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

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May 2026

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 explain 27.3% of the unemployment-education gap.

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

*This paper benefited greatly from the comments of the editor and two anonymous referees. We also thank Ismail Baydur, Carlos Carrillo-Tudela, Chaoran Chen, Kevin Devereux, David Dorn, Ying Feng, Siddharth George, Aspen Gorry, Benjamin Lester, Chen Liu, Simon Mongey, Xincheng Qiu, Michelle Rendall, Guillaume Rocheteau, Henry Siu, Serene Tan, Shu Lin Wee, Donghai Zhang, Lichen Zhang, Shengxing Zhang, and audiences at the Asian and European meetings of the Econometric Society, Ashoka University, Bank of Canada, CUFE, Georgian Economic Association, Miami University, Monash Macro and Money Workshop, NUS, NTU, OzMac, PHBS, Renmin U., SUFE, SWUFE, UIBE, WAMS, West Coast Search and Matching, and Xiamen U. for their insightful comments. The first version of this paper was presented under the title "On the Unemployment-Education Gap." Errors are our own.
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1 Introduction

The unemployment rate among those with at least a bachelor's degree in the US is 2.7%, while it is nearly 7.5% for those without a degree. Most of the unemployment-education gap is driven by higher separation rates among non-college workers (Elsby et al., 2010).[1] While these facts are well established, little 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, unemployment is associated with sharp and persistent declines in earnings (Guvenen et al., 2021; Jarosch, 2023), and heterogeneity in separations plays an important role in explaining variation in lifetime earnings (Ozkan et al., 2023). 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 different, and inform policies which aim to reduce unemployment. Therefore, this paper's objectives are to (i) propose and provide empirical support for a novel mechanism to explain the unemployment-education gap and (ii) evaluate its quantitative role within a search model of unemployment.

We hypothesize that college graduates enter the labor market with a clearer understanding of which career is their best fit (i.e., the career they are most productive in).[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 into unemployment. A faster learning speed allows college graduates to find their best fit, which they are less likely to separate from, earlier in their work-life.

Our most direct evidence for the uncertainty channel is from the National Longitudinal Survey of Youth 1979 (NLSY79), where we show that college graduates form more accurate expectations about their occupation. In our preferred forecast-error measure, the cosine similarity in skill requirements between occupations (Gathmann and Schönberg, 2010; Baley et al., 2022), forecast errors are 31.6% smaller among college graduates.

Further, we compile evidence from the NLSY79 and Current Population Survey (CPS) which indirectly supports the uncertainty channel. There are two main supporting facts.

[1] Unemployment and transition rates calculated using the Current Population Survey between 1976-2019. See Appendix A.4.1.

[2] Broadly speaking, a career is a set of occupations which share a similar composition of skill requirements. Section 2.3.1 provides a precise definition. We use "best" and "good" fit interchangeably.

First, the unemployment-education gap narrows over the life cycle. As non-college workers begin with higher uncertainty, they experience more separations early on and 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 (Topel and Ward, 1992), the latter is a new fact aligned with the uncertainty channel: if non-college workers rely more on experience to learn their best fit, then prior experience should be associated with a more pronounced decline in separations for non-college workers.

Having established empirical support for the uncertainty channel, we develop a life cycle search model of unemployment. Workers are assigned one good fit, where they are most productive, out of a set of careers. Their good fit is initially unknown and workers sample careers to learn their good fit as in Gervais et al. (2016). If the worker learns they are not in their good fit, they can destroy the match in favor of becoming unemployed and sampling a different career. Workers are heterogeneous in their education (college and non-college). We assume (and find in the calibration) that college workers (i) are more productive in their good fit, (ii) face a lower exogenous separation rate, (iii) enter the labor market with fewer careers that are potentially their good fit, and (iv) learn their career fit faster. The first and second differences capture the fact that non-college and college workers tend to work in occupations that differ in their average wages and underlying separation risk. The third and fourth differences capture the uncertainty channel.

The model is calibrated by matching a set of moments from the CPS and NLSY79. The calibrated model indicates large differences in uncertainty by education. For example, non-college workers enter the labor market with twice the number of careers that are a potential good fit as college workers. We validate the model by showing that it generates an unemployment-education gap that narrows over the life cycle and a stronger correlation between experience and separations among non-college workers.

We carry out two decompositions of the unemployment-education gap. In the first, we shut down sources of the gap until all that is left is the uncertainty channel. At that point, 6.5% of the gap remains. This reveals how much of the gap is attributable to non-college workers' greater likelihood of a bad career fit, which lowers the match's expected output and increases the endogenous separation rate. We then carry out a Shapley-Owen-Shorrocks decomposition to capture the interactions between the uncertainty channel and other drivers of the unemployment-education gap. In that decomposition, the uncertainty channel explains 27.3% of the difference in unemployment rates. Together, the decompositions reveal that higher career uncertainty among non-college workers (i) accounts for a meaningful share of the unemployment-education gap and (ii) has a strong interaction with the other channels. In particular, the effect of career uncertainty is amplified when non-college workers also work in occupations with a high exogenous separation rate.

It is important to note that the hypothesis and analysis described to this point do not take a stand on what the sources of the uncertainty channel are. Our last set of analyses takes some first steps in this direction. We document two facts that, together, indicate that selection plays a prominent role in shaping the correlation between forecast errors and educational attainment. First, an Oaxaca-Blinder decomposition reveals that years of college completed accounts for 10.9% of the education gap in average forecast errors. By contrast, differences in high school GPA, test scores, income, and parental education accounts for 41.4% of the gap in forecast errors. Second, individuals who have not yet enrolled in college, but eventually obtain a degree, make lower forecast errors than individuals of the same age who do not obtain a degree.

Finally, we use the model to analyze when an individual should lower their career uncertainty by obtaining a college degree versus learning through labor market experience. We find that the value of lowering uncertainty through work experience is higher than doing so through college. Taken together, our analysis suggests that reducing career uncertainty among non-college workers before they enter the labor market is an admirable policy objective. However, expanding access to college is unlikely to be a suitable policy for this purpose and interventions may need to occur during high school or earlier.

This 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.[3] 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 life cycle unemployment-education gap 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 explanation

[3]Several studies have documented higher unemployment rates among college graduates than non-college workers outside of the US (Feng et al., 2024; Coskun, 2026; Girsberger and Meango, 2025) and focus on differences in productivity and search frictions across education groups. Our framework allows for differences in labor productivity but does not emphasize differences in search frictions as this margin directly impacts job finding rates which, as we show in Figure 3, do not vary systematically by education and contribute much to the unemployment-education gap in the US.

[4]In 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.

for the unemployment-education gap. 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 core, driven by exogenous differences in labor productivity.

The uncertainty channel is related to the literature studying the life cycle implications of learning about one's comparative advantage in the labor market. Papageorgiou (2014) and Gorry et al. (2019) 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.[5] Gervais et al. (2016) develop a model that generates 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 incorporating Gervais et al. (2016)'s formalization of uncertainty and learning one's best occupational fit into a life cycle search model with heterogeneous education, that differences in uncertainty by education can account for a sizeable portion of the unemployment-education gap.

Finally, this paper is related to a literature on life cycle labor market flows. Menzio et al. (2016) and Cajner et al. (2025) 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.[6] 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.[7]

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 analyzes the role of education policy in reducing career uncertainty. Section 6 concludes.

[5] Neal (1999) develops a model that can replicate a declining complex transition rate over the life cycle, but does not focus on unemployment. Wee (2014) shows that recessions can disrupt the process of learning about one's ability, thereby generating scarring effects of graduating in a recession.

[6] Chéron et al. (2013) emphasize the effect of retirement on flows over the life cycle while Créchet et al. (2026) analyze how differences in flows by age and gender can explain differences in unemployment rates across European countries. 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.

[7] Section 4.5 relates our 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.

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. Sections 2.3 and 2.4 discuss additional facts. Section 2.5 summarizes the evidence and transitions to the theory.

Our first data source is the monthly Current Population Survey (CPS) covering 1976-2019, which are downloaded from IPUMS (Flood et al., 2022) and described in Appendix A.1. Second is the Occupation Information Network (O*NET), which measures occupational attributes. 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. Appendix A.2 details our panel of 4,695 male respondents.[8]

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 4,695 respondents in our sample, 2,542 listed an expected occupation at age 35 and had a realized occupation at that age.[9] While this is a relatively large drop in sample size, Appendix A.9 shows that individuals that we can and cannot compare their expected and realized occupations have similar observable characteristics. Further, the sample size increases from 2,542 to 3,242 when comparing the expected occupation at 35 years old to all occupations worked at between 30 and 40 years old, instead of only at age 35. Table 2 below shows that this does not impact our results.

For a first pass at measuring forecast errors, we compute the fraction of individuals with the same expected and realized occupation code at age 35.[10] Table 1 shows that, at each occupation code level, college graduates are nearly two times more likely to end up in their expected occupation than those without a college degree.

[8] Appendix C.5.4 shows that our findings are not impacted by restricting the sample to males only.

[9] As respondents were between 15-22 years old during the initial interview, an individual is labeled as "college" within this section if they eventually obtained a BA or above.

[10] College respondents expect to be working in occupations with higher and more dispersed skill requirements. For example, college respondents most commonly expected to work as managers, lawyers or judges, and physicians, while non-college respondents most commonly expected to work as managers, mechanics or repairers, and truck/delivery drivers. See Appendix A.9.

Table 1: Comparison of Expected and Realized Occupations

Occupation Code Level	Non-College	College
occ1990dd	7.64	17.56
Second-level	15.74	37.69
First-level	29.42	60.93

Notes: There are 321 unique occ1990dd codes in our sample. The occ1990dd codes are mapped to first- and second-level categories following Dorn (2009). See Appendix Table A23 for a list of the first- and second-level occupation categories.

While Table 1 shows that college graduates form more accurate forecasts of their future occupation, it paints an incomplete picture because this comparison does not quantify how different the expected and realized occupations are in terms of their skill requirements. Moreover, it does not illuminate whether the forecast errors are driven by ending up in an occupation with a different composition or magnitude of skill requirements. Therefore, we compute the distance in skill and task requirements between the realized and expected occupation. To do so, we first 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.[11] Second, we compute two measures of distance between the vector of requirements for individual i's realized occupation, $\mathbf{s}_i$, and predicted occupation, $\hat{\mathbf{s}}_i$. The first is the angular distance, ϕ: $\mathbb{R}^5 \times \mathbb{R}^5 \to [0, \pi/2]$:

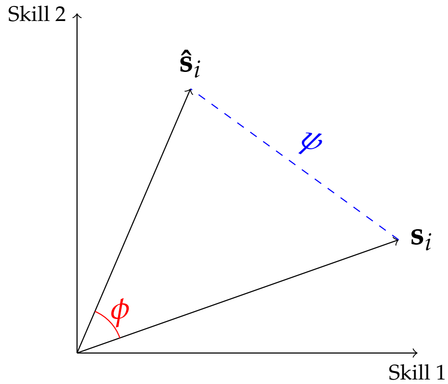
$$\phi(\mathbf{s}_i, \hat{\mathbf{s}}_i) = \cos^{-1}\left(\frac{\mathbf{s}_i \cdot \hat{\mathbf{s}}_i'}{||\mathbf{s}_i|| \, ||\hat{\mathbf{s}}_i||}\right). \quad (1)$$

Figure 1(a) illustrates the angular distance. Notably, the angular distance captures the difference in the composition of skill requirements. The second measure is the Euclidean distance, $\psi(\mathbf{s}_i, \hat{\mathbf{s}}_i) = \sqrt{\sum_k (s_{i,k} - \hat{s}_{i,k})^2}$, where $s_{i,k}$ and $\hat{s}_{i,k}$ denote worker i's realized and expected occupation's requirement in attribute k, respectively. The Euclidean distance accounts for differences in both the composition and magnitude of skill requirements.[12]

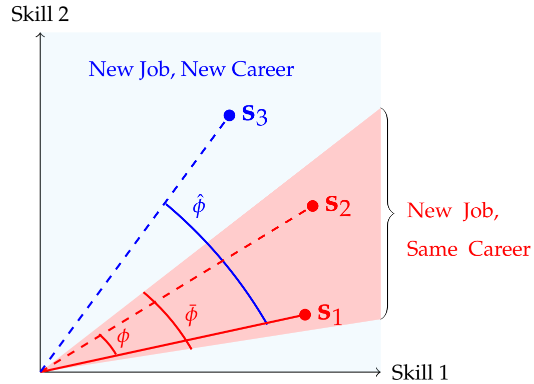
Table 2 reinforces that college workers form more accurate forecasts. From Panel A, college graduates have an average Euclidean distance that is 25% smaller and an angular distance that is 31.6% smaller for their occupation at age 35. Panels B-D show similar differences if we (i) compare all realized occupations between ages 30 and 40 to the ex-

[11] See Appendix A.1.1 for more details on the measurement of skill and task requirements.

[12] Appendix Figure A2 demonstrates how the skill mix in eight occupations relative to Accountants and Auditors translates into angular and Euclidean distances.



(a) Distance Measurements



(b) Career Transitions

Figure 1: Distance and Career Transitions. *Notes*: Panel (a) depicts the angular, ϕ, and Euclidean, ψ, distance in two-dimensional skill space. Panel (b) demonstrates job changes within and across careers.

pected occupation at 35 years old, (ii) examine the forecast error in 5 years, and (iii) use an alternate approach that is based on the respondent's first realized occupation instead of their expected occupation. The third rows within each panel shows that 65-77% of the Euclidean distance is attributable to the composition of skill requirements.[13] 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 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, we do not claim that Table 2 shows that attending college has a causal effect on an individual's knowledge of their best fit in the labor market. Our objective in Section 2 is to present evidence to support the notion that college graduates enter the labor market with less uncertainty about which career is their best fit than those without a college degree. We then take this difference as given in our model, estimate the differences in uncertainty, and quantify the uncertainty channel's contribution to the unemployment-education gap. We analyze sources of the uncertainty channel within Section 5, where we discuss the policy implications of the uncertainty channel.

2.2 Unemployment-Education Gap

Figure 2 shows the unemployment rate by age and education. The solid lines show that the unemployment rate for college graduates is lower than those without a college degree

[13] From the Law of cosines, the fraction of the Euclidean distance that is attributable to differences in the angle, ϕ, is $2\|\mathbf{s}_i\|\|\hat{\mathbf{s}}_i\|(1-\cos(\phi))/\psi^2$. See Appendix A.9.1.

Table 2: Angular and Euclidean Distances by Education

	Non-College	College
Panel A: Occupation at Age 35		
Angular Distance	29.90	20.46
Euclidean Distance	0.77	0.58
% of Euclidean Driven by Angle	74.27	77.00
Observations	1,939	603
Panel B: Occupations Between Ages 30 and 40		
Angular Distance	27.61	19.44
Euclidean Distance	0.73	0.56
% of Euclidean Driven by Angle	69.94	73.31
Observations	2,434	808
Panel C: Expected Occupation in 5 Years		
Angular Distance	25.94	20.28
Euclidean Distance	0.66	0.57
% of Euclidean Driven by Angle	65.32	70.26
Observations	1,440	128
Panel D: First and Mid-life Occupation		
Angular Distance	25.54	18.15
Euclidean Distance	0.57	0.47
% of Euclidean Driven by Angle	73.56	75.12
Observations	2,709	868

Notes: Angular distance is measured in degrees. Panel A compares an individual's expected occupation at age 35 with their realized occupations at age 35. Panel B compares the expected occupation at age 35 to the average of skill requirements across all realized occupations between ages 30 and 40. Panel C compares an individual's expected occupation in 5 years with the realized occupation 5 years after their initial interview. Panel D compares an individual's first occupation to the average skill requirements across all realized occupations between ages 30 and 40. A paired sample t-test indicates that the forecast error of non-college workers is statistically larger than that of college workers, with the null hypothesis (H_0 : $diff < 0$) being rejected at the 1% significance level. The third row within each panel is the proportion of the Euclidean distance attributable to the angular distance. Data are from the NLSY79.

and that the unemployment-education gap narrows over the life cycle.[14] Next, Figure 3 presents the job finding and separation probabilities by age and educational attainment.[15] There are several takeaways. First, separations decline with age for each education group. Second, college workers consistently exhibit a lower separation probability. Third, the

[14] Appendix A.10 shows that individuals with an associate's degree and college dropouts fall in-between those with no college experience and graduates with a BA or above in our main outcomes of interest. Further, Appendix A.4.4 shows a similar pattern for the non-employment rate by adding workers who are outside the labor force and discouraged to the pool of unemployed workers.

[15] 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.

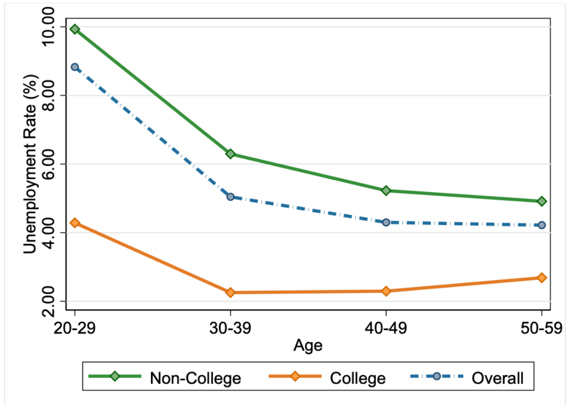


Figure 2: Unemployment-Education Gap over the Life Cycle. *Note*: Unemployment life cycle profiles are computed using CPS data between 1976 and 2019.

gap in separation probabilities also narrows over the life cycle.[16]

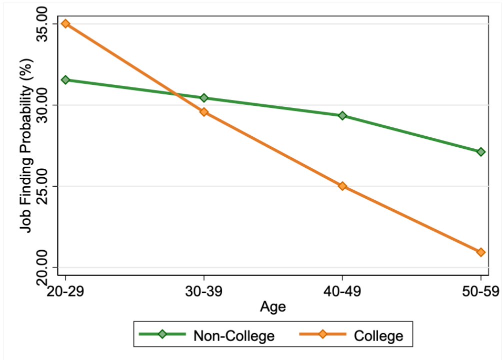
Figure 3 suggests that the unemployment-education gap is primarily driven by differences in separations, as the job finding probability is lower among college graduates throughout most of the life cycle. Applying a decomposition as in Pissarides (2009) shows that differences in separations explain at least 85% of the unemployment-education gap at each age bin.[17] It is for this reason we propose a mechanism that is tightly linked to the separation margin. Intuitively, non-college workers enter a match with greater uncertainty about whether they are well-suited for that career, making them more 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 non-college and college workers who were employed in their anticipated occupation at age 35 have average separation probabilities that are 31% and 32% lower, respectively, than those who were not.[18]

It is important to reemphasize that the education-gaps in unemployment and separations narrow over the life cycle. Our hypothesis is consistent with this because college workers, having entered the labor market with less uncertainty, begin their careers with lower separations and a lower unemployment rate. Non-college workers enter with more uncertainty and experience more separations. As their career advances, they learn about

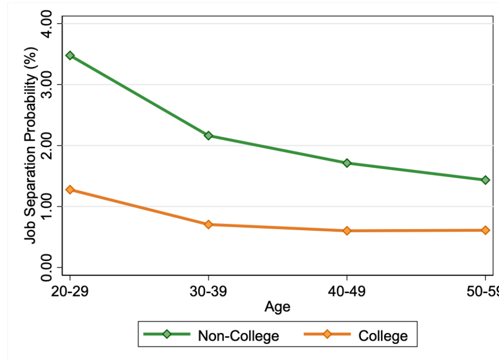
[16] Appendix A.4.1 shows this pattern emerges in both voluntary and involuntary separations. Later, in Section 4.2, we discuss how our model does capture some distinguishing features of voluntary and involuntary separations observed in the data. Moreover, recent work has documented that a small proportion of workers frequently transition between employment and unemployment and can account for a disproportionate amount of aggregate unemployment (Hall and Kudlyak, 2022; Gregory et al., 2025). Appendix A.7 demonstrates that the narrowing unemployment-education gap over the life cycle is not driven by "unemployable" non-college workers who exhibit an abnormally large number of separations.

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

[18] We 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.



(a) Job Finding Probability



(b) Separation Probability

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 as in Shimer (2012).

their best fit, separate less frequently, and the unemployment-education gap narrows. This will be formalized in Section 3 and quantified in Section 4.

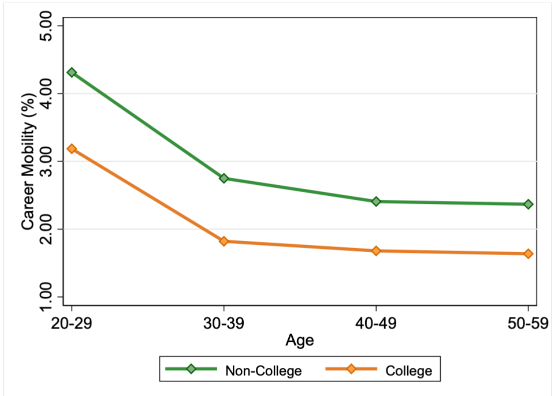
2.3 Supporting Evidence

This section presents additional evidence to support the uncertainty channel.

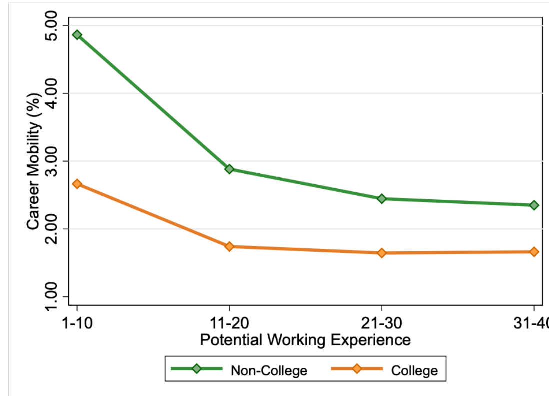
2.3.1 Career Mobility

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

We measure career mobility based on the angular distance in occupation switches, following Baley et al. (2022). Specifically, a career transition is an occupation switch where the angular distance between the current and previous job exceeds a threshold, $\bar{\phi} = 21.5$. The threshold is chosen so that the average correlation in skill requirements is zero in career switches, meaning that the skill composition of a worker's origin and destination occupations are, on average, orthogonal. This provides a natural benchmark for identifying a career switch, as this definition captures when a worker switches between occupations that are in fundamentally different regions of the skill requirement space. 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 moves to a new occupation within the same career. If the worker transitions to occupation 3, it is a career switch as $\hat{\phi} > \bar{\phi}$. Appendix Figure A2 further illustrates this definition by comparing several occupations to



(a) Age



(b) Potential Experience

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. The first year of potential experience for non-college workers is at 18 years old, whereas it is at 22 years old for college graduates.

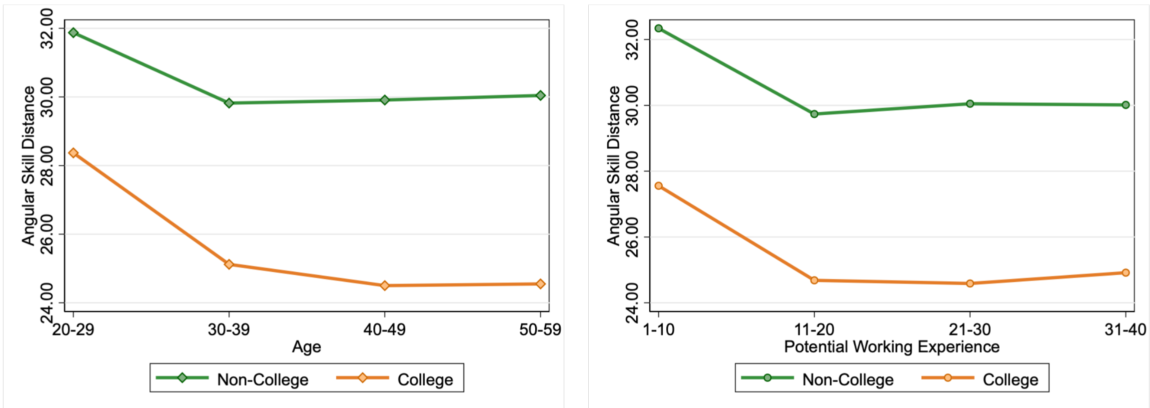
accountants and auditors. While this is our preferred measure of career mobility, as it is based on the worker undergoing a transition that involves a stark difference in the composition of skills required, there are alternative ways to define career mobility. Section 4.4 and Appendix Section C.5.5 discuss robustness to alternative definitions.

Figure 4(a) shows that career mobility is decreasing in age and that non-college workers change careers at a higher rate. Figure 4(b) illustrates that the initial gap in career mobility is larger when we compare by potential experience, and narrows over the life cycle. Following the intuition at the beginning of this section, these patterns are consistent with the uncertainty channel.

2.3.2 Occupational Distance

We examine another implication of our hypothesis: college graduates should transition between similar occupations whereas those without a college degree make larger changes when switching occupations. The intuition is that, 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 similar characteristics to their current job.

To test this, 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 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.



(a) Age (b) Potential Experience

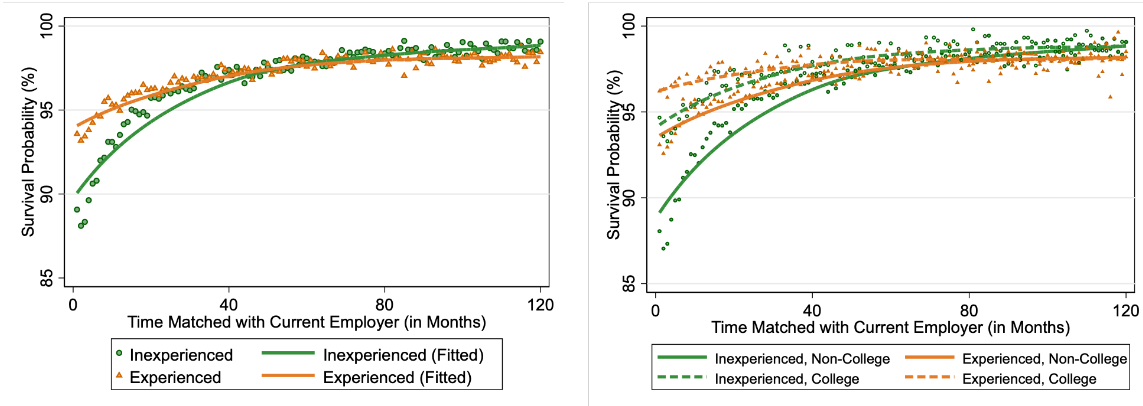
Figure 5: Angular Distance in Occupation Transitions. *Note*: The series are computed using CPS data between 1994-2019 and after applying the Moscarini and Thomsson (2007) correction for measurement error in occupational mobility in the CPS.

2.3.3 Experience and Match Duration

An important feature of our hypothesis is that workers learn their best fit by working, and that they can transfer what they have learned about their best fit between matches. A corollary to this is that the expected duration of a match between a worker and firm is increasing in the worker's prior experience at the time the match is formed. We use the NLSY79 to explore whether the relationship between prior experience and the survival probability of a match is consistent with this intuition.

As a first step, we group workers based on their experience at the beginning of a match. The first group, experienced, are those who enter the match with more than 77 months of work experience, where 77 months is the median months of experience at the formation of new matches in our sample. The second group, inexperienced, are those who begin a match with no more than 77 months of experience. The survival probability is simply the fraction of matches that survive between months t and $t+1$.

Figure 6 presents the match 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 2–4 years of the match. 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 allowing prior experience to be measured in months rather than



(a) All Workers

(b) By Education

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.

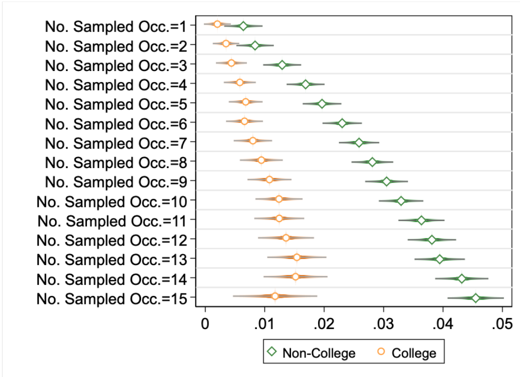
two categories, and controlling for observable characteristics such as age.

An additional aspect of our hypothesis is that workers learn not just from work experience, but particularly from sampling occupations and careers. Therefore, we estimate the relationship between the survival probability 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:

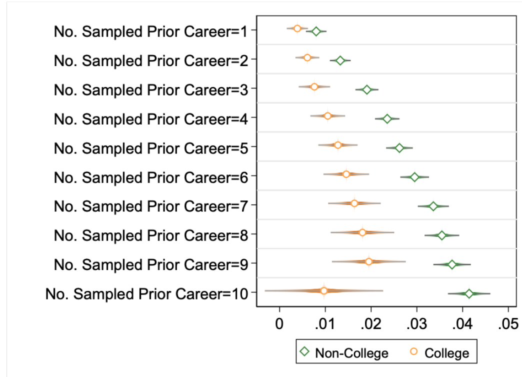
$$y_{it} = \beta_0 + \sum_{j=1}^{J} \beta_j \mathbb{I}\{\text{NumSam} = j\}_{it} + \gamma \text{Tenure}_{it} + \delta \text{Exp}_{it} + \Phi_i + \epsilon_{it}, \tag{2}$$

where y_{it} is equal to one (zero) if individual i is employed in month t and employed in the same occupation/career match in month $t+1$ (unemployed in month $t+1$), $\mathbb{I}\{\text{NumSam} = j\}$ is an indicator for the number of occupations or careers worked in at the time their current occupation/career match was formed, Tenure_{it} is the occupation/career match tenure, Exp_{it} is total work experience, and Φ_i is an individual fixed effect. The coefficients, β_j for $j = 1, 2, \ldots, J$, capture the association between the j^{th} occupation or career sampled and the survival probability, relative to a worker forming their first match, where $J = 15$ when the unit of observation is an occupation and $J = 10$ when it is a career.

Figures 7(a) and 7(b) display the β_j coefficients for occupation and career matches, respectively. The results show that, especially for non-college workers, the survival probability increases with the number of sampled occupations and careers. These findings support our hypothesis that non-college workers learn more about their best fit by sampling occupations and careers than college workers do.



