from the multi-method data collection methodology used in later versions of O*NET. The current methodology incorporates data from sources such as job incumbents, occupational experts, big data, and other relevant sources, resulting in a more comprehensive and accurate dataset.

Second, we normalize the standard deviation of each score to one and reduce these four scores into two composite indicators, r_{verbal} and r_{math}, by applying principal component analysis (PCA). To be specific, the verbal skill is the first principal component of word knowledge and paragraph comprehension, and the math skill is the first principal component of arithmetic reasoning and mathematics knowledge. To account for the arbitrary nature of the skill score scales, the verbal and math skills were subsequently transformed into percentile ranks relative to all occupations in the dataset.

The social skill requirement can be identified similarly. By applying PCA to six scaled O*NET descriptors, we construct a single index to reflect the social skill requirement, which was subsequently transformed into percentile ranks relative to all occupations in the dataset. The six descriptors used to construct the social skill requirement are listed at the bottom of Table A5. Based on the skill requirement along each dimension $(r_{verbal}, r_{math}, r_{social})$, we proceed to calculate the average skill requirement for each occupation by taking the unweighted average across the three dimensions.

A.10.2 Estimation of the Effect of Education on Skill Distance

Table A6: Euclidean Distance in Corrected Occupational Transitions

	(1)	(2)	(3)	(4)	(5)	(6)
College	-0.01218	-0.01866**	-0.01866**	-0.01700*	-0.01787**	-0.01460
Presumed Pot. Exp.	-0.00133**	-0.00107	-0.00083	-0.00072	-0.00071	-0.00135*
Presumed Pot. Exp. (Squared)	0.00405***	0.00331**	0.00275*	0.00252*	0.00240	0.00390**
College $\times$ Presumed Pot. Exp.	-0.00097***	-0.00087**	-0.00088**	-0.00094**	-0.00093**	-0.00085**
Race: Black	0.01590**	0.01227*	0.01235*	0.01472**	0.01444**	0.00830
Race: Others	0.01008	0.00712	0.00744	0.00184	-0.00023	0.00137
Marst: Single	0.00013	-0.00028	-0.00347	-0.00384	-0.00455	-0.00332
More than One Child			-0.00648	-0.00710	-0.00727	-0.00417
Faminc: 5000-7499						-0.00871
Faminc: 7500-9999						-0.02827
Faminc: 10000-14999						-0.02153
Faminc: 15000-19999						-0.02861
Faminc: 20000-24999						-0.03373**
Faminc: 25000-49999						-0.00852
Faminc: 50000 and over						-0.02616*
Constant	0.70139***	0.72125***	0.72401***	0.71836***	0.71773***	0.74248***
2-digit Occ. FE		✓	✓	✓	✓	✓
2-digit Ind. FE		✓	✓	✓	✓	✓
State FE				✓	✓	✓
Year FE					✓	✓
N	28765	28738	28738	28738	28738	26325
R^2	0.003	0.028	0.029	0.031	0.032	0.033

Notes: Industrial and occupational codes for the unemployed are classified according to their last job. Standard errors are robust to heteroskedasticity. *($p < 0.10$), **($p < 0.05$), ***($p < 0.01$).

Table A7: Angular Distance in Corrected Occupational Transitions

	(1)	(2)	(3)	(4)	(5)	(6)
College	-4.66182***	-3.06667***	-3.06683***	-3.01134***	-3.04012***	-2.68086***
Presumed Pot. Exp.	-0.26163***	-0.15415***	-0.14423***	-0.13900***	-0.13783***	-0.16239***
Presumed Pot. Exp. (Squared)	0.53942***	0.34332***	0.31935***	0.30989***	0.30477***	0.36689***
College $\times$ Presumed Pot. Exp.	-0.00497	-0.02008	-0.02061	-0.02242	-0.02200	-0.02053
Race: Black	2.57219***	1.54501***	1.54834***	1.67708***	1.67038***	1.28143***
Race: Others	1.09650***	0.46379	0.47742	0.22920	0.15831	0.26350
Marst: Single	0.90136***	0.37354*	0.23864	0.21227	0.18455	0.13761
More than One Child			-0.27338	-0.31317	-0.31771	-0.21818
Faminc: 5000-7499						-0.84956
Faminc: 7500-9999						-0.66873
Faminc: 10000-14999						-0.68407
Faminc: 15000-19999						-1.36009
Faminc: 20000-24999						-1.12217
Faminc: 25000-49999						-0.56107
Faminc: 50000 and over						-1.96181**
Constant	32.04143***	28.29465***	28.41102***	29.35442***	29.56007***	30.92434***
2-digit Occ. FE		✓	✓	✓	✓	✓
2-digit Ind. FE		✓	✓	✓	✓	✓
State FE				✓	✓	✓
Year FE					✓	✓
N	28765	28738	28738	28738	28738	26325
R^2	0.026	0.078	0.078	0.081	0.082	0.084

Notes: Industrial and occupational codes for the unemployed are classified according to their last job. Standard errors are robust to heteroskedasticity. *($p < 0.10$), **($p < 0.05$), ***($p < 0.01$).

Table A8: Euclidean Distance in Complex Transitions

	(1)	(2)	(3)	(4)	(5)	(6)
College	0.01667	-0.00080	-0.00088	0.00036	0.00167	0.00936
Presumed Pot. Exp.	-0.00090	-0.00088	-0.00024	-0.00008	0.00006	-0.00041
Presumed Pot. Exp. (Squared)	0.00348*	0.00315*	0.00164	0.00119	0.00115	0.00215
College $\times$ Presumed Pot. Exp.	-0.00164***	-0.00140***	-0.00143***	-0.00144***	-0.00142***	-0.00148***
Race: Black	-0.00210	-0.00764	-0.00761	-0.00189	-0.00170	-0.00744
Race: Others	0.00169	-0.00150	-0.00074	-0.00675	-0.00502	-0.00250
Marst: Single	-0.00134	-0.00209	-0.01078*	-0.01147*	-0.01086*	-0.01049
More than One Child			-0.01771***	-0.01817***	-0.01778***	-0.01394**
Faminc: 5000-7499						-0.03213
Faminc: 7500-9999						-0.03343
Faminc: 10000-14999						-0.04788**
Faminc: 15000-19999						-0.06088***
Faminc: 20000-24999						-0.04914**
Faminc: 25000-49999						-0.02869
Faminc: 50000 and over						-0.04220**
Constant	0.70574***	0.70159***	0.70927***	0.70133***	0.73606***	0.78068***
2-digit Occ. FE		✓	✓	✓	✓	✓
2-digit Ind. FE		✓	✓	✓	✓	✓
State FE				✓	✓	✓
Year FE					✓	✓
N	16443	16443	16443	16443	16443	14930
R^2	0.002	0.031	0.032	0.036	0.039	0.040

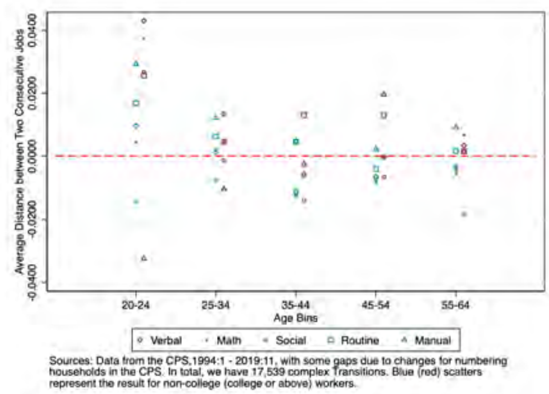
Notes: Industrial and occupational codes for the unemployed are classified according to their last job. Standard errors are robust to heteroskedasticity. *($p < 0.10$), **($p < 0.05$), ***($p < 0.01$).

Table A9: Angular Distance in Complex Transitions

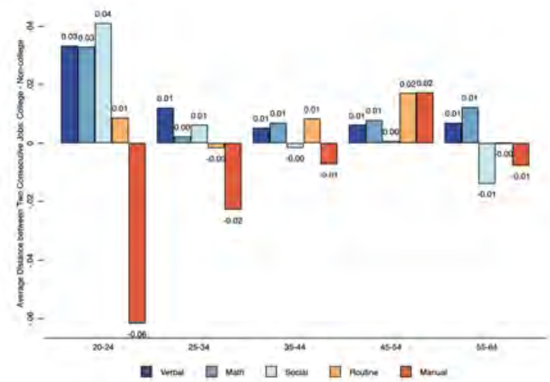
	(1)	(2)	(3)	(4)	(5)	(6)
College	-3.86516***	-2.72355***	-2.72700***	-2.73125***	-2.65114***	-2.12398***
Presumed Pot. Exp.	-0.23538***	-0.15322***	-0.12640***	-0.11887***	-0.11095**	-0.12485***
Presumed Pot. Exp. (Squared)	0.50144***	0.35070***	0.28729***	0.26658***	0.26497***	0.29889***
College $\times$ Presumed Pot. Exp.	-0.03570	-0.04278*	-0.04407*	-0.04234*	-0.04132*	-0.04711*
Race: Black	1.72102***	0.75813*	0.75947*	0.99599**	1.00667**	0.57990
Race: Others	0.45327	-0.09160	-0.05976	-0.36168	-0.24474	-0.11733
Marst: Single	0.93370***	0.42954	0.06443	0.00333	0.03245	0.01522
More than One Child			-0.74393**	-0.78241**	-0.77144**	-0.61897*
Faminc: 5000-7499						-2.14510
Faminc: 7500-9999						-1.59055
Faminc: 10000-14999						-2.02821*
Faminc: 15000-19999						-3.21776***
Faminc: 20000-24999						-2.07403*
Faminc: 25000-49999						-1.50087
Faminc: 50000 and over						-2.76653***
Constant	32.74233***	27.52543***	27.84806***	28.22386***	30.27718***	32.39945***
2-digit Occ. FE		✓	✓	✓	✓	✓
2-digit Ind. FE		✓	✓	✓	✓	✓
State FE				✓	✓	✓
Year FE					✓	✓
N	16443	16443	16443	16443	16443	14930
R^2	0.024	0.069	0.069	0.074	0.077	0.079

Notes: Industrial and occupational codes for the unemployed are classified according to their last job. Standard errors are robust to heteroskedasticity. *($p < 0.10$), **($p < 0.05$), ***($p < 0.01$).

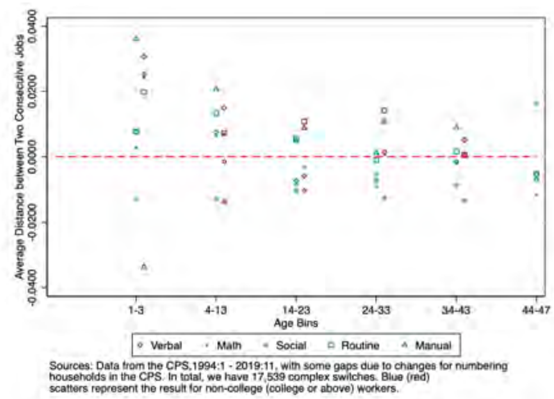
A.10.3 Average Skill Distance in Different Types of Transitions



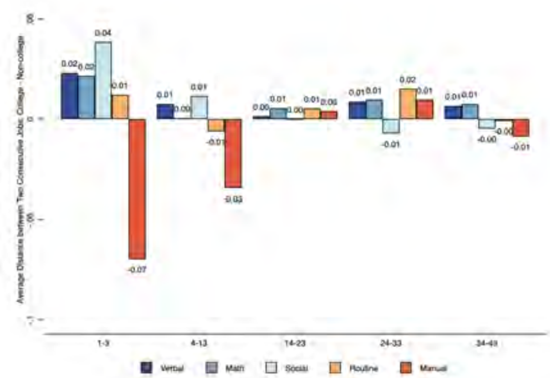
(a) Age



(b) Age, College - Non-college

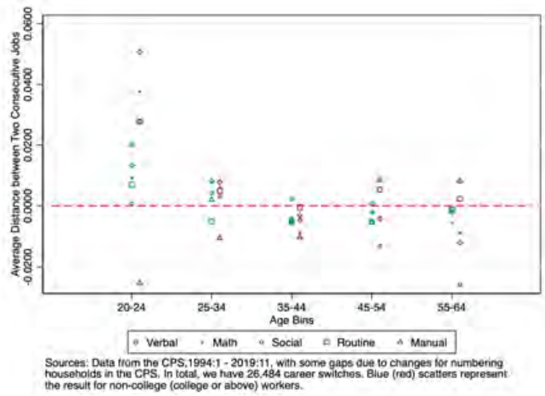


(c) Years of Potential Working

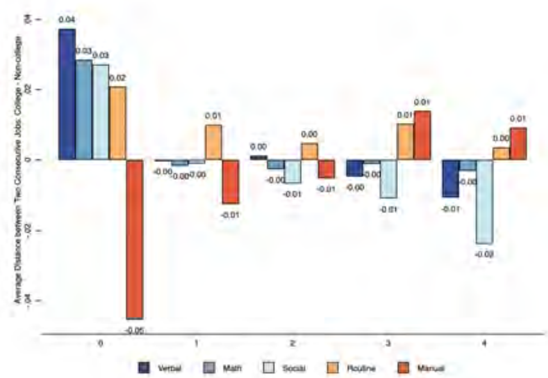


(d) Years of Potential Working, College - Non-college

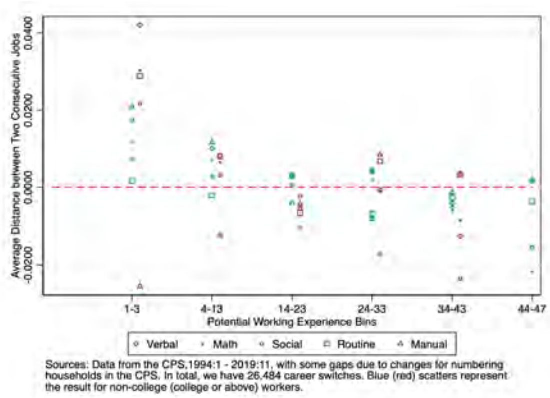
Figure A10: Average Skill Distance in Complex Transitions



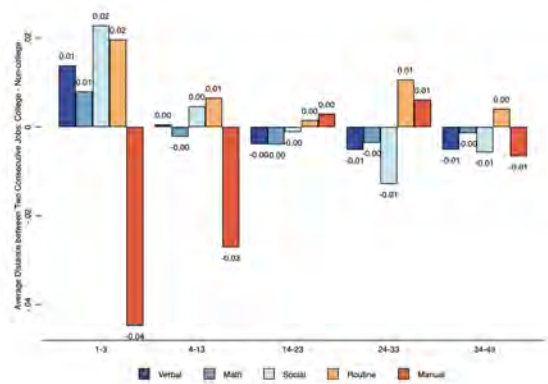
(a) Age



(b) Age, College - Non-college



(c) Years of Potential Working



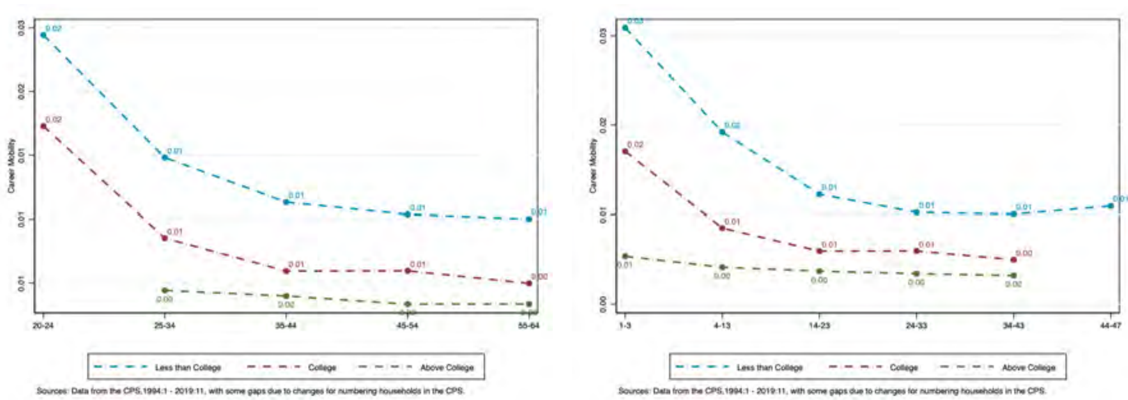
(d) Years of Potential Working, College - Non-college

Figure A11: Average Skill Distance in Career Transitions

A.11 Career Mobility

Given that the skill distance in occupation and complex changes varies across education groups, we proceed to study an alternative measure of career changes that is based on occupational skill requirements. To do so, we follow the approach of Baley et al. (2022) and define a career transition as an occupation switch where the angular distance between the current and previous job exceeds a threshold value of $\bar{\phi}$. We choose this threshold so that the average correlation in skill requirements across aptitudes k is zero in career moves, i.e., $\sum_{k\in v,m,s} Corr(r_{k,t-1}, r_{k,t}) \approx 0$.[27] We find that $\bar{\phi} = 24.4280$ yields an (unweighted) average correlation in skill requirements across dimensions that is near zero, i.e., $\sum_{k\in v,m,s} Corr(r_{k,t-1}, r_{k,t}) = 0.0013$, among the 27,275 job transitions in our sample. Of these transitions, approximately 24.63% are defined as career transitions based on the angular distance threshold, with proportions of 30.73%, 25.03%, 22.02%, and 21.47% for the age groups of 20-24, 25-34, 35-44, and 45-54, respectively.

The comparison of career mobility rates across different education levels is shown in Figure A12. Notably, career mobility tends to decrease as workers age. Moreover, by comparing the values of the colored dashed lines, we find that career mobility is decreasing in education, indicating that college graduates are more likely to maintain a consistent career trajectory.[28]



(a) Age

(b) Potential Experience

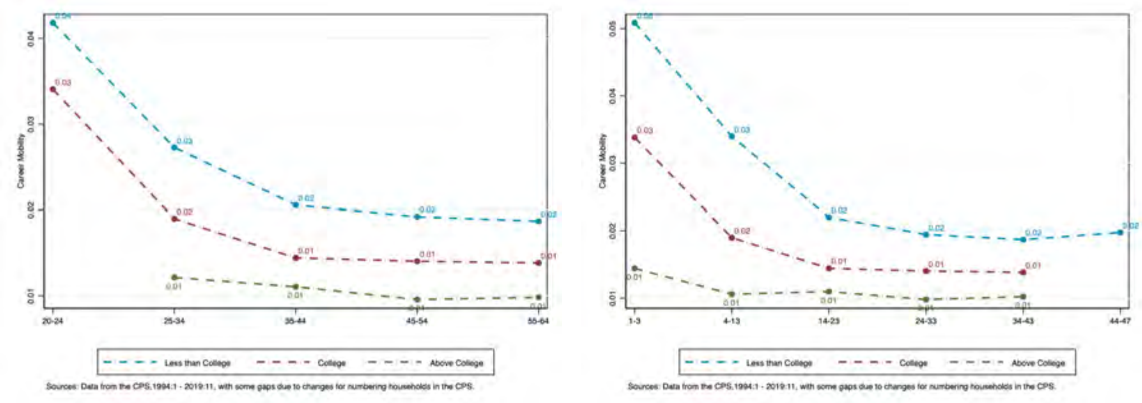
Figure A12: Career Mobility

A.12 Robustness

This section seeks to further validate the stylized facts that higher-educated workers enjoy greater employment stability due to lower job separation rates and lower propensities to change jobs or career paths. Moreover, if such transitions do occur, higher-educated workers tend to switch to jobs that are more similar to their previous roles, compared to their less-educated counterparts. In spite of the evident pattern observed across different education groups, some demographic, job-related, spatial, and macroeconomic factors possibly influence workers' employment outcomes, potentially biasing the observed patterns. To

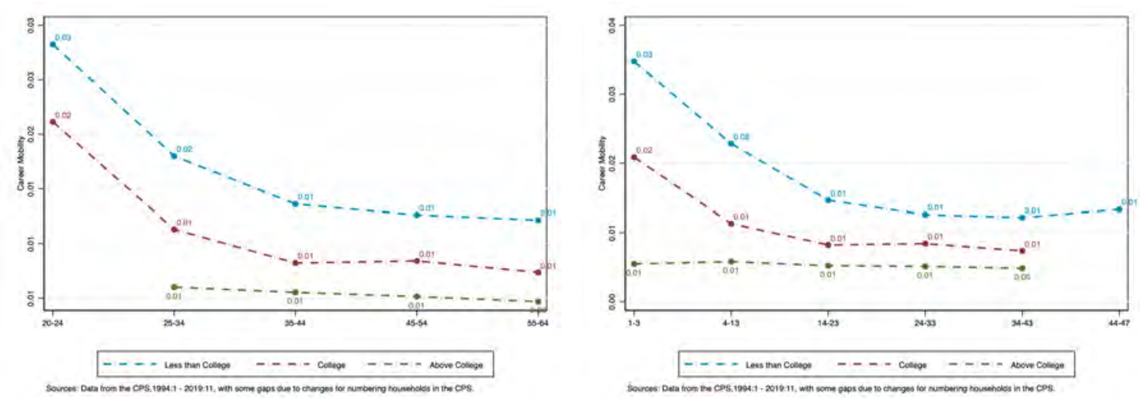
[27] We adopt an unweighted average of correlations across each skill dimension, as we treat every skill category equally when determining skill differences between the current and subsequent job positions.

[28] The pattern of career mobility is not sensitive to the choice of threshold. We have defined career mobility using two alternative thresholds: (i) $\bar{\phi} = 14.8000$, which is the same as that used by Baley et al. (2022); and (ii) $\bar{\phi} = 21.4560$, which is determined by minimizing the weighted average correlation ($Corr \approx 0.0002$), where the weights, $(0.15, 0.64, 0.21)$, are drawn from Baley et al. (2022). The corresponding patterns are provided in Appendix Figures A13 and A14.



