Uncertainty, Learning, and the Unemployment-Education Gap Over the Life Cycle[*]

Jie Duan[†]
National University of Singapore

Paul Jackson[‡]
National University of Singapore

October 2024

Abstract

We document that college graduates predict their future occupation more accurately than those without a college degree. Based on this fact and additional evidence, we hypothesize that college graduates start their career with less uncertainty regarding their best fit in the labor market. We refer to this difference by education as the uncertainty channel. To quantify the uncertainty channel, we develop a life cycle search model where workers learn their best fit by sampling careers. A quantitative decomposition places a lower bound on the uncertainty channel's contribution to the gap in unemployment rates between college and non-college workers at 24%.

JEL Classification: E24; J24; J62; J64
Keywords: Unemployment; Education; Learning; Life Cycle

[*]We thank Ismail Baydur, Carlos Carrillo-Tudela, Kevin Devereux, Siddharth George, Aspen Gorry, Benjamin Lester, Francesco Lippi, Chen Liu, Simon Mongey, Xincheng Qiu, Michelle Rendall, Serene Tan, Shu Lin Wee, Donghai Zhang, Lichen Zhang, Shengxing Zhang, and audiences at NUS, PHBS, Monash Macro and Money Workshop, Georgian Economic Association, and Asian and European meetings of the Econometric Society for their insightful comments. The first version of this paper was presented under the title "On the Unemployment-Education Gap."

[†]Department of Economics, National University of Singapore. Blk AS1, #01-02, 1 Arts Link, Singapore 117570. *Email*: duanjie@u.nus.edu.

[‡]Department of Economics, National University of Singapore. Blk AS2, #04-22, 1 Arts Link, Singapore 117570. *Email*: ecspgj@nus.edu.sg.

1 Introduction

The unemployment rate among those with at least a bachelor's degree in the US is 2.7%, whereas it is nearly 7% for workers without a degree.[1] While the unemployment-education gap is well documented, little quantitative research has been done to explain it. This is surprising, as the unemployment rate is one of the most paid attention to measures of labor market performance. Additionally, identifying the sources of the unemployment-education gap has the potential to deepen our understanding of the differences between workers with and without a college degree, why their labor market outcomes are vastly different, and inform policies which aim to reduce unemployment among less-educated workers. With this in mind, this paper's objectives are to (i) propose and provide empirical support for a novel mechanism to explain the unemployment-education gap and (ii) evaluate its quantitative role within a search model of unemployment.

Our hypothesis is that college graduates start their career with a clearer understanding of their best fit in the labor market.[2] As such, they (i) enter the labor market having narrowed down the set of careers that are potentially their best fit and (ii) can quickly decipher whether a career is a good fit or not. We refer to these differences between college and non-college workers as the *uncertainty channel*. The connection between the uncertainty channel and the unemployment-education gap is straightforward. If college workers begin their career with fewer potential best fits, then they are less likely to learn they are not in their best fit and subsequently separate from their job, thereby becoming unemployed. Additionally, a faster learning speed allows college workers to find their best fit earlier in their work-life.

We provide empirical support for the uncertainty channel. Most prominently and directly, we document that college graduates form more accu-

[1]Unemployment rates are derived from the Current Population Survey between 1976-2019 and include workers between 20–59 years old.

[2]Broadly speaking, a career is a set of occupations which share a similar composition of skill requirements. Section 2.3.1 provides a precise definition. We use "true calling", "best fit" and "good fit" interchangeably throughout the paper. The terminology follows Gervais et al. (2016) and refers to the career a worker is most productive in.

rate expectations about their future occupation. Using the National Longitudinal Survey of Youth 1979 (NLSY79), we compare the skill and task requirements of workers' expected and realized occupations. In our preferred measure, the cosine similarity between occupations (Gathmann and Schönberg, 2010; Baley et al., 2022), forecast errors are 32% smaller among college graduates.

Further, we compile an extensive set of evidence from the NLSY79 and Current Population Survey (CPS) which indirectly support the uncertainty channel. There are two main supporting facts. First, the unemployment-education gap narrows over the life cycle. Intuitively, as non-college workers begin with higher uncertainty, they experience more separations early on and slowly catch up to college workers as they sample careers, experience fewer separations, and exhibit lower unemployment rates. This is consistent with how separation and career mobility rates behave by age and educational attainment in the data. Second, prior work experience is associated with a lower separation rate. Moreover, this correlation is stronger for non-college workers. While the former has been documented (e.g., Topel and Ward (1992)), the latter is a new fact that is aligned with the uncertainty channel. If non-college workers rely more on actual work experience to learn their best fit, then prior experience should be associated with a more pronounced decline in separations for workers without a college degree.

Having established empirical support for the uncertainty channel, we proceed to develop a life cycle directed search model with endogenous separations and unemployment. Workers are assigned one best fit, where they are most productive, out of a set of careers. As in Gervais et al. (2016), workers begin their career not knowing their best fit and sample careers to learn which is their true calling. Employed workers learn about their best fit probabilistically. If the worker learns they are not in their best fit, they can destroy the match in favor of becoming unemployed and sampling a different career. Separations and unemployment decrease with age as older workers are more likely to have found their best fit.

Workers are heterogeneous in their educational attainment (college and non-college), which is fixed upon entering the labor market. There are three exogenous differences between college and non-college workers. College workers (i) are more productive in their best fit, (ii) enter the labor market with fewer careers that are potentially their best fit, and (iii) learn about their fit with a higher probability. The second and third differences encompass the uncertainty channel and contribute to the unemployment-education gap, as these differences allow college workers to have fewer separations while they are still searching for their best fit and to find their true calling earlier on. Non-college workers take longer to find their best fit. However, as more of them do, the difference in separation and unemployment rates by education narrows over the life cycle.

We calibrate the model by matching a set of moments from the CPS and NLSY79. The uncertainty channel is pinned down by matching the number of unique careers worked in by education and the shape of the life cycle separation rate profiles. The calibrated model indicates large differences in uncertainty by education. For example, college (non-college) workers enter their labor market with three (eight) careers that are a potential best fit. We validate the model by showing it matches a set of untargeted moments well. For example, the model generates an unemployment-education gap that narrows over the life-cycle and replicates the empirical relationship between experience, separations, and educational attainment.

To decompose the unemployment-education gap, we shut down sources of the gap until all that is left is the uncertainty channel. At that point, 24.45% of the gap remains, which defines the lower bound on the uncertainty channel's contribution. Moreover, our decomposition places an upper bound on the uncertainty channel's contribution at 96.72%. The difference between the lower and upper bound stems from a higher (lower) separation rate when a worker knows that they are not (are) in their best fit.[3] This feature of the model contributes to the unemployment-education gap

[3] We interpret the difference in separations rates as the outcome of an interaction between match-specific productivity shocks and workers producing less output outside their best fit.

because non-college workers are less likely to be in their best fit. As such, they are hit with separation shocks more frequently than college workers.

Finally, the model suggests that there are potentially large benefits to reducing uncertainty among non-college workers. These benefits emerge in the form of lower separations and higher average labor productivity. However, they may not be evenly distributed over the life cycle, as increasing the speed at which non-college workers learn their best fit may increase (lower) separations and unemployment earlier (later) in their careers.

Our paper is related to the literature on the unemployment-education gap. Cairó and Cajner (2018) and Sengul (2017) document that most of the gap is driven by separation rates and develop models where it is more costly to match with a college worker. In Cairó and Cajner (2018), those are training costs while in Sengul (2017), they are screening costs. The additional costs lead to the formation of higher match-specific productivity and lower separations for matches with college workers.[4] While both papers make important advancements, they do not speak to the unemployment-education gap over the life cycle or why separations are decreasing in prior experience. We propose and provide empirical support for the uncertainty channel. We show that the uncertainty channel can not only explain a sizeable portion of the unemployment-education gap, but it is consistent with the evolution of the gap over the life cycle and the relationship between prior experience, separations, and educational attainment.

The uncertainty channel is closely related to work that emphasizes learning about one's best occupational fit. Papageorgiou (2014) and Gorry et al. (2019) show that learning can explain several wage and occupational mobility patterns over the life cycle, but do not emphasize separations, unemployment, or differences by educational attainment. Neal (1999) develops a model that can replicate a declining complex transition rate over the life cycle, but does not focus on unemployment. Wee (2013) shows that recessions

[4]The uncertainty channel and training as in Cairó and Cajner (2018) may complement each other, as firms may be more willing to train workers whom are more likely to be in their true calling.

can disrupt the process of learning about one's ability, thereby generating scarring effects of graduating in a recession. Finally, Gervais et al. (2016) develop a model that can generate declining separation, occupational mobility, and unemployment life cycle profiles. However, their paper does not study these patterns by educational attainment. We build on their work by proposing that college graduates face less uncertainty over their best fit, provide empirical support for this hypothesis, and show by extending the model of Gervais et al. (2016) that differences in uncertainty can account for a sizeable portion of the unemployment-education gap.

Finally, this paper is related to the literature which studies life cycle labor market flows. Menzio et al. (2016) and Cajner et al. (2023) generate separation profiles that decrease over the life cycle in environments where older workers are more likely to have formed a match with high match-specific productivity.[5] Gorry (2016) and Esteban-Pretel and Fujimoto (2014) develop models where experienced workers can identify and reject matches with a low productivity. Both models generate decreasing job finding, separation, and unemployment rate profiles over the life cycle. Our contribution to this literature is to study life cycle separations and unemployment by educational attainment. Further, we emphasize the uncertainty channel, rather than learning about match-specific productivity. Section 4.5 details the relationship between our model and those of match-specific productivity.

The rest of the paper is organized as follows. Section 2 presents our empirical analysis. Section 3 develops a life cycle directed search model. Section 4 conducts the quantitative analysis. Section 5 concludes. The online appendix contains complementary analysis and is referenced throughout.

[5] Chéron et al. (2013) emphasize the effect of retirement on flows over the life cycle while Créchet et al. (2024) analyze how differences in flows by age and gender can explain differences in unemployment rates across European countries.

2 Empirical Analysis

This section presents the empirical analysis which supports the uncertainty channel. Section 2.1 shows that college graduates form more accurate forecasts of their future occupation. Section 2.2 presents the unemployment-education gap over the life cycle and shows that differences in separations account for most of the gap. Section 2.3 discusses additional evidence to support the uncertainty channel. Section 2.4 summarizes further evidence that is left to the appendix. Section 2.5 transitions to the theory.

To begin, we introduce the data used throughout our analysis. The first is the Current Population Survey (CPS), which provides information about the representative civilian, household-based population in the US. We download the monthly CPS files, covering 1976-2019, from IPUMS (Flood et al., 2022). Second is the Occupation Information Network (O*NET), which measures occupational attributes through survey questionnaires covering skills, knowledge, general work activities, and work context. Third is the National Longitudinal Survey of Youth (1979), which tracks the lives of 12,686 individuals born between 1957 and 1964. As the NLSY79 is a panel encompassing respondents' entire careers, it allows us to document several patterns that are not feasible in the CPS.[6] Appendix A.2 details our construction of a monthly panel of 4,823 male respondents that contains information on demographics, education, and employment.[7]

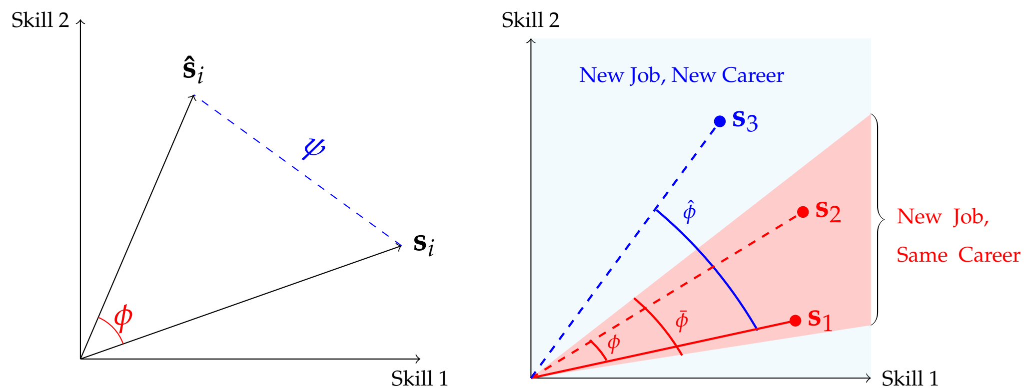
2.1 Expected Occupation

This section measures the accuracy of workers' expectations of their future occupation. To do so, we leverage the NLSY79 where respondents were asked, during their initial interview, what kind of work they would like to be doing when they are 35 years old and in 5 years. Among the 4,823 respondents in our sample, 2,565 (1,620) listed an expected occupation at

[6]We primarily use the CPS due to its larger sample size and that NLSY79 results could be driven by a cohort effect.

[7]We also restrict to males in the CPS. Our findings are not impacted by this restriction.

age 35 (in 5 years) and had a realized occupation. Among those, 604 (129) obtained a BA or above.[8] As respondents were between 15-22 years old during the initial interview, an individual is labelled as "college" within this section if they eventually obtained a BA or above.



(a) Distance Measurements

(b) Career Transitions

Figure 1: Distance Measurements and Career Transitions

We measure forecast errors by computing the distance in skill and task requirements between the realized and expected occupation.[9] As a first step, we measure the verbal, math, and social skill requirements for each occupation as in Guvenen et al. (2020).[10] To capture lower-order skills, we measure an occupation's routine and manual task intensity (Autor and Dorn, 2013). This produces a five-dimensional vector summarizing the skill requirements and task intensity for each occupation. Second, we compute two measures of distance between individual i's realized occupations vector of requirements, $\mathbf{s}_i$, and predicted occupations requirements, $\hat{\mathbf{s}}_i$. The first

[8]We find stark differences in the anticipated occupations by education. In general, college (non-college) workers expect to be working in occupations that require relatively more higher-order (lower-order) skills. See Appendix A.9.1 for more details, and for a list of the ten most common expected occupations by education.

[9]We compute the average requirements across the jobs worked while 35 years old and 5 years from their initial interview.

[10]See Appendix A.1.2 for details on measuring skill requirements.

is the angular distance ϕ: $\mathbb{R}^5 \times \mathbb{R}^5 \to [0, \pi/2]$, and is given by:

$$\phi(\mathbf{s}_i, \hat{\mathbf{s}}_i) = \cos^{-1}\left(\frac{\mathbf{s}_i \cdot \hat{\mathbf{s}}_i'}{\|\mathbf{s}_i\| \|\hat{\mathbf{s}}_i\|}\right). \tag{1}$$

Figure 1(a) illustrates the angular distance in the case of two skills. Notably, the angular distance captures the difference in the composition of skill requirements. The second measure is the Euclidean distance, $\psi(\mathbf{s}_i, \hat{\mathbf{s}}_i) = \sqrt{\sum_k (s_{i,k} - \hat{s}_{i,k})^2}$, where $s_{i,k}$ ($\hat{s}_{i,k}$) denotes worker i's realized (expected) occupation's requirement in attribute k. The Euclidean distance accounts for differences in both the composition and magnitude of skill requirements.

Table 1 shows that college workers form more accurate forecasts. From Panel A, the average Euclidean (angular) distance for their occupation at 35 years old is 26% (32%) smaller for college graduates. Panel B shows similar differences for the anticipated occupation in 5 years. The third row within each panel shows the fraction of the Euclidean distance which is attributable to differences in the composition of skill requirements.[11] As we can see, between 65-77% of the Euclidean distance is driven by the composition of skills, suggesting that workers have more uncertainty about which composition of skill requirements they are best suited for. This is why we focus on *career* sampling in our model, where a career is broadly defined as a group of occupations with a similar composition of skill requirements. We precisely define a career and measure career mobility in Section 2.3.1.

Finally, Figure A21 in the Appendix shows that the gap in age 35 forecast errors is present at each age at which respondent's expectations were measured. Given that there is a sizeable gap in forecast errors even among 15-18 year olds who had not enrolled in college yet, we do not claim that attending college has a causal effect on an individual's knowledge of their best fit in the labor market. While this is an interesting question, it is beyond the scope of this paper. Instead, we propose that college workers enter the labor market with less uncertainty about which career is their best fit than those

[11] From the Law of cosines, the fraction of the Euclidean distance that is attributable to differences in the angle, ϕ, is $2\|\mathbf{s}_i\|\|\hat{\mathbf{s}}_i\|(1 - \cos(\phi))/\psi^2$. See Appendix A.9.2 for details.

	Non-College	College
Panel A: Expected Occupation at Age 35		
Angular Distance	29.83	20.31
Euclidean Distance	0.77	0.57
% of Euclidean Driven by Angle	73.90	77.04
Panel B: Expected Occupation in 5 Years		
Angular Distance	25.84	20.09
Euclidean Distance	0.66	0.56
% of Euclidean Driven by Angle	64.85	70.16

Table 1: Angular and Euclidean Distances by Education

without a college degree. We take this difference as given in our model and study its implications for the unemployment-education gap.

2.2 Unemployment-Education Gap

This section presents several facts related to the unemployment-education gap that we argue are consistent with the uncertainty channel.

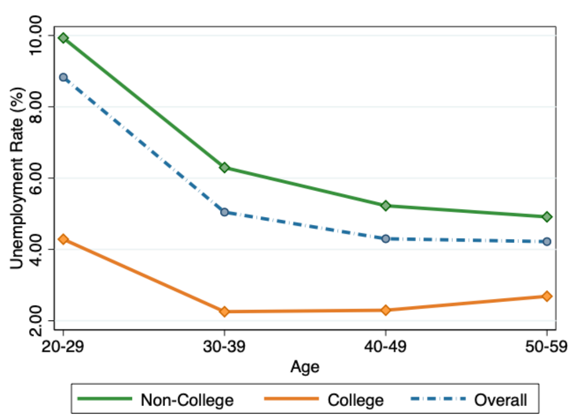
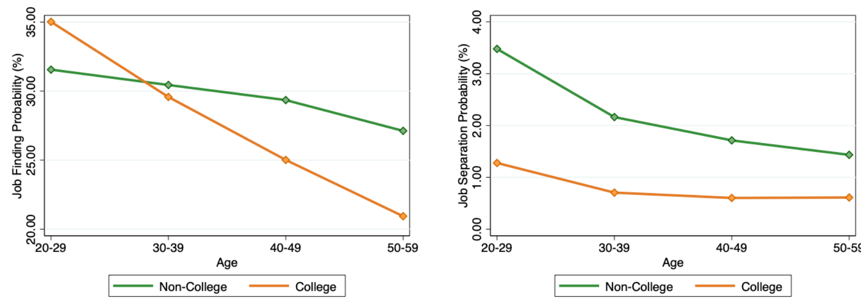


Figure 2: Unemployment-Education Gap over the Life Cycle

Figure 2 shows the unemployment rate by age and education, using CPS



(a) Job Finding Probability (b) Separation Probability

Figure 3: Job-Finding and Separation Probabilities over the Life Cycle

data from 1976 through 2019.[12] The solid lines show that the unemployment rate for college graduates is lower than those without a college degree and that the unemployment-education gap narrows over the life cycle. Next, Figure 3 presents the job finding and separation probabilities by age and educational attainment.[13] There are several takeaways. First, separations decline with age for each education group. Second, college workers consistently exhibit a lower separation probability. Third, the gap in separation probabilities is widest early in the life cycle and decreases with age.[14]

Figure 3 also suggests that the unemployment-education gap is primarily driven by differences in separations, as the job finding rate is lower among college graduates throughout most of the life cycle. Applying a decomposition as in Pissarides (2009) shows that differences in separations explains at least 70% of the unemployment-education gap at each age bin.[15] It is for this reason we propose a mechanism that is tightly linked to the sep-

[12] Appendices A.10 and A.11 show that individuals with an Associate's degree and college dropouts fall in-between those with no college experience and graduates with a BA or above in our main outcomes of interest.

[13] We correct for time aggregation bias as in Shimer (2012). See Appendix A.4.1 for details. We also compute the job finding and separation rates as in Shimer (2005) and Elsby et al. (2009). This gives the same conclusions presented in this section. See Appendix A.4.1.

[14] Appendix A.4.1 shows this pattern emerges in both voluntary and involuntary separations. Moreover, Appendix A.7 demonstrates that our findings are not driven by "unemployable" non-college workers who experience an abnormally large amount of separations.

[15] Appendix A.4.2 provides a description of the decomposition, as well as results with alternative transition probabilities and rates.

aration margin. Intuitively, if non-college (college) workers enter a match with more (less) uncertainty whether they are well-suited for that career, they are more (less) likely to learn it is a bad match and separate from it.