(a) Occupation Matches



(b) Career Matches

Figure 7: Career Sampling and Match Survival. *Notes*: Panels (a) and (b) display β_j coefficients for occupation and career matches, respectively. All figures present point estimates with 99% confidence intervals. Regressions use the NLSY79 sample and full regression output is provided in Appendix A.8.

2.4 Additional Evidence and Robustness

This section lists additional evidence that complements the analysis in Sections 2.1-2.3. First, college graduates exhibit lower rates of occupational mobility (Appendix A.3.2), consistent with the patterns observed in career mobility. Second, college graduates experience lower skill mismatch throughout the life cycle (Appendix A.3.3), as their lower uncertainty leads to better-suited matches. Third, college graduates work in occupations with more dispersed skill requirements (Appendix A.3.4), which is consistent with the notion that workers with less uncertainty about their skills may be more willing to work in jobs with relatively high requirements in a subset of skills. Fourth, college graduates experience fewer employer, occupation, and career switches (Appendix A.3.5). Fifth, the unemployment-education gap is evident across distinct undergraduate majors, which shows that the gap is not overwhelmingly driven by majors associated with providing specific skills and thereby "locking" graduates into a particular field (Appendix A.3.6).

Further, the CPS patterns can be replicated in the NLSY79 (Appendix A.5.1). Finally, 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.5.2 for NLSY79 analyses, respectively.

2.5 Summary and Transition

This section has presented a combination of new and previously documented facts and outlined how each supports the uncertainty channel.[19] As mentioned in Section 1, a leading alternative theory of the unemployment-education gap is that college workers have higher match-specific productivity. These models are consistent with separation rates that (i) are lower among college graduates and (ii) decrease over the life cycle as shown in Figure 3(b). However, these models do not speak to the other patterns shown in this section that are related to occupations and careers. We revisit and elaborate more on the relation between our findings and the match-specific productivity theory in Section 4.5.

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 career fit. Following the evidence on forecast errors in Section 2.1, workers do not know their best fit. Further, and based on the evidence in Section 2.3.3, workers sample careers to learn their suitability in each. A match may be destroyed upon learning the worker is not in their good fit. We embed these ingredients within a competitive search model (Menzio and Shi, 2011), which allows for a rich amount of heterogeneity among workers in a tractable environment.

3 Model

This section develops a life cycle directed search model. Section 3.1 details the environment. Section 3.2 characterizes the equilibrium. Section 3.3 provides an overview of how a worker's career develops and how differences in career uncertainty contribute to the unemployment-education gap.

3.1 Environment

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

Workers are heterogeneous in several dimensions. The first is age: $a \in \{y, o\}$ for young and old, respectively. Second is educational attainment: $e \in \{0, 1\}$ where workers with

[19] To the best of our knowledge, the new facts reported in Section 2 are occupational forecast errors (Table 1), life cycle patterns in unemployment and flows by education (Figures 2 and 3), distance in occupational switches (Figure 5), and the relationship between separations and prior experience by education (Figures 6(b) and 7).

$e = 0$ have less than a college education and those with $e = 1$ are college graduates. Education is fixed and observable. Third, each worker is best suited for one career, c^*, which we refer to as their good fit. For workers with education e, $c^* \in \mathbb{C}_e$ where $\mathbb{C}_e \subset \mathbb{Z}_+$ and $3 \leq N_e \equiv |\mathbb{C}_e|$. In words, there are N_e careers that are potentially a good fit for workers with education e. One of these careers is the worker's good fit while the remaining $N_e - 1$ careers are bad fits. Fourth is a worker's history, i, which denotes the number of careers the worker has learned are a bad fit. As each worker is a bad fit in $N_e - 1$ careers, their history can take values $i \in \{0, 1, \ldots, N_e - 1\}$.

Upon entering the labor market, each worker is endowed with a good fit, c^*. The good fit is initially unobserved and the worker's initial beliefs are uniform over $\mathbb{C}_e$, i.e., $\Pr(c = c^*) = 1/N_e$ for all $c \in \mathbb{C}_e$. The worker's status in a career is denoted by $s \in \{un, b, g\}$ where $s = un$ indicates that the worker is unsure/has not learned their fit in the career, $s = b$ signifies that the worker knows the career is a bad fit, and $s = g$ establishes that the career is the worker's good fit. There is no private information: a worker's status in each career is observable.

The labor market is segmented into submarkets indexed by $\omega = (a, e, s, i, x)$. In submarket ω, firms search for workers with age a, education e, status s, history i, and offer contracts that deliver lifetime discounted utility x to the worker.

Each time period is divided into five stages: learning, separation, search, production, and demographics. We proceed by detailing each stage.

Employed workers with education e, history i, and an unknown fit ($s = un$) enter stage 1 believing that they are in their good fit with probability $p_e(i)$ where

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

Workers with an unknown fit learn their fit in stage 1 with probability $\phi_e \in [0, 1]$.[20] If the worker learns that they are in a good fit, their status changes from un to g. If the worker learns that their current career is a bad fit, their status becomes $s = b$ and they rule out $1 + \eta$ careers in total. Here, $\eta \in \{0, 1, \ldots, \bar{\eta}_e\}$ is a random variable drawn immediately after learning that their current career is a bad fit. The history-dependent probability mass function of η is denoted $\pi_e(i, \eta)$ where $\sum_{\eta=0}^{\bar{\eta}_e} \pi_e(i, \eta) = 1$ for all i. The realization of η captures learning spillovers: in addition to the current career, the worker can perfectly identify η additional careers as bad fits.

[20] We interpret the learning probability as a reduced form representation of a signal extraction problem where, with probability ϕ_e, the observed match output is perfectly informative of the worker's career fit and with a complementary probability is completely uninformative. See, for example, Pries and Rogerson (2022) for a similar approach.

Upon drawing η, the worker's history updates from i to $i' = \min\{i + 1 + \eta, N_e - 1\}$.[21] Further, the worker updates their beliefs over the $N_e - i'$ remaining careers they do not know their fit in according to Bayes' rule. In particular, the worker believes that the next career they sample will be their good fit with probability $p_e(i')$.

In stage 2, a match with a type (e, i) worker and status s is destroyed with probability $\delta \in [\delta_e(s), 1]$ where $\delta_e(un, i) = p_e(i)\delta_e(g) + (1 - p_e(i))\delta_e(b)$ and $\delta_e(g) < \delta_e(b)$.[22] The lower bound, $\delta_e(s)$, represents exogenous separations. The decision to destroy a match is determined by the employment contract. A worker who transitions from employment to unemployment must wait one period before looking for another job.

After learning that the worker is in a bad fit and the worker updates their history to i', the worker and firm may initiate a separation. After initiating a separation, the match is destroyed and the worker becomes unemployed with probability $1 - \gamma_e$. With complementary probability γ_e, after initiating a separation, the worker and firm maintain their match where the worker has an updated history, i', and status that is a function of i'.[23] If $i' = N_e - 1$, then the worker has learned the $N_e - 1$ careers they are a bad fit in and therefore identified the one career that is their good fit. Thus, if $i' = N_e - 1$, the worker's updated status is $s = g$. If $i' < N_e - 1$, then the new status is unsure ($s = un$).

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.[24] Workers choose which submarket to search in. The decision to leave a career is irreversible. There is no search on the job.

Let $v(\omega)$ and $u(\omega)$ denote the measure of vacancies and unemployed workers, respectively, searching in submarket ω. The number of hires is given by the CRS matching func-

---

[21] In the quantitative analysis, we parameterize the upper bound of the spillovers, $\bar{\eta}_e$, and the probability mass function, $\pi_e(i, \eta)$, to ensure that a worker cannot draw a higher amount of spillovers than remaining bad fits. For example, suppose that after learning they are in a bad fit, a worker has four careers left that they are unsure about. One of these careers is their good fit while three are bad fits. We parameterize $\pi_e(i, \eta)$ to ensure that the maximum spillover draw, given their history, is $\bar{\eta}_e = 3$.

[22] We find that much of the heterogeneity in occupation-specific returns among the most commonly sampled occupations, as measured by wages and separation risk, emerges at the level of educational attainment. In Appendix A.12, we show that non-college workers tend to sample occupations with lower wages and higher separation risk. College workers sample occupations with higher wages and a lower separation risk. Therefore, we account for occupation-specific returns by indexing the separation probabilities and match output by educational attainment.

[23] This assumption captures, in a simple manner, that many career changes occur without an intervening spell of non-employment, which has been discussed in closely related contexts by Mercan (2017), Pries and Rogerson (2022), and Baksy et al. (2026). In our NLSY79 sample, approximately 50% of career switches following a voluntary separation among non-college workers occur without an intervening spell of non-employment, compared to 60% among college workers. See Appendix A.11 for details on the measurement of voluntary separations and the associated fraction of career switches with and without an intervening spell of non-employment in the NLSY79.

[24] We allow for heterogeneity in the vacancy posting costs to ensure that the model generates a life cycle job finding profile that is decreasing in potential experience.

tion $F(u(\omega), v(\omega))$. Define $\theta(\omega) = v(\omega)/u(\omega)$ as tightness in submarket ω. A worker finds a job with probability $f(\theta(\omega)) = F/u(\omega)$ where $f\colon \mathbb{R}_+ \to [0,1]$ is twice continuously differentiable, strictly increasing, and strictly concave. Firms fill their vacancy with probability $q(\theta(\omega)) = F/v(\omega)$ where $q\colon \mathbb{R}_+ \to [0,1]$ is twice continuously differentiable, strictly decreasing, and strictly convex.

In the production stage, stage 4, unemployed workers produce z units of output. Employed workers in their good fit produce y_e units of output, while those in a bad fit produce $y_e - \alpha$ where $\alpha > 0$ and $y_e - \alpha > z$ for $e \in \{0,1\}$. The output in unsure matches is $y_e(un, i) = p_e(i)y_e + (1 - p_e(i))(y_e - \alpha)$.

At the beginning of stage 5, young agents become old with probability λ_o and old agents die with probability λ_d. To maintain a constant population, a measure $\lambda_{\text{new}} = \frac{\lambda_o \lambda_d}{\lambda_o + \lambda_d}$ of workers enter the economy as young and unemployed. A fraction μ_e of entrants are endowed with education e where $\mu_0 + \mu_1 = 1$.

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

This section presents the recursive formulation that defines the value of unemployment and of a match, characterizes the entry of firms, and defines a stationary recursive equilibrium. All value functions are measured from the beginning of the production stage.

Let $U_{a,e}(s,i)$ denote the value of unemployment for a worker with age a, education e, status s in their current career, and history i. Consider an old worker 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 search stage, the worker chooses the optimal submarket ω and finds 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. It follows that $U_{o,e}(s,i)$ satisfies

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

where

$$Q_{a,e}(s,i) = \max\{\underbrace{U_{a,e}(s,i) + R(x, U_{a,e}(s,i))}_{\text{Do not switch careers}}, \underbrace{\overline{U}_{a,e}(i) + R(x, \overline{U}_{a,e}(i))}_{\text{Switch careers}}\}, \tag{5}$$

$$R(x,U) = \max_{(\theta,x)} f(\theta)(x-U), \tag{6}$$

and

$$\overline{U}_{a,e}(i) = \begin{cases} U_{a,e}(un,i) & \text{if } \ i < N_e - 1, \\ U_{a,e}(g,i) & \text{if } \ i = N_e - 1. \end{cases} \tag{7}$$

We can understand the worker's submarket choice as happening in two steps. First, from (6), the worker chooses (θ, x) to maximize the expected gain of finding a job in their current career, $R(x, U_{a,e}(s,i))$, and switching careers, $R(x, \overline{U}_{a,e}(i))$. Second, from (5), the worker decides whether to switch careers or not. If they switch, the worker enters their new career with a fit that is determined by their history. From (7), the worker enters the new career with an unsure fit ($s = un$) if $i < N_e - 1$ and a good fit ($s = g$) if $i = N_e - 1$.

Now consider a young unemployed worker. The difference relative to old workers is that the young worker transitions from young to old between periods with probability λ_o. Therefore, $U_{y,e}(s,i)$ satisfies

$$U_{y,e}(s,i) = z + \beta\big\{\lambda_o Q_{o,e}(s,i) + (1-\lambda_o) Q_{y,e}(s,i)\big\}. \tag{8}$$

We now proceed to the value of a match, 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. The value of a match between a firm and worker with characteristics (a,e,s,i) is denoted by $V_{a,e}(s,i)$.

Consider an old worker who is employed in a bad fit. The match output is $y_e - \alpha$. The job is destroyed with probability $\delta_e(b)$ in the subsequent separation stage, in which case the worker receives the value of unemployment, $U_{o,e}(b,i)$, and the firm earns the value of a vacancy, which is zero through free entry.[25] If the match is not destroyed, the continuation value is given by $V_{o,e}(b,i)$. It follows that $V_{o,e}(b,i)$ satisfies

$$V_{o,e}(b,i) = y_e - \alpha + \beta(1-\lambda_d)\big\{\delta_e(b) U_{o,e}(b,i) + (1-\delta_e(b)) V_{o,e}(b,i)\big\}. \tag{9}$$

Now consider an old worker with education e and history i who is employed in their good fit. The match produces y_e units of output and is destroyed in the separation stage with probability $\delta_e(g)$. It follows that $V_{o,e}(g,i)$ satisfies

$$V_{o,e}(g,i) = y_e + \beta(1-\lambda_d)\{\delta_e(g) U_{o,e}(g,i) + (1-\delta_e(g)) V_{o,e}(g,i)\}. \tag{10}$$

[25]Bad 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.

As for old workers with education e and history i who are employed in an unknown fit, the match produces $p_e(i)y_e + (1 - p_e(i))(y_e - \alpha)$ units of output. The worker learns their fit in the subsequent learning stage with probability ϕ_e. Conditional on learning, they are in their good fit with probability $p_e(i)$. With probability $1 - p_e(i)$, the worker learns they are in a bad fit and draws the number of additional careers ruled out, η. The worker and firm then enter the separation stage and choose whether to initiate a separation or not. If they initiate a separation, with probability γ_e, the worker directly transitions to employment in a new career and updated history i' with the same firm. With probability $1 - \gamma_e$ the worker becomes unemployed. If the worker and firm do not initiate a separation, the match is destroyed in the separation stage with probability $\delta_e(b)$. Finally, with probability $1 - \phi_e$, the worker does not learn their fit. In this case, the worker maintains the status $s = un$, does not update their history i, and the match is destroyed in the separation stage with probability $\delta_e(un, i)$. The value of the match with an unsure fit, $V_{o,e}(un, i)$, is given by

$$
\begin{aligned}
V_{o,e}(un,i) = {} & p_e(i)y_e + (1-p_e(i))(y_e-\alpha) + \\
& \beta(1-\lambda_d)\Bigg\{\phi_e\Big[p_e(i)\Big(\delta_e(g)U_{o,e}(g,i) + (1-\delta_e(g))V_{o,e}(g,i)\Big) + \\
& (1-p_e(i))\sum_{\eta=0}^{\bar{\eta}_e}\{d^*_{o,e}(i')[\gamma_e\overline{V}_{o,e}(i') + (1-\gamma_e)U_{o,e}(b,i')] + \\
& (1-d^*_{o,e}(i'))[\delta_e(b)U_{o,e}(b,i') + (1-\delta_e(b))V_{o,e}(b,i')]\}\pi_e(i,\eta)\Big] + \\
& (1-\phi_e)\Big[\delta_e(un,i)U_{o,e}(un,i) + (1-\delta_e(un,i))V_{o,e}(un,i)\Big]\Bigg\},
\end{aligned}
\tag{11}
$$

where $i' = \min\{i+1+\eta, N_e - 1\}$, $\overline{V}_{a,e}(i')$ is

$$
\overline{V}_{a,e}(i') = \begin{cases} V_{a,e}(un,i') & \text{if } i' < N_e - 1, \\ V_{a,e}(g,i') & \text{if } i' = N_e - 1, \end{cases} \tag{12}
$$

and $d^*_{a,e}(i')$ is defined by

$$
d^*_{a,e}(i') = \begin{cases} 1 & \text{if } S_{a,e}(i') > K_{a,e}(i'), \\ 0 & \text{if } S_{a,e}(i') \leq K_{a,e}(i'), \end{cases} \tag{13}
$$

where

$$S_{a,e}(i') \equiv \gamma_e \overline{V}_{a,e}(i') + (1-\gamma_e) U_{a,e}(b,i'), \tag{14}$$

$$K_{a,e}(i') \equiv \delta_e(b) U_{a,e}(b,i') + (1-\delta_e(b)) V_{a,e}(b,i'). \tag{15}$$

From (13), the worker and firm initiate a separation if the expected benefit of the worker switching careers within the firm is greater than the expected value of entering the separation stage when the worker is in a bad fit.

For young workers, the value of a bad match satisfies

$$\begin{aligned} V_{y,e}(b,i) = y_e - \alpha + \beta\{\lambda_o[\delta_e(b)U_{o,e}(b,i) + (1-\delta_e(b))V_{o,e}(b,i)] \\ +(1-\lambda_o)[\delta_e(b)U_{y,e}(b,i) + (1-\delta_e(b))V_{y,e}(b,i)]\}, \end{aligned} \tag{16}$$

and the value of a good match with a young worker is

$$\begin{aligned} V_{y,e}(g,i) = y_e + \beta\{\lambda_o[\delta_e(g)U_{o,e}(g,i) + (1-\delta_e(g))V_{o,e}(g,i)] \\ +(1-\lambda_o)[\delta_e(g)U_{y,e}(g,i) + (1-\delta_e(g))V_{y,e}(g,i)]\}. \end{aligned} \tag{17}$$

Last, we have the value of a match between a firm and young worker with an unsure fit:

$$\begin{aligned} V_{y,e}(un,i) = p_e(i)y_e + (1-p_e(i))(y_e-\alpha) + \\ \beta \sum_{a\in\{y,o\}} \chi_a \Bigg\{ \phi_e \Big[p_e(i) \Big(\delta_e(g)U_{a,e}(g,i) + (1-\delta_e(g))V_{a,e}(g,i) \Big) + \\ (1-p_e(i)) \sum_{\eta=0}^{\bar{\eta}_e} \{ d^*_{a,e}(i')[\gamma_e \overline{V}_{a,e}(i') + (1-\gamma_e)U_{a,e}(b,i')] + \\ (1-d^*_{a,e}(i'))[\delta_e(b)U_{a,e}(b,i') + (1-\delta_e(b))V_{a,e}(b,i')]\} \pi_e(i,\eta) \Big] + \\ (1-\phi_e)\Big[\delta_e(un,i)U_{a,e}(un,i) + (1-\delta_e(un,i))V_{a,e}(un,i)\Big] \Bigg\}, \end{aligned} \tag{18}$$

where $\chi_a = 1 - \lambda_o$ if $a = y$ and $\chi_a = \lambda_o$ if $a = o$. Equations (16)-(18) have a similar interpretation as equations (9)-(11) except that young workers transition from young to old between periods with probability λ_o.

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

$$\kappa_a \geq q(\theta)[V_{a,e}(s, i) - x], \tag{19}$$

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

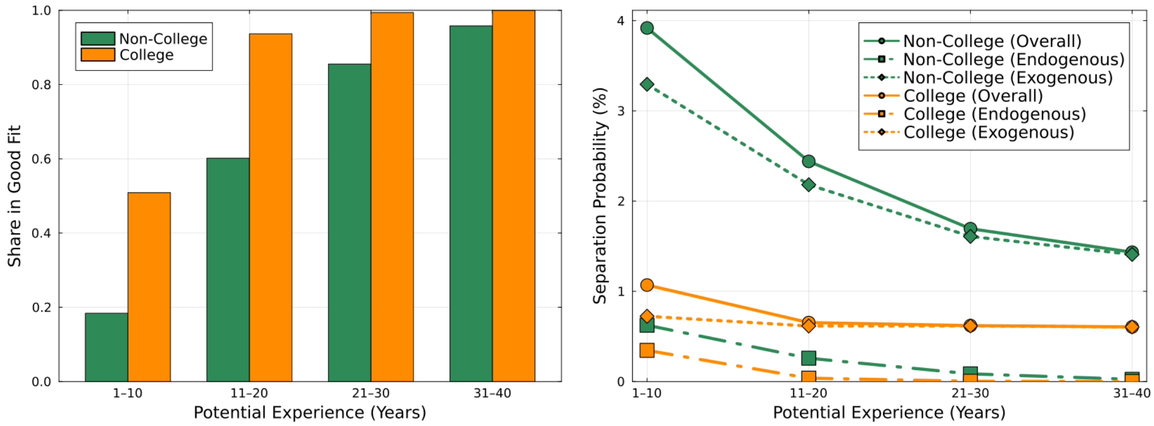
Definition 1. A stationary recursive equilibrium consists of value and policy functions for unemployed workers, $U_{a,e}(s, i)$ and $\omega^*_{a,e}(s, i)$, joint value and policy functions, $V_{a,e}(s, i)$, $d^*_{a,e}(i)$, a tightness function $\theta(\omega)$, and a distribution of workers that satisfies the following conditions. First, the value and policy functions of unemployed workers satisfy equations (4)-(8). Second, the value of a match and its associated policy function satisfy equations (9)-(18). Third, $\theta(\omega)$ satisfies (19). 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 bilaterally efficient contracts, a recursive equilibrium exists and is block-recursive. 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.

3.3 How the Model Works

This section details the stages of a worker's career and how differences in career uncertainty contribute to the unemployment-education gap. Let us think of a worker's career as having two stages: early and late. The distinction between these stages is the number of bad fits the worker has learned, i. Early in a worker's career, they have a low i. This has two implications for separations. First, while workers are in an unsure career fit, the exogenous separation probability, $\delta_e(un, i) = p_e(i)\delta_e(g) + (1 - p_e(i))\delta_e(b)$, is weighted more towards $\delta_e(b)$. This means that young workers are hit by exogenous separation shocks at a high rate. Second, conditional on learning, the worker is more likely to be in a bad fit and destroy their match in favor of sampling a new career. These two factors lead to separations occuring more frequently among young workers.

Separations decrease over the life cycle for two reasons. First, for those who are still in the learning phase, they have a higher history i. Therefore, the separation probability



(a) Share in Good Fit (b) Separation Profiles

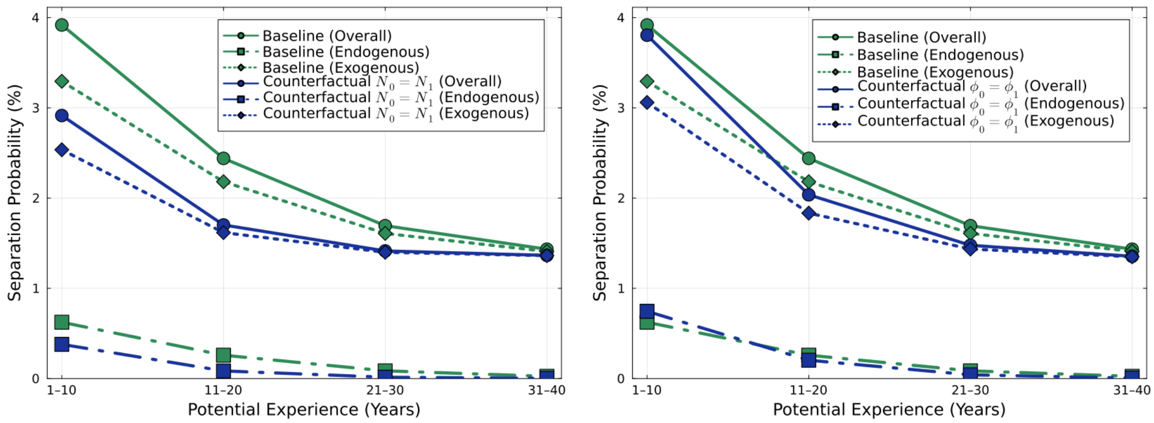
Figure 8: Life Cycle Dynamics. *Notes*: Panel (a) displays the fraction of workers in the simulated economy, by education and potential experience, who have learned their good fit. Panel (b) shows the separation probability by type (overall, exogenous, endogenous), education, and potential experience. Both panels are produced using the parameter values listed in Table 5.

in the learning phase, $\delta_e(un, i)$, is weighted more towards $\delta_e(g)$, the exogenous separation probability of a good fit. Second, older workers are more likely to have found their good fit, where they no longer face any risk of an endogenous separation. Taken together, separations decline over the life cycle because career sampling leads to (i) a lower exogenous separation rate during the learning phase, $\delta_e(un, i)$, and (ii) more workers who have found their good fit. Figure 8(a) shows the fraction of workers who have found their good fit while Figure 8(b) illustrates that each type of separation decreases in potential experience as workers sample more careers and identify their good fit.

Next, we examine how career uncertainty influences the education gap in unemployment. We focus on differences in the number of potential careers, N_e, and learning speed, ϕ_e. Suppose that $N_0 > N_1$ and $\phi_0 < \phi_1$.[26] With more careers to choose from, $N_0 > N_1$, non-college workers in the learning phase are more likely to be in a bad fit than a college worker for the same history. Therefore, the exogenous separation rate for non-college workers is weighted even more towards $\delta_0(b)$ than for college workers. Another implication of $N_0 > N_1$ is that, conditional on learning, non-college workers are more likely to be in a bad fit and undergo an endogenous separation. Figure 9(a) demonstrates the effect of decreasing N_0 to N_1 on the separation profile for non-college workers. We can see that a lower value of N_0 reduces the frequency of both exogenous and endogenous separations at each life cycle stage.

The primary impact of slower learning, $\phi_0 < \phi_1$, is that it slows down the transition

[26] These assumptions are consistent with our quantitative results in Section 4.



(a) $N_0 = N_1$　　(b) $\phi_0 = \phi_1$

Figure 9: Counterfactual Separation Profiles. *Notes*: Panel (a) shows the baseline separation profiles and the separation profiles after setting N_0 to N_1 for non-college workers. Panel (b) compares the baseline separation profiles to those where ϕ_0 is set equal to ϕ_1 for non-college workers. All other parameters take the values presented in Table 5 except the one parameter that is varied within each panel, respectively.

between the early and late career stages described above. With a lower learning speed, non-college workers will have learned their fit in fewer careers than college workers and will be less likely to have found their good fit. Figure 9(b) shows the effect of increasing ϕ_0 to ϕ_1. The initial decline in overall separations is not large, as a higher learning speed increases the rate of endogenous separations. The endogenous separation rate is lower after the first potential experience bin as more workers are in their good fit.

We conclude this section by noting that the status-specific separation risk, $\delta_e(b) > \delta_e(g)$, contributes to the unemployment-education gap. This is the feature of the model that generates variation in the exogenous separation probability during the learning phase, $\delta_e(un, i)$, which as described above contributes to the high separation probability among workers early in their career. We interpret $\delta_e(b) > \delta_e(g)$ 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, $\delta_e(b) > \delta_e(g)$ as workers produce less in a bad fit.

4 Quantitative Analysis

This section presents the calibration strategy, model validation, decomposition of the unemployment-education gap, robustness checks, 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 $F(u,v) = \frac{uv}{(u^\iota + v^\iota)^{1/\iota}}$. The PMF of the learning spillovers, $\pi_e(i,\eta)$, is a Poisson distribution that is truncated according to the number of bad fits the worker has not yet learned. For a worker with education e and history i, they have not learned their fit in $N_e - i$ careers. One of these careers is their good fit and if they learn that they are in a bad fit, the worker will eliminate one career out of the $N_e - i$ remaining careers. Therefore, the support of $\pi_e(i,\eta)$ is $\{0, 1, \ldots, \bar{\eta}_e(i)\}$ where $\bar{\eta}_e(i) = \max\{0, N_e - i - 2\}$ and the PMF is given by:

$$\pi_e(i,\eta) = \frac{e^{-\tilde{\lambda}_e}(\tilde{\lambda}_e)^\eta/\eta!}{\sum_{k=0}^{\bar{\eta}_e(i)} e^{-\tilde{\lambda}_e}(\tilde{\lambda}_e)^k/k!}, \tag{20}$$

for $\eta = 0, 1, \ldots, \bar{\eta}_e(i)$ so that $\sum_{\eta=0}^{\bar{\eta}_e(i)} \pi_e(i,\eta) = 1$.

The model is, in part, calibrated by matching the college wage premium and validated by analyzing wage growth over the life cycle. There are many wage contracts that can deliver the lifetime utility to the worker prescribed by the bilaterally efficient contract (Menzio and Shi, 2010). We assume that wages are determined through Nash bargaining with constant renegotiation. See Appendix B.2 for more details on wages and their computation.

There are 24 parameters: 9 are set externally and 15 are calibrated via simulated method of moments. We proceed by describing how we arrive at the value of each parameter.

4.1.1 Externally Calibrated Parameters

The discount factor is $\beta = (0.97)^{1/12}$, and the probabilities of becoming old and dying are $\lambda_o = \lambda_d = 1/(12 \times 20)$ so workers expect to spend 20 years in each age. The fraction of non-college workers is set equal to the fraction of workers with less than a bachelor's degree in our CPS sample, giving $\mu_0 = 0.731$ and $\mu_1 = 0.269$. The matching parameter is set to $\iota = 0.5$.[27] The probability of switching careers within a match, γ_e, is set equal to the fraction of career switchers following a voluntary separation who change careers without an intervening spell of non-employment. We find $\gamma_0 = 0.500$ and $\gamma_1 = 0.595$ in the NLSY79.[28] The economy is normalized by setting the production of unemployed workers to $z = 1$.

[27] The model produces an average elasticity of job finding probabilities with respect to market tightness of 0.534, which is within an empirically supported range of 0.5 to 0.7 (Petrongolo and Pissarides, 2001).

[28] See Appendix A.11.