(a) Age (b) Potential Experience

Figure A13: Career Mobility Defined over $\bar{\phi} = 14.8000$



(a) Age (b) Potential Experience

Figure A14: Career Mobility Defined over $\bar{\phi} = 21.4560$

help address this concern, we estimate regressions of the form:

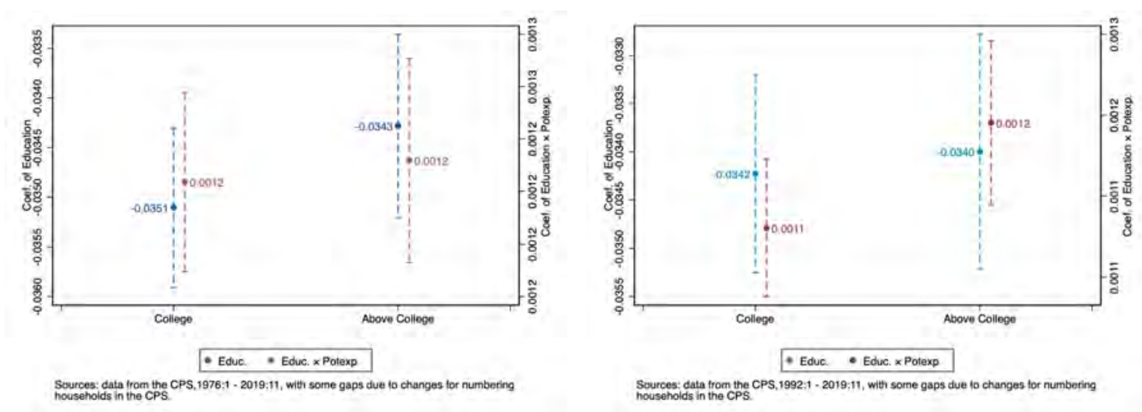
$$\begin{aligned} Y_{i,t} =& \beta_0 EduCat_i + \beta_1 Potexp_{i,t} + \beta_2 Potexp_{i,t}^2 + \beta_3 EduCat_i * Potexp_{i,t} + \beta_4 Race_i \\ &+ \beta_5 MarStatus_{i,t} + \beta_6 Child_{i,t} + \Phi_{Year} + \Phi_{State} + \Phi_{Occ2} + \Phi_{Ind2} + \epsilon_{i,t}. \end{aligned} \tag{A.23}$$

The dependent variable $Y_{i,t}$ is a dummy variable that takes on different forms. It indicates that in period t, the worker i: (i) is unemployed or not; (ii) transitions from unemployment to employment or not; (iii) transitions from employment to unemployment or not; (iv) transitions to a different occupation or not; (v) transitions to a different occupation or not after correcting for the suspicious transitions; (vi) goes through a complex transition or not; or (vii) goes through a career transition or not. Our primary variable of interest is the education category of worker i, denoted as $EduCat_i$, which is a categorical variable taking on the values of 0, 1, or 2 to represent workers with less than a college education, exactly a college education, or above a college education, respectively. The coefficient of educational category (β_0) captures the effect of a higher education on the probability of either type of transition occurring while the coefficient of $EduCat_i * Potexp_{i,t}$ (β_3) indicates how the education effect varies over years of potential experience.

To account for potential confounding factors that could affect a worker's employment profile and outcomes, we control for various demographic and job characteristics, including a quadratic in presumed years of potential experience from the modal graduation age, race, marital status, and whether the respondent has a child or not. In addition, we include the effect of job features by controlling for 2-digit occupation and 2-digit industry fixed effects. Finally, we also incorporate year and state fixed effects to control for time-varying and spatial differences in the aggregate economy.

To enhance clarity and facilitate a comparison across different education levels, we created scatter plots that present the coefficients of interest and the interval with three standard deviations around the point estimate for the variable $EduCat$ and $EduCat_i * Potexp_{i,t}$. The full regression results can be found in Appendix Section A.13. Overall, the estimated employment stability among different education groups aligns with the previously observed patterns.

Beginning with the occurrence of unemployment, Figure A15 indicates that individuals with either a college degree (above college) have significantly lower unemployment probabilities by about 3.5 percentage points (PP) (3.4 PP) relative to their counterparts with less than a college education. Moreover, the education gap diminishes by 0.12 PP per year of potential working experience. This pattern holds true for both the full sample and the post-1992 subsample.[29]



(a) Full Sample

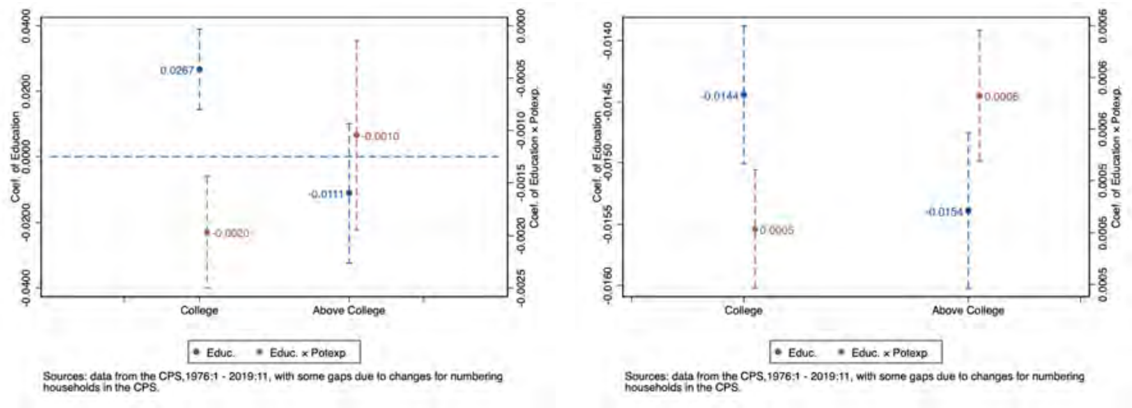
(b) Post-1992 Sample

Figure A15: Probability of Unemployed

By disentangling the unemployment probability into the probabilities of transitioning into and out of unemployment separately, Figure A16 reveals that individuals holding a college degree (or above) exhibit significantly lower job separation probabilities by nearly 1.4 (1.5) percentage points compared to their counterparts with less than a college degree.

The impact of education on job finding probabilities is more nuanced. Specifically, our findings indicate that workers with a college degree have higher job finding probabilities by 2.6 percentage points compared to their observationally equivalent counterparts with less than a college degree, while those with above college do not exhibit any significant differences in the job finding probability compared to those with less than a college education. In addition, the job finding probabilities of workers with less than college education progressively increases over the course of working years, relative to both college graduates and

[29]The post-1992 sample is of particular interest due to changes in how educational attainment is measured in the CPS. Before 1992, educational attainment was measured by years of completed schooling. From 1992, respondents were asked to list their highest level of degree obtained.

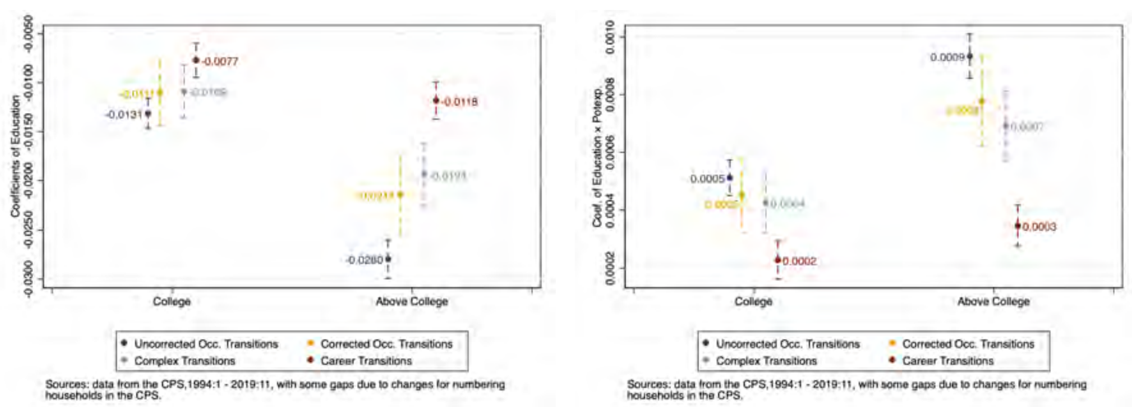


(a) Job Finding Probabilities (b) Job Separation Probabilities

Figure A16: Transition Probabilities into/out of Unemployment

individuals with education beyond college, as indicated by the negative coefficients of the interaction terms between education and potential experience.

We proceed to examine the employment dynamics in different education groups after accounting for various demographic, job, and economic factors. Figure A17 demonstrates a consistent pattern where individuals with higher levels of education exhibit lower probabilities of occupational transitions, as measured by either uncorrected occupation switches or corrected transitions with adjustment for suspicious transitions. Additionally, individuals with higher education levels are associated with a lower likelihood of complex and career transitions. More importantly, the education gap in transition probabilities between less than college workers and their counterparts with higher education diminishes over the years of potential work experience, as shown by a significantly positive coefficient of education interacted with potential experience.



(a) Coefficient of $EduCat_i$ (b) Coefficient of $EduCat_i \times Potexp_{i,t}$

Figure A17: Employment Transitions

A.13 Full Regression Results

A.13.1 The Probability of Being Unemployed

Table A10: Regression with Categorical Variables in Full Sample

	(1)	(2)	(3)	(4)	(5)	(6)
College	-0.06372***	-0.03636***	-0.03630***	-0.03623***	-0.03510***	-0.02541***
Above College	-0.07032***	-0.03427***	-0.03404***	-0.03460***	-0.03428***	-0.02233***
Presumed Pot. Exp.	-0.00318***	-0.00216***	-0.00204***	-0.00207***	-0.00189***	-0.00114***
Presumed Pot. Exp. (Squared)	0.00474***	0.00324***	0.00297***	0.00305***	0.00271***	0.00163***
College $\times$ Presumed Pot. Exp.	0.00156***	0.00123***	0.00123***	0.00123***	0.00122***	0.00107***
Above College $\times$ Presumed Pot. Exp.	0.00163***	0.00123***	0.00122***	0.00124***	0.00123***	0.00109***
Race: Black	0.04932***	0.04381***	0.04384***	0.04669***	0.04675***	0.03796***
Race: Others	0.01913***	0.01602***	0.01617***	0.01706***	0.01831***	0.01265***
Marst: Single	0.03642***	0.03223***	0.03095***	0.03047***	0.03148***	0.02180***
More than One Child			-0.00274***	-0.00287***	-0.00310***	-0.00256***
Faminc: 5000-7499						-0.05205***
Faminc: 7500-9999						-0.07707***
Faminc: 10000-14999						-0.10731***
Faminc: 15000-19999						-0.13054***
Faminc: 20000-24999						-0.14472***
Faminc: 25000-49999						-0.16260***
Faminc: 50000 and over						-0.17873***
Constant	0.08566***	0.04557***	0.04637***	0.04379***	0.04912***	0.17709***
2-digit Occ. FE		✓	✓	✓	✓	✓
2-digit Ind. FE		✓	✓	✓	✓	✓
State FE				✓	✓	✓
Year FE					✓	✓
N	17549406	17519203	17519203	17519203	17519203	13875096
R^2	0.022	0.034	0.034	0.035	0.040	0.062

Notes: Industrial and occupational codes for the unemployed are classified according to their last job.
Standard errors are robust to heteroskedasticity. *($p < 0.10$), **($p < 0.05$), ***($p < 0.01$).

Table A11: Regression with Categorical Variables in Post-1992 Sample

	(1)	(2)	(3)	(4)	(5)	(6)
College	-0.05810***	-0.03425***	-0.03427***	-0.03460***	-0.03423***	-0.02501***
Above College	-0.06626***	-0.03356***	-0.03342***	-0.03448***	-0.03400***	-0.02250***
Presumed Pot. Exp.	-0.00271***	-0.00179***	-0.00173***	-0.00178***	-0.00174***	-0.00129***
Presumed Pot. Exp. (Squared)	0.00417***	0.00286***	0.00272***	0.00282***	0.00271***	0.00208***
College × Presumed Pot. Exp.	0.00144***	0.00114***	0.00114***	0.00115***	0.00113***	0.00100***
Above College × Presumed Pot. Exp.	0.00159***	0.00120***	0.00119***	0.00121***	0.00120***	0.00102***
Race: Black	0.04488***	0.04196***	0.04198***	0.04379***	0.04383***	0.03621***
Race: Others	0.01740***	0.01508***	0.01514***	0.01493***	0.01487***	0.01020***
Marst: Single	0.03637***	0.03266***	0.03191***	0.03121***	0.03104***	0.02053***
More than One Child			-0.00150***	-0.00178***	-0.00192***	-0.00196***
Faminc: 5000-7499						-0.03979***
Faminc: 7500-9999						-0.05838***
Faminc: 10000-14999						-0.09634***
Faminc: 15000-19999						-0.12177***
Faminc: 20000-24999						-0.14099***
Faminc: 25000-49999						-0.16306***
Faminc: 50000 and over						-0.18110***
Constant	0.07605***	0.04502***	0.04562***	0.03942***	0.05871***	0.20504***
2-digit Occ. FE		✓	✓	✓	✓	✓
2-digit Ind. FE		✓	✓	✓	✓	✓
State FE				✓	✓	✓
Year FE					✓	✓
N	10649393	10632936	10632936	10632936	10632936	9768508
R^2	0.020	0.031	0.031	0.033	0.038	0.059

Notes: Industrial and occupational codes for the unemployed are classified according to their last job. Standard errors are robust to heteroskedasticity. *($p < 0.10$), **($p < 0.05$), ***($p < 0.01$).

Table A12: Comparison of Separate Regressions (Full Sample)

	(1)	(2)	(3)	(4)	(5)	(6)
Less than College	0.03486***	0.02452***				
College			-0.02890***	-0.02129***		
Above College					-0.02241***	-0.01327***
Presumed Pot. Exp.	-0.00189***	-0.00114***	-0.00157***	-0.00094***	-0.00130***	-0.00071***
Presumed Pot. Exp. (Squared)	0.00271***	0.00163***	0.00233***	0.00139***	0.00199***	0.00112***
College $\times$ Presumed Pot. Exp.	0.00121***	0.00103***	0.00107***	0.00096***	-0.00005***	0.00015***
Above College $\times$ Presumed Pot. Exp.	0.00125***	0.00117***	-0.00000	0.00029***	0.00093***	0.00086***
Race: Black	0.04675***	0.03795***	0.04708***	0.03812***	0.04712***	0.03814***
Race: Others	0.01832***	0.01271***	0.01729***	0.01193***	0.01770***	0.01216***
Marst: Single	0.03147***	0.02177***	0.03230***	0.02228***	0.03223***	0.02231***
More than One Child	-0.00309***	-0.00254***	-0.00341***	-0.00277***	-0.00319***	-0.00254***
Faminc: 5000-7499		-0.05205***		-0.05205***		-0.05207***
Faminc: 7500-9999		-0.07707***		-0.07713***		-0.07722***
Faminc: 10000-14999		-0.10731***		-0.10742***		-0.10754***
Faminc: 15000-19999		-0.13054***		-0.13070***		-0.13092***
Faminc: 20000-24999		-0.14472***		-0.14496***		-0.14527***
Faminc: 25000-49999		-0.16260***		-0.16300***		-0.16350***
Faminc: 50000 and over		-0.17871***		-0.17939***		-0.17984***
Constant	0.01429***	0.15264***	0.04190***	0.17254***	0.03683***	0.16833***
N	17519203	13875096	17519203	13875096	17519203	13875096
R^2	0.040	0.062	0.040	0.062	0.039	0.062

Notes: Industrial and occupational codes for the unemployed are classified according to their last job.
Standard errors are robust to heteroskedasticity. *($p < 0.10$), **($p < 0.05$), ***($p < 0.01$).
All regressions include industry (2-digit), occupation (2-digit), state and year fixed effects.

A.13.2 Transition Probabilities (Job Finding/Separation Probabilities)

Table A13: Regress JF over Categorical Variables (Full Sample)

	(1)	(2)	(3)	(4)	(5)	(6)
College	0.01614***	0.02191***	0.02182***	0.02630***	0.02667***	0.01827***
Above College	-0.01704**	-0.01498**	-0.01506**	-0.01123	-0.01114	-0.02481***
Presumed Pot. Exp.	-0.00525***	-0.00711***	-0.00704***	-0.00687***	-0.00682***	-0.00616***
Presumed Pot. Exp. (Squared)	0.00564***	0.00917***	0.00900***	0.00869***	0.00894***	0.00769***
College × Presumed Pot. Exp.	-0.00233***	-0.00179***	-0.00179***	-0.00195***	-0.00197***	-0.00186***
Above College × Presumed Pot. Exp.	-0.00144***	-0.00076**	-0.00076**	-0.00089***	-0.00104***	-0.00090***
Race: Black	-0.08471***	-0.07357***	-0.07354***	-0.07540***	-0.07628***	-0.06650***
Race: Others	-0.03627***	-0.03270***	-0.03253***	-0.04258***	-0.04159***	-0.03613***
Marst: Single	-0.03888***	-0.03846***	-0.03960***	-0.03966***	-0.03922***	-0.03040***
More than One Child			-0.00238	-0.00175	0.00174	0.00460**
Faminc: 5000-7499						0.02047***
Faminc: 7500-9999						0.03276***
Faminc: 10000-14999						0.05075***
Faminc: 15000-19999						0.06419***
Faminc: 20000-24999						0.07132***
Faminc: 25000-49999						0.08354***
Faminc: 50000 and over						0.10850***
Constant	0.41862***	0.44759***	0.44862***	0.44536***	0.43521***	0.32890***
2-digit Occ. FE		✓	✓	✓	✓	✓
2-digit Ind. FE		✓	✓	✓	✓	✓
State FE				✓	✓	✓
Year FE					✓	✓
N	547983	522232	522232	522232	522232	426846
R^2	0.012	0.018	0.018	0.023	0.036	0.041

Notes: Industrial and occupational codes for the unemployed are classified according to their last job. Standard errors are robust to heteroskedasticity. *($p < 0.10$), **($p < 0.05$), ***($p < 0.01$).

Table A14: Regress JF over Categorical Variables (Post-1992 Sample)

	(1)	(2)	(3)	(4)	(5)	(6)
College	0.00738	0.01502***	0.01503***	0.02165***	0.02450***	0.01793***
Above College	-0.05329***	-0.04947***	-0.04946***	-0.04327***	-0.04274***	-0.04916***
Presumed Pot. Exp.	-0.00487***	-0.00723***	-0.00724***	-0.00695***	-0.00657***	-0.00587***
Presumed Pot. Exp. (Squared)	0.00429***	0.00882***	0.00883***	0.00837***	0.00833***	0.00718***
College × Presumed Pot. Exp.	-0.00216***	-0.00149***	-0.00149***	-0.00166***	-0.00176***	-0.00178***
Above College × Presumed Pot. Exp.	-0.00036	0.00039	0.00039	0.00027	0.00009	-0.00005
Race: Black	-0.08165***	-0.07206***	-0.07206***	-0.07025***	-0.07147***	-0.06439***
Race: Others	-0.03528***	-0.03071***	-0.03071***	-0.03711***	-0.03554***	-0.03217***
Marst: Single	-0.04790***	-0.04726***	-0.04720***	-0.04645***	-0.04401***	-0.03408***
More than One Child			0.00012	0.00126	0.00369*	0.00637***
Faminc: 5000-7499						0.01683***
Faminc: 7500-9999						0.02056***
Faminc: 10000-14999						0.03300***
Faminc: 15000-19999						0.04540***
Faminc: 20000-24999						0.05138***
Faminc: 25000-49999						0.06250***
Faminc: 50000 and over						0.09152***
Constant	0.42744***	0.44466***	0.44460***	0.44695***	0.39831***	0.34615***
2-digit Occ. FE		✓	✓	✓	✓	✓
2-digit Ind. FE		✓	✓	✓	✓	✓
State FE				✓	✓	✓
Year FE					✓	✓
N	320367	306562	306562	306562	306562	286387
R^2	0.013	0.020	0.020	0.025	0.041	0.044

Notes: Industrial and occupational codes for the unemployed are classified according to their last job. Standard errors are robust to heteroskedasticity. *($p < 0.10$), **($p < 0.05$), ***($p < 0.01$).

Table A15: Comparison of JF in Separate Regressions (Full Sample)

	(1)	(2)	(3)	(4)	(5)	(6)
Less than College	-0.01844***	-0.00933**				
College			0.03008***	0.02358***		
Above College					-0.01140	-0.02245***
Presumed Pot. Exp.	-0.00862***	-0.00788***	-0.00694***	-0.00635***	-0.00708***	-0.00646***
Presumed Pot. Exp. (Squared)	0.00900***	0.00778***	0.00919***	0.00808***	0.00919***	0.00802***
Less than College × Presumed Pot. Exp.	0.00178***	0.00169***				
College × Presumed Pot. Exp.			-0.00190***	-0.00178***		
Above College × Presumed Pot. Exp.					-0.00084***	-0.00069**
Race: Black	-0.07619***	-0.06639***	-0.07565***	-0.06577***	-0.07605***	-0.06608***
Race: Others	-0.04174***	-0.03633***	-0.04190***	-0.03670***	-0.04170***	-0.03634***
Marst: Single	-0.03902***	-0.03013***	-0.03862***	-0.02959***	-0.03899***	-0.03002***
More than One Child	0.00172	0.00459**	0.00214	0.00513***	0.00197	0.00497***
Faminc: 5000-7499		0.02052***		0.02066***		0.02061***
Faminc: 7500-9999		0.03274***		0.03280***		0.03292***
Faminc: 10000-14999		0.05074***		0.05083***		0.05101***
Faminc: 15000-19999		0.06423***		0.06430***		0.06440***
Faminc: 20000-24999		0.07138***		0.07132***		0.07150***
Faminc: 25000-49999		0.08360***		0.08335***		0.08357***
Faminc: 50000 and over		0.10842***		0.10656***		0.10712***
Constant	0.45304***	0.33746***	0.43075***	0.32237***	0.43485***	0.32595***
N	522232	426846	522232	426846	522232	426846
R^2	0.036	0.041	0.036	0.041	0.035	0.041

Notes: Industrial and occupational codes for the unemployed are classified according to their last job.
Standard errors are robust to heteroskedasticity. *($p < 0.10$), **($p < 0.05$), ***($p < 0.01$).
All regressions include industry (2-digit), occupation (2-digit), state and year fixed effects.

