Lifelong Gains from a Strong Start: Early Career Fit and the College Wage Premium*

Ismail Baydur† Özyeğin University

Jie Duan‡ Zhejiang University

Paul Jackson§ NUS

October 24, 2026

Abstract

This paper quantifies the contribution of career uncertainty to the college wage premium. Our analysis is motivated by educational differences early in workers' careers. Non-college workers frequently separate into unemployment and switch careers while experiencing sluggish wage growth. College graduates separate and switch less often, see rapid wage growth, and better anticipate their future occupation. We build a general equilibrium search model wherein workers more certain of their career fit invest more in on-the-job human capital and experience faster wage growth. Equalizing career uncertainty by education reduces the wage premium by 19.9%. Non-college workers who find their best career fit early as a direct result of the reduction in career uncertainty enjoy lifelong gains, earning 29.3% more over their working lives. In quantitative applications, AI-driven career uncertainty lowers the wage premium, and training subsidies for young workers can lock them into a bad career fit.

JEL Classification: E24; J24; J62; J64
Keywords: College wage premium; Income inequality; Human capital; Career uncertainty

*For helpful comments and suggestions, we thank Benjamin Born, Niklas Engbom, Zhen Huo, Pete Klenow, David Lagakos, Mi Luo, Andreas Mueller, Victor Ortego-Marti, Xincheng Qiu, Vincenzo Quadrini, Petr Sedlacek, Kurt See, Randall Wright and audiences at NUS, Peking University Guanghua School of Management, Renmin University of China, Shanghai University of Finance and Economics, UC Riverside, WESEAMS (Hong Kong), Wuhan University, and Zhejiang University.

†Faculty of Business, Özyeğin University. *Email:* baydur@gmail.com.

‡School of Economics, Zhejiang University. *Email*: jieduan@zju.edu.cn.

§Department of Economics, National University of Singapore. *Email*: ecspgj@nus.edu.sg.

1 Introduction

The college wage premium is one of the leading indicators of income inequality and is often cited in support of expanding access to higher education.[1] While the evolution of the wage premium over time has been studied extensively (e.g., Katz and Murphy (1992), Acemoglu and Autor (2011)), less emphasis has been placed on its variation over the life cycle. We posit that the wage premium's evolution over the life cycle offers insights into its underlying sources that are masked in the aggregate. Accordingly, this paper's objectives are to (i) propose and provide empirical support for a novel mechanism explaining the evolution of the college wage premium over the life cycle, and (ii) evaluate its quantitative contribution to wage and income inequality within a macroeconomic model of the labor market.

We hypothesize that college graduates start their work-life with a clearer understanding of their best career fit in the labor market and that this characteristic accounts for a meaningful share of the college wage premium. This hypothesis is motivated by three aspects of the skill premium. First, the college wage premium grows over the life cycle. Second, there exists a clear synchronization in wage growth, separations from employment to unemployment, and career mobility over the life cycle. Third, there are stark differences in these outcomes over the life cycle between non-college and college workers. Non-college workers frequently separate into unemployment and switch careers while exhibiting sluggish wage growth early in their work-life. College graduates separate and switch careers at a low rate while experiencing rapid wage growth. The connection between our hypothesis and this set of facts is straightforward. If college graduates start their work-life with less uncertainty over their best career fit, then they are less likely to end up in a bad career fit and separate into unemployment in favor of switching careers. With less uncertainty over their career fit and a higher expected duration of a match in the labor market, college graduates and their employers have a stronger incentive to invest in on-the-job human capital accumulation, leading to faster wage growth and a college wage premium that grows over the life cycle.

Our hypothesis is motivated and supported by an empirical analysis using the National Longitudinal Survey of Youth 1979 (NLSY79) and Current Population Survey (CPS). First, we affirm that the college wage premium is increasing over the life cycle.[2] Second, we

[1] For example, President Obama described higher education as "the single best investment that you can make in yourselves and your future" and cited "the typical American with a bachelor's degree or higher earns over $28,000 more per year than somebody with just a high school education" in remarks titled "Opportunity for All: Making College More Affordable" (Obama, 2014).