4.1.2 Internally Calibrated Parameters

The remaining 15 parameters are calibrated via simulated method of moments to match 19 moments. Appendix C.1 details the calculation of the targets. The first and second are the job finding probabilities for non-college (0.391) and college workers (0.338) in the first ten years of potential experience. Next are the average number of unique careers worked by non-college (3.039) and college workers (2.118) in the first forty years of potential experience. Further, we target the fraction of workers, by education, who sample less than three unique careers in forty years of potential experience. We find that 36.531% of non-college and 69.608% of college workers sample less than three careers. Next are the job finding probabilities for all workers between (i) 1 and 20 years of potential experience (0.312) and (ii) 21 and 40 years of potential experience (0.278). We target the median potential experience (in months) at which workers undergo their first career switch, by education, among those who sampled two unique careers in the NLSY79. For non-college workers, we find this to be 44 months whereas it is 29 months for college workers. The next target is a college wage premium of 27.6% in the NLSY79. The remaining eight moments are the separation probabilities, by education and potential experience.[29]

Next, we provide an intuitive overview of how the model is identified, while Appendix C.3 produces the Jacobian of the model and the responsiveness of the education-specific moments to each education-specific parameter. While each moment is impacted by multiple parameters, the heatmaps in Appendix Figure C3 show that most moments are clearly linked to one parameter.

We view $\delta_e(b)$ as targeting the separation probability in the first two bins of potential experience, as the highest concentration of bad matches is found early in a worker's career. Relatedly, $\delta_e(g)$, has a pronounced effect on the separation probability in the third and fourth potential experience bins as experienced workers are more likely to be in a good fit. Next, κ_y targets the job finding probability of young workers, as it affects firm entry for young workers. The same logic applies to κ_o being used to target the job finding probability of old workers and $\{y_0, y_1\}$ targeting the job finding probability at 1-10 years of potential experience, by education. As non-college workers are more likely to be in a bad fit, α has a more pronounced impact on wages for non-college workers. Therefore, α targets the college wage premium.

As for the uncertainty channel, $\{N_0, N_1\}$ targets the average number of unique careers

[29] A common target is the ratio of z/[average labor productivity]. We opted not to include this as a target, as there is a wide range of targets used in the literature. We find that at the calibrated values reported in Table 5, the model produces z/[average labor productivity] = 0.5311 which is well within the range of typical targets in the literature of 0.4 (Shimer, 2005) and 0.71 (Hall and Milgrom, 2008).

Table 3: Learning Parameters Comparative Statics

Panel A: Identification of N_e					
N_0	6	7	8	9	10
# of careers, non-college	2.538	2.776	3.005	3.232	3.500
N_1	3	4	5	6	7
# of careers, college	1.802	2.083	2.372	2.654	2.939
Panel B: Identification of $\tilde{\lambda}_e$					
$\tilde{\lambda}_0$	0.754	1.130	1.507	1.884	2.261
% with <3 careers, non-college	31.752	33.043	34.314	36.052	38.206
$\tilde{\lambda}_1$	0.642	0.964	1.285	1.601	1.927
% with <3 careers, college	61.018	65.473	69.305	72.466	75.104
Panel C: Identification of ϕ_e					
ϕ_0	0.005	0.010	0.015	0.020	0.025
Pot. exp. at first switch, non-college	125	81	56	42	34
ϕ_1	0.015	0.020	0.025	0.030	0.035
Pot. exp. at first switch, college	47	36	29	25	21

Notes: All panels simulate the model economy for 30,000 workers of each education group over forty years of potential experience. Panel A reports the average number of careers worked by the time workers exit the labor market. Panel B reports the fraction of workers who work in fewer than three careers over their work-life. Panel C reports the median potential experience (in months) at the time of first career switch among workers who sampled exactly two unique careers. In each panel, all parameters except the one varied are held constant at their calibrated values in Table 5.

worked by education. With a larger set of careers, workers expect to sample more careers before finding their good fit. This is demonstrated in Table 3, Panel A. The parameter governing the Poisson distribution, $\tilde{\lambda}_e$, targets the fraction of workers who sample one or two unique careers, as a higher spillover parameter increases the likelihood that workers whose first was a bad fit draw a large value of η and immediately pivot to their good fit as their second career sampled. This is demonstrated in Panel B of Table 3. The learning speeds, $\{\phi_0, \phi_1\}$, are pinned down by matching the median potential experience at which workers undergo their first career switch, as a higher learning speed causes workers to learn and switch careers earlier in their work-life, as demonstrated in Panel C of Table 3.

Denoting $\tilde{m}$ and m as the vectors of 19 model-generated and empirical moments, respectively, the vector of 15 parameters, $\hat{\vartheta}$, is given by

$$\hat{\vartheta} = \arg\min\,(\tilde{m} - m)' W (\tilde{m} - m), \tag{21}$$

Table 4: Model and Data Comparison

Moment	Target	Model
JFP, 1-10, non-college	0.319	0.309
JFP, 1-10, college	0.338	0.370
JFP, 1-20	0.312	0.301
JFP, 21-40	0.278	0.275
SP by pot. exp., non-college ($\times 10^{-2}$)	[4.08, 2.30, 1.78, 1.48]	[3.92, 2.44, 1.69, 1.43]
SP by pot. exp., college ($\times 10^{-2}$)	[1.08, 0.64, 0.59, 0.66]	[1.07, 0.65, 0.62, 0.61]
College wage premium	1.276	1.256
# Careers, non-college	3.039	3.005
# Careers, college	2.118	2.083
% with <3 careers, non-college	36.531	34.314
% with <3 careers, college	69.608	69.305
Pot. exp. at first switch, non-college	44.0	44.0
Pot. exp. at first switch, college	29.0	29.0

Notes: Moments are computed by simulating the model economy. JFP and SP stand for job finding probability and separation probability, respectively, while pot. exp. is short for potential experience. The four potential experience bins are: [1-10, 11-20, 21-30, 31-40]. The college wage premium in the model is the ratio of average wage among college workers to the average wage among non-college workers. See the notes under Table 3 for details on how the median potential experience at the first career switch is computed.

where $W = I/m^2$ and I is the identity matrix. From (21), $\hat{\vartheta}$ minimizes the sum of squared percentage deviations between the model and data. Table 4 shows that the model matches the targeted moments well.

Table 5 displays the parameter values. Non-college workers have a slower learning speed than college workers as $\phi_1 = 0.025$ and $\phi_0 = 0.019$. Next, $N_1 = 4$ and $N_0 = 8$, indicating that non-college workers enter the labor market with twice 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 be interpreted as college workers entering the labor market having narrowed down which careers are potentially their good fit. Finally, $y_1/y_0 = 1.086$, indicating modest differences in productivity in the best fit. However, the gap in average labor productivity by education is 23.01%, as college workers are more likely to be in their good fit.

Table 5: Parameter Values

	Definition	Value		Definition	Value
β	Discount factor	0.997	y_0	Prod. of non-college	1.923
λ_o	Pr. of becoming old	0.004	y_1	Prod. of college	2.089
λ_d	Pr. of death	0.004	$\delta_0(b)$	Bad sep. pr., non-college	0.044
μ_0	Pr. endowed with $e = 0$	0.731	$\delta_1(b)$	Bad sep. pr., college	0.010
μ_1	Pr. endowed with $e = 1$	0.269	$\delta_0(g)$	Good sep. pr., non-college	0.013
z	Utility while unemployed	1.000	$\delta_1(g)$	Good sep. pr., college	0.006
ι	Matching parameter	0.500	ϕ_0	Learning pr., non-college	0.019
γ_0	Within-match switch, non-college	0.500	ϕ_1	Learning pr., college	0.025
γ_1	Within-match switch, college	0.595	N_0	# of careers, non-college	8
κ_y	Vacancy cost, young	0.176	N_1	# of careers, college	4
κ_o	Vacancy cost, old	0.947	$\tilde{\lambda}_0$	Spillovers, non-college	1.507
α	Penalty, bad fit	1.030	$\tilde{\lambda}_1$	Spillovers, college	1.285

Notes: "Pr." is short for probability, "sep." is short for separation, and "prod." is short for productivity. The first nine parameters in the left column are assigned while the remaining fifteen are calibrated.

4.2 Model Validation

Table 6 compares the model and data along some untargeted moments. The first two rows show that the model generates a life cycle unemployment pattern that tracks the data. The third row shows that, just as in the data, most of the unemployment-education gap (U-E gap for brevity, henceforth) in the model is driven by separation probabilities.

As discussed in Section 2.3.3, the relationship between prior experience and expected duration of a match is consistent with the uncertainty channel. The fourth row of Table 6 presents the estimated coefficient from regressing prior experience (in months) on the survival probability of the match in both the NLSY79 and simulated data.[30] The model captures this association well. The fifth row shows that, just as in the data, the association between prior experience and match survival is significantly lower for college workers.

The sixth row shows that the model matches the life cycle wage growth among non-college workers. The seventh row shows that the model does not capture the rapid wage growth exhibited by college workers. While this is a shortcoming of the model, it illuminates that finding one's good fit is a key driver of wage growth for non-college workers and that the learning process in our model, despite its simplicity, captures this well. For college workers, wage growth may be more nuanced. As the life cycle separation profile for college workers indicates, they find their good fit very early in their career. The life cycle wage profile shows that college workers continue to experience rapid wage growth

[30]The regression specification is detailed in Appendix A.6.

Table 6: Model Validation

Untargeted Moments	Data	Model
Urate by pot. exp., non-college (%)	[11.7, 6.7, 5.4, 5.0]	[11.0, 8.2, 5.9, 5.0]
Urate by pot. exp., college (%)	[3.5, 2.2, 2.4, 2.9]	[2.8, 2.0, 2.0, 2.0]
Frac. of U-E gap explained by SP	1.190	0.800
β(PriorExp)	7×10^{-5}	7×10^{-5}
β(PriorExp $\times$ College)	-4×10^{-5}	-5×10^{-5}
Wage growth by pot. exp., non-college	[1.0, 1.3, 1.5, 1.6]	[1.0, 1.3, 1.5, 1.6]
Wage growth by pot. exp., college	[1.0, 1.6, 1.9, 1.9]	[1.0, 1.2, 1.2, 1.2]

Notes: "Urate" refers to the unemployment rate, "frac." is fraction, "SP" is separation probability, and pot. exp. is short for potential experience. The four potential experience bins are: [1-10, 11-20, 21-30, 31-40]. Rows four and five contain regression coefficients from estimating the regression detailed in Appendix A.6 on both the NLSY79 sample and simulated data. Rows six and seven show the average wages by potential experience, relative to the average wage in the first potential experience bin.

beyond that stage of their career, indicating that there are factors outside our model that drive wage growth for college workers.[31]

We conclude this section by discussing involuntary and voluntary separations. While the difference between these types of separations can be difficult to interpret, let us label an exogenous separation as involuntary and an endogenous separation as voluntary. In our calibration, the involuntary separation probability for non-college workers is 2.28 and 0.65 for college workers. The voluntary separation probability for non-college workers is 0.30 for non-college workers and 0.13 for college workers. While these do not exactly match the empirical rates shown in Appendix A.4.1, they are consistent in three ways. First, the separation probabilities for non-college are higher than college for both types of separations. Second, the education gap in separation probabilities is higher for involuntary than voluntary separations. Third, the model captures that involuntary separations occur at a higher rate than voluntary separations. The model's involuntary separation rate is 7.6 times higher than the voluntary separation rate for non-college workers and 5 times higher for college workers, whereas this ratio falls between 3 and 6 at different stages of the life cycle for each education group in the data.

4.3 Decompositions

Table 7 presents the average unemployment rate, wages, and lifetime earnings by education. The first two rows show that there is a nearly 6 percentage point difference in the

[31] If college workers are more likely to be in their good fit, they and/or their firm may invest more in training, generating more human capital accumulation and wage growth.

Table 7: Education Gaps in Unemployment, Wages, and Earnings

	Non-college	College	College - Non-college	%Δ
Unemployment rate	8.114	2.223	-5.891	-72.603
Wage	1.541	1.936	0.395	25.633
Lifetime earnings	494.008	660.964	166.956	33.796

Notes: Lifetime earnings are the cumulative wages earned. The unemployment rate is in percentage points. The first two columns are the average outcome across all workers within an education group in the simulated economy. The third column is the difference, in levels, between college and non-college while the last column is the percentage difference between college and non-college.

unemployment rates and a 25.63% gap in average wages. Given that non-college workers are unemployed more frequently and earn lower wages, there is an even larger gap in lifetime earnings between the two groups of nearly 34%.

There are seven parameters that are indexed by education and contribute to the gaps shown in Table 7. We group the parameters together as follows: $\{N_e, \phi_e, \tilde{\lambda}_e\}$ govern the uncertainty channel, $\{\delta_e(b), \delta_e(g)\}$ capture the differences in underlying separation risk between non-college and college occupations, and $\{y_e, \gamma_e\}$ are grouped together as "other". As discussed in Section 3.3, an additional contributing factor is $\delta_e(b) > \delta_e(g)$.

To begin, we shut down all channels except the uncertainty channel. Specifically, we first set the values of $\{\delta_0(b), \delta_0(g), \gamma_0, y_0\}$ equal to the college values $\{\delta_1(b), \delta_1(g), \gamma_1, y_1\}$ shown in Table 5. Next, we eliminate the role of status-specific separations by setting $\delta_1(b)$ equal to $\delta_1(g)$. At this point, the only differences between the two groups of workers are the uncertainty channel parameters. We then compare the remaining gaps in the unemployment rate, wages, and lifetime earnings to the baseline gaps in Table 7. Panel A of Table 8 presents the results. The first column shows that that 6.53% of the U-E gap remains when the uncertainty channel is the only difference between the two groups. Further, 47.59% and 39.35% of the gaps in wages and lifetime earnings, respectively, remain. The subsequent columns perform the same decomposition within each potential experience bin and show that the uncertainty channel makes a larger contribution to the education gaps earlier in the life cycle. Panel B performs a similar decomposirion, but instead begins by setting $\{\delta_1(b), \delta_1(g), \gamma_1, y_1\}$ equal to $\{\delta_0(b), \delta_0(g), \gamma_0, y_0\}$ and then setting $\delta_0(b)$ equal to $\delta_0(g)$. That is, in Panel B, the non-college parameters are used as the baseline. From Panel B, the uncertainty channel explains a slightly higher share of the education gaps when the reference group is non-college.

Table 8 indicates that between 6.53-9.97% of the overall U-E gap is attributable to the uncertainty channel. As this decomposition first eliminated all other differences by edu-

Table 8: Decomposition I

	Overall	Pot. exp. 1	Pot. exp. 2	Pot. exp. 3	Pot. exp. 4
Panel A: College baseline					
Unemployment rate	6.533	6.584	8.874	4.903	0.988
Wage	47.599	60.530	50.165	24.732	7.694
Lifetime earnings	39.355	–	–	–	–
Panel B: Non-college baseline					
Unemployment rate	9.971	10.317	13.146	7.822	0.759
Wage	48.703	60.222	52.045	27.585	9.202
Lifetime earnings	41.048	–	–	–	–

Notes: Each cell presents the fraction of the original education gap that remains after eliminating all channels that contribute to the education gaps except the uncertainty channel. The first column is the fraction of the overall gap attributable to the uncertainty channel, whereas the last four columns present the fraction of the gap within a specific bin of potential experience. Pot. exp. x is short for potential experience bin x where $x \in \{1, 2, 3, 4\}$. Panel A contains the decomposition results when non-college parameters are set equal to their college counterparts. Panel B presents the decomposition when the value of college parameters is set equal to the non-college values.

cation, it addresses how much of the U-E gap can be explained by the uncertainty channel *if there were no other differences* between the two education groups. Moreover, it captures how much of the unemployment-education gap is driven by (i) matches with non-college workers are more likely to be destroyed upon learning, and (ii) the response of firm entry to the lower expected output with non-college workers during the learning phase.

The decomposition shown in Table 8 does not capture interactions between the channels that contribute to the education gaps. For example, $N_0 > N_1$ interacts with the status-specific separations, $\delta_e(b) > \delta_e(g)$, as non-college workers are more likely to be in a bad fit and are hit by exogenous separation shocks at a higher rate. Relatedly, because there are interactions between the channels, the order in which they are shut down leads to different contributions from each channel. For example, if instead we first shut down the uncertainty channel by setting $\{N_0, \phi_0, \tilde{\lambda}_0\}$ equal to $\{N_1, \phi_1, \tilde{\lambda}_1\}$ while all other parameters take the calibrated values shown in Figure 5, 43.9% of the U-E gap is eliminated. To address these shortcomings, we carry out a Shapley-Owen-Shorrocks decomposition.

The Shapley-Owen-Shorrocks decomposition computes the contribution of each parameter to an education gap by first evaluating the marginal contribution of that parameter to the gap for a particular order in which the factors that contribute to the gap are eliminated. For example, in the previous decomposition we first eliminated differences in $\{\delta_e(b), \delta_e(g), \gamma_e, y_e\}$, leaving $\{N_e, \phi_e, \tilde{\lambda}_e\}$ as the last factors that differed by education.

Table 9: Shapley-Owen-Shorrocks Decomposition

	Unemployment	Wage	Lifetime earnings
Panel A: Uncertainty			
N_e	21.677	37.459	33.366
ϕ_e	7.229	15.065	13.826
$\tilde{\lambda}_e$	-1.613	-2.252	-1.973
Within-panel total	27.293	50.272	45.219
Panel B: Occupation-specific separations			
$\delta_e(b)$	35.496	3.596	10.361
$\delta_e(g)$	30.192	4.335	10.004
Within-panel total	65.688	7.931	20.365
Panel C: Other			
γ_e	2.090	0.257	0.609
y_e	4.923	41.540	33.808
Within-panel total	7.013	41.797	34.417
Total	99.994	100.000	100.001

Notes: Each cell represents the percentage of the education gaps in unemployment, wages, and lifetime earnings that is attributable to a specific parameter. The contribution of each parameter is given by equation (C.2) in Appendix C.4. The rows labelled "Within-panel total" show the sum of the contributions of the individual parameters within the panel. Not all entries in the last row are equal to 100 due to rounding.

In a second step, the average marginal contribution across all sequences of elimination is computed, where each marginal contribution is weighted according to the probability of randomly selecting that sequence of elimination. Shorrocks (2013) shows that this delivers a decomposition where the contribution of each parameter is invariant to the order in which factors are eliminated. Further, because the decomposition considers all orders in which differences by education can be removed, it captures the interactions between the parameters. Table 9 presents the results for the education gaps over the entire life cycle, while Appendix C.4 describes the decomposition in greater detail and shows the decomposition results by potential experience.

From the first column of Table 9, the uncertainty channel explains 27.29% of the U-E gap.[32] Panels B and C show that most of the remainder of the U-E gap is attributable

[32] The contributions of $\tilde{\lambda}$ to the education gaps are negative as $\tilde{\lambda}_0 > \tilde{\lambda}_1$, implying that non-college workers rule out more careers in absolute terms through a spillover draw on average. However, this comparison does not account for the differences in the size of the career sets. As $N_1 < N_0$, each spillover draw eliminates a larger fraction of the remaining unknown careers for college workers than for non-college workers. See Appendix Figure C2, which plots both the expected number of careers ruled out through a spillover draw and the fraction of the career set eliminated through spillovers for both education groups.

to the status-specific separation probabilities, $\delta_e(b)$ and $\delta_e(g)$. The second column shows that nearly half of the gap in wages is attributable to the uncertainty channel, as non-college workers are more likely to be in a bad fit. From Panel C, most of the remainder of the gap in wages is explained by differences in y_e. The last column shows that each set of parameters makes substantive contributions to the gap in lifetime earnings.

While the decomposition in Table 8 measured how much of the U-E gap is driven by differences in uncertainty if there were no other differences by education, the Shapley-Owen-Shorrocks decomposition measures the uncertainty channel's contribution to the U-E gap *given that there are other differences by education*. As such, this exercise reveals that the uncertainty channel makes a larger contribution to the U-E gap when non-college workers also work in occupations with a higher underlying separation rate, are less likely to switch careers within a match, and produce less output at their best fit.

Taken together, the decompositions in this section reveal that, at a minimum, the uncertainty channel explains between 6.53-9.97% of the U-E gap. Further, there is a strong interaction between the uncertainty channel and other non-college primitives, and once these interactions are considered, the uncertainty channel explains 27.29% of the U-E gap. The juxtaposition of the two decompositions shows that the effect of reducing career uncertainty among non-college workers, through lowering N_0 or increasing ϕ_0, on the U-E gap will depend on whether non-college workers also exhibit a change in the other education-specific parameters. For example, the effect of reducing career uncertainty depends heavily on whether non-college workers are employed in occupations with an underlying separation risk of $\{\delta_0(b), \delta_0(g)\}$ or $\{\delta_1(b), \delta_1(g)\}$.

4.4 Robustness Checks

This section discusses the robustness of the decomposition of the U-E gap into the underlying channels. To do so, we conduct two alternative calibrations and repeat the decomposition exercises within each. In the first, we set $\gamma_e = 0$ for both education groups, so that workers must switch careers through unemployment, and re-calibrate the model to the same set of moments in Table 4. We find that the learning speed and career set sizes are largely unchanged relative to the baseline values shown in Table 5. Further, the uncertainty channel explains, at a minimum, between 16.92 and 20.21% of the U-E gap. In the Shapley-Owen-Shorrocks decomposition, the uncertainty channel explains 28.14% of the U-E gap, which is similar to our baseline result of 27.29%. Therefore, allowing workers to switch careers within a match, which is a proxy for job-to-job transitions, reduces the share of the U-E gap that is accounted for by the higher endogenous separation risk among non-college workers but does not impact the overall share of the U-E gap that is accounted for by the uncertainty channel. Appendix C.5.1 presents the detailed calibration and decomposition results for this exercise.

Our second alternative calibration uses a different identification strategy from the one outlined in Section 4.1.2. In this alternative strategy, we set $\delta_e(s)$ for $e \in \{0, 1\}$ and $s \in \{b, g\}$ externally, and calibrate the learning speed, ϕ_e, by matching the separation profile. The intuition for this strategy is that for a given set of exogenous separation rates, a higher learning speed generates a separation profile that rapidly decreases between the first and second potential experience bins as workers sort into their good fit faster. Through this strategy, we estimate a higher learning speed for non-college workers ($\phi_0 = 0.0245$) than in the baseline calibration. Apart from this, the other uncertainty channel parameters are largely unchanged, and we find that the uncertainty channel explains at least 5.06-8.13% of the U-E gap. The Shapley-Owen-Shorrocks decomposition shows that the uncertainty channel accounts for 25.32% of the U-E gap, which closely aligns with the results in the other calibrations. Appendix C.5.2 details the calibration, identification, and decomposition under this identification strategy.

Next, we address a limitation of using the cosine similarity in skill requirements to measure the accuracy of an individual's uncertainty over which career they are best suited for. While the angle between two occupations may be small, legal restrictions or education requirements may prevent workers from switching between them.[33] Therefore, the low forecast errors among college graduates may not fully capture the distance between their expected and realized occupations and their low career switching rates could be the result of occupational lock-in rather than being in a good career fit. In Appendix C.5.3, we measure the lock-in rating of occupations based on occupational outflow rates and show that our motivating facts (e.g., the education gap in forecast errors) and targeted moments are largely unchanged if we drop workers from our sample who ever worked in occupations with a high lock-in ranking.

Finally, Appendices C.5.4 and C.5.5 show that the moments we use to discipline the model in our baseline calibration are largely unchanged if we (i) include both males and females in the CPS and NLSY79 samples, and (ii) use alternative definitions of career switches. As the targeted moments are similar to those shown in Table 5, calibrating the model to these alternative samples is unlikely to change the parameter values and the uncertainty channel's contribution to the U-E gap.

[33] For example, dentists and biological scientists have similar skill and task requirements. However, there are very few flows between these occupations.

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, on average, higher skills and labor productivity common to all matches, then they can sustain matches with a lower match-specific productivity and experience fewer separations and lower unemployment.[34] This environment 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 actually higher among college graduates. Second, environments that rely exclusively on variation in match-specific productivity to generate separations predict that the expected duration of a match formed through unemployment is independent of the worker's prior experience at the time a match is formed. However, this "resetting" property is counterfactual, as shown in Section 2.3.3 and Appendix A.6. Third, one would expect the separation profile to continuously decline in age as older workers have higher match-specific productivity. From Figure 3, the separation profile for college workers is essentially flat from 30 to 59 years old. As displayed in Table 4, our model matches this pattern well by having almost all college workers settled into their best fit after their first ten years of potential experience. Fourth, 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.

5 Education Policy Implications

To this point, we have proposed that college graduates enter the labor market with less career uncertainty. Section 2 presents a set of facts to support this hypothesis and the quantitative analysis in Section 4 finds that the uncertainty channel accounts for 27.3% of

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

the U-E gap. What we have not done is address *why* college graduates have lower career uncertainty, which is particularly relevant for the policy implications of the hypothesis, evidence, and analysis presented in Sections 2-4.

The quantitative model suggests that lowering career uncertainty among non-college workers reduces unemployment, increases wages, and increases lifetime earnings. However, this does not imply that randomly assigning an individual to obtain a bachelor's degree would have this effect. This is because the model is calibrated to data that is the result of any causal effect of college and selection into college. To provide a more nuanced set of policy implications, this section sheds some light on the role of selection in driving the empirical patterns shown to this point. Then, through the lens of the quantitative model, we carry out a cost-benefit analysis that compares the value of lowering career uncertainty through college to learning through work experience.

5.1 Forecast Errors and Years of Schooling

To begin, we revisit the relationship between education and our most direct measure of career uncertainty, an individual's forecast error, by estimating

$$\text{FCE}_i = \beta_0 + \beta_1 \text{Educ}_i + \Gamma X_i + \epsilon_i, \quad (22)$$

where FCE is individual i's standardized forecast error and Educ is educational attainment. The vector X contains high school GPA, average ability, log of average adolescent family income, parental educational attainment, race, and whether individual i was ever married and whether they ever had a child.[35]

Table 10 presents the results. Columns (1) and (2) indicate that completing a bachelor's degree is associated with a 0.30 standard deviation decrease in forecast error. Columns (3)-(6) show that an additional year of schooling is associated with a 0.05-0.07 standard deviation decline in forecast error. These results suggest that college provides individuals a better understanding of their best career fit. However, higher GPA, ability, income, and parental educational attainment are also associated with a lower forecast error. As each of these factors is positively correlated with educational attainment, the estimates of β_1 are likely biased, as individuals are selecting into college based on factors that are not controlled for in (22) that are associated with a lower forecast error. In Section 5.2, we estimate the explanatory power of years of college completed relative to selection in accounting for the education gap in forecast errors.

[35] Average ability is defined as the average of a worker's aptitudes in the verbal, math, and social domains. A detailed measurement of workers' multidimensional aptitudes can be found in Appendix A.2.3.

Table 10: Years of Schooling and Forecast Errors

	(1) Euclidean	(2) Angle	(3) Euclidean	(4) Angle	(5) Euclidean	(6) Angle
College	-0.301***	-0.278***				
Education Years			-0.050***	-0.049***		
College Years					-0.069***	-0.065***
GPA	-0.061**	-0.082***	-0.056*	-0.075**	-0.055*	-0.074**
Avg. Ability	-0.120	-0.232	-0.115	-0.219	-0.056	-0.165
Family Inc.	-0.019	-0.007	-0.014	-0.003	-0.018	-0.007
College, M	-0.035	-0.103	-0.046	-0.112*	-0.027	-0.094
College, F	-0.270***	-0.200**	-0.268***	-0.196**	-0.247***	-0.177**
Observations	1,726	1,726	1,726	1,726	1,726	1,726
R^2	0.061	0.079	0.057	0.076	0.063	0.081

Notes: The dependent variable is the standardized Euclidean and Angular distance between an individual's expected and realized occupation at age 35. College is a binary variable that indicates whether or not the respondent ever obtained a bachelor's degree or not. Education years is the number of years of schooling completed. College years are the number of years of college completed. College, M (F) is an indicator for whether individual i's mother (father) holds a bachelor's degree or higher. All specifications include the full vector of individual controls, X, listed below (22). Results are unchanged if we instead use the forecast error based on all occupations worked in between 30 and 40 years old. Levels of statistical significance are denoted by ***($p < 0.01$), **($p < 0.05$), *($p < 0.1$).

5.2 Forecast Error Decomposition

We focus on two channels through which selection may account for the correlation between education and forecast errors. The first, the good learners channel, is that individuals who perform well academically may also be better at learning their best fit. As good learners are more likely to enroll in college, the negative correlation in Table 10 could be driven by the high ability of college graduates to learn their best fit. The second, the family background channel, is that individuals from wealthier families can afford experiences that identify their best fit (e.g., attend a summer robotics program). Further, individuals whose parents are also college graduates may have access to more information about careers or may want to follow in their parents' footsteps. Either way, individuals who are more certain of their best fit select into college through the family background channel.

To estimate how much of the education gap in forecast errors is explained by the good learners and family background channels relative to years of college completed, we carry out an Oaxaca-Blinder decomposition of the following specification:

$$\Delta\text{FCE}_i = \underbrace{\text{ColY}_i}_{\text{College}} + \underbrace{\text{Ability}_i + \text{GPA}_i}_{\text{Good Learners}} + \underbrace{\text{FamInc}_i + \text{ColM}_i + \text{ColF}_i}_{\text{Family Background}} + \underbrace{X_i}_{\text{Other}}, \tag{23}$$

Table 11: Oaxaca-Blinder Decomposition of Mean Forecast Errors by Education

	Euclidean	Angular
Differential:		
Non-College	0.074***	0.064**
College	-0.399***	-0.443***
Difference	0.473***	0.507***
Explained by:		
College Years	0.068***	0.055***
Good Learners	0.089**	0.139***
Family Background	0.066***	0.071***
Others	0.013	0.015
Total	0.235***	0.279***
Observations	1,726	1,726

Notes: Results are based on a twofold Oaxaca-Blinder decomposition. The outcome variable to be decomposed is the education gap in the standardized Euclidean or angular distance between an individual's expected and realized occupation at age 35. The *Differential* represents the mean forecast error gap between the college and the non-college. The *Explained by* component measures the portion of the gap attributable to compositional differences in covariates. Levels of statistical significance are indicated by *($p < 0.10$), **($p < 0.05$), ***($p < 0.01$).