Table A16: Regress JS over Categorical Variables (Full Sample)

	(1)	(2)	(3)	(4)	(5)	(6)
College	-0.02245***	-0.01500***	-0.01500***	-0.01488***	-0.01444***	-0.01273***
Above College	-0.02481***	-0.01548***	-0.01548***	-0.01549***	-0.01539***	-0.01329***
Presumed Pot. Exp.	-0.00135***	-0.00125***	-0.00125***	-0.00126***	-0.00121***	-0.00110***
Presumed Pot. Exp. (Squared)	0.00192***	0.00183***	0.00183***	0.00186***	0.00179***	0.00166***
College × Presumed Pot. Exp.	0.00057***	0.00052***	0.00052***	0.00052***	0.00052***	0.00049***
Above College × Presumed Pot. Exp.	0.00062***	0.00057***	0.00057***	0.00057***	0.00057***	0.00055***
Race: Black	0.00968***	0.00982***	0.00982***	0.01062***	0.01071***	0.00891***
Race: Others	0.00240***	0.00242***	0.00242***	0.00265***	0.00349***	0.00254***
Marst: Single	0.00762***	0.00691***	0.00691***	0.00684***	0.00757***	0.00578***
More than One Child			0.00001	-0.00003	0.00012	0.00008
Faminc: 5000-7499						-0.00862***
Faminc: 7500-9999						-0.01470***
Faminc: 10000-14999						-0.02071***
Faminc: 15000-19999						-0.02624***
Faminc: 20000-24999						-0.02941***
Faminc: 25000-49999						-0.03323***
Faminc: 50000 and over						-0.03580***
Constant	0.03205***	0.02436***	0.02436***	0.02406***	0.02381***	0.05351***
2-digit Occ. FE		✓	✓	✓	✓	✓
2-digit Ind. FE		✓	✓	✓	✓	✓
State FE				✓	✓	✓
Year FE					✓	✓
N	10697748	10697747	10697747	10697747	10697747	8639115
R^2	0.007	0.013	0.013	0.013	0.014	0.016

Notes: Industrial and occupational codes for the unemployed are classified according to their last job. Standard errors are robust to heteroskedasticity. *($p < 0.10$), **($p < 0.05$), ***($p < 0.01$).

Table A17: Regress JS over Categorical Variables (Post-1992 Sample)

	(1)	(2)	(3)	(4)	(5)	(6)
College	-0.01961***	-0.01344***	-0.01343***	-0.01338***	-0.01323***	-0.01195***
Above College	-0.02259***	-0.01477***	-0.01479***	-0.01484***	-0.01461***	-0.01291***
Presumed Pot. Exp.	-0.00111***	-0.00106***	-0.00107***	-0.00108***	-0.00109***	-0.00106***
Presumed Pot. Exp. (Squared)	0.00160***	0.00158***	0.00161***	0.00163***	0.00167***	0.00164***
College $\times$ Presumed Pot. Exp.	0.00049***	0.00045***	0.00045***	0.00045***	0.00045***	0.00044***
Above College $\times$ Presumed Pot. Exp.	0.00057***	0.00053***	0.00053***	0.00053***	0.00053***	0.00051***
Race: Black	0.00797***	0.00862***	0.00861***	0.00924***	0.00931***	0.00799***
Race: Others	0.00243***	0.00263***	0.00261***	0.00262***	0.00287***	0.00210***
Marst: Single	0.00737***	0.00676***	0.00690***	0.00678***	0.00697***	0.00516***
More than One Child			0.00028***	0.00020*	0.00024**	0.00021*
Faminc: 5000-7499						-0.00350***
Faminc: 7500-9999						-0.00792***
Faminc: 10000-14999						-0.01589***
Faminc: 15000-19999						-0.02118***
Faminc: 20000-24999						-0.02528***
Faminc: 25000-49999						-0.02992***
Faminc: 50000 and over						-0.03311***
Constant	0.02776***	0.02455***	0.02443***	0.02252***	0.02664***	0.05455***
2-digit Occ. FE		✓	✓	✓	✓	✓
2-digit Ind. FE		✓	✓	✓	✓	✓
State FE				✓	✓	✓
Year FE					✓	✓
N	6667665	6667665	6667665	6667665	6667665	6166971
R^2	0.006	0.011	0.011	0.011	0.011	0.014

Notes: Industrial and occupational codes for the unemployed are classified according to their last job. Standard errors are robust to heteroskedasticity. *($p < 0.10$), **($p < 0.05$), ***($p < 0.01$).

Table A18: Comparison of JS in Separate Regressions (Full Sample)

	(1)	(2)	(3)	(4)	(5)	(6)
Less than College	0.01475***	0.01295***				
College			-0.01184***	-0.01065***		
Above College					-0.01069***	-0.00918***
Presumed Pot. Exp.	-0.00067***	-0.00058***	-0.00109***	-0.00098***	-0.00102***	-0.00092***
Presumed Pot. Exp. (Squared)	0.00179***	0.00165***	0.00167***	0.00152***	0.00161***	0.00148***
Less than College × Presumed Pot. Exp.	-0.00054***	-0.00051***				
College × Presumed Pot. Exp.			0.00045***	0.00043***		
Above College × Presumed Pot. Exp.					0.00046***	0.00044***
Race: Black	0.01071***	0.00891***	0.01082***	0.00895***	0.01080***	0.00894***
Race: Others	0.00347***	0.00254***	0.00299***	0.00211***	0.00320***	0.00230***
Marst: Single	0.00758***	0.00578***	0.00800***	0.00609***	0.00799***	0.00612***
More than One Child	0.00011	0.00007	-0.00001	-0.00008	0.00014*	0.00011
Faminc: 5000-7499		-0.00862***		-0.00865***		-0.00867***
Faminc: 7500-9999		-0.01470***		-0.01475***		-0.01479***
Faminc: 10000-14999		-0.02071***		-0.02080***		-0.02084***
Faminc: 15000-19999		-0.02624***		-0.02635***		-0.02643***
Faminc: 20000-24999		-0.02940***		-0.02956***		-0.02966***
Faminc: 25000-49999		-0.03323***		-0.03345***		-0.03362***
Faminc: 50000 and over		-0.03578***		-0.03603***		-0.03616***
Constant	0.00904***	0.04056***	0.02084***	0.05114***	0.01925***	0.04962***
N	10697747	8639115	10697747	8639115	10697747	8639115
R^2	0.014	0.016	0.014	0.016	0.014	0.016

Notes: Industrial and occupational codes for the unemployed are classified according to their last job.
Standard errors are robust to heteroskedasticity. *($p < 0.10$), **($p < 0.05$), ***($p < 0.01$).
All regressions include industry (2-digit), occupation (2-digit), state and year fixed effects.

A.13.3 Occurrence Probabilities of Job Mobilities

Table A19: Probabilities of Uncorrected Job-to-Job Transitions

	(1)	(2)	(3)	(4)	(5)	(6)
College	-0.01640***	-0.01156***	-0.01160***	-0.01188***	-0.01314***	-0.01201***
Above College	-0.03324***	-0.02487***	-0.02472***	-0.02615***	-0.02797***	-0.02692***
Presumed Pot. Exp.	-0.00258***	-0.00242***	-0.00235***	-0.00238***	-0.00229***	-0.00237***
Presumed Pot. Exp. (Squared)	0.00399***	0.00377***	0.00360***	0.00368***	0.00331***	0.00346***
College × Presumed Pot. Exp.	0.00059***	0.00051***	0.00050***	0.00051***	0.00051***	0.00050***
Above College × Presumed Pot. Exp.	0.00100***	0.00089***	0.00088***	0.00090***	0.00093***	0.00096***
Race: Black	0.01788***	0.01762***	0.01765***	0.01555***	0.01525***	0.01215***
Race: Others	0.01081***	0.01035***	0.01042***	0.00848***	0.00685***	0.00555***
Marst: Single	0.00842***	0.00733***	0.00650***	0.00603***	0.00466***	0.00273***
More than One Child			-0.00169***	-0.00188***	-0.00237***	-0.00165***
Faminc: 5000-7499						-0.00120
Faminc: 7500-9999						-0.00703***
Faminc: 10000-14999						-0.01041***
Faminc: 15000-19999						-0.01651***
Faminc: 20000-24999						-0.02090***
Faminc: 25000-49999						-0.02492***
Faminc: 50000 and over						-0.02822***
Constant	0.07822***	0.06785***	0.06855***	0.06450***	0.05890***	0.08319***
2-digit Occ. FE		✓	✓	✓	✓	✓
2-digit Ind. FE		✓	✓	✓	✓	✓
State FE				✓	✓	✓
Year FE					✓	✓
N	6076773	6076773	6076773	6076773	6076773	5611866
R^2	0.004	0.006	0.006	0.007	0.009	0.011

Notes: Industrial and occupational codes for the unemployed are classified according to their last job. Standard errors are robust to heteroskedasticity. *($p < 0.10$), **($p < 0.05$), ***($p < 0.01$).

Table A20: Probabilities of Corrected Job-to-Job Transitions

	(1)	(2)	(3)	(4)	(5)	(6)
College	-0.01456***	-0.01068***	-0.01070***	-0.01067***	-0.01108***	-0.01009***
Above College	-0.02705***	-0.02066***	-0.02057***	-0.02083***	-0.02144***	-0.02044***
Presumed Pot. Exp.	-0.00229***	-0.00212***	-0.00209***	-0.00210***	-0.00207***	-0.00209***
Presumed Pot. Exp. (Squared)	0.00355***	0.00329***	0.00320***	0.00323***	0.00311***	0.00316***
College × Presumed Pot. Exp.	0.00052***	0.00045***	0.00045***	0.00045***	0.00045***	0.00043***
Above College × Presumed Pot. Exp.	0.00086***	0.00077***	0.00077***	0.00077***	0.00078***	0.00078***
Race: Black	0.00794***	0.00771***	0.00773***	0.00761***	0.00753***	0.00617***
Race: Others	0.00542***	0.00494***	0.00498***	0.00399***	0.00354***	0.00304***
Marst: Single	0.00476***	0.00387***	0.00343***	0.00320***	0.00277***	0.00144***
More than One Child			-0.00088**	-0.00103**	-0.00119***	-0.00100**
Faminc: 5000-7499						0.00476
Faminc: 7500-9999						0.00314
Faminc: 10000-14999						-0.00000
Faminc: 15000-19999						-0.00768***
Faminc: 20000-24999						-0.01123***
Faminc: 25000-49999						-0.01309***
Faminc: 50000 and over						-0.01562***
Constant	0.05741***	0.05779***	0.05816***	0.05567***	0.05580***	0.06763***
2-digit Occ. FE		✓	✓	✓	✓	✓
2-digit Ind. FE		✓	✓	✓	✓	✓
State FE				✓	✓	✓
Year FE					✓	✓
N	905420	905420	905420	905420	905420	851409
R^2	0.004	0.005	0.005	0.006	0.006	0.007

Notes: Industrial and occupational codes for the unemployed are classified according to their last job. Standard errors are robust to heteroskedasticity. *($p < 0.10$), **($p < 0.05$), ***($p < 0.01$).

Table A21: Probabilities of Complex Transitions

	(1)	(2)	(3)	(4)	(5)	(6)
College	-0.01311***	-0.01033***	-0.01034***	-0.01038***	-0.01089***	-0.01015***
Above College	-0.02288***	-0.01837***	-0.01833***	-0.01865***	-0.01940***	-0.01863***
Presumed Pot. Exp.	-0.00203***	-0.00186***	-0.00184***	-0.00185***	-0.00181***	-0.00183***
Presumed Pot. Exp. (Squared)	0.00319***	0.00291***	0.00287***	0.00289***	0.00274***	0.00279***
College $\times$ Presumed Pot. Exp.	0.00048***	0.00042***	0.00042***	0.00042***	0.00042***	0.00041***
Above College $\times$ Presumed Pot. Exp.	0.00075***	0.00068***	0.00068***	0.00068***	0.00069***	0.00069***
Race: Black	0.00742***	0.00691***	0.00692***	0.00670***	0.00658***	0.00538***
Race: Others	0.00510***	0.00450***	0.00452***	0.00419***	0.00340***	0.00304***
Marst: Single	0.00414***	0.00334***	0.00316***	0.00301***	0.00243***	0.00143***
More than One Child			-0.00036	-0.00046	-0.00066*	-0.00050
Faminc: 5000-7499						0.00433
Faminc: 7500-9999						0.00342
Faminc: 10000-14999						-0.00023
Faminc: 15000-19999						-0.00582***
Faminc: 20000-24999						-0.00849***
Faminc: 25000-49999						-0.00987***
Faminc: 50000 and over						-0.01193***
Constant	0.04282***	0.04345***	0.04360***	0.04215***	0.03965***	0.04831***
2-digit Occ. FE		✓	✓	✓	✓	✓
2-digit Ind. FE		✓	✓	✓	✓	✓
State FE				✓	✓	✓
Year FE					✓	✓
N	905420	905420	905420	905420	905420	851409
R^2	0.005	0.006	0.006	0.006	0.007	0.008

Notes: Industrial and occupational codes for the unemployed are classified according to their last job. Standard errors are robust to heteroskedasticity. *($p < 0.10$), **($p < 0.05$), ***($p < 0.01$).

Table A22: Probabilities of Career Transitions

	(1)	(2)	(3)	(4)	(5)	(6)
College	-0.01159***	-0.00740***	-0.00741***	-0.00743***	-0.00770***	-0.00696***
Above College	-0.01665***	-0.01130***	-0.01127***	-0.01144***	-0.01182***	-0.01123***
Presumed Pot. Exp.	-0.00108***	-0.00091***	-0.00089***	-0.00090***	-0.00088***	-0.00087***
Presumed Pot. Exp. (Squared)	0.00172***	0.00143***	0.00140***	0.00141***	0.00133***	0.00133***
College $\times$ Presumed Pot. Exp.	0.00028***	0.00023***	0.00023***	0.00023***	0.00023***	0.00022***
Above College $\times$ Presumed Pot. Exp.	0.00040***	0.00034***	0.00034***	0.00034***	0.00035***	0.00035***
Race: Black	0.00646***	0.00504***	0.00505***	0.00504***	0.00499***	0.00415***
Race: Others	0.00428***	0.00301***	0.00302***	0.00229***	0.00194***	0.00202***
Marst: Single	0.00322***	0.00222***	0.00203***	0.00192***	0.00161***	0.00097***
More than One Child			-0.00037	-0.00045*	-0.00055**	-0.00042*
Faminc: 5000-7499						0.00183
Faminc: 7500-9999						-0.00413**
Faminc: 10000-14999						-0.00278*
Faminc: 15000-19999						-0.00461***
Faminc: 20000-24999						-0.00587***
Faminc: 25000-49999						-0.00739***
Faminc: 50000 and over						-0.00871***
Constant	0.02366***	0.02024***	0.02040***	0.02018***	0.01952***	0.02619***
2-digit Occ. FE		✓	✓	✓	✓	✓
2-digit Ind. FE		✓	✓	✓	✓	✓
State FE				✓	✓	✓
Year FE					✓	✓
N	1022976	1022976	1022976	1022976	1022976	958653
R^2	0.004	0.007	0.007	0.007	0.008	0.008

Notes: Industrial and occupational codes for the unemployed are classified according to their last job. Standard errors are robust to heteroskedasticity. *($p < 0.10$), **($p < 0.05$), ***($p < 0.01$).

B Empirical Appendix (NLSY79)

B.1 NLSY79 Variables

Table B1: NLSY79 Variables

Variable	Variable Label	Interpretation
Panel A: Demographic Variables		
AGE	Age	Computed from the birth date by $Current\ YM - Birth\ YM$. $Q1\_3\_A\_Y(M)\_1981$ reports individual's birth year (month) at survey conducted in 1981. In case where the birth date is missing at this survey round, we rely on the $Q1\_3\_A\_Y(M)\_1979$ reported at 1979.
SEX	Gender	Male (1) and Female (2)
$RACE$	Race	Hispanic (1), Black (2) and Non-Black and Non-Hispanic (3)
$MARST$	Marital status	Regroup into 3 broad categories: Married (including married and remarried), Single (that includes never married, separated, divorced and widowed), and Missing (non-reported)
$CHILDBEARING$	Child bearing	Regroup into 3 broad categories: No children (0), At least one child (1), and Missing (non-reported)
$REGION$	Region	Northeast (1), North Central (2), South (3), West (4) and Missing (non-reported)
$FAMINC$	Family income (truncated) in each survey year	Regroup into 9 groups: Missing, 0-4999, 5000-7499, 7500-9999, 10000-14999, 15000-19999, 20000-24999, 25000-49999, 50000+.
Panel B: Education		
$HIGHESTGRADE$	Highest grade completed	Ranging from None (0) to 8th year college or more (20), in terms of continuous grade variables, as well as Missing (non-reported)
$SURVEYYEAR\_HGC$	Graduation survey year	The identification involves three steps: (i) determining the highest grade completed for each survey year using $HGCREV$ for 1979-2010 and HGC_NOREV for post-2010, (ii) merging the data with the highest grade completed, and (iii) identifying the graduation survey year based on the earliest survey year reporting the highest grade
$ENROLL$	Enrollment status at school	Regroup into 3 broad categories: Not enrolled, Enrolled and Missing
Panel C: Employment Variables		
$STATUS$	Weekly-array labor force status reported in the main array	It includes: 0 (no information reported), 2 (not working, but unemployed or OLF is not determined), 3 (associated with emplpyer but gap dates are missing), 4 (unemployed), 5 (out of labor force), 7(active military service), >100 (actual survey round/job number)
$STATUS\_DUAL$	Weekly-array labor force status reported for dual jobs	Reported the job code for dual jobs if any
$HRWKD\_EMP\#$	Working hours for each job during each survey year, up to 5 jobs	Use $QES-52A$ for the years 1979 to 2012, which provides hours per week worked in a specific job for each survey year. For 2014 onwards, we utilize $QES-52D$, which includes hours per week usually worked, including those worked at home
$IND\_EMP\#$	Industry codes for up to 5 jobs	3-digit 1970 industry codes from survey 1979 to 2000, 3-digit 2000 Census industry codes for survey 2002, 4-digit 2002 Census industry codes from the year 2004 and onwards

OCC_EMP#	Occupation codes for up to 5 jobs	3-digit 1970 occupation codes from survey 1979 to 2000, 3-digit 2000 Census occupation codes for survey 2002, 4-digit 2002 Census occupation codes from the year 2004 and onwards
CPSIND	Industry codes for CPS jobs[30]	Census 1970 for jobs reported from survey year 1979 to 2000, Census 2000 for jobs reported in year 2002, Census 2002 for jobs reported after year 2002
CPSOCC	Occupation codes for CPS jobs	Same as above
CHECK_CPS_EMP#	Is job # same as current job?	For up to 5 jobs
HRWKD_CPS	Hours worked during survey week in CPS item	Ranging from 1 to 168 hours per week
OCC_LAST_EMP	Occupation codes for job in last employer	Same as above
IND_LAST_EMP	Industry codes for job in last employer	Same as above
PREV_EMP#	Previous job number at last interview	Used for cross-survey check and filling in missing item in the labor history array
HRP_#	Hourly rate of pay in #*th* job in a particular survey year	With two decimals, and for up to 5 jobs and the CPS job
EMP_NUM_ARRAY	Job number which is loaded into the work history array	It helps to figure out the distinct employers worked for
Panel D: Worker's Aptitudes		
ASVAB_#	ASVAB score for each subtest	The ASVAB consists of a battery of 10 tests that measure knowledge and skill in the following areas: general science, arithmetic reasoning, word knowledge, paragraph comprehension, numerical operations, coding speed, auto and shop information, mathematics knowledge, mechanical comprehension, and electronics information.
ROTTER_SCORE	Rotter Locus of Control Score	It was collected during the initial round in 1979 and is scored in the external direction, indicating that a higher score reflects a greater external orientation in individuals.
ROSENBERG_SCORE	Rosenberg Self-Esteem Scale	It describes the level of self-approval or disapproval, and it needs to be reversed prior to scoring. This reversal ensures that a higher score indicates higher self-esteem.
Panel E: Technical Variables		
PANELWEIGHT	Custom panel weight	In order to account for longitudinal data across multiple survey years, we utilize custom weights with two implied decimal places. This weight provides an estimate of how many individuals in the United States each respondent's answers represent.

[30] CPS job refers to his/her most recent job.

B.2 Construction of NLSY79 Panel Data

B.2.1 Weekly History Panel Data

This section details the construction process of week-by-week panel from the NLSY79. The process primarily involves three key steps: (i) cleaning the employer history roster and determining the employer characteristics, (ii) identifying necessary demographic variables for each respondent in each survey year, and (iii) identifying the primary job for each week if employed by multiple employers.

We start with the processing of the employer history roster, that consists of two primary steps. The first step is to unify the occupational and industrial codes across various census classification schemes to the 1990dd scheme developed by David Dorn for both NLSY and CPS jobs.[31] This scheme consolidates US Census codes into a balanced panel of occupations or industries for the 2000 and 2002 Census. Furthermore, it enables the creation of an unbalanced panel of occupational and industrial codes for the Census years 1970. In cases where occupation and industry codes lack corresponding 1990dd codes in the crosswalk file, we examine the contents of the classification files and manually determine their counterparts with the closest content in the 1990dd classification scheme.

In particular, for occupation codes (for both civilian jobs, CPS jobs and the job at last employer) spanning survey year 1979 (round 1) to 2000 (round 19), we need to convert the original 1970 census occupational codes to the 1990dd classification scheme. For employer characteristics in the survey year 2002 (round 20), we must convert the original 3-digit 2000 census occupation codes to the 1990dd classification scheme. However, for occupation codes from survey year 2004 onwards, we need to convert the original 4-digit 2002 occupation codes into 2000 census codes in 3-digit by directly taking the first three digits, and then transfer them to the 1990dd classification scheme. The crosswalk for industry codes is very similar to that for occupation codes, the only difference is for the industry codes reported from survey year 1979 (round 1) to 2000 (round 19), we first need to crosswalk IND70 codes to IND80 codes, and then crosswalk from 1980 census industry codes to the 1990dd industry classification scheme.

Subsequently, our task involves determining the employer characteristics for each job in every survey year. Initially, we utilize the original employer history roster (EHR) from the NLSY79 dataset. In cases where the EHR lacks occupational and industry codes, we utilize the corresponding codes from Current Population Survey (CPS) jobs. It is important to note that while the CPS employer is typically the first employer, this is not always the case during the survey years 1980-1992. To address this discrepancy in the order, we refer to the question: "IS JOB # SAME AS CURRENT JOB?" If the answer is affirmative, we fill in the missing information using the CPS job information. Additionally, we consider the industry and occupation codes from the last employer to complete any remaining missing information.

