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

Jie Duan[†] National University of Singapore

Paul Jackson[‡] National University of Singapore

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Abstract

We propose that college graduates enter the labor market with less uncertainty regarding which career they are most productive in, and study how this characteristic contributes to the unemployment-education gap. We document several novel facts to support our hypothesis. Notably, college graduates predict their occupation more accurately than those without a college degree. We then develop and calibrate a life cycle search model featuring differences in uncertainty by education and learning about one's best career fit. Our quantitative analysis suggests large disparities in uncertainty by education, and that such differences can explain a sizeable portion of the unemployment-education gap.

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⁺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 those without a degree. Moreover, most of the unemploymenteducation gap is driven by higher separation rates among non-college workers.¹ While these facts are well documented, little quantitative research has been done to explain them. 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. Therefore, this paper's objectives are to (i) propose and provide empirical support for a novel mechanism to explain the 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 their best 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, which they are less likely to separate from, earlier in their work-life.

We provide empirical support for the uncertainty channel. Our most direct evidence comes from the National Longitudinal Survey of Youth 1979 (NLSY79), where we document that college graduates form more accurate expectations about their future occupation. In our preferred measure of forecast errors, the cosine similarity in skill and task requirements between occupations (Gathmann and Schönberg, 2010; Baley et al., 2022), forecast errors are 32% smaller among college graduates.

Further, we compile a 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,

¹Unemployment rates are from the Current Population Survey between 1976-2019. See Section 2.2.

²Broadly 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. The terminology follows Gervais et al. (2016).

as non-college workers begin with higher uncertainty, they experience more separations early on and gradually catch up to college workers as they sample careers, experience fewer separations, and exhibit lower unemployment rates. This is consistent with how separation, unemployment, 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 (to the best of our knowledge) a new fact that is aligned with the uncertainty channel: if non-college workers rely more on 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. Their best fit is initially unknown and, as in Gervais et al. (2016), workers sample careers to learn which is their true calling. 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 at a higher rate. 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 searching for their best fit and to find their true calling earlier in their career. Non-college workers take longer to find their best fit. However, as they sample careers and find their best fit, the gap in separation and unemployment rates by education narrows.

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 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 the 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, such as an unemployment-education gap that narrows over the life-cycle and the 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 because non-college workers are less likely to be in their best fit. Thus, they are hit with exogenous separation shocks more frequently than college workers.

Finally, our quantitative analysis suggests that there are 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 can increase (decrease) 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 in matches with college workers. While both papers make important contributions, they do not address the unemployment-education gap over the life cycle or why separations are, especially for non-college workers, decreasing in prior experience.⁴ We propose and provide empirical support for the uncertainty channel as an alternative, and perhaps complementary, explanation for the unemployment-education gap.⁵ We show that the uncertainty channel can not only explain a decent share 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. Apart from these empirical and quantitative implications, the uncertainty channel implies a novel difference in workers by educational attainment. Namely, that these two groups of workers differ in how much knowledge they have about their best fit in the labor market, whereas existing work focuses on mechanisms that are, at their

³We 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.

⁴In models which generate endogenous separations only through variation in match-specific productivity, the expected duration of a match formed with an unemployed worker is independent of the worker's prior experience as nothing about the worker's prior experience is transferrable across matches.

⁵The 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.

core, driven by exogenous differences in labor productivity.⁶ We argue that viewing noncollege and college workers through this additional layer of heterogeneity opens up new insights into what drives their labor market outcomes and how policy may help improve the labor market experience for non-college workers.

The uncertainty channel is closely related to literature which studies the life cycle implications of learning about one's comparative advantage in the labor market. Papageorgiou (2014) and Gorry et al. (2019) who show that learning about occupational fit can explain several life cycle wage and occupational mobility patterns, but do not emphasize separations, unemployment, or differences in uncertainty by educational attainment.⁷ 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 propose 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 a growing 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.⁸ Gorry (2016) and Esteban-Pretel and Fujimoto (2014) develop models where experienced workers can 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 relates our model and findings to the class of models which focus on the formation of match-specific productivity as a driving force of separation rates over the life cycle.

The rest of the paper is organized as follows. Section 2 presents our empirical analysis. Section 3 develops the model. Section 4 carries out the quantitative analysis. Section 5 concludes. Supplementary material from the online appendix is referenced throughout.

⁶While our model allows for such differences in productivity by education, most of the gap in average labor productivity by education in our quantitative analysis is driven by non-college workers being more likely to be in a bad career fit.

⁷Neal (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 can disrupt the process of learning about one's ability, thereby generating scarring effects of graduating in a recession.

⁸Chéron 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 online appendix. Section 2.5 transitions to the theory.

To begin, we introduce the data sources 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.⁹ Appendix A.2 details our construction of a monthly panel of 4,823 male respondents that contains information on demographics, education, and employment.¹⁰

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 age 35 (in 5 years) and had a realized occupation at that point in time. Among those, 604 (129) obtained a BA or above.¹¹ 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.

We measure forecast errors by computing the distance in skill and task requirements

⁹We use the CPS for its large sample size and because NLSY79 results could be driven by a cohort effect. ¹⁰We also restrict to males in the CPS. Our findings are not impacted by this restriction.

¹¹We 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. Also, college workers anticipate occupations with more dispersed skill requirements. See Appendix A.8 for details and a list of the ten most common expected occupations by education.



Figure 1: Distance Measurements and Career Transitions. Panel (a) depicts the angular, ϕ , and Euclidean, ψ , distance. Panel (b) demonstrates job changes within and across careers.

between the realized and expected occupation.¹² As a first step, we measure the verbal, math, and social skill requirements for each occupation as in Guvenen et al. (2020). 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.¹³ Second, we compute two measures of distance between the vector of requirements for individual *i*'s realized occupation, \mathbf{s}_i , and predicted occupation, $\mathbf{\hat{s}}_i$. The first is the angular distance $\phi: \mathbb{R}^5 \times \mathbb{R}^5 \to [0, \pi/2]$, and is given by:

$$\phi(\mathbf{s}_i, \mathbf{\hat{s}}_i) = \cos^{-1}\left(\frac{\mathbf{s}_i \cdot \mathbf{\hat{s}}_i'}{\|\mathbf{s}_i\| \|\mathbf{\hat{s}}_i\|}\right).$$
(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, $\psi(\mathbf{s}_i, \mathbf{\hat{s}}_i) = \sqrt{\sum_k (s_{i,k} - \hat{s}_{i,k})^2}$, 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 that between 65-77% of the Euclidean distance is attributable to differences in the composition of skill require-

¹²We compute the average requirements across the jobs worked while 35 years old and 5 years from their initial interview.

¹³Appendix A.1.2 presents the correlations between skill and task requirements.

	Non-College	College
Panel A: Expected Occupation at Age 35		
Angular Distance	29.83	20.31
Euclidean Distance	0.770	0.507
% of Euclidean Driven by Angle	73.90	77.04
Panel B: Expected Occupation in 5 Years		
Angular Distance	25.84	20.09
Euclidean Distance	0.660	0.560
% of Euclidean Driven by Angle	64.85	70.16

Table 1: Angular and Euclidean Distances by Education

Notes: Angular distance is measured in degrees. The third row within each panel is the proportion of the Euclidean distance attributable to the angular distance. Data are from the NLSY79.

ments.¹⁴ This suggests 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 A16 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 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 shows the unemployment rate by age and education, using CPS data from 1976 through 2019.¹⁵ The solid lines show that the unemployment rate for college gradu-

¹⁴From the Law of cosines, the fraction of the Euclidean distance that is attributable to differences in the angle, ϕ , is $2\|\mathbf{s}_i\|\|\mathbf{\hat{s}}_i\|(1-\cos(\phi))/\psi^2$. See Appendix A.8.1 for details.

¹⁵Appendex A.9 shows that individuals with an associate's degree and college dropouts fall in-between



Figure 2: Unemployment-Education Gap over the Life Cycle. *Note*: Unemployment life cycle profiles computed using CPS data between 1976 and 2019.

ates 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.¹⁶ 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.¹⁷

Figure 3 suggests that the unemployment-education gap is primarily driven by differences in separations, as the job finding probability 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.¹⁸ It is for this reason we propose a mechanism that is tightly linked to the separation 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. To support the connection between the uncertainty channel and the separation margin, we find that the average separation probability among non-college (college) workers in the NLSY79 who were employed in

those with no college experience and graduates with a BA or above in our main outcomes of interest.

¹⁶We correct for time aggregation bias as in Shimer (2012). 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.

¹⁷Appendix A.4.1 shows this pattern emerges in both voluntary and involuntary separations.

¹⁸Appendix A.4.2 provides a description of the decomposition, as well as results with alternative transition probabilities and rates.



Figure 3: Job Finding and Separation Probabilities over the Life Cycle. *Note*: All series are computed using CPS between 1976 and 2019 and are corrected for time aggregation bias.

their anticipated occupation at 35 years old is 34% (32%) lower than those who do not.¹⁹

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 the 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 uncer-

¹⁹We also find that, within each education group, the difference in separation rates by forecast error is widest early in workers' careers. See Appendix A.3.1. This supports the notion that workers with more uncertainty over their best fit exhibit higher separations, especially early in their career. Over time, they find their true calling and experience fewer separations.

tainty 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.

Following Baley et al. (2022), we define a career transition as an occupation switch where the angular distance between the current and previous job exceeds a threshold, $\bar{\phi}$. 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 corrected occupational transitions in our CPS sample.²⁰ 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.²¹ 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. Following the intuition at the beginning of this section, these patterns are consistent with the uncertainty channel.