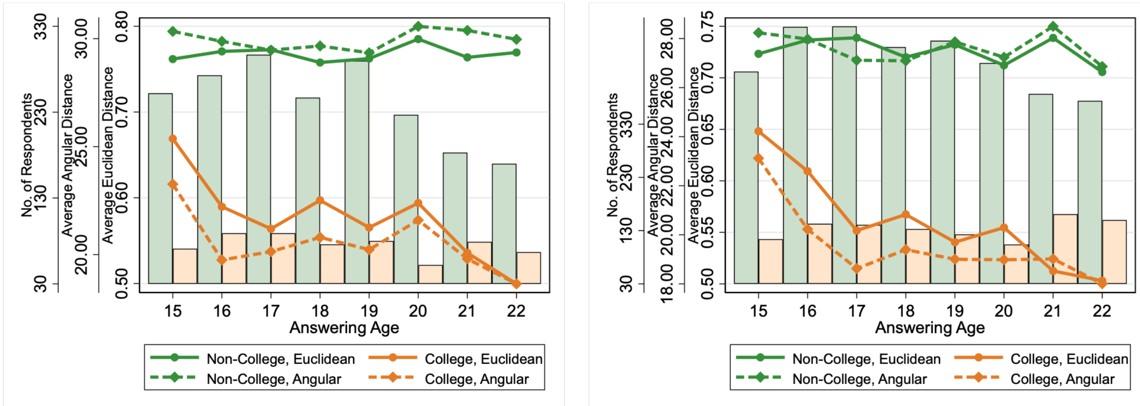
where ΔFCE is the education gap in standardized forecast errors. From (23), ΔFCE is decomposed into four components: (i) years of college education completed when the expected occupation was recorded (ColY); (ii) the good learners channel which is proxied by average ability (Ability) and high school GPA (GPA); (iii) the family background channel that is captured by adolescent family income (FamInc), and parental college status (ColM and ColF); and (iv) other observables (race, marital, and childbearing status).

Table 11 shows that differences in years of college completed account for 10.85–14.38% of the educational gap in forecast errors.[36] By contrast, the good learners and family background channels explain between 18.82–27.42% and 13.95–14.00%, respectively.[37] Therefore, the good learners and family background channels collectively explain between 32.8-41.4% of the education gap in forecast errors.

An alternate exercise to show that selection plays a prominent role in shaping the correlation between education and forecast errors is to plot the average forecast error by

[36] If we instead decompose the educational gap in the forecast error measured by the distance between the expected occupation and the realized occupations between ages 30 and 40, the portion of that gap attributed to the college effect lies between 11.31% and 15.98%, similar to the results here. See Appendix A.14.

[37] We adopt the two-fold decomposition with a pooled regression, including the grouping variable as an additional control, as the reference coefficients (Neumark, 2004; Fortin, 2008; Jann, 2008).



(a) Age 35 Occupation (b) Occupations between 30 and 40 years old

Figure 10: Forecast Error and Answering Age. *Notes*: Answering age is the respondent's age in the initial NLSY79 interview, when their expected occupation was recorded. The green bars represent the number of non-college respondents with a non-missing forecast error at each answering age. The orange bars are the number of college respondents with a non-missing forecast error at each answering age. Panel (a) uses the forecast error based on the realized occupation at age 35 while panel (b) uses the forecast error based on all occupations worked in between 30 and 40 years old (inclusive).

education and age at which the respondents listed their expected occupation. Figure 10 does this and shows that the gap in forecast errors is present at all ages.[38] Further, the forecast error decreases between 15 and 18 years old for the college group. These patterns suggest that (i) those with a good sense of their best fit are more likely to complete a college degree and (ii) individuals are learning their best career fit before college.

We decompose the education gap in forecast errors among 22 years old into three components: (1) the gap at 15 years old, (2) the widening of the gap between 15-18 years old, and (3) the widening of the gap between 18-22 years old. Components (2) and (3) can be interpreted as the portion of the education gap in forecast errors attributable to learning during high school and college, respectively. Table 12 presents this decomposition and shows that, for each measure of the forecast errors, the gap between non-college and college grows between 15 and 22 years old. The last two columns compute the fraction of the gap at 22 years old, Δ_{22}, that is attributable to the widening of the gap between ages 15-18 and 18-22, respectively. If we assume that the widening of the gap in forecast errors between ages 18-22 is caused by college, the last column indicates that between 13% and 41% of the gap in forecast errors at 22 years old is attributable to learning during college.

[38]Recall that an individual is labelled as "college" if they ever obtained a bachelor's degree. So, for most of the individuals labelled as "college", they eventually obtained a bachelor's degree but had not done so when their expected occupation was recorded.

Table 12: A Simple Decomposition of Forecast Errors

	Δ_{15}	$\Delta_{18}-\Delta_{15}$	$\Delta_{22}-\Delta_{18}$	Δ_{22}	$\frac{\Delta_{18}-\Delta_{15}}{\Delta_{22}}$	$\frac{\Delta_{22}-\Delta_{18}}{\Delta_{22}}$
Panel A: Forecast Error at Age 35						
Euclidean	0.09	0.07	0.11	0.27	0.26	0.41
Angular	7.08	1.79	2.46	11.33	0.16	0.22
Panel B: Forecast Error during Ages 30 to 40						
Euclidean	0.08	0.07	0.05	0.20	0.35	0.25
Angular	5.12	2.58	1.15	8.85	0.29	0.13

Notes: Δ_a represents the education gap in raw forecast errors at age a. Panel A decomposes the gap in forecast error at age 35, which is measured by comparing the expected occupation and realized occupation at age 35, while Panel B decomposes the gap in forecast error during ages 35 to 40 by comparing the expected occupation at age 35 to the realized occupations during ages 30 to 40.

5.3 Cost-Benefit Analysis

Section 5.2 indicates that selection plays a large role in explaining the education gap in career uncertainty. Despite that, there is a portion of the difference in forecast errors that is attributable to years of college completed. Given that the results suggest that there is a role for educational attainment in decreasing career uncertainty, we revisit the model to carry out a cost-benefit analysis. Specifically, we are interested in answering if and when an individual should lower their career uncertainty by obtaining a bachelor's degree or to use four years of potential experience to learn about their best fit.

Consider the calibrated model from Section 4. First, we set $\{N_0, \phi_0, \tilde{\lambda}_0\}$ equal to $\{N_1, \phi_1, \tilde{\lambda}_1\}$ while keeping all other parameters at the values in Table 5. Doing so increases the lifetime earnings of non-college workers from $E_0 = 494.01$ to $\hat{E}_0 = 576.96$.[39] Now let $\Gamma \in [0,1]$ represent the fraction of the difference $\hat{E}_0 - E_0$ that is attributable to college. In other words, Γ represents how much of the gain in earnings associated with having lower career uncertainty, $\hat{E}_0 - E_0$, that would be realized by an individual who is randomly assigned to complete a bachelor's degree. Further, let $\hat{T}$ be the pecuniary cost of completing a bachelor's degree. As such, the net benefit of reducing career uncertainty through completing a bachelor's degree is $\Gamma[\hat{E}_0 - E_0] - \hat{T}$.

The worker's alternative is to learn through work experience. To measure the value of learning through experience in the first four years of potential experience, we first reset the clock of potential experience for non-college workers so that their first year of potential experience is at 22 years old. Then, we compute the three moments associated

[39]For simplicity, we abstract from discounting in this cost-benefit analysis.

Table 13: Learning Through Experience

	Baseline		Augmented	
	Target	Model	Target	Model
Panel A: Non-College Moments				
# Careers	3.039	3.005	2.847	2.740
% with $<$ 3 careers	36.531	34.314	42.200	40.403
Pot. exp. at first switch	44.000	44.000	43.500	43.000
Panel B: Uncertainty Channel Parameters				
N_0	8		7	
ϕ_0	0.019		0.019	
$\tilde{\lambda}_0$	1.507		1.607	
Panel C: Labor Market Outcomes				
Unemployment rate	8.114		7.506	
Wage	1.541		1.582	
Lifetime earnings	494.008		510.712	

Notes: The augmented calibration re-estimates $\{N_0, \phi_0, \tilde{\lambda}_0\}$ to match the career sampling moments after resetting the potential experience clock for non-college workers. The augmented moments are still computed over forty years of potential experience. All other parameters are held fixed at their baseline values reported in Table 5. Panel C reports model outcomes for non-college workers under each calibration.

with career sampling in the new window of potential experience for non-college workers. Finally, we re-estimate $\{N_0, \phi_0, \tilde{\lambda}_0\}$ to match the new set of career sampling moments while all other parameters remain fixed at their values shown in Table 5.

Table 13 presents the results. Panel A displays that resetting the potential experience clock leads to a smaller number of sampled careers, slightly more workers who sample one or two careers, and a small decline in the level of potential experience at which the first career switch occurs. From Panel B, N_0 decreases from 8 to 7 and $\tilde{\lambda}_0$ increases from 1.5 to 1.6. Panel C shows that simultaneously changing $\{N_0, \phi_0, \tilde{\lambda}_0\}$ from their baseline values to those in the augmented sample reduces the average unemployment rate from 8.1% to 7.5%, and increases wages and lifetime earnings by 2.6% and 3.4%, respectively.

Let $\bar{E}_0$ denote the lifetime earnings of a non-college worker with the set of uncertainty channel parameters after their first four years of potential experience. The value of lowering uncertainty through college is higher than learning through experience if

$$\Gamma[\hat{E}_0 - E_0] - \hat{T} > \bar{E}_0 - E_0. \tag{24}$$

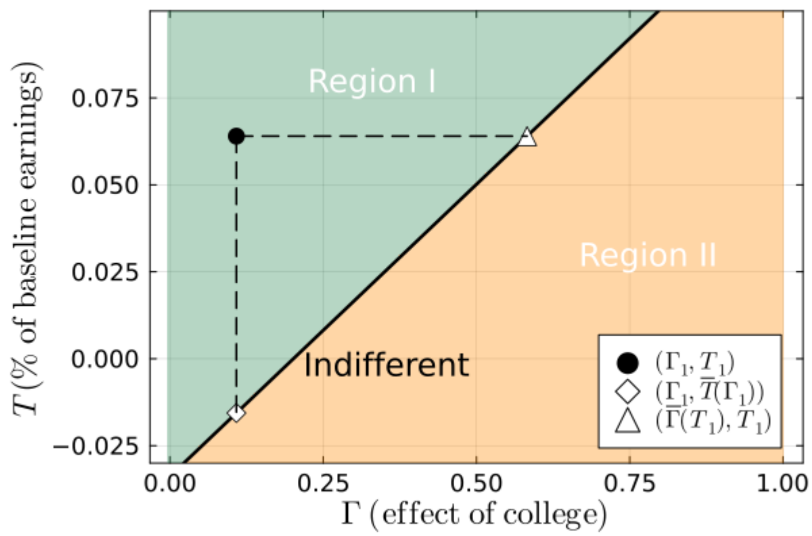


Figure 11: Cost-Benefit Analysis. *Notes*: Region I corresponds to all points where $\Gamma[\hat{E}_0 - E_0]/E_0 - T > [\bar{E}_0 - E_0]/E_0$. Region II is where $\Gamma[\hat{E}_0 - E_0]/E_0 - T < [\bar{E}_0 - E_0]/E_0$. The black line is where $\Gamma[\hat{E}_0 - E_0]/E_0 - T = [\bar{E}_0 - E_0]/E_0$. The values of E_0, $\bar{E}_0$, and $\hat{E}_0$ are generated by the quantitative model. The value of Γ_1 is based on the Oaxaca-Blinder decomposition in Section 5.2. The value of T_1 is based on data from the National Center for Education Statistics and the March Supplement to the CPS.

The left side of (24) is the increase in earnings associated with completing a college degree net of the pecuniary cost of college. The right side is the increase in earnings from lowering uncertainty via learning in the first four years of potential experience. To map the model to the data, we divide (24) by E_0 to arrive at

$$\frac{\Gamma[\hat{E}_0 - E_0]}{E_0} - T > \frac{\bar{E}_0 - E_0}{E_0}, \tag{25}$$

where $T = \hat{T}/E_0$. Given the model generated values of E_0, $\bar{E}_0$, and $\hat{E}_0$, Figure 11 plots (25), in (Γ, T) space. The solid black line is where (25) holds with equality. Region I is where the value of lowering uncertainty through experience is higher than lowering uncertainty through college. In the orange area, region II, the benefit of lowering uncertainty through college is higher than learning through experience.

The black circle in Figure 11 corresponds to $(\Gamma_1, T_1) = (0.109, 0.064)$. This value of Γ_1 is based on the Oaxaca-Blinder decomposition in the previous section, which estimated that 10.9% of the difference in average forecast errors by educational attainment is explained by years of college.[40] The value of T_1 is based on the ratio of tuition to earnings in the

[40] Here we make two simplifying assumptions to link the Oaxaca-Blinder decomposition to the quantitative model. First, we assume that the fraction of the gap in forecast errors attributable to years of college completed is equal to the fraction of the gap in uncertainty channel parameters that is attributable to college attendance. Second, we assume that closing a fraction Γ of the uncertainty channel parameter gap generates a fraction Γ of the gain in earnings, $\hat{E}_0 - E_0$. We scale the earnings gain, $\hat{E}_0 - E_0$, by Γ directly, as we have

data. From the National Center of Education Statistics, the average annual cost (tuition, room, board, and fees) of a four-year college between 1978-2019, in 2022 dollars, was $22,568.3. Thus, the four-year cost is $90,273.2. Second, using the March Supplement to the CPS, we find that the median annual earnings among non-college workers, in 2022 dollars, are $34,991.2. Multiplying by forty gives a cumulative earnings over forty years of potential experience of nearly $1.4 million. Taking the ratio of the four-year cost to cumulative earnings gives $T_1 = 0.064$.

We can see that (Γ_1, T_1) is within Region 1, where it is not worth it to buy lower uncertainty through college. Further, the dashed verticle line down to the indifference line at $(\Gamma_1, \overline{T}(\Gamma_1))$ shows that, at Γ_1, T would need to be $\overline{T}(\Gamma_1) = -0.0156$ in order for the net benefit of lowering uncertainty through college to be the same as doing so through learning in the labor market. Given that the median cumulative earnings over forty years of potential experience is $1.4 million, workers would need to receive a subsidy of $21,840 to complete four years of college in order to be indifferent between lowering career uncertainty through college and learning through work experience. Another perspective is that starting at (Γ_1, T_1) and following the dashed horizontal line to $(\overline{\Gamma}(T_1), T_1)$ tells us the minimum value of Γ, given T_1, to make the worker indifferent. We find $\overline{\Gamma}(T_1) = 0.583$, which is much larger than the baseline of $\Gamma_1 = 0.109$.

An alternate approach to discipline Γ is to set it equal to the portion of the gap in forecast errors among 22 year olds that is attributable to the widening of the gap between ages 18-22. From Table 12, this produces $\Gamma \in [0.13, 0.41]$. From Figure 11, (Γ, T_1) for $\Gamma \in [0.13, .41]$ is clearly in region I despite making a strong assumption that the widening of the forecast error gap between 18 and 22 years old is caused by college.

This cost-benefit analysis leads us to conclude that the value of lowering career uncertainty through labor market experience is higher than doing so through college. Of course, there are many other potential benefits of college that we have abstracted from in this exercise, so the results in this section should not be interpreted as saying that college is not a worthwhile investment. Further, this analysis does not imply that there is no policy intervention that can lower career uncertainty among non-college workers and is worthwhile to implement. Given that the gap in forecast errors is sizeable among 15-18 year olds, policy interventions may need to occur earlier than college.[41]

no well-defined way to simultaneously scale the uncertainty channel parameters by a factor Γ, given that the size of the career set is an integer.

[41] One intervention that could reduce career uncertainty is exposing high school students to role models working in specific fields. 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.

6 Conclusion

This paper posits the uncertainty channel as a new explanation for the unemployment-education 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 decompositions reveal that the uncertainty channel accounts for meaningful shares of the model-generated education gaps in unemployment, wages, and lifetime earnings.

There are several areas in which future research could enhance our understanding of the role of career uncertainty in shaping labor market outcomes. An alternate approach to modelling career uncertainty is to instead have workers draw career specific match qualities. Workers would observe a signal of their career quality both before a match is formed and on the job. Lower career uncertainty could be captured by increasing the precision of the signals. This approach would allow one to estimate the contribution of the pre- and post-match formation signals to the unemployment-education gap and develop more targeted policy interventions. On the empirical front, we have only taken the first steps towards identifying the sources of the unemployment-education gap. More work is needed in this area to develop policies that are effective at lowering career uncertainty.

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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 demographics of the U.S. labor force. The survey follows a 4-8-4 rotation design, and we use the individual identifier, CPSIDP, to link individual records across time.

In CPS, 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 with either a professional or a doctorate degree. Overall, ''College'' refers to 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.1.1 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 requirements across multiple dimensions: (i) verbal, math, social, and technical skill requirements as in Guvenen et al. (2020); and (ii) abstract, routine, and manual task intensities as in Autor and Dorn (2013).[42] 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, and technical skill requirements, as well as

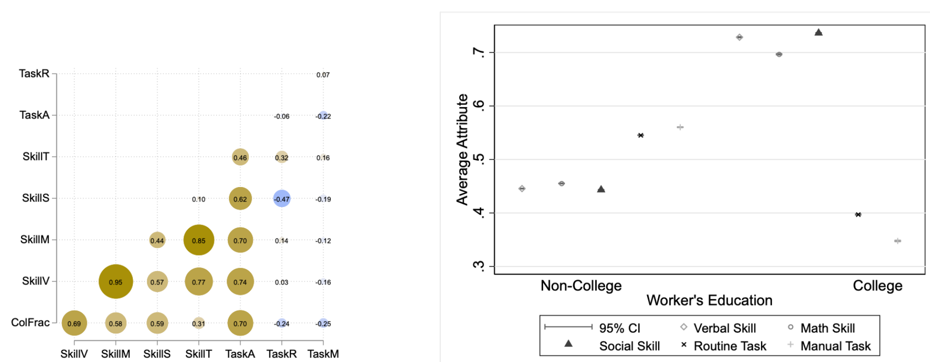
[42] We follow the steps outlined by both Guvenen et al. (2020) and Autor and Dorn (2013) in the measurement of occupational attributes and, for brevity, omit those detailed steps here.

Table A1: Potential Experience by Education

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

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

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 high-order skills and incorporate routine and manual task intensity to capture the low-order skills.[43] Furthermore, we examine the average occupational attributes in jobs held by non-college and college workers in the NLSY79 sample. Figure A1(b) shows that jobs held by college graduates have higher requirements for verbal, math, and social skills, but lower routine and manual task intensities.



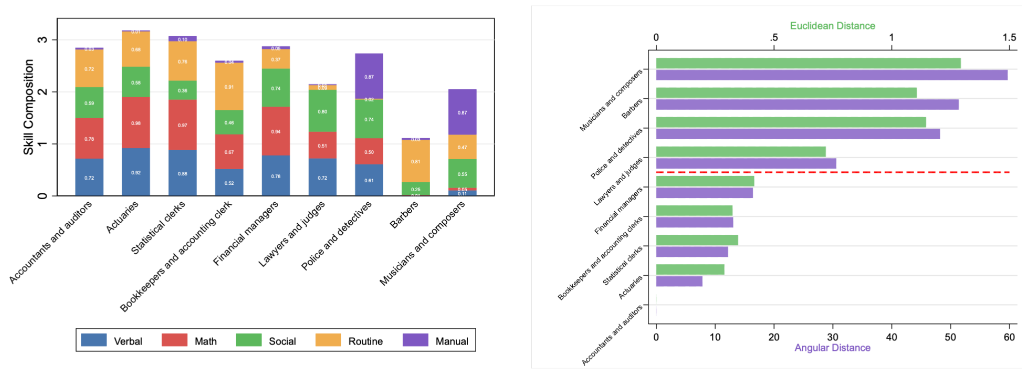
(a) Correlogram of Occupation Attributes (b) Average Attributes

Figure A1: Occupation Attributes. *Source*: NLSY79 sample.

Figure A2 provides an illustrative example of the skill measures and their mapping

[43]We do not incorporate technical skill requirements or abstract task intensities in the skill vector, as both are highly correlated with verbal and math skill requirements.

to skill distance metrics by comparing eight occupations to Accountants and Auditors. Specifically, Figure A2(a) depicts the skill profile of each occupation, and Figure A2(b) displays the angular and Euclidean distances from Accountants and Auditors to each comparison occupation.



(a) Skill Mix

(b) Distance to Accountants and Auditors

Figure A2: Comparison of Eight Occupations to Accountants and Auditors. *Notes*: Panel (a) shows the skill and task requirements for each of the nine occupations used in this example. Panel (b) displays the angular and Euclidean distance between each of the listed occupations and Accountants and Auditors.

A.2 National Longitudinal Survey of Youth (NLSY79)

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

A.2.1 Sample Construction

We first construct a weekly panel from the original NLSY79 files through three steps. First, we clean the employer history roster (EHR) by standardizing industry and occupation codes to the 1990dd scheme and extracting employer characteristics. Second, we identify relevant demographic variables for each respondent in each survey year based on the EHR. Third, for respondents holding multiple jobs simultaneously, we designate the job with the most hours worked during a given week as the primary job.

To align the NLSY79 with the CPS time structure, we convert the weekly panel into a monthly format by aggregating labor force statuses. A respondent is classified as non-employed if they experience any week of non-employment during the month. For those who are continuously employed, we identify a single primary job using a hierarchical selection process. First, we choose the job with the highest monthly hours. If multiple jobs have identical hours, we prioritize those with complete occupation and industry codes, then those with valid occupation codes only, then those with valid industry codes only. If ties remain, we select the earliest reported job based on the job identifier.

A.2.2 Sample Selection

Table A2 details our sample selection criteria. We start with monthly employment histories of 12,686 respondents and restrict the sample to 6,403 males, as female labor force participation changed substantially during the survey period.[44] Next, we filter the observations to include only those from the earliest survey year (1978) until 2018.

We assume that individuals entered the labor market upon completing their highest level of education. For those whose highest education is recorded as ''None'', we set their employment histories to start in 1978, the earliest year in our dataset. We drop respondents with unknown graduation dates, yielding a sample of 6,386 respondents. We then exclude individuals who served in the military, leaving 5,351 respondents. Next, we drop those with incomplete cognitive or non-cognitive scores, which reduces the sample to 4,814. We then restrict the data to the first 40 years of potential work experience, resulting in 4,807 respondents. Finally, we remove individuals who were never employed during the survey periods, arriving at a final sample of 4,695 respondents.

Table A2: NLSY79 Sample Selection

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	5,351	1,587,420
Complete ASVAB	5,020	1,509,160
Complete non-cognitive scores	4,814	1,450,597
Potential work experience, 1-40 years	4,807	1,430,948
Drop persons who are never employed	4,695	1,421,934

Note: This table details the NLSY79 sample construction steps and sample size after each restriction.

[44] The labor force participation rate of females increases from 50% in 1978 to about 60% in 1997.

A.2.3 Measurement of Worker's Aptitudes

To measure a worker's verbal and math abilities, we begin with a sample of 4,695 respondents who have complete scores for word knowledge, paragraph comprehension, arithmetic reasoning, and mathematics knowledge sub-tests of the Armed Services Vocational Aptitude Battery (ASVAB). After normalizing each test score by age cohort, we perform the Principal Component Analysis (PCA) separately on the first two sub-tests (word knowledge and paragraph comprehension) and the last two sub-tests (arithmetic reasoning and mathematics knowledge). By extracting the first component from each PCA, we obtain measures of verbal and math abilities. Subsequently, we convert these ability measures into percentile ranks across all individuals.

To measure social ability, we use the Rotter Locus of Control Scale and the Rosenberg Self-Esteem Scale. Applying the same methodology, we adjust for test-taking age, perform principal component analysis to extract the first component, and convert the results to percentile ranks across individuals.

A.2.4 Measurement of Skill Mismatch

We quantify skill mismatch by computing the distance between worker abilities and occupational attributes. The mismatch in skill j between worker i and occupation o is:

$$m_{i,j,o} = \left| q(A_{i,j}) - q(s_{o,j}) \right|, \tag{A.26}$$

where $q(A_{i,j})$ is 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:

$$m_{i,o} = \sum_j \{\omega_j \left| q(A_{i,j}) - q(s_{o,j}) \right| \}, \tag{A.27}$$

where ω_j are weights assigned to skill j from PCA factor loadings, reflecting its relative importance to aggregate mismatch. The weights for verbal, math, and social skill are $(0.43, 0.42, 0.15)$, similar to Guvenen et al. (2020).

A.3 Additional Motivating Facts

A.3.1 Forecast Error and Separations

This section compares separation profiles of workers with and without forecast errors within each education group. In the NLSY79, 116 out of $1,939$ non-college workers and

88 out of 603 college workers precisely predicted their occupation at age 35.

As shown in Figure A3, within each education group, workers who did not make any forecast errors, i.e., had little uncertainty about their best fit, exhibit fewer separations than those who did. Furthermore, the gap in separation rates by forecast error is widest early in workers' careers, supporting the notion that workers with greater uncertainty about their best fit experience higher initial separation rates. Over time, as they find their good fits, these separation rates decline.

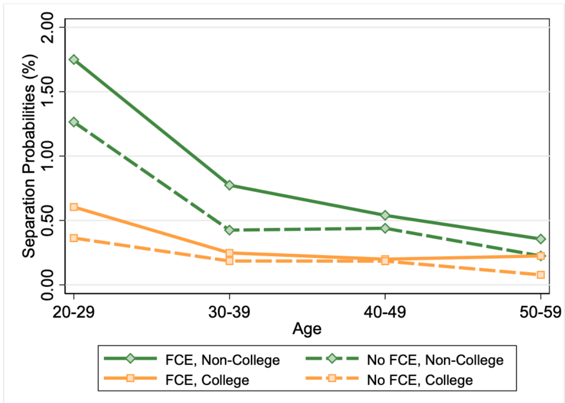


Figure A3: Forecast Error and Separations. *Source*: NLSY79.

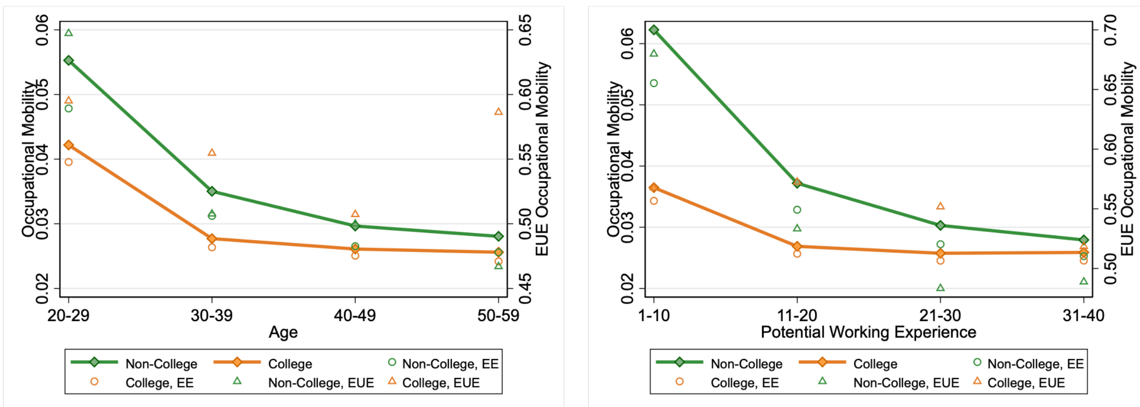
A.3.2 Occupational Mobility

Using the CPS data from 1994 to 2019, we compute 3-digit occupational mobility rates by age and education.[45] We first compute occupational mobility for job-to-job (EE) transitions and transitions from unemployment (EUE) separately. For EE transitions, we restrict to observations with known occupations for two consecutive months. For EUE switches, we track occupations before and after the unemployment spell. We then compute the aggregate mobility rate by taking a weighted average across all transitions.

Figure A4(a) presents occupational mobility rates over ages. The circles (triangles) represent occupational switches in EE (EUE) transitions, while the solid line is the aggregate occupational mobility. Three patterns emerge. First, occupational mobility is decreasing in age, consistent with the findings of Kambourov and Manovskii (2008). Second, non-college workers change occupations more frequently. Third, similar to unemployment and separations, the gap in occupational mobility rates across education groups decreases

[45] Occupational records in survey data are prone to measurement error. To mitigate this, we apply the methodology of Moscarini and Thomsson (2007), which uses dependent questions introduced in the CPS since 1994. The correction process has three stages: flagging transitions susceptible to measurement error in occupational codes; subjecting dubious transitions to the $ANY3$ filter; and passing the remaining suspicious transitions through the *Flag* filter. Detailed procedures are omitted for brevity but available upon request.

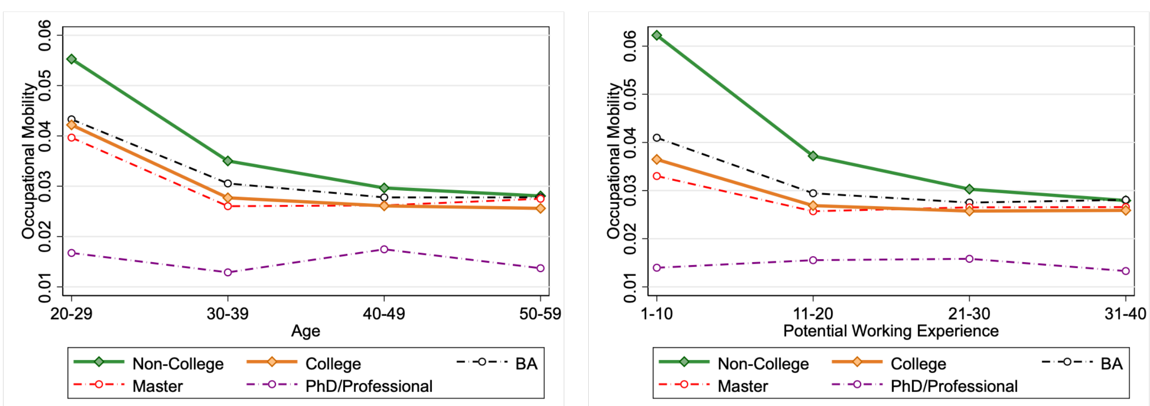
with age. To further support the notion that highly educated workers experience less occupational mobility given their lower uncertainty, we report the occupational mobility rates for detailed educational attainments. Figure A5(a) shows that holding a Master's, Ph.D., or Professional degree is associated with even lower occupational mobility rates.