It is important to reemphasize that the differences in unemployment and separations by educational attainment are widest early in workers' careers. Our hypothesis is also consistent with this for this simple reason that college workers, having entered the labor market with less uncertainty, begin their careers with lower separations and hence, a lower unemployment rate. Non-college workers enter with more uncertainty and experience more separations. As their career advances, they learn about their best fit, separate from their jobs less frequently, and the unemployment-education gap narrows. This intuition builds on Gervais et al. (2016), where we argue that learning about one's best fit from work experience and the resulting decline in separations is more prevalent among non-college workers. This will be formalized in Section 3 and quantified in Section 4.

2.3 Supporting Evidence

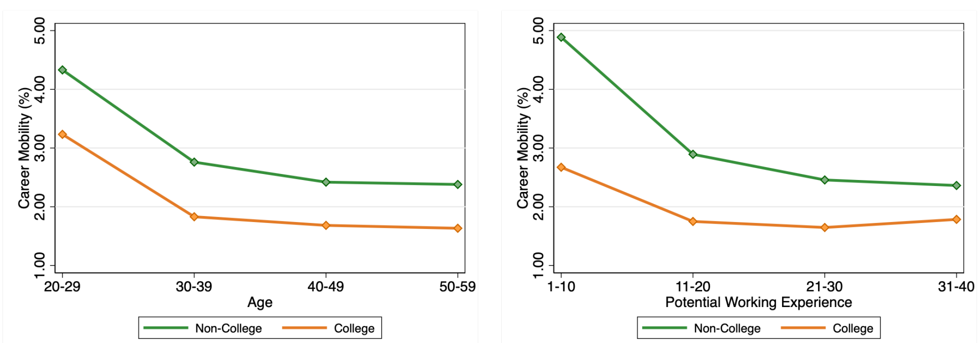
Section 2.1 presented our most direct evidence for the uncertainty channel. This section presents additional, indirect, evidence for our hypothesis.

2.3.1 Career Mobility

We begin by comparing career mobility rates by age and education. The motivation for doing so is the following: if non-college workers enter the labor market with more uncertainty about their best fit, then they should switch careers at a higher rate, particularly early in their career, as they sample careers and gradually transition to their best fit.

We follow 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, $\bar{\phi}$. The threshold is chosen so that the average correlation in occupational requirements is zero in career switches. We find $\bar{\phi} = 21.3$ yields an average correlation in occupational attributes of 0.00016 among the 25,882 occupational transitions in our CPS sample.[16] Intuitively, a career switch occurs when the worker transitions between occupations with very different compositions of skill requirements. This is depicted in Figure 1(b). If the worker switches from occupation 1 to 2, the angle between the skill requirements $\mathbf{s}_1$ and $\mathbf{s}_2$ is $\phi < \bar{\phi}$. So, the worker is moving to a new job within the same career. If the worker transitions between occupation 1 and 3, the distance is $\hat{\phi} > \bar{\phi}$. In this case, the composition of skill requirements are sufficiently different, leading to a career switch.

Figure 4 presents the career mobility rates. There are two patterns to highlight. First, career mobility is decreasing in age. Second, non-college workers change careers more frequently.[17] As education impacts the timing of entry to the labor market, we also show the career mobility rates by years of potential experience, where we assume non-college (college) workers enter the labor market at the age of 18 (22). Figure 4(b) illustrates that while the overall patterns are unchanged, the gap in career mobility rates in the early stages of workers' careers is even larger than when we compare by age, and narrows over the course of workers' careers.



(a) Age (b) Potential Experience

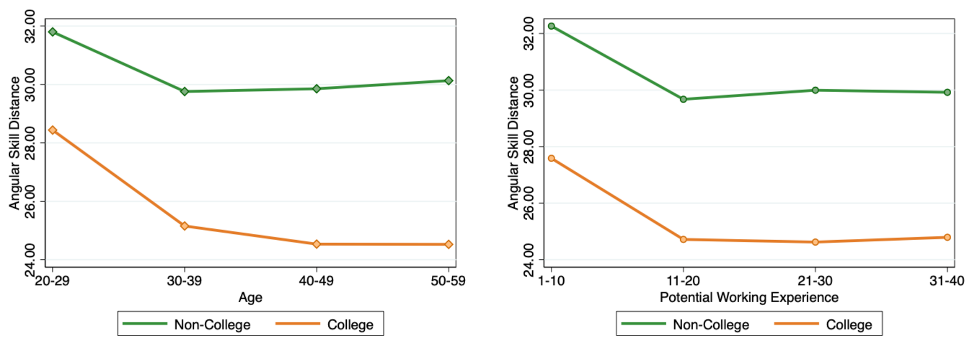
Figure 4: Career Mobility

[16]We first correct for measurement error in occupational mobility following Moscarini and Thomsson (2007a). See Appendix A.3.1.

[17]We find similar patterns when considering "complex" switches, or a concurrent change in employer, occupation, and industry (Neal, 1999). See Appendix D.1.

2.3.2 Occupational Distance

Next, we examine another implication of our hypothesis: college graduates should transition between similar occupations whereas those without a college degree make more significant changes when switching occupations. The idea here is, given their lower uncertainty, if college workers learn that their current job is not their best fit, it is still more likely they are in a decent match and that a better match will have fairly similar characteristics to their current job. To evaluate this in the data, we use the CPS to compare skill and task requirements in occupation switches.



(a) Age

(b) Potential Experience

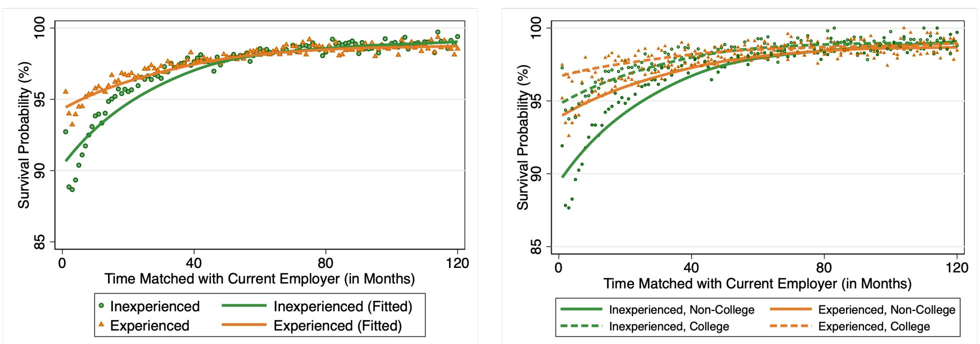
Figure 5: Angular Distance in Occupation Transitions

Figure 5 presents the average angular distance in occupational switches. The average distance is lower for college graduates across the life cycle. This shows that not only do college graduates switch careers at a lower rate, but when they do switch occupations, they tend to transition into occupations with a (relatively) similar composition of skill requirements.

2.3.3 Experience and Match Duration

An important feature of our hypothesis is that workers learn about their best fit through work experience, and that they can transfer what they have learned about their best fit between jobs. A corollary to this in the data is that the expected duration of a match is increasing in the worker's prior experience at the time the match is formed. With this in mind, we use the consecutive records in NLSY79 to explore the relationship between prior experience and the survival probability of a match.[18]

As a first step, we place workers into two groups based on their level of accumulated experience at the beginning of a match. The first group, experienced workers, consists of those who enter the new match with more than 76 months of work experience, where 76 months is the median months of experience at the formation of new matches in our sample. The second group, inexperienced workers, are those who begin a match with no more than 76 months of experience. The survival probability is simply the fraction of matches that survive between months t and $t+1$.



(a) All Workers (b) By Education

Figure 6: Prior Experience and Match Survival

Figure 6 presents the survival probability as a function of tenure and prior experience. As seen in Figure 6(a), experienced workers exhibit a higher survival probability for the first 2–3 years of the match. This finding echoes Topel and Ward (1992), who found that the expected match duration is increasing in prior experience. Figure 6(b) shows that the association between prior experience and the survival probability is stronger among less-educated workers. This can be seen by noting the larger gap in the

[18]To identify matches that survive between periods, it is vital to have complete employer ID records for employed workers. Accordingly, we drop respondents with incomplete employer ID records, leaving 4,697 respondents.

survival probability between inexperienced and experienced workers for workers with less than a college degree than those with a college degree. This is consistent with the uncertainty channel as non-college workers rely more on experience to find their best fit. Appendix A.6 shows that these findings are robust to excluding matches formed through a job-to-job transition, allowing prior experience to be measured in months rather than two categories, and controlling for observable characteristics such as age.

A key feature of our hypothesis is that workers learn not just from experience, but particularly from sampling occupations. Therefore, we estimate the relationship between the match survival probability and the number of occupations the worker had formerly worked in when the match was formed. To do so, we separately estimate the following specification on 3,609 non-college and 1,064 college workers in the NLSY79 with complete employment histories across their first 10 occupational switches:

$$y_{it} = \beta_0 + \sum_{j=1}^{10} \beta_j \times \mathbb{1}\{\text{OccNum} = j\}_{it} + \gamma \times \text{OccTenure}_{it} + \delta \times \text{Age}_{it} + \epsilon_{it}, \quad (2)$$

where y_{it} is a indicator for whether individual i remains employed in the same occupation between month $t-1$ and t, $\mathbb{1}\{\text{OccNum} = j\}$ is an indicator for the number of occupations individual i had worked in at the time their current match was formed, OccTenure_{it} is tenure in their current occupation, and Age_{it} is age at time t. The coefficients of interest, β_j for $j \in \{1, \ldots, 10\}$, capture the association between the j^{th} occupation formerly worked in at the time a match is formed and the survival probability, relative to a worker who is forming their first match.

Figure 7 displays the β_j coefficients and shows that, especially for non-college workers, the survival probability increases with the number of occupations formerly worked in, lending support to our hypothesis that non-college workers learn more about their best fit from sampling occupations.

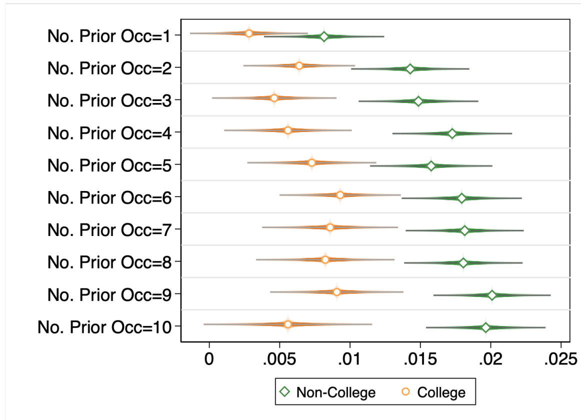


Figure 7: Prior Occupations and Match Survival

2.4 Robustness and Additional Evidence

This section summarizes additional evidence that complements the analysis presented in Sections 2.1-2.3. First, college graduates exhibit lower rates of occupational mobility (Appendix A.3.1). Second, college graduates experience lower skill mismatch throughout the life cycle (Appendix A.3.2). Third, college graduates work in jobs with more dispersed skill requirements (Appendix A.3.3).[19] Finally, college graduates experience fewer employer, occupation, and career switches (Appendix A.3.4).

As for the robustness of findings presented throughout this section, the patterns presented from the CPS can be replicated in the NLSY79. See Appendices A.5.1-A.5.4. Finally, the relationships between having a college degree and the various outcomes of interest are robust to controlling for standard observable characteristics, including occupation and industry. See Appendices A.4.3 for the CPS and A.5.5 for NLSY79 analyses, respectively.[20]

[19]The intuition is that workers with greater certainty about their abilities may be more willing to take jobs with an imbalanced set of skill requirements, in contrast to uncertain workers who may prefer jobs with balanced skill demands.

[20]In Appendix A.8, we conduct an additional robustness check in the NLSY79 by controlling for parental occupation.

2.5 From Empirics to Theory

We have proposed and provided empirical support for the uncertainty channel. Our remaining primary objective is to quantify the uncertainty channel's contribution to the unemployment-education gap.

To do so, we develop a search model where workers are heterogeneous in their education and their best fit. Workers do not know their best fit and sample careers to learn their suitability in each. A match may be destroyed upon learning the worker is not in their true calling. Underlying these ingredients are differences by education in productivity, the number of careers that are a potential best fit, and the speed at which workers learn their fit in a career. Section 3.3 outlines how each difference contributes to the unemployment-education gap and Section 4 quantifies their contributions.

3 Model

This section develops a life cycle directed search model. Section 3.1 introduces the environment. Section 3.2 characterizes the equilibrium and Section 3.3 details the sources of the unemployment-education gap.

3.1 Environment

Time is discrete and indexed by $t = 0, 1, \ldots, \infty$. At $t = 0$, there is a unit measure of workers and a large measure of firms. All agents are risk neutral and discount the future according to the discount factor β.

Workers are heterogeneous in four dimensions. The first is age, $a \in \{y, o\}$, for young and old, respectively. Second is educational attainment, $e \in \{0, 1\}$ where $e = 0$ ($e = 1$) is non-college (college). Education is fixed and observable. Third, as in Gervais et al. (2016), each worker is best suited for one career, c^*, which we refer to as their best fit. For workers with education e, $c^* \in \mathbb{C}_e$ where $\mathbb{C}_e \subset \mathbb{Z}^+$ and $2 < N_1 \equiv |\mathbb{C}_1| < |\mathbb{C}_0| \equiv N_0$. In words, there are fewer careers that are potentially a best fit for college workers. Fourth is a worker's history, i, which denotes one plus the number of careers that the worker has learned is not their true calling. Initially, a worker's true calling is unknown to both the worker and firms. Once the worker learns about their fit in a career, it becomes public information.

The labor market is organized in a continuum of submarkets indexed by $\omega = (a, e, i, s, x)$. In submarket ω, firms search for workers with age a, education e, history i, the worker's status in career i: $s \in \{un, b, g\}$ (unsure, bad, or good fit), and offer workers contracts with lifetime discounted utility x.

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

In stage 1, employed workers with characteristics (i, e) who are unsure about their current career learn about their fit with probability $\phi_e \in [0, 1]$. Workers who learn that their current career is their true calling become type $i = N_e$. Those who learn that their current career is not their true calling become type $\max\{i + 1, N_e\}$ workers and update their beliefs over the careers they have not sampled according to Bayes rule. A type i worker who has learned that $i - 1$ careers are not their best fit believes that the i^{th} career is their best fit with probability p_{ie}, where

$$p_{ie} = \frac{1}{N_e - (i - 1)}. \tag{3}$$

In stage 2, a match with a type (i, e) worker and status s is destroyed with probability $\delta \in [\delta^s, 1]$ where $\delta^{un}_{ie} = p_{ie}\delta^g + (1 - p_{ie})\delta^b$ and $\delta^g < \delta^b$. The destruction probability is chosen by the worker and firm, and the lower bound represents exogenous separations. A worker who loses their job must wait one period before looking for another.

Next, in stage 3, firms choose which submarket, if any, to post a vacancy in. The vacancy posting in submarkets with age a workers is κ_a. Workers choose which submarket to search in. Old workers who look for a new career incur a switching cost ζ. The decision to leave a career is irreversible.

Let $v(\omega)$ and $u(\omega)$ denote the measure of vacancies and unemployed workers, respectively, searching in submarket ω. The number of matches is given by the CRS matching function $F(u(\omega), v(\omega))$. Define $\theta = v/u$ as tightness in submarket ω. A worker finds a job with probability $f(\theta(\omega)) = F/u(\omega)$ where $f : \mathbb{R}_+ \to [0,1]$ is twice continuously differentiable, strictly increasing, and strictly concave. Firms fill their vacancy with probability $q(\theta(\omega)) = F/v(\omega)$ where $q : \mathbb{R}_+ \to [0,1]$ is twice continuously differentiable, strictly decreasing, and strictly convex.

In the production stage, stage 4, unemployed workers produce z units of output. Workers in their true calling produce y_e units of output where $y_1 > y_0$. Workers in a bad match produce $y_e - \alpha > z$ for $e \in \{0,1\}$. The output in unsure matches is $y_{ie}^{un} = p_{ie} y_e + (1 - p_{ie})(y_e - \alpha)$.

At the beginning of stage 5, a fraction λ_o of young agents become old and a fraction λ_d of old agents die. To maintain a constant population, a measure $\mu = \frac{\lambda_o \lambda_d}{\lambda_o + \lambda_d}$ of workers enter the economy as young and unemployed. A fraction π_0 $(1 - \pi_0)$ enter the economy with education $e = 0$ $(e = 1)$. New entrants have their true calling assigned by nature, where the probability any career is their true calling is $1/N_e$.

Finally, the contract space is complete, giving rise to bilaterally efficient employment contracts (Menzio and Shi, 2011). Therefore, employment contracts offered by firms will maximize the joint value of the match.

3.2 Equilibrium

We begin with the value functions for unemployed workers and the value of a match, which are measured from the beginning of the production stage.

Let $U_{a,e,i}$ denote the value of a worker with age a, education e, and history i searching for their i^{th} career in which they have an unknown fit if $i < N_e$ or a good fit if $i = N_e$. Consider workers who are old at the beginning of the production stage. The worker produces z units of output and remains alive between periods with probability $1 - \lambda_d$. In the subsequent search stage, they search for a job in submarket ω and find a job with probability $f(\theta(\omega))$. If they find a job, they earn the continuation value of the employment contract, x. If they don't find a job, they earn the value of unemployment, $U_{o,e,i}$. It follows that $U_{o,e,i}$ satisfies

$$U_{o,e,i} = z + \beta(1-\lambda_d)\big\{U_{o,e,i} + R(x, U_{o,e,i})\big\}, \tag{4}$$

where

$$R(x, U) = \max_{(\theta,x)} f(\theta)(x - U). \tag{5}$$

Now let $\overline{U}_{a,e,i}$ denote the value of an unemployed worker with characteristics (a, e) who knows that career i is a bad fit. The worker decides in the subsequent search stage whether to look for a new career or not. If they leave their current career, they incur the switching cost ζ and search in a submarket for type $i+1$ workers, as they know that their previous i careers are not their best fit. It follows that, for old workers, we have:

$$\begin{aligned}\overline{U}_{o,e,i} = z + \beta(1-\lambda_d)\big\{l^*_{o,e,i}[U_{o,e,i+1} - \zeta + R(x, U_{o,e,i+1})] + \\ (1 - l^*_{o,e,i})[\overline{U}_{o,e,i} + R(x, \overline{U}_{o,e,i})]\big\},\end{aligned} \tag{6}$$

where $l^*_{o,e,i}$ denotes the worker's choice to leave their career and is given by

$$l^*_{o,e,i} = \begin{cases} 1 & \text{if } U_{o,e,i+1} - \zeta + R(x, U_{o,e,i+1}) \geq \overline{U}_{o,e,i} + R(x, \overline{U}_{o,e,i}), \\ 0 & \text{if } U_{o,e,i+1} - \zeta + R(x, U_{o,e,i+1}) < \overline{U}_{o,e,i} + R(x, \overline{U}_{o,e,i}). \end{cases} \tag{7}$$

Next, consider a young worker who is unemployed. The only difference relative to old workers is that with probability λ_o, the worker becomes old between periods. Hence, $U_{y,e,i}$ and $\overline{U}_{y,e,i}$ satisfy:

$$U_{y,e,i} = z + \beta\big\{\lambda_o[U_{o,e,i} + R(x, U_{o,e,i})] + (1-\lambda_o)[U_{y,e,i} + R(x, U_{y,e,i})]\big\}, \tag{8}$$

$$\begin{aligned}\overline{U}_{y,e,i} = z + \beta\big\{\lambda_o\big[l^*_{o,e,i}[U_{o,e,i+1} - \zeta + R(x, U_{o,e,i+1})] + (1 - l^*_{o,e,i})[\overline{U}_{o,e,i} + R(x, \overline{U}_{o,e,i})]\big] \\ + (1-\lambda_o)\big[l^*_{y,e,i}[U_{y,e,i+1} + R(x, U_{y,e,i+1})] + (1 - l^*_{y,e,i})[\overline{U}_{y,e,i} + R(x, \overline{U}_{y,e,i})]\big]\big\}.\end{aligned} \tag{9}$$

We now proceed to values of a match, or the sum of the worker's utility and firm's profits, which is sufficient to characterize the entry of firms and separation decisions as the contracts offered by firms maximize the joint surplus of the match. Starting with an old worker who is employed in a bad match, the match output is $y_e - \alpha$. In the subsequent separation stage, the job is destroyed with probability δ^b, in which case the worker receives the value of unemployment and the firm receives the value of a vacancy (zero).[21] If the match is not destroyed, the continuation value is given by the value of the match. It follows that the value of a bad match with an old worker with education e and history i, $\overline{V}_{o,e,i}$, satisfies

$$\overline{V}_{o,e,i} = y_e - \alpha + \beta(1-\lambda_d)\big\{\delta^b \overline{U}_{o,e,i} + (1-\delta^b)\overline{V}_{o,e,i}\big\}. \tag{10}$$

As for old workers with education e and history i who are employed in an unknown or a good fit, the match produces $p_{ie}y_e + (1-p_{ie})(y_e - \alpha)$ units of output. The worker learns about their suitability for their career in the learning stage with probability ϕ_e. Conditional on learning about their fit, they are in their true calling with probability p_{ie} and the worker's type becomes $i = N_e$. With probability $1 - p_{ie}$, the worker learns they are in a bad fit. In this case, the worker and firm enter the separation stage and choose whether to destroy the match or not. The value of the match, $V_{o,e,i}$, satisfies

$$V_{o,e,i} = p_{ie}y_e + (1-p_{ie})(y_e-\alpha) + \beta(1-\lambda_d)\big\{\phi_e[p_{ie}(\delta^g U_{o,e,N_e} + (1-\delta^g)V_{o,e,N_e}) +$$
$$(1-p_{ie})(d^*_{o,e,i}\overline{U}_{o,e,i} + (1-d^*_{o,e,i})\overline{V}_{o,e,i})] + (1-\phi_e)[\delta^{un}_{ie}U_{o,e,i} + (1-\delta^{un}_{ie})V_{o,e,i}]\big\}, \tag{11}$$

where $d^*_{o,e,i}$ is the separation probability after learning the match is a bad fit and is given by

$$d^*_{o,e,i} = \begin{cases} \delta^b & \text{if } \overline{U}_{o,e,i} < \overline{V}_{o,e,i}, \\ 1 & \text{if } \overline{U}_{o,e,i} \geq \overline{V}_{o,e,i}. \end{cases} \tag{12}$$

[21] Bad matches with old workers that were not destroyed endogenously in the previous separation stage will not be destroyed endogenously in the subsequent separation stage as nothing about a bad match changes between periods.