[2] This finding is consistent with Deming (2024). We also verify that the college wage premium is increasing over the life cycle after stripping out time and cohort effects using both the Heckman-Lochner-Taber (Heckman et al., 1998; McKenzie, 2006; Huggett et al., 2011; Schulhofer-Wohl, 2018) and Deaton-Hall (Hall, 1968; Deaton, 1997; Aguiar and Hurst, 2013) approaches.

directly support the notion that college graduates have less uncertainty over their best career fit by presenting evidence detailed in a companion paper, Duan and Jackson (2026). In particular, college graduates form more accurate expectations about their future 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 21% smaller among college graduates. Third, to support the notion that lower career uncertainty is associated with higher quality career matches, we show that college graduates are in higher quality matches, where career-match quality is proxied by skill mismatch (Guvenen et al., 2020) and career tenure length. Fourth, to support our emphasis on the connection between career uncertainty and human capital, we draw on training records in the NLSY79 as a proxy for on-the-job human capital investment. Workers in high-quality career matches receive training more frequently and earlier in their career. Given facts three and four, it is unsurprising that we find that college graduates receive training at a higher rate and earlier than those without a college degree.[3]

We then build a structural model that can explain the empirical evidence and be used to perform a quantitative decomposition of the college wage premium. As the evolution of career switching and separations into unemployment over the life cycle are crucial components of our hypothesis, we develop a life cycle search model with endogenous career mobility and separations à la Diamond (1982) and Mortensen and Pissarides (1994). To introduce career uncertainty, newborn workers are assigned one good career fit and are a bad fit in all other careers as in Gervais et al. (2016). The worker's good fit is initially unobserved and they must work in a career to learn their fit. Workers who learn they are in a bad fit decide whether to stay or to separate into unemployment and switch careers.

A novel feature of our model is that it incorporates human capital dynamics both on and off the job. On the job, a worker-firm pair chooses how much effort the worker should undertake to accumulate human capital. As such, the model generates endogenous variation in the rate of human capital accumulation by career-match quality. Workers who are more certain that they are in a good fit invest more in human capital and experience higher wage growth. Off the job, human capital depreciates over an unemployment spell and in career switches.[4] Workers can become "stuck" in a bad career fit if they accumulate enough human capital such that switching careers is too costly. However, if they experience a long unemployment spell and lose enough human capital, the cost to switch careers decreases,

[3] Cairó and Cajner (2018) also find that college graduates are more likely to receive training.

[4] Human capital depreciation during unemployment follows Pissarides (1992), Ljungqvist and Sargent (1998), and Ortego-Marti (2016). The imperfect transferability of human capital in career switches is consistent with the notion that human capital is, in-part, occupation-specific (Kambourov and Manovskii, 2009).

making it more likely that a worker switches careers the longer they have been unemployed.[5]

The model produces life cycle profiles that are realistic and simple to interpret. Workers face the highest amount of career uncertainty early in their work-life. Therefore, young workers frequently separate into unemployment and switch careers. Over time, as workers sort into their good fit, the average separation and career switching rates decline. Further, as workers invest in human capital at a higher rate in their good fit, wages grow with the resolution in career uncertainty. A reduction in career uncertainty upon entering the labor market causes more workers to be in a good career fit at all points throughout their work-life, which leads to higher wages as workers (i) are more productive and (ii) accumulate more human capital in their good fit. This mechanism rationalizes why lower career uncertainty can contribute to the college wage premium. Beyond career uncertainty, the model incorporates additional drivers of the college wage premium by allowing for differences in the ability of workers to learn on the job, the rate of human capital depreciation in career switches, and the productivity and fundamental separation risk of the jobs they work in.

The model is calibrated via simulated method of moments separately for non-college and college workers by matching a set of moments from the NLSY79 and CPS. Together, the calibrated parameters paint a picture that shows that college graduates enter the labor market with less career uncertainty. For example, non-college workers enter the labor market with nearly twice the number of careers that are potentially a good fit as college workers. Moreover, college workers retain a higher fraction of their human capital in career switches, a result we interpret as college graduates switching between relatively similar careers that allow for a high degree of transferability in human capital. The model is in-part validated by showing that it generates a higher incidence of training among college workers. Further, just as in the data, the majority of the model-generated wage growth is explained by within-career wage growth, as opposed to wage growth from career switches.

Our main quantitative exercise equalizes the level of career uncertainty between non-college and college workers. Doing so increases the average wage among non-college workers by 14.9% and reduces the college wage premium by 19.9%. Nearly 60% of the wage gains are accounted for by the shift in their career fit composition. In particular, the reduction in career uncertainty allows more non-college workers to locate their good fit earlier in their work-life, where they are more productive and experience more human capital growth. The reduction in career uncertainty also increases the present discounted value of lifetime earnings by 19% among non-college workers, which represents a 16.5% reduction in the lifetime earnings gap between non-college and college workers.