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 intuition 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.

Figure 5 shows that the average angular distance in occupational switches is lower for college graduates across the life cycle. Therefore, not only do college graduates switch

²⁰We correct for measurement error in occupational mobility following Moscarini and Thomsson (2007).

²¹We find similar patterns when considering "complex" switches, or a concurrent change in employer, occupation, and industry (Neal, 1999). Results are available upon request.



Figure 4: Career Mobility. *Notes*: Career mobility rates are computed using CPS data between 1994-2019 and after applying the Moscarini and Thomsson (2007) correction for measurement error in occupational mobility in the CPS.

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 NLSY79 to explore the relationship between prior experience and the survival probability of a match.²²

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.

Figure 6 presents the survival probability as a function of match 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

²²To identify matches that survive between periods, it is vital to have complete employer ID records. Accordingly, we drop respondents with incomplete employer ID records, leaving 4,697 respondents.



Figure 5: Angular Distance in Occupation Transitions. *Note*: The series are computed using CPS data between 1994-2019 and after applying the Moscarini and Thomsson (2007) correction for measurement error in occupational mobility in the CPS.

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 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.

An additional aspect of our hypothesis is that workers learn not just from work experience, but particularly from sampling different occupations and careers. Therefore, we estimate the relationship between the survival probability of a match and the number of occupations or careers the worker had formerly worked in when the match was formed. To do so, we separately estimate the following specification on non-college and college workers in the NLSY79:

$$y_{it} = \beta_0 + \sum_{j=1}^{J} \beta_j \mathbb{I}\{\text{NumSam} = j\}_{it} + \gamma \text{Tenure}_{it} + \delta \text{Exp}_{it} + \Phi_i + \epsilon_{it},$$
(2)

where y_{it} is equal to one (zero) if individual *i*'s match survives (individual *i* transitions to unemployment) between months *t* and t + 1, $\mathbb{I}\{\text{NumSam} = j\}$ is an indicator for the number of occupations or careers individual *i* had worked in at the time their current



Figure 6: Prior Experience and Match Survival. *Notes*: Panel (a) shows the survival probability of a match over match tenure for experienced and inexperienced workers. Panel (b) further disaggregates by the worker's educational attainment. Data are from the NLSY79.

match was formed, Tenure_{*it*} is match tenure, Exp_{it} is total work experience, and Φ_i is an individual fixed effect. The coefficients, β_j for j = 1, 2, ..., J with J = 15 (J = 10), capture the association between the j^{th} occupation (career) sampled at the time a match is formed and the survival probability, relative to a worker who is forming their first match.²³

Figure 7 displays the β_j coefficients with 99% confidence intervals for sampled occupations and careers, respectively.²⁴ The results show that, especially for non-college workers, the survival probability increases with the number of occupations or careers formerly worked in, lending support to our hypothesis that non-college workers learn more about their best fit by working and sampling careers than college workers do.

2.4 Additional Evidence and Robustness

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.3.2). Second, college graduates experience lower skill mismatch throughout the life cycle (Appendix A.3.3). Third, college graduates work in occupations with more dispersed skill requirements (Appendix A.3.4).²⁵ Finally, college graduates experience fewer employer, occupation, and career switches (Appendix A.3.5).

²³Sample sizes beyond these cutoffs become small, with the first 10 career switches and 15 occupational switches accounting for 86.40% and 95.51% of the sample, respectively.

²⁴See Appendix A.7 for the detailed regression results.

²⁵The intuition here 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.



(a) Sampled Occupations

(b) Sampled Careers

Figure 7: Job Sampling and Match Survival. *Notes*: Panel (a) displays the β_j coefficients and 99% confidence intervals for sampled occupations from estimating equation (2) by education. Panel (b) displays the coefficients for the number of sampled careers. Full regression output is provided in Appendix A.7. Regressions are estimated using the NLSY79 sample.

Finally, the CPS patterns can be replicated in the NLSY79. See Appendices A.5.1-A.5.4. Additionally, the correlation between educational attainment and our outcomes of interest are robust to controlling for standard observable characteristics. See Appendix A.4.3 for the CPS and A.5.5 for NLSY79 analyses, respectively.

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 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. Finally, we embed these ingredients within a competitive search model with bilaterally efficient contracts (e.g., Menzio and Shi (2011)), which allows for a rich amount of heterogeneity among workers while maintaining computational tractability.

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 $t = 0, 1, ..., \infty$. 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 $\beta \in (0, 1)$.

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, each worker is best suited for one career, c^* , which we refer to as their best fit (Gervais et al., 2016). 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 $\phi_e \in [0, 1]$.²⁶ 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 believes that the *i*th career

²⁶We interpret the learning probability as a reduced form representation of a signal extraction problem where, with some probability, the observed match output is perfectly informative of the worker's career fit and with a complementary probability is completely uninformative.

is their best fit with probability p_{ie} , where

$$p_{ie} = \frac{1}{N_e - (i-1)}.$$
(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 $\delta_{ie}^{un} = p_{ie}\delta^g + (1 - p_{ie})\delta^b$ and $\delta^g < \delta^b$. The destruction probability is specified by the employment contract, 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 cost in submarkets with age *a* workers is κ_a .²⁷ 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. There is no search on the job.²⁸

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 concave.

In the production stage, stage 4, unemployed workers produce *z* units of output. Employed workers in their true calling produce y_e , whereas those in a bad fit produce $y_e - \alpha$ units of output where $y_1 > y_0$ and $y_0 - \alpha > z$. 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 $\pi_0 (1 - \pi_0)$ enter the economy with education e = 0 (e = 1). New entrants have their true calling assigned by nature, where the probability any single career is their true calling is $1/N_e$.

²⁷Our main intention is not to explain the life cycle job finding profiles shown in Figure 3(a), as these patterns do not contribute much to the unemployment-education gap (see Appendix A.4.2). However, we include age-specific posting costs to ensure the model is broadly in line with these patterns.

²⁸In our NLSY79 sample, the probability a worker changes careers through unemployment, i.e. experiences a career switch through an "EUE" transition, is 37%. The probability of switching careers during consecutive months of employment is 1.44%. As workers are much more likely to careers through unemployment than employment, we abstract from including on the job search in the model due to the added complexity incorporating it would bring. Moreover, including on the job search is unlikely to alter our quantitative findings, as the model with on the job search would be parameterized to match the frequency of career switches through unemployment and thus, would still give a tight connection between the uncertainty channel and the separation margin.

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

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 survives between periods with probability $1 - \lambda_d$. In the subsequent search stage, they search 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

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

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

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

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

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

Consider a young unemployed worker. The difference relative to old workers is the

worker becomes old between periods with probability λ_0 . Hence, $U_{y,e,i}$ and $\overline{U}_{y,e,i}$ satisfy:

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

$$\overline{U}_{y,e,i} = z + \beta \left\{ \lambda_o \left[l_{o,e,i}^* [U_{o,e,i+1} - \zeta + R(x, U_{o,e,i+1})] + (1 - l_{o,e,i}^*) [\overline{U}_{o,e,i} + R(x, \overline{U}_{o,e,i})] \right] + (1 - \lambda_o) \left[l_{y,e,i}^* [U_{y,e,i+1} + R(x, U_{y,e,i+1})] + (1 - l_{y,e,i}^*) [\overline{U}_{y,e,i} + R(x, \overline{U}_{y,e,i})] \right] \right\}.$$
(9)

We now proceed to value 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 separations 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).²⁹ 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

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

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

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

$$d_{o,e,i}^{*} = \begin{cases} \delta^{b} & \text{if } \overline{U}_{o,e,i} < \overline{V}_{o,e,i}, \\ 1 & \text{if } \overline{U}_{o,e,i} \ge \overline{V}_{o,e,i}. \end{cases}$$
(12)

²⁹Bad matches with old workers that were not destroyed in the previous separation stage will not be destroyed endogenously as nothing about a bad match changes between periods.

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

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

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

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

$$(15)$$

and $\theta \ge 0$ with complementary slackness.

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 for a match 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 unemploymenteducation 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, from (3), $\partial p_{i1}/\partial i > \partial p_{i0}/\partial i$. 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 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} 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 $\delta^b > \delta^g$ 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 output in a bad career fit.

Finally, the role of the uncertainty channel and its interaction with $\delta^b > \delta^g$ is more prominent early in a worker's career. 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, decomposition of the unemployment-education gap, policy insights, 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 function is $F(u, v) = \frac{uv}{(u^t + v^t)^{1/t}}$. There are 18 parameters. The discount factor is $\beta = (0.97)^{1/12}$, and the probabilities of becoming old and dying $\lambda_o = \lambda_d = 1/(12 \times 20)$ so workers expect to spend 20 years in each age. The fraction of college workers is $\pi = 0.30$.³⁰ The economy is normalized by setting z = 1.

The remaining 13 parameters are calibrated via simulated method of moments to match 14 moments. The first moment is z/[average labor productivity] = 0.4 (Shimer, 2005). The second and third 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).³¹ Next are the job finding probabilities for workers between 40 and 59 years old (27.61%). The remaining eight moments are the separation profiles, by education and age bin, shown in Figure 3(b).³²

While the targeted moments are affected by more than one parameter, one can view $\{\delta^g, \delta^b\}$ as targeting the separation probability for college workers in the last age group and non-college workers in the first age group. This is because the matches of college (non-college) workers are primarily composed of good (bad) matches in the last (first) age group. Next, κ_y targets the z/[average labor productivity] ratio, as κ_y impacts the age composition of employment and the expected output of a match is lower among young workers. The posting cost, κ_o , targets the job finding probability for old workers, as it affects firm entry for old workers. Next, $\{y_0, y_1\}$ target the job finding probability of the young, by education, as higher output is associated with a higher match value, more vacancies, and a higher job finding probability.