For young workers, the value of a bad match satisfies:

$$\overline{V}_{y,e,i} = y_e - \alpha + \beta\big\{(1-\lambda_o)[\delta^b \overline{U}_{y,e,i} + (1-\delta^b)\overline{V}_{y,e,i}] \\ + \lambda_o[\delta^b \overline{U}_{o,e,i} + (1-\delta^b)\overline{V}_{o,e,i}]\big\}. \quad (13)$$

Finally, we have the value of a young worker in a match with an unsure or good fit, which follows a similar intuition as with old workers:

$$V_{y,e,i} = p_{ie}y_e + (1-p_{ie})(y_e - \alpha) + \beta \sum_a \chi_a \{\phi_e[p_{ie}(\delta^g U_{a,e,N_e} + (1-\delta^g)V_{a,e,N_e}) + \\ (1-p_{ie})(d^*_{a,e,i}\overline{U}_{a,e,i} + (1-d^*_{a,e,i})\overline{V}_{a,e,i})] + (1-\phi_e)[\delta^{un}_{ie}U_{a,e,i} + (1-\delta^{un}_{ie})V_{a,e,i}]\}, \quad (14)$$

where $\chi_a = 1 - \lambda_o$ if $a = y$ and $\chi_a = \lambda_o$ if $a = o$.

The firm's cost to post a vacancy in a submarket with age a workers is κ_a. The expected benefit to posting a vacancy in submarket $\omega = (a, e, i, s, x)$ is $q(\theta(\omega))[V_{a,e,i} - x]$ if $s \in \{un, g\}$ and $q(\theta(\omega))[\overline{V}_{a,e,i} - x]$ if $s = b$. In submarkets visited by a positive amount of workers, tightness is consistent with firms' incentives to create vacancies if

$$\kappa_a \geq \begin{cases} q(\theta)[V_{a,e,i} - x] & \text{for } i \in \{1, 2, \ldots, N_e\} \text{ and } s \in \{un, g\}, \\ q(\theta)[\overline{V}_{a,e,i} - x] & \text{for } i \in \{1, 2, \ldots, N_e - 1\} \text{ and } s = b. \end{cases} \quad (15)$$

Definition 1. A stationary recursive equilibrium consists of a tightness function $\theta(\omega)$, value and policy functions for unemployed workers, $U_{a,e,i}$, $\overline{U}_{a,e,i}$, and $\omega^*_{a,e,i}$, $l^*_{a,e,i}$, joint value and policy functions, $V_{a,e,i}$, $\overline{V}_{a,e,i}$, $d^*_{a,e,i}$, and a distribution of workers that satisfies the following conditions. First, $\theta(\omega)$ satisfies (15) for all ω. Second, the value and policy functions of unemployed workers satisfy equations (4)-(9). Third, the joint value and associated policy functions for a match satisfy equations (10)-(14). Finally, the distribution of workers satisfies the laws of motion specified in Appendix B.1.

As established by Menzio and Shi (2011) for directed search models with free entry and bilateral efficiency, a recursive equilibrium exists and is block-recursive (BRE). As workers self-select into submarkets based on their observable characteristics, firms know they will only meet one type of worker in each submarket. Hence, tightness in each submarket is independent of the distribution of workers across age, educational attainment, history i, and the worker's status in their current career.

3.3 The Unemployment-Education Gap

This section details two broad sources of the unemployment-education gap. The first is the differences in fundamentals by education: labor productivity, y_e, number of potential careers, N_e, and learning speed, ϕ_e. Second is the difference in separations by match status ($\delta^b > \delta^g$). We now proceed to discuss the contribution of each to the unemployment-education gap. First, higher labor productivity ($y_1 > y_0$) leads to a higher match value with college workers, inducing more firms to post vacancies, and for college workers to exit unemployment with a higher probability.

Fewer potential careers, $N_0 < N_1$, has several effects. The first is $p_{i1} > p_{i0}$. Therefore, college workers produce more output in unsure matches, $y_{i1}^{un} > y_{i0}^{un}$, which leads to a higher job finding probability. Also, college workers experience fewer separations as they are more likely to be in their true calling. Moreover, we see from (3) that $\partial p_{i1}/\partial i > \partial p_{i0}/\partial i$. So, ruling out a career has a larger impact on the probability the worker's next career is their true calling for college workers. This enables college workers to find their true calling, where they are most productive and experience fewer separations, earlier in their career. The difference in learning speeds, $\phi_1 > \phi_0$, has a similar effect as it enables college workers to swiftly decipher a good fit from a bad fit, and quickly find their true calling.

The final implication of $N_0 < N_1$ is that college workers experience fewer separations when their status is unsure. This can be seen by noting

$$\delta_{i1}^{un} = p_{i1}\delta^g + (1 - p_{i1})\delta^b < p_{i0}\delta^g + (1 - p_{i0})\delta^b = \delta_{i0}^{un}, \tag{16}$$

as $p_{i1} > p_{i0}$. From (16), $N_0 < N_1$ generates differences in δ_{ie}^{un} only if $\delta^b \neq \delta^g$.

In particular, we have assumed $\delta^b > \delta^g$, which is why differences in separation probabilities by status contribute to the unemployment-education gap. It is important to note, however, that the difference between δ^b and δ^g contributes to the unemployment-education gap because $p_{i1} > p_{i0}$.

What, then, drives the gap between δ^b and δ^g? We interpret $\delta^b > \delta^g$ as the manifestation of underlying match-specific productivity shocks. In a model where match output is made up of a common and idiosyncratic component, matches with a higher common productivity are less likely to be destroyed (e.g., Mortensen and Pissarides (1994)). In our model, $\delta^b > \delta^g$ as workers produce less outside their true calling.

Finally, the role of the uncertainty channel and its interaction with the differences in separations by status are more prominent early in a worker's career, as this is when workers face the most uncertainty over their best fit. As workers age and sample more careers, they are more likely to have found their true calling, experience fewer separations, and are less likely to be unemployed. This is especially true for non-college workers, as they face more uncertainty upon entering the labor market.

4 Quantitative Analysis

This section presents our calibration strategy, model validation, quantitative findings, policy implications, and compares the implications of our model to those centered around match-specific productivity shocks.

4.1 Calibration

A unit of time is one month. The matching technology is $F(u, v) = \frac{uv}{(u^\iota + v^\iota)^{1/\iota}}$. There are 18 parameters. The discount factor is $\beta = (0.97)^{1/12}$, and the probabilities of becoming old (λ_o) and dying (λ_d) are set at 1/240 so that workers expect to spend 20 years each as young and old. The fraction of college workers is $\pi = 0.30$. The economy is normalized by setting $z = 1$.

The remaining 13 parameters are calibrated via simulated method of moments (SMM) to match 15 moments. The first moment is $z/$[average labor productivity] $= 0.4$ (Shimer, 2005). The second and third moments are the job finding probabilities for non-college (31.06%) and college workers (32.53%) aged 20 to 39. We also target the average number of unique careers worked by non-college (2.83) and college workers (2.00).[22] Next are the job-finding probabilities for workers between 20 and 39 years old (31.12%) and 40 to 59 years old (27.61%). The remaining eight moments are the job separation probability profiles for non-college and for college workers (the green and red curves in Figure 3(b), respectively).[23]

While the targeted moments are affected by more than one remaining parameter, one can view $\{\delta^g, \delta^b\}$ as targeting the job separation probability for college workers in the last age group and non-college workers in the first age group, respectively. This is because the matches of college (non-college) workers are primarily composed by good (bad) matches in the last (first) age group. Next, $\{\kappa_y, \kappa_o\}$ targets the job finding probability for young and old workers, respectively, as the entry costs affects firm entry.

As for the parameters governing the uncertainty channel, $\{N_0, N_1\}$, are chosen to match the average number of unique careers worked by education. With a larger set of potential careers, workers face more uncertainty upon entering the labor market and expect to undergo more career experimentation until eventually settling into their best fit. This is demonstrated in Panel A of Table 2, where the number of careers is increasing in N_e.

We then use the "convexity" of the separation profile to pin down the probabilities of learning, $\{\phi_0, \phi_1\}$. As ϕ_e increases, workers learn about their fit at a higher rate. Once they realize that the current match is an unfit, they may endogenously separate from that match, leading to higher separations (especially in their early career stages). However, with more learning occurring early in the worker's career, a larger fraction of workers settle into

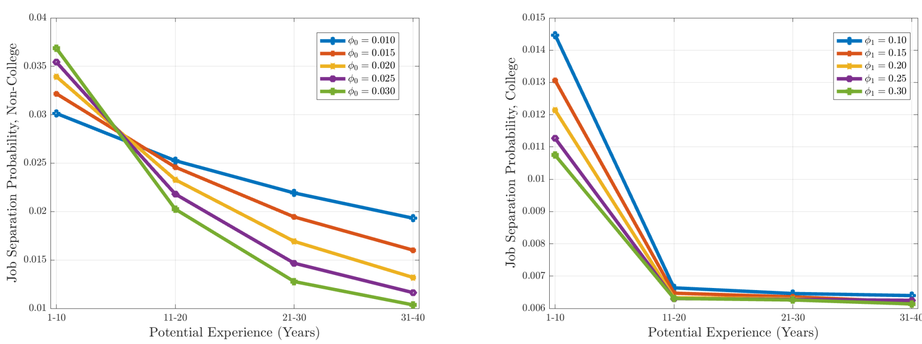
[22] Appendix C.1 details how we identify unique careers in the data.

[23] To compute the moments, we first solve the model through value function iteration and then simulate the careers of 30,000 workers. Each worker's history begins at 19.5 years old and we track their career outcomes between 20 and 59 years old. We then compute the average value of each moment across 10 simulation rounds.

Table 2: Identification of N_e and y_e

Panel A: Comparative statics with respect to N_e					
N_0	5	6	7	8	9
# of Careers, Non-college	2.206	2.405	2.559	2.700	2.812
N_1	1	3	5	7	9
# of Careers, College	1	1.940	2.815	3.636	4.401
Panel B: Comparative statics with respect to y_e					
y_0	2.625	2.719	2.813	2.906	3.000
Job Finding Pr., Non-College	0.295	0.303	0.310	0.315	0.321
y_1	2.625	2.719	2.813	2.906	3.000
Job Finding Pr., College	0.330	0.331	0.332	0.333	0.333

their best fit, leading to fewer separations later in their career. Therefore, a higher ϕ_e is associated with a more convex separation profile with higher separations early on, a rapid decline in separations, and a flatter separation profile at the later career stages. This is demonstrated in Figure 8.



(a) ϕ_0, Non-College (b) ϕ_1, College

Figure 8: Job Separation Profile and ϕ_e

Next, we utilize the job finding probability of the young (aged 20-39) to calibrate the productivity parameters, $\{y_0, y_1\}$. This is intuitive, as higher output is associated with a higher match value, more vacancies and hence, a higher job finding probability. This is shown in Panel B of Table 2.

There are three remaining parameters, $\{\alpha, \zeta, \iota\}$, that can be interpreted as being chosen to fine-tune the model fit's to the 15 moments. Intuitively, α governs the penalty for a bad match, which incentivizes workers to separate from bad matches and to find their best fit. As such, this impacts the separation profile. Next, ζ governs the cost for old workers to change careers. It follows that adjusting ζ improves the model's fit of the separation profile in the later half of workers' careers, as it impacts how many old workers will stay in a bad match and be subject to a higher job destruction probability. Finally, ι impacts the responsiveness of job finding probabilities to changes in tightness and improves the fit of moments related to job finding.

Denoting $\tilde{m}$ (m) as the vector of 15 model generated (empirical) moments, the vector of 13 parameters, $\hat{\vartheta}$, is given by

$$\hat{\vartheta} = \arg\min\,(\tilde{m} - m)' W (\tilde{m} - m), \tag{17}$$

where $W = I/m^2$ and I is the identity matrix. From (17), ϑ minimizes the sum of squared percentage deviations between the model and data and does not place more weight on moments which are larger in magnitude. Table 3 and Figure 9 show that the model matches the data well.

Table 3: Model and Data Comparison

Moment	Target	Model
Pr. Job Finding, 20-39, Non-College	0.311	0.306
Pr. Job Finding, 20-39, College	0.325	0.332
No. of Unique Careers Worked, Non-College	2.830	2.713
No. of Unique Careers Worked, College	2.000	1.937
Pr. Job Finding, 20-39	0.311	0.309
Pr. Job Finding, 40-59	0.276	0.276
z/[Average labor productivity]	0.400	0.400

Table 4 displays the parameter values. As aforementioned, the uncer-

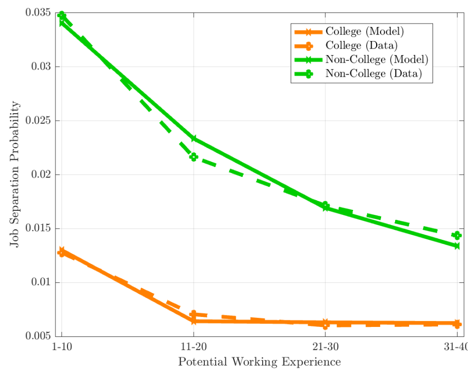


Figure 9: Separation Profile in the Model and Data

tainty channel is governed by both ϕ_e and N_e. We find $\phi_1 = 0.156$ and $\phi_0 = 0.020$, indicating that college workers learn much faster about their fit in a career.[24] As for N_e, we find $N_1 = 3$ and $N_0 = 8$, indicating that non-college workers enter the labor market with nearly three times as many careers that are potentially their best fit. Here, it is important to emphasize that our results do not imply that college workers can work in fewer careers than non-college workers. Rather, our results suggest that college workers enter the labor market having narrowed down which careers are potentially their best fit. Taken together, the calibration implies a large gap in uncertainty by education, enabling them to experience fewer separations and settle into their best fit at an earlier career stage.

Finally, the calibrated values of y_1 and y_0 are close to each other, indicating that there is little difference in productivity between college and non-college workers in their best fit. However, this does not mean there are small differences in average labor productivity. As college workers being more likely to be in their best fit, there is a sizeable gap in average labor productivity among non-college and college workers of 16.64%.

[24]The weighted average of the learning probabilities is given by $\pi \times 0.156 + (1-\pi) \times 0.02 = 0.061$, which is similar to learning probability of 0.055 used in the baseline calibration of Gervais et al. (2016).

Table 4: Parameter Values

	Definition	Value		Definition	Value
β	Discount factor	0.997	α	Penalty, bad fit	0.701
λ_o	Pr. of becoming old	0.004	y_0	Prod. of non-college	2.754
λ_d	Pr. of becoming retired	0.004	y_1	Prod. of college	2.850
π	Pr. of being college	0.300	ζ	Switching cost	150
z	Utility while unemployed	1.000	N_0	# of careers, non-college	8
δ^g	Sep. pr., good fit	0.006	N_1	# of careers, college	3
δ^b	Sep. pr., bad fit	0.028	κ_y	Vacancy cost, young	1.097
ϕ_0	Learning pr., non-college	0.020	κ_o	Vacancy cost, old	2.965
ϕ_1	Learning pr., college	0.156	ι	Matching parameter	0.673

4.2 Model Validation

To evaluate the model's validity, we assess how well it matches some untargeted moments. The comparisons between untargeted moments and model generated moments are listed in Table 5. The first two rows show that the model generates a life-cycle unemployment pattern that closely mirrors the data. This occurs even though we do not target the job finding profiles because, as shown in the third row, the unemployment-education gap is driven primarily by differences in separation probabilities.

As we discussed in Section 2.3.3 and demonstrated in Figure 6, the relationship between prior experience and expected duration of a match is an important piece of empirical evidence which is consistent with the uncertainty channel. The fourth row of Table 5 presents the estimated coefficient from regressing prior experience (in months) on the survival probability of the match in both the NLSY79 and simulated data.[25] The model captures this association well. Moreover, the fifth row shows that, just as in the data, the association between prior experience and match survival is significantly lower for college workers. This lends support to our hypothesis

[25]The regression specification is detailed in Appendix A.6 and the untargeted moments are presented in Table A8, Panel B, Column (4).

that the weaker association between prior experience and match duration for college workers is driven by the uncertainty channel.

The sixth and seventh rows show that the model generates a learning trajectory similar to data for each education group. In particular, it predicts that college workers settle into a fit career sooner and experience fewer unique careers, while non-college workers have sampled more careers at each stage. Lastly, the model generates an average elasticity of job-finding probabilities with respect to market tightness that is within an empirically supported range of 0.5 to 0.7 (Petrongolo and Pissarides, 2001).

Table 5: Model Validation – Untargeted Moments Comparison

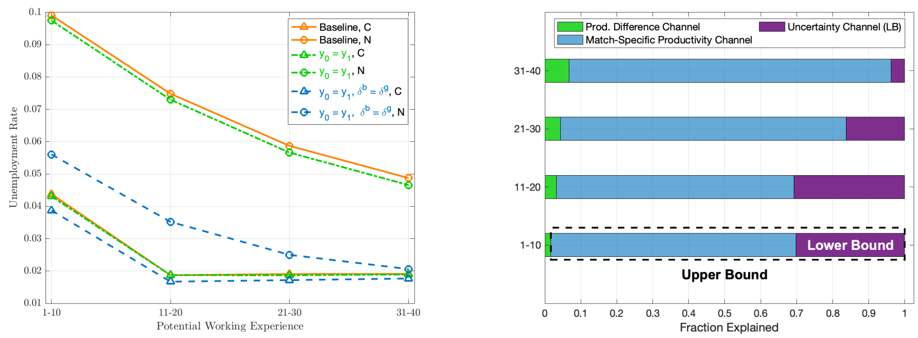
Untargeted Moments	Data	Model
Urate in age X, non-college (%)	[9.9, 6.3, 5.2, 4.9]	[9.9, 7.5, 5.9, 4.9]
Urate in age X, college (%)	[4.3, 2.3, 2.3, 2.7]	[4.4, 1.9, 1.9, 1.9]
U-E gap explained by JSP	1.213	0.842
β(PriorExp)	0.00005	0.00005
β(PriorExp $\times$ College)	-0.00004	-0.00002
# of careers by age, non-college	[2.56, 2.76, 2.80, 2.83]	[2.19, 2.58, 2.69, 2.71]
# of careers by age, college	[1.86, 1.98, 1.98, 2.00]	[1.94, 1.94, 1.94, 1.94]
Elasticity of JFP with respect to θ	0.5 - 0.7	0.568

4.3 Decomposing the U-E Gap

As discussed in Section 3.3, there are three sources of the unemployment-education gap: (i) productivity differences in good matches, (ii) the uncertainty channel, and (iii) the differences in the exogenous separation probabilities of good and bad matches. This section evaluates the relative contributions of each to the model generated unemployment-education gap.