Next, we ask how much a worker's lifetime earnings would increase by if they were able to

[5]This is consistent with the findings of Carrillo-Tudela and Visschers (2023).

find their good fit early in their career. To do so, we compare the outcomes among non-college workers who do not find their good fit within their first four years of potential experience in the baseline economy but do so in the counterfactual economy. Lifetime earnings are 29.3% higher among these workers in the counterfactual, indicating that there are indeed lifelong gains to finding one's best career fit early in their work-life.

Finally, we leverage the model's combination of learning about one's best career fit and endogenous on-the-job human capital investment to study two applications in which these elements play a central role. First, drawing on survey evidence that indicates that artificial intelligence (AI) is leading college students to reconsider which career best suits them,[6] we introduce uncertainty shocks into the model that reset the worker's knowledge of their best career fit. The uncertainty shock leads to a modest decline in the college wage premium, by 4.8% when the shock arrives once every ten years, and generates a decline in career switching, separations, and unemployment through what we term "wait-and-see" and "discouragement" effects. The anticipation of the shock causes more workers to stay in a bad fit because (i) the shock offers them a potential path to a good fit without switching careers (the wait-and-see effect) and (ii) lowers the returns to finding a good fit because workers can have their good fit status reset by the uncertainty shock (the discouragement effect).

The second application analyzes the effects of subsidizing on-the-job human capital investment. Subsidies that target non-college workers reduce the college wage and earnings premia, particularly early in the life cycle. However, subsidies targeted at young workers can cause workers to accumulate human capital to the point where they become locked into a bad fit. For example, a subsidy given only to workers in their first four years of potential experience can reduce lifetime career switches by nearly 50% and lower the share of workers in a good career fit by nearly 20 percentage points. These applications highlight that technological changes and policies can have large effects on career dynamics, especially early in the life cycle, when career uncertainty is at its highest.

Before turning to the related literature, it is important to clarify that our analysis does not take a stand on the sources of the differences in career uncertainty between non-college and college graduates. Relatedly, we do not claim that a college education has a causal effect in reducing career uncertainty. Instead, this paper proposes career uncertainty as a contributory factor to the college wage premium, presents a set of empirical evidence to support this hypothesis, develops a structural model that takes differences in career uncertainty upon entering the labor market as given, and carries out a quantitative analysis to estimate the contribution of career uncertainty to wage and income inequality.

[6] According to Lumina Foundation and Gallup (2026), nearly half of college students in the US have considered changing their major because of AI's potential impact on the labor market.

This paper contributes to the literature on the college wage premium over the life cycle. Numerous studies have documented wage growth profiles over the life cycle by educational attainment (e.g., Lagakos et al. (2018) and Deming (2024)). Many of these papers are primarily empirical and do not perform a decomposition of the college wage premium over the life cycle through the lens of a structural model. The closest study to do so is Rubinstein and Weiss (2006), who qualitatively analyze how search frictions, human capital, and learning can explain wage growth over the life cycle. Our model incorporates all of these channels and provides a quantitative decomposition of the college wage premium over the life cycle.

Our work is related to a group of papers that use labor search models to explain life cycle wage dynamics (Bagger et al., 2014; Menzio et al., 2016; Engbom, 2026). The main difference in our framework relative to those is that the effort input to human capital accumulation on the job is endogenous in our framework. Further, as our environment features uncertainty over career fit, our model generates endogenous variation in human capital accumulation across the quality of a match between the worker and the career. There are existing frameworks with endogenous on-the-job human capital accumulation in a search model (e.g., Wasmer (2006) and Flinn et al. (2017)). The paper most closely related to ours in terms of topic and methodology is Doepke and Gaetani (2024), who develop a quantitative search model to study the role of employment protections in shaping the college wage premium's evolution over time in the US and Germany. The mechanism at the core of our model is the same: matches with a longer expected duration have a stronger incentive to invest in human capital accumulation. In our model, it is career uncertainty that shapes the expected duration of a match. Further, our interest is in the college wage premium over the life cycle, not in a cross-country comparison of the skill premium.