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

³⁰The fraction of 25-30 years old with at least a bachelor's degree between 1992-2017 in the CPS is 30%.

³¹Appendix C.1 details how we identify unique careers in the data.

³²To 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 apply the same correction for time aggregation bias to the simulated data as we did with the CPS data, following Shimer (2012).

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

Table 2: Identification of N_e

Note: The number of careers is computed by simulating the model economy and counting the number of careers each worker had worked in by the time they exit the labor market.

of potential careers, workers expect to undergo more career experimentation before eventually settling into their best fit. This is demonstrated in Table 2.

We then use the "convexity" of the separation profile to pin down the probabilities of learning, { ϕ_0 , ϕ_1 }. As ϕ_e increases, workers learn about their fit at a higher rate. Once they realize that the current match is bad, they may endogenously separate from that match, leading to higher separations earlier in their career. However, with more learning occurring early in the worker's career, workers settle into their best fit, leading to fewer separations later in their career. Therefore, varying ϕ_e influences the convexity of the separation profile, as it impacts how many separations workers experience early on and how quickly they can find their best fit (and therefore how rapidly separations decline over the life cycle). This is demonstrated in Figure 8.



Figure 8: Separation Profile and ϕ_e . *Notes*: The separation profiles are computed by simulating the model economy and computing the separation probability within each bin of potential experience. The separation probabilities are corrected for time aggregation bias, just as we do with the CPS data.

There are three remaining parameters, $\{\alpha, \zeta, \iota\}$, that can be interpreted as being chosen

Moment	Target	Model
JFP, 20-39, Non-College	0.311	0.306
JFP, 20-39, College	0.325	0.332
# Unique Careers, Non-College	2.830	2.713
# Unique Careers, College	2.000	1.937
JFP, 40-59	0.276	0.276
z/[Labor Productivity]	0.400	0.400

Table 3: Model and Data Comparison

Notes: Moments are computed by simulating the model economy. JFP stands for job finding probability. Labor productivity is the average output across all matches.

to fine-tune the model fit's to the 14 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, the switching cost for old workers, ζ , improves the model's fit of the separation profile in the later half of workers' careers, as it influences 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 14 model generated (empirical) moments, the vector of 13 parameters, $\hat{\vartheta}$, is given by

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

where $W = I/m^2$ and *I* is the identity matrix. From (17), $\hat{\vartheta}$ 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 targeted moments well.

Table 4 displays the parameter values. As aforementioned, the uncertainty channel is governed by both ϕ_e and N_e . We find $\phi_1 = 0.156$ and $\phi_0 = 0.020$. The calibration ascribes the gradual decline in the separation profile of non-college workers to a slower learning speed than college workers.³³ Next, 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. It is important to emphasize that our results do not imply that college workers can work in fewer careers than non-college workers. Rather, they should

³³The weighted average of the two, $0.3 \times 0.156 + (1 - 0.3) \times 0.02 = 0.061$, is similar to the learning probability of 0.055 used in the baseline calibration of Gervais et al. (2016).



Figure 9: Separation Profile in the Model and Data. *Notes*: The dashed (solid) lines represent the separation profiles from the data (model). Data are from the CPS between 1976-2019. Model profiles are computed by simulating the model economy.

be interpreted as 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 college workers 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 are 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%.

4.2 Model Validation

Table 5 compares the model and data along some untargeted moments. 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 complete job finding profiles because, as shown in the third row, the unemployment-education gap (U-E gap for brevity, henceforth) is primarily driven by differences in separation probabilities.

As discussed in Section 2.3.3, the empirical relationship between prior experience and expected duration of a match 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.³⁴ The model

³⁴The regression specification is detailed in Appendix A.6 and the untargeted moments are presented in

	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. endowed with $e = 1$	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	l	Matching parameter	0.673

Table 4: Parameter Values

Note: "Pr." is short for probability and "sep" is short for separation.

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 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, 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).

4.3 Decomposing the U-E Gap

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

Figure 10(a) presents the life cycle unemployment 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 the unemployment rate for non-college workers drops modestly from the orange curve with circle markers to the green curve. In particular, equating y_0 with y_1 eliminates 1.7% (6.8%) of the U-E gap in

Table A9, Panel B, Column (4).

Untargeted Moments	Data	Model
Urate by age bin, non-college (%)	[9.9, 6.3, 5.2, 4.9]	[9.9, 7.5, 5.9, 4.9]
Urate by age bin, college (%)	[4.3, 2.3, 2.3, 2.7]	[4.4, 1.9, 1.9, 1.9]
Frac. of U-E gap explained by SP	1.213	0.842
β (PriorExp)	$5 imes 10^{-5}$	$5 imes 10^{-5}$
β (PriorExp × College)	$-4 imes 10^{-5}$	$-2 imes 10^{-5}$
# of careers by age bin, non-college	[2.6, 2.8, 2.8, 2.8]	[2.2, 2.6, 2.7, 2.7]
# of careers by age bin, college	[1.9, 2.0, 2.0, 2.0]	[1.9, 1.9, 1.9, 1.9]
Elasticity of JFP with respect to θ	0.5 - 0.7	0.568

Table 5: Model Validation – Untargeted Moments Comparison

Notes: "Urate" refers to the unemployment rate, "frac." is fraction, "SP" is separation probability, and "JFP" is job finding probability. The four age bins are: [20 - 29, 30 - 39, 40 - 49, 50 - 59]. Rows four and five contain regression coefficients from estimating the regression detailed in Appendix A.6 on both the NLSY79 sample and simulated data.

the first (last) age bin.

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. Doing so results in a large reduction in unemployment for non-college workers and a modest reduction for college workers. More precisely, setting $\delta^b = \delta^g$ closes 68.15%, 65.91%, 79.39%, and 89.43% of the U-E gap in each age bin, respectively. Altogether, the portion of the U-E gap that is accounted for by differences in labor productivity and separations by match status is represented by the orange shaded region in Figure 10(a).

At this point, we have shut down two sources of the U-E gap and the only one remaining is the uncertainty channel. The blue shaded region in Figure 10(a) represents the gap in unemployment rates that is due to non-college workers (i) being more likely to end up in a bad match and endogenously separate from it and (ii) learning their best fit at a lower rate. The fraction of the U-E gap at each age bin which is attributed to the uncertainty channel 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.³⁵ The purple bars represent the portion of the U-E gap which is entirely attributed to the uncertainty channel (i.e., the blue shaded region in Figure 10(a)). The blue bars represent the fraction of the U-E explained by shutting down the match-specific productivity channel. As explained in Section 3.3, we interpret $\delta^b > \delta^g$ as the result of the interaction between underlying match-specific productivity shocks and the uncertainty channel, as workers

³⁵Our 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 C.2.



Figure 10: Decomposition of the U-E Gap. *Notes*: Panel (a) shows the unemployment rate profiles, by education, after simulating the model economy under the specified parameters. A "C" ("N") in the legend indicates that the line is for college (non-college) workers. The orange shaded region represents the difference in unemployment rates for non-college workers after increasing y_0 to y_1 and lowering δ^b to δ^g . The blue shaded region is the portion of the unemployment-education gap which is attributable to the uncertainty channel. Panel (b) shows the corresponding fraction of the unemployment-education gap that closes after each successive change in the model's parameters.

are 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, through our interpretation of $\delta^b > \delta^g$, part of the blue bars in Figure 10(b) are 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 labor productivity, 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 evaluate the workings of its two components: the number of careers, N_e , and learning speed, ϕ_e . Figure 11(a) shows that raising ϕ_0 to ϕ_1 increases the unemployment rate early in the career of non-college workers, as they learn faster and are more likely to be in a bad match. Hence, they experience more separations. However, due to the higher learning speed and experiencing more separations early on, more 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-



Figure 11: Dissecting the Uncertainty Channel. *Notes*: Panel (a) shows the response of the unemployment rate profile for non-college workers after increasing ϕ_0 to ϕ_1 . Panel (b) shows the same, but after decreasing N_0 to N_1 . The baseline unemployment profiles, labelled "College" and "Non-College" in both panels are the result of (i) increasing y_0 to y_1 and (ii) decreasing δ^b to δ^g . All series in this figure are computed by simulating the model economy.

college workers reduces unemployment for non-college workers at all age bins.

4.4 Policy Implications

To this point, our analysis indicates that non-college workers face significant uncertainty upon entering the labor market and that reducing uncertainty can lower separations and unemployment. 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.³⁶

Within the context of our model, such policies would operate by reducing the number of 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 have 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. When the number of careers is large, $N_0 = 8$, a higher learning probability initially increases separations as workers have more careers to sample, but reduces separations later

³⁶One example of an intervention which could be used to reduce career uncertainty is by exposing students to role models working in specific fields who share about their career path. For example, Breda et al. (2023) find that exposure to female role models working in scientific fields increased the probability of females enrolling in selective STEM programs.



Figure 12: Policy Analysis. *Notes*: Panel (a) shows the separation profile for non-college workers at combinations of N_0 and ϕ_0 . Separation profiles are computed using simulated data. Panel (b) displays the numerical derivative of $U_{y,0,1}$ with respect to ϕ_0 at different values of N_0 . All other parameters take the value shown in Table 4.

on in non-college workers' careers. However, the increased separations should not necessarily be viewed as a negative byproduct of increasing the learning speed, as it indicates that non-college workers are finding their best fit earlier in their career. In fact, under the higher (lower) learning speed, 71% (35%) of the separations are endogenous, workers sample an average of 4.01 (2.20) careers, and 84% (32%) find their best fit within the first 10 years of potential experience.