Figure 10(a) presents the unemployment rate profile by education from the model, the model without productivity differences, and the model with uncertainty channel only. To begin, we turn off the productivity differences in good matches across education by setting $y_0 = y_1$. Doing so causes the

U-E gap to slightly close, as indicated by the modest shrinking of the gap from the orange curves to the green curves. In particular, equating y_0 with y_1 eliminates 1.7% (6.8%) of the U-E gap in the first (last) career stage.



(a) Urate Profiles

(b) Fraction Explained

Figure 10: Decomposition of U-E Gap

Next, setting $\delta^b = \delta^g$ shuts down any underlying match-specific productivity shocks which give rise to a higher separation probability in bad matches. Unsurprisingly, and demonstrated by the blue dashed lines, this significantly narrows the U-E gap, explaining 68.15%, 65.91%, 79.39%, and 89.43% of the U-E gap in each age bin, respectively.

At this point, the remaining U-E gap is attributed to the uncertainty channel, as non-college workers are likely to end up in a bad match and endogenously separate from it in favor of searching for a new career. With more workers resolving their career uncertainty, the separation rate gradually declines and converges with that of college workers. It is this remaining portion of the gap which defines the lower bound of the uncertainty channel's contribution to the U-E gap. Specifically, the lower bound at each age bin is 30.16%, 30.81%, 16.27%, and 3.79%, respectively.

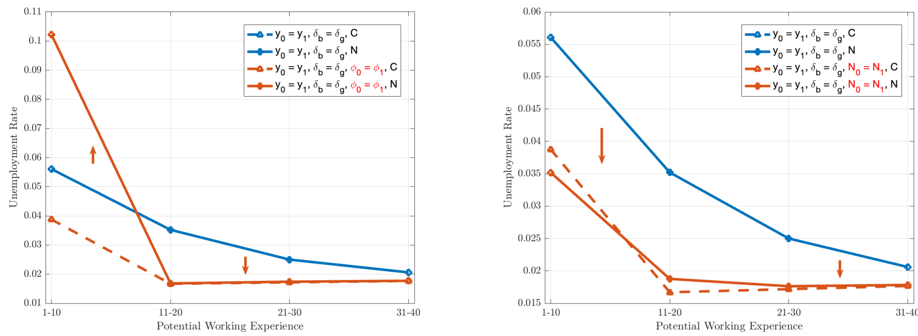
Figure 10(b) illustrates the fraction explained by each channel at each age bin.[26] The purple bars represent the lower bound for the uncertainty's

[26]Our decomposition result is robust to the order of decomposition, i.e., the results remain unchanged regardless of the sequence in which we break down the U-E gap into different channels. See Appendix Section C.2.

channel's contribution. The blue bars represent the fraction of the U-E explained by shutting down the match-specific productivity channel. As we explained in Section 3.3, there is an interaction between underlying match-specific productivity shocks and the uncertainty channel as $\delta^b > \delta^g$ emerges due to workers being more productive at their best fit. Further, $\delta^b > \delta^g$ contributes to the U-E gap because college workers are more likely to be in their best fit ($p_{i1} > p_{i0}$). Therefore, part of the blue bar is attributable to the uncertainty channel and the sum of the purple and blue bars represents the upper bound of the uncertainty channel's contribution to the U-E gap.

To arrive at an aggregate decomposition, we compute the weighted average of the fraction explained by each channel across age bins, where the weights are the fraction of employment observations at each bin. After eliminating differences in productivity by education, 96.72% of the U-E gap remains. After setting $\delta^b = \delta^g$, 24.45% of the U-E gap remains. Therefore, the uncertainty channel explains between 24.45% and 96.72% of the U-E gap.

To further understand the uncertainty channel's contribution to the U-E gap, we dissect it by evaluating the workings of its two components: (i) the initial uncertainty a worker faces at the beginning of their career (N_e) and (ii) how long a worker can expect to wait to learn about their fit in a career (ϕ_e). Figure 11(a) shows the effect of setting $\phi_0 = \phi_1$. We see that when the learning probability for non-college workers is raised to match that of college workers, their unemployment rate significantly increases early in their career, as they learn faster and are more likely to be in a bad match. Hence, they experience more separations. The flip side of this effect is that, due to the higher learning speed and experiencing more separations early on, many non-college workers find their best fit by the second age bin and are less likely to be unemployed at the later stages of their career. Figure 11(b) shows that reducing the number of potential best fits for non-college workers reduces unemployment at all age bins.



(a) $\phi_0 = \phi_1$

(b) $N_0 = N_1$

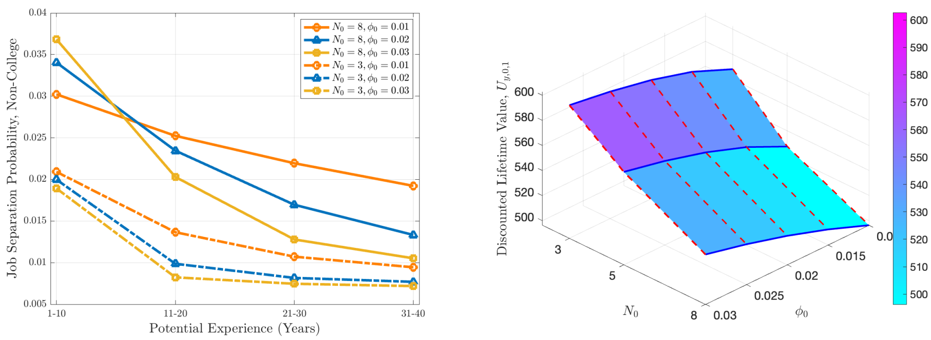
Figure 11: Dissecting the Uncertainty Channel

4.4 Policy Implications

Figure 11 demonstrates that reducing uncertainty can lower separations and unemployment among non-college workers. Given that non-college workers face significant uncertainty upon entering the labor market, we use this section to explore the potential benefits of policies which aim to reduce workers' uncertainty and some factors that such policies should consider.

The most straightforward approach is to reduce the number of potential careers, N_0, and/or accelerate the learning process, ϕ_0, for non-college workers. Figure 12(a) demonstrates that reducing N_0 and increasing ϕ_0 has distinct effects on the separation profile, as discussed in Section 4.3. Moreover, Figure 12(a) reveals an interaction between ϕ_e and N_e. Consider the dashed lines. When the number of careers is small, $N_0 = 3$, increasing the learning probability reduces separations across all career stages. Whereas when the number of careers is large, $N_0 = 8$ and represented by the solid lines, a higher learning probability initially increases separations as workers have more careers to sample, but reduces separations later on in non-college workers' careers. An implication of this is that N_e and ϕ_e should not be viewed in isolation from each other.

Figure 12(b) presents the lifetime value of a non-college worker upon entering the labor market for each combination of $\{N_0, \phi_0\}$. Despite a short increase in separations during the early career stage in the case $N_0 = 8$, the lifetime discounted value increases by 8% when the learning probability rises from 0.01 to 0.03. On the whole, reducing uncertainty, regardless of the method, leads to an increase in lifetime utility.



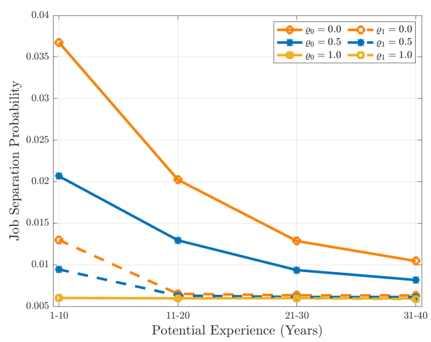
(a) Separation Profile (b) Lifetime Discounted Value $U_{y,0,1}$

Figure 12: Policy Analysis: N_0 or ϕ_0

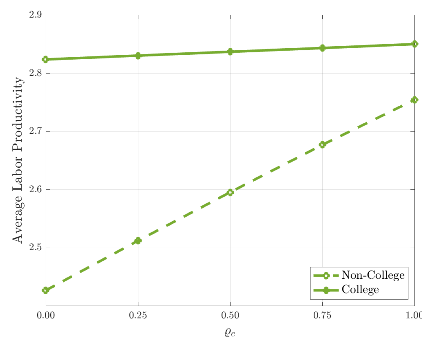
Beyond these two approaches, we propose a third alternative: to reduce the average level of uncertainty by introducing a fraction of workers who have perfect information regarding their best fit when entering the labor market. Specifically, we assume that a fraction ϱ_e of new entrants to the labor market immediately learn their best fit. Figure 13(a) shows that increasing the proportion of workers with perfect information significantly decreases separations, and that this effect is more pronounced among non-college workers. This is intuitive, as even college workers who do not know their best fit upon entry only need to sample a few careers to find their best fit. As such, reducing the initial uncertainty for college workers has a marginal effect on their separation profile.

Figure 13(b) shows the implications of increasing ϱ_e on average labor productivity by education. While increasing ϱ_e increases average productivity for all workers, the effect is more pronounced among non-college workers. For example, increasing ϱ_e from 0 to 1 increases average labor productivity by 32.70 (2.63) percentage points among non-college (college) workers. Again, this is because non-college workers take significantly longer to find their best fit. As such, increasing the proportion who knows their best fit upon entering the labor market leads to significant productivity gains.

In summary, there are potentially large benefits to policies which aim to reduce the uncertainty faced by non-college workers, as doing so can reduce separations and increase labor productivity. Moreover, the benefits of such policies may not be evenly distributed across the life cycle.



(a) Job Separation Profile



(b) Average Labor Productivity

Figure 13: Policy Implications, ϱ_e

4.5 Match-Specific Productivity

Our paper is closely related to existing models which generate decreasing separation profiles over the life cycle through the formation of match-specific productivity (e.g., Menzio et al. (2016)). The intuition is that older workers are more likely to have found a match with high productivity and therefore experience fewer separations. This logic could be extended the unemployment-education gap. If college workers have a higher labor productivity common to all matches, then they can sustain matches with a lower match-specific productivity and experience fewer separations from the very start of their career.[27]

[27] This intuition follows from a standard search model with shocks to match-specific productivity (e.g., Mortensen and Pissarides (1994)).

A key question, then, is what distinguishes the uncertainty channel from models which focus on the formation of match-specific productivity? First, following the intuition above, the average match-specific component of productivity is lower in matches with college workers. As discussed in Guvenen et al. (2020), skill mismatch can serve as a proxy for match-specific productivity. We show in Appendix A.3.2 that skill mismatch is decreasing in educational attainment. This suggests that the average idiosyncratic component of match productivity is higher among college graduates. Second, environments that rely exclusively on shocks to match-specific productivity to generate separations predict that the expected duration of a match formed through unemployment is independent of the worker's prior experience. However, this "resetting" property is counterfactual, as shown in Section 2.3.3 and Appendix A.6. Third, models of match-specific productivity do not speak to patterns in occupational and career mobility, nor do they address the differences in forecast errors by educational attainment we documented in Section 2.1.

As discussed in Section 3.3, the presence of match-specific productivity shocks can rationalize why bad fits are destroyed at a higher rate. However, this is because workers are less productive outside their true calling, which is tied to the uncertainty channel. Our decomposition exercise suggests that the interaction between the uncertainty channel and shocks to match-specific productivity are quantitatively meaningful. In this sense, our paper indicates that these two channels should not be viewed in isolation from each other.

5 Conclusion

This paper posits the uncertainty channel as a novel mechanism to explain the difference in unemployment rates between workers with and without a college degree. Using the NLSY79 and CPS, we document an extensive set of facts to support the uncertainty channel. Most notably, college graduates form more accurate expectations regarding their future occupation, the unemployment-education gap narrows over the life cycle, and separations are, especially for non-college workers, negatively associated with prior work experience. To formalize the uncertainty channel, we develop a life cycle search model with uncertainty over one's best career fit, learning, and endogenous separations. The model is parameterized by matching features of the NLSY79 and CPS, including the life cycle separation profiles and number of careers worked in by educational attainment. A decomposition reveals that the uncertainty channel accounts for between 24.45% and 96.72% of the unemployment-education gap.

Existing research has primarily focused on differences in the level of workers' skills by educational attainment. However, less attention has been given to how certain workers are about their own abilities, and how that certainty—or lack thereof—affects their capability to find their best fit in the labor market. Our empirical and quantitative findings indicate that not only do such differences in uncertainty exist between these two groups of workers, but that they play a significant role in generating differences in separations, labor productivity, and unemployment by educational attainment. With that said, this paper has not addressed the sources of the uncertainty channel. We leave this to future research.

References

AUTOR, D., D. DORN, AND G. HANSON (2019): "When work disappears: Manufacturing decline and the falling marriage market value of young men," *American Economic Review: Insights*, 1, 161–178.

AUTOR, D. H. AND D. DORN (2013): "The Growth of Low-Skill Service Jobs and the Polarization of the US Labor Market," *American Economic Review*, 103, 1553–97.

BALEY, I., A. FIGUEIREDO, AND R. ULBRICHT (2022): "Mismatch Cycles," *Journal of Political Economy*, 130, 2943–2984.

BOVER, O., M. ARELLANO, AND S. BENTOLILA (2002): "Unemployment Duration, Benefit Duration and the Business Cycle," *The Economic Journal*, 112, 223–265.

CAIRÓ, I. AND T. CAJNER (2018): "Human Capital and Unemployment Dynamics: Why More Educated Workers Enjoy Greater Employment Stability," *The Economic Journal*, 128, 652–682.

CAJNER, T., İ. GÜNER, AND T. MUKOYAMA (2023): "Gross Worker Flows over the Life Cycle," *Journal of Money, Credit and Banking*, forthcoming.

CHÉRON, A., J.-O. HAIRAULT, AND F. LANGOT (2013): "Life-cycle equilibrium unemployment," *Journal of Labor Economics*, 31, 843–882.

CRÉCHET, J., E. LALÉ, AND L. TARASONIS (2024): "Life-Cycle Worker Flows and Cross-Country Differences in Aggregate Employment," .

ELSBY, M. W. L., R. MICHAELS, AND G. SOLON (2009): "The Ins and Outs of Cyclical Unemployment," *American Economic Journal: Macroeconomics*, 1, 84–110.

ESTEBAN-PRETEL, J. AND J. FUJIMOTO (2014): "Life-cycle Labor Search with Stochastic Match Quality," *International Economic Review*, 55, 575–599.

FLOOD, S., M. KING, R. RODGERS, S. RUGGLES, J. R. WARREN, AND M. WESTBERRY (2022): "Intergrated Public Use Microdata Series, Current Population Survey: Version 10.0 [dataset]," Minneapolis, MN: IPUMS 2022.

GATHMANN, C. AND U. SCHÖNBERG (2010): "How general is human capital? A task-based approach," *Journal of Labor Economics*, 28, 1–49.

GERVAIS, M., N. JAIMOVICH, H. E. SIU, AND Y. YEDID-LEVI (2016): "What should I be when I grow up? Occupations and unemployment over the life cycle," *Journal of Monetary Economics*, 83, 54–70.

GORRY, A. (2016): "Experience and worker flows," *Quantitative Economics*, 7, 225–255.

GORRY, A., D. GORRY, AND N. TRACHTER (2019): "Learning and Life Cycle Patterns of Occupational Transitions," *International Economic Review*, 60, 905–937.

GUVENEN, F., B. KURUSCU, S. TANAKA, AND D. WICZER (2020): "Multidimensional Skill Mismatch," *American Economic Journal: Macroeconomics*, 12, 210–44.

KAMBOUROV, G. AND I. MANOVSKII (2008): "Rising Occupational and Industry Mobility in the United States: 1968-97," *International Economic Review*, 49, 41–79.

MENZIO, G. AND S. SHI (2011): "Efficient Search on the Job and the Business Cycle," *Journal of Political Economy*, 119, 468–510.

MENZIO, G., I. A. TELYUKOVA, AND L. VISSCHERS (2016): "Directed search over the life cycle," *Review of Economic Dynamics*, 19, 38–62, special Issue in Honor of Dale Mortensen.

MORTENSEN, D. T. AND C. A. PISSARIDES (1994): "Job creation and job destruction in the theory of unemployment," *Review of Economic Studies*, 61, 397–415.

MOSCARINI, G. AND K. THOMSSON (2007a): "Occupational and Job Mobility in the US," *Scandinavian Journal of Economics*, 109, 807–836.

——— (2007b): "Occupational and Job Mobility in the US," *The Scandinavian Journal of Economics*, 109, 807–836.

NEAL, D. (1999): "The Complexity of Job Mobility among Young Men," *Journal of Labor Economics*, 17, 237–61.

PAPAGEORGIOU, T. (2014): "Learning Your Comparative Advantages," *Review of Economic Studies*, 81, 1263–1295.

PETRONGOLO, B. AND C. A. PISSARIDES (2001): "Looking into the black box: A survey of the matching function," *Journal of Economic literature*, 39, 390–431.

PISSARIDES, C. A. (2009): "The Unemployment Volatility Puzzle: Is Wage Stickiness the Answer?" *Econometrica*, 77, 1339–1369.

SENGUL, G. (2017): "Learning about match quality: Information flows and labor market outcomes," *Labour Economics*, 46, 118–130.

SHIMER, R. (2005): "The Cyclical Behavior of Equilibrium Unemployment and Vacancies," *American Economic Review*, 95, 25–49.

——— (2012): "Reassessing the ins and outs of unemployment," *Review of Economic Dynamics*, 15, 127–148.

TOPEL, R. H. AND M. P. WARD (1992): "Job Mobility and the Careers of Young Men," *Quarterly Journal of Economics*, 107, 439–479.

VARDISHVILI, O. (2023): "The Macroeconomic Cost of College Dropout," Working paper.

WEE, S. L. (2013): "Born Under a Bad Sign: The Cost of Entering the Job Market During a Recession," Working paper.

Online Appendix

A Empirical Appendix

A.1 Current Population Survey (CPS)

The Current Population Survey (CPS) is a monthly survey conducted by the U.S. Census Bureau and the Bureau of Labor Statistics, providing information on employment, earnings, and demographic characteristics of the U.S. labor force. The survey follows a rotation pattern in which households are interviewed for four consecutive months, then not interviewed for the next eight months, and finally interviewed again for another four months. We use the individual identifier, CPSIDP, to link individual records across time.

A.1.1 Educational Categories

The measurement of educational attainment was modified in January 1992. Prior to 1992, the CPS recorded the highest grade attended and years of education completed. Since 1992, the CPS has switched to reporting the highest degree obtained. To ensure comparability between them, we create harmonized educational categories based on years of education or degree attainment, as demonstrated in Table A1. Specifically, "Non-College" includes individuals who have completed up to three years of college before 1992 or have obtained at most an associate's degree after 1992. "BA" includes those who have completed four years of college in the old question or have obtained a bachelor's degree in the new question. Finally, "Above BA" includes individuals who have completed at least five years of college in the old question or have obtained a master's, professional, or doctorate degree in the new question.

Table A1: Potential Experience by Education

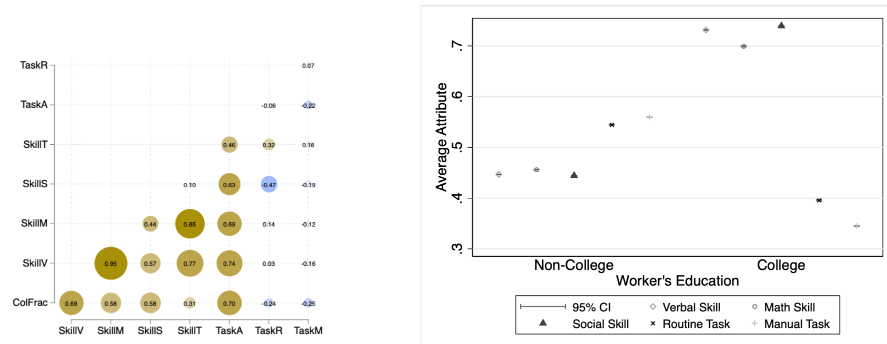
Category	Refined Category	CPS Education	Potential Exp.
Non-College	Non-College	$<$ 4 years of college (110)	$Age - 18 + 1$
College	BA	4 years of college (110)	$Age - 22 + 1$
		Bachelor's degree (111)	
	Master	5+ years of college (120)	$Age - 23 + 1$
		5 years of college (121)	$Age - 23 + 1$
		6+ years of college (122)	$Age - 24 + 1$
		Master degree (123)	$Age - 24 + 1$
	Professional and Doctorate Degree	Professional degree (124)	$Age - 28 + 1$
		Doctorate degree (125)	

A.1.2 Occupation Distance Measurement

To measure the distance between occupations, we begin by characterizing each occupation by a skill vector, where each element represents the required level of a specific skill to perform that job. In particular, we measure occupational requirement across multiple dimensions: (i) verbal, math, social, and technical skill requirements as in Guvenen et al. (2020); and (ii) abstract, routine, and manual task intensities as in Autor and Dorn (2013). Figure A1(a) displays the pairwise correlation between these attributes and the fraction of workers in that occupation who have a college degree. Jobs with a higher college fraction are positively related to the amount of verbal, math, social, technical skill requirements, as well as the abstract task intensity. Conversely, routine and manual task intensity is negatively correlated with the college fraction. As such, we select verbal, math, and social skills to capture the high-order skills and incorporate the routine and manual task intensity to capture the low-order skills.[28] Furthermore, we examine the average occupational attributes in jobs held by non-college and college workers in the CPS sample of $1,152,280$ employment observations. Figure A1(b)

[28]We do not incorporate technical skill requirement or abstract task intensity measure in the skill vector as both are highly correlated with verbal and math skill requirements.

shows that the average social, verbal, and math requirements for jobs held by college graduates are higher, while they are lower in the routine and manual task intensity measures. Overall, these five attributes capture well the lower- and higher-order skills required by occupations.