There is a large literature that studies the sources of inequality in wage and lifetime earnings. Our quantitative findings suggest (i) there are differences in career uncertainty between college and non-college graduates upon entering the labor market and (ii) these differences make substantive contributions to the college wage and earnings premia. These results are aligned with studies that find initial characteristics explain a large portion of the variation in lifetime earnings (Heckman et al., 2006; Huggett et al., 2011). Our paper adds career uncertainty at labor market entry to the set of characteristics that shape variation in wages and earnings and, given the magnitude of the quantitative results, motivates future research into understanding the determinants of career uncertainty. Our results are also aligned with Guvenen (2009) and Qiu et al. (2026), who find that the majority of the variation in life cycle wage growth and income inequality is explained by heterogeneity in returns to experience and income profiles across workers. Through the lens of our model, variation in returns to experience can, in-part, be explained by the differences in career

uncertainty within and across levels of educational attainment.

Finally, our paper is related to the extensive body of work that has studied the determinants of the college wage premium *over time*. Our focus is not the time trend in the skill premium. Instead, we are interested in the *level* of the wage premium and how it evolves *over the life cycle*. However, our model incorporates the broad themes that have been emphasized in this literature. Specifically, our model allows for differences in (i) the productivity of the jobs worked in and (ii) the worker's ability to learn on the job by educational attainment. We view these components as capturing differences in the skill and the production technology between non-college and college graduates emphasized in the papers that propose skill-biased technological change as a driver of the skill premium (Katz and Murphy, 1992; Autor et al., 1998; Krusell et al., 2000; Acemoglu and Autor, 2011). Further, our model allows for differences in the separation rate and capacity for human capital accumulation by educational attainment. These features capture that non-college workers are employed in industries that face a different set of shocks, have fewer employment protections, and work in careers with a smaller scope for advancement/promotion. These and related factors have been identified as being viable inputs into the skill premium (Farber et al., 2021; Card and Lemieux, 2001; Lemieux, 2006; Buera et al., 2022).

The rest of this paper is organized as follows. Section 2 presents the facts that motivate and support our hypothesis. Section 3 develops the model. Section 4 calibrates the model and carries out the quantitative exercises. Section 5 concludes. Supplementary material is delegated to the appendix and referenced throughout.

2 Motivating Evidence

This section presents our empirical analysis. Section 2.1 introduces the data sources. Then, Section 2.2 shows that the college wage premium increases over the life cycle, particularly early in workers' careers. To explain this pattern, we propose that college graduates face less uncertainty regarding their best career fit, a hypothesis supported by our finding presented in Section 2.3 that they make smaller forecast errors when predicting their future occupations. As a result, we find and show in Section 2.4 that college workers are more likely to start out in good-fit careers and thus have, on average, higher career match quality. Since high-quality matches have longer expected durations, they strengthen the incentives for human capital investment, which is supported by the facts presented in Section 2.5, leading to faster wage growth. These results indicate that the faster wage growth among college graduates is, in-part, driven by lower initial uncertainty and the associated increase in human capital accumulation.

2.1 Data

Our primary dataset is the National Longitudinal Survey of Youth (NLSY79), a longitudinal survey conducted by the US Bureau of Labor Statistics. The NLSY79 follows a nationally representative cohort of individuals who were aged 14 to 22 in 1979.

There are three aspects of the NLSY79 that make it well-suited for our analysis. First, the consecutive employment histories allow us to trace respondents' almost four-decade working lives. Our analysis specifically restricts the sample to ages 18 through 57 for non-college workers and 22 through 57 for college workers. Second, the survey includes rich measures of cognitive ability, non-cognitive traits, and occupational expectations for respondents, which we use to explore the evidence relating to career fit or match quality. Third, the comprehensive training records provide a high-quality proxy of on-the-job human capital investment. Following the sample selection criteria detailed in Appendix A.1, we arrive at an annual sample of $10,278$ respondents.