Now, shifting our focus to the weekly employment histories with primary job codes, these are expressed as the formula $Survey\ Round * 100 + Job\ Number$. We proceed to determine the survey round for each reported job, which corresponds to the first one or two digits of the job code. By leveraging the information on unique respondent ID, the survey round and job number, we can crosswalk with the employer history roster and obtain the employer characteristics (including occupation code, industry code, and hourly pay rate) for the reported job. Next, through cross-referencing EMP_NUM_ARRAY with the job number in the work history array, we can ascertain the current employer is the x^{th} employer the worker has worked for.

Next, we proceed to work with the demographic variables. It is necessary to identify the demographic characteristics of each respondent in every survey year. To integrate them with the corresponding demo-

[31] See https://www.ddorn.net/data.htm for more details.

graphic characteristics, we need to determine the survey year associated with each weekly observation by utilizing the available survey dates. For surveys conducted before 1994 (inclusive), only the survey month is reported. Therefore, we need to impute the survey year based on the corresponding survey round. The identification process is as follows: we first determine the continuous week corresponding to each survey date. Then, for each weekly observation, we check if its week number falls within the range between the survey date of the most recent preceding survey round (not inclusive) and the current survey round (inclusive).[32] If it does, we assign the survey year of the current round to the observation. Once we have identified the survey year, we can gather information on various demographic characteristics such as race, gender, birth year (or age), marital status, childbearing, residential region, highest grade completed, (imputed) graduation year, enrollment status, ASVAB scores, and non-cognitive test scores (including the Rotter Locus of Control Score and Rosenberg Self-Esteem Scale).

Finally, we identify the primary job for each week. If the respondent is employed, whether it be through a single job or multiple jobs, the main job for each week is determined based on the job that has the longest working hours during that week.[33] If the reported multiple jobs have the same working hours per week, we keep the one reported in the main array.

B.2.2 Constructing a Monthly Panel

In this section, we describe the process employed to convert the weekly panel data to monthly panel data by identifying the primary labor force status for each calendar month and year.

To begin, we determine the calendar year and calendar month for each continuous week by utilizing the time crosswalk file. Next, we proceed to determine the primary labor force status for each month of each respondent. Firstly, if the respondent is employed at any point during a particular month, the primary job is determined as the one with the most working hours within that month. In the case where there are multiple civilian jobs with the same total working hours for that month, we consider the job with complete occupation and industry records as the primary one. If there are several jobs with complete records, we retain the one with known employer ID as the primary monthly job. If there are still multiple civilian jobs in a particular year-month cell, we keep the earliest reported one, indicated by a lower job code in the weekly array.

Secondly, if the respondent does not hold any job with assigned job codes for a given month, we prioritize the remaining labor force statuses following the precedence order adopted by the NLSY79 data set: 3 (employed, but periods not working with an employer are missing) > 4 (unemployed) > 5 (out of the labor force) > 2 (period not working with an employer, unsure if unemployed or out of the labor force) > 7 (military) > 0 (no information). If a status with higher precedence appears during the month, it is regarded as the primary labor force status for that specific month.

[32] An important characteristic of the NLSY surveys (with few exception) is that each respondent in a survey round may have a distinct reference period. Specifically, the reference period is defined as the time between the date of the last interview and the date of the current interview. If a respondent participates in consecutive rounds, they report on events since their last interview date. Even if a respondent misses one or more interviews, they are still asked to report events since their last interview. This approach ensures that all time is captured until a respondent's most recent interview.

[33] In the case where a respondent simultaneously holds multiple jobs, the job number assigned to the main array is determined based on the starting date of the job with the lowest job number. This selection is not influenced by any specific attributes of the job, such as the number of hours worked.

B.2.3 Sample Selection

Table B2 summarizes the criteria used for our sample selection. Initially, we collect month-by-month employment histories of 12,686 respondents from the first survey until the most recent one. In particular, we drop certain survey observations that occur after the most recent interview round, as not all individuals participate in every survey round. We then restrict to 6,403 males as the period covered by the NLSY79 encompasses a time of substantial changes in the female labor force participation rate. Next, we filter the observations to include only those from the earliest survey year (1978) until 2018.

We assume that individuals enter the labor market upon completing their highest level of education. For respondents with the highest education level of "None," we set their employment histories to start from 1978, which corresponds to the earliest year in our dataset. We also drop respondents with unknown graduation dates from our sample. These steps lead us to a sample of 6,386 respondents.

Subsequently, we exclude individuals who have served in the military, leaving a sample size of 5,361 respondents. Finally, we drop individuals with either incomplete cognitive or non-cognitive scores, resulting in a sample size of 4,823 respondents.

It is worth noting that in our constructed sample, some monthly employment observations may lack complete employer characteristics such as occupation and industry codes, even if the individual was employed during that period. This absence of certain employer variables is a common occurrence given the survey's span of over 30 years. Nevertheless, this limitation has minimal impact on our analysis, as we focus on average indicators within the sample.

As this sample traces the labor market histories of individuals from the survey year they reported attaining their highest education degree, it is unbalanced owing to variations in the timing of individuals' entry into the labor market. Furthermore, our dataset is truncated at the year 2018. Consequently, it is expected that the number of observations pertaining to individuals in later stages of their careers, such as those in the group of older ages or longer working years, will be limited. Due to this data limitation, the computation of outcomes within such groups, characterized by a small sample size, can be more susceptible to biases.

Table B2: NLSY79 Sample Selection

Criteria	*No*. of Resp.	*No*. of Obs.
Drop monthly observations from the last interview round	12,686	4,679,382
Restrict to males only	6,403	2,317,473
Restrict to monthly histories from 1978 to 2018	6,403	2,307,286
Start from the (known) graduation survey year	6,386	1,805,924
Drop individuals who ever served in army force	5,361	1,589,597
Complete ASVAB	5,030	1,511,337
Complete non-cognitive scores	4,823	1,452,307

B.2.4 Measurement of Worker's Aptitudes in NLSY79

In this section, we provide an overview of the multi-dimensional measurement of workers' aptitudes in verbal, math, and social skills using scores from the Armed Services Vocational Aptitude Battery (CAT-

ASVAB) and attitude tests such as the Rotter Locus of Control Score and the Rosenberg Self-Esteem Scale.[34] The Armed Services Vocational Aptitude Battery (ASVAB) assesses the respondent's knowledge and skills in 12 different topical areas. However, our focus is on four areas that are most relevant to verbal and math abilities: word knowledge, paragraph comprehension, arithmetic reasoning, and mathematics knowledge.

To assess a worker's cognitive ability, we begin with a sample of $4,823$ respondents who have complete scores for all four sub-tests of the ASVAB. Recognizing that differences in test-taking age can potentially influence ASVAB scores systematically, we account for the test-taking age effect by normalizing the mean and variance of each test score within each age cohort, following the procedure outlined by Altonji et al. (2012). To identify verbal and math abilities for each individual, we perform Principal Component Analysis (PCA) separately on the first two sub-tests (word knowledge and paragraph comprehension) and the last two sub-tests (arithmetic reasoning and mathematics knowledge). By extracting the first component from each PCA, we measure the verbal and math abilities of the individuals. Subsequently, we convert these ability indicators into percentile ranks across all individuals, as the scales of the principal components are arbitrary.

For measuring social ability, we utilize the Rotter Locus of Control Scale and the Rosenberg Self-Esteem Scale. We begin with the same sample of $4,823$ respondents who possess complete scores for both attitude tests. Similar to the approach used for cognitive ability, we account for the effect of test-taking age. By extracting the first principal components from the standardized scores of these two tests, we obtain the social ability measure. Again, it is necessary to transform these principal components into percentile ranks due to the arbitrary scale of the scores.[35]

B.2.5 Measurement of Skill Mismatch in NLSY79

To empirically quantify the mismatch between workers' abilities and occupational requirements, we proceed by measuring the distance between the percentile ranks of worker abilities and their corresponding occupational requirements. First, we compute the (contemporary) mismatch for each worker-occupation pair along each skill dimension. The absolute mismatch in skill dimension j between individual i and occupation o is defined as

$$m_{i,j,o} = \left|q(A_{i,j}) - q(r_{o,j})\right|, \tag{B.1}$$

where $q(A_{i,j})$ represents the percentile rank of worker i in skill dimension j, and $q(r_{o,j})$ denotes the requirement percentile of occupation o in skill dimension j.

After obtaining the measured indicators for each skill dimension, we proceed to measure the aggregate mismatch between individual i and occupation o. The aggregate mismatch is calculated by

$$m_{i,o} = \sum_j \{\omega_j \left|q(A_{i,j}) - q(r_{o,j})\right|\}, \tag{B.2}$$

where ω_j represents the weights assigned to each skill dimension j, which reflect the relative importance of that skill. These weights are determined as the factor loadings obtained from the normalized first principal component analysis. In particular, it is $(0.43, 0.42, 0.15)$ in our sample. This is almost the same as the weights

[34] The CAT-ASVAB covers various subjects, including arithmetic reasoning, electronics information, numerical operations, assembling objects, general science, paragraph comprehension, auto information, mathematics knowledge, shop information, coding speed, mechanical comprehension, and word knowledge. The Rotter Locus of Control Scale measures individuals' belief in their control over their lives through self-motivation or self-determination, while the Rosenberg Self-Esteem Scale assesses the degree of approval or disapproval individuals hold toward themselves.

[35] The skill requirement measurement for occupations has been skipped as this has been introduced in Appendix A.10.

$(0.43, 0.43, 0.12)$ in Guvenen et al. (2020).

B.3 Life-cycle Unemployment Rate in NLSY79

To compute the average unemployment rate, we employ equation (B.3) by dividing the number of unemployed observations by the total number of observations in the labor force within a specific disaggregated group characterized by age group i and education level j.

The first panel of B3 presents the average unemployment rate across different age groups. In general, we observe a decline in the unemployment rate as individuals age, which aligns with the patterns observed in the CPS data. However, there are two noteworthy points that require additional attention. First, the average unemployment rate in the NLSY79 data is lower than that in the CPS data. Second, we observe a noticeable increase in the unemployment rate within the 45-54 age group, followed by a subsequent recovery in the 55-64 age group. This finding is reasonable considering that respondents were in the 45-54 age group during the Great Recession. Consequently, it is expected that this specific age group experienced a surge in the unemployment rate, reflecting the specific cohort effect.

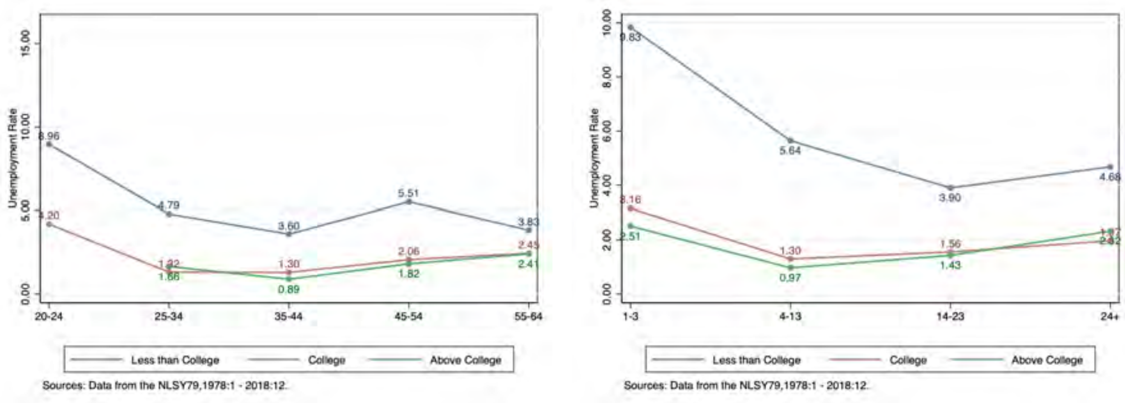
Additionally, the bottom panels of Table B3 and Figure B1 present the average unemployment rate across different age-education groups. Consistent with the patterns observed in the CPS data, we find that the unemployment rate decreases as individuals age or progress through potential experience for each specific education level. Importantly, we also observe that having less than a college degree is associated with a higher average unemployment rate at each stage of the career.

$$u_{ij} = \frac{N(U_{ij})}{N(U_{ij}) + N(E_{ij})}. \tag{B.3}$$

Table B3: Average Unemployment Rate

	20-24	25-34	35-44	45-54	55-64
Overall					
Average (%)	8.53	3.94	2.88	4.37	3.37
Normalized	1.95	0.90	0.66	1	0.77
By education					
Less than College (%)	8.96	4.79	3.60	5.51	3.83
Bachelors (%)	4.20	1.32	1.30	2.06	2.45
Above Bachelors (%)	-	1.66	0.89	1.82	2.41
Differences					
Less than College - Bachelors (PP)	4.76	3.47	2.30	3.45	1.38
Less than College - Above Bachelors (PP)	-	2.71	2.60	3.69	3.10

Notes: Data from NLSY79, 1979:1-2018:12. In the last panel, PP references to percentage points.



(a) Age

(b) Potential Experience

Figure B1: Life-cycle Unemployment Rates

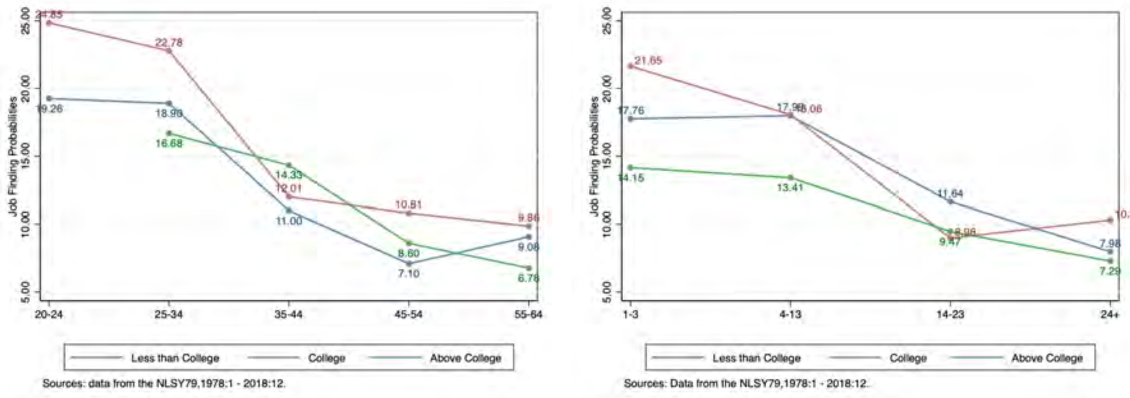
B.4 Life-cycle Job Finding and Separation Probabilities

To delve into the factors contributing to the disparities in the unemployment rates across age-education groups, we employ equation (B.4) to compute the probabilities of transitioning into or out of unemployment:

$$JFP^{ij} = \sum_t \omega_t^{ij} \frac{N(UE)_t^{ij}}{N(U)_t^{ij}} \times 100, \qquad JSP^{ij} = \sum_t \omega_t^{ij} \frac{N(EU)_t^{ij}}{N(E)_t^{ij}} \times 100. \tag{B.4}$$

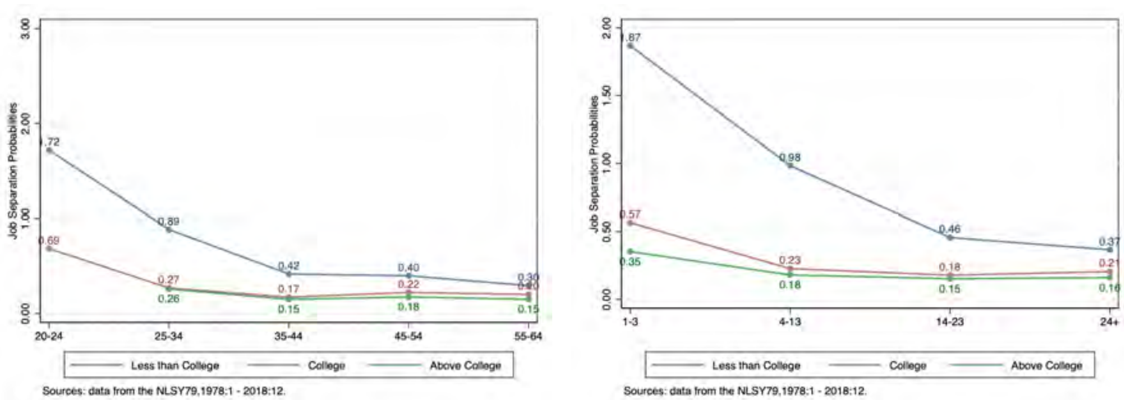
Here, ω_t^{ij} denotes the weight assigned to observations in calendar month t within a specific age group i and education level j where the panel weights are employed to count the number of observations, as they estimate how many individuals in the United States each respondent's answers represent.

Figures B2 and B3 present the transition probabilities in the NLSY79 sample. Concerning the job finding probabilities, there is no systematic difference among education groups that could explain the lower unemployment rate among those with more than a Bachelors degree. However, consistent with the patterns observed in the CPS data, individuals with higher levels of education tend to exhibit systematically lower job separation probabilities.



(a) Age (b) Potential Experience

Figure B2: Job Finding Probabilities



(a) Age (b) Potential Experience

Figure B3: Job Separation Probabilities

B.5 Firm, Occupation, Complex, and Career Switches

To gain insight into the employment stability experienced by individuals with different education levels, we examine the average number of cumulative transitions experience up until a specific career stage, categorized by age or potential experience. This computation involved a two-step process. First, within each subgroup disaggregated by education level and either age or potential experience, we calculate the average number of employer/occupation/complex/career switches by dividing the number of observed switches by the number of individuals within the respective subgroup. Second, we compute the cumulative average transitions by aggregating the average transitions across all subgroups that precede the given career stage.[36] These results are presented in Tables B4 and B5, with the first (second) table representing the average number of transitions over age (potential experience).[37] Notably, individuals tend to accumulate more transitions as they age or increase their potential experience. More importantly, individuals with higher educational attainment tend to experience fewer switches across all transition types at any career stage. One result of note is that workers with less than a college degree undergo an average of nearly three career transitions over their life-cycle, whereas workers with a Bachelors degree accumulate nearly half as many career transitions while workers with above a Bachelors degree, on average, experience less than one career transition over their career.

[36]The computation of the number of unique employers an individual has worked at is done differently. Initially, we preserve all employment observations belonging to a specific education group until a particular age bin or potential experience bin. Subsequently, we count the number of unique employers up to a particular career stage, alongside the number of distinct respondents observed. Finally, the average count of unique employers for a specific subgroup is derived by calculating the ratio between these two quantities. Notably, the average number of unique employers in each subgroup is lower than 1 plus the average number of employer transitions, which suggests that workers move back and forth among the same employers.

[37]Appendix Tables B6 and B7 present the average number of transitions, as well as the average number of unique employers by filtering the data to only include individuals who appear in all career stages. In particular, 1481/222/192 workers with less than a bachelor's degree, a bachelor's degree or above a bachelor's degree appear in all age bins, while 2291/348/217 workers with less than a bachelor's degree, a bachelor's degree or above a bachelor's degree appear show in all bins of potential experience.

Table B4: The Average Number of Transitions over Age

	$20-24$	≤ 34	≤ 44	≤ 54	≤ 64
Average Employer Transitions					
Less than College	2.61	5.93	7.82	8.94	9.24
Bachelors	1.00	3.41	4.96	6.03	6.37
Above Bachelors	-	1.85	3.06	4.16	4.55
Average Number of Unique Employers					
Less than College	3.34	5.95	6.99	7.59	7.72
Bachelors	1.97	3.86	4.78	5.30	5.44
Above Bachelors	-	2.75	3.30	3.82	4.00
Average Occupation Transitions					
Less than College	2.74	6.76	8.66	9.63	9.88
Bachelors	1.30	5.44	7.36	8.42	8.73
Above Bachelors	-	2.75	4.09	5.06	5.39
Average Complex Transitions					
Less than College	1.18	2.66	3.61	4.21	4.37
Bachelors	0.44	1.49	2.18	2.70	2.89
Above Bachelors	-	0.76	1.25	1.76	1.97
Average Career Transitions					
Less than College	0.88	1.96	2.39	2.64	2.71
Bachelors	0.25	0.97	1.22	1.36	1.40
Above Bachelors	-	0.40	0.51	0.59	0.64

Notes: Data from NLSY79, 1979:1-2018:12.

Table B5: The Average Number of Transitions over Potential Experience

	$1-3$	≤ 13	≤ 23	$24+$
Average Employer Transitions				
Less than College	1.66	5.56	7.60	9.06
Bachelors	1.28	3.41	4.64	5.84
Above Bachelors	0.88	2.52	3.51	4.25
Average Number of Unique Employers				
Less than College	2.61	5.98	7.35	8.18
Bachelors	2.20	4.01	4.83	5.44
Above Bachelors	1.82	3.15	3.72	4.00
Average Occupation Transitions				
Less than College	1.58	6.23	8.31	9.56
Bachelors	1.69	5.26	6.81	7.92
Above Bachelors	1.27	3.29	4.21	4.89
Average Complex Transitions				
Less than College	0.70	2.49	3.49	4.25
Bachelors	0.59	1.48	2.08	2.66
Above Bachelors	0.43	1.05	1.46	1.86
Average Career Transitions				
Less than College	0.51	1.79	2.31	2.63
Bachelors	0.33	0.91	1.10	1.25
Above Bachelors	0.20	0.41	0.51	0.59

Notes: Data from NLSY79, 1979:1-2018:12.

Table B6: The Average Number of Transitions over Age (Restrictive Sample)

	$20-24$	≤ 34	≤ 44	≤ 54	≤ 64
Average Employer Transitions					
Less than College	2.60	6.67	8.72	9.91	10.20
Bachelors	0.94	3.56	5.20	6.45	6.79
Above Bachelors	-	1.96	3.27	4.46	4.77
Average Number of Unique Employers					
Less than College	3.33	6.92	8.75	9.82	10.08
Bachelors	1.88	4.19	5.67	6.68	6.95
Above Bachelors	-	2.83	4.05	5.04	5.30
Average Occupation Transitions					
Less than College	2.75	7.83	9.94	11.00	11.23
Bachelors	1.37	6.57	8.64	9.78	10.08
Above Bachelors	-	3.28	4.76	5.82	6.09
Average Complex Transitions					
Less than College	1.16	2.98	4.00	4.64	4.78
Bachelors	0.42	1.52	2.23	2.81	3.00
Above Bachelors	-	0.85	1.33	1.91	2.07
Average Career Transitions					
Less than College	0.91	2.29	2.79	3.07	3.14
Bachelors	0.27	1.21	1.51	1.69	1.73
Above Bachelors	-	0.49	0.64	0.74	0.77

Notes: Data from NLSY79, 1979:1-2018:12.