(a) Correlogram of Occupation Attributes (b) Average Attributes

Figure A1: Occupation Attributes

Skill and Task Measurement To measure verbal and mathematical skill requirements, we follow the methodology used by Guvenen et al. (2020). The first step is to construct four scores for each occupation in our CPS sample: (i) word knowledge, (ii) paragraph comprehension, (iii) arithmetic reasoning, and (iv) mathematics knowledge. To construct these scores, we use 26 O*NET descriptors that are chosen by the Defense Manpower Data Center (DMDC) and are listed in Panel A of Table A2. In the raw data, these descriptors range in value from 0 to 5. We re-scale their values to fall between 0 and 1 and then take the average value for each descriptor across O*NET version 5.0 (published in April 2003) to version 24.0 (published in August 2019).[29] It is noteworthy that skill information for five occupations, namely *Other Telecom Operators, Gardeners and Groundskeepers, Other Preci-*

[29]We focus on version 5.0 and onwards as the earlier versions relied exclusively on occupational analysts. Starting with version 5.0, the program was expanded to include additional sources such as job incumbents, big data, and others, to provide more comprehensive occupational information.

Table A2: 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

sion 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 impute their skill information by using the occupations that are adjacent in the occupational code lists. This has a negligible impact on our results, as these five occupations account for only 0.8% of the 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

$$S_{o,wk} = \sum_{i=1}^{26} s_{o,i} * \omega_{wk,i}, \tag{A.18}$$

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.

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). Specifically, r_{verbal} is the first principal component of word knowledge and paragraph comprehension, and r_{math} is the first principal component of arithmetic reasoning and mathematics knowledge. The verbal and math measures are then converted into percentile ranks among all occupations in our sample.

The social skill requirement is measured similarly. By applying PCA to six scaled O*NET descriptors in Panel B of Table A2, we construct a single index to reflect the social skill requirement, which was subsequently transformed into percentile ranks within our sample.

Finally, the task intensity indices are provided by Autor and Dorn (2013). Like the skill measurement, the task intensities have been transformed into percentile ranks within our sample.

A.2 National Longitudinal Survey of Youth (NLSY79)

The National Longitudinal Survey of Youth (NLSY79) is a longitudinal survey that tracks the labor market experiences of a youth cohort aged 14 to 22 when first surveyed in 1979. Conducted by the U.S. Bureau of Labor Statistics, it provides comprehensive information on employment, education, training, income, and family dynamics.

A.2.1 Sample Construction

We first construct a weekly panel data from original NLSY79 files, involving three key steps: (i) cleaning the employer history roster and determining employer characteristics, (ii) identifying necessary demographic variables for each respondent in each survey year, and (iii) identifying the primary job for each week if the worker holds multiple jobs.

Next, to match the time structure of the NLSY79 sample with the CPS, we convert the weekly panel to a monthly panel by identifying the primary labor force status for each month. The primary job for each month is determined as the one with the most working hours. If multiple civilian jobs have the same total working hours, we consider the job with complete occupation and industry records as the primary one. If several jobs have complete records, we retain the one with a known employer ID. If there are still multiple civilian jobs in a particular month, we keep the earliest reported one, indicated by a lower job code in the weekly array.

If the respondent does not hold any job with valid job codes for a given month, we prioritize the remaining labor force statuses in the following order: 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). The highest precedence status during the month is assigned as the respondent's primary labor force status for that month. Online Appendix D.2 contains further details on the NLSY79 sample construction.

A.2.2 Sample Selection

We start with monthly employment histories of $12,686$ respondents and subsequently restrict the sample to $6,403$ males, as female labor force participation exhibited large changes throughout the period covered by the NLSY79.[30] Next, we filter the observations to include only those from the earliest survey year (1978) until 2018. Table A3 summarizes the sample selection criteria.

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 $6,386$. 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.

[30] For example, the labor force participation rate of female increases from 50% in 1978 to around 60% starting in 1997.

Table A3: NLSY79 Sample Selection

Criteria	N	Total Obs.
Restrict to males	6,403	2,317,473
Monthly histories from 1978 to 2018	6,403	2,307,286
Start from the (known) graduation year	6,386	1,805,924
Never served in the military	5,361	1,589,597
Complete ASVAB	5,030	1,511,337
Complete non-cognitive scores	4,823	1,452,307

A.2.3 Measurement of Worker's Aptitudes

To measure a worker's verbal and math skills, we begin with a sample of $4,823$ respondents who have complete scores for the word knowledge, paragraph comprehension, arithmetic reasoning, and mathematics knowledge sub-tests of the Armed Services Vocational Aptitude Battery (ASVAB). We then normalize the mean and variance of each test score within each age cohort. 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.

To measure social skills, we utilize the Rotter Locus of Control Scale and the Rosenberg Self-Esteem Scale. Similar to the approach used for math and verbal skills, we account for the effect of test-taking age and extract the first principal components from the standardized scores of these two tests as the social ability measure.

A.2.4 Measurement of Skill Mismatch

To quantify the mismatch between workers' abilities and occupational requirements, we compute the distance between the percentile ranks of worker abilities and their corresponding occupational requirements. In particular, the mismatch in aptitude j between worker i and occupation o:

$$m_{i,j,o} = \left|q(A_{i,j}) - q(s_{o,j})\right|, \tag{A.19}$$

where $q(A_{i,j})$ represents the percentile rank of worker i in skill j, and $q(s_{o,j})$ denotes the requirement percentile of occupation o in skill j. Further, the aggregate mismatch is given by

$$m_{i,o} = \sum_{j}\{\omega_j \left|q(A_{i,j}) - q(s_{o,j})\right|\}, \tag{A.20}$$

where ω_j represents the weights assigned to each skill j, which reflect the relative importance of the difference in that skill to the aggregate skill mismatch. These weights are determined as the factor loadings obtained from the normalized first principal component analysis. In particular, the respective weights for verbal, math, and social are $(0.43, 0.42, 0.15)$, which is similar to the weights in Guvenen et al. (2020).

A.3 Additional Motivating Facts

A.3.1 Occupational Mobility

Using CPS data from 1994 to 2019, we compute monthly 3-digit occupational mobility rates by age and education. We do this by separately computing occupational mobility for job-to-job (EE) transitions and transitions from unemployment (EUE). For EE transitions, we restrict to observations with known occupations for two consecutive months. For EUE switches, we track the occupations before and immediately following the unemployment spell. We arrive at the aggregate occupational mobility rate by taking a weighted average across all transitions, incorporating essential correction to address potential measurement error in the mobility rates.

Correction of 3-Digit Occupational Mobility Occupational records in survey data are prone to measurement error. To mitigate this concern, we apply the methodology proposed by Moscarini and Thomsson (2007b) which leverages the dependent questions introduced in the CPS starting in 1994. This process involves 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.

We now proceed to detail the correction for occupational mobility. First, we restrict to individuals with complete data for the first four consecutive survey months, aged between 18 and 64, and were in the CPS between January 1994 and November 2019.[31] We identify a job-to-job (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 response to the "same activity?" question in the subsequent month $t+1$.[32] The identification process is depicted in Figure A2.

Next, we pass the suspicious transitions through the $ANY3$ Filter. The underlying idea is that if certain conditions undergo changes during two consecutive months coinciding with a change in the Occupational Classification Codes (OCC), this alteration in the OCC code indicates genuine occupational mobility. Three variables are pertinent to this filter: (i) change

[31] Our rationale for limiting the analysis to the first four consecutive months is twofold: first, the longitudinal structure is indispensable for filtering suspicious transitions during the correction process. To do that, each transition is inspected under a "global" view of the worker's employment history over four consecutive months, including one month before and one month 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.

[32] This step differs slightly from Moscarini and Thomsson (2007b) 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 besides yes or no.

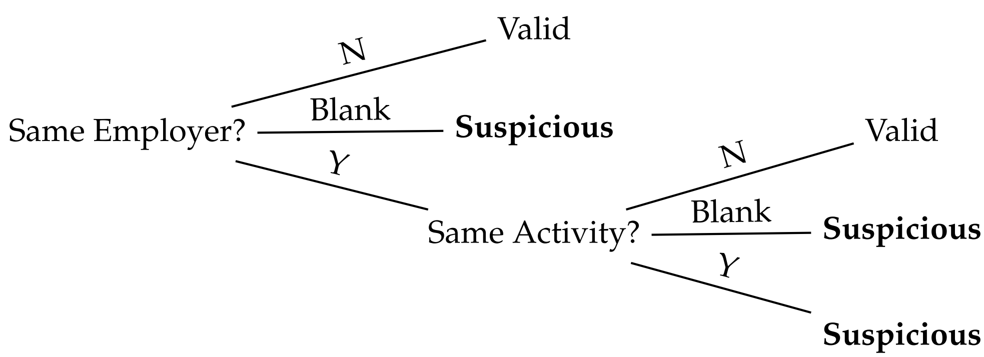
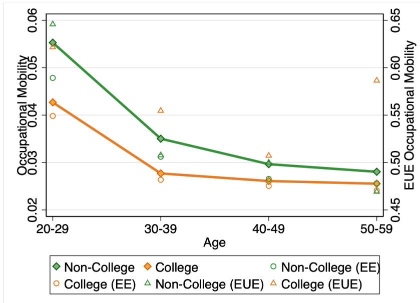


Figure A2: Identification of Suspicious Transitions

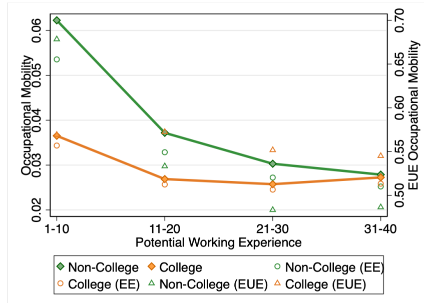
of class of worker (private firm, federal, state or local government, or self-employed, ...) at period $t+1$; (ii) change of three-digit industry codes at period $t+1$; (iii) look for work in past four weeks, labelled as active search, at period $t+1$. We regard any occupational change as fake if there was no change in industry, no change in the class of worker, and no active job search in the past four weeks. If a 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 utilizes the longitudinal component of the CPS and is based on the idea that certain occupational sequences are more likely to be fake. For suspicious transitions (from employment) that survive the ANY3 Filter, we classify the patterns "AABU," "ABCU," "NABU," "UABA," and "ABAU" as fake transitions, where U denotes being unemployed, while A and B denote different occupations.

3-Digit Occupational Mobility Figure A3 presents occupational mobility rates over ages or potential working years. The diamonds (triangles) represent occupational switches in EE (EUE) transitions, while the solid line is the overall fraction of workers who switch occupations each month. There are three patterns to highlight. First, occupational mobility is decreasing in age (Kambourov and Manovskii, 2008). Second, non-college workers



(a) Age



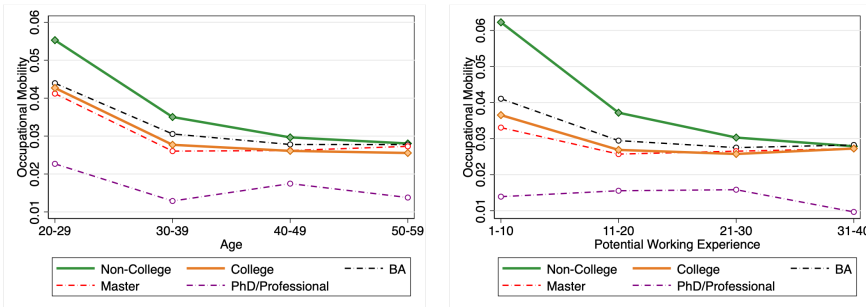
(b) Potential Experience

Figure A3: Occupational Mobility

change occupations more frequently. Third, just as unemployment and separations, the difference in occupational mobility rates across two education groups decreases with age. To further support the notion that highly educated workers experience less occupational mobility given their lower uncertainty, we report the 3-digit occupational mobility rates for detailed educational attainments. A4 shows that holding a Master's, Ph.D., or Professional degree is associated with even lower occupational mobility rates.

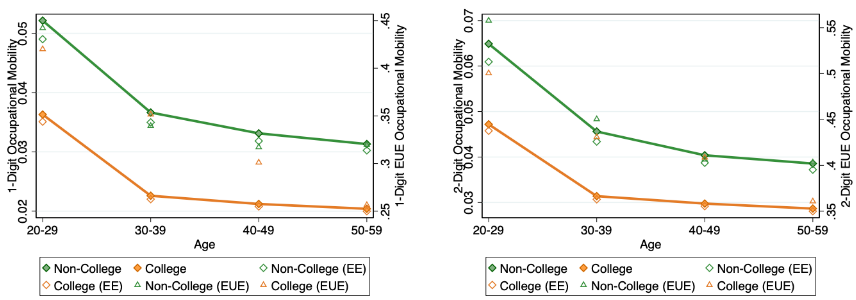
One factor complicating the interpretation of mobility over age is that educational attainment affects the timing of labor market entry. Hence, we also show the occupational mobility rates along presumed years of potential experience, where we assume non-college (college) workers enter the labor market at the age of 18 (22). Figure A3(b) illustrates that while the overall pattern is unchanged, the gap in occupational mobility rates in the early stages of workers' careers is even larger than when we compare by age.

Mobility at Broader Occupational Levels Occupational mobility within broader occupation categories is less susceptible to measurement error because there is less overlap between occupations and, hence, less of a chance that a worker's occupation is misclassified. Figure A5 presents the raw occupational mobility rates by age and education using 1- and 2-digit occupational codes. The patterns are consistent with those shown in Figure A3.



(a) Age (b) Potential Experience

Figure A4: Occupational Mobility Across Specific College Degrees



(a) 1-digit (b) 2-digit

Figure A5: Occupational Mobility at 1- and 2-digit Occupation Codes

A.3.2 Skill Mismatch

After obtaining the skill mismatch for each worker-job pair as outlined in Appendix A.2.4, we compute the average skill mismatch within age and education groups, $\overline{MM}_{i,j}$:

$$\overline{MM}_{i,j} = \frac{\sum_{k \in i \cap j} MM_k \times \omega_k}{\sum_k \mathbb{1}\{k \in i \cap j\} \times \omega_k}. \tag{A.21}$$

From equation (A.21), $\overline{MM}_{i,j}$ is given by the ratio of the aggregate mismatch within individuals with education i and age j to the number of individuals within that subgroup. Note that we use the technical weight ω_k, which captures the representation of the respondent within the U.S. population.

Figure A6 shows that overall skill mismatch is decreasing in educational attainment. Similar patterns emerge when looking at each individual skill dimension and are available upon request.

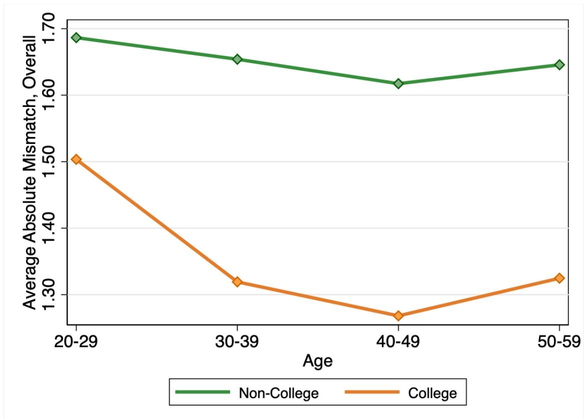


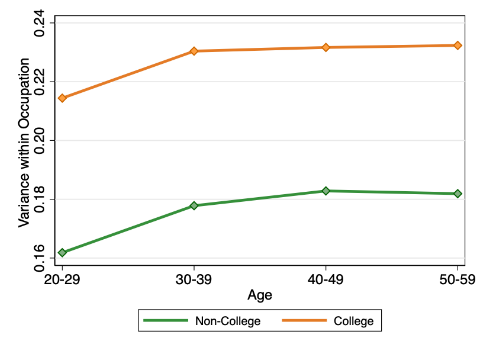
Figure A6: Skill Mismatch by Age and Educational Attainment

A.3.3 Dispersion in Skill Requirements

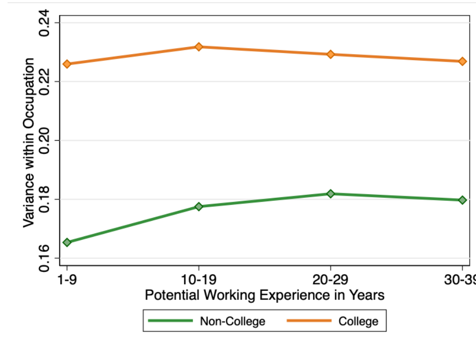
In this section, we compare the variance of occupational skill requirements across age/potential experience and educational attainment. The degree of dispersion is suggestive of workers' uncertainty regarding their abilities. Specifically, workers with greater certainty about their best fit may pursue occupations with more imbalanced skill requirements, as they are confident in their capability to excel in jobs that emphasize a particular type of skills.

Figure A7 shows that the college workers are employed in occupations with a higher variance of skill requirements, lending support to the notion that highly-educated individuals have a higher degree of certainty regarding which kind of job is a best fit for them.[33]

[33]Several alternative measures of dispersion in skill requirements include the max-min difference, mean absolute deviation, and median absolute deviation. These indicators produce similar patterns as in Figure A7 and are available upon request.



(a) Age



(b) Potential Experience

Figure A7: Comparison of Within-Occupation Variance

A.3.4 Number of employer, occupation, and career changes

To compare career stability across educational attainment, we examine the average number of cumulative transitions experienced by age and educational attainment. This computation involves a two-step process. First, within each subgroup, we calculate the average number of employer, occupational, and career switches. Second, we compute the cumulative average transitions by aggregating the average transitions across all subgroups that precede the given age bin.[34]

Table A4 shows that individuals tend to accumulate transitions as they age. More importantly, individuals with higher educational attainment tend to experience fewer switches across all transition types at any career stage. Notably, workers without a college degree experience nearly twice as many career transitions over their life cycle.

[34]To compute the number of unique employers, we take the ratio of the number of unique employers up to a particular career stage to the number of distinct respondents.

Table A4: Cumulative Transitions by Age

	$20-29$	≤ 39	≤ 49	≤ 59
Employer Transitions				
Non-College	4.43	6.90	8.35	9.08
College	1.91	3.57	4.73	5.57
Unique Employers				
Non-College	5.01	6.56	7.33	7.71
College	2.76	3.82	4.37	4.78
Occupation Transitions				
Non-College	4.97	7.80	9.13	9.76
College	3.02	5.40	6.61	7.38
Career Transitions				
Non-College	3.00	4.65	5.41	5.78
College	1.44	2.44	2.85	3.17

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

A.4 Robustness Checks

A.4.1 Transition Probabilities

Aggregate Employment Profile Table A5 shows that, when aggregating across age, college graduates are less likely to be unemployed and have a lower separation risk. College graduates also exhibit a lower job finding probability and rate than those without a college degree.

Correction for Time Aggregate Bias As a first step, we directly compute the transition probabilities. We start with the longitudinal labor market flows between employment statuses at the individual level from 1976:1 through 2019:11.[35] We then count the number of transitions that occurred in period

[35]We link individuals over time using the IPUMS produced individual identifier *CPSIDP*. Further, we drop observations with inconsistent age, race, and gender records.

Table A5: Aggregate Employment Profile, by Education, PP

	Urate	JFP	JSP	JFR	JSR
Non-College	6.88	27.92	1.87	37.81	2.21
College	2.74	27.19	0.63	32.37	0.79

Note: The first three columns are computed from CPS, 1976:1 - 2019:12 white the last two are computed from CPS: 1994:1-2019:11.

t in the group of age i and education j using the longitudinal weights.[36] 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 and $N(U)_t^{ij}$ ($N(E)_t^{ij}$) denote the population of unemployed (employed) workers in the group of age i and education j in period t. The average transition probabilities in each age-education group are given by:

$$JFP^{ij} = \sum_t \omega_t^{ij} \frac{N(UE)_t^{ij}}{N(U)_t^{ij}} \times 100, \quad JSP^{ij} = \sum_t \omega_t^{ij} \frac{N(EU)_t^{ij}}{N(E)_t^{ij}} \times 100, \tag{A.22}$$

where JFP^{ij} (JSP^{ij}) is the job finding (separation) probability and ω_t^{ij} is the share of observations at period t among those with age i and education j.