Figure 12(b) presents the effect of increasing ϕ_0 on the lifetime discounted utility of a non-college worker, $U_{y,0,1}$, at different values of N_0 . Increasing the learning speed from lower values, e.g., around the calibrated value of $\phi_0 = 0.02$, leads to large increases in lifetime utility. This is because the expected duration to learn about the fit, $1/\phi_0$, is especially sensitive to increases the learning speed when ϕ_0 is small. Figure 12(b) also shows that increasing the learning speed generally has a larger impact on lifetime utility when N_0 is larger, as workers can quickly identify and move on from bad fits. Taken together, Figure 12(b) shows that increasing the learning speed, especially from low values of ϕ_0 , can lead to large increases in lifetime utility even though, as shown in Figure 12(a), such an increase can be associated with more separations early in workers' careers.

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 know their best fit before sampling any careers. Figure 13(a) shows that increasing the proportion of workers with perfect in-



Figure 13: Policy Implications, ϱ_e . *Notes*: Panel (a) shows the separation profile by education at different values of ϱ_e . Panel (b) the average output among employed workers, by age, at each value of ϱ_e . All series in this figure are computed by simulating the model economy.

formation significantly decreases separations, and that this effect is more pronounced among non-college workers. This reason is intuitive: 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 relatively small 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 raises 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 13.49% (0.94%) among non-college (college) workers. Again, this is because non-college workers take significantly longer to find their best fit. Therefore, increasing the proportion who know their best fit upon entering the labor market leads to significant productivity gains.

4.5 Match-Specific Productivity

An alternative mechanism to generate the unemployment-education gap is the formation of match-specific productivity. 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 and lower unemployment.³⁷ This environment

³⁷This intuition follows from a standard search model with shocks to match-specific productivity (e.g., Mortensen and Pissarides (1994)).

could also generate the differences in separation rates, by education, over the life cycle shown in Figure 3(b) as older non-college workers are more likely to have found a match with high productivity and thus, exhibit a lower separation rate.

What, then, distinguishes the uncertainty channel from a mechanism which focuses only on the formation of match-specific productivity? First, following the intuition above, a model of match-specific productivity would predict that the match-specific component of productivity is lower among college graduates. While match-specific productivity is not directly observable, Guvenen et al. (2020) argue that skill mismatch can serve as a proxy for it. We show in Appendix A.3.3 that skill mismatch is, throughout the life cycle, lower among college graduates. This suggests that the average idiosyncratic component of match productivity is higher among college graduates and is contrary to what a simple model of match-specific productivity predicts. Second, environments that rely exclusively on shocks to or learning about match-specific productivity to generate separations predict that the expected duration of a match formed through unemployment is independent of the worker's 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 career mobility, nor do they address the differences in forecast errors by educational attainment we documented in Section 2.1.

As we 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 suggests that the interaction between the uncertainty and match-specific productivity channels are quantitatively meaningful, as $\delta^b/\delta^g = 4.66$ from Table 4. In this sense, our quantitative results suggest that the two channels should not be viewed in isolation from each other.

5 Conclusion

This paper posits the uncertainty channel as a new explanation for the unemploymenteducation gap. Using the NLSY79 and CPS, we document a set of facts to support the uncertainty channel: 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 and career sampling. To quantify 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. Our 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 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(2), 161–78.
- Autor, D. H. and D. Dorn (2013, August). The growth of low-skill service jobs and the polarization of the US labor market. *American Economic Review* 103(5), 1553–97.
- Baley, I., A. Figueiredo, and R. Ulbricht (2022). Mismatch cycles. *Journal of Political Economy* 130(11), 2943–2984.
- Bover, O., M. Arellano, and S. Bentolila (2002). Unemployment duration, benefit duration and the business cycle. *The Economic Journal* 112(479), 223–265.
- Breda, T., J. Grenet, M. Monnet, and C. Van Effenterre (2023). How Effective are Female Role Models in Steering Girls Towards STEM? Evidence from French High Schools. *The Economic Journal* 133(653), 1773–1809.
- Cairó, I. and T. Cajner (2018). Human capital and unemployment dynamics: Why more educated workers enjoy greater employment stability. *The Economic Journal* 128(609), 652–682.
- Cajner, T., I. Güner, and T. Mukoyama (2023). Gross worker flows over the life cycle. *Journal of Money, Credit and Banking forthcoming*(n/a).
- Chéron, A., J.-O. Hairault, and F. Langot (2013). Life-cycle equilibrium unemployment. *Journal of Labor Economics* 31(4), 843–882.
- Créchet, J., E. Lalé, and L. Tarasonis (2024). Life-cycle worker flows and cross-country differences in aggregate employment. Working paper.
- Elsby, M. W. L., R. Michaels, and G. Solon (2009). The ins and outs of cyclical unemployment. *American Economic Journal: Macroeconomics* 1(1), 84–110.

- Esteban-Pretel, J. and J. Fujimoto (2014). Life-cycle labor search with stochastic match quality. *International Economic Review* 55(2), 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), 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(1), 225–255.
- Gorry, A., D. Gorry, and N. Trachter (2019). Learning and life cycle patterns of occupational transitions. *International Economic Review* 60(2), 905–937.
- Guvenen, F., B. Kuruscu, S. Tanaka, and D. Wiczer (2020). Multidimensional skill mismatch. *American Economic Journal: Macroeconomics* 12(1), 210–44.
- Kambourov, G. and I. Manovskii (2008). Rising occupational and industry mobility in the United States: 1968–97. *International Economic Review* 49(1), 41–79.
- Menzio, G. and S. Shi (2011). Efficient search on the job and the business cycle. *Journal of Political Economy* 119(3), 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(3), 397–415.
- Moscarini, G. and K. Thomsson (2007). Occupational and job mobility in the US. *Scandinavian Journal of Economics* 109(4), 807–836.
- Neal, D. (1999). The complexity of job mobility among young men. *Journal of Labor Economics* 17(2), 237–61.
- Papageorgiou, T. (2014). Learning your comparative advantages. *Review of Economic Studies* 81(3 (288)), 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(2), 390–431.
- Pissarides, C. A. (2009). The unemployment volatility puzzle: Is wage stickiness the answer? *Econometrica* 77(5), 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(1), 25–49.
- Shimer, R. (2012). Reassessing the ins and outs of unemployment. *Review of Economic Dynamics* 15(2), 127–148.
- Topel, R. H. and M. P. Ward (1992). Job mobility and the careers of young men. *Quarterly Journal of Economics* 107(2), 439–479.
- Vardishvili, O. (2024). 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 harmonize educational categories based on years of education or degree attainment. As shown in Table A1, "Non-College" includes individuals who have completed up to three years of college before 1992 or obtained at most an associate's degree afterward. "BA" encompasses those who completed four years of college in the old question or obtained a bachelor's degree in the new question. We also classify individuals who completed five or more years of college in the old question or obtained a master's degree in the new question as "Master". Additionally, "Professional and Doctorate Degree" includes individuals who completed at least four years of college in the old question or attained at least a bachelor's degree in the new question.

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

Category	Refined Category	CPS Education	Potential Exp.
Non-College	Non-College	< 4 years of college	Age - 18 + 1
	BA	4 years of college Bachelor's degree	Age - 22 + 1
College	Master	5+ years of college 5 years of college 6+ years of college Master degree	$\begin{array}{c} Age - 23 + 1 \\ Age - 23 + 1 \\ Age - 24 + 1 \\ Age - 24 + 1 \end{array}$
	Professional and Doctorate Degree	Professional degree Doctorate degree	Age - 28 + 1

Table A1: Potential Experience by Education

Note: This table shows the mapping between a respondent's educational attainment and presumed years of potential experience.

(2013).³⁸ Figure A1(a) displays the pairwise correlation between these attributes and the proportion of respondents in the O*NET survey reporting that at least a bachelor's degree is required to perform that job. 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.³⁹ Furthermore, we examine the average occupational attributes in jobs held by non-college and college workers in the NLSY79 sample of 1, 152, 280 employment observations. Figure A1(b) shows that jobs held by college graduates have higher requirements for verbal, math, and social skills, whereas routine and manual task intensities are lower. Overall, these five attributes capture well the lower- and higher-order skills required by occupations.

A.2 National Longitudinal Survey of Youth (NLSY79)

The National Longitudinal Survey of Youth (NLSY79) is a longitudinal survey that tracks the labor market histories of a youth cohort aged 14 to 22 when first surveyed in 1979.

³⁸We follow the steps outlined by both Guvenen et al. (2020) and Autor and Dorn (2013) in the measurement of occupational attributes and, for brevity, omit those detailed steps here.

³⁹We 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.





Conducted by the U.S. Bureau of Labor Statistics, it provides comprehensive information on employment, education, training, income, and family status.

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-priority status for the month is assigned as the respondent's primary labor force status. Online Appendix D contains further details on the NLSY79 sample construction.

Criteria	No. Respondents	No. Observations
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

Table A2: NLSY79 Sample Selection

Note: This table details the steps taken to construct the NLSY79 sample and the corresponding sample size after each sample restriction is implemented.

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 substantial changes throughout the survey period.⁴⁰ Next, we filter the observations to include only those from the earliest survey year (1978) until 2018. Table A2 summarizes the sample selection criteria.

We assume that individuals enter the labor market upon completing their highest level of education. For those whose highest education level is recorded as "None", we set their employment histories to start in 1978, the earliest year available in our dataset. We drop respondents with unknown graduation dates from our sample, which leads 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.