Table B7: The Average Number of Transitions over Potential Experience (Restrictive Sample)

	$1-3$	≤ 13	≤ 23	24+
Average Employer Transitions				
Less than College	1.82	6.18	8.43	9.89
Bachelors	1.39	3.83	5.25	6.45
Above Bachelors	1.04	3.02	4.18	4.92
Average Number of Unique Employers				
Less than College	2.72	6.61	8.61	9.92
Bachelors	2.27	4.44	5.72	6.72
Above Bachelors	1.97	3.76	4.77	5.38
Average Occupation Transitions				
Less than College	1.79	7.13	9.43	10.69
Bachelors	1.90	6.12	7.86	8.97
Above Bachelors	1.62	4.34	5.40	6.08
Average Complex Transitions				
Less than College	0.78	2.77	3.87	4.63
Bachelors	0.64	1.63	2.31	2.88
Above Bachelors	0.52	1.28	1.74	2.13
Average Career Transitions				
Less than College	0.58	2.04	2.61	2.93
Bachelors	0.37	1.09	1.30	1.45
Above Bachelors	0.31	0.63	0.75	0.84

Notes: Data from NLSY79, 1979:1-2018:12.

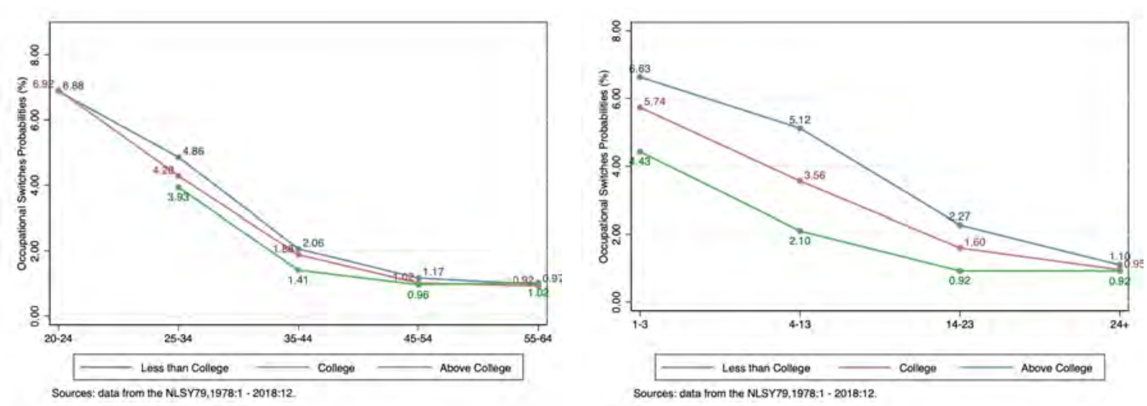
B.6 Occupation and Complex Switching Probabilities in the NLSY79

We compute the average probability of an occupational or complex transition occurring within each subgroup, disaggregated by education and age or education and potential experience. This probability is computed by dividing the number of transitions by the number of monthly observations within each subgroup, taking into account the weight of *PANELWEIGHT*.

B.6.1 Occupational Switches

Occupational switches are defined as changes in the occupational code between two consecutive months within the 1990dd classification. When examining occupational transitions for any two consecutive months, we take into account two key points. First, our analysis is limited to pairs of consecutive months when valid occupational codes are available. If the occupational code is missing or unknown for the preceding month, we do not determine whether a transition occurred or not for the consecutive months. Second, if the preceding month indicates non-employment, we identify the occupation that precedes the period of non-employment.

Figure B4 presents the proportion of occupational switches across different age groups or potential experience. It is evident that the probabilities of occupational switches decline as individuals age or progress through potential experience. Furthermore, the proportion of occupational transitions is lower in more advanced education groups, which aligns with the observed pattern in the CPS data.

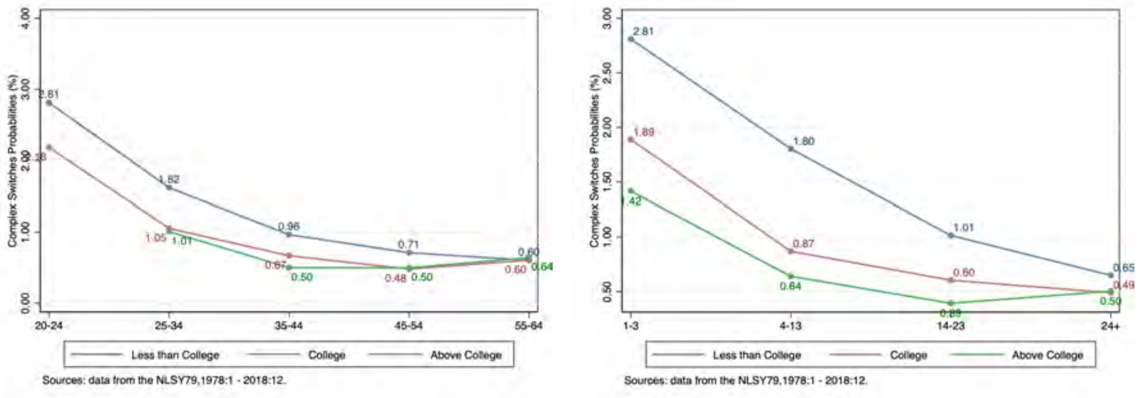


(a) Age (b) Potential Experience

Figure B4: Occupational Transitions

B.6.2 Complex Switches

Figure B5 illustrates the pattern of complex transitions (which follows the same definition as in the CPS) across different age groups or potential experience. Similar to the pattern observed in occupational transitions, the proportion of complex transitions declines as individuals age or progress through potential experience. Additionally, it is evident that workers with lower levels of education are more prone to conduct complex transitions.



(a) Age

(b) Potential Experience

Figure B5: Complex Transitions

B.7 Average Skill Distance and Career Mobility

In this section, we analyze the average skill distance between current and most recent preceding jobs, employing both the Euclidean and angular distance measures. The computation of these skill distances is contingent upon switching behaviors. In particular, we examine the average skill distance in occupational and complex switches over the life-cycle. Figures B6 and B7 contain the results.

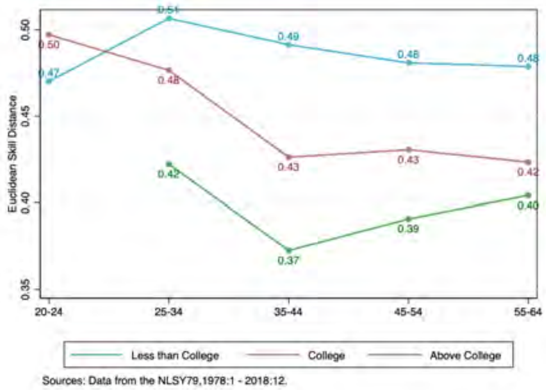
Consistent with the trends observed in the CPS data, our analysis reveals that higher educational attainment is associated with lower skill distances in both Euclidean and angular skill distance at each career stage, encompassing age and potential experience. This finding holds for both occupational and complex transitions. This observed pattern implies that, conditional on the occurrence of mobility, those with higher levels of education are more inclined to transition into jobs that are more similar to their previous job in terms of skill requirements.

To corroborate the observed pattern of average skill distance in job transitions, we employ regressions that account for various observable characteristics and job features that could potentially influence individuals' working profiles and labor market decisions. The coefficients obtained from these regressions are visually represented in Figure B8. It should be noted that, in the unconditional calculation, individuals with a college education display higher Euclidean distances in occupation and complex transitions compared to those with less than a college education during the early stages of their careers. However, except for the Euclidean distance in complex transitions, the conditional patterns confirm that higher levels of education are associated with lower Euclidean and angular distances.[38]

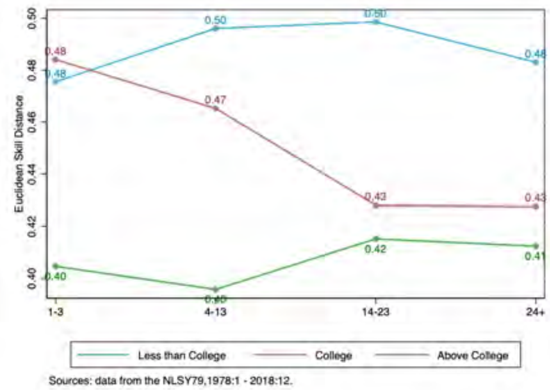
B.7.1 Career Transitions

In this section, we aim to uncover the pattern of career transitions using the NLSY79 panel data. Initially, it is necessary to establish a threshold, denoted as $\bar{\phi}$, that delineates career transitions. To determine this threshold, we examine a set of $37,084$ occupational transitions, where multidimensional skill requirements are available for both the current and previous occupations. Specifically, we identify $\bar{\phi}$ to be 22.7500 as

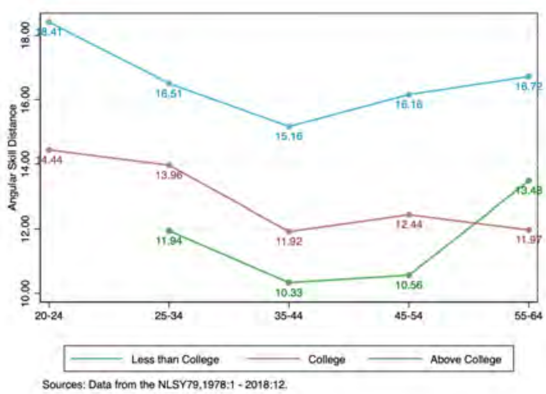
[38]Specifically, when compared to individuals without a college education, college graduates initially experience a higher Euclidean distance of approximately 0.0300 in complex transitions. However, this distance exhibits a statistically significant decrease of 0.0038 for an additional potential working year.



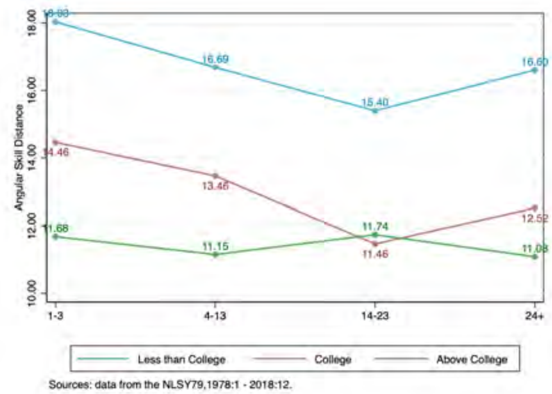
(a) Euclidean Distance over Age



(b) Euclidean Distance over Potential Experience



(c) Angular Distance over Age



(d) Angular Distance over Potential Experience

Figure B6: Average Skill Distances in Occupational Transitions

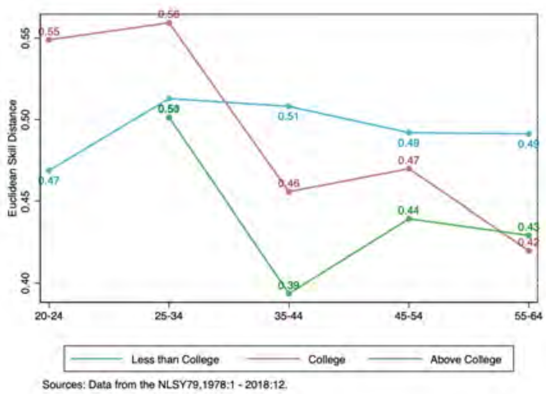
that ensures that the unweighted average correlation of multidimensional skill requirements ($k \in v, m, s$) is approximately 0.0001 for career moves, where career switches are identified as occupational transitions characterized by an angular skill distance larger than the threshold $\bar{\phi}$.

The pattern of career transitions is presented in Figure B9. Consistent with the observed trends in other types of transitions, the proportion of career switches exhibits a declining trend as individuals progress in age or potential experience. Notably, the analysis reveals that individuals with higher education are less likely to engage in career switches compared to their counterparts with lower levels of education.

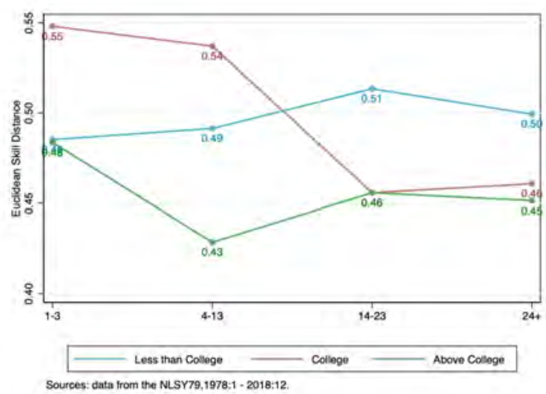
B.8 Skill Mismatch

The NLSY79 allows us to ascertain the multidimensional aptitudes of workers, enabling the measurement of skill mismatch, that quantifies the magnitude of the discrepancy between workers' abilities and the occupational requirements of their jobs.[39] After obtaining the skill mismatch for each worker-job pair,

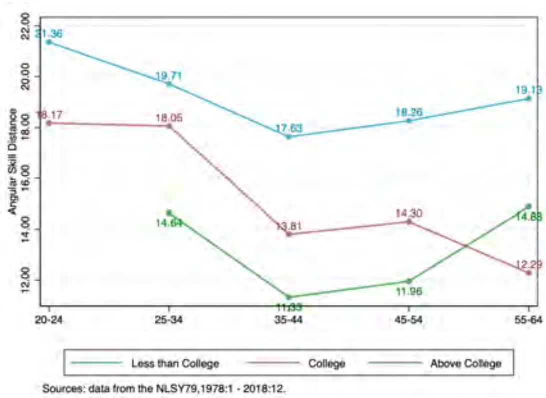
[39] The skill mismatch between individual i and the occupation o along skill-aptitude j is detailed in Appendix B.2.5.



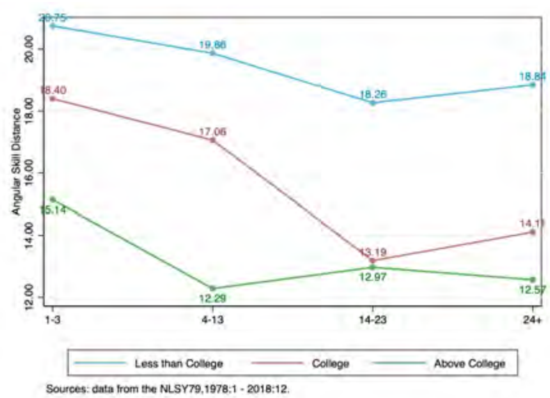
(a) Euclidean Distance over Age



(b) Euclidean Distance over Potential Experience

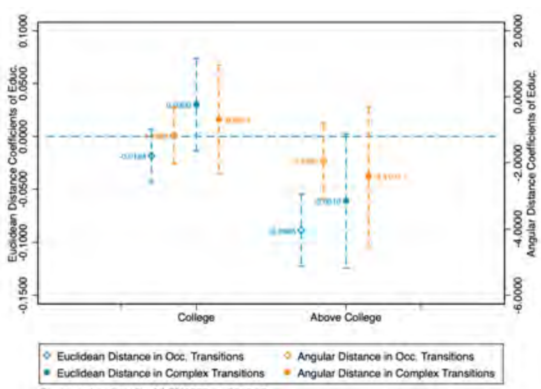


(c) Angular Distance over Age

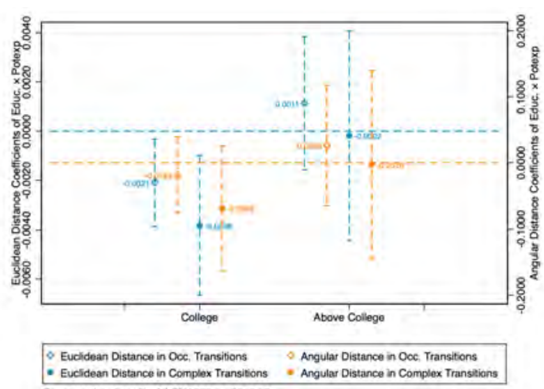


(d) Angular Distance over Potential Experience

Figure B7: Average Skill Distances in Complex Transitions



(a) Coefficients of Edu

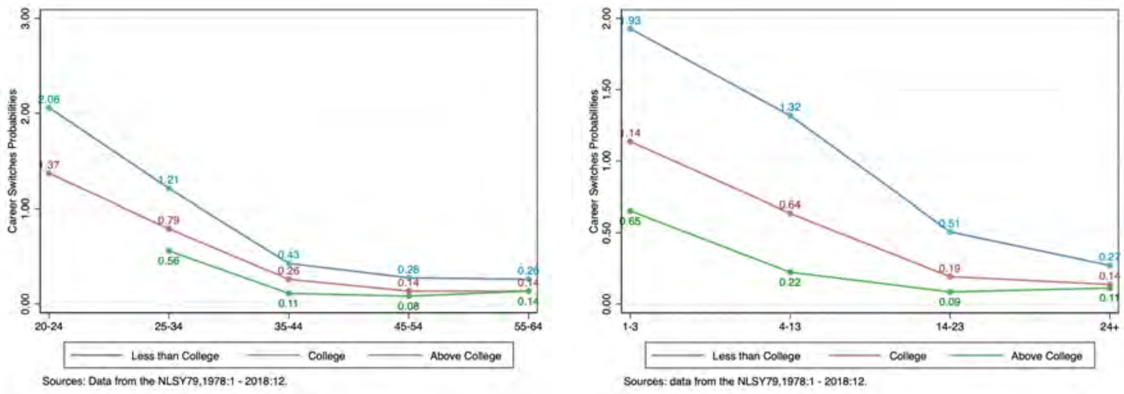


(b) Coefficients of $Edu \times Potexp$

Figure B8: Skill Distance in Regressions

MM_k, we proceed to compute the average skill mismatch within specific age and education groups, $\overline{MM}_{i,j}$:

$$\overline{MM}_{i,j} = \frac{\sum_{k \in i \cap j} MM_k \times \omega_k}{\sum_k \mathbb{1}\{k \in i \cap j\} \times \omega_k}. \tag{B.5}$$



(a) Age

(b) Potential Experience

Figure B9: Career Switches

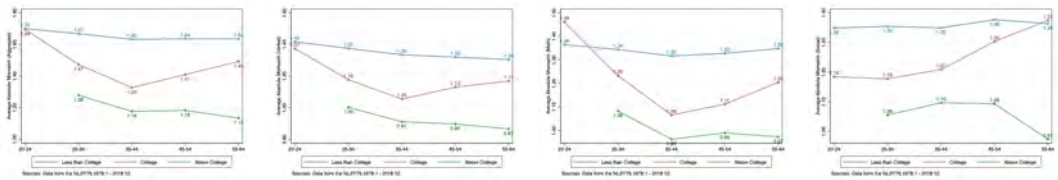
As indicated by equation (B.5), the average value of the aggregate skill mismatch for each education-age group can be calculated through the following steps. First, we sum up the aggregate mismatch within the subgroup of education i and age j, taking into account the technical weight ω_k, which estimates the representation of the respondent within the US population. Second, we count the number of observations with valid skill mismatch magnitudes within the subgroup of education i and age j. Finally, we compute the ratio between the two sums to get the average skill mismatch. In the same vein, we can compute the average mismatch along each dimension by replacing the aggregate mismatch with the absolute mismatch at each skill dimension.

The first and second row of Figure B10 illustrates the average skill mismatch over age and potential experience, respectively. There are two notable patterns. First, individuals with higher educational attainment demonstrate a greater likelihood of being employed in occupations that closely align with their aptitudes, leading to a reduced magnitude of skill mismatch. Second, the aggregate skill mismatch generally declines as individuals progress through their career. However, it is important to note an exception to this trend in the later stages of the career for college-educated workers. This anomaly may be attributed to the cohort effect stemming from the impact of the Great Recession.

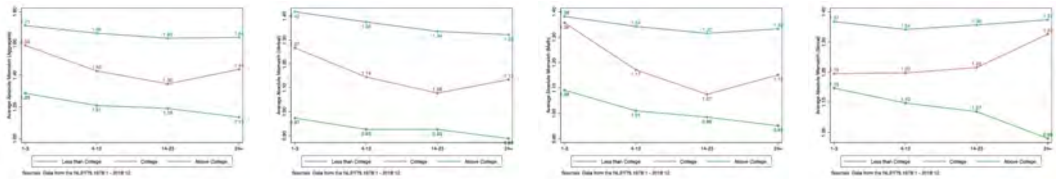
B.9 Dispersion in Skill Requirements

In this section, we compare the dispersion in skill requirements within an occupation across age/potential experience and educational attainment. The idea is the following: occupations with a higher dispersion in skill requirements have a high skill requirement in one dimension relative to the others. Another way to think of this is that occupations with no dispersion in their skill requirements have equal skill requirements across all three skill dimensions. If a worker is more certain about their ability and/or fit with an occupation, they may be more willing to work in a job with a relatively imbalanced set of skill requirements as they have greater certainty that they can perform the set of tasks that are tied to the high skill requirement. Workers with less certainty about their ability may be inclined to take jobs with equal skill requirements across each dimension because, if it turns out they do not have high enough skills in one dimension, they may be able to make up for it with their skills in the other two dimensions.