(a) Age (b) Potential Experience

Figure A4: Occupational Mobility. *Source*: CPS, 1994-2019.

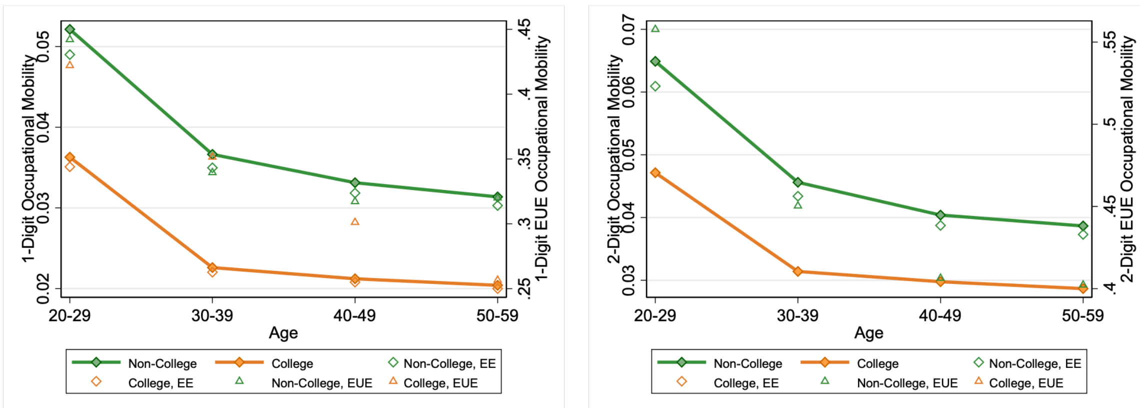
One factor complicating the interpretation of mobility over ages is that educational attainment affects labor market entry timing. To address this, we examine occupational mobility by years of potential experience, assuming non-college workers enter at age 18 and college workers at age 22. Figures A4(b) and A5(b) show that the gap in occupational mobility is even larger in early career stages when measured by experience than by age.



(a) Age (b) Potential Experience

Figure A5: Occupational Mobility Across Specific College Degrees. *Source*: CPS, 1994-2019.

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 A6 presents raw occupational mobility rates using 1- and 2-digit occupational codes, showing patterns consistent with Figure A4.



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

Figure A6: Occupational Mobility at 1- and 2-digit Occupation Codes. *Source*: CPS, 1994-2019.

A.3.3 Skill Mismatch

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

$$\overline{MM}_{i,j} = \frac{\sum_{k \in i \cap j} MM_k \times \omega_k}{\sum_k \mathbb{1}\{k \in i \cap j\} \times \omega_k}. \tag{A.28}$$

From (A.28), $\overline{MM}_{i,j}$ is given by the ratio of the aggregate mismatch among workers with age i and education j to the number of workers within that subgroup. We apply the technical weight ω_k to account for each respondent's representation in the U.S. population. Table A3 shows that the average skill mismatch is decreasing with educational attainment.[46]

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 who are more certain of their best fit may choose occupations with more imbalanced skill

[46]Similar patterns are observed for each single skill dimension and are available upon request.

Table A3: Skill Mismatch, by Educational Attainment

	Age	Work Experience
Non-College	[1.69, 1.66, 1.62, 1.65]	[1.70, 1.66, 1.62, 1.65]
College	[1.51, 1.33, 1.28, 1.34]	[1.45, 1.29, 1.29, 1.38]

Notes: The first column reports the average skill mismatch for each education group across age bins (20–29, 30–39, 40–49, 50–59), while the second column reports the average skill mismatch across years of potential work experience (1–10, 11–20, 21–30, 31–40). Data are from NLSY79, 1979:1-2018:12.

requirements, indicating their assurance in excelling in jobs that emphasize particular skills. We measure the degree of skill dispersion using the following metrics:

$$Var_i = \frac{\sum_j (r_{i,j} - \bar{r}_i)^2}{5}, \quad Max - Min_i = max_j(r_{i,j}) - min_j(r_{i,j}),$$
$$MeanDev_i = \frac{|\sum_j (r_{i,j} - \bar{r}_i)|}{5}, \quad MedianDev_i = \frac{|\sum_j (r_{i,j} - Median_i)|}{5},$$

where $r_{i,j}$ denotes the skill requirement along skill j by occupation i , and $\bar{r}_i$ and $Median_i$ denote the mean and median value of the skill requirement in occupation i, respectively.

Table A4 shows that 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.

A.3.5 Number of Employer, Occupation, and Career Transitions

To compare career stability across education groups, we examine the average number of transitions and unique employers. For each education-age subgroup, we first calculate the average number of employer, occupational, and career switches, as well as the average number of unique employers. We then aggregate these averages cumulatively across age bins.

Table A5 reveals that workers accumulate transitions as they age, but the rate varies substantially by education. Workers with higher educational attainment consistently experience fewer switches across all transition types and work for fewer employers at each career stage.

Table A4: Degree of Skill Requirement Imbalance

	Age	Working Experience
Panel A: Variance		
Non-College	[0.057, 0.059, 0.057, 0.058]	[0.057, 0.059, 0.057, 0.058]
College	[0.066, 0.070, 0.069, 0.070]	[0.067, 0.070, 0.069, 0.068]
Panel B: Max-Min Differences		
Non-College	[0.604, 0.607, 0.605, 0.608]	[0.603, 0.607, 0.606, 0.607]
College	[0.647, 0.658, 0.655, 0.660]	[0.650, 0.659, 0.657, 0.655]
Panel C: Mean Absolute Deviation		
Non-College	[0.202, 0.206, 0.200, 0.201]	[0.201, 0.205, 0.201, 0.201]
College	[0.219, 0.230, 0.228, 0.228]	[0.223, 0.231, 0.228, 0.225]
Panel D: Median Absolute Deviation		
Non-College	[0.177, 0.180, 0.176, 0.176]	[0.177, 0.180, 0.176, 0.176]
College	[0.196, 0.206, 0.205, 0.205]	[0.200, 0.207, 0.205, 0.202]

Notes: The first column reports the average skill dispersion for each education group across age bins (20–29, 30–39, 40–49, 50–59), while the second column reports the average skill dispersion across years of potential work experience (1–10, 11–20, 21–30, 31–40). Data are from NLSY79, 1979:1-2018:12.

Table A5: Cumulative Transitions by Age

	20-29	≤ 39	≤ 49	≤ 59
Panel A: Employer Transitions				
Non-College	4.12	6.51	7.93	8.61
College	1.84	3.48	4.63	5.47
Panel B: Unique Employers				
Non-College	4.69	6.20	6.96	7.31
College	2.68	3.73	4.29	4.69
Panel C: Occupation Transitions				
Non-College	4.98	7.82	9.13	9.73
College	3.01	5.41	6.62	7.39
Panel D: Career Transitions				
Non-College	3.00	4.66	5.40	5.75
College	1.43	2.43	2.85	3.17

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

A.3.6 Unemployment Rate by College Major

We use the American Community Survey (ACS) to compute the unemployment rate by college major, as the CPS lacks a college major variable while NLSY79 sample sizes by college major are small. To do so, we download the ACS data covering 2009-2019 from IPUMS (Ruggles et al., 2025), and restrict to white males aged 16-59 who are not in school, not veterans, and have a valid undergraduate major, which yields a sample of 1.6 million observations. Following Choi et al. (2025), we classify original undergraduate majors into five broader major categories: Engineering and Computer Science, Business, Life and Physical Sciences, Social Sciences, and Other. We then compute the unemployment rate by college major category. Figure A7 presents the results.

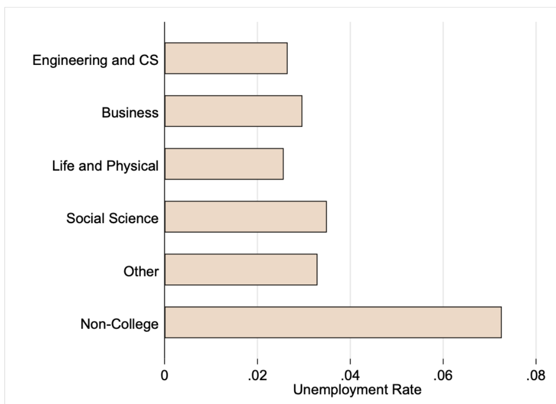


Figure A7: Unemployment Rate by College Major. *Notes:* The categorization of majors follows Choi et al. (2025). Non-college includes all respondents who acquired less than a bachelor's degree. Data are from the American Community Survey between 2009-2019.

A.4 Robustness Checks

A.4.1 Transition Probabilities

Aggregate Employment Profile Table A6 shows that college graduates are less likely to be unemployed and separated, and also have a lower job finding probability and rate.

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 from the law of motion for unemployment:

$$u_{t+1} = (1 - F_t)u_t + u^s_{t+1} \quad \Rightarrow \quad F_t = 1 - \frac{u_{t+1} - u^s_{t+1}}{u_t}, \tag{A.29}$$

Table A6: Aggregate Employment Profile, by Education, PP

	Urate	JFP	JSP	JFR	JSR
Non-College	7.48	30.55	2.50	39.64	2.57
College	2.72	28.27	0.76	31.93	0.77

Note: Urate refers to the unemployment rate, JFP denotes the job finding probability, and JSP denotes the job separation probability. JFR and JSR are the job finding and separation rate, respectively. The first three columns are computed from CPS, 1976:1 - 2019:12, while the last two are from CPS: 1994:1-2019:11.

where F_t is the monthly outflow probability. Equation (A.29) states that the number of unemployed workers at month $t+1$, denoted as 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, i.e., u^s_{t+1}. Therefore, the outflow rate f_t can be derived from $f_t = -\log(1 - F_t)$.

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

$$\dot{u} = s_t(l_t - u_t) - u_t f_t = -(s_t + f_t)(u_t - u^*), \tag{A.30}$$

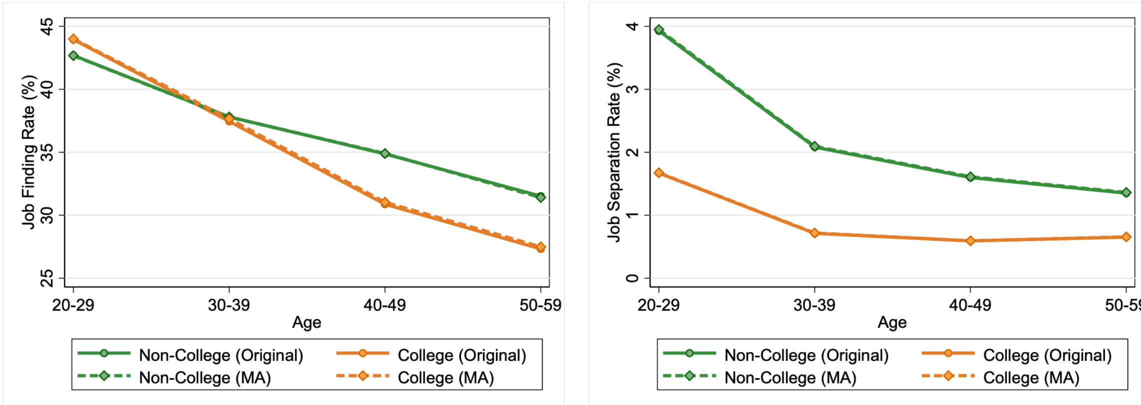
where u^* is the steady state unemployment and l_t is the size of the labor force. The second equality comes from the labor market equilibrium condition $s_t e^*_t = u^* f_t$. By solving (A.30) and assuming s_t, f_t and l_t are constant between surveys, we can infer s_t from

$$u_{t+1} = \frac{(1 - e^{(-s_t - f_t)})s_{t+1}}{f_{t+1} + s_{t+1}} l_t + u_t e^{(-s_t - f_t)}. \tag{A.31}$$

To compute the inflow and outflow rates, we first compute the unemployment rate for each subgroup by age i and education j. Similarly, we calculate the short-term unemployment rate (duration $<$ 5 weeks) per subgroup. We thus infer hazard rates from equations (A.29) and (A.31).[47] We then take a 12-month moving average. Figure A8 shows that age profiles of transition rates mirror those of transition probabilities 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 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

[47] Observations before 1994 are discarded since the unemployment duration variable is only available in IPUMS-CPS from 1994.



(a) Job Finding Rate

(b) Job Separation Rate

Figure A8: Original and 12-month Moving Average Transition Rate. *Note*: Figures are constructed using CPS data between 1994 and 2019. Original represents the hazard rates equations (A.29) and (A.31), while MA represents the 12-month moving average.

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%/97%/95% for college workers. Second, Table A7 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.

Table A7: Separation Probability over Ages by Working Status

	Non-College	College
Full Time	[2.33, 1.48, 1.17, 0.98]	[0.76, 0.46, 0.43, 0.43]
Part Time	[5.74, 7.27, 6.19, 4.15]	[3.60, 3.57, 3.51, 2.66]

Notes: This table reports the separation probability for each education group across age bins (20–29, 30–39, 40–49, 50–59). Data are from CPS between 1976 and 2019.

Involuntary and Voluntary Separations To examine voluntary and involuntary separations in the CPS, we use the reason for unemployment. 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 voluntarily unemployed.

Table A8 shows that both separation types occur at higher rates among non-college workers, and the gap in each narrows over the life cycle. Section 4.2 discusses how our quantitative model is consistent with the fact that involuntary separations exceed voluntary ones for both education groups, and that non-college workers separate at a higher rate for both types.

Table A8: Involuntary Separations and Quits

	Non-College	College
Involuntary Separations	[2.01, 1.47, 1.19, 1.02]	[0.56, 0.41, 0.40, 0.43]
Quits	[0.38, 0.15, 0.10, 0.07]	[0.18, 0.09, 0.06, 0.05]

Notes: Age bins are 20-29, 30-39, 40-49, and 50-59, respectively. Data are from CPS 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 this subgroup is given by:

$$u_{ij} = \frac{s_{ij}}{s_{ij} + f_{ij}}. \tag{A.32}$$

Taking first differences of (A.32) between education levels j and j' gives

$$1 = \underbrace{\frac{(1-u_{ij})u_{ij'}\frac{(s_{ij}-s_{ij'})}{s_{ij'}}}{\Delta u_i}}_{\text{Fraction explained by SP}} + \underbrace{\frac{-u_{ij}(1-u_{ij'})\frac{(f_{ij}-f_{ij'})}{f_{ij'}}}{\Delta u_i}}_{\text{Fraction explained by JFP}}. \tag{A.33}$$

Table A9 presents the fraction of the U-E gap at each age bin i that is attributable to the 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 or rate. In the aggregate, the unemployment gap attributable to the gap of job separation probabilities is 1.19, with the frequency of observations within each age bin serving as the weight.

Table A9: Decomposition of the U-E Gap by Age Bin

	20-29	30-39	40-49	50-59
Panel A: Job Finding/Separation Probability				
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

Notes: Panel A uses CPS data from 1976-2019, while Panels B and C use CPS data from 1994-2019.

A.4.3 Regression Results

To assess the robustness of the descriptive patterns presented in graphs throughout the paper, we estimate:

$$Y_{it} = \beta_0 College_i + \beta_1 Potexp_{it} + \beta_2 Potexp_{it}^2 + \beta_3 College_i * Potexp_{it} + Race_i + MarStatus_{it} + Child_{it} + FamInc_{it} + \Phi_{Occ2} + \Phi_{Ind2} + \Phi_{State} + \Phi_{Year} + \Phi_{Month} + \epsilon_{it}. \quad (A.34)$$

Our outcomes, $Y_{i,t}$, 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) career transitions or not; and (vi) standardized magnitude of skill distance in occupational transitions. We control for a quadratic in 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. The coefficient β_0 captures the association between a college degree ($College_i$) and the outcome, while β_3 shows how this varies with potential experience.

Table A10 shows college graduates have statistically significant lower probabilities of unemployment, job separation, occupational switching, and career switching, but higher job finding probabilities than non-college workers. Moreover, conditional on changing occupations, college graduates switch to occupations similar to their prior ones. Besides that, the education gap narrows with potential experience for each outcome except skill distance in occupational switches. Overall, these results align with descriptive patterns.

Table A10: Regression Results in the CPS

	(1)	(2)	(3)	(4)
Panel A: Unemployed Indicator				
College	-0.03844***	-0.03853***	-0.03785***	-0.02996***
College × PotExp	0.00131***	0.00132***	0.00133***	0.00127***
Observations	16,974,803	16,974,803	16,974,803	13,435,791
R^2	0.036	0.038	0.044	0.065
Panel B: Job Finding Indicator				
College	0.01766***	0.02213***	0.02219***	0.01271***
College × PotExp	-0.00182***	-0.00198***	-0.00205***	-0.00191***
Observations	494,820	494,820	494,820	404,061
R^2	0.018	0.023	0.041	0.045
Panel C: Job Separation Indicator				
College	-0.01540***	-0.01531***	-0.01495***	-0.01302***
College × PotExp	0.00053***	0.00053***	0.00054***	0.00051***
Observations	9,976,616	9,976,616	9,976,616	8,077,115
R^2	0.013	0.014	0.015	0.017
Panel D: Occupational Mobility Indicator				
College	-0.01802***	-0.01798***	-0.01841***	-0.01730***
College × PotExp	0.00068***	0.00067***	0.00068***	0.00068***
Observations	846,570	846,570	846,570	796,683
R^2	0.007	0.008	0.008	0.010
Panel E: Career Mobility Indicator				
College	-0.01374***	-0.01379***	-0.01446***	-0.01360***
College × PotExp	0.00042***	0.00042***	0.00042***	0.00043***
Observations	841,141	841,141	841,141	791,552
R^2	0.007	0.007	0.008	0.009
Panel F: Standardized Angular Distance in Occupation Switches				
College	-0.18468***	-0.18084***	-0.18034***	-0.16404***
College × PotExp	-0.00240**	-0.00257**	-0.00264**	-0.00237**
Observations	28,696	28,696	28,696	26,309
R^2	0.080	0.082	0.084	0.086
State FE		✓	✓	✓
Year FE			✓	✓
Month FE			✓	✓

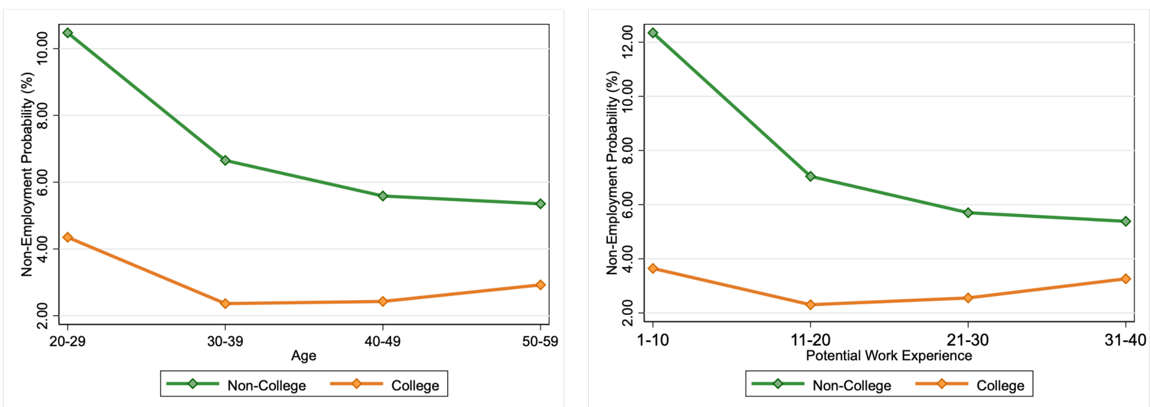
Notes: All specifications control for industry and occupation fixed effects, where industry and occupational codes for the unemployed are their last job. Standard errors are robust to heteroskedasticity. The last column additionally controls for family income. Levels of statistical significance are indicated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

A.4.4 Life Cycle Pattern of Non-Employment

This section complements our evidence on the unemployment-education gap with the non-employment gap by education, as prolonged unemployment spells may drive workers out of the labor force, particularly non-college workers who experience unemployment spells more frequently than college workers. We construct the non-employment gap using both unemployed workers and discouraged workers who leave the labor force.

To identify discouraged workers, we utilize the variable *WNLOOK* in the CPS, which records why individuals who want a job did not search for work in the prior four weeks. We classify individuals as discouraged if they report any of the following: a belief that no work is available in their area of expertise, an inability to find any work, a lack of necessary schooling or training, perceived age discrimination, or other forms of discrimination.

As illustrated in Figure A9, college workers exhibit a persistently lower probability of non-employment. This educational gap, however, narrows with age and potential experience, a pattern that echoes the life cycle profile of the unemployment rate.



(a) Age (b) Potential Experience

Figure A9: Education Gap in Non-Employment. *Note*: Constructed using CPS sample.

To assess the robustness of descriptive patterns, we estimate the specification in (A.34) with the outcome variable being an indicator of whether worker i in period t is non-employed instead. Table A11 shows a pattern identical to the pattern in Figure A9.

A.5 NLSY79 Patterns

A.5.1 Replicative Patterns

In this section, we replicate CPS patterns using the NLSY79, and display the results in Table A12.

Table A11: Life Cycle Pattern of Non-Employment by Educational Attainment

	(1)	(2)	(3)	(4)
College	-0.03857***	-0.03866***	-0.03800***	-0.03013***
College × PotExp	0.00131***	0.00133***	0.00133***	0.00128***
Observations	16,979,302	16,979,302	16,979,302	13,439,722
R^2	0.037	0.039	0.044	0.065
State FE		✓	✓	✓
Year FE			✓	✓
Month FE			✓	✓

Notes: All specifications control for industry and occupation fixed effects, with unemployed workers coded by their last job. Standard errors are robust to heteroskedasticity. The last column additionally controls for family income. Levels of statistical significance are indicated by *($p < 0.10$), **($p < 0.05$), ***($p < 0.01$).

Panel A shows the unemployment rate by age/potential experience and education. Patterns align with the CPS: the U-E gap narrows over the life cycle. Notably, the unemployment rate rises in later career stages, which is plausible given that about 90% of NLSY79 respondents were aged 40-49 and 10% aged 50-59 during the Great Recession.

Panels B and C present the job finding and separation probabilities by age/potential experience and education. Job finding probabilities show no systematic difference between education groups, especially over potential work experience. Consistent with CPS patterns, college workers have systematically lower separation probabilities, with the gap widest in early career stages and gradually narrowing with age or work experience.

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 to month pairs with valid occupational codes. If the worker was non-employed in the prior month, we identify the occupation preceding the non-employment. Panel D shows that occupational mobility patterns in the NLSY79 align with those in the CPS: occupational mobility decreases with age/potential experience and educational attainment.

Panel E shows the average angular distance in occupation switches. Consistent with the CPS pattern, workers with higher educational attainment switch among similar occupations at each career stage.

To measure career mobility in the NLSY79, we first identify a threshold, $\bar{\phi}$, among $36,286$ occupational transitions, where skill requirements and task intensities are available for both current and previous occupations. We find that setting $\bar{\phi} = 23.1290$ yields an average correlation of 2.17E−06 across occupational attributes among transitions. A career switch is thus defined as an occupational transition where the angular distance exceeds the threshold, i.e., $\phi \geq 23.1290$.

Panel F shows that career mobility decreases with both age/potential experience and educational attainment, and the gap across education groups narrows over the life cycle.

Table A12: NLSY79 Life-Cycle Pattern, by Educational Attainment

	Age	Work Experience
Panel A: Unemployment Rate (%)		
Non-College	[9.69, 4.96, 5.44, 5.48]	[10.83, 5.35, 5.11, 5.85]
College	[3.10, 1.50, 1.88, 2.48]	[2.58, 1.47, 2.05, 2.78]
Panel B: Job Finding Probability (%)		
Non-College	[19.72, 16.30, 9.69, 7.81]	[19.46, 17.54, 10.39, 7.75]
College	[25.24, 19.78, 11.29, 10.64]	[22.84, 16.94, 10.98, 9.81]
Panel C: Job Separation Probability (%)		
Non-College	[1.82, 0.80, 0.54, 0.38]	[2.02, 0.92, 0.56, 0.42]
College	[0.59, 0.25, 0.21, 0.23]	[0.48, 0.22, 0.23, 0.23]
Panel D: Occupation Transition Probability (%)		
Non-College	[6.42, 3.32, 1.50, 1.04]	[6.72, 3.83, 1.65, 1.07]
College	[5.63, 2.69, 1.22, 0.96]	[4.88, 2.01, 1.08, 1.01]
Panel E: Angular Distance in Occupational Transitions		
Non-College	[29.20, 28.67, 27.43, 28.37]	[29.41, 28.62, 27.60, 28.43]
College	[25.22, 23.11, 20.95, 22.85]	[24.87, 21.98, 21.92, 22.84]
Panel F: Career Mobility (%)		
Non-College	[3.81, 1.91, 0.83, 0.60]	[4.03, 2.19, 0.91, 0.62]
College	[2.70, 1.10, 0.40, 0.40]	[2.26, 0.75, 0.40, 0.44]

Notes: Age bins are 20–29, 30–39, 40–49, and 50–59; work experience bins are 1–10, 11–20, 21–30, and 31–40. All data are drawn from the NLSY79.

A.5.2 Robustness of NLSY79 Results

This section examines the robustness of the NLSY79 patterns by extending the specification in (A.34) to control for parental occupation (*ParentOcc*), as occupational inheritance may affect employment stability through parental networking ties. *ParentOcc* is measured in two ways: at the individual level, it equals one if the worker has ever held a job identical to a parent's; 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, except with an additional focus on skill mismatch.

Table A13 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 lower probabilities of unemployment, separating from employment, switching occupations or careers. Moreover, college workers have lower 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 the educational gap in our outcomes of interest generally narrows with work experience, but not for switching distance in occupational transitions.

Table A13: NLSY79 Regression Results

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Unemployed Indicator						
College	-0.03964***	-0.04008***	-0.02441***	-0.01150***	-0.02447***	-0.02334***
College × PotExp	0.00138***	0.00141***	0.00073***	0.00044***	0.00073***	0.00069***
Observations	1,169,170	1,159,737	1,159,737	980,839	1,159,737	1,154,813
R^2	0.056	0.057	0.062	0.124	0.062	0.061
Panel B: Job Finding Indicator						
College	0.03890***	0.03742**	0.02949*	0.04395**	0.03163**	0.03071*
College × PotExp	-0.00148**	-0.00143**	-0.00080	-0.00178**	-0.00083	-0.00081
Observations	77,306	76,590	76,590	58,337	76,590	74,564
R^2	0.043	0.043	0.051	0.069	0.051	0.051
Panel C: Job Separation Indicator						
College	-0.01602***	-0.01603***	-0.01187***	-0.00992***	-0.01186***	-0.01126***
College × PotExp	0.00067***	0.00067***	0.00049***	0.00042***	0.00049***	0.00047***
Observations	1,087,936	1,079,258	1,079,258	919,270	1,079,258	1,076,373
R^2	0.012	0.012	0.014	0.017	0.014	0.013
Panel D: Occupational Mobility Indicator						
College	-0.02234***	-0.02209***	-0.01551***	-0.01263***	-0.01544***	-0.01546***
College × PotExp	0.00076***	0.00076***	0.00065***	0.00057***	0.00065***	0.00066***
Observations	1,079,557	1,070,998	1,070,998	913,232	1,070,998	1,070,998
R^2	0.020	0.020	0.026	0.028	0.026	0.026
Panel E: Career Mobility Indicator						
College	-0.01925***	-0.01920***	-0.01584***	-0.01385***	-0.01578***	-0.01581***
College × PotExp	0.00067***	0.00067***	0.00060***	0.00055***	0.00060***	0.00060***

Observations	1,079,551	1,070,992	1,070,992	913,228	1,070,992	1,070,992
R^2	0.015	0.015	0.018	0.019	0.018	0.018
Panel F: Angular Distance in Occupational Switches						
College	-2.85712***	-2.98946***	-3.04405***	-2.99453***	-3.03753***	-3.04155***
College × PotExp	-0.04057*	-0.04032*	-0.03963	-0.02455	-0.03985	-0.03951
Observations	35,918	35,687	35,687	29,175	35,687	35,687
R^2	0.194	0.194	0.197	0.202	0.197	0.197
Panel G: Skill Mismatch						
College	-0.16545***	-0.17350***	-0.21084***	-0.20479***	-0.21071***	-0.20994***
College × PotExp	-0.00093***	-0.00063***	0.00108***	0.00206***	0.00108***	0.00111***
Observations	1,088,371	1,079,739	1,079,739	920,138	1,079,739	1,079,739
R^2	0.167	0.165	0.166	0.178	0.166	0.167
State FE		✓	✓	✓	✓	✓
Year FE			✓	✓	✓	✓
Month FE			✓	✓	✓	✓

Notes: All specifications control for industry and occupation fixed effects, with unemployed workers coded by their last job. The fourth column controls for family income, while the last two columns additionally control for the intergenerational occupational following. Standard errors are robust to heteroskedasticity. 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:

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

where Survival_{it} indicates whether the match survives to the next period. We flexibly capture the duration dependence in the survival probability by introducing an additive dummy variable corresponding to each monthly duration, denoted by Dur_{it}. We also control for white race, age, and year, season, and industry fixed effects. The main explanatory variables are experience the worker had accumulated at the match formation (Exp_{it}), and its interaction with education attainment ($\text{Exp}_{it} * \text{College}_i$).[48]

Table A14 shows that prior experience is associated with a higher survival probability,

[48] Exp_{it} is either a binary variable indicating prior working experience longer than 77 months (the median among 1,083,414 employment observations) or prior working experience in months.

and that effect dissipates with tenure. In addition, $\beta_3 < 0$ suggests that the association between experience and the survival probability is weaker for college workers.