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 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

⁴⁰For example, the labor force participation rate of female increases from 50% in 1978 to around 60% starting in 1997.

knowledge and paragraph comprehension) and the last two sub-tests (arithmetic reasoning and mathematics knowledge). By extracting the first component from each PCA, we obtain measures of verbal and math abilities. Subsequently, we convert these ability indicators into percentile ranks across all individuals.

To measure social skills, we use the Rotter Locus of Control Scale and the Rosenberg Self-Esteem Scale. Following a similar approach as with math and verbal skills, we adjust 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 attributes. In particular, the mismatch in aptitude *j* between worker *i* and occupation *o* is given by:

$$m_{i,j,o} = |q(A_{i,j}) - q(s_{o,j})|, \qquad (A.18)$$

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*. The aggregate mismatch is then defined as:

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

where ω_j represents the weights assigned to each skill *j*, reflecting the relative importance of the difference in that skill to the aggregate skill mismatch. These weights are determined by 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 Forecast Error and Separations

From the NLSY79, we observe that 115 (88) out of 1,961 (604) non-college (college) workers accurately predicted their occupation at age 35. This section compares the separation profiles of workers with and without forecast errors within each education group. As shown in Figure A2, within each education group, workers who did not make forecast errors – or, had little uncertainty about their best career – exhibit lower separations than

those who did. Furthermore, the difference in separation rates by forecast error is widest early in workers' careers, supporting the notion that individuals with greater uncertainty about their best fit experience higher separation rates in the initial stages of their careers. Over time, as they find their true calling, these separation rates decline.



Figure A2: Forecast Error and Separations. *Note*: Constructed using NLSY79 sample.

A.3.2 Occupational Mobility

Using CPS data from 1994 to 2019, we compute monthly 3-digit occupational mobility rates by age and education.⁴¹ 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.

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

⁴¹Occupational records in survey data are prone to measurement error. To mitigate this concern, we apply the methodology proposed by Moscarini and Thomsson (2007) which leverages the dependent questions introduced in the CPS starting in 1994. The correction 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. Detailed procedures are omitted here but are available upon request.



Figure A3: Occupational Mobility. *Note*: Figures are constructed using CPS data between 1994-2019.

are three patterns to highlight. First, occupational mobility is decreasing in age (Kambourov and Manovskii, 2008). Second, non-college workers change occupations more frequently. Third, similar to 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 by presumed years of potential experience, assuming that 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 becomes even larger in early career stages than when compared by age.

Occupational Mobility in Broader Categories 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 using 1- and 2-digit occupational codes. The patterns are consistent with those shown in Figure A3.



Figure A4: Occupational Mobility Across Specific College Degrees. *Note*: Figures are constructed using CPS data between 1994-2019.



Figure A5: Occupational Mobility at 1- and 2-digit Occupation Codes. *Note*: Figures are constructed using CPS data between 1994-2019.

A.3.3 Skill Mismatch

Based on the skill mismatch for each worker-job pair as outlined in Appendix A.2.4, we compute the average skill mismatch disaggregated by age and educational attainment, denoted as $\overline{MM}_{i,j}$:

$$\overline{MM}_{i,j} = \frac{\sum_{k \in i \cap j} MM_k \times \omega_k}{\sum_k \mathbb{1}\{k \in i \cap j\} \times \omega_k}.$$
(A.20)

From equation (A.20), $\overline{MM}_{i,j}$ is given by the ratio of the aggregate mismatch among individuals with age *i* and education *j* to the number of individuals within that subgroup. We apply the technical weight ω_k to accounts for each respondent's representation in the U.S. population. Figure A6 shows that aggregate skill mismatch is decreasing with higher educational attainment.42



Figure A6: Skill Mismatch by Age and Educational Attainment. *Note*: Constructed using NLSY79 sample.

A.3.4 Dispersion in Skill Requirements

In this section, we compare the variance of occupational skill requirements across age or potential experience and educational attainment. The degree of dispersion is suggestive of workers' uncertainty regarding their comparative advantages. Specifically, workers more certain of their best fit may choose occupations with more imbalanced skill requirements, indicating their assurance in excelling in jobs that emphasize particular skills. We measure the degree of skill dispersion using the following metrics:

$$Var_{i} = \frac{\sum_{j}(r_{i,j} - \bar{r}_{i})^{2}}{5}, \quad Max - Min_{i} = max(r_{i,j}) - min(r_{i,j}),$$
$$MeanDev_{i} = \frac{|\sum_{j}(r_{j} - \bar{r}_{i})|}{5}, \quad MedianDev_{i} = \frac{|\sum_{j}(r_{i,j} - Median_{i})|}{5},$$

where $r_{i,j}$ denotes the skill requirement along skill *j* by occupation *i*, and \bar{r}_i (*Median*_i) denotes the mean (median) value of the skill requirement in occupation *i*.

Table A3 shows that the college workers are employed in occupations with more dispersed skill requirements, lending support to the notion that more educated workers have a higher degree of certainty regarding which kind of job is a best fit for them.

⁴²Similar patterns are observed for each single skill dimension and are available upon request.

	Age	Working Experience
Panel A: Variance		
Non-College	[0.16, 0.18, 0.18, 0.18]	[0.17, 0.18, 0.18, 0.18]
College	[0.21, 0.23, 0.23, 0.23]	[0.23, 0.23, 0.23, 0.23]
Panel B: Max-Min	Differences	
Non-College	[0.60, 0.61, 0.60, 0.61]	[0.60, 0.61, 0.60, 0.61]
College	[0.65, 0.66, 0.66, 0.66]	[0.66, 0.66, 0.66, 0.67]
Panel C: Mean Abso	olute Deviation	
Non-College	[0.35, 0.37, 0.37, 0.37]	[0.35, 0.37, 0.37, 0.37]
College	[0.39, 0.40, 0.41, 0.41]	[0.40, 0.41, 0.40, 0.40]
Panel D: Median Al	bsolute Deviation	
Non-College	[0.18, 0.18, 0.18, 0.18]	[0.18, 0.18, 0.18, 0.18]
College	[0.20, 0.21, 0.21, 0.21]	[0.20, 0.21, 0.21, 0.21]

Table A3: Degree of Skill Requirement Imbalance

Notes: Working experience refers to years of potential experience. Data from NLSY79, 1979:1-2018:12.

A.3.5 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 involves a two-step process. First, we calculate the average number of employer, occupational, and career switches within each subgroup. Second, we compute the cumulative average transitions by aggregating these averages across all preceding age bins.

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.

A.4 Robustness Checks

A.4.1 Transition Probabilities

Aggregate Employment Profile Table A5 shows that, in the aggregate, 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.

	20 - 29	≤ 39	≤ 49	≤ 59
Panel A: Employ	er Transitions			
Non-College	4.43	6.90	8.35	9.08
College	1.91	3.57	4.73	5.57
Panel B: Unique	Employers			
Non-College	5.01	6.56	7.33	7.71
College	2.76	3.82	4.37	4.78
Panel C: Occupat	tion Transition	ns		
Non-College	4.97	7.80	9.13	9.76
College	3.02	5.40	6.61	7.38
Panel D: Career	Transitions			
Non-College	3.00	4.65	5.41	5.78
College	1.44	2.44	2.85	3.17

Table A4: Cumulative Transitions by Age

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

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, while the last two are computed from CPS: 1994:1-2019:11.

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:

$$u_{t+1} = (1 - F_t)u_t + u_{t+1}^s \quad \Rightarrow \quad F_t = 1 - \frac{u_{t+1} - u_{t+1}^s}{u_t},$$
 (A.21)

where F_t is the monthly outflow probability. Equation (A.21) 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 $f_t = -\log(1 - F_t)$.



Figure A7: Original and 12-month Moving Average Transition Rate. *Note*: Figures are constructed using CPS data between 1994-2019.

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

$$\dot{u} = \overbrace{s_t(l_t - u_t)}^{inflow} - \overbrace{u_t f_t}^{outflow} = -(s_t + f_t)(u_t - u^*), \tag{A.22}$$

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.22) and assuming s_t , f_t and l_t are constant between surveys, we can infer s_t from

$$u_{t+1} = \frac{(1 - e^{(-s_t - f_t)})s_{t+1}}{f_{t+1} + s_{t+1}}l_t + u_t e^{(-s_t - f_t)}.$$
(A.23)

To compute the inflow and outflow rates, we first compute the unemployment rate for each subgroup defined by age *i* and education *j*. In the same manner, we calculate the short-term unemployment rate for each subgroup, where short-term unemployment (denoted $u_{t,s}^{ij}$) is defined as a duration of less than 5 weeks. From here, we can readily infer the hazard rates from equations (A.21) and (A.23).⁴³ Finally, we take a 12-month moving average. Figure A7 shows that the age profile patterns of the transition rates closely resemble those of the transition probabilities shown in Figure 3.

Separation Probability by Working Status Workers without a college degree are more likely to hold part-time jobs, which might lead to more separations unrelated to their certainty of comparative advantage, such as seasonal employment. To demonstrate that

⁴³Observations before 1994 were discarded because the unemployment duration variable is only available in IPUMS-CPS data starting from 1994.



Figure A8: Separation Probability by Working Status. *Note*: Figures are constructed using CPS data between 1976-2019.

part-time employment 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. For example, 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 A8 shows that, even among full-time workers, those with less education have higher separation rates. Finally, as shown in Section A.4.3, the observed patterns persist after controlling for month fixed effects.