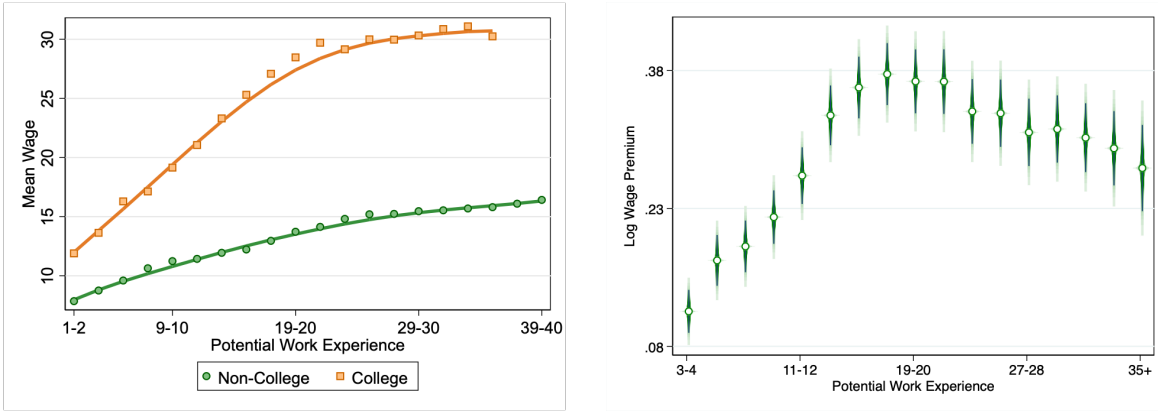
We supplement the NLSY79 analyses with cross-sectional data from the 1978-2018 March Current Population Survey Annual Social and Economic Supplement (ASEC). The data contain 3.6 million observations, including complete demographic and employment information. Beyond that, we also replicate the life cycle college premium pattern using the NLSY97 dataset, which is designed along the same lines as the NLSY79 but follows a different cohort: it comprises 8,984 respondents who were ages 12 to 17 at the time of their first interview in 1997. To maintain sample comparability, we arrive at a sample of 5,786 respondents spanning observations through 2019. Detailed introductions to the data and sample selection can be found in Appendix A.1.

2.2 Fact I: The Life Cycle Pattern of College Premium

We begin with the life cycle wage profiles of college workers, defined as those with at least a bachelor's degree, and non-college workers. Figure 1(a) plots mean wages by potential experience. Two key findings emerge.[7] First, we observe a persistent *college wage premium*, with college workers earning higher wages than non-college workers at each career stage. Second, wages for college workers grow faster than those of non-college workers, particularly during early career stages, indicating a widening college wage premium during early life cycles. For example, the mean wage increases by 139% (75%) for college (non-college) workers during the first 20 years of potential experience.

The discernible life cycle pattern seen by plotting average wages within potential ex-

[7]The results are robust to alternative measures of life cycle stage, such as age and actual work experience. See Appendix Section A.2.



(a) Descriptive Pattern

(b) Conditional Estimate

Figure 1: Mean Wage Over Life Cycle. *Notes:* NLSY79 Sample. In the left panel, each pairwise t-test yields a p-value of 0.0000, which rejects the null hypothesis of zero difference. The right panel displays point estimates with 90% confidence intervals; standard errors are clustered at the individual level.

perience bins, while heuristically valuable as a starting point, does not account for certain confounding factors that may bias the estimated college premium. Following Deming (2024), we estimate the college premium over life cycles as follows:

$$\ln(wage_{it}) = \alpha College_i + \sum_k Exp_{it} + \sum_k \gamma_k College_i \times Exp_{it} + Urate_{it} + \mathbb{X}_i + \mathbf{\Phi} + \epsilon_{it},$$

where $wage_{it}$ is the hourly wage of individual i at time t, $College_i$ is a binary indicator for college education attainment, and Exp_{it} is a vector of experience bins that is specified as potential experience intervals. The annual unemployment rate, $Urate_{it}$, is included to control for business cycle effects. The vector of individual-level attributes, $\mathbb{X}_i$, includes race, gender, and cognitive test scores. We also incorporate occupation and industry fixed effects.

Our interest is in the sequence $\{\alpha + \gamma_k\}_{k=2}^{K}$, the partial derivative of $log(wage_{it})$ with respect to $College_i$, as it traces the college premium at the k^{th} career stage. Figure 1(b) plots the conditional estimates with their 90% confidence interval. Notably, the college premium grows substantially during early career stages, rising from about 11% in the third and fourth years of potential experience to 36% by year 20. To demonstrate the generalizability of this pattern in the US labor market, we replicate this exercise using the ASEC and the NLSY97. As demonstrated in Appendix A.2, the results deliver a consistent finding that the college wage premium grows over the life cycle.

A fundamental challenge in estimating life cycle wage growth is that the effects of experience, birth cohort, and time are collinear and thus cannot be separately identified. Since we calibrate our structural model to the wage profiles in the large and highly representa-