Table A14: Prior Experience and Match Survival

	(1)	(2)	(3)
Panel A: Experience > 77 Months Indicator			
Exp	0.01694***	0.00206	0.01148***
Log(Dur) * Exp	-0.00181***	-0.00102***	-0.00271***
Exp * College		-0.00544***	-0.00534***
Log(Dur) * College		-0.00632***	-0.00563***
Observations	1,036,382	1,036,382	990,969
R^2	0.016	0.022	0.020
Panel B: Months of Prior Experience			
Exp	0.00010***	0.00003***	0.00007***
Log(Dur) × Exp	-0.00001***	-0.00001***	-0.00002***
Exp × College		-0.00004***	-0.00004***
Log(Dur) * College		-0.00657***	-0.00577***
Observations	1,036,382	1,036,382	990,969
R^2	0.016	0.022	0.020
Year FE		✓	✓
Season FE		✓	✓
1990dd Industry FE			✓

Notes: The second and third specifications include the interaction between Log(Dur) and College, and White. 1990dd are industry fixed effects according to the industrial classification scheme compiled by Autor et al. (2019). Standard errors are robust to heteroskedasticity. Levels of statistical significance are indicated by *($p < 0.10$), **($p < 0.05$), ***($p < 0.01$).

A.7 Unemployable Workers

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

Table A15 shows that removing the unemployable workers shifts down the unemployment and separation probabilities for non-college workers, while making little difference in the job finding probability. Overall, the gaps in unemployment and separations persist and narrow with age after excluding unemployable workers.

Table A15: Life Cycle Patterns Excluding Unemployable Workers

	Age	Work Experience
Panel A: Unemployment Rate (%)		
Non-College	[9.69, 4.96, 5.44, 5.48]	[10.83, 5.35, 5.11, 5.85]
Non-College Excluding Unemployable	[7.17, 4.26, 4.96, 5.16]	[8.01, 4.48, 4.61, 5.50]
College	[3.10, 1.50, 1.88, 2.48]	[2.58, 1.47, 2.05, 2.78]
Panel B: Job Finding Probability (%)		
Non-College	[19.72, 16.30, 9.69, 7.81]	[19.46, 17.54, 10.39, 7.75]
Non-College Excluding Unemployable	[18.04, 15.80, 9.80, 7.73]	[17.81, 16.86, 10.30, 7.71]
College	[25.24, 19.78, 11.29, 10.64]	[22.84, 16.94, 10.98, 9.81]
Panel C: Job Separation Probability (%)		
Non-College	[1.82, 0.80, 0.54, 0.38]	[2.02, 0.92, 0.56, 0.42]
Non-College Excluding Unemployable	[1.11, 0.66, 0.49, 0.35]	[1.21, 0.74, 0.50, 0.38]
College	[0.59, 0.25, 0.21, 0.23]	[0.48, 0.22, 0.23, 0.23]

Notes: Age bins are 20–29, 30–39, 40–49, and 50–59; work experience bins are 1–10, 11–20, 21–30, and 31–40. An unemployable non-college worker is defined as one who experiences at least four transitions from employment to unemployment in their first ten years of potential experience. All data are drawn from the NLSY79.

A.8 Sampled Jobs and Match Survival

This section presents the complete estimation for the association between sampled jobs and match survival, following specification (2). As shown in Table A16, learning from prior working experience, whether through sampled occupations or careers, is always associated with a higher survival probability for the current occupation or career. Notably, this effect is more pronounced for non-college workers.

A.9 More Details on Anticipated Occupations

As noted in the main text, only a modest share of our NLSY79 sample has valid forecast error (FCE) measures. Calculating FCE requires both an expected occupation and a realized occupation at age 35 or five years after the initial interview. While 86% of the 4,695 respondents reported expected occupations, a substantial portion lacks realized occupation data at the relevant point.

Table A16: Sampled Jobs and Survival Probability of Occupation/Career Matches

	Sampled Occupations			Sampled Careers	
	Non-College	College		Non-College	College
Sampled Occ.=1	0.00641***	0.00204**	Sampled Career=1	0.00799***	0.00388***
Sampled Occ.=2	0.00838***	0.00349***	Sampled Career=2	0.01326***	0.00606***
Sampled Occ.=3	0.01294***	0.00440***	Sampled Career=3	0.01908***	0.00760***
Sampled Occ.=4	0.01688***	0.00581***	Sampled Career=4	0.02352***	0.01052***
Sampled Occ.=5	0.01965***	0.00680***	Sampled Career=5	0.02619***	0.01275***
Sampled Occ.=6	0.02304***	0.00660***	Sampled Career=6	0.02951***	0.01457***
Sampled Occ.=7	0.02588***	0.00801***	Sampled Career=7	0.03360***	0.01635***
Sampled Occ.=8	0.02811***	0.00944***	Sampled Career=8	0.03546***	0.01811***
Sampled Occ.=9	0.03051***	0.01080***	Sampled Career=9	0.03769***	0.01951***
Sampled Occ.=10	0.03295***	0.01241***	Sampled Career=10	0.04142***	0.00969*
Sampled Occ.=11	0.03637***	0.01245***			
Sampled Occ.=12	0.03813***	0.01359***			
Sampled Occ.=13	0.03944***	0.01541***			
Sampled Occ.=14	0.04316***	0.01519***			
Sampled Occ.=15	0.04550***	0.01175***			
Tenure	0.00005***	0.00002***	Tenure	0.00006***	0.00002***
Exp	-0.00006***	-0.00002***	Exp	-0.00004***	-0.00002***
Observations	703,539	240,721	Observations	779,203	248,417
R^2	0.034	0.015	R^2	0.028	0.015

Notes: The dependent variable in the left panel is an indicator for whether the worker remains employed in the same occupation or becomes unemployed, and in the right panel it is the same indicator defined at the career level. The tenure variable in the left panel is the worker's cumulative experience in their current occupation, and in the right panel it is cumulative experience in their current career. All specifications control for individual fixed effects. Standard errors are robust to heteroskedasticity. Levels of statistical significance are indicated by *($p < 0.10$), **($p < 0.05$), ***($p < 0.01$).

To address concerns that the educational gap in forecast errors is driven by selection, we compare respondents with valid and non-valid age 35 forecast errors across observable characteristics in Table A17. Comparisons show that non-college workers with a valid forecast error resemble those without, and the same holds for college workers. Further, Table A18 compares those who listed an expected occupation to those who did not. Likewise, workers with missing expected occupations resemble those with valid ones within each education group. For both education groups, individuals with higher wages and abilities are more likely to both list an expected occupation and have a valid FCE.

Another concern is that the educational gap in forecast errors may reflect aspirational bias rather than genuine uncertainty about comparative advantage. All workers may optimistically expect to enter prestigious, well-regarded occupations, but non-college work-

Table A17: Observable Characteristics by FCE Validity at 35 years old and College Status

	College		Non-College	
	Valid	Non-Valid	Valid	Non-Valid
Race (%)	11, 18, 71	8, 16, 76	21, 30, 49	15, 25, 60
% with at least one child	77.78	58.89	77.62	59.19
Ability: verbal	0.76	0.75	0.44	0.41
Ability: math	0.79	0.77	0.43	0.41
Ability: social	0.64	0.63	0.47	0.45
Skill required: verbal	0.73	0.72	0.44	0.40
Skill required: math	0.69	0.68	0.45	0.41
Skill required: social	0.73	0.72	0.44	0.40
Skill required: routine	0.40	0.40	0.55	0.55
Skill required: manual	0.34	0.38	0.57	0.56
Mismatch	1.39	1.39	1.61	1.61
Hourly wage	31.14	29.41	13.21	6.38
Unemployed probability	0.02	0.03	0.06	0.10

Notes: Those with a valid FCE are respondents who both listed an expected occupation at age 35 and had at least one observed occupation at age 35. Race is the percentages who are Hispanic, Black, and non-Hispanic and non-Black, respectively. Ability, skill requirements, and mismatch measures are detailed in Appendix A.3.3.

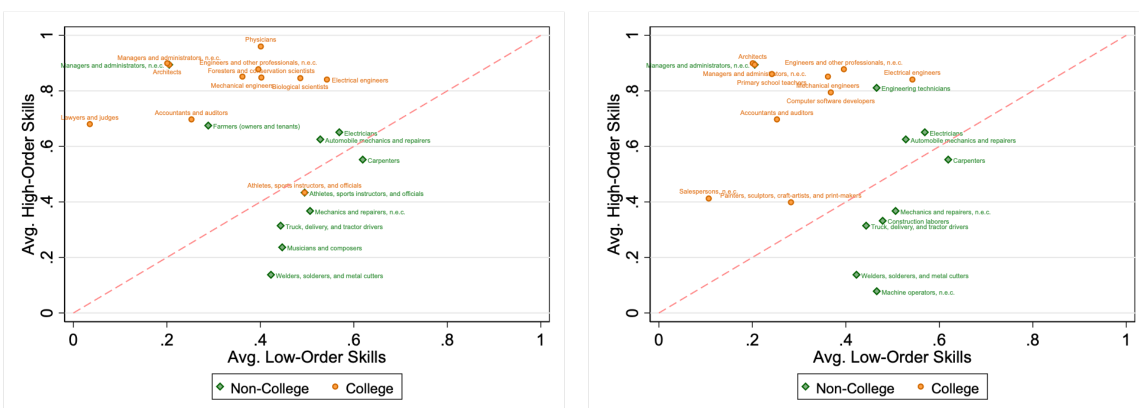
ers are less likely to actually secure positions that typically require college credentials, resulting in their larger forecast errors. Figure A10 displays the most frequently anticipated occupations at age 35 or in 5 years by education. The x-axis shows average low-order skill requirements (routine and manual) of these anticipated occupations, while the y-axis shows average high-order skills (verbal, math, and social). A clear distinction emerges. College workers tend to anticipate working in high-skill occupations (e.g., lawyers, judges, physicians, electrical engineers, biological scientists), while non-college workers expect low-skill jobs (e.g., automobile mechanics, repairers, truck drivers, carpenters). This pattern holds both at age 35 and 5-year expectation, indicating that education differences in forecast errors are not driven by common occupational aspirations.

Beyond that, college workers tend to anticipate occupations with higher dispersion in skill requirements. As shown in Table A19, 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- or long-term. This aligns with the intuition that workers would anticipate an occupation that has balanced skill requirements if

Table A18: Observable Characteristics by Expected Occupation Validity at Age 35 and College Status

	College		Non-College	
	Valid	Non-Valid	Valid	Non-Valid
Race (%)	11, 17, 72	5, 16, 79	18, 27, 55	21, 27, 52
% with at least one child	69	73	69	69
Ability: verbal	0.76	0.77	0.43	0.38
Ability: math	0.78	0.78	0.42	0.39
Ability: social	0.64	0.58	0.47	0.43
Skill required: verbal	0.73	0.69	0.42	0.41
Skill required: math	0.69	0.67	0.43	0.42
Skill required: social	0.73	0.69	0.43	0.41
Skill required: routine	0.40	0.42	0.55	0.55
Skill required: manual	0.36	0.37	0.56	0.57
Mismatch	1.39	1.46	1.61	1.58
Hourly wage	31.02	24.36	10.36	8.24
Unemployed probability	0.02	0.02	0.08	0.08
No. Respondents	967	103	3,067	558

Notes: Race is the percentages who are Hispanic, Black, and non-Hispanic and non-Black, respectively. Ability, skill requirements, and mismatch measures are detailed in Appendix A.3.3.



(a) At Age 35

(b) In 5 Years

Figure A10: Most Common Anticipated Occupations. *Note*: Constructed using NLSY79 sample.

they are not sure of their own skills. Conversely, an individual who knows they have, for example, high math skills may anticipate working in an occupation with relatively high math requirements.

Table A19: Skill Dispersion in Expected Occupation

	Variance	Max-Min	Mean Deviation	Median Deviation
Panel A: Expected Occupation at Age 35				
Non-College	0.062	0.637	0.212	0.188
College	0.070	0.653	0.229	0.206
Panel B: Expected Occupation in 5 Years				
Non-College	0.057	0.617	0.201	0.178
College	0.072	0.679	0.232	0.206

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 0.05. Formulas for each measure of dispersion are provided in Appendix A.3.4.

A.9.1 Decomposition of the Euclidean Distance

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

$$\|\mathbf{s}_i\|^2 + \|\hat{\mathbf{s}}_i\|^2 - 2\|\mathbf{s}_i\|\|\hat{\mathbf{s}}_i\|\cos(\phi) = \psi^2. \tag{A.35}$$

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

$$\underbrace{\frac{(\|\mathbf{s}_i\| - \|\hat{\mathbf{s}}_i\|)^2}{\psi^2}}_{\text{Diff. in Skill Magnitude}} + \underbrace{\frac{2\|\mathbf{s}_i\|\|\hat{\mathbf{s}}_i\|(1-\cos(\phi))}{\psi^2}}_{\text{Diff. in Cosine Similarity}} = 1. \tag{A.36}$$

From (A.36), the first term captures the contribution of skill magnitude to the Euclidean distance between vectors, while the second is driven by the angular distance.

A.10 Associate's Degree and College Dropouts

An associate's degree (AA) provides vocational training that equips individuals with specific skills or prepares them for particular careers. It offers workers greater certainty about their comparative advantage, but with shorter schooling than a four-year college.

In Table A20 Panel A, we compare employment stability across three groups: non-college workers without AA, AA holders, and college workers in the CPS (patterns are similar in the NLSY79). Notably, the separation probability among AA graduates is lower than that of those without an AA but slightly higher than that of 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 completed at least two years of college and accounts for nearly 59% of the 766 college dropouts.[49] Table A20 Panel B presents the unemployment rate and separation probability over the life cycle. College dropouts are more likely to be unemployed than graduates, and within college dropouts, more years of completed schooling are associated with a lower unemployment rate. Similarly, the job separation probability decreases with years of college completed.

Table A20: Associate's Degrees and College Dropouts

	Unemployment Rate (%)	Separation Prob. (%)
Panel A: Associate's Degree, CPS		
Non-College	[10.13, 6.51, 5.56, 5.18]	[3.48, 2.20, 1.79, 1.48]
Associate's Degree	[5.57, 3.93, 3.72, 4.08]	[1.89, 1.83, 1.12, 1.10]
College	[4.34, 2.33, 2.42, 2.88]	[1.24, 0.72, 0.62, 0.70]
Panel B: College Dropouts, NLSY79		
College Dropouts	[6.70, 3.79, 4.37, 3.87]	[1.31, 0.60, 0.49, 0.34]
Less-Educated Dropouts	[8.52, 5.44, 5.24, 4.02]	[1.63, 0.81, 0.56, 0.36]
More-Educated Dropouts	[5.47, 3.15, 4.17, 4.10]	[1.18, 0.52, 0.48, 0.35]
College Graduates	[3.10, 1.50, 1.88, 2.48]	[0.59, 0.25, 0.21, 0.23]

Notes: This table reports the profile across age bins (20–29, 30–39, 40–49, 50–59). "Prob." refers to probability. Panel A uses the CPS between 1992 and 2019, while Panel B uses the NLSY79 sample.

A.11 Career Switches Through Employment and Non-employment

Data on separation reasons in the NLSY79 are available from two sources: the *job number records*, which provide information on why a respondent left each job reported in a given survey year (typically covering at most five jobs annually), and the *employer roster records*, which tracks separation reasons for each unique employer ID ever associated with the respondent across the entire survey. Using each source, we categorize all separations into three mutually exclusive groups: involuntary separations, voluntary separations for non-occupational reasons, and voluntary separations for occupation-related reasons. Original separation reasons and our categorization can be found in Table A21.

[49] 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 54.83%, close to the 54% reported by Vardishvili (2024).

Table A21: Definition of Voluntary and Involuntary Separations in the NLSY79

Separation Category	Definition	Original Reported Separation Reasons
Involuntary Separations	A termination that occurs independently of the worker's own initiative or willingness to leave the prior employer.	• Layoff • Plant Closed • End Of Temporary or Seasonal Job • Discharged or Fired • Program Ended or Job Ended • Government Program Ended • Went to Jail or Prison, Had Legal Problems • Business Failed or Bankruptcy • Business Temporarily Inactive • Closed Business Down or Dissolved Partnership • Sub-Par Qualifications
Voluntary Separations for Non-Occupation Reasons	Worker-initiated separations driven by personal or exogenous factors, including health, family, schooling, or relocation.	• Quit Due to Own Illness, Disability • Quit Because Interfered with School • Quit To Enter Armed Forces • Pregnancy • Husband or Wife Changed Jobs and/or Moved • Mother/Father Changed Jobs and/or Moved • Family Reasons (to Get Married, to Care for Children, Illness of Other Family Members) • Quit for pregnancy or family reasons • Quit for pregnancy, childbirth or adoption of a child • Moved to another geographic area • Quit to spend time with or take care of children, spouse, parents, or other family members • Quit to attend school or training • Transportation problems • Retired
Voluntary Separations for Occupation Reasons	Worker-initiated separations motivated by job-related factors.	• Quit Because Found Better Job • Quit Because of Employment Conditions (Didn't Like Work, Hours, Working Conditions, or Location, Didn't Get Along with Other Employees or Boss) • Quit Because Wages Too Low • Quit to Look for Another Job • Quit to Take Another Job • No desirable assignments available • Job assigned through a temporary help agency or a contract firm became permanent • Dissatisfied with job matching service • Quit because didn't like job, boss, coworkers, pay or benefits • Sold business to another person or firm • Other

By combining identified career switches with reported separation reasons, we can distinguish the group of career switches into involuntary career switches, voluntary career switches for non-occupational reasons, and voluntary career switches for occupational reasons. The third category most closely represents endogenous separations in the model. Consequently, we calculate the respective fraction of career switches that occur through a job-to-job transition and those involving intervening periods of non-employment among the voluntary switches for occupation-related reasons.

Table A22: Breakdown of Career Switches

	W/ Intervening Non-Employment	W/O Intervening Non-Employment
Panel A: Classification Using Job Number Records		
Pooled Sample	2,453 (48.92%)	2,561 (51.08%)
Non-College	2,216 (50.05%)	2,212 (49.95%)
College	237 (40.44%)	349 (59.56%)
Panel B: Classification Using Employer Roster Records		
Pooled Sample	2,503 (48.91%)	2,615 (51.09%)
Non-College	2,260 (50.09%)	2,252 (49.91%)
College	243 (40.10%)	363 (59.90%)

Notes: This table reports the number and share of voluntary career switches for occupation-related reasons that occur through a job-to-job transition versus those involving an intervening period of non-employment. Panel A uses the job number records, and Panel B uses the employer roster records.

As indicated in Table A22, about 50% of career switches among non-college workers occur without an intervening period of non-employment; for college workers, this figure rises to roughly 60%. These results are almost identical regardless of which source of separation reasons is used for identification.

A.12 Occupation-Specific Returns

This section examines the extent to which workers sample high-return occupations first. To do so, we estimate the average wage returns and separation probabilities for each occupation, and then examine the distribution of first sampled occupations within each level of educational attainment.

To measure the expected payoff, we first estimate:

$$Y_{it} = i.Occ2 + \beta_1 Potexp_{it} + \beta_2 Potexp_{it}^2 + Race_i + MarStatus_{it} + Child_{it} + \Phi_{Ind2} + \Phi_{Region} + \Phi_{Year} + \Phi_{Month} + \epsilon_{it}. \tag{A.37}$$

From (A.37), Y_{it} denotes either the log hourly wage or a binary indicator for separating into unemployment for individual i in month t. We additionally control for a quadratic in potential experience, race, marital status, childbearing status, as well as industry, region, year, and month fixed effects. Finally, $i.Occ2$ is a fixed effect at the two-digit occupation group in the Occ1990dd classification.

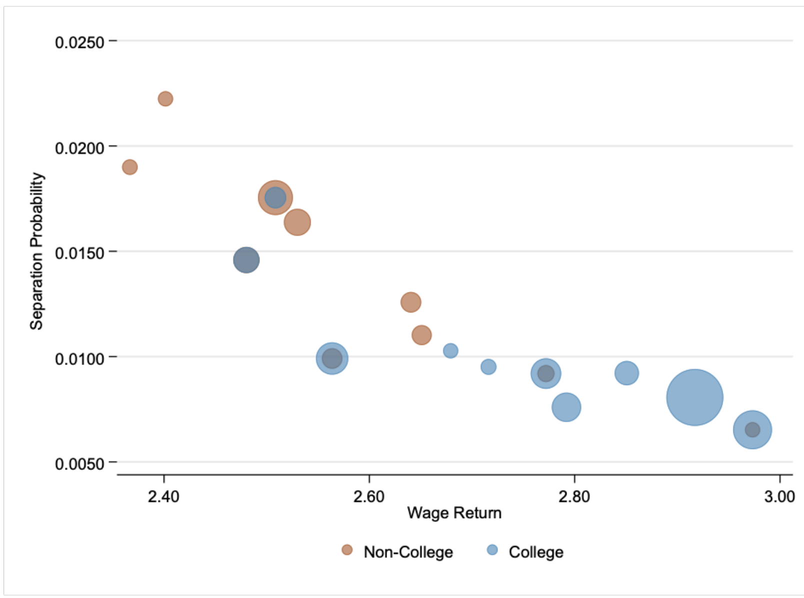


Figure A11: Wage Return and Separation Probability among First Sampled Occupations. *Source*: NLSY79.

After estimating (A.37), we then compute the average wage and separation probability for each of the 17 two-digit occupations, holding all other covariates at their respective sample means. Figure A11 illustrates the distribution of the first sampled occupation within the space of estimated wage returns and separation probabilities, where marker sizes are proportional to the number of workers in each occupation.[50]

There are a few takeaways from Figure A11. First, there is substantial dispersion in the first occupations sampled. Or, in other words, we do not observe workers systematically sampling occupations with higher wages and/or lower separation risk first. This supports the notion that idiosyncratic match quality between workers and specific occupations is a key driver of which occupation a worker samples first. Second, there is a

[50]For brevity, we present the distribution for the ten most common first occupations; the observed patterns are robust to the inclusion of all first-sampled occupations.

distinction in the types of occupations sampled by educational attainment: non-college occupations are clustered in the upper-left of the graph, while occupations typically sampled by college workers are concentrated in the lower-right quadrant. This systematic difference motivates the education-specific parameters in output at the best fit, y_e, and separation probabilities $\delta_e(b)$ and $\delta_e(g)$.

A.13 Occupation Codes

Table A23 displays the first- and second-level occupation categories following the occupation scheme developed by Autor and Dorn (2013) and is originally presented as part of Appendix Table 2 in Dorn (2009).

Table A23: Occ1990dd Occupation Categories

First-Level Code	First-Level Occupation Title	Second-Level Code	Second-Level Occupation Title
A.1	Executive, Administrative, and Managerial Occupations	A	Managerial and Professional Specialty Occupations
A.2	Management Related Occupations		
A.3	Professional Specialty Occupations		
B.1	Technicians and Related Support Occupations	B	Technical, Sales, and Administrative Support Occupations
B.2	Sales Occupations		
B.3	Administrative Support Occupations		
C.1	Housekeeping and Cleaning Occupations	C	Service Occupations
C.2	Protective Service Occupations		
C.3	Other Service Occupations		
D.1	Farm Operators and Managers	D	Farming, Forestry, and Fishing Occupations
D.2	Other Agricultural and Related Occupations		
E.1	Mechanics and Repairers	E	Precision Production, Craft, and Repair Occupations
E.2	Construction Trades		
E.3	Extractive Occupations		
E.4	Precision Production Occupations		
F.1	Machine Operators, Assemblers, and Inspectors	F	Operators, Fabricators, and Laborers
F.2	Transportation and Material Moving Occupations		

A.14 Robustness of Oaxaca-Blinder Decomposition

For robustness, we decompose the educational gap in forecast error in terms of the distance between the expected occupation at age 35 and their realized occupations during ages 30 to 40. Table A24 presents the results.

Table A24: Oaxaca-Blinder Decomposition of Mean Forecast Errors by Education

	Euclidean	Angular
Differential:		
Non-College	0.088***	0.078***
College	-0.394***	-0.418***
Difference	0.482***	0.495***
Explained by:		
College Years	0.077***	0.056***
Good Learners	0.024	0.097***
Family Background	0.059***	0.065***
Others	0.011	0.005
Total	0.171***	0.223***
Observations	2156	2156

Notes: Results are based on a twofold Oaxaca-Blinder decomposition. The outcome variable to be decomposed is the education gap in the standardized Euclidean or angular distance between an individual's expected occupation at age 35 and their realized occupations during ages 30 to 40. The *Differential* represents the mean forecast error gap between the college and the non-college. The *Explained by* component measures the portion of the gap attributable to compositional differences in covariates. Levels of statistical significance are indicated by *($p < 0.10$), **($p < 0.05$), ***($p < 0.01$).

B Theory Appendix

B.1 Laws of Motion

Let $u_{a,e}(s,i)$ 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 status s. Further, $n_{a,e}(s,i)$ is the measure of workers employed in a career with status s. A "+" superscript denotes the measures in the next time period.

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

$$u_{y,e}(un,i)^{+} = \begin{cases} \lambda_{\text{new}}\mu_e + (1-\lambda_o)\left[(1-f^*)u_{y,e}(un,i) + (1-\phi_e)\delta_e(un,i)n_{y,e}(un,i)\right] & \text{for} \quad i=0, \\ (1-\lambda_o)\left[(1-f^*)(u_{y,e}(un,i) + l^* u_{y,e}(b,i)) + (1-\phi_e)\delta_e(un,i)n_{y,e}(un,i)\right] & \text{for} \quad i=1,\ldots,N_e-2, \end{cases} \tag{B.1}$$

where f^* and $l^* \in \{0,1\}$ represent the job finding probability and decision to leave a career. For brevity, we suppress the arguments (a,e,s,i) from the policy functions. Starting with the first line of (B.1), the first term represents newborn workers, who can not be hit with an aging shock in the same period in which they enter the labor market. The second term is 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.

The law of motion for young, unemployed workers with a good career fit is

$$u_{y,e}(g,i)^{+} = \begin{cases} (1-\lambda_o)\left[(1-f^*)u_{y,e}(g,i) + \delta_e(g)[n_{y,e}(g,i) + \phi_e n_{y,e}(un,i)p_e(i)]\right] & \text{for} \quad i=0,\ldots,N_e-2, \\ (1-\lambda_o)\left[(1-f^*)(u_{y,e}(g,i) + l^* u_{y,e}(b,i)) + \delta_e(g)[n_{y,e}(g,i) + \phi_e n_{y,e}(un,i)p_e(i)]\right] & \text{for} \quad i=N_e-1. \end{cases} \tag{B.2}$$

The first case in (B.2) captures unemployed workers with a known good career fit who do not find a job. The second term captures employed workers with a known good fit who lose their job, and those with an unsure fit who learn that they are in a good fit during the learning stage and separate in the subsequent separation stage. The difference in the second case is that the pool of unemployed workers includes those in a known bad fit with history $i = N_e - 1$ who switch careers, as these workers have learned all of their bad fits and, by process of elimination, have identified their good fit.

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

$$
n_{y,e}(un,i)^{+} = \begin{cases} (1-\lambda_o)\left[f^* u_{y,e}(un,i) + (1-\phi_e)(1-\delta_e(un,i))n_{y,e}(un,i)\right] & \text{for} \quad i=0, \\ (1-\lambda_o)\left[f^*(u_{y,e}(un,i) + l^* u_{y,e}(b,i)) + (1-\phi_e)(1-\delta_e(un,i))n_{y,e}(un,i) \right. & \\ \qquad \left. + \phi_e(1-p_e(0))d^*\gamma_e n_{y,e}(un,0)\pi_e(0,0)\right] & \text{for} \quad i=1, \\ (1-\lambda_o)\left[f^*(u_{y,e}(un,i) + l^* u_{y,e}(b,i)) + (1-\phi_e)(1-\delta_e(un,i))n_{y,e}(un,i) \right. & \\ \qquad \left. + \phi_e\gamma_e \sum_{j=0}^{i-1}(1-p_e(j))d^*\pi_e(j,i-j-1)n_{y,e}(un,j)\right] & \text{for} \quad i=2,\ldots,N_e-2, \end{cases} \tag{B.3}
$$

where $d^* \in \{0,1\}$ is the policy function that captures where a separation is initiated or not. Equation (B.3) 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. Further, the last term for the cases of $i = 1,\ldots,N_e - 2$ captures the workers with history $j < i$ who learn they are in a bad fit, draw a spillover η such that their updated history is i, and transition careers without entering unemployment.

Next, we have the law of motion for young workers employed in a good fit:

$$
n_{y,e}(g,i)^{+} = \begin{cases} (1-\lambda_o)\left[f^* u_{y,e}(g,i) + (1-\delta_e(g))[n_{y,e}(g,i) + \phi_e p_e(i) n_{y,e}(un,i)]\right] & \text{for} \quad i=0,\ldots,N_e-2, \\ (1-\lambda_o)\left[f^*(u_{y,e}(g,i) + l^* u_{y,e}(b,i)) + (1-\delta_e(g))n_{y,e}(g,i) \right. & \\ \qquad \left. + \phi_e\gamma_e \sum_{j=0}^{i-1}(1-p_e(j))d^*\pi_e(j,N_e-2-j)n_{y,e}(un,j)\right] & \text{for} \quad i=N_e-1. \end{cases} \tag{B.4}
$$

The first case in (B.4) captures unemployed workers in a good fit who find a job and employed workers in a good fit, or those who learn they are in a good fit, who do not separate. The second case captures those unemployed workers in a bad fit with history $N_e - 1$ who switch careers and find a job. Further, the last term captures those with an unsure fit who learn that they are in a bad fit, initiate a separation, and draw a spillover such that their new history is $i = N_e - 1$ and therefore have identified their good fit. Further, this term is multiplied by γ_e to capture the fraction of workers who switch careers within the match.

The law of motion for young workers who are unemployed in a bad fit is given by:

$$
\begin{aligned} u^{+}_{y,e}(b,i) = &(1-\lambda_o)\big[(1-l^*)(1-f^*)u_{y,e}(b,i) + \delta_e(b)n_{y,e}(b,i) \\ &+ \phi_e(1-\gamma_e)\sum_{j=0}^{i-1}(1-p_e(j))d^*\pi_e(j,i-j-1)n_{y,e}(un,j) \\ &+ \phi_e\delta_e(b)\sum_{j=0}^{i-1}(1-p_e(j))(1-d^*)\pi_e(j,i-j-1)n_{y,e}(un,j)\big], \end{aligned} \tag{B.5}
$$

for $i = 1,2,\ldots,N_e - 1$. The first term in (B.5) are unemployed workers in a bad fit who do not switch careers and do not find a job and those who were employed in a bad fit and lost their job, which occurs with probability $\delta_e(b)$. The second line captures workers who began the period prior with an unsure fit, learned that they were in a bad fit, initiated a separation, drew a spillover such that their new history is i, and entered unemployment (which occurs with probability $1 - \gamma_e$ after a separation is initiated). The last term is similar, except that this captures workers who learned they are in a bad fit, did not initiate a separation, but separated from their job at the exogenous probability $\delta_e(b)$.