Involuntary and Voluntary Separations Learning that a career is not a good fit and seeking another tends to result in a voluntary quit. If this holds, less-educated workers should quit their jobs at a higher rate. To examine this, we leverage the reason for unemployment in the CPS. Respondents listing "job loser – on layoff", "other job loser", or "temporary job ended" as their reason for being unemployed are classified as involuntarily unemployed, while those listing "job leaver" are classified as voluntarily unemployed.

Figure A9 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.



Figure A9: Involuntary Separations and Quits. *Note*: Figures are constructed using CPS data between 1976-2019.

A.4.2 U-E Gap Decompositions

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

$$u_{ij} = \frac{s_{ij}}{s_{ij} + f_{ij}}.\tag{A.24}$$

Taking first differences of (A.24) between education levels j and j' gives

$$1 = \underbrace{\frac{(1 - u_{ij})u_{ij'} \frac{(s_{ij} - s_{ij'})}{s_{ij'}}}{\Delta u_i}}_{\text{Fraction explained by SP}} + \underbrace{\frac{-u_{ij}(1 - u_{ij'}) \frac{(f_{ij} - f_{ij'})}{f_{ij'}}}{\Delta u_i}}_{\text{Fraction explained by JFP}}.$$
 (A.25)

Table A6 presents the fraction of the U-E gap at each age bin *i* that is attributable to difference in the job finding and separation probabilities (rates). Each decomposition indicates that the U-E gap is primarily driven by differences in separation probability/rate.

	20-29	30-39	40-49	50-59	
Panel A: Job Finding/Separa	tion Probab	ility			
Separation Probability	0.85	1.04	1.29	1.66	
Job Finding Probability	0.15	-0.04	-0.29	-0.66	
Panel B: Job Finding/Separation Rate					
Separation Rate	0.95	1.01	1.22	1.35	
Job Finding Rate	0.05	-0.01	-0.22	-0.35	
Panel C: Moving Average Job Finding/Separation Rate					
MA Separation Rate	0.95	1.01	1.21	1.32	
MA Job Finding Rate	0.05	-0.01	-0.21	-0.32	

Table A6: Decomposition of the U-E Gap by Age Bin

Notes: Panel A is constructed using CPS data from 1976-2019. Panels B and C are constructed using CPS data from 1994-2019.

A.4.3 Regression Results

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

$$Y_{i,t} = \beta_0 College_i + \beta_1 Potexp_{i,t} + \beta_2 Potexp_{i,t}^2 + \beta_3 College_i * Potexp_{i,t} + Race_i + MarStatus_{i,t} + Child_{i,t} + FamInc_{i,t} + \Phi_{Occ2} + \Phi_{Ind2} + \Phi_{State} + \Phi_{Year} + \Phi_{Month} + \epsilon_{i,t}.$$
 (A.26)

Our outcomes of interest, $Y_{i,t}$, include indicators for worker *i* in period *t*: (i) unemployed or not; (ii) transitions from unemployment to employment; (iii) transitions from employment to unemployment; (iv) transitions to a different occupation; (v) transitions to a different career; and (vi) the magnitude of 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 shown in equation (A.26), 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.

Table A7 indicates that college graduates have statistically significant lower proba-

bilities of unemployment, job separation, occupational switching, career switching, while notable higher job finding probabilities relative to non-college counterparts. Furthermore, conditional on changing occupations, college graduates switch to occupations similar to their prior ones. Besides that, the education gap in each outcome dissipates with potential experience. Overall, these results align with the descriptive patterns.

	(1)	(2)	(3)	(4)
Panel A: Unemployed I	ndicator			
College	-0.03750***	-0.03762***	-0.03672***	-0.02638***
$College \times PotExp$	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 In	dicator			
College	0.01749***	0.02223***	0.02304***	0.01415***
$College \times PotExp$	-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: Job Separation	Indicator			
College	-0.01617***	-0.01608***	-0.01571***	-0.01392***
College \times 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 imes 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 Mobilit	y Indicator			
College	-0.01499***	-0.01505***	-0.01582***	-0.01501***
College imes 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 Dista	nce in Occupation S	Switches		
College	-2.88222***	-2.81939***	-2.80947***	-2.60987***
$College \times PotExp$	-0.04694**	-0.04996**	-0.05127***	-0.04174**

Table A7: Regression Results in the CPS

Observations R ²	28,940 0.078	28,940 0.080	28,940 0.082	26,537 0.084
State FE		\checkmark	\checkmark	\checkmark
Year FE			\checkmark	\checkmark
Month FE			\checkmark	\checkmark

Notes: All specifications control for industry and occupation fixed effects, where 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. Levels of statistical significance are indicated by *(p < 0.10), **(p < 0.05), ***(p < 0.01).

A.5 NLSY79 Patterns

A.5.1 Unemployment-Education Gap

Figure A10 displays the unemployment rate by age/potential experience and educational attainment in the NLSY79 sample. The overall patterns are consistent with the CPS, with the U-E gap narrowing as individuals age or gain potential experience. Notably, there is an increase in the unemployment rate in later career stages, which 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.



Figure A10: Unemployment-Education Gap in the NLSY79. *Note*: Constructed using NLSY79 sample.

A.5.2 Job Finding and Separation Probabilities

Figure A11 presents the job finding and separation probabilities by age/potential experience and educational attainment. Concerning the job finding probabilities, there is no

systematic difference among education groups, particularly over potential experience. However, consistent with CPS patterns, college workers have systematically lower separation probabilities, with the gap widest in the early career stages and gradually narrowing with age or work experience.



Figure A11: NLSY79 Job Finding and Separation Probabilities. *Note*: Constructed using NLSY79 sample.

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, weighting each observation by the *PANELWEIGHT*. We restrict the sample to pairs of months with valid occupational codes. If the worker was non-employed in the previous month, we identify the occupation preceding the non-employment period. Figure A12 shows that occupational mobility patterns in the NLSY79

align with those in the CPS, with occupational mobility is decreasing with age/potential experience and educational attainment.



Figure A12: Occupational Transitions. Note: Constructed using NLSY79 sample.

Figure A13 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.



Figure A13: Angular Distance in Occupational Transitions. *Note*: Constructed using NLSY79 sample.

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 that setting $\bar{\phi} = 23.08$ yields an unweighted average correlation of aptitudes $k \in \{verbal, math, social, manual, routine\}$ of approximately 0.00005. As such, a career switch is defined as an occupational transition where the angular distance exceeds the threshold, i.e., $\phi \geq 23.08$.

Figure A14 shows that, similar to occupational mobility, that career mobility in the NLSY79 decreases with both age/potential experience and educational attainment. Moreover, the gap in career mobility rates across education levels narrows over the life cycle.



Figure A14: Career Switches. Note: Constructed using NLSY79 sample.

A.5.5 Robustness of NLSY79 Results

This section examines the robustness of the NLSY79 patterns after controlling for standard observables. The regression specification is the same as equation (A.26). Given that occupational inheritance may impact employment stability through parental networking ties, we additionally control for parental occupation, denoted by *ParentOcc*, which is measured in two ways: at the individual level, it equals one if the worker has ever held a job similar to a parent's, and at the observation level, it equals one if the worker's current job matches a parent's. The outcomes of interest remain the same as in the CPS regressions, with an additional focus on skill mismatch, as detailed in Section A.3.3.

Table A8 presents the estimated coefficients for college and the interaction term between college and potential experience. We can see that after 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 narrow with work experience.

			0			
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Unemployed Indicator						
College	-0.01986***	-0.02005***	-0.01296***	-0.00279***	-0.01298***	-0.01294***
$College \times PotExp$	0.00062***	0.00065***	0.00012***	-0.00011**	0.00012***	0.00011**
Observations	1,197,087	1,187,574	1,187,574	1,003,608	1,187,574	1,183,448
R^2	0.051	0.051	0.057	0.118	0.057	0.056
Panel B: Job Finding	Indicator					
College	0.01004	0.00742	0.02036	0.03187*	0.02179	0.02339
College imes PotExp	-0.00033	-0.00018	-0.00028	-0.00134	-0.00030	-0.00039
Observations	63,714	63,042	63,042	47,568	63,042	61,634
<i>R</i> ²	0.043	0.044	0.055	0.070	0.055	0.054
Panel C: Job Separati	ion Indicator					
College	-0.00927***	-0.00931***	-0.00585***	-0.00433***	-0.00585***	-0.00567***
$College \times PotExp$	0.00044***	0.00044***	0.00027***	0.00021***	0.00027***	0.00026***
Observations	1,129,938	1,121,132	1,121,132	953,230	1,121,132	1,118,434
R^2	0.009	0.009	0.010	0.013	0.010	0.010
Panel D: Occupation	al Mobility Ind	licator				
College	-0.01854***	-0.01840***	-0.00763***	-0.00561***	-0.00760***	-0.00763***
$College \times Potexp$	0.00070***	0.00070***	0.00036***	0.00029***	0.00036***	0.00036***
Observations	1,120,216	1,111,460	1,111,460	945,932	1,111,460	1,111,460
R^2	0.017	0.017	0.024	0.026	0.024	0.024
Panel E: Career Mob	ility Indicator					
College	-0.01562***	-0.01563***	-0.00951***	-0.00815***	-0.00949***	-0.00952***
$College \times PotExp$	0.00059***	0.00059***	0.00039***	0.00034***	0.00039***	0.00039***
Observations	1,120,210	1,111,454	1,111,454	945,928	1,111,454	1,111,454
R^2	0.014	0.014	0.017	0.018	0.017	0.017
Panel F: Angular Distance in Occupational Switches						
College	-2.89147***	-3.05840***	-3.16422***	-3.04611***	-3.16346***	-3.16341***
$College \times Potexp$	-0.05265**	-0.04957**	-0.03879	-0.02232	-0.03864	-0.03860
Observations	36,687	36,444	36,444	29,754	36,444	36,444
<i>R</i> ²	0.196	0.196	0.199	0.203	0.199	0.199

Table A8: NLSY79 Regression Results

Panel G: Skill Mismatch							
College	-0.01562***	-0.01563***	-0.00951***	-0.00815***	-0.19913***	-0.19922***	
$College \times PotExp$	0.00059***	0.00059***	0.00039***	0.00034***	-0.00002	0.00006	
Observations	1,120,210	1,111,454	1,111,454	945,928	1,121,392	1,121,392	
<i>R</i> ²	0.014	0.014	0.017	0.018	0.163	0.164	
State FE		\checkmark	\checkmark	\checkmark	\checkmark	\checkmark	
Year FE			\checkmark	\checkmark	\checkmark	\checkmark	
Month FE			\checkmark	\checkmark	\checkmark	\checkmark	

Notes: All specifications control for industry and occupation fixed effects, where industry and occupation codes for the unemployed are classified according to their last job. Standard errors are robust to heteroskedasticity. The fourth column controls for family income, while the last two columns additionally control for parents' occupation. Levels of statistical significance are indicated by *(p < 0.10), **(p < 0.05), ***(p < 0.01).