Next, using the employment status of individuals in group ij for consecutive months from January 1976 through November 2019, we construct a time series of gross flow of workers ($F(XY)_t$) between unemployment (U), employment (E), inactivity (I) and missing (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. We then compute the original monthly transition probability between different labor force statuses by $n(AB)_t = \frac{F(AB)_t}{\sum_{M\in\{U,E,I\}} F(AM)_t}$, where $A, B \in \{U, E, I\}$.

Next, we seasonally adjust the time-series using a ratio-to-moving average (RMA) technique. First, we calculate the moving average (MA) by

[36] 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.

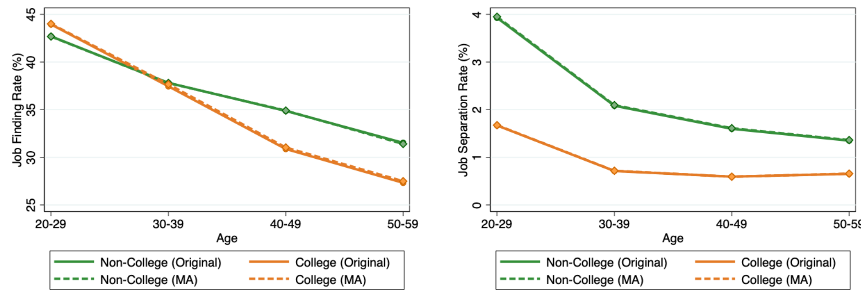
taking the weighted average of the prior six months and the six months lagged around the targeted month. Then, we divide the flow value by the MA and compute the average ratio for each month by taking the average across different years. We then compute the ratio between the average ratio in each month with the base ratio, where the base ratio is the mean of the average ratio in 1998. Finally, we 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, $\tilde{n}_t$, in hand, we follow Shimer (2012) in computing the instantaneous transition rate matrix $\lambda_t = P_t \times \tilde{u}_t \times P_t$, 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 adjusted 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 corrected transition probabilities for each subgroup by taking the average of $\Lambda_t^{ij}(AB)$ across all t.

Job Finding and 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 can be derived starting with the law of motion for unemployment:

$$u_{t+1} = (1 - F_t)u_t + u_{t+1}^s \quad \Rightarrow \quad F_t = 1 - \frac{u_{t+1} - u_{t+1}^s}{u_t}, \tag{A.23}$$

where F_t is the monthly outflow probability. Equation (A.23) 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_{t+1}^s. Therefore, the outflow rate f_t can be derived from $f_t = -\log(1 - F_t)$.



(a) Job Finding Rate (b) Separation Rate

Figure A8: Original and 12-month Moving Average Transition Rate

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

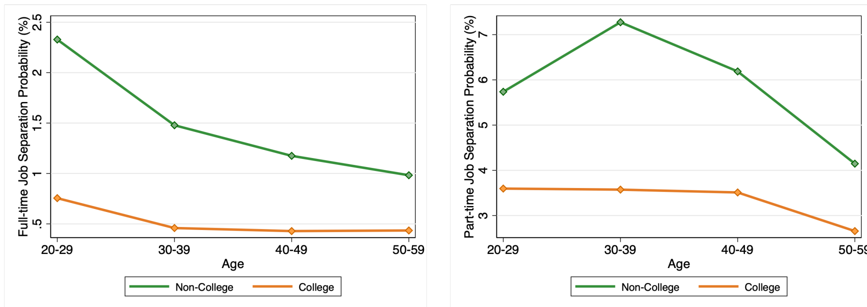
$$\dot{u} = \overbrace{s_t(l_t - u_t)}^{inflow} - \overbrace{u_t f_t}^{outflow} = -(s_t + f_t)(u_t - u^*), \tag{A.24}$$

where u^* is the steady state unemployment and l_t is the size of the labor force. The second equality comes from the labor market equilibrium condition $s_t e_t^* = u^* f_t$. By solving (A.24) and assuming s_t, f_t and l_t are constant between surveys, we can infer s_t from

$$u_{t+1} = \frac{(1 - e^{(-s_t - f_t)})s_{t+1}}{f_{t+1} + s_{t+1}} l_t + u_t e^{(-s_t - f_t)}. \tag{A.25}$$

To compute the inflow and outflow rates, we first compute the unemployment rate for each subgroup ij. 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 from equations (A.23) and (A.25).[37] Finally, we take a 12-month moving average. Figure A8 shows that the age profile patterns of the transition rates are similar to those seen in the transition probabilities shown in Figure 3.

[37] Observations before 1994 were discarded because the unemployment duration variable is only available in IPUMS-CPS data starting from 1994.



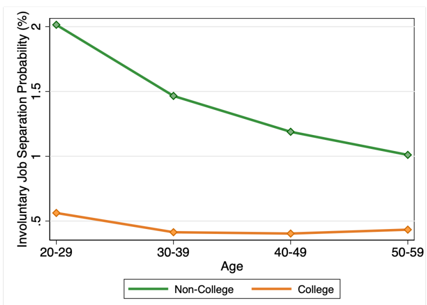
(a) Full Time (b) Part Time

Figure A9: Separation Probability by Working Status

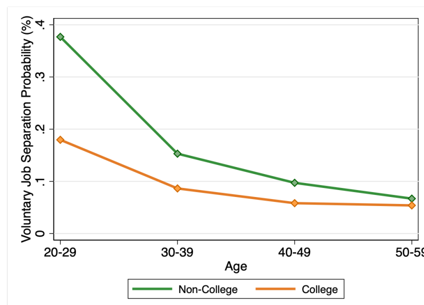
Separation Probability by Working Status Workers without a college degree are more likely to be employed in part-time jobs, which might lead to more separations that are not related to the worker's comparative advantage (e.g., seasonal jobs). To show that this is not a key driver of the U-E gap, we provide several pieces of evidence. First, there is no systematic compositional difference across education-age groups in terms of working status. In particular, the fraction of full-time employment for non-college workers is about 85%/95%/95%/94% at each age bin, which is close to 91%/96%/96%/95% for college workers. Second, Figure A9 shows that, even among those in full-time jobs, less-educated workers exhibit higher rates of separation. Finally, as shown in Section A.4.3, the observed patterns persist when we control for seasonality by including monthly fixed effects in our conditional estimations.

Involuntary and Voluntary Separations Learning that one is not a good fit for a career and wanting to sample another may be more likely to result in a voluntary quit. If true, then less-educated workers should quit their jobs at a higher rate. To examine this, we leverage the reason for unemployment in the CPS, where those who list ''job loser – on layoff'', ''other job loser'', or ''temporary job ended'' as their reason for being unemployed are labelled as involuntarily unemployed. Those who list ''job leaver'' are labelled as being voluntarily unemployed/having quit their job.

Figure A10 shows that the voluntary separation probability for non-college workers is higher than their college-educated counterparts, and the gap notably narrows with age. This is consistent with our hypothesis of greater uncertainty over one's best fit among non-college workers. Further, involuntary separations exhibit similar patterns, which may be interpreted as a result of firm learning. It is for this reason that we do not distinguish between voluntary and involuntary separations in our baseline analysis.



(a) Involuntary Separations



(b) Quits

Figure A10: Involuntary Separations and Quits

A.4.2 U-E Gap Decompositions

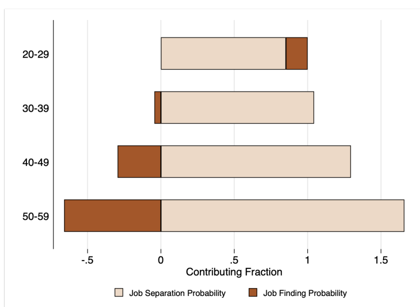
To quantify the sources of the U-E gap, we employ the method by Pissarides (2009) to decompose the U-E gap at each age bin into differences in the separation and job finding probabilities. Denoting s_{ij} and f_{ij} as the job separation and finding probabilities for age group i with educational attainment j, the steady-state unemployment rate for subgroup ij is

$$u_{ij} = \frac{s_{ij}}{s_{ij} + f_{ij}}. \tag{A.26}$$

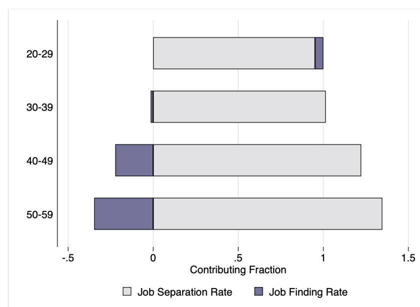
Taking first differences of (A.26) between education levels j and j' gives

$$1 = \underbrace{\frac{(1-u_{ij})u_{ij'}\frac{(s_{ij}-s_{ij'})}{s_{ij'}}}{\Delta u_i}}_{\text{Fraction explained by JSP}} + \underbrace{\frac{-u_{ij}(1-u_{ij'})\frac{(f_{ij}-f_{ij'})}{f_{ij'}}}{\Delta u_i}}_{\text{Fraction explained by JFP}}. \tag{A.27}$$

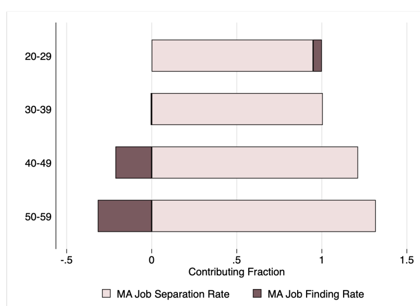
Figure A11 presents the fraction of the U-E gap at each age bin i that is attributable to difference in the job separation and finding probabilities, and alternative measures of the inflow and outflows rates that have been detailed in prior appendices. Each decomposition tells us that the U-E gap is primarily driven by differences in the separation probability/rate.



(a) JF/JS Probabilities



(b) JF/JS Rates



(c) Moving Average JF/JS Rates

Figure A11: Decomposition of the U-E Gap

A.4.3 Regression Results

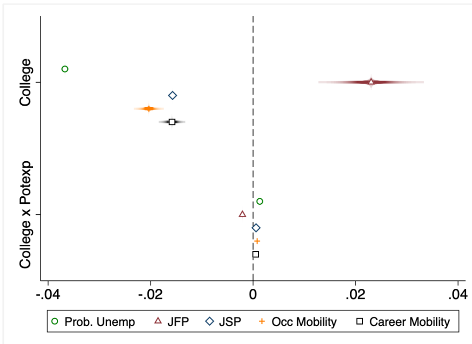
To assess the robustness of the patterns presented in graphs throughout the paper to controlling for standard observables, we estimate:

$$
\begin{aligned}
Y_{i,t} &= \beta_0 College_i + \beta_1 Potexp_{i,t} + \beta_2 Potexp_{i,t}^2 + \beta_3 College_i * Potexp_{i,t} + Race_i + \\
&FamInc_{i,t} + MarStatus_{i,t} + Child_{i,t} + \Phi_{Occ2} + \Phi_{Ind2} + \Phi_{State} + \Phi_{Year} + \Phi_{Month} + \epsilon_{i,t}.
\end{aligned} \tag{A.28}
$$

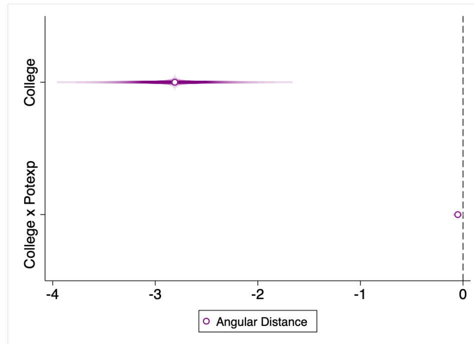
Our outcomes of interest, $Y_{i,t}$, include indicators for whether worker i in period t: (i) is unemployed or not; (ii) transitioned from unemployment to employment; (iii) transitioned from employment to unemployment; (iv) transitioned to a different occupation; (v) transitions to a different career; and (vi) the skill distance in occupational transitions. Our primary variable of interest is $College_i$, which is an indicator for whether individual i has a college degree. The coefficient β_0 captures the association between a college degree and the outcome of interest, while β_3 indicates how this association varies over years of potential experience.

As seen in (A.28), we control for a quadratic in years of potential experience, race, marital status, whether the respondent has a child or not, and family income. In addition, we control for job characteristics by including 2-digit occupation and industry fixed effects. Finally, we incorporate year, month, and state fixed effects.

To facilitate a comparison across different education levels, Figure A12 plots the point estimates and their 99% confidence intervals for $College_i$ and $College_i * Potexp_{i,t}$. In particular, college graduates have statistically significant lower unemployment/job separation/occupation switching/career switching probabilities and a significantly higher job finding relative to their counterparts without a college education. Figure 12(b) shows that conditional on changing occupations, college graduates switch to occupations with a lower distance from their prior occupations. Moreover, the education gap diminishes over potential experience for each outcome. Overall, the results align with the descriptive patterns. The detailed regression results can be found in Table A6.



(a) Unemp, JFP, JSP, Occ and Career Mobility



(b) Occupational Distance

Figure A12: Estimates of β_0 and β_3

Table A6: Regression Results

	(1)	(2)	(3)	(4)
Panel A: *Unemployed Indicator*				
College	-0.03750***	-0.03762***	-0.03672***	-0.02638***
College × PotExp	0.00130***	0.00131***	0.00131***	0.00116***
Observations	16,531,741	16,531,741	16,531,741	13,097,696
R^2	0.034	0.036	0.042	0.064
Panel B: *Job Finding Indicator*				
College	0.01749***	0.02223***	0.02304***	0.01415***
College × PotExp	-0.00176***	-0.00194***	-0.00207***	-0.00198***
Observations	501,664	501,664	501,664	409,425
R^2	0.018	0.022	0.040	0.045
Panel C: *Separation Indicator*				
College	-0.01617***	-0.01608***	-0.01571***	-0.01392***
College × PotExp	0.00058***	0.00058***	0.00059***	0.00057***
Observations	10,083,104	10,083,104	10,083,104	8,145,221
R^2	0.013	0.014	0.015	0.017
Panel D: *Occupational Mobility Indicator*				
College	-0.01985***	-0.01981***	-0.02034***	-0.01927***

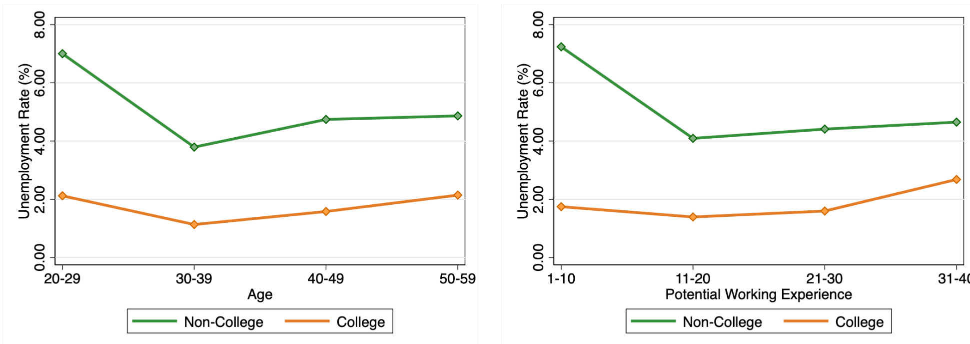
College × PotExp	0.00079***	0.00079***	0.00080***	0.00080***
Observations	852,249	852,249	852,249	801,775
R^2	0.007	0.008	0.008	0.010
Panel E: *Career Mobility Indicator*				
College	-0.01499***	-0.01505***	-0.01582***	-0.01501***
College × PotExp	0.00050***	0.00050***	0.00051***	0.00052***
Observations	827,086	827,086	827,086	778,243
R^2	0.007	0.007	0.008	0.009
Panel F: *Angular Distance in Occupation Switches*				
College	-2.88222***	-2.81939***	-2.80947***	-2.60987***
College × PotExp	-0.04694**	-0.04996**	-0.05127***	-0.04174**
Observations	28,940	28,940	28,940	26,537
R^2	0.078	0.080	0.082	0.084
2-digit Occ. FE	✓	✓	✓	✓
2-digit Ind. FE	✓	✓	✓	✓
State FE		✓	✓	✓
Year FE			✓	✓
Month FE			✓	✓

Notes: Industry and occupational codes for the unemployed are classified according to their last job. Standard errors are robust to heteroskedasticity. The last column additionally controls for family income. *($p < 0.10$), **($p < 0.05$), ***($p < 0.01$).

A.5 NLSY79 Patterns

A.5.1 Unemployment-Education Gap

Figure A13 displays the unemployment rate by age/potential experience and educational attainment in our NLSY79 sample. The overall patterns are consistent with the CPS, as the U-E gap narrows as individuals age or gain potential experience. Additionally, there is a notable increase in the unemployment rate during the later career stages. This trend is reasonable, given that around 85% (15%) of respondents were 40-49 (50-59) years old in 2008 at the onset of the Great Recession.



(a) Age (b) Potential Experience

Figure A13: Unemployment-Education Gap in the NLSY79

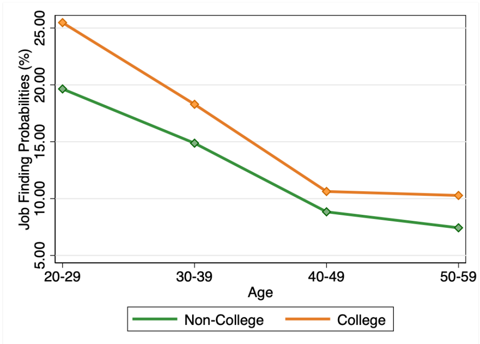
A.5.2 Job Finding and Separation Probabilities

Figure A14 presents the job finding and separation probabilities. Concerning the job finding probabilities, there is no systematic difference among education groups, especially over potential experience. However, consistent with the patterns observed in the CPS, college workers have systematically lower separation probabilities.

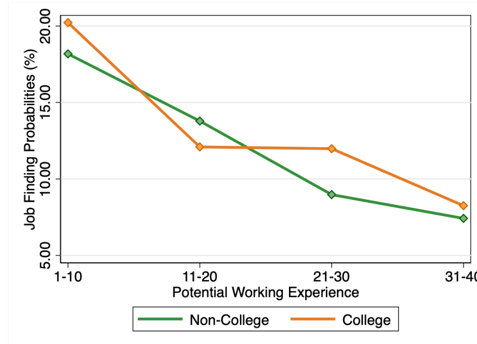
A.5.3 Occupation Mobility

To measure occupational mobility in the NLSY79, we compute the fraction of workers within each age/potential experience and education subgroup who switch occupations between months $t-1$ and t and weight each observation according to the $PANELWEIGHT$ variable. We limit to pairs of months with valid occupational codes. If the worker was non-employed in the previous month, we identify the occupation that precedes the period of non-employment. Figure A15 shows that occupational mobility patterns in the NLSY79 align with those in the CPS in that occupational mobility is decreasing with age/potential experience and educational attainment.

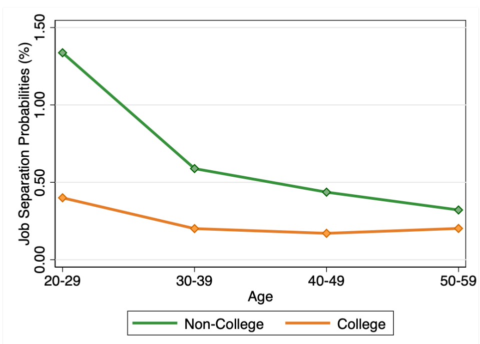
Figure A16 shows the average angular distance in occupation switches. Consistent with the trends observed in the CPS, higher educational attainment is associated with a lower angular distance at each career stage.