We begin by examining the distribution of multidimensional skill requirements. Figure 11(a) illus-



(a) Aggregate (b) Verbal (c) Math (d) Social



(e) Aggregate (f) Verbal (g) Math (h) Social

Figure B10: Average Skill Mismatch

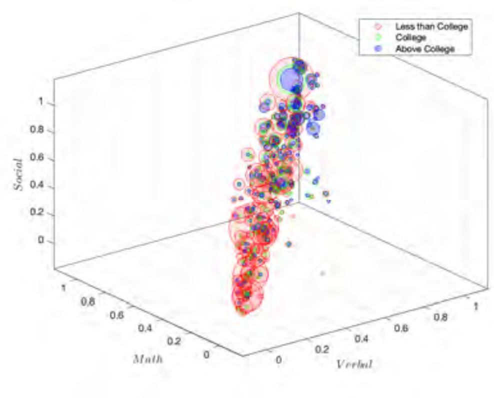
trates the skill requirement distribution for 316/247/199 distinct occupations within workers with less than college/college/above college, respectively. Each observed occupation is represented by a circle, with red/green/blue circles representing workers with less than college/college/above college education. The size of each circle corresponds to the number of monthly observations for that occupation. Notably, workers with higher levels of education tend to be employed in occupations with higher skill requirements along all three dimensions.

The remaining three plots in Figure B11 show the distribution of within-occupation variance of skill requirements for each level of educational attainment. In particular, the color represents the within-occupation variance, while the circle size represents the number of monthly observations for each occupation. Notably, workers with higher education tend to be employed in occupations with darker circles, suggesting a larger dispersion in skill requirements in their jobs.

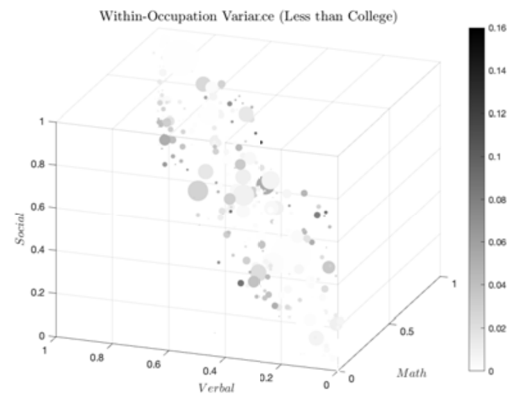
To understand the disparity of skill dispersion across occupations and education levels, we turn to several indicators that capture within-occupation skill variation: variance, max-min difference, mean absolute deviation, and median absolute deviation.[40] Figure B12 presents a comparison of within-occupation variance across different education levels and career stages. The comparison among education levels suggests that more educated workers are engaged in occupations with a higher degree of skill variation.

Furthermore, Figure B12 shows that the dispersion of skills tends to decrease over time. This phenomenon may be attributed to climbing a job ladder. As workers age or accumulate more work experience, they often transition to occupations that require a more balanced set of skills across different dimensions. This transition could be driven by the evolution of skills during one's career or promotions. To illustrate this pattern, consider the example of a worker who graduates with a computer science major. Initially, upon entering the labor market after graduation, the worker is likely to search for and be employed in a technical job that with a high math skill requirement, while not placing much emphasis on social or verbal skills. However, as the worker ages or gains more seniority, she is more likely to transition to a managerial

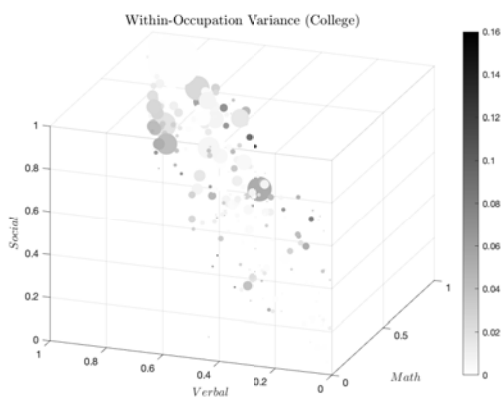
[40] In particular, the mathematical expression for variance, max-min difference, mean absolute deviation, and median absolute deviation in occupation i are: $\sigma_i^2 = \frac{\sum_j (r_{i,j}-\mu_i)^2}{3}$, $mm_i = max(r_{i,j}) - min(r_{i,j})$, $MeanDev_i = \frac{|\sum_j (r_j - \mu_i)|}{3}$, and $MedianDev_i = \frac{|\sum_j (r_{i,j} - Median_i)|}{3}$, where $r_{i,j}$ denotes the skill requirement along skill j by job i , and μ_i ($Median_i$) denote the mean (median) value of the skill requirement in job i.



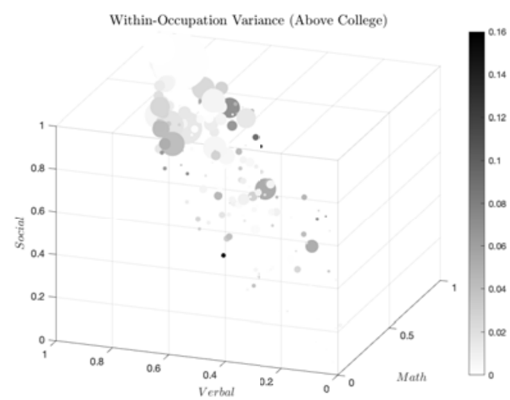
(a) Skill Requirements and Educational Attainment



(b) Less than College



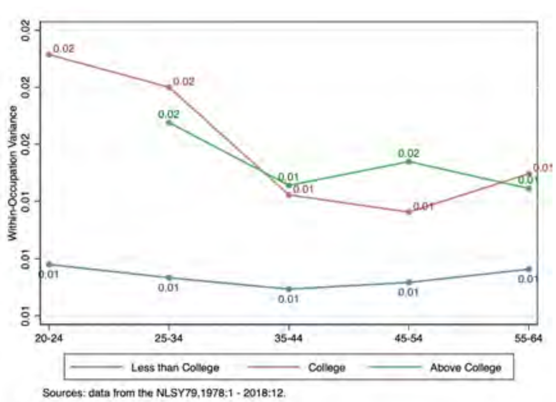
(c) Bachelor



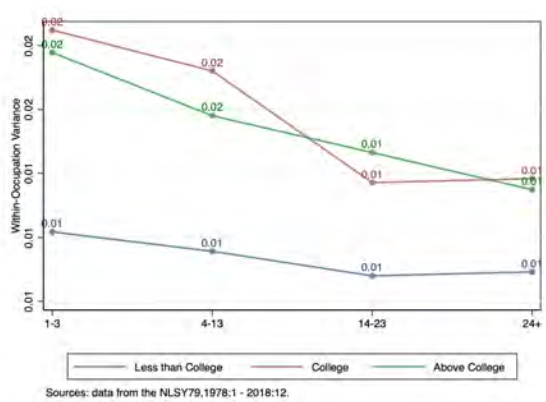
(d) Above Bachelor

Figure B11: Distribution of Skill Dispersion

role that necessitates a well-rounded mix of skills.[41]



(a) Age



(b) Potential Experience

Figure B12: Comparison of Within-Occupation Variance

[41] For comparisons using other dispersion measurements, see Appendix Figure B15.

B.10 Robustness of NLSY79 results

This section provides further validation for the stylized facts regarding the employment stability of higher-educated workers in the NLSY79. To be specific, more-educated workers tend to experience lower rates of job separation and exhibit lower propensities to switch jobs or career paths. Moreover, when such transitions do occur, higher-educated workers are more likely to transition to jobs that exhibit higher similarity to their previous jobs. While these patterns emerge in the unconditional patterns in the NLSY79, it is essential to consider the potential impacts of demographic, job-related, spatial, and macroeconomic factors on workers' employment outcomes, otherwise they might introduce biases to the observed patterns in unconditional computation. To address this concern, we estimate regressions of the following form:

$$\begin{aligned} Y_{i,t} =& \beta_0 EduCat_i + \beta_1 Potexp_{i,t} + \beta_2 Potexp_{i,t}^2 + \beta_3 EduCat_i * Potexp_{i,t} + \beta_4 Race_i \\ &+ \beta_5 MarStatus_{i,t} + \beta_6 Child_{i,t} + \Phi_{Year} + \Phi_{Region} + \Phi_{Occ1990} + \Phi_{Ind1990} + \epsilon_{i,t}. \end{aligned} \tag{B.6}$$

The dependent variable $Y_{i,t}$ can take on different forms. In particular, it indicates that in period t, the worker i: (i) is unemployed or not; (ii) transitions from unemployment to employment or not; (iii) transitions from employment to unemployment or not; (iv) transitions to a different occupation or not; (v) goes through a complex transition or not; (vi) goes through a career transition or not; or (vii) the magnitude of skill mismatch. Our primary variable of interest is the education category of worker i, denoted as $EduCat_i$, which is a categorical variable taking on the values of 1, 2, or 3 to represent workers with less than a college education, exactly a college education, or above a college education, respectively. The coefficient of educational category, β_0, captures the effect of a higher education on a specific event captured by $y_{i,t}$, while the coefficient of $EduCat_i * Potexp_{i,t}$, β_3, indicates how the effect of education varies over years of potential experience.

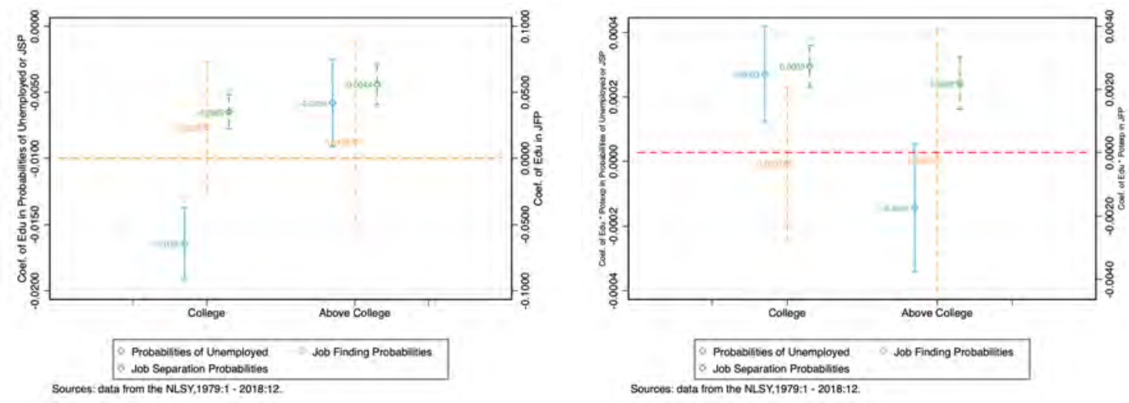
To control for factors that may affect workers' employment profiles and outcomes, we incorporate various demographic and job characteristics. These include a quadratic term representing presumed years of potential experience from the modal graduation, race, marital status, and whether the worker has children. Additionally, we account for job-specific characteristics by introducing fixed effects for occupation and industry. Furthermore, we incorporate fixed effects for year and region to control for time-varying and spatial differences in the overall economy.[42]

To enhance clarity and facilitate comparisons across different education levels, we have created scatter plots that illustrate the coefficients of interest along with the interval representing three (robust) standard deviations around the point estimate for the variables $EduCat$ and $EduCat_i * Potexp_{i,t}$. Overall, the estimated employment stability for different education groups aligns with the patterns observed in the previous graphs.

Figure B13 presents the estimated coefficients for the probabilities of unemployment and transition probabilities into and out of unemployment. Starting with the probabilities of unemployment, the blue rhombus indicates that individuals with a college (above college) degree exhibit significantly lower unemployment probabilities, with a reduction of approximately 1.7(0.60) percentage points compared to their counterparts with less than a college education. Moving on to the probabilities of transitioning into and out of unemployment separately, the green rhombus in Figure suggests that individuals with a college degree (or above) have significantly lower job separation probabilities, with a decrease of nearly 0.65 (0.44)

[42] For the unemployed observations lacking industry and occupation codes, we adopt an imputation approach wherein we assume these missing codes to correspond to the industry and occupation codes recorded in their most recent prior job.

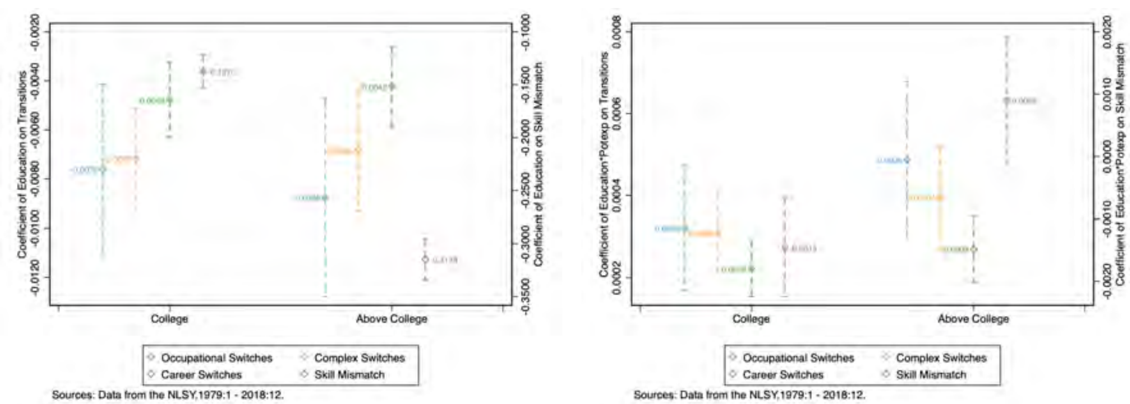
percentage points compared to those with less than a college degree. Additionally, the negative effect of education on job separation diminishes by 0.03% (0.02%) for one more potential working year. Conversely, the impact of education on job finding probabilities, as indicated by the orange rhombus, is found to be insignificant.



(a) Coefficients of *Education* (b) Coefficients of *Education* × *Potexp*

Figure B13: Unemployment, Job Finding, and Job Separation Probabilities

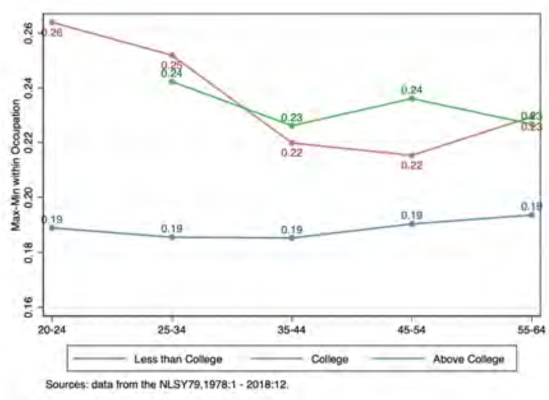
We then proceed to examine the employment dynamics within different education groups, with consideration for various demographic, job, and economic factors. Figure B14 demonstrates a consistent pattern where individuals with higher levels of education exhibit lower probabilities of occupational transitions, including occupation switches, complex switches, and career switches. Moreover, individuals with higher education levels are associated with lower levels of skill mismatch.



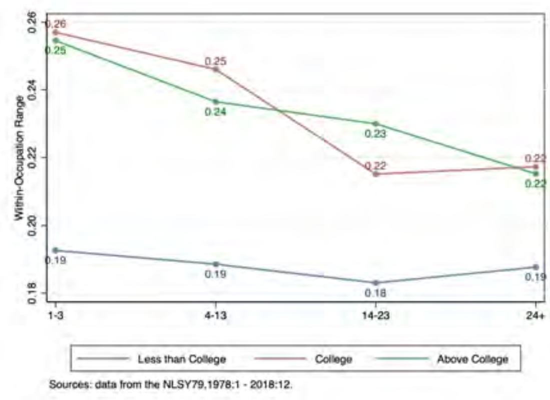
(a) Coefficients of *Education* (b) Coefficients of *Education* × *Potexp*

Figure B14: Transition Probabilities and Skill Mismatch

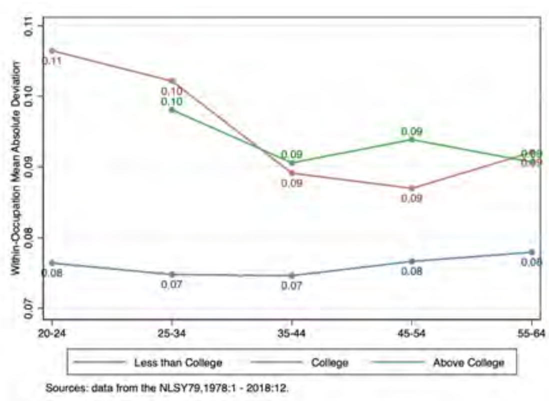
B.11 Comparison of Skill Dispersion Measures



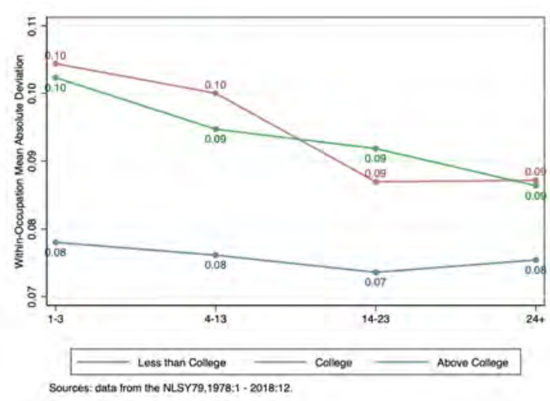
(a) Max-Min Difference Over Age



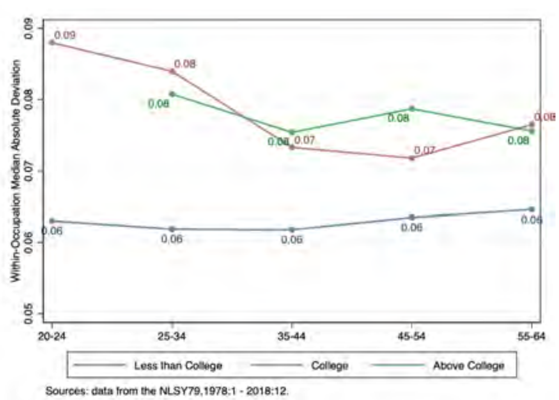
(b) Max-Min Difference Over Potential Experience



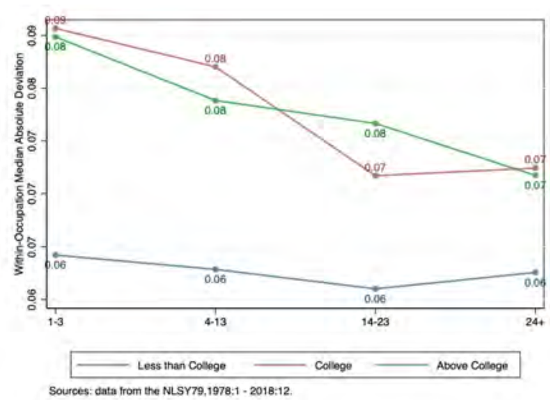
(c) Mean Absolute Deviation Over Age



(d) Mean Absolute Deviation Over Potential Experience



(e) Median Absolute Deviation Over Age



(f) Median Absolute Deviation Over Potential Experience

Figure B15: Comparison of Skill Dispersion

B.12 Prior Experience and Match Survival Regressions

Our specification follows that of Bover et al. (2002). To gauge the effect of prior working experience on the survival probability, we use the logistic model and estimate it by maximum likelihood.

$$\begin{aligned}\text{SurvivalDummy}_{it} = &\sum_{n=2}^{120} \mathbb{1}(\text{MatchTenure}_{it} = n) + \beta_1 \text{PriorExp}_{it} + \beta_2 \log(\text{MatchTenure}_{it}) \times \text{PriorExp}_{it} \\ &+ \beta_3 \text{PriorExp}_{it} \times i.\text{AboveCol}_i + \beta_4 \log(\text{MatchTenure}_{it}) \times i.\text{AboveCol}_i + i.\text{AboveCol}_i \\ &+ \beta_5 \log(\text{MatchTenure}_{it}) \times + i.\text{White}_i + i.\text{Year}_t + i.\text{Season}_t + \beta_6 \text{Age}_{it} + i.\text{Ind}_{it} + \epsilon_{it},\end{aligned}$$

where the dependent variable, $\text{SurvivalDummy}_{it}$, is a dummy variable indicating if the current match survives into the subsequent period. Instead of imposing a predetermined functional form, we flexibly capture the duration dependence of survival probability by introducing an additive dummy variable corresponding to each monthly duration. The primary explanatory variables include the accumulated working experience prior to the formation of the match at period t by worker i (PriorExp_{it}), its interaction with the logarithm tenure in the current match as of t ($\log(\text{MatchTenure}_{it}) \times \text{PriorExp}_{it}$), and its interaction with education attainment level ($\text{PriorExp}_{it} \times i.\text{AboveCol}_i$).[43] In addition, we control for race, age, business cycle indicator (yearly and seasonally fixed effects), and industrial fixed effect. Notably, the effect of prior working experience on survival probability is captured by $\beta_1 + \beta_2 \log(\text{MatchTenure}_{it}) + \beta_3 \text{AboveCol}_i$.

As shown in Tables B8 and B9, a longer prior actual working experience is associated with higher survival probability, that is captured by the statistically significant positive coefficient β_1. Nevertheless, the effect of prior working experience dissipates over the individual's tenure with their current employer, suggesting the gap of survival probability between groups disaggregated by the duration of prior-working-experience narrows over the time matched with the current employer. Last, $\beta_3 < 0$ suggests the effect of prior working experience is smaller for the more-educated workers with college degree or above. In other words, the discrepancy in survival probabilities across groups defined by the length of prior work experience narrows more markedly within the more-educated group. All econometric findings from the maximum likelihood estimation are consistent with trends displayed in Figure 10.

[43] The explanatory variable PriorExp_{it} could be either a binary variable indicating if the prior working experience is longer than 76 months (the median prior working experience among $1,108,438$ employment observations) or a continuous measure of prior working experience in months.

Table B8: Estimate of Logistic Survival Probability (w/ Binary Variable)

	(1)	(2)	(3)
1.Prior Exp. Group	0.36951***	-0.00552	0.24086***
1.College and Above		0.67832***	0.61545***
Log(Dur) * 1.Prior Exp. Group	-0.04777***	-0.01959***	-0.07857***
1.Prior Exp. Group * 1.College and Above		-0.14019***	-0.10555***
Log(Dur) * 1.College and Above		-0.08805***	-0.10186***
Log(Dur) * 1.White		0.16051***	0.08525***
1.White		-0.37528***	-0.18377***
Age		0.01893***	0.00997***
Constant	3.86697***	3.07297***	3.59580***
Year FE		✓	✓
Season FE		✓	✓
1990dd Industry FE			✓
Observations	1,108,438	1,108,438	1,058,790
Log likelihood	-163,152.31	-157,879	-137,050.31

Notes: All specifications include the additive dummy variable for each duration. The second and third specifications additionally include the interaction between $Log(Dur)$ and $collegeandAbove$, and $White$. *($p < 0.10$), **($p < 0.05$), ***($p < 0.01$).