A.6 Experience and Match Survival

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, Exp_{it} , and its interaction with education attainment, $Exp_{it} * College_i$.⁴⁴

Table A9 shows that prior experience is associated with a higher survival probability, and that this effect dissipates with tenure. In addition, $\beta_3 < 0$ suggests that the association between experience and the survival probability is weaker for college workers.

A.7 Sampled Jobs and Match Survival

This section presents the complete estimation results for the association between sampled jobs and match survival, following specification (2). As shown in Table A10, learning from

⁴⁴Exp_{*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.

	(1)	(2)	(3)	(4)	
Panel A: Experience > 76 Months Indicator					
Exp	0.02037***	0.00731***	0.01157***	0.00790***	
Log(Dur) imes Exp	-0.00295***	-0.00232***	-0.00282***	-0.00248***	
$Exp \times College$		-0.00498***	-0.00427***	-0.00755***	
$Log(Dur) \times College$		-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 Prio	r Experience				
Exp	0.00012***	0.00006***	0.00008***	0.00005***	
Log(Dur) imes Exp	-0.00002***	-0.00002***	-0.00002***	-0.00001***	
$Exp \times College$		-0.00004***	-0.00003***	-0.00004***	
$Log(Dur) \times College$		-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		\checkmark	\checkmark	\checkmark	
Season FE		\checkmark	\checkmark	\checkmark	
1990dd Industry FE			\checkmark	\checkmark	

Table A9: Prior Experience and Match Survival

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 job-to-job transitions. Standard errors are robust to heteroskedasticity. Levels of statistical significance are indicated by *(p < 0.10), **(p < 0.05), ***(p < 0.01).

prior working experience, whether through sampled occupations or careers, is always associated with a higher survival probability for the current match. Notably, this effect is more pronounced for non-college workers.

Regarding the control variables, a longer match tenure is, as expected, associated with a higher survival probability. However, working experience in months is surprisingly associated with a higher separation probability. By accounting for learning from sampling difference occupations/careers, the remaining effect of working experience on match duration becomes negligible, or potentially negative. The fact that experience can be associated with a higher separation risk is theoretically possible, as shown in Menzio et al. (2016). The intuition is that workers may prefer to destroy a job with low match-specific

	Sampled Occupations			Sampled	Careers
	Non-College	College		Non-College	College
No. Sampled Occ.=1	0.00090	0.00105	No. Sampled Career=1	0.00524***	0.00243***
No. Sampled Occ.=2	0.00493***	0.00228***	No. Sampled Career=2	0.00861***	0.00420***
No. Sampled Occ.=3	0.00770***	0.00393***	No. Sampled Career=3	0.01199***	0.00533***
No. Sampled Occ.=4	0.01123***	0.00507***	No. Sampled Career=4	0.01366***	0.00564***
No. Sampled Occ.=5	0.01304***	0.00537***	No. Sampled Career=5	0.01546***	0.00666***
No. Sampled Occ.=6	0.01692***	0.00577***	No. Sampled Career=6	0.01717***	0.00795***
No. Sampled Occ.=7	0.01868***	0.00601***	No. Sampled Career=7	0.01820***	0.00707***
No. Sampled Occ.=8	0.02180***	0.00742***	No. Sampled Career=8	0.01998***	0.00835***
No. Sampled Occ.=9	0.02261***	0.00838***	No. Sampled Career=9	0.02130***	0.00920***
No. Sampled Occ.=10	0.02422***	0.00963***	No. Sampled Career=10	0.02180***	0.00810***
No. Sampled Occ.=11	0.02677***	0.01002***			
No. Sampled Occ.=12	0.02880***	0.01135***			
No. Sampled Occ.=13	0.03153***	0.01243***			
No. Sampled Occ.=14	0.03155***	0.01049***			
No. Sampled Occ.=15	0.03448***	0.01049***			
Tenure	0.00002***	0.00001***	Tenure	0.00001***	0.00001***
Exp	-0.00004***	-0.00002***	Exp	-0.00001***	-0.00001***
Observations	747,187	252,383	Observations	820,893	252,662
<i>R</i> ²	0.034	0.013	R^2	0.023	0.011

Table A10: Sampled Jobs and Survival Probability

Notes: All specifications control for individual fixed effects. Standard errors are robust to heteroskedasticity. Levels of statistical significance are indicated by (p < 0.10), **(p < 0.05), ***(p < 0.01).

productivity before accumulating more experience, as the returns to accumulating human capital are higher in a match with high match-specific productivity.

A.8 More Details on Anticipated Occupations

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 A15 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-



Figure A15: Most Frequent Anticipated Occupations. *Note*: Constructed using NLSY79 sample.

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, such as 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.

Beyond that, college workers tend to anticipate occupations with more dispersion in skill requirements. As shown in Table A11, the degree of skill dispersion in expected occupations for college workers is consistently higher than that for non-college workers, regardless of whether the expectations are short-term or long-term. This aligns with the intuition that workers would anticipate an occupation that has balanced skill requirements if they are not sure of their own skills. On the other hand, an individual who knows that they have, e.g., high math skills may anticipate working in an occupation with relatively high math skill requirements.

A.8.1 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,

$$\|\mathbf{s}_i\|^2 + \|\mathbf{\hat{s}}_i\|^2 - 2\|\mathbf{s}_i\|\|\mathbf{\hat{s}}_i\|\cos(\phi) = \psi^2.$$
(A.27)

	Variance	Max-Min	Mean Deviation	Median Deviation	
Panel A: Expected Occupation at Age 35					
Non-College	0.0620	0.6361	0.2112	0.1878	
College	0.0701	0.6549	0.2297	0.2062	
Panel B: Expected Occupation in 5 Years					
Non-College	0.0569	0.6148	0.1996	0.1774	
College	0.0725	0.6804	0.2327	0.2068	

Table A11: Skill Dispersion in Expected Occupation

Notes: Data from NLSY79, including 1,961 (604) non-college (college) workers. Let Diff represent the difference in skill dispersion between non-college and college respondents. The *p* values for a *t*-test of the null hypothesis H_0 : Diff = 0 versus the alternative hypothesis H_a : Diff < 0 are all less than 0.01. Formulas for each measure of dispersion are provided in Appendix A.3.4.

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

$$\underbrace{\frac{(\|\mathbf{s}_i\| - \|\mathbf{\hat{s}}_i\|)^2}{\psi^2}}_{\text{Diff. in Skill Magnitude}} + \underbrace{\frac{2\|\mathbf{s}_i\|\|\mathbf{\hat{s}}_i\|(1 - \cos(\phi))}{\psi^2}}_{\text{Diff. in Cosine Similarity}} = 1.$$
 (A.28)

From (A.28), 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.8.2 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 A16(a) shows there is no systematic difference in the age at which expectations were recorded across the different education levels. Moreover, Figure A16(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.9 Associate's Degrees and College Dropouts

Associate's degree provides specialized technical or vocational training aimed at equipping individuals with a specific skill set or preparing them for particular careers, similar to four-year college degree in offering workers greater certainty about their comparative advantage, albeit with a shorter exploration period.

In Panel A in Table A12, we compare employment stability across three groups: noncollege workers without an associate's degree, associate's degree holders, and college workers in the CPS (the patterns are very similar in the NLSY79). Notably, the separation probability among AA graduates is significantly lower than those without an AA while slightly higher than four year degree holders.

We also examine the employment profile for college dropouts by comparing "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. Using the NLSY79 sample, we define dropouts as those who enrolled full-time in college but did not attain a Bachelor's degree or higher, yielding a dropout rate of 57.65%, closely aligned with the 54% reported by Vardishvili (2024). 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.

Panel B in Table A12 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.

	Unemployment Rate (%)	Separation Prob. (%)
Panel A: Associate's Degree, CPS	5	
Non-College	[10.13, 6.51, 5.56, 5.18]	[2.72, 1.78, 1.45, 1.21]
Associate's Degree	[5.57, 3.93, 3.72, 4.08]	[1.48, 0.98, 0.92, 0.92]
College	[4.34, 2.33, 2.42, 2.88]	[0.99, 0.56, 0.53, 0.59]
Panel B: College Dropouts, NLS	(79	
College Dropouts	[4.80, 3.03, 3.82, 3.55]	[0.96, 0.48, 0.40, 0.31]
Less-Educated Dropouts	[6.03, 4.23, 4.51, 3.59]	[1.20, 0.57, 0.46, 0.28]
More-Educated Dropouts	[3.70, 2.30, 3.45, 3.54]	[0.75, 0.43, 0.37, 0.32]
College Graduates	[2.12, 1.13, 1.58, 2.14]	[0.40, 0.20, 0.17, 0.20]

Table A12: Associate's Degrees and College Dropouts

Notes: "Prob." refers to probability. Panel A is constructed using the CPS sample between 1992-2019. Panel B is constructed using the NLSY79 sample.