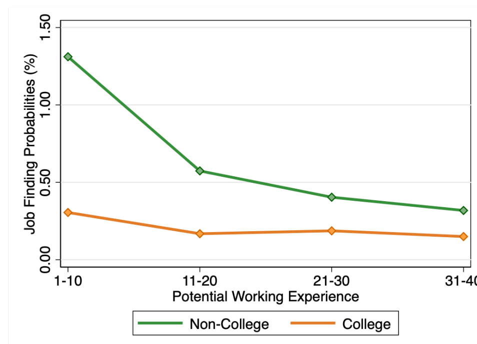
(a) JFP: Age



(b) JFP: Potential Experience

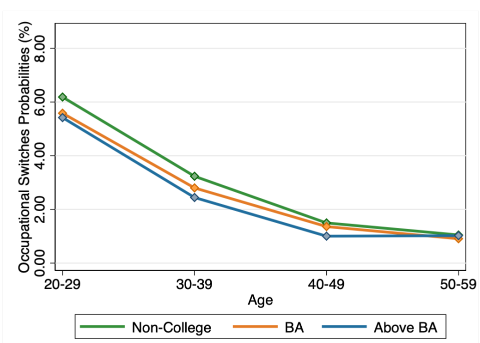


(c) SP: Age

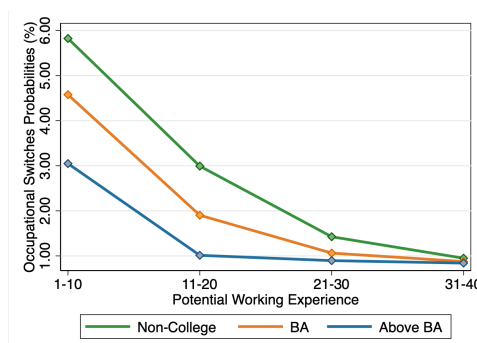


(d) SP: Potential Experience

Figure A14: Job Finding (JFP) and Separation (SP) Probabilities

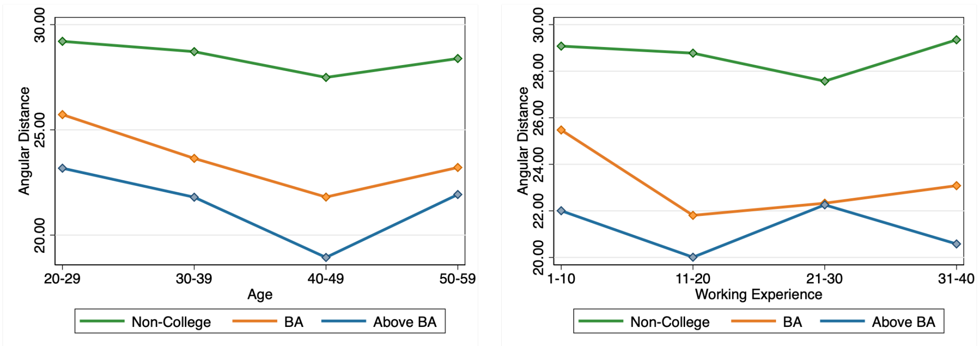


(a) Age



(b) Potential Experience

Figure A15: Occupational Transitions



(a) Age

(b) Potential Experience

Figure A16: Angular Distance in Occupational Transitions

A.5.4 Career Mobility

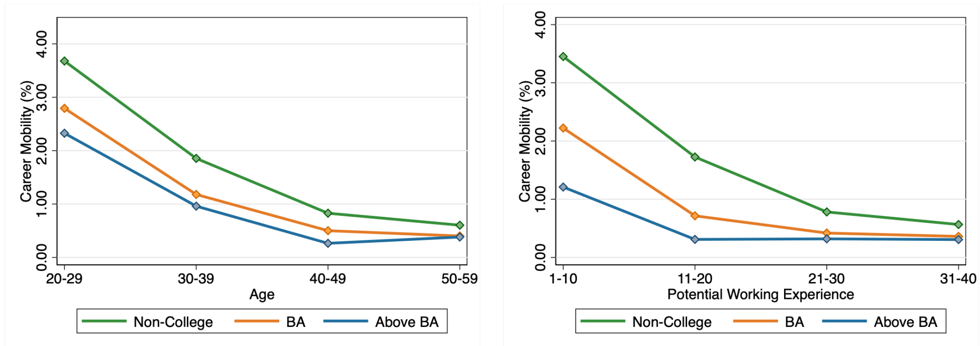
To measure career mobility in the NLSY79, we first identify a threshold, $\bar{\phi}$, for career transitions. That is determined by examining $37,084$ occupational transitions, where both skill requirements and task intensities are available for both the current and previous occupations. Next, we find $\bar{\phi} = 23.08$ gives an unweighted average correlation of aptitudes $k \in \{verbal, math, social, manual, routine\}$ of approximately 0.00005. As such, a career switch in the NLSY79 data are defined as occupational transitions where $\phi \geq 23.08$.

Figure A17 shows that, just as with occupational mobility, that career mobility in the NLSY79 is decreasing with both age/potential experience and educational attainment. Moreover, the gap in career mobility rates across educational attainment decreases over the career.

A.5.5 Robustness of NLSY79 Results

This section probes the robustness of the NLSY79 patterns to controlling for standard observables. The regression specification is the same as equation (A.28). The outcomes of interest are the same as in the CPS regressions and skill mismatch as detailed in Section A.3.2.

Table A7 presents the estimated coefficients for college and the interaction term between college and potential experience. We can see that after



(a) Age

(b) Potential Experience

Figure A17: Career Switches

controlling for observables, having a college degree is still associated with significantly lower probabilities of being unemployed, separating from employment, switching occupations or careers. Moreover, college workers have less skill mismatch and, conditional on switching occupations, have a lower angular distance in the switch. The interaction terms between college and potential experience suggest that, in general, the education gap in our outcomes of interest tend to dissipate with potential experience.

Table A7: NLSY79 Regression Results

	(1)	(2)	(3)	(4)
Panel A: *Unemployed Indicator*				
College	-0.01986***	-0.02005***	-0.01296***	-0.00279***
College × PotExp	0.00062***	0.00065***	0.00012***	-0.00011**
Observations	1,197,087	1,187,574	1,187,574	1,003,608
R^2	0.051	0.051	0.057	0.118
Panel B: *Job Finding Indicator*				
College	0.01004	0.00742	0.02036	0.03187*
College × PotExp	-0.00033	-0.00018	-0.00028	-0.00134
Observations	63,714	63,042	63,042	47,568
R^2	0.043	0.044	0.055	0.070
Panel C: *Separation Indicator*				
College	-0.00927***	-0.00931***	-0.00585***	-0.00433***

College × PotExp	0.00044***	0.00044***	0.00027***	0.00021***
Observations	1,129,938	1,121,132	1,121,132	953,230
R^2	0.009	0.009	0.010	0.013
Panel D: *Occupational Mobility Indicator*				
College	-0.01854***	-0.01840***	-0.00763***	-0.00561***
College × Potexp	0.00070***	0.00070***	0.00036***	0.00029***
Observations	1,120,216	1,111,460	1,111,460	945,932
R^2	0.017	0.017	0.024	0.026
Panel E: *Career Mobility Indicator*				
College	-0.01562***	-0.01563***	-0.00951***	-0.00815***
College × PotExp	0.00059***	0.00059***	0.00039***	0.00034***
Observations	1,120,210	1,111,454	1,111,454	945,928
R^2	0.014	0.014	0.017	0.018
Panel F: *Angular Distance in Occupational Switches*				
College	-2.89147***	-3.05840***	-3.16422***	-3.04611***
College × Potexp	-0.05265**	-0.04957**	-0.03879	-0.02232
Observations	36,687	36,444	36,444	29,754
R^2	0.196	0.196	0.199	0.203
Panel G: *Skill Mismatch*				
College	-0.01562***	-0.01563***	-0.00951***	-0.00815***
College × PotExp	0.00059***	0.00059***	0.00039***	0.00034***
Observations	1,120,210	1,111,454	1,111,454	945,928
R^2	0.014	0.014	0.017	0.018
2-digit Occ. FE	✓	✓	✓	✓
2-digit Ind. FE	✓	✓	✓	✓
State FE		✓	✓	✓
Year FE			✓	✓
Month FE			✓	✓

Notes: Industry and occupational codes for the unemployed are classified according to their last job. Standard errors are robust to heteroskedasticity. The last column also controls for family income. *($p < 0.10$), **($p < 0.05$), ***($p < 0.01$).

A.6 Experience and Match Survival Regressions

Following Bover et al. (2002), we estimate the association between prior experience and match survival by estimating:

$$\begin{aligned}\text{Survival}_{it} = &\sum_{n=2}^{120} \mathbb{1}(\text{Dur}_{it} = n) + \beta_1 \text{Exp}_{it} + \beta_2 \log(\text{Dur}_{it}) * \text{Exp}_{it} + \beta_3 \text{Exp}_{it} * \text{College}_i \\ &+ \beta_4 \log(\text{Dur}_{it}) * \text{College}_i + \beta_5 \log(\text{Dur}_{it}) * \text{White}_i + \text{College}_i + \text{Age}_{it} \\ &+ \text{White}_i + \Phi_{Year} + \Phi_{Season} + \Phi_{Ind} + \epsilon_{it},\end{aligned}$$

where Survival_{it} is an indicator for whether the match survives into the subsequent period. We flexibly capture the duration dependence in the survival probability by introducing an additive dummy variable corresponding to each monthly duration. The primary explanatory variables include the amount of experience the worker had accumulated at the formation of the match, and its interaction with education attainment.[38]

Table A8 shows that prior experience is associated with a higher survival probability, and that this effect dissipates with tenure. Finally, we find $\beta_3 < 0$, which suggests that the association between experience and the survival probability is weaker for college workers.

A.7 Unemployable Workers

The higher unemployment rate and separation probability for non-college workers might be driven by a group of "unemployable" workers, i.e. workers who experience an unusually high number of separations. We define unemployable workers as those with at least four EU transitions within the first ten years of their career, representing the 90^{th} percentile of EU transitions among non-college workers during this period.

Figure A18 shows that removing the unemployable workers shifts down the unemployment and separation probabilities for non-college workers, while making little difference in the job finding probability. Overall, the

[38] Exp_{it} is 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 prior working experience in months.

Table A8: Prior Experience and Match Survival

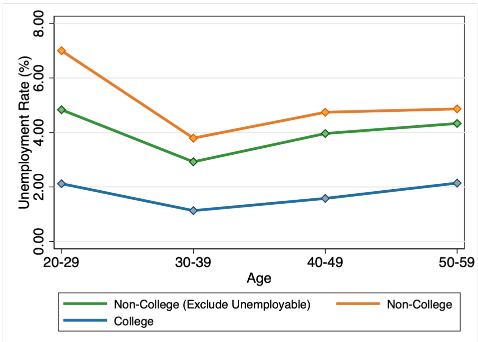
	(1)	(2)	(3)	(4)
Panel A: *Experience > 76 months indicator*				
Exp	0.02037***	0.00731***	0.01157***	0.00790***
Log(Dur) × Exp	-0.00295***	-0.00232***	-0.00282***	-0.00248***
Exp × College		-0.00498***	-0.00427***	-0.00755***
Log(Dur) × College		-0.00721***	-0.00561***	-0.00602***
Observations	1,105,229	1,105,229	1,055,676	484,382
R^2	0.019	0.024	0.019	0.022
Panel B: *Months of Prior Experience*				
Exp	0.00012***	0.00006***	0.00008***	0.00005***
Log(Dur) × Exp	-0.00002***	-0.00002***	-0.00002***	-0.00001***
Exp × College		-0.00004***	-0.00003***	-0.00004***
Log(Dur) × College		-0.00745***	-0.00574***	-0.00620***
Observations	1,105,229	1,105,229	1,055,676	484,382
R^2	0.019	0.024	0.019	0.022
Year FE		✓	✓	✓
Season FE		✓	✓	✓
1990dd Industry FE			✓	✓

Notes: The second and third specifications include the interaction between Log(Dur) and College, and White. 1990dd are industry fixed effects according to the industrial classification scheme compiled by Autor et al. (2019). Column (4) excludes matches formed through a job-to-job transition. Robust standard errors are in parentheses. *($p < 0.10$), **($p < 0.05$), ***($p < 0.01$).

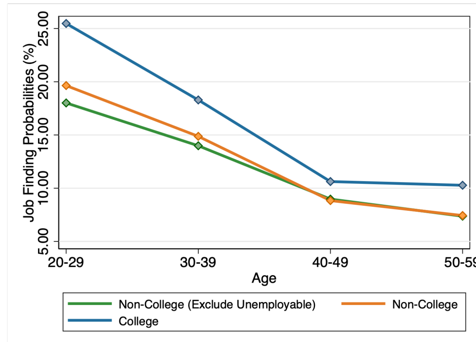
gaps in unemployment and separations persist and narrow with age after excluding unemployable workers.

A.8 Parents' Occupation

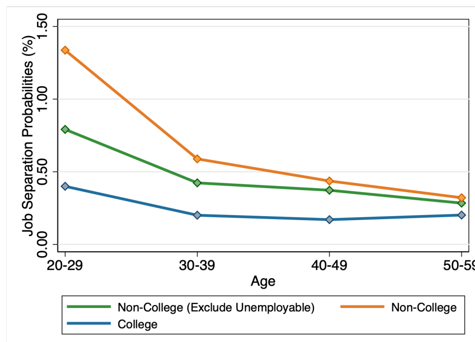
Given that occupational inheritance may affect employment stability through networking inherited from one's parents, we examine whether the previous evidence is robust to controlling for parental occupation. Specifically, we extend the NLSY79 regressions to include an indicator, *ParentOcc*. We



(a) Unemployment Rate



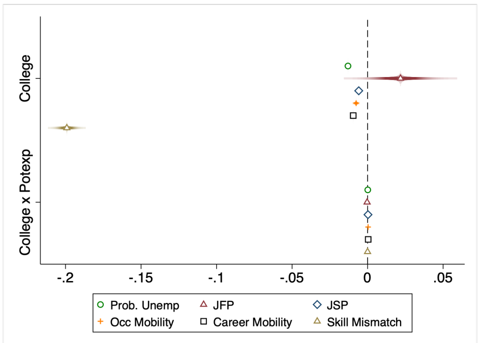
(b) Job Finding Probability



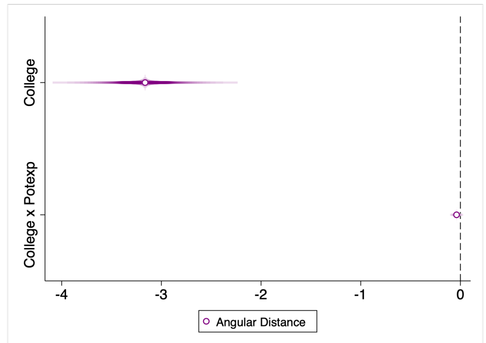
(c) Separation Probability

Figure A18: Life Cycle Patterns Excluding Unemployable Workers

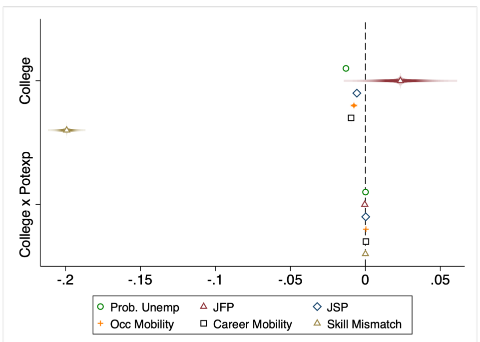
measure *ParentOcc* in two ways: at the individual level, where it takes the value of one if the worker has ever held a job similar to one of their parents' occupations, even if only once; or at the observation level, where it takes the value of one if the worker's current job is the same as that of their parents. Figures A19 present the estimated coefficients and 99% confidence intervals after controlling for *ParentOcc*, which remain consistent with the patterns observed in Table A7.



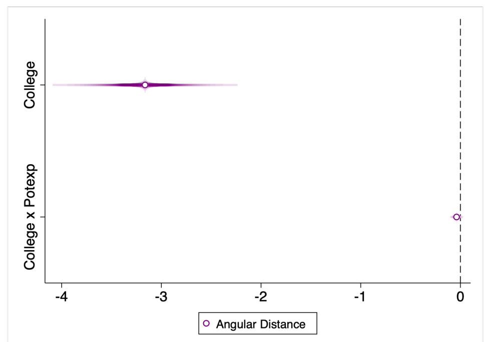
(a) *ParentOcc* at Individual Level



(b) *ParentOcc* at Individual Level

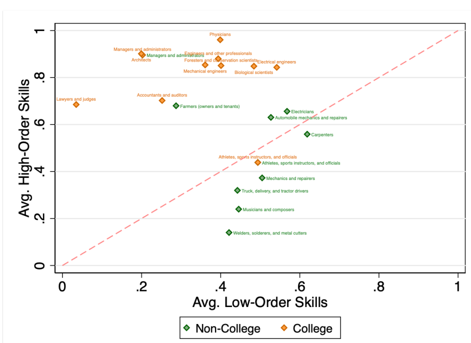


(c) *ParentOcc* at Observation Level

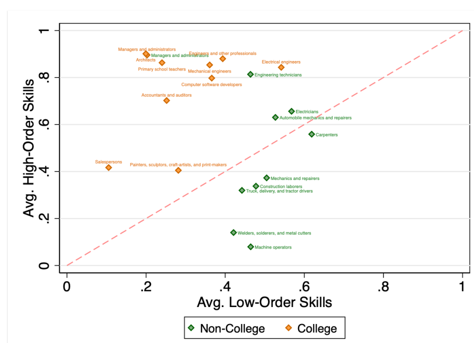


(d) *ParentOcc* at Observation Level

Figure A19: Estimated Coefficients with Parents' Occupation



(a) At Age 35



(b) In 5 Years

Figure A20: Most Commonly Anticipated Occupation by Education

A.9 More Details on Anticipated Occupations

A.9.1 Anticipated Occupation by Education

A concern regarding the differences in forecast errors across education attainments is that, irrespective of their understanding of their own comparative advantage, workers may optimistically aspire to land in prestigious, well-regarded occupations. As a result, forecast errors tend to be larger for non-college workers, as they are less likely to secure jobs that typically require higher educational qualifications.

Figure A20 displays the most frequently anticipated occupations at age 35 or in 5 years, categorized by educational attainment. The x-axis shows the average low-order (routine and manual) skill requirements of these anticipated occupations, while the y-axis reflects the average high-order (verbal, math, and social) skill requirements. A clear distinction emerges between the expectations of college and non-college workers. College workers, for example, tend to anticipate working in high-skill occupations by the time they are 35, such as lawyers, judges, physicians, electrical engineers, and biological scientists. In contrast, non-college workers are more likely to expect employment in occupations that emphasize low-order skills, including roles like automobile mechanics, repairers, truck drivers, and carpenters. This pattern holds when looking at their anticipated occupations in 5 years as well. These observations indicate that differences in forecast errors by education are not driven by common occupational aspirations.

A.9.2 Decomposition of the Euclidean Distance

Let ψ denote the Euclidean distance between two vectors, $\mathbf{s}_i$ and $\hat{\mathbf{s}}_i$. From the Law of cosines,

$$\|\mathbf{s}_i\|^2 + \|\hat{\mathbf{s}}_i\|^2 - 2\|\mathbf{s}_i\|\|\hat{\mathbf{s}}_i\|\cos(\phi) = \psi^2 \tag{A.29}$$

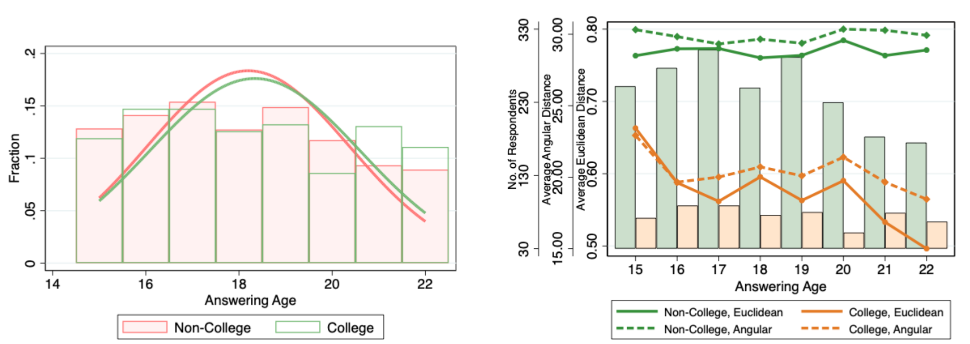
Adding and subtracting $2\|\mathbf{s}_i\|\|\hat{\mathbf{s}}_i\|$ to the left-hand side and dividing by ψ^2 gives:

$$\underbrace{\frac{(\|\mathbf{s}_i\| - \|\hat{\mathbf{s}}_i\|)^2}{\psi^2}}_{\text{Diff. in Skill Magnitude}} + \underbrace{\frac{2\|\mathbf{s}_i\|\|\hat{\mathbf{s}}_i\|(1-\cos(\phi))}{\psi^2}}_{\text{Diff. in Cosine Similarity}} = 1 \tag{A.30}$$

From (A.30), the first term is the contribution of the difference in the norms of the two vectors to the Euclidean distance, while the second is driven by the angular distance.