Table B9: Estimate of Logistic Survival Probability (w/ Continuous Prior Experience in Months)

	(1)	(2)	(3)
Prior Exp. in Months	0.00244***	0.00033**	0.00197***
1.College and Above		0.71528***	0.65703***
Log(Dur) * Prior Exp. in Months	-0.00048***	-0.00025***	-0.00056***
Prior Exp. in Months * 1.College and Above		-0.00101***	-0.00089***
Log(Dur) * 1.College and Above		-0.09267***	-0.10255***
Log(Dur) * 1.White		0.16603***	0.09461***
1.White		-0.38848***	-0.21247***
Age		0.01950***	0.00864***
Constant	3.91965***	3.07967***	3.67255***
Year FE		✓	✓
Season FE		✓	✓
1990dd Industry FE			✓
Observations	1,108,438	1,108,438	1,058,790
Log likelihood	-163,168.28	-157,847.25	-137,001.58

Notes: All specifications include the additive dummy variable for each duration. The second and third specifications additionally include the interaction between $Log(Dur)$ and $collegeandAbove$, and $White$. *($p < 0.10$), **($p < 0.05$), ***($p < 0.01$).

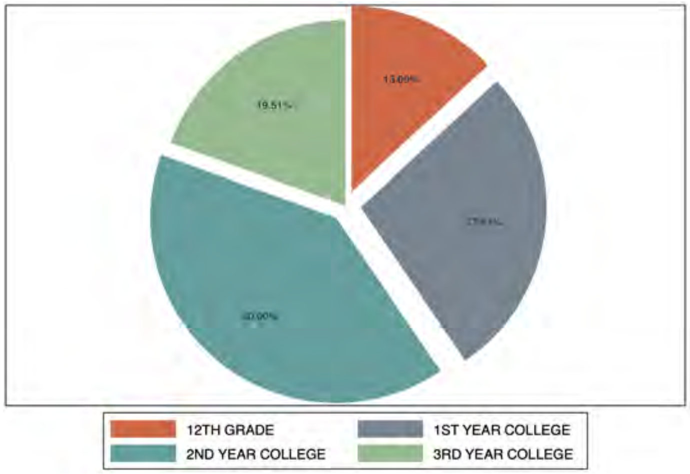


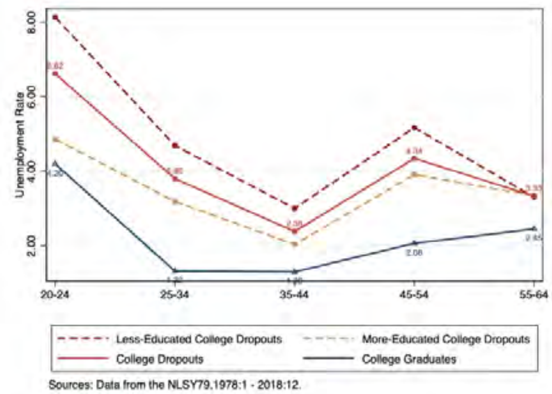
Figure B16: Years of Schooling Completed Among College Dropouts

B.13 College Dropouts

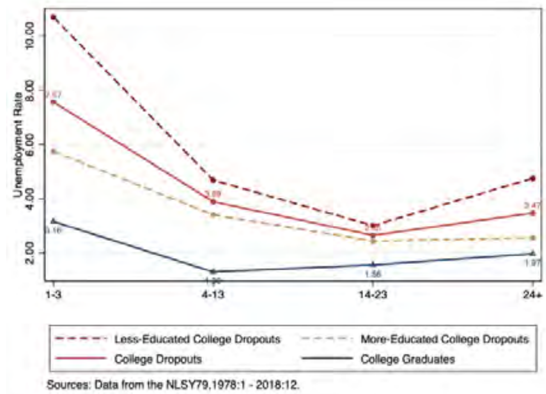
In this section, we present life-cycle patterns of unemployment, job finding, separation, and mobility for college dropouts in the NLSY79. We begin by first describing how we identify college dropouts. First, we identify individuals who were, at any time, enrolled full-time at college using the school enrollment status and college status indicators. Second, we use the highest degree to identify individuals who had ever obtained a Bachelors degree or above. Third, we use the highest grade to correct for the individual's highest degree. That is, if the individual had completed at least their fourth year of college, they are marked to have obtained a Bachelors degree or above even if that was not indicated by the highest degree. Fourth, we identify college dropouts as those individuals who had ever enrolled full-time in college but did not obtain a Bachelors degree or above. Through these steps, we identify 810 college dropouts and 595 college graduates in our sample, which gives a 57.65% college dropout rate. This dropout rate is similar to the 54% reported in Vardishvili (2023).

The NLSY79 reports the reason a respondent drops out of school (including college). To identify the dropout reason, we first identify the earliest survey year in which the individual enrolled in college and then focus on the dropout reasons reported in the earliest college enrollment year. Out of the 810 college dropouts, 15 respondents indicate "lack of ability, poor grades" and 4 respondents report "expelled or suspended" as their reason for dropping out.

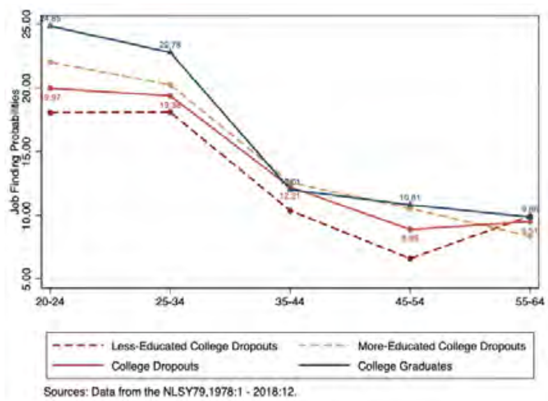
Figure B16 shows the distribution of years of completed schooling among the college dropouts and shows that a vast majority (80.4%) have completed two years or less of college. In what follows, we regroup college dropouts into two groups: (i) less-educated college dropouts (those who have completed less than two years of college) and (ii) more-educated college dropouts (those who have completed at least two years of college). Figure B17 presents the unemployment rate, job finding probability, and job separation probability over the life-cycle for college graduates and dropouts. From panels (a) and (b), we see that college dropouts are more likely to be unemployed than graduates and that, within the group of dropouts, more years of completed schooling is associated with a lower unemployment rate. Panels (c) and (d) show that the effect of completed years of college on the job finding probability is more nuanced while panels (e) and (f) show that the separation probability is, at each stage of the career, monotonically decreasing in years of college completed.



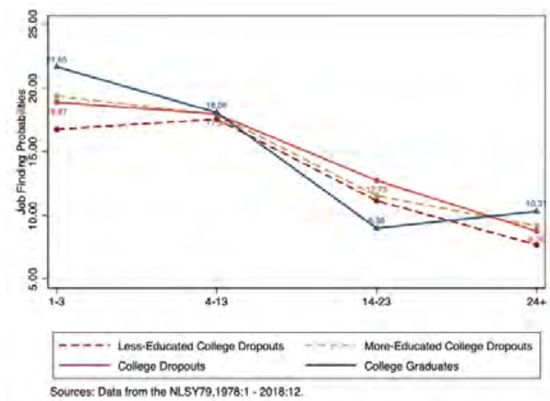
(a) Unemployment rate: Age



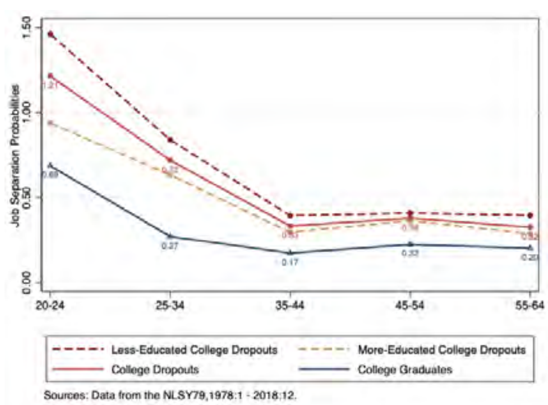
(b) Unemployment rate: Potential Experience



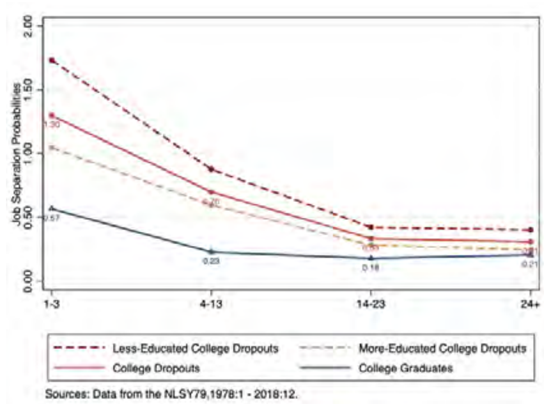
(c) Job Finding Probability: Age



(d) Job Finding Probability: Potential Experience



(e) Job Separation Probability: Age

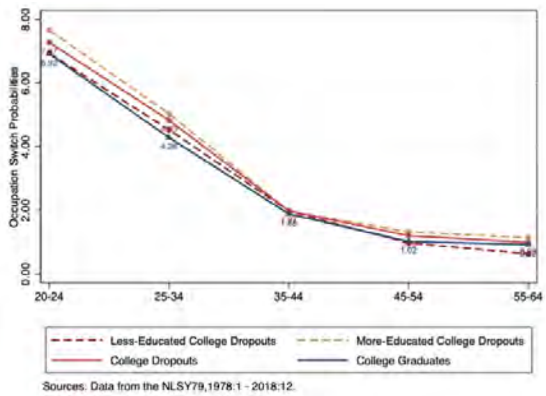


(f) Job Separation Probability: Potential Experience

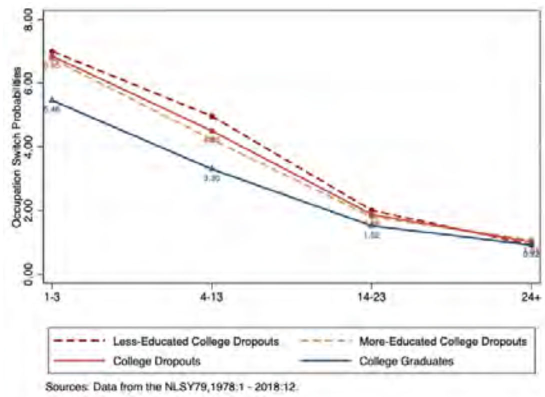
Figure B17: Life-Cycle Unemployment and Transition Probabilities among College Dropouts and Graduates

Next, Figure B18 compares the rates of occupational and complex mobility rates between college dropouts and graduates. Panel (a) shows that, at the disaggregated 3-digit level, there are minor differences in the occupational mobility rates among college dropouts and graduates.[44] Panel (b) shows that there is a wider

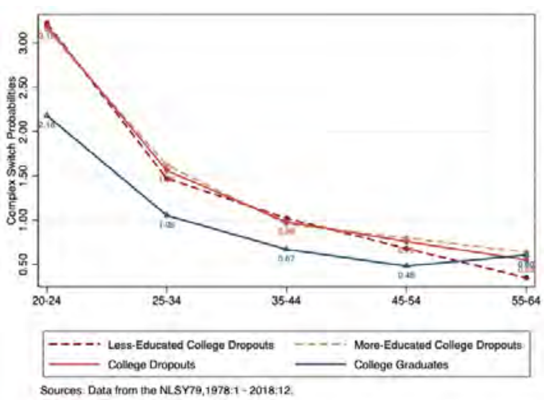
[44]If we examine the mobility rates at the broader 1- and 2-digit levels, the gap in occupational mobility rates between dropouts and



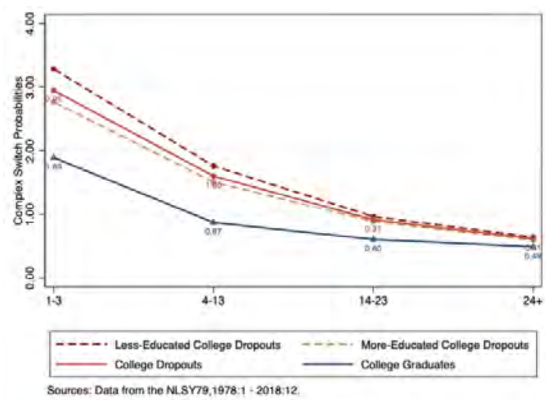
(a) Occupational Mobility: Age



(b) Occupational Mobility: Potential Experience



(c) Complex Mobility: Age



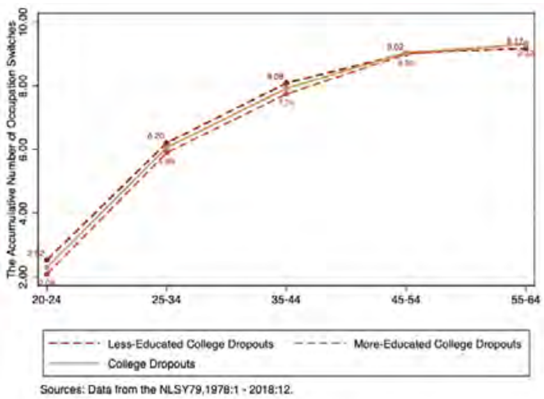
(d) Complex Mobility: Potential Experience

Figure B18: Life-Cycle Occupational and Complex Mobility Rates among College Dropouts and Graduates

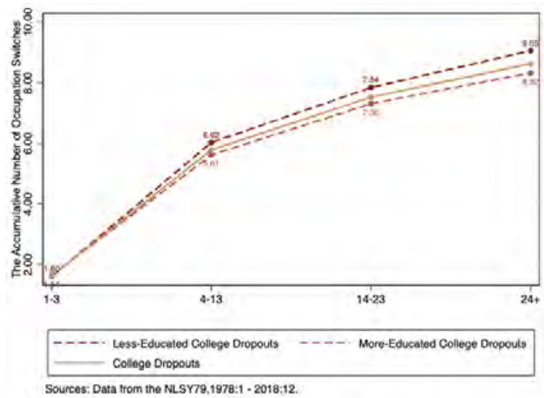
gap in occupational mobility rates, particularly early in the career, when comparing mobility rates across years of potential experience. Panels (c) and (d) show that there is a wider gap in complex mobility rates between dropouts and graduates. However, there is very little difference in complex mobility rates within the group of college dropouts.

Finally, Figure B19 presents the accumulated occupation, complex, and career changes among college dropouts. We can see that, even within the group of college dropouts, the number of accumulated transitions is decreasing in educational attainment. Moreover, as seen by comparing to Tables B4 and B5, college graduates accumulate less occupation, complex, and career transitions at each age and level of potential experience.

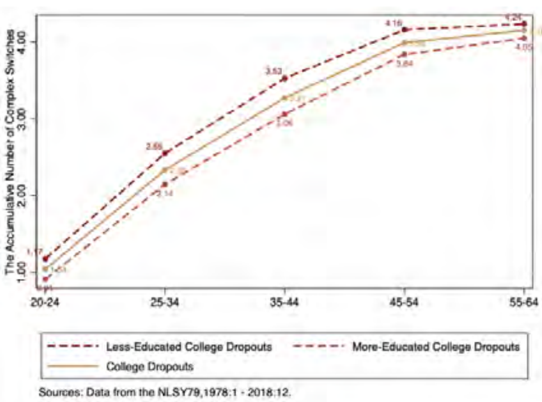
graduates widens. Results are available upon request.



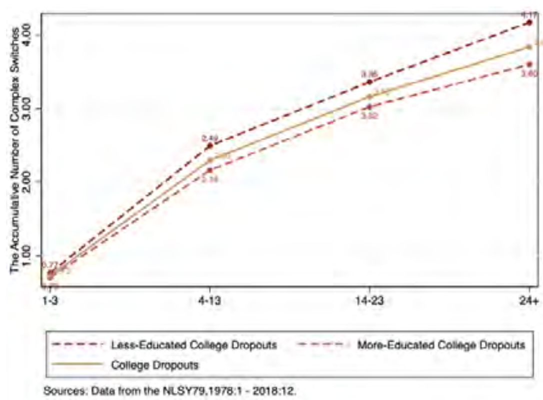
(a) Occupation Switches: Age



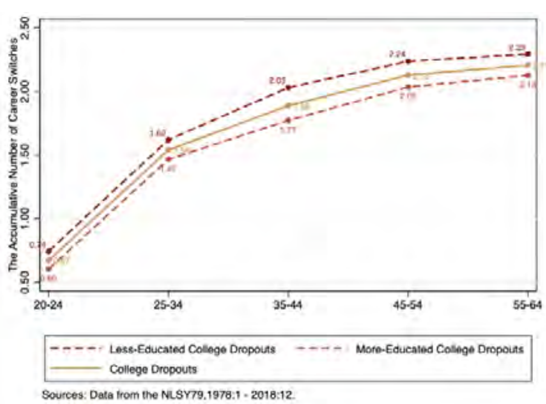
(b) Occupation Switches: Potential Experience



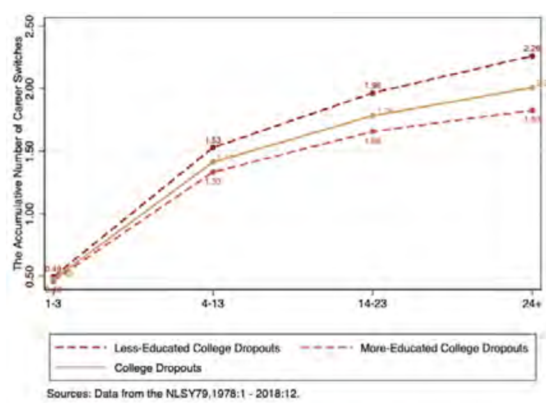
(c) Complex Switches: Age



(d) Complex Switches: Potential Experience



(e) Career Switches: Age



(f) Career Switches: Potential Experience

Figure B19: Accumulated Occupation, Complex, and Career changes among College Dropouts

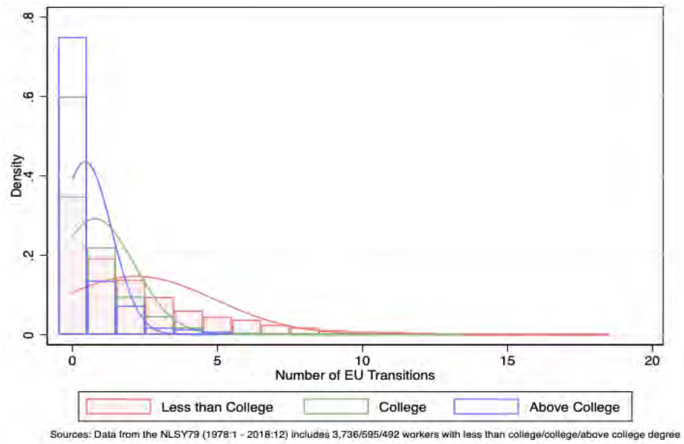


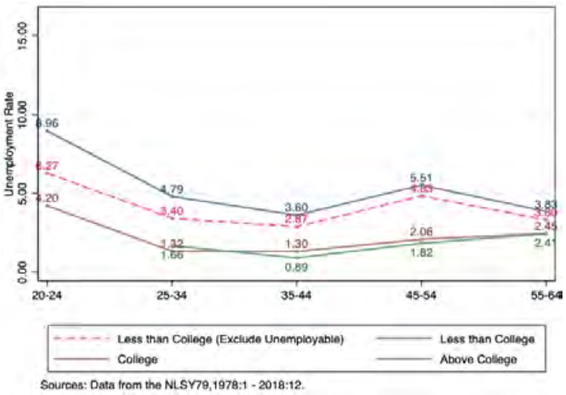
Figure B20: Distribution of EU transitions in the First 10 Years of Potential Experience

B.14 Unemployable Workers

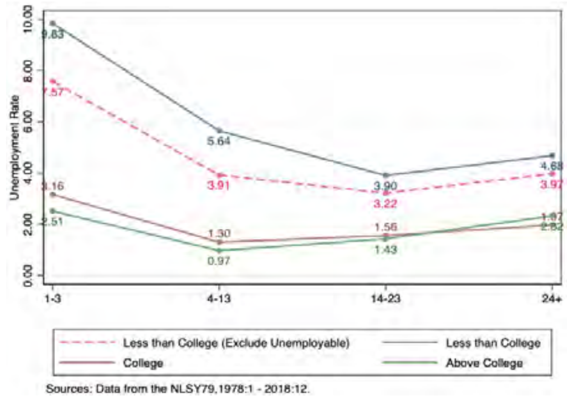
In this section, we leverage the NLSY79 to identify what we call "unemployable" workers with less than a college degree, i.e., workers who experience many separations from employment to unemployment. To identify the group of unemployable workers, we first count the number of transitions from employment to unemployment in a worker's first ten years of potential experience among workers with less than a Bachelors degree, a Bachelors degree, and above a Bachelors degree. As seen in Figure B20, which plots the distribution of EU transitions within each level of educational attainment, the distribution of EU transitions shifts to the left as the level of educational attainment increases. However, we can see that there does not appear to be a significant proportion of workers with less than a college degree who experience a very high number of EU transitions.

We then define unemployable workers as those whose number of EU transitions within the first ten years of their career is at or exceeds the 90th percentile of the number of EU transitions among workers with less than a college degree in their first ten years potential experience. This corresponds to four EU transitions. Therefore, a worker with less than a college degree is defined to be unemployable if they experience four or more EU transitions within their first ten years of potential experience.

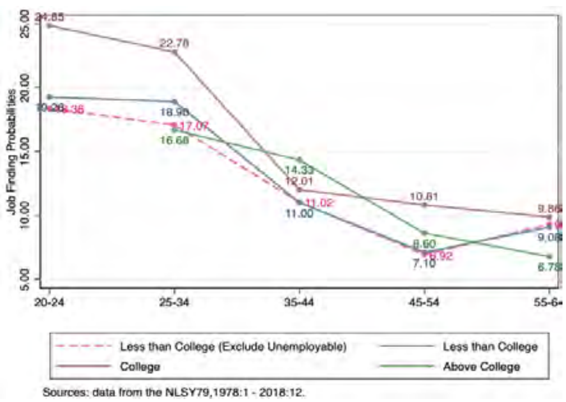
Figure B21 compares the life-cycle patterns in unemployment, job finding probability, and separation probability across levels of educational attainment. The difference from our main analysis is that we also include the patterns for the less than college group when excluding the identified group of unemployable workers. Removing the unemployables shifts down the life-cycle unemployment and separation probabilities. Moreover, excluding the unemployables makes little difference in the job finding probability.