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

$$u_{y,e,i}^{+} = \begin{cases} \mu \pi_{e} + (1 - \lambda_{o}) \left[(1 - f^{*}) u_{y,e,1} + (1 - \phi_{e}) \delta_{1e}^{un} n_{y,e,1} \right] & \text{for } i = 1, \\ (1 - \lambda_{o}) \left[(1 - f^{*}) (u_{y,e,i} + l^{*} \overline{u}_{y,e,i-1}) + (1 - \phi_{e}) \delta_{ie}^{un} n_{y,e,i} \right] & \text{for } i = 2, \dots, N_{e} - 1, \\ (1 - \lambda_{o}) \left[\delta^{g} \left(\phi_{e} \sum_{i=1}^{N_{e}-1} p_{ie} n_{y,e,i} + n_{y,e,N_{e}} \right) + (1 - f^{*}) (u_{y,e,N_{e}} + l^{*} \overline{u}_{y,e,N_{e}-1}) \right] & \text{for } i = N_{e}, \end{cases}$$
(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

$$n_{y,e,i}^{+} = \begin{cases} (1-\lambda_{o}) \left[f^{*} u_{y,e,i} + (1-\phi_{e})(1-\delta_{1e}^{un})n_{y,e,i} \right] & \text{for } i = 1, \\ (1-\lambda_{o}) \left[f^{*} (u_{y,e,i} + l^{*}\overline{u}_{y,e,i-1}) + (1-\phi_{e})(1-\delta_{ie}^{un})n_{y,e,i} \right] & \text{for } i = 2, \dots, N_{e} - 1, \\ (1-\lambda_{o}) \left[(1-\delta^{g}) \left(\phi_{e} \sum_{i=1}^{N_{e}-1} p_{ie}n_{y,e,i} + n_{y,e,N_{e}} \right) + f^{*} (u_{y,e,N_{e}} + l^{*}\overline{u}_{y,e,N_{e}-1}) \right] & \text{for } i = N_{e}, \end{cases}$$
(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:

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

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

for $i = 1, 2, ..., N_e - 1$ 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:

$$u_{o,e,i}^{+} = \begin{cases} \sum_{a} \chi_{a} \left[(1 - f^{*}) u_{a,e,i} + (1 - \phi_{e}) \delta_{ie}^{un} n_{a,e,i} \right] & \text{for } i = 1, \\ \sum_{a} \chi_{a} \left[(1 - f^{*}) (u_{a,e,i} + l^{*} \overline{u}_{a,e,i-1}) + (1 - \phi_{e}) \delta_{ie}^{un} n_{a,e,i} \right] & \text{for } i = 2, \dots, N_{e} - 1, \\ \sum_{a} \chi_{a} \left[\delta^{g} \left(\phi_{e} \sum_{i=1}^{N_{e}-1} p_{ie} n_{a,e,i} + n_{a,e,N_{e}} \right) + (1 - f^{*}) (u_{a,e,N_{e}} + l^{*} \overline{u}_{a,e,N_{e}-1}) \right] & \text{for } i = N_{e}, \end{cases}$$

$$n_{o,e,i}^{+} = \begin{cases} \sum_{a} \chi_{a} \left[f^{*} u_{a,e,1} + (1 - \phi_{e}) (1 - \delta_{ie}^{un}) n_{a,e,1} \right] & \text{for } i = 1, \\ \sum_{a} \chi_{a} \left[f^{*} (u_{a,e,i} + l^{*} \overline{u}_{a,e,i-1}) + (1 - \phi_{e}) (1 - \delta_{ie}^{un}) n_{a,e,i} \right] & \text{for } i = 2, \dots, N_{e} - 1, \\ \sum_{a} \chi_{a} \left[(1 - \delta^{g}) \left(\phi_{e} \sum_{i=1}^{N_{e}-1} p_{ie} n_{a,e,i} + n_{a,e,N_{e}} \right) + f^{*} (u_{a,e,N_{e}} + l^{*} \overline{u}_{a,e,N_{e}-1}) \right] & \text{for } i = N_{e}, \end{cases}$$

$$(B.6)$$

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

$$\overline{u}_{o,e,i}^{+} = \sum_{a} \chi_{a} \left[\delta^{b} \overline{n}_{a,e,i} + (1-l^{*})(1-\overline{f}^{*}) \overline{u}_{a,e,i} + \phi_{e}(1-p_{ie})d^{*}n_{a,e,i} \right],$$
(B.7)

$$\overline{n}_{o,e,i}^{+} = \sum_{a} \chi_{a} \left[(1 - \delta^{b}) \overline{n}_{a,e,i} + (1 - l^{*}) \overline{f}^{*} \overline{u}_{a,e,i} + \phi_{e} (1 - p_{ie}) (1 - d^{*}) n_{a,e,i} \right],$$
(B.8)

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

C Quantitative Appendix

C.1 Counting Unique Careers

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 $\bar{\phi} = 23.08$. That is, career *i* is considered unique if its angular distance relative to any previously held career *j*, denoted by ϕ_{ij} , is greater than $\bar{\phi}$.

C.2 Alternative Decomposition

In the decomposition presented in Section 4.3, we first shut down the differences in labor productivity and then eliminated the difference in separation probabilities between good and bad matches. In this section, we reverse the order by first equation δ^b with δ^g and then set y_0 equal to y_1 . Proceeding in this way delivers a decomposition where the differences in productivity account 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. This decomposition is presented in Figure C1.

D NLSY79 Panel Construction

Weekly Panel This section details the construction of the weekly panel from the NLSY79. The process involves three steps: (i) cleaning the employer history and determining employer characteristics; (ii) identifying demographic variables in each survey year; and (iii) identifying the primary job for each week if employed by multiple employers.



Figure C1: Alternative Decomposition. *Notes*: Panel (a) shows the unemployment rate profiles, by education, after simulating the model economy under the specified parameters. Panel (b) shows the corresponding fraction of the unemployment-education gap that closes after each successive change in the model's parameters.

We start by processing the employer history roster, which involves two steps. The first is to standardize the occupation and industry codes across various census classification schemes to the 1990dd scheme developed by David Dorn.⁴⁵ This scheme consolidates US Census codes into a balanced panel of occupations or industries for the 2000 and 2002 Census, and also an unbalanced panel for the 1970 Census. When occupation and industry codes do not have corresponding 1990dd codes in the crosswalk file, we review the classification files and manually assign the closest equivalent within the 1990dd classification scheme.

In particular, for occupation codes (for 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. For occupation codes from survey year 2004 onwards, we convert the original 4-digit 2002 occupation codes into 3-digit 2000 census codes by taking the first three digits, and then covert them to the 1990dd classification scheme. The crosswalk process for industry codes is similar to that for occupation codes, with one key difference: for industry codes reported from survey years 1979 (round 1) to 2000 (round 19), we first convert IND70 codes to IND80 codes before mapping them to the 1990dd industry classification scheme.

⁴⁵See https://www.ddorn.net/data.htm for more details.

We then identify the employer characteristics for each job in every survey year by referring to the original employer history roster (EHR). When the EHR lacks occupational and industry codes, we supplement this with the corresponding codes from Current Population Survey (CPS) jobs. While the CPS employer is typically the first employer, this is not always the case during the survey years 1980 to 1992. To address job order discrepancies, we refer to the question: "IS JOB # SAME AS CURRENT JOB? " If the answer is affirmative, we use the CPS job information to fill in the missing data. We also use industry and occupation codes from the last employer to complete any remaining gaps.

Now, turning to the weekly employment histories with primary job codes, these codes follow the format *Survey Round* * 100 + *Job Number*. We first determine the survey round for each reported job, which corresponds to the first one or two digits of the job code. Using the unique respondent ID, survey round, and job number, we merge the weekly employment history with the employer history roster to 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 process the demographic variables. Since we already have the demographic characteristics for each respondent in each survey year, we need to align these with the weekly employment history. To do so, we need to determine the survey year associated with each weekly observation using the available survey dates. For surveys conducted up to 1994, only the survey month is reported, so we need to impute the survey year. 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).⁴⁶ If it does, we assign the survey year of the current round to the observation. Once the survey year is identified, we can pinpoint 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, which is defined as the job with the

⁴⁶An 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.

most working hours during that week.⁴⁷ If multiple jobs have the same working hours per week, we keep the job reported in the main array.

Monthly Panel Next, we outline the process for converting a weekly panel to a monthly panel. To begin, we determine the calendar year and calendar month for each continuous week using the time crosswalk file. We then determine the primary labor force status of each respondent in each month. If the respondent is employed during a particular month, the primary job is determined as the one with the most working hours within that month. If multiple civilian jobs with the same total working hours, we consider the job with complete occupation and industry records as the primary job. If there are several jobs with complete records, we retain the one with known employer ID as the primary job. If there still exist multiple civilian jobs, 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 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). The status with higher precedence is regarded as the primary labor force status for that month.

⁴⁷In the case where a respondent simultaneously holds multiple jobs, the job number assigned to the main array is determined based on the start 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.