A.9.3 Forecast Error by Age and Educational Attainment

As the occupational expectation questions are asked upon respondents' entry into the survey, the difference in forecast errors by educational attainment may be biased if respondents who eventually obtained a college degree were, on average, older when they recorded their expected occupation. Figure A21(a) shows there is no systematic difference in the age at which expectations were recorded across the different education levels. Moreover, Figure A21(b) shows that the gap in forecast errors is present at each age. These findings suggest that the difference in forecast errors by education is not driven by differences in the ages at which occupational expectations were recorded.



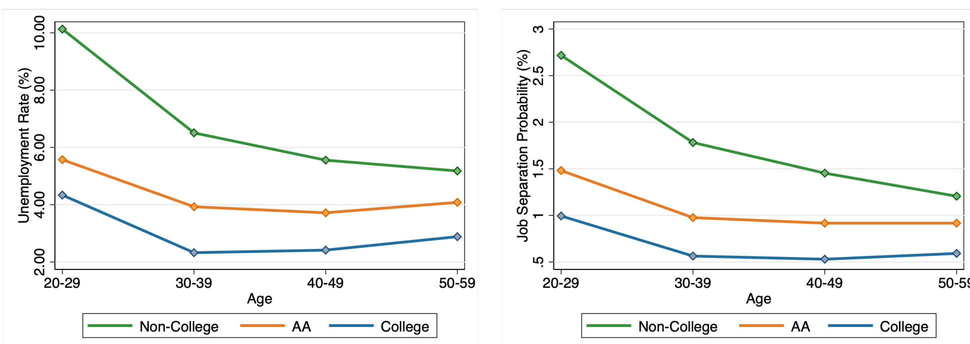
(a) Answering Age

(b) FCE by Education and Answering Age

Figure A21: Forecast Error and Answering Age

A.10 Associate's Degrees

Associate degrees offer specialized technical or vocational courses tailored for those seeking to acquire a specific skill set or train for a certain profession, thus serving a similar role as a four-year college degree by providing workers with more certainty about their comparative advantage; however, it may be lower than a bachelor's degree because it offers a shorter exploration period. With this in mind, we compare employment stability across three groups: non-college workers without an associate degree, associate degree workers, and college workers in the CPS data (the patterns are very similar in the NLSY79). As depicted in Figure A22, the separation probability among AA graduates is significantly lower than those without an AA and slightly higher than four year degree holders.



(a) Unemployment Rate (b) Separation Probability

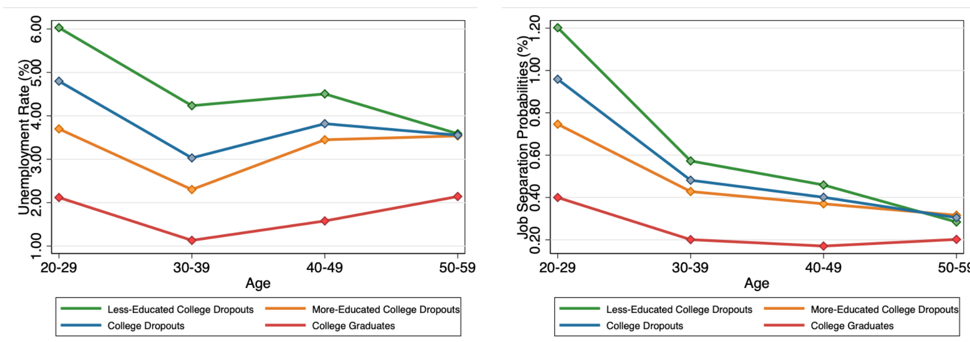
Figure A22: Employment Outcomes for AA Workers

A.11 College Dropouts

In this section, we compare "less" and "more" educated dropouts to college graduates, where the latter group of dropouts have completed at least two years of college and account for nearly 60% of the 810 college dropouts.

We use the NLSY79 sample and define college dropouts as individuals who had previously enrolled full-time in college but did not obtain a Bachelor's degree or higher. Following this approach, we find a college dropout rate of 57.65%, which aligns closely with the 54% rate reported in Vardishvili (2023). Furthermore, we exclude 15 respondents who report "lack of ability or poor grades" and 4 respondents who report being "expelled or suspended" as their reasons for dropping out.

Figure A23 presents the unemployment rate and separation probability over the life cycle for college graduates and dropouts. College dropouts are more likely to be unemployed than graduates, and within the group of dropouts, more years of completed schooling is associated with a lower unemployment rate. Similarly, the job separation probability is, at each age bin, decreasing in years of college completed. Moreover, Table A9 shows that the number of employer, occupation, and career switches is decreasing in years of college completed.



(a) Unemployment rate (b) Job Separation Probability

Figure A23: Life Cycle Patterns among College Dropouts

Table A9: The Average Number of Transitions over Age

	$20-29$	≤ 39	≤ 49	≤ 59
Employer Transitions				
Less-educated College Dropouts	4.28	6.88	8.23	9.02
More-educated College Dropouts	2.93	5.11	6.58	7.45
College Dropouts	3.53	5.88	7.30	8.14
Occupation Transitions				
Less-educated College Dropouts	4.36	7.11	8.33	8.90
More-educated College Dropouts	3.85	6.73	8.12	9.01
College Dropouts	4.08	6.91	8.23	8.99
Career Transitions				
Less-educated College Dropouts	2.74	4.26	4.98	5.35
More-educated College Dropouts	2.34	3.85	4.57	5.11
College Dropouts	2.52	4.03	4.75	5.23

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

B Theory Appendix

B.1 Laws of Motion

Let $u_{a,e,i}$ denote the measure of unemployed workers of age a, education e, and history i who are unemployed at the beginning of the learning stage and are searching in a submarket for a career with which they have an unknown or good fit. Further, $\overline{u}_{a,e,i}$ denotes the measure of unemployed workers with a bad fit, $n_{e,a,i}$ the measure of workers employed in a career of unknown or good fit, and $\overline{n}_{e,a,i}$ the measure employed in matches that are a bad fit. A "+" superscript denotes the measures in the next time period.

The law of motion for young, unemployed workers in a career with an unsure or good fit is

$$u^{+}_{y,e,i} = \begin{cases} \mu\pi_e + (1-\lambda_o)\left[(1-f^*)u_{y,e,1} + (1-\phi_e)\delta^{un}_{1e} n_{y,e,1}\right] & \text{for} \quad i = 1, \\ (1-\lambda_o)\left[(1-f^*)(u_{y,e,i} + l^*\overline{u}_{y,e,i-1}) + (1-\phi_e)\delta^{un}_{ie} n_{y,e,i}\right] & \text{for} \quad i = 2,\dots,N_e-1, \\ (1-\lambda_o)\left[\delta^g\left(\phi_e \sum_{i=1}^{N_e-1} p_{ie} n_{y,e,i} + n_{y,e,N_e}\right) + (1-f^*)(u_{y,e,N_e} + l^*\overline{u}_{y,e,N_e-1})\right] & \text{for} \quad i = N_e, \end{cases} \tag{B.1}$$

where f^* and l^* represent the job finding probability and decision to leave a career. For brevity, we suppress the subscript a, e, i on the policy functions. Starting with the first line of (B.1), the first term represents new entrants to the labor market, the second term are unemployed workers who do not find a job or become old, and the third term is employed workers who do not learn their fit, lose their job, and are not hit with an aging shock. As for the second line, the first term is unemployed workers with an unsure fit, including those who switched from a bad fit, who do not find a job. The second term is employed workers who do not learn their fit and lose their job. Each measure is multiplied by $1 - \lambda_o$, as these are the young workers who are not hit with an aging shock. Finally, in the third line, the first term represents all young workers who exited the previous period's learning stage knowing their best fit and were hit with a separation shock. The second term represents unemployed workers who do not find a job.

The law of motion for young, employed workers in a career with an unsure or good fit is

$$n^+_{y,e,i} = \begin{cases} (1-\lambda_o)\left[f^* u_{y,e,1} + (1-\phi_e)(1-\delta^{un}_{1e})n_{y,e,1}\right] & \text{for} \quad i=1, \\ (1-\lambda_o)\left[f^*(u_{y,e,i} + l^*\overline{u}_{y,e,i-1}) + (1-\phi_e)(1-\delta^{un}_{ie})n_{y,e,i}\right] & \text{for} \quad i=2,\dots,N_e-1, \\ (1-\lambda_o)\left[(1-\delta^g)\left(\phi_e \sum_{i=1}^{N_e-1} p_{ie} n_{y,e,i} + n_{y,e,N_e}\right) + f^*(u_{y,e,N_e} + l^*\overline{u}_{y,e,N_e-1})\right] & \text{for} \quad i=N_e, \end{cases} \tag{B.2}$$

Equation (B.2) has a similar interpretation as (B.1), except that the measure of employed workers consists of unemployed workers who find a job and employed workers who do not lose their job.

Next, the laws of motion for young workers in a bad fit are given by:

$$\overline{u}^+_{y,e,i} = (1-\lambda_o)\left[\delta^b \bar{n}_{y,e,i} + (1-l^*)(1-\overline{f}^*)\overline{u}_{y,e,i} + \phi_e(1-p_{ie})d^* n_{y,e,i}\right], \tag{B.3}$$

$$\overline{n}^+_{y,e,i} = (1-\lambda_o)\left[(1-\delta^b)\bar{n}_{y,e,i} + (1-l^*)\overline{f}^*\overline{u}_{y,e,i} + \phi_e(1-p_{ie})(1-d^*)n_{y,e,i}\right], \tag{B.4}$$

for $i = 1, 2, \dots, N_e - 1$ and where $\overline{f}^*$ is the job finding probability of the workers in submarkets for bad matches and d^* is the separation probability upon learning the worker is not in their true calling. The first term of (B.3) represents employed workers in a bad fit who lose their job. The second term is workers who are unemployed in a bit fit, do not leave their current career, and do not find a job. The last term captures workers who were employed in an unsure fit, learn that they are in a bad fit, and separate from the match. Equation (B.4) follows a similar intuition.

We now proceed to the laws of motion for old workers, and begin with those who are in a career with an unknown or a good fit:

$$u^+_{o,e,i} = \begin{cases} \sum_a \chi_a\left[(1-f^*)u_{a,e,1} + (1-\phi_e)\delta^{un}_{ie} n_{a,e,1}\right] & \text{for} \quad i=1, \\ \sum_a \chi_a\left[(1-f^*)(u_{a,e,i} + l^*\overline{u}_{a,e,i-1}) + (1-\phi_e)\delta^{un}_{ie} n_{a,e,i}\right] & \text{for} \quad i=2,\dots,N_e-1, \\ \sum_a \chi_a\left[\delta^g\left(\phi_e \sum_{i=1}^{N_e-1} p_{ie} n_{a,e,i} + n_{a,e,N_e}\right) + (1-f^*)(u_{a,e,N_e} + l^*\overline{u}_{a,e,N_e-1})\right] & \text{for} \quad i=N_e, \end{cases} \tag{B.5}$$

$$n^+_{o,e,i} = \begin{cases} \sum_a \chi_a\left[f^* u_{a,e,1} + (1-\phi_e)(1-\delta^{un}_{ie})n_{a,e,1}\right] & \text{for} \quad i=1, \\ \sum_a \chi_a\left[f^*(u_{a,e,i} + l^*\overline{u}_{a,e,i-1}) + (1-\phi_e)(1-\delta^{un}_{ie})n_{a,e,i}\right] & \text{for} \quad i=2,\dots,N_e-1, \\ \sum_a \chi_a\left[(1-\delta^g)\left(\phi_e \sum_{i=1}^{N_e-1} p_{ie} n_{a,e,i} + n_{a,e,N_e}\right) + f^*(u_{a,e,N_e} + l^*\overline{u}_{a,e,N_e-1})\right] & \text{for} \quad i=N_e, \end{cases} \tag{B.6}$$

where $a \in \{y, o\}$, $\chi_a = \lambda_o$ if $a = y$, and $\chi_a = 1 - \lambda_d$ if $a = o$. The components of (B.5)-(B.6) are very similar to (B.1)-(B.2), except that there are additional flows into the stocks of old workers from young workers who are hit with an aging shock.

Finally, the law of motion for old workers in a bad fit is

$$\overline{u}^{+}_{o,e,i} = \sum_{a} \chi_a \big[\delta^b \bar{n}_{a,e,i} + (1-l^*)(1-\overline{f}^*)\overline{u}_{a,e,i} + \phi_e(1-p_{ie})d^* n_{a,e,i}\big], \tag{B.7}$$

$$\overline{n}^{+}_{o,e,i} = \sum_{a} \chi_a \big[(1-\delta^b)\bar{n}_{a,e,i} + (1-l^*)\overline{f}^*\overline{u}_{a,e,i} + \phi_e(1-p_{ie})(1-d^*)n_{a,e,i}\big], \tag{B.8}$$

for $i = 1, 2, \ldots, N_e - 1$.

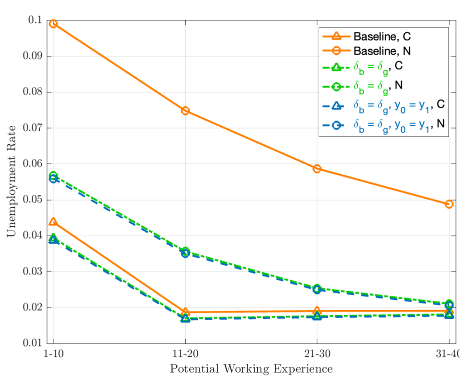
C Quantitative Appendix

C.1 Data Moments

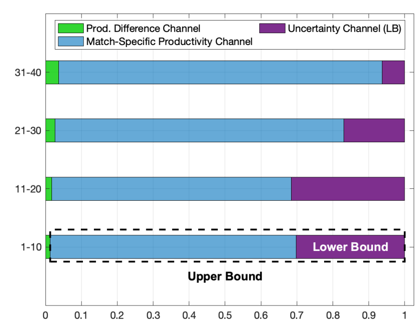
To identify and count the number of unique careers each worker held over their lifetime using the NLSY79 data, we start with individuals with complete occupational information, including occupation codes, skill requirements, and task intensity. A unique career is defined as one where the angular distance between that career and all previous careers is greater than or equal to the threshold $\bar{\phi} = 23.077$. That is, career i is considered unique if its angular distance relative to any career formerly worked in j, ϕ_{ij}, is greater than $\bar{\phi}$.

C.2 Decomposition in A Different Order

As illustrated in Figure C1, the difference in productivity accounts for approximately 2% of the U-E gap, while the uncertainty channel explains between 25.13% and 98.01%, which is consistent with the contribution of each channel shown in the main text.



(a) Graphical Illustration of Decomposition



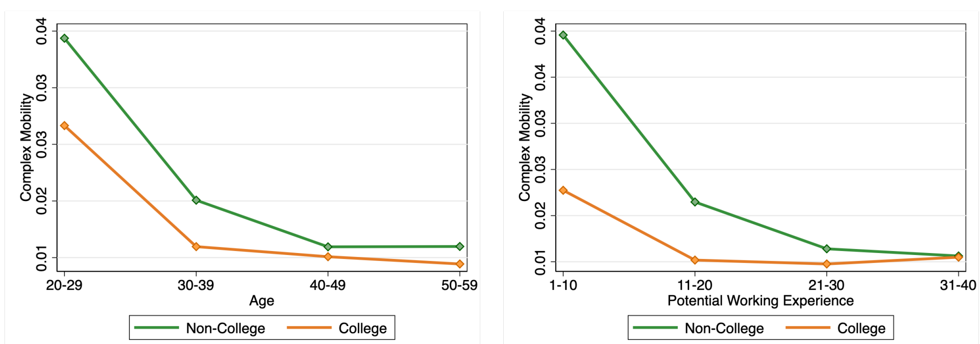
(b) Decomposition Fraction

Figure C1: Alternative Decomposition

D Further Empirical Details

D.1 Complex Transitions

An alternative criterion to identify large changes in one's career is to study "complex" transitions following Neal (1999). Specifically, it is defined as the occurrence of a 3-digit occupational change adjusted for suspicious transitions (see Appendix A.3.1), 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.[39] Specifically, we observe a 31.29% blank response rate to "EMPSAME" out of the corrected occupational transitions, which is significantly higher than that in occupational stayers (5.36%). 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 (2007b), and described in Section D.1.1, by assigning a probability that a blank answer actually corresponded with a change in employer.



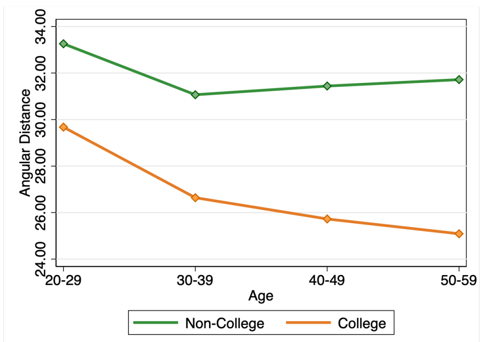
(a) Age

(b) Potential Experience

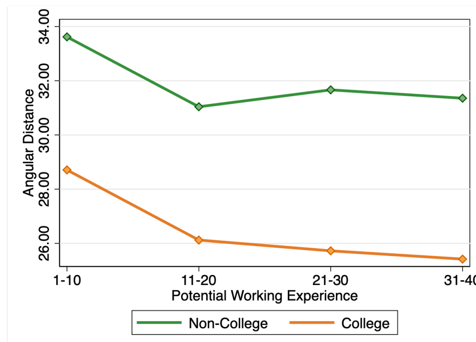
Figure D2: Complex Mobility Rates

[39]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 D2 shows the complex mobility rates by age and potential experience. Individuals with higher levels of education exhibit lower propensities to go through complex changes, relative to their less-educated counterparts. Collectively, these results are consistent with the pattern observed in the separation and occupational mobility rates presented in the main text. Further, Figure D3 shows that the angular distance between occupations in complex switches is lower among college graduates, which is consistent with the patterns shown in Figure 5.



(a) Age



(b) Potential Experience

Figure D3: Angular Distance in Complex Transitions

D.1.1 Correction for Employer Switches in the CPS

Following Moscarini and Thomsson (2007b), we compute the probability that a blank answer to the "EMPSAME" question in the CPS 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 (δ^{ik}). In particular, we allocate blank answers to "EMPSAME" to Yes and No based on their proportionate frequency in the corrected occupational mobility measure. Formally, the adjustment parameters are given by

$$\delta = \frac{\Pr(\text{OCCMOB} \mid \text{No}) - \Pr(\text{OCCMOB} \mid \text{Yes})}{\Pr(\text{OCCMOB} \mid \text{No}) + \Pr(\text{OCCMOB} \mid \text{Yes})}, \tag{D.1}$$

where “No” and “Yes” represent the responses to the “SAMEJOB” question indicating whether an individual has stayed with the same employer or switched employers and “OCCMOB” is the number of occupational switches. Equation (D.1) measures the extent to which blank responses to the “EMPSAME” question are likely to reflect a change in employer. An equivalent interpretation is that (D.1) captures the likelihood that an individual who has changed occupations also changed employers. After applying this correction to our sample, we find an average monthly job-to-job transition probability of 3.23%, which aligns with Moscarini and Thomsson (2007b), who found 3.2%.

D.2 NLSY79 Panel Construction

D.2.1 Weekly Panel

This section details the construction of the weekly panel from the NLSY79. The process involves three key steps: (i) cleaning the employer history roster and determining the employer characteristics, (ii) identifying necessary demographic variables 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, which consists of two primary steps. The first 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.[40] 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.

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

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 convert the original 1970 census occupational codes to the 1990dd classification scheme. For employer characteristics in the survey year 2002 (round 20), we convert the original 3-digit 2000 census occupation codes to the 1990dd classification scheme. However, for occupation codes from survey year 2004 onwards, we convert the original 4-digit 2002 occupation codes into 3-digit 2000 census codes by directly taking the first three digits, and then covert 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 convert IND70 codes to IND80 codes, and then from 1980 census industry codes to the 1990dd industry classification scheme.

We then determine the employer characteristics for each job in every survey year. Initially, we utilize the original employer history roster (EHR) from the NLSY79. 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 job 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 unique respondent ID, survey round, and job number, we can merge the weekly history with the employer history roster and obtain the employer characteristics 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 demographic 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).[41] 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 most working hours during that week.[42] If the reported multiple jobs have the same

[41] An important characteristic of the NLSY surveys is that, with a few exceptions, 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 the entire time between a respondent's most recent and current interviews is recorded.

[42] 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.

working hours per week, we keep the job reported in the main array.

D.2.2 Monthly Panel

In this section, we describe the process to convert from a weekly to monthly panel. 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: 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.