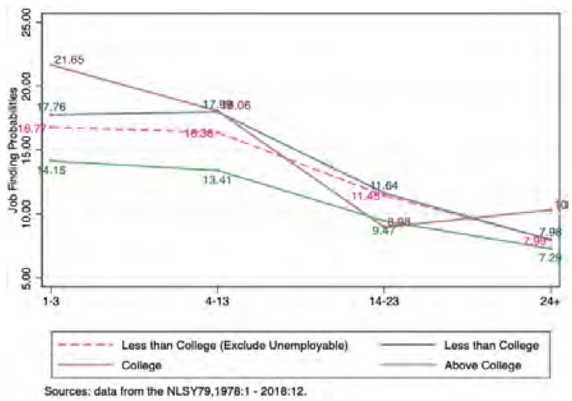
(a) Unemployment: Age



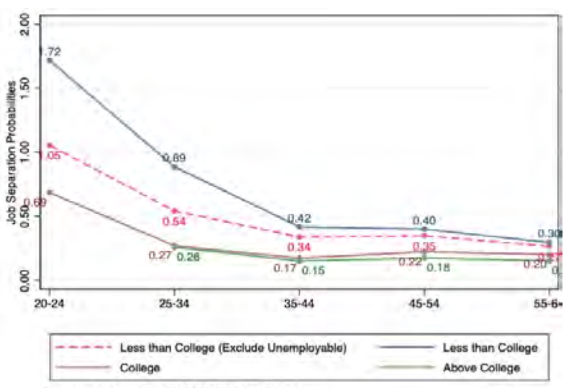
(b) Unemployment: Potential Experience



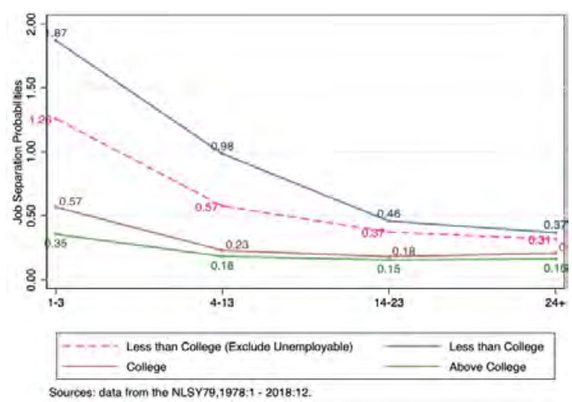
(c) Job Finding Probability: Age



(d) Job Finding Probability: Potential Experience



(e) Separation Probability: Age



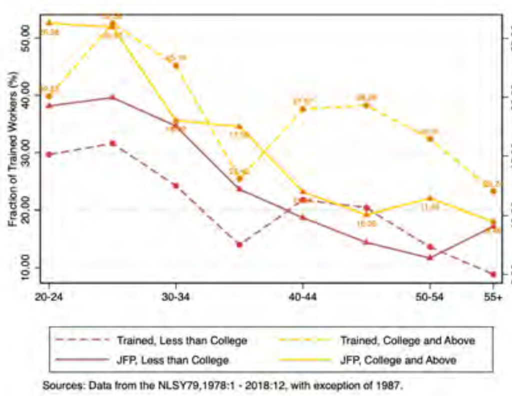
(f) Separation Probability: Potential Experience

Figure B21: Life-Cycle Patterns Excluding Unemployable Workers

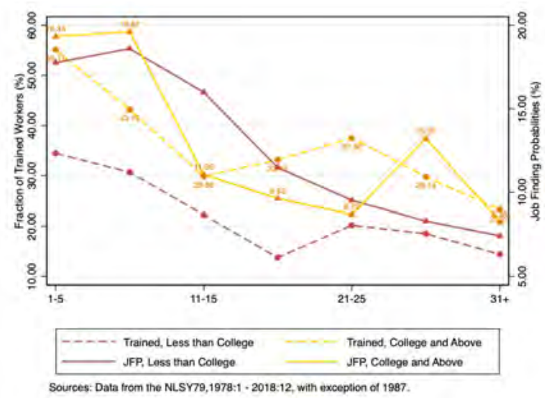
B.15 Training

This section analyzes several features of the training data available in the NLSY79. We begin by studying the proportion of respondents who reported participating in any training/vocational program between their current and previous interview. This question was asked of each respondent in the survey years 1979-2018, except for 1987. Based on the responses to this question, we construct the proportion of individuals within an education-age/potential experience bin who report having participated in a training program since their last interview.

Figure B22 shows the proportion of respondents in each education and age/potential experience bin who reported participating in any training/vocational program since their last survey interview. We also display the job-finding probabilities for each education and age/potential experience bin. Panel (a) reveals two patterns. First, workers with a Bachelors degree or above are more likely to participate in a training program. Second, participation in training programs is generally decreasing in age/potential experience. We can also see, from panel (a), that college graduates are more likely to participate in training programs during stages of the life-cycle where they also experience a higher job finding probability.



(a) Training and Job Finding: Age



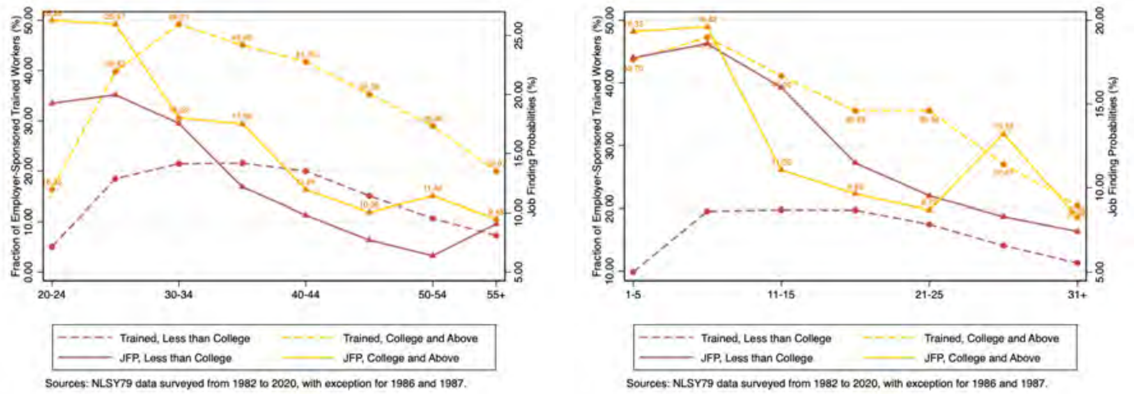
(b) Training and Job Finding: Potential Experience

Figure B22: Participation in Training and Job Finding over the Life-cycle

Relatedly, Figure B23 reports the fraction of workers in each education-age/potential experience bin who were enrolled in an employed-financed vocational/technical training program since their last interview.[45] Figures B23 shows that participation in employed financed training programs is hump-shaped over the life-cycle and is generally decreasing in potential experience. From panel (a), we see that college graduates are still more likely to participate in employed sponsored training programs for ages where they exhibit a higher job finding probability.

Next, we draw upon a supplementary set of training data collected by the NLSY79 for the survey year 1993. In 1993, respondents who were enrolled in an employer sponsored training program since their last interview were asked questions about the transferability of skills acquired in the training program. That is, respondents were asked about the amount of skills learned in each training program that they thought would be useful for (i) doing the same job, but for a different employer and (ii) doing a different job, but for the same employer. Panel (a) of Figure B24 reports the responses to "Useful in Doing Different Work

[45]The NLSY79 defines a training program to be employed-financed if (i) the vocational/technical program's costs were covered by the employer in survey years 1982 through 2000, except for 1986 and 1987) or (ii) the employer has ever paid for any portion or the entire training cost (applicable to survey years 2002 through 2020).



(a) Employer Provided Training and Job Finding: Age

(b) Employer Provided Training and Job Finding: Potential Experience

Figure B23: Participation in Employer Provided Training and Job Finding over the Life-cycle

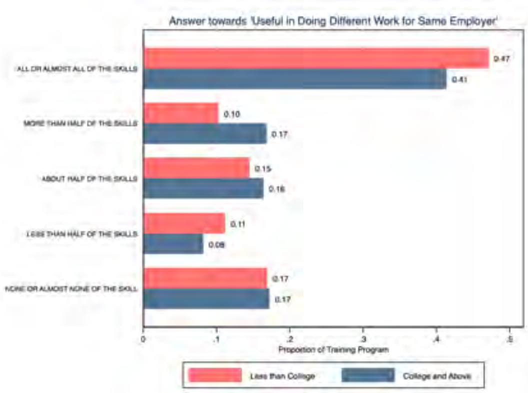
for Same Employer" among the training programs that our final sample had participated in since their last interview date in 1993. We can see that only 17% report that none or almost of the skills would be transferable to doing different work for the same employer. Moreover, 73% report that at least half of the skills would be useful in doing different work for the same employer. Panel (b) shows a similar set of responses to the question "Useful in Doing Same Work, Different Employer". Here, we find that 86.6% of respondents indicate that at least half of the skills acquired in an employer sponsored training program would be useful in doing the same work at a different employer.

(a) Different Work for the Same Employer

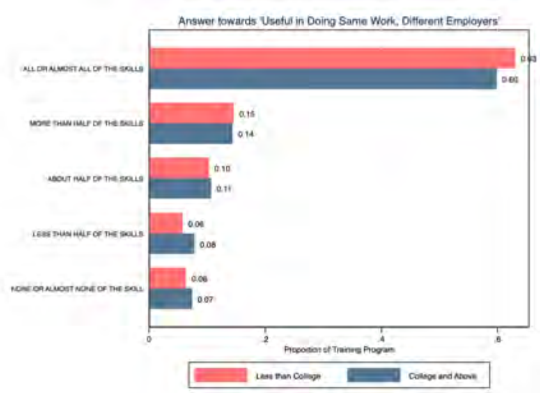
(b) Same Work at a Different Employer

Figure B24: Transferability of Skills Acquired through Training

Finally, Figure B25 shows that there is little difference in the responses across educational attainment regarding the transferability of skills acquired through employer sponsored training.



(a) Different Work for the Same Employer



(b) Same Work at a Different Employer

Figure B25: Transferability of Skills Acquired through Training by Education

C Theory Appendix

C.1 Simple Model with Match-Specific Productivity

In this section, we write a model with endogenous job creation and job destruction with match-specific productivity shocks. Section C.1.1 presents the environment while C.1.2 walks through the equilibrium and shows that the model can produce an unemployment-education gap that is driven by both a higher job finding and lower separation rate among highly educated workers.

C.1.1 Environment

Time is discrete and continues forever. There is a measure one of workers and a large measure of homogenous firms. Workers are endowed with an indivisible unit of labor. All agents are risk neutral and share the discount factor $\beta \in (0,1)$. Each firm corresponds to one job that is either filled or vacant.

Workers are ex-ante heterogeneous in their educational attainment $e \in \{0,1\}$ where $e = 1$ ($e = 0$) denotes a worker with (less than) a college degree. A worker's educational attainment is fixed and is public information. A measure $\pi_0 \in [0,1]$ of workers are endowed with $e = 0$ and $\pi_1 = 1 - \pi_0$ with $e = 1$.

Firms operate a technology that maps one unit of labor into $y_e z$ units of output where $y_1 > y_0$ and is common to all matches with a worker with educational attainment e while z is specific to the worker-firm match. The value of the match-specific productivity lies in the set $Z = \{z_0, z_1, \ldots, z_N\}$ where $N \geq 2$ and $N \in \mathbb{Z}$.

Upon meeting, the worker and firm draw their match-specific productivity z_i with probability f_i where $\sum_{i=0}^{N} f_i = 1$ and $\sum_{i=0}^{N} f_i z_i = 1$. However, z is only observed after the match is formed. That is, matches are experience goods. Moreover, the match-specific productivity is fixed upon the formation of the match.

The labor market is organized in a continuum of submarkets indexed by $\omega = (e,x) \in \{0,1\} \times \mathbb{R}$. In submarket ω, firms search for workers with education e and offer contracts which deliver x in lifetime utility to the worker.

At the beginning of each period, the state of the economy can be summarized by the distribution of workers across types and employment states. The state of the economy is given by $\psi \equiv \{u_e, n_e, g_e\}$ where $u_e \in [0, \pi_e]$ is the measure of type-e workers who are unemployed, $n_e \in [0, \pi_e]$ is the measure of type-e agents who are in a match with unknown productivity, and $g_e : Z \to [0, \pi_e]$ where $g_e(z)$ is the measure of type-e workers who are employed in a match of known productivity z.

Each period is divided into four stages: learning, separation, search and matching, and production. At the learning stage, a worker and firm in a match of unknown productivity learn their match-specific productivity z with probability one.

At the separation stage, a match between a worker with education e and a firm destroy the match with probability $d \in [\delta, 1]$. The separation probability is specified by the employment contract and the lower bound δ represents separations which occur due to exogenous reasons. A worker who loses their job in the separation stage must wait one period before they can search for another job.

In the search and matching stage, firms first decide whether to create a vacancy and, if so, which submarket to post it in. Workers choose which submarket to search in. Firms incur a cost $k > 0$ to open and maintain a vacancy for one period. Workers who begin the period unemployed search with probability one. There is no search on the job.

Next, workers and firms who search in the same market are brought together by a constant returns to scale matching technology. Let $v(\omega)$ denote the measure of vacancies in submarket ω and $u_e(\omega)$ the measure of unemployed workers with educational attainment e searching in submarket ω. The number of matches in a submarket ω is given by the matching function $F(u(\omega), v(\omega))$ where $u(\omega) = u_0(\omega) + u_1(\omega)$. Define $\theta(\omega) = v(\omega)/u(\omega)$ as tightness in submarket ω. The probability that a worker matches with a vacancy is given by $p(\theta(\omega)) = F/u(\omega)$ where $p : \mathbb{R}_+ \to [0,1]$ is twice continuously differentiable, strictly increasing, strictly concave, $p(0) = 0$, and $p(\infty) = 1$. The probability that a vacancy matches with a worker is given by $q(\theta(\omega)) = F/v(\omega)$ where $q : \mathbb{R}_+ \to [0,1]$ is twice continuously differentiable, strictly decreasing, strictly convex, $q(0) = 1$, and $q(\infty) = 0$.

In the production stage, unemployed workers produce b units of output. Matches between a type-e worker and a firm with known productivity z produce $y_e z$ units of output. Finally, matches between a type-e worker and a firm with unknown match quality produce, in expectation, y_e units of output.

The contract space is complete, giving rise to bilaterally efficient employment contracts. Therefore, employment contracts offered by the firm will maximize the joint surplus of the match.

C.1.2 Equilibrium

We focus on stationary equilibria. Moreover, following Menzio and Shi (2011), it is straightforward to show that the equilibrium is block-recursive. Therefore, in what follows, we abstract from including the aggregate state, ψ, as an argument in the value functions.

Consider an unemployed worker with educational attainment e at the production stage. In the current period, they produce output b and search in the next period's search and matching stage. If they search in submarket $\omega = (e, x)$, they find a job with probability $p(\theta(e, x))$ and their continuation value is x, the value of the employment contract. If they don't find a job, their continuation value is the value of unemployment, U_e. It follows that the value of unemployment satisfies:

$$U_e = b + \beta\{U_e + R(x, U_e)\}, \tag{C.1}$$

where

$$R(x, U_e) = \max_x p(\theta(e, x))(x - U_e). \tag{C.2}$$

Now consider a match between a worker with educational attainment e and known match-specific productivity z. In the production stage, the worker and firm produce output $y_e z$. With probability $d \in [\delta, 1]$, the match is destroyed in the next period's separation stage. In this case, the worker's continuation value is U_e and the firm's continuation profit is 0. With probability $1 - d$, the match is not destroyed. In this case, the sum of the worker's utility and the firm's profits are given by the sum of the worker's utility and firm's profits, $V_e(z)$, which satisfies:

$$V_e(z) = y_e z + \max_{d \in [\delta, 1]} \beta\{dU_e + (1 - d)V_e(z)\}. \tag{C.3}$$

Finally, consider a newly formed match between a worker with educational attainment e and unknown match-specific productivity. In the production stage, the expected output of the match is y_e. In the following period, the worker and firm learn their match-specific productivity, after which the match is destroyed with probability $d \in [\delta, 1]$. If the match is destroyed, the worker's continuation utility is U_e while the firm's continuation profit is zero. If the match is not destroyed, the sum of the worker's utility and firm's continuation profit is equal to $V_e(z)$. It follows that the value of a match with unknown productivity, $\tilde{V}_e$, satisfies:

$$\tilde{V}_e = y_e + \max_{d \in [0,1]} \beta \mathbb{E}_z \{ dU_e + (1-d) V_e(z) \}. \tag{C.4}$$

In the search stage, firms decide whether to create a vacancy or not and, if yes, which submarket to post it in. The firm's cost to create a vacancy is k. The firm's benefit to creating a vacancy in submarket $\omega = (e, x)$ is given by $q(\theta(e,x))\{\tilde{V}_e - x\}$ where $q(\theta(e,x))$ is the probability of matching with a worker, $\tilde{V}_e$ is the joint value of a match, and x is the portion of the joint value that the firm delivers to the worker.

In any submarket visited by a positive number of workers, tightness is consistent with the firm's incentives to create vacancies if and only if

$$k \geq q(\theta(e,x))\{\tilde{V}_e - x\}, \tag{C.5}$$

and $\theta(e,x) \geq 0$ with complementary slackness. We restrict attention to equilibria in which $\theta(e,x)$ satisfies the complementary slackness condition in every submarket, even those that are not visited by workers.

We now turn to characterizing the solution to the separation problems. Beginning with a match of known productivity, we have $d \in [\delta, 1]$ determined by the inequality $V_e(z) \lesseqgtr U_e$. If $V_e(z) > U_e$, the value of continuing the match is greater than the value of destroying it, giving $d = \delta$. If $V_e(z) \leq U_e$, the value of destroying the match is greater than the value of maintaining it and hence, $d = 1$. However, if a match with known quality z is still formed after learning z, it must be the case that $V_e(z) > U_e$, $d = \delta$, and $V_e(z)$ satisfies:

$$V_e(z) = \frac{y_e z + \beta \delta U_e}{1 - \beta(1-\delta)}. \tag{C.6}$$

From equation (C.6), we can see that $V_e(z)$ is strictly increasing in z. Thus, there exists a reservation productivity, R_e such that $V_e(z) \leq U_e$ for all $z \leq R_e$ and $V_e(z) > U_e$ for all $z > R_e$.

Our primary objective is to compare the job-finding and separation probabilities by educational attainment. Beginning with the job-finding probability, we can substitute the firm's free entry-condition into (C.2) to reduce the worker's submarket choice to:

$$\max_{\theta} -k\theta + p(\theta)[\tilde{V}_e - U_e]. \tag{C.7}$$

From (C.7), the first order condition is given by

$$k \geq p'(\theta)[\tilde{V}_e - U_e], \tag{C.8}$$

with $\theta \geq 0$ with complementary slackness. Assuming an interior solution, we can see that tightness, and hence the job-finding probability, among type-e workers crucially depends on the size of the surplus generated by a match, $\tilde{V}_e - U_e$. It is straightforward to show that

$$\tilde{V}_e - U_e = \frac{y_e\{[1 + \beta(1-\delta)[\bar{z}_e - 1]] - \beta(1-\delta)R_e[1 - F(R_e)]\}}{1 - \beta(1-\delta)}, \tag{C.9}$$

where $V_e(R_e) = U_e$, $F(R_e) = \sum_i^N f_i \mathbb{I}_{\{z_i \leq R_e\}}$, and $\bar{z}_e = [1 - F(R_e)]^{-1} \sum_{i=0}^N f_i z_i \mathbb{I}_{\{z_i > R_e\}}$. From (C.9), we can easily show that $V_e - U_e$ is increasing in y_e. Hence, in combination with (C.8), we have that $\theta_1 > \theta_0$ and that the job-finding probability is increasing in educational attainment. Intuitively, highly educated workers produce more output and hence generate a higher match surplus which induces firms to post more vacancies in the submarket with type $e = 1$ workers.

Turning to the separation probabilities, we simply need to compare the reservation thresholds R_0 and

R_1. If $R_1 < R_0$, it follows that $F(R_1) < F(R_0)$ and the separation probability is higher among less-educated workers. To show this, we first note that we can write the surplus of a match, $V_e(z) - U_e$, as

$$V_e(z) - U_e = \frac{y_e[z - R_e]}{1 - \beta(1 - \delta)}, \tag{C.10}$$

which makes use of the indifference condition, $V_e(R_e) = U_e$. To show that $R_1 < R_0$, we proceed via proof by contradiction. Suppose that $R_1 > R_0$. This implies that

$$V_0(R_0) - U_0 = 0 > V_1(R_0) - U_1. \tag{C.11}$$

However, it is straightforward to construct an example where $V_1(R_0) - U_1 > 0$. To do so, we look for a $z^* < R_0$ such that $V_1(z^*) - U_1 = V_0(z^*) - U_0$. Such a z^* exists if

$$y_1 = y_0 \frac{z^* - R_0}{z^* - R_1}. \tag{C.12}$$

As $R_1 > R_0$ (by assumption), we have $\frac{z^* - R_0}{z^* - R_1} > 1$, which is consistent with the assumption that $y_1 > y_0$. Hence, there exists a $z^* < R_0$ such that $V_1(z^*) - U_1 = V_0(z^*) - U_0$. As $y_1 > y_0$, it follows that $V_1(z) - U_1 > V_0(z) - U_0$ for all $z > z^*$, including $z = R_0$. This implies that $V_1(R_0) - U_1 > V_0(R_0) - U_0 = 0$, which contradicts equation (C.11). Having arrived at a contradiction, we have $R_1 < R_0$, giving the result that type $e = 1$ workers experience a lower separation probability. The intuition is simple: due to the fact that $y_1 > y_0$, matches with highly educated workers can generate a positive surplus at lower values of the match-specific productivity, z.