The law of motion for young workers employed in a bad career fit is

$$n^+_{y,e}(b,i) = (1-\lambda_o)\big[(1-l^*)f^* u_{y,e}(b,i) + (1-\delta_e(b))n_{y,e}(b,i) + \phi_e(1-\delta_e(b))\sum_{j=0}^{i-1}(1-p_e(j))(1-d^*)\pi_e(j,i-j-1)n_{y,e}(un,j)\big], \tag{B.6}$$

for $i = 1, 2, \ldots, N_e - 1$. The first term of (B.6) represents workers who are unemployed in a bad fit, do not leave their current career, and find a job. The second term is employed workers in a bad fit who do not lose their job. The last term captures workers who were employed in an unsure fit, learn that they are in a bad fit, do not initiate a separation, do not have the match destroyed, and end the period with history i.

We now proceed to the laws of motion for old workers. The law of motion for old, unemployed workers in a career with an unsure fit is

$$u_{o,e}(un,i)^+ = \begin{cases} \sum_{a\in\{y,o\}} \chi_a\big[(1-f^*)u_{a,e}(un,i) + (1-\phi_e)\delta_e(un,i)n_{a,e}(un,i)\big] & \text{for } i = 0, \\ \sum_{a\in\{y,o\}} \chi_a\big[(1-f^*)(u_{a,e}(un,i) + l^* u_{a,e}(b,i)) + (1-\phi_e)\delta_e(un,i)n_{a,e}(un,i)\big] & \text{for } i = 1,\ldots,N_e-2, \end{cases} \tag{B.7}$$

where $\chi_a = \lambda_o$ if $a = y$ and $\chi_a = 1 - \lambda_d$ if $a = o$. The interpretation here is the same as with young workers, except that the flows now include both young workers who are hit by an aging shock and old workers who survive between periods.

The law of motion for old, unemployed workers with a good career fit is

$$u_{o,e}(g,i)^+ = \begin{cases} \sum_{a\in\{y,o\}} \chi_a\big[(1-f^*)u_{a,e}(g,i) + \delta_e(g)[n_{a,e}(g,i) + \phi_e n_{a,e}(un,i)p_e(i)]\big] & \text{for } i = 0,\ldots,N_e-2, \\ \sum_{a\in\{y,o\}} \chi_a\big[(1-f^*)(u_{a,e}(g,i) + l^* u_{a,e}(b,i)) + \delta_e(g)[n_{a,e}(g,i) + \phi_e n_{a,e}(un,i)p_e(i)]\big] & \text{for } i = N_e-1. \end{cases} \tag{B.8}$$

Further, the law of motion for old, employed workers in a career with an unsure fit is

$$
n_{o,e}(un,i)^{+} = \begin{cases} \sum_{a\in\{y,o\}} \chi_a \big[f^* u_{a,e}(un,i) + (1-\phi_e)(1-\delta_e(un,i)) n_{a,e}(un,i)\big] & \text{for} \quad i = 0, \\ \sum\limits_{a\in\{y,o\}} \chi_a \big[f^*(u_{a,e}(un,i) + l^* u_{a,e}(b,i)) + (1-\phi_e)(1-\delta_e(un,i)) n_{a,e}(un,i) & \\ \qquad + \phi_e (1-p_e(0)) d^* \gamma_e n_{a,e}(un,0) \pi_e(0,0)\big] & \text{for} \quad i = 1, \\ \sum\limits_{a\in\{y,o\}} \chi_a \big[f^*(u_{a,e}(un,i) + l^* u_{a,e}(b,i)) + (1-\phi_e)(1-\delta_e(un,i)) n_{a,e}(un,i) & \\ \qquad + \phi_e \gamma_e \sum\limits_{j=0}^{i-1} (1-p_e(j)) d^* \pi_e(j, i-j-1) n_{a,e}(un,j)\big] & \text{for} \quad i = 2, \ldots, N_e - 2, \end{cases} \tag{B.9}
$$

while the law of motion for old workers employed in a good fit is

$$
n_{o,e}(g,i)^{+} = \begin{cases} \sum_{a\in\{y,o\}} \chi_a \big[f^* u_{a,e}(g,i) + (1-\delta_e(g))[n_{a,e}(g,i) + \phi_e p_e(i) n_{a,e}(un,i)]\big] & \text{for} \quad i = 0, \ldots, N_e - 2, \\ \sum\limits_{a\in\{y,o\}} \chi_a \big[f^*(u_{a,e}(g,i) + l^* u_{a,e}(b,i)) + (1-\delta_e(g)) n_{a,e}(g,i) & \\ \qquad + \phi_e \gamma_e \sum\limits_{j=0}^{i-1} (1-p_e(j)) d^* \pi_e(j, N_e - 2 - j) n_{a,e}(un,j)\big] & \text{for} \quad i = N_e - 1. \end{cases} \tag{B.10}
$$

Finally, the laws of motion for old workers who are unemployed in a bad fit and employed in a bad fit are given by

$$
\begin{aligned} u_{o,e}^{+}(b,i) = \sum_{a\in\{y,o\}} \chi_a \big[& (1-l^*)(1-f^*) u_{a,e}(b,i) + \delta_e(b) n_{a,e}(b,i) \\ & + \phi_e (1-\gamma_e) \sum_{j=0}^{i-1} (1-p_e(j)) d^* \pi_e(j, i-j-1) n_{a,e}(un,j) \\ & + \phi_e \delta_e(b) \sum_{j=0}^{i-1} (1-p_e(j))(1-d^*) \pi_e(j, i-j-1) n_{a,e}(un,j)\big], \end{aligned} \tag{B.11}
$$

and

$$
\begin{aligned} n_{o,e}^{+}(b,i) = \sum_{a\in\{y,o\}} \chi_a \big[& (1-l^*) f^* u_{a,e}(b,i) + (1-\delta_e(b)) n_{a,e}(b,i) \\ & + \phi_e (1-\delta_e(b)) \sum_{j=0}^{i-1} (1-p_e(j))(1-d^*) \pi_e(j, i-j-1) n_{a,e}(un,j)\big], \end{aligned} \tag{B.12}
$$

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

B.2 Wages

This section details how we compute the model's wages via Nash bargaining and constant renegotiation that are used in the quantitative analysis. For brevity, we outline the approach to compute wages for an old worker with education e, an unknown fit ($s = un$), and history i.

In the main text, firms post bilaterally efficient contracts that deliver a worker the value of employment, x. Let $\theta_{o,e}(un,i)$ be the value of tightness in the submarket for old workers with education e, unknown fit, and history i. The value of searching in this submarket is:

$$U_{o,e}(un,i) = z + \beta(1-\lambda_d)\{U_{o,e}(un,i) + f(\theta_{o,e}(un,i))[x - U_{o,e}(un,i)]\}. \tag{B.13}$$

The free entry condition is given by

$$-\kappa_a + q(\theta_{o,e}(un,i))[V_{o,e}(un,i) - x] = 0. \tag{B.14}$$

Rewriting the entry condition gives

$$x = V_{o,e}(un,i) - \frac{\kappa_a}{q(\theta_{o,e}(un,i))}. \tag{B.15}$$

Substituting (B.15) into (B.13) gives

$$\begin{aligned} U_{o,e}(un,i) = z + \beta(1-\lambda_d)\Bigg\{ & U_{o,e}(un,i) + \\ & \max_{\theta_{o,e}(un,i)} f(\theta_{o,e}(un,i))\left[V_{o,e}(un,i) - U_{o,e}(un,i) - \frac{\kappa_a}{q(\theta_{o,e}(un,i))}\right]\Bigg\}, \end{aligned} \tag{B.16}$$

where the first order condition with respect to $\theta_{o,e}(un,i)$ is

$$f'(\theta_{o,e}(un,i))[V_{o,e}(un,i) - U_{o,e}(un,i)] = \kappa_a, \tag{B.17}$$

as $f(\theta_{o,e}(un,i))/q(\theta_{o,e}(un,i)) = \theta_{o,e}(un,i)$. Substituting (B.17) into (B.15) gives

$$x = U_{o,e}(un,i) + \varepsilon(\theta_{o,e}(un,i))[V_{o,e}(un,i) - U_{o,e}(un,i)], \tag{B.18}$$

where $\varepsilon(\theta) = 1 - f'(\theta)\frac{\theta}{f(\theta)}$. From (B.18), workers receive the value of unemployment plus a share, $\varepsilon(\theta_{o,e}(un,i))$, of the match surplus.

Let us now denote $w_{o,e}(un,i)$ as the worker's wage and the value of employment as $W_{o,e}(un,i)$. The value of employment for an old worker with education e, unknown fit, and history i satisfies

$$\begin{aligned}W_{o,e}(un,i) =& w_{o,e}(un,i)+ \\ & \beta(1-\lambda_d)\Bigg\{\phi_e\Big[p_e(i)\Big(\delta_e(g)U_{o,e}(g,i)+(1-\delta_e(g))W_{o,e}(g,i)\Big)+ \\ & (1-p_e(i))\sum_{\eta=0}^{\bar{\eta}_e}\{d^*_{o,e}(i')[\gamma_e\overline{W}_{o,e}(i')+(1-\gamma_e)U_{o,e}(b,i')]+ \\ & (1-d^*_{o,e}(i'))[\delta_e(b)U_{o,e}(b,i')+(1-\delta_e(b))W_{o,e}(b,i')]\}\pi_e(i,\eta)\Big]+ \\ & (1-\phi_e)\Big[\delta_e(un,i)U_{o,e}(un,i)+(1-\delta_e(un,i))W_{o,e}(un,i)\Big]\Bigg\},\end{aligned} \tag{B.19}$$

where $W_{o,e}(b,i)$ is the value of employment in a bad fit, $W_{o,e}(g,i)$ is the value of employment in a good fit, and

$$\overline{W}_{a,e}(i') = \begin{cases} W_{a,e}(un,i') & \text{if } \ i' < N_e - 1, \\ W_{a,e}(g,i') & \text{if } \ i' = N_e - 1. \end{cases} \tag{B.20}$$

The value of a filled job to the firm, $J_{o,e}(un,i)$, satisfies

$$\begin{aligned}J_{o,e}(un,i) =& p_e(i)y_e + (1-p_e(i))(y_e-\alpha) - w_{o,e}(un,i)+ \\ & \beta(1-\lambda_d)\Bigg\{\phi_e\Big[p_e(i)\Big(\delta_e(g)*0+(1-\delta_e(g))J_{o,e}(g,i)\Big)+ \\ & (1-p_e(i))\sum_{\eta=0}^{\bar{\eta}_e}\{d^*_{o,e}(i')[\gamma_e\overline{J}_{o,e}(i')+(1-\gamma_e)*0]+ \\ & (1-d^*_{o,e}(i'))[\delta_e(b)*0+(1-\delta_e(b))J_{o,e}(b,i')]\}\pi_e(i,\eta)\Big]+ \\ & (1-\phi_e)\Big[\delta_e(un,i)*0+(1-\delta_e(un,i))J_{o,e}(un,i)\Big]\Bigg\},\end{aligned} \tag{B.21}$$

where $J_{o,e}(b,i)$ is the value of filled job in a bad fit, $J_{o,e}(g,i)$ is the value of a filled job that is a good fit,

$$\bar{J}_{a,e}(i') = \begin{cases} J_{a,e}(un, i') & \text{if } i' < N_e - 1, \\ J_{a,e}(g, i') & \text{if } i' = N_e - 1, \end{cases} \tag{B.22}$$

and we have incorporated that the value of a vacancy is equal to zero through free entry.

Bilateral efficiency implies that $J_{o,e}(un,i) > 0 \iff W_{o,e}(un,i) > U_{o,e}(un,i) \iff V_{o,e}(un,i) > U_{o,e}(un,i)$ where $V_{o,e}(un,i) = W_{o,e}(un,i) + J_{o,e}(un,i)$. As x, the value of the employment contract delivered to the worker, is equal to the value of employment ($x = W_{o,e}(un,i)$), we can rewrite the surplus sharing rule (equation (B.18)) as:

$$W_{o,e}(un,i) - U_{o,e}(un,i) = \varepsilon(\theta_{o,e}(un,i))[V_{o,e}(un,i) - U_{o,e}(un,i)]. \tag{B.23}$$

The wage, $w_{o,e}(un,i)$, can then be computed via the following steps:

1. Compute $\{U_{o,e}(s,i), V_{o,e}(s,i), d^*_{o,e}(i), \theta_{o,e}(s,i)\}$ for $s \in \{un, b, g\}$ and $i \in \{0, 1, \ldots, N_e - 1\}$ via value function iteration.

2. Calculate the value of employment, $W_{o,e}(s,i)$ for $s \in \{un, b, g\}$ and $i \in \{0, 1, \ldots, N_e - 1\}$, using the output from step 1 and equation (B.23).

3. Obtain $w_{o,e}(un,i)$ by substituting $U_{o,e}(s,i)$ and $W_{o,e}(s,i)$ for $s \in \{un, b, g\}$ and $d^*_{o,e}(i)$ into (B.19).

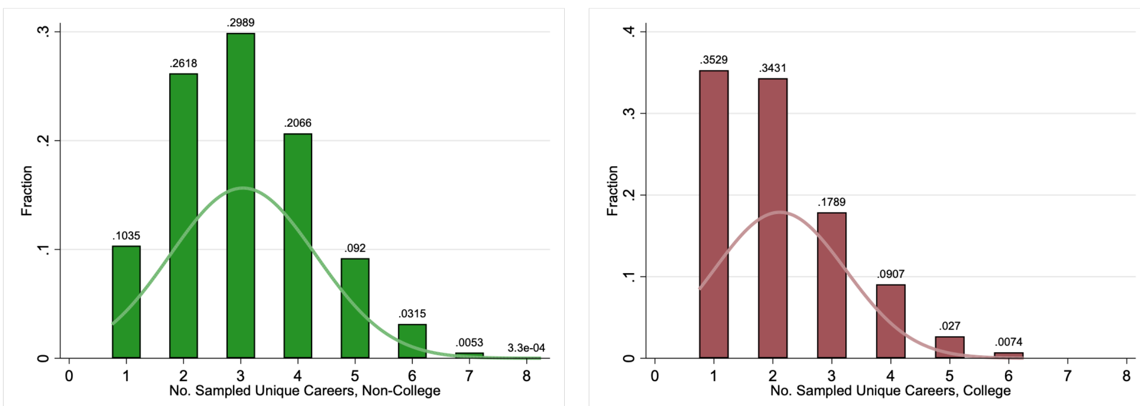
It is straightforward to apply this approach in computing the wages for young workers in unsure matches, $w_{y,e}(un,i)$, the wages of workers in a bad fit, $w_{a,e}(b,i)$ for $a \in \{y, o\}$, and the wage paid to workers in a good fit, $w_{a,e}(g,i)$ for $a \in \{y, o\}$.

C Quantitative Appendix

C.1 Data Moments

C.1.1 Distribution of Cumulative Unique Careers

We first identify the number of unique careers sampled by each individual in the NLSY79 sample. Our panel consists of 3,044 non-college workers and 816 college workers, all of whom have at least 10 years of potential work experience. We then define a career as "unique" if its angular distance, relative to all careers previously worked for, exceeds a threshold, $\bar{\phi} = 23.1290$. Formally, the i^{th} career is classified as a unique career if the angular distance $\phi_{ij} \geq \bar{\phi}$ for all $j < i$. Finally, we construct the distribution of the number of unique careers by education, as illustrated in Figure C1. Accordingly, the average number of sampled unique careers for non-college is 3.0391, while 2.1176 for college.



(a) Non-College (b) College

Figure C1: Distribution of the Number of Unique Careers by Education. *Source*: NLSY79.

C.1.2 Transition Probabilities

We first compute job separation probabilities by education and potential experience bins. Following the methodology in Shimer (2012) to adjust for time aggregation bias, we obtain separation probabilities of [0.0408, 0.0230, 0.0178, 0.0148] for non-college workers and [0.0108, 0.0064, 0.0059, 0.0066] for college workers.

Second, we calculate job finding probabilities during the first ten years of potential work experience. These are 0.3191 for non-college workers and 0.3383 for college workers. Finally, we compute the average finding probabilities for the 1–20 and 21–40 years of potential work experience across the whole sample, which yield values of 0.3118 and 0.2784, respectively.

C.1.3 Duration to First Career Transition

We restrict our estimation sample to 317 non-college and 174 college workers who transitioned careers exactly once, i.e., individuals who sampled exactly two unique careers during their whole life. This sample restriction addresses a key identification challenge: workers who ultimately make many career switches likely had greater initial uncertainty about their best fit than those who switch only once. By conditioning on exactly one career transition, we compare workers with similar uncertainty levels. Under this condition, differences in the timing of the first career switch primarily reflect differences in how quickly each education group learns about career fit, rather than differences in initial uncertainty. Using median duration for robustness to outliers, we find that non-college workers take 44 months to make their first career switch, while college workers take 29 months.

C.1.4 College Wage Premium

This section details the estimated college wage premium within our NLSY79 sample. We deflate each individual's originally reported hourly wage using the PCE2000 index, and values are coded as missing if they fall below 3 or above 200 per hour. We then estimate:

$$log(w_{it}) = \beta_0 + \beta_1 \text{College}_i + \Gamma X_i + \beta_2 \text{Urate}_t + \Phi_{Occ2} + \Phi_{Ind2} + \epsilon_{it}, \tag{C.1}$$

where $log(w_{it})$ is worker i's log real hourly wage in month t, College indicates a BA or above, X includes fixed worker characteristics (race and AFQT score), Urate is the yearly national unemployment rate, while Φ_{Occ2} and Φ_{Ind2} are occupation and industry fixed effects. Table C1 presents β_1 across different specifications of (C.1).

C.1.5 Wage Growth

In the NLSY79 sample, we calculate the mean deflated wage for each education group and potential work experience bin, and then compute the growth over potential work experience by taking the ratio of the wage in a given potential work experience bin relative to the wage in the first bin. This yields the following growth profiles: for non-college workers, the ratios across the four potential work experience bins are [1.0000, 1.2725, 1.5395, 1.6073]; for college workers, they are [1.0000, 1.5843, 1.9440, 1.9035].

Table C1: College Wage Premium

	(1)	(2)	(3)	(4)
College	0.38376***	0.29679***	0.37779***	0.27666***
1990dd Occupation FE		✓		✓
1990dd Industry FE			✓	✓
Observations	1,085,034	1,060,633	1,044,989	1,043,942
R^2	0.248	0.301	0.289	0.326

Notes: All specifications include the vector of individual controls, X, listed below equation (C.1). 1990dd occupation fixed effects are the second-level occupation codes constructed by Dorn (2009). 1990dd industry fixed effects are second-level industry codes according to the industrial classification scheme compiled by Autor et al. (2019). Levels of statistical significance are denoted by ***($p < 0.01$). Data are from the NLSY79.

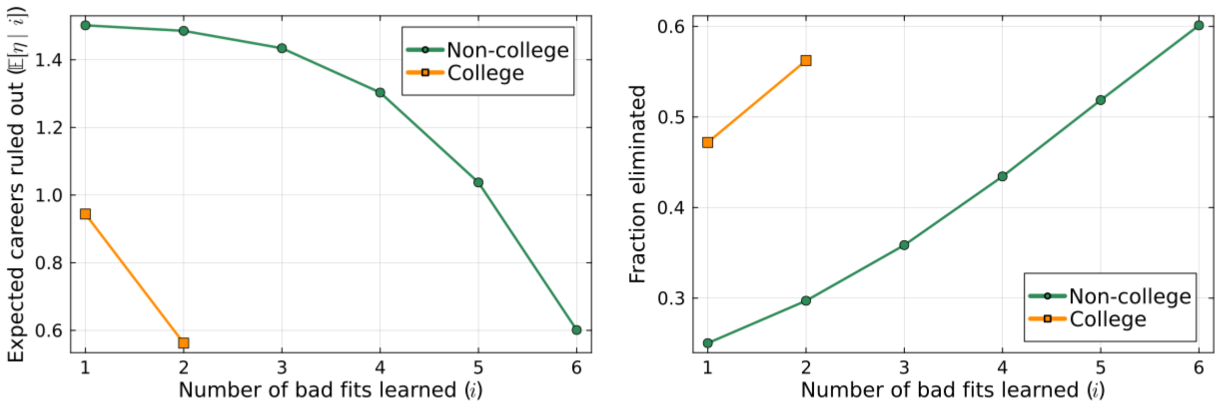
C.2 Learning Spillovers

Figure C2 demonstrates how learning spillovers manifest across the career histories of workers. Figure C2(a) shows the expected number of additional careers ruled out through a spillover draw, $\mathbb{E}[\eta|i]$, as a function of the number of bad fits learned, i. For both education groups, $\mathbb{E}[\eta|i]$ is decreasing in i: as a worker accumulates more information about their bad fits, the number of remaining unknown careers shrinks, which reduces the scope for additional learning through spillovers.

Figure C2(b) complements this by plotting the expected fraction of remaining unknown careers eliminated through spillovers, $\mathbb{E}[\eta|i]/(N_e - i - 1)$. Comparing across education groups, college workers have a smaller expected number of careers ruled out at each history i relative to non-college workers, reflecting their lower calibrated spillover parameter $\tilde{\lambda}_1 < \tilde{\lambda}_0$. However, as college workers face a considerably smaller career set to begin with ($N_1 < N_0$), each spillover draw eliminates a larger fraction of their remaining unknown careers.

C.3 Heatmaps

This section details the construction of the model Jacobian. For each of the 15 calibrated parameters, we compute the elasticity of every targeted moment with respect to that parameter, holding all other parameters fixed at their calibrated values in Table 5. For continuous parameters, we approximate the derivative using a central difference with step size $h = 0.001 \times \theta_j$, where θ_j is the calibrated value. For N_e, which is an integer, we use a one-sided difference, evaluating the model at $N_e + 1$. This yields the Jacobian $\partial m / \partial \theta$, where m is the vector of targeted moments and θ is the vector of calibrated parameters.



(a) Number of Careers Ruled Out

(b) Fraction of Remaining Careers

Figure C2: Learning Spillovers. *Notes*: *Notes*: Panel (a) displays the expected number of additional careers ruled out through learning spillovers, $\mathbb{E}[\eta \mid i]$, as a function of the number of bad fits learned, i, by education. Panel (b) displays the expected fraction of remaining unknown careers ruled out through spillovers, which is computed as $\mathbb{E}[\eta \mid i]/(N_e - i - 1)$, where $N_e - i - 1$ is the number of careers whose fit remains unknown after learning i bad fits. In both panels, the expectation is taken over the PMF $\pi_e(i, \eta)$. Both panels are computed at the calibrated parameter values reported in Table 5.

We convert to elasticities by computing $(\partial m/\partial\theta)(\theta/m)$ and row-normalize by each moment's maximum absolute elasticity, so that the most responsive parameter in each row takes the value one. Figure C3 displays the resulting heatmaps, with panel (a) covering non-college moments and parameters and panel (b) covering their college counterparts.

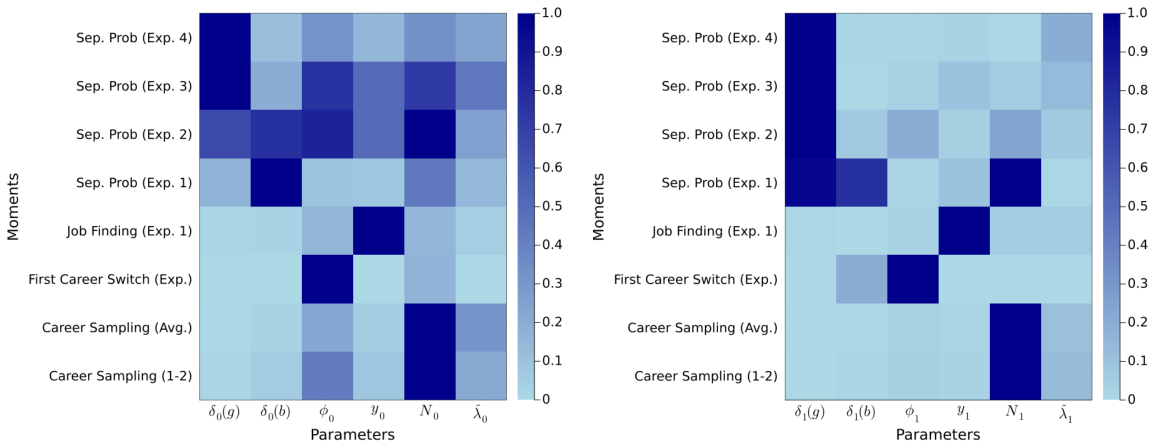
C.4 Shapley-Owen-Shorrocks Decomposition

This section details the Shapley-Owen-Shorrocks decomposition used in Section 4.3 and throughout the robustness checks in Section C.5.[51]

Suppose that we have an outcome, Y, that can be expressed as $Y = f(x_1, x_2, \ldots, x_n)$. In our context, Y is the difference between education groups in outcomes such as the unemployment rate, $\{x_1, x_2, \ldots, x_n\}$ are the education-specific parameters/factors that contribute to differences in outcomes by education, and $f(\cdot)$ is the model that maps the parameters to an education gap. Our objective is to compute the contribution of x_j to Y, denoted as C_j. Shorrocks (2013) shows that the contribution of x_j can be expressed as:

$$C_j = \sum_{k=0}^{n-1} \frac{(n-k-1)!k!}{n!} \left(\sum_{s \subseteq S_k \setminus \{x_j\}:|s|=k} [f(s \cup \{x_j\}) - f(s)] \right), \tag{C.2}$$

[51] We refer interested readers to Shorrocks (2013) for a more in-depth description of the Shapley-Owen-Shorrocks decomposition and Audoly et al. (2025) for a survey of the different contexts in which the decomposition has been applied.



(a) Non-college (b) College

Figure C3: Heatmaps. *Notes*: Each panel displays the row-normalized elasticity of the model outcomes listed on the vertical axis with respect to each parameter shown on the horizontal axis. Sep. Prob (Exp. x) is the average separation probability in potential experience bin x. First Career Switch (Exp.) is the median potential experience at the first career switch, career sampling (avg.) is the average number of careers sampled over the work-life, and career sampling (1-2) is the fraction of workers who sample less than 3 careers throughout their work-life. The moments are computed by simulating the model economy for 30,000 workers in each education group. The elasticity with respect to N_e is the effect of increasing N_e by one from the calibrated values shown in Table 5. For the other parameters, which are continuous, we compute the change in the moment in response to increasing and decreasing the parameter from its calibrated by $+/-0.0001$ in each direction and take the average of the two.

where $k \in \{0, 1, \ldots, n-1\}$. We will now explain each term in (C.2). With n factors, there are $n!$ possible ways in which the factors can be eliminated (i.e., set equal across non-college and college). For example, we can first eliminate differences by education in ϕ_e, the learning speed, then the number of careers N_e, and so on. The idea behind the Shapley-Owen-Shorrocks decomposition is to compute the marginal effect of factor x_j when a subset of factors, s, remain. Going back to equation (C.2), s represents a subset of factors that remain "turned on" after x_j is "turned off". The marginal contribution of x_j here is given by $f(s \cup \{x_j\}) - f(s)$.[52] As this represents the marginal contribution over x_j when a particular subset of factors remain, we take the sum over all subsets s that are of size k (i.e., $|s| = k$). This is captured by the sum within the parentheses in (C.2). A crucial component of the decomposition is to weight the marginal contribution according to the probability of selecting that particular sequence of elimination. With n total factors and k factors remaining after x_j is eliminated, the probability of selecting a particular sequence of elimination is $(n-k-1)!k!/n!$, which defines the weight of the marginal contribution

[52] To continue the example of our context, suppose that we are computing the contribution of ϕ_e to the unemployment-education gap. Suppose that $k = 2$ so that there are two factors left after ϕ_0 is set equal to ϕ_1. The subset of remaining factors could be $s = \{y_e, \delta_e(b)\}$ or $s = \{\delta_e(b), \delta_e(g)\}$ and so on, depending on which factors were turned off before setting ϕ_0 equal to ϕ_1.

of x_j over all subsets s of size k. Finally, the process is repeated for all $k \in \{0, 1, \ldots, n-1\}$ to ensure that all possible orderings of the factors being eliminated are covered. Shorrocks (2013) shows that doing so generates a decomposition where $\sum_{j=1}^{n} C_j = Y$, i.e. the sum of the individual contributions add up to the original gap, and that the contributions, C_j, are independent of the order in which the factors are eliminated.

Table 9 in the main text presents the decomposition results for the average gaps in unemployment, wages, and lifetime earnings across the entire life cycle. Table C2 presents the decomposition results within each bin of potential experience for unemployment and wages.

Table C2: Shapley-Owen-Shorrocks Decomposition by Potential Experience

	Unemployment				Wages			
	Exp. 1	Exp. 2	Exp. 3	Exp. 4	Exp. 1	Exp. 2	Exp. 3	Exp. 4
Panel A: Uncertainty								
N_e	25.112	24.968	14.027	4.972	50.230	37.803	18.807	6.298
ϕ_e	3.570	12.044	10.020	4.864	13.747	19.342	13.787	5.681
$\tilde{\lambda}_e$	-1.342	-2.151	-1.671	-1.195	-2.171	-2.846	-2.018	-0.973
Within-panel total	27.340	34.861	22.376	8.641	61.806	54.299	30.576	11.006
Panel B: Occupation-specific separations								
$\delta_e(b)$	52.793	28.208	13.408	5.653	5.404	4.457	3.710	1.897
$\delta_e(g)$	12.156	30.471	57.861	79.419	1.836	3.875	6.893	9.623
Within-panel total	64.949	58.679	71.269	85.072	7.240	8.332	10.603	11.520
Panel C: Other								
γ_e	3.111	1.660	0.853	0.235	0.440	0.270	0.213	0.077
y_e	4.599	4.800	5.502	6.052	30.515	37.099	58.608	77.397
Within-panel total	7.710	6.460	6.355	6.287	30.955	37.369	58.821	77.474
Total	99.999	100.000	100.000	100.001	100.000	100.000	100.000	100.000

Notes: Exp. x is short for potential experience bin x for $x \in \{1, 2, 3, 4\}$. Each cell represents the percentage of the education gaps in unemployment and wages that is attributable to a specific parameter within a potential experience bin. The contribution of each parameter is given by equation (C.2). The rows labelled "Within-panel total" show the sum of the contributions of the individual parameters within the panel. Not all entries in the last row are equal to 100 due to rounding.

C.5 Alternative Calibrations and Targeted Moments

C.5.1 Alternative Calibration I

This section presents the first alternative calibration we use to assess the robustness of our main quantitative findings. In this alternative calibration, we set $\gamma_0 = \gamma_1 = 0$ so that workers cannot switch careers within a match. As a result, all matches that initiate an endogenous separation are destroyed. Apart from this, the calibration strategy is unchanged. There are still 15 parameters to calibrated and we target the same set of moments described in Section 4.1.

Table C3: Model and Data Comparison in the $\gamma_e = 0$ Calibration

Moment	Target	Model
JFP, 1-10, non-college	0.319	0.302
JFP, 1-10, college	0.338	0.370
JFP, 1-20	0.312	0.296
JFP, 21-40	0.278	0.277
SP by pot. exp., non-college ($\times 10^{-2}$)	[4.08, 2.30, 1.78, 1.48]	[4.04, 2.44, 1.68, 1.42]
SP by pot. exp., college ($\times 10^{-2}$)	[1.08, 0.64, 0.59, 0.66]	[1.33, 0.62, 0.57, 0.56]
College wage premium	1.276	1.261
# Careers, non-college	3.039	3.013
# Careers, college	2.118	1.968
% with <3 careers, non-college	36.531	33.889
% with <3 careers, college	69.608	69.164
Pot. exp. at first switch, non-college	44.0	44.0
Pot. exp. at first switch, college	29.0	29.0

Notes: Moments are computed by simulating the model economy. JFP and SP stand for job finding probability and separation probability, respectively, while pot. exp. is short for potential experience. The four potential experience bins are: [1-10, 11-20, 21-30, 31-40]. The college wage premium in the model is the ratio of average wage among college workers to the average wage among non-college workers. See the notes under Table 3 for details on how the median potential experience at the first career switch is computed.

Table C3 shows the fit of the model to the targeted moments. While the fit is similar to that in the main text, a notable exception is the separation probability of college workers in the first potential experience bin, which is larger in the model (1.33%) than in the data (1.08%). The reason for this discrepancy is that when $\gamma_e = 0$, all college workers must separate from a match to switch careers. Since college workers have a higher learning speed (see Table C4) to match the low potential experience at their first career switch, they have a high endogenous separation probability. As such, it is difficult for this calibration to jointly match the speed at which college workers have their first career switch and the average separation probability in the first potential experience bin.

Table C4: Parameter Values in the $\gamma_e = 0$ Calibration

	Definition	Value		Definition	Value
β	Discount factor	0.997	y_0	Prod. of non-college	1.923
λ_o	Pr. of becoming old	0.004	y_1	Prod. of college	2.040
λ_d	Pr. of becoming retired	0.004	$\delta_0(b)$	Bad sep. pr., non-college	0.036
μ_0	Pr. endowed with $e = 0$	0.731	$\delta_1(b)$	Bad sep. pr., college	0.006
μ_1	Pr. endowed with $e = 1$	0.269	$\delta_0(g)$	Good sep. pr., non-college	0.013
z	Utility while unemployed	1.000	$\delta_1(g)$	Good sep. pr., college	0.006
ι	Matching parameter	0.500	ϕ_0	Learning pr., non-college	0.020
γ_0	Within-match switch, non-college	0.000	ϕ_1	Learning pr., college	0.026
γ_1	Within-match switch, college	0.000	N_0	# of careers, non-college	8
κ_y	Vacancy cost, young	0.176	N_1	# of careers, college	3
κ_o	Vacancy cost, old	0.947	$\tilde{\lambda}_0$	Spillovers, non-college	1.507
α	Penalty, bad fit	1.220	$\tilde{\lambda}_1$	Spillovers, college	0.045

Notes: "Pr." is short for probability, "sep." is short for separation, and "prod." is short for productivity. The first nine parameters in the left column are assigned while the remaining fifteen are calibrated via simulated method of moments.

Table C4 presents the parameter values. The parameter values are similar to the baseline calibration with three exceptions. First, there is no difference between $\delta_1(b)$ and $\delta_1(g)$ for college workers in this calibration, as the calibration lowers $\delta_1(b)$ to obtain a better fit to the separation probability in the first bin of potential experience. Second, to obtain a better fit for the separation profile, we estimate $N_1 = 3$ instead of the baseline value of $N_1 = 4$. This causes a large change in the spillover parameter for college workers, as $\tilde{\lambda}_1 = 0.045$, indicating that there is little learning from spillovers in this calibration.

Table C5: Education Gaps in Unemployment, Wages, and Earnings for Alternative Calibration I

	Non-college	College	College - Non-college	%Δ
Unemployment rate	8.278	2.375	-5.903	-71.309
Wage	1.495	1.885	0.390	26.087
Lifetime earnings	479.891	644.340	164.449	34.268

Notes: Lifetime earnings are the cumulative wages earned across a worker's entire labor market history. The unemployment rate is in percentage points. The first two columns are the average outcome across all workers within an education group in the simulated economy. The third column is the difference, in levels, between college and non-college while the last column is the percentage difference between college and non-college.

Next, Table C5 presents the education gaps in unemployment, wages, and lifetime earnings. Despite some differences in the calibrated parameters, the education gaps are very similar to those in the baseline analysis and presented in Table 7.

Table C6 presents the results from applying decomposition I to the alternative calibration. For brevity, we just present the results for the overall education gaps and omit the results by potential experience. Comparing Tables 8 and C6 illuminates that the uncertainty channel explains a larger share of the education gaps in this calibration when $\gamma_e = 0$. The difference is (relatively) more pronounced when it comes to the share of the U-E gap that is attributable to the uncertainty channel. This is natural because in this version of the model where $\gamma_e = 0$, workers must change careers through unemployment. This amplifies the effect of low career uncertainty, because it means there are more endogenous separations upon learning that a worker is in a bad career fit.

Table C6: Decomposition I, $\gamma_e = 0$ Calibration

	Overall (College baseline)	Overall (Non-college baseline)
Unemployment rate	16.923	20.205
Wage	60.691	61.801
Lifetime earnings	52.610	54.101

Notes: Each cell presents the fraction of the original education gap that remains after eliminating all channels that contribute to the education gaps except the uncertainty channel. College baseline refers to the decomposition when non-college parameters are set equal to their college counterparts, and non-college baseline refers to the decomposition when college parameters are set equal to their non-college counterparts.

The last exercise we conduct within the $\gamma_e = 0$ calibration is the Shapley-Owen-Shorrocks decomposition. The procedure is the same as in the baseline calibration, except that γ_e is no longer a factor that contributes to the education gaps as it is set equal to zero. Table C7 presents the results and shows that the contribution of the uncertainty channel to the U-E gap is largely unchanged relative to the baseline calibration.

Table C7: Shapley-Owen-Shorrocks Decomposition, $\gamma_e = 0$ Calibration

	Unemployment	Wage	Lifetime earnings
Panel A: Uncertainty			
N_e	44.328	69.849	64.091
ϕ_e	6.463	17.096	14.756
$\tilde{\lambda}_e$	-22.654	-24.745	-23.416
Within-panel total	28.137	62.200	55.431
Panel B: Occupation-specific separations			
$\delta_e(b)$	34.593	3.302	9.730
$\delta_e(g)$	32.431	4.794	10.515
Within-panel total	67.024	8.096	20.245
Panel C: Other			
y_e	4.839	29.705	24.324
Total	100.000	100.001	100.000

Notes: Each cell represents the percentage of the (overall) education gaps in unemployment, wages, and lifetime earnings that is attributable to a specific parameter. The contribution of each parameter is given by equation (C.2). The rows labelled "Within-panel total" show the sum of the contributions of the individual parameters within the panel. Not all entries in the last row are equal to 100 due to rounding.

C.5.2 Alternative Calibration II

This section details our second alternative calibration. In this calibration, we calibrate the learning speed to match the separation profile. Specifically, we discipline ϕ_e by matching the separation probability in the second potential experience bin, as the decline in separations between the first and second potential experience bin is strongly connected to the learning speed: a faster learning speed sorts workers into their good fit earlier in their career, where they are less likely to experience a separation, and thus causes the separation profile to decrease faster in potential experience. As the separation profile is also responsive to changes in the exogenous status-specific separation probabilities, $\delta_e(b)$ and $\delta_e(g)$, we externally set $\delta_e(b)$ and $\delta_e(g)$ instead of calibrating them in this calibration.

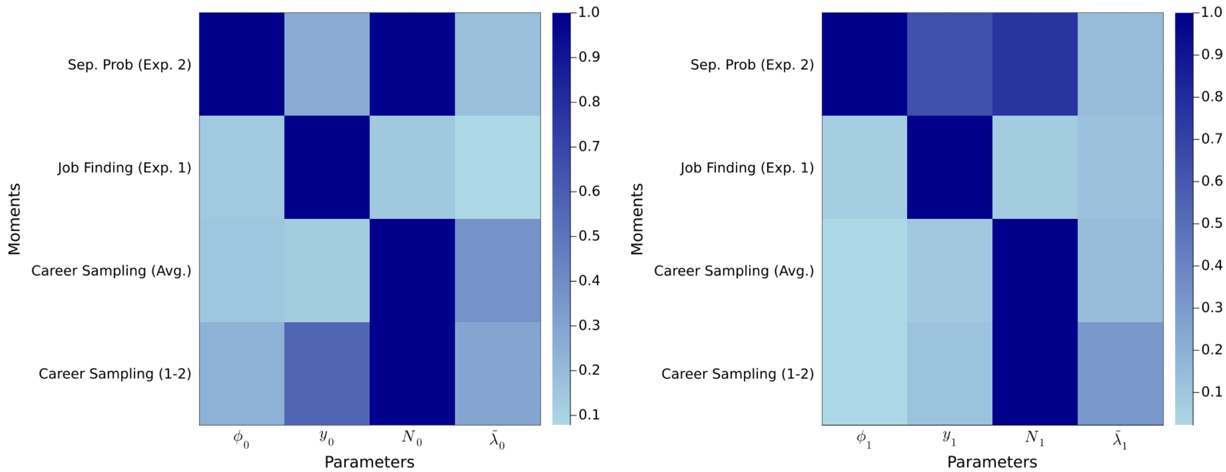
Table C8: Model and Data Comparison for Alternative Calibration II

Moment	Target	Model
JFP, 1-10, non-college	0.319	0.300
JFP, 1-10, college	0.338	0.367
JFP, 1-20	0.312	0.297
JFP, 21-40	0.278	0.277
SP pot. exp. 2, non-college ($\times 10^{-2}$)	2.30	2.30
SP pot. exp. 2, college ($\times 10^{-2}$)	0.64	0.64
College wage premium	1.276	1.262
# Careers, non-college	3.039	2.952
# Careers, college	2.118	2.080
% with <3 careers, non-college	36.531	33.565
% with <3 careers, college	69.608	69.439

Notes: Moments are computed by simulating the model economy. JFP and SP stand for job finding probability and separation probability, respectively, while pot. exp. is short for potential experience. The four potential experience bins are: [1-10, 11-20, 21-30, 31-40]. The college wage premium in the model is the ratio of average wage among college workers to the average wage among non-college workers. In this alternative calibration, separation rates are set externally rather than calibrated, and the median potential experience at first career switch is not targeted.

Here is how we set the values of $\delta_e(b)$ and $\delta_e(g)$. We compute the separation probability by education and potential experience for years $x \in \{1, 2, \ldots, 40\}$. We then set $\delta_e(b)$ equal to the maximum separation probability for education group e across the forty years of potential experience. The separation rate in good fits, $\delta_e(g)$, is set equal to the minimum separation probability for education group e across the forty years.

Apart from replacing the median potential experience at the first career switch with the separation probability in the second potential experience bin, the targeted moments and mapping between parameters and moments remain the same. Table C8 shows that the model matches the targets well. Figure C4 presents the identification heatmaps for the education-specific parameters and shows that the separation probability in potential experience bin 2 is responsive to the learning speed, ϕ_e.



(a) Non-college (b) College

Figure C4: Heatmaps in Alternative Calibration II. *Notes*: Each panel displays the row-normalized elasticity of the model outcomes listed on the vertical axis with respect to each parameter shown on the horizontal axis. Sep. Prob (Exp. 2) is the average separation probability in potential experience bin 2. Career sampling (avg.) is the average number of careers sampled over the work-life, and career sampling (1-2) is the fraction of workers who sample less than 3 careers throughout their work-life. Job Finding (Exp. 1) is the average job finding probability in the first potential experience bin. The moments are computed by simulating the model economy for 30,000 workers in each education group. The elasticity with respect to N_e is the effect of increasing N_e by one from the calibrated values shown in Table C9. For the other parameters, which are continuous, we compute the change in the moment in response to increasing and decreasing the parameter from its calibrated by $+/-0.0001$ in each direction and take the average of the two.

Table C9 presents the parameter values. One particular note is that in this strategy, the separation probability in bad fits is much larger than in the baseline calibration: 0.061 vs. 0.044 for non-college and 0.026 vs. 0.01 for college. As a result, this implies a much higher learning speed for non-college workers relative to the baseline (0.025 vs. 0.019) to match the rapid decline in separations between potential experience bins 1 and 2 for non-college workers.

Next, Table C10 shows that the education gaps in unemployment, wages, and earnings are similar to the previous calibrations. Table C11 repeats the first decomposition exercise and shows that the share of the U-E gap attributable to the uncertainty channel is similar in magnitude to the baseline calibration. In particular, we find that the uncertainty channel explains between 5.06% and 8.13% in this calibration. The lower magnitude is primarily driven by the smaller difference in learning speeds, ϕ_e in this calibration. Fi-

Table C9: Parameter Values for Alternative Calibration II

	Definition	Value		Definition	Value
β	Discount factor	0.997	y_0	Prod. of non-college	1.700
λ_o	Pr. of becoming old	0.004	y_1	Prod. of college	1.940
λ_d	Pr. of becoming retired	0.004	$\delta_0(b)$	Bad sep. pr., non-college	0.061
μ_0	Pr. endowed with $e = 0$	0.731	$\delta_1(b)$	Bad sep. pr., college	0.026
μ_1	Pr. endowed with $e = 1$	0.269	$\delta_0(g)$	Good sep. pr., non-college	0.013
z	Utility while unemployed	1.000	$\delta_1(g)$	Good sep. pr., college	0.005
ι	Matching parameter	0.500	ϕ_0	Learning pr., non-college	0.025
γ_0	Within-match switch, non-college	0.500	ϕ_1	Learning pr., college	0.025
γ_1	Within-match switch, college	0.595	N_0	# of careers, non-college	8
κ_y	Vacancy cost, young	0.164	N_1	# of careers, college	4
κ_o	Vacancy cost, old	0.721	$\tilde{\lambda}_0$	Spillovers, non-college	1.814
α	Penalty, bad fit	0.957	$\tilde{\lambda}_1$	Spillovers, college	1.280

Notes: "Pr." is short for probability, "sep." is short for separation, and "prod." is short for productivity. The separation rate parameters ($\delta_e(b)$ and $\delta_e(g)$) are set externally as described in the text.

nally, Table C12 presents the Shapley-Owen-Shorrocks decomposition and shows that the contribution of the uncertainty channel to the U-E gap is similar to the results in previous calibrations.

Table C10: Education Gaps in Unemployment, Wages, and Earnings in Alternative Calibration II

	Non-college	College	College - Non-college	%Δ
Unemployment rate	8.593	2.494	-6.099	-70.976
Wage	1.425	1.799	0.374	26.246
Lifetime earnings	456.270	613.761	157.491	34.517

Notes: Lifetime earnings are the cumulative wages earned across a worker's entire labor market history. The unemployment rate is in percentage points. The first two columns are the average outcome across all workers within an education group in the simulated economy. The third column is the difference, in levels, between college and non-college while the last column is the percentage difference between college and non-college.

C.5.3 Alternative Sample I: Lock-in Occupations

Lower rates of occupational switching among college graduates may suggest "occupational lock-in" rather than better initial matching. For instance, a physician cannot easily reallocate from being an M.D. to an unrelated field. To address this concern, we conduct a robustness check using the CPS, which provides a sufficiently large sample size to rep-

Table C11: Decomposition I in Alternative Calibration II

	Overall (College baseline)	Overall (Non-college baseline)
Unemployment rate	5.064	8.126
Wage	27.340	27.893
Lifetime earnings	22.365	23.176

Notes: Each cell presents the fraction of the original education gap that remains after eliminating all channels that contribute to the education gaps except the uncertainty channel. College baseline refers to the decomposition when non-college parameters are set equal to their college counterparts, and non-college baseline refers to the decomposition when college parameters are set equal to their non-college counterparts.

Table C12: Shapley-Owen-Shorrocks Decomposition in Alternative Calibration II

	Unemployment	Wage	Lifetime earnings
Panel A: Uncertainty			
N_e	29.060	32.646	31.492
ϕ_e	0.985	1.182	1.075
$\tilde{\lambda}_e$	-4.726	-4.477	-4.246
Within-panel total	25.319	29.351	28.321
Panel B: Occupation-specific separations			
$\delta_e(b)$	30.502	2.972	8.901
$\delta_e(g)$	32.650	4.203	10.452
Within-panel total	63.152	7.175	19.353
Panel C: Other			
γ_e	2.072	0.201	0.451
y_e	9.457	63.274	51.875
Within-panel total	11.529	63.475	52.326
Total	100.000	100.001	100.000

Notes: Each cell represents the percentage of the (overall) education gaps in unemployment, wages, and lifetime earnings that is attributable to a specific parameter. The contribution of each parameter is given by equation (C.2). The rows labelled "Within-panel total" show the sum of the contributions of the individual parameters within the panel. Not all entries in the last row are equal to 100 due to rounding.

resent the U.S. occupational distribution, to identify specific "lock-in" occupations. Our identification strategy relies on a data-driven, revealed-preference approach, in which occupations characterized by a sufficiently low switching probability are classified as ''locked-in,'' as such inertia reflects either highly specialized licensing or legal barriers to entry. Having established that, we assess the robustness of our results by examining how the targeted moments and key motivating facts shift when we exclude individuals who have ever been employed within these identified occupations.

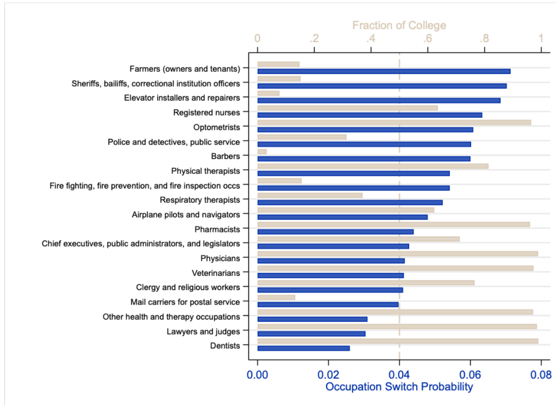


Figure C5: Occupational Switch Probability and College Fraction. *Notes*: The occupational switch probability is the monthly probability that the worker transitions to a different occupation. Fraction of College is the fraction of workers employed in the occupation who have at least a bachelor's degree. Constructed using the CPS sample.

Figure C5 presents the twenty occupations with the lowest average switching probabilities, plotting these values on the bottom axis alongside the fraction of college workers on the upper axis. This demonstrates that college workers are indeed concentrated in several high-barrier occupations, such as dentists, lawyers, judges, physicians, and pharmacists, which are typically characterized by strict legal entry requirements. However, the data also reveal that certain occupations dominated by non-college workers, as captured by a sufficiently low fraction of college employment, exhibit similarly low occupational switching probability, such as mail carriers, firefighters, barbers, and elevator repairers. This piece of evidence suggests that ′′lock-in′′ occupations are not exclusive to college workers, which to some extent alleviates the concern that the observed educational gap in unemployment or separations is driven solely by a ′′lock-in′′ occupation effect.

As a robustness check, we recalculate forecast errors and calibration moments excluding workers in lock-in occupations. If these moments remain largely unchanged, occupational differences across education groups, though present, would contribute negligibly to our quantitative findings.

As indicated in Panel A of Table C13, our targeted moments for calibration remain stable when excluding individuals who were ever employed in the 10, 20, or 30 most "lock-in" occupations. In terms of forecast errors in Panel B of Table C13, a crucial piece of evidence for uncertainty differences across education groups, the exclusion of these workers in ′′lock-in′′ occupations results in only negligible changes. Most importantly, the educational gap in forecast error persists as a robust pattern, suggesting that our main findings are not driven by lock-in occupations.

Table C13: Targeted Moments and Forecast Error Excluding Workers Ever Worked in Lock-in Occupations

	Full Sample	Drop Top 10 Lock-in Occ.	Drop Top 20 Lock-in Occ.	Drop Top 30 Lock-in Occ.
Panel A: Targeted Moments				
Separation Prob.(%), N	[4.08, 2.30, 1.78, 1.48]	[4.09, 2.32, 1.80, 1.50]	[4.15, 2.41, 1.87, 1.55]	[4.16, 2.42, 1.87, 1.55]
Separation Prob.(%), C	[1.08, 0.64, 0.59, 0.66]	[1.15, 0.70, 0.65, 0.73]	[1.17, 0.72, 0.67, 0.73]	[1.17, 0.72, 0.66, 0.73]
Job Finding Prob.(%), 1-10, N	31.91	31.88	31.83	31.78
Job Finding Prob.(%), 1-10, C	33.83	33.54	33.39	33.32
Job Finding Prob.(%), 1-20	31.18	31.15	31.07	31.02
Job Finding Prob.(%), 21-40	27.84	27.85	27.74	27.67
No. of sampled unique careers, N	3.0391	3.0356	3.0047	2.9762
No. of sampled unique careers, C	2.1176	2.1729	2.1323	2.1158
% with $<$ 3 careers, N	36.53	36.53	37.33	38.14
% with $<$ 3 careers, C	69.60	67.44	68.68	67.5
Month until 1st career switch, N	44	44	42	42
Month until 1st career switch, C	29	25	29	29
College Premium	1.2766	1.2430	1.2476	1.2489
Panel B: Forecast Error in [Non-College, College]				
Euclidean Distance at Age 35	[0.77, 0.58]	[0.77, 0.60]	[0.78, 0.60]	[0.77, 0.59]
Angular Distance at Age 35	[29.90, 20.46]	[30.12, 21.50]	[30.40, 21.33]	[30.06, 20.97]
Euclidean Distance, 30-40	[0.73, 0.56]	[0.73, 0.58]	[0.73, 0.58]	[0.73, 0.58]
Angular Distance, 30-40	[27.61, 19.44]	[27.78, 20.40]	[27.93, 20.30]	[27.78, 20.17]
Euclidean Distance, 5 years	[0.66, 0.57]	[0.65, 0.60]	[0.65, 0.57]	[0.65, 0.57]
Angular Distance, 5 years	[25.94, 20.28]	[25.81, 21.36]	[25.78, 20.09]	[25.67, 19.94]
CPS, No. Observations	17,423,518	16,708,320	15,980,542	15,819,512
NLSY79, No. Non-College Workers	3,625	3,523	3,309	3,193
NLSY79, No. College Workers	1,070	862	807	796
NLSY79, No. Observations	1,421,934	1,323,452	1,232,548	1,186,607

Notes: A paired sampled t-test indicates that the forecast error of non-college workers is statistically larger than that of college workers, with the null hypothesis ($H_0 : diff < 0$) being rejected at the 5% significance level. N denotes non-college workers, while C signifies college workers. In the last three columns, we drop workers who ever worked in the 10, 20, and 30 most lock-in occupations, respectively.

C.5.4 Alternative Sample II: Including Females and Males

To ensure the results are not driven by gender selection, we conducted a comprehensive robustness check by extending our analysis to a pooled sample comprising both male and female workers. The empirical patterns, targeted moments, and core evidence remain largely unchanged, thereby reinforcing the validity of our baseline findings. Notwithstanding this consistency, we retain our focus on the male-only sample in the main context, as doing so allows us to abstract from the confounding effects of secular changes in female labor force participation over the study period, as well as social norms such as gender discrimination and the potential role of fertility in shaping forecast errors.

Table C14 details the construction of our pooled sample. This yields a sample of both male and female workers with $9,844$ individuals and $2,943,187$ person-month observations.

Table C14: NLSY79 Sample Selection in the Pooled Sample

Criteria	No. Respondents	No. Observations
Monthly histories from 1978 to 2018	12,686	4,659,433
Start from the (known) graduation year	12,649	3,544,212
Never served in the military	11,198	3,286,758
Complete ASVAB	10,561	3,136,747
Complete non-cognitive scores	10,156	3,020,623
Potential work experience, 1-40 years	10,148	2,978,536
Drop persons who are never employed	9,844	2,943,187

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

First, we compare the targeted moments used for parameter identification between the pooled gender sample and our baseline male-only sample. As shown in Panel A of Table C15, the empirical moments calculated from the pooled sample deviate negligibly from those from the male-only sample. This implies that our calibrated parameters and subsequent quantitative results are robust to excluding females from the baseline sample.

We further examine direct evidence of uncertainty differentials by comparing the magnitude of forecast errors across education groups. As reported in Panel B of Table C15, the educational gap in forecast errors remains robust across both long- and short-horizon forecasts. A closer inspection of the data reveals that female workers generally have slightly larger forecast errors than males, except for the 5-year forecast error. This finding suggests that including females in the sample would likely amplify the observed educa-

Table C15: Comparison with the Female and Male Sample

	Sample with Male Only	Sample with Both Gender
Panel A: Targeted Moments		
Separation Prob.(%), N	[4.08, 2.30, 1.78, 1.48]	[3.64, 2.11, 1.61, 1.35]
Separation Prob.(%), C	[1.08, 0.64, 0.59, 0.66]	[1.07, 0.74, 0.66, 0.67]
Job Finding Prob.(%), 1-10, N	31.91	31.12
Job Finding Prob.(%), 1-10, C	33.83	35.70
Job Finding Prob.(%), 1-20	31.18	30.34
Job Finding Prob.(%), 21-40	27.84	26.73
No. of sampled unique careers, N	3.0391	3.0237
No. of sampled unique careers, C	2.1176	2.1764
% with $<$ 3 careers, N	36.53	37.66
% with $<$ 3 careers, C	69.6	66.21
Month until 1st career switch, N	44	52
Month until 1st career switch, C	29	29
College Premium	1.2766	1.2592
Panel B: Forecast Error in [Non-College, College]		
Euclidean Distance at Age 35	[0.77, 0.58]	[0.77, 0.60]
Angular Distance at Age 35	[29.90, 20.46]	[30.22, 21.26]
Euclidean Distance, 30-40	[0.73, 0.56]	[0.73, 0.56]
Angular Distance, 30-40	[27.61, 19.44]	[28.26, 19.77]
Euclidean Distance, 5 years	[0.66, 0.57]	[0.65, 0.55]
Angular Distance, 5 years	[25.94, 20.28]	[27.05, 20.22]
Panel C: Others		
Unemployment Rate (%), N	[11.72, 6.68, 5.35, 4.98]	[11.36, 6.91, 5.34, 4.75]
Unemployment Rate (%), C	[3.50, 2.19, 2.40, 2.94]	[3.53, 2.47, 2.51, 2.94]
β(PriorExp)	7×10^{-5}	8×10^{-5}
β(PriorExp$\times$College)	-4×10^{-5}	-5×10^{-5}

Notes: A paired sample t-test indicates that the forecast error of non-college workers is statistically larger than that of college workers, with the null hypothesis ($H_0 : diff < 0$) being rejected at the 1% significance level. N denotes non-college workers, while C signifies college workers.

tional gap. Furthermore, the results presented in Panel C of Table C15 indicate that the unemployment gap and the labor market learning effect remain similar to those obtained from the male-only baseline.

C.5.5 Alternative Definitions of Career Transitions

To assess the robustness of our definition of career switches based on the angular distance between occupations, we test whether the targeted moments used to discipline the uncertainty channel parameters are similar under alternative definitions of career switches. We consider two alternatives. In the first, we identify a career switch if the worker simultaneously changes employer, industry, and occupation, that is, if the worker undergoes a complex transition as in Neal (1999). The second alternative identifies career switches as transitions across six 1-digit broad occupational categories (see Table A23 for the category definitions). Following Carrillo-Tudela and Visschers (2023) among others, these major group transitions capture meaningful career changes.

As shown in Table C16, the educational gaps in the distribution of sampled careers and the duration to the first career switch remain largely unchanged under these alternative definitions. For example, non-college workers sample an average of 3.27 unique broad occupations, compared to 2.35 for college workers. Furthermore, 24% of the non-college group sample fewer than three unique broad occupations, whereas 63% of college workers do so. Among individuals who sampled exactly two unique broad occupations, the first switch occurs at an average of 39 months for non-college workers and 22 months for college workers. Overall, the educational gaps produced by these alternative definitions of career switches mirror our baseline moments, implying that the calibrated educational differences in uncertainty and their contributions to the U-E gap are robust to the specific definition of a career switch.

Table C16: Select Targeted Moments Using Alternative Definitions of Career Transitions

	Complex Transitions	1-Digit Occupations	Baseline Definition
No. of sampled careers, N	4.050	3.271	3.039
No. of sampled, C	2.243	2.350	2.118
% with <3 careers, N	28.581	24.318	36.531
% with <3 career, C	50.000	63.067	69.608
Month until 1st career switch, N	55	39	44
Month until 1st career switch, C	47.5	22	29

Notes: N denotes non-college workers, while C denotes college workers. The complex transitions column corresponds to when a career switch is identified based on a complex transition as in Neal (1999). The 1-digit occupation column displays the moments when a career switch is defined as a transition between 1-digit occupation codes. The last column presents the moments under our baseline definition of a career switch that is based on the angular distance between two occupations. See Section 2.3.1 for details on this definition.