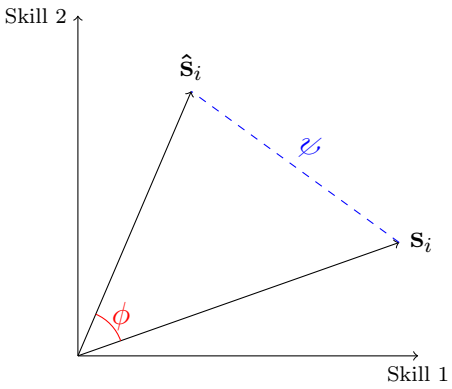


Figure 2: Distance Measurements

tive ASEC sample, we are keenly aware of this identification issue and how it may affect the interpretation of our quantitative findings. As such, we apply two standard and widely acknowledged approaches, *Heckman-Lochner-Taber* and *Deaton-Hall*, to disentangle experience effects from cohort and time effects in the ASEC life cycle wage profiles. We find that while the level of wage growth for each education group changes modestly, the increase in the college wage premium over the life cycle remains very close to that in the raw wage profiles that we use for calibration. This suggests that our calibrated model and the subsequent quantitative results are largely unaffected by any impact of cohort and time effects, which our quantitative model does not account for. Appendix A.3 presents the details behind each correction method and the findings when applied to our sample.

2.3 Fact II: Forecast Error by Education

Having established the heterogeneity of wage profiles across education groups, we next investigate the underlying differences between these two groups that could potentially drive these diverging life cycle wage profiles. In particular, we present supportive evidence that initial uncertainty regarding the best fit career differs by education. To do so, this section measures the accuracy of workers' expectations of their future occupation by leveraging 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 10,278 respondents in our sample, 4,243 listed an expected occupation at age 35 and had a realized occupation at that age.[8] In particular, the proportion of workers engaged in their precisely anticipated occupation (i.e., no forecast error) was 16% within the college group, in contrast to 7% within the non-college group.

[8]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.

Table 1: Angular and Euclidean Distances by Education

	Non-College	College
Panel A: Forecast Error at Age 35		
Angular Distance	30.15	21.40
Euclidean Distance	0.77	0.61
N	3,194	1,049
Panel B: Forecast Error in 5 Years		
Angular Distance	27.49	21.67
Euclidean Distance	0.67	0.57
N	3,004	424

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 an individual's expected occupation in 5 years with the realized occupation 5 years after their initial interview. 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. Data are from the NLSY79.

We further 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. 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: $\mathbb{R}^5 \times \mathbb{R}^5 \to [0, \pi/2]$:

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

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. Figure 2 illustrates the two distance measures.

Table 1 reinforces that college workers form more accurate forecasts. From Panel A, college graduates have an average Euclidean distance that is 29% smaller and an angular distance that is 21% smaller for their occupation at age 35. Panel B shows similar differences if we examine the forecast error in 5 years.[9]

[9]Appendix Figure A9 shows that the education gap in forecast errors extends beyond the mean and remains evident at all other percentiles.

Table 2: Comparison of Match Quality across Education Groups

	Non-College	College
Panel A: Skill Mismatch		
Skill Mismatch	1.64	1.43
N	167,143	48,848
Panel B: Career Tenure (Years)		
Career Duration	8.05	10.46
N	20,763	4,670

Notes: NLSY79 Sample, 1978-2018. The null hypothesis was rejected for all pairwise comparisons ($p < 0.0001$).

2.4 Fact III: Career Match Quality by Education

Given that initial uncertainty regarding career match quality differs across education groups, a natural question is whether that shapes career sampling and, ultimately, the realized career match quality. Here, we are faced with a measurement challenge in quantifying the career match quality. Drawing upon available data and relevant literature, we employ three candidate indicators: forecast error, skill mismatch, and career tenure. Details regarding the construction of each measure is available in Appendix A.5.

Forecast errors, as defined in Section 2.3, quantify how accurately workers foresee their future occupation. It is posited that individuals who are better at predicting their future occupation, which is indicative of a better understanding of their best career fit, are more likely to form better matches. As shown in Table 1, college workers make smaller forecast errors compared to their non-college counterparts.

The second indicator, skill mismatch, provides a direct measure of match quality by quantifying the distance between a worker's skills and the requisite skills for their occupation. As shown in Panel A of Table 2, skill mismatch tends to be lower for college workers, implying a higher career match quality within this group.

The third indicator is career tenure.[10] Presumably, a well-matched pair is less likely to be separated, and thus, we anticipate a protracted career tenure as an ex-post manifestation of a good match. As indicated in Panel B in Table 2, the average career tenure for college workers is about 30% longer than that of non-college workers.[11]

[10] A career is defined as a set of occupations sharing a similar skill set, and a career switch thus occurs when the destination occupation is considerably different in skill composition from the origin occupation. Crucially, our skill-based career switch is not a conventional career ladder progression. See Appendix A.4.

[11] We also compare employer, occupation, and industry tenures by education. As demonstrated in Appendix Table A5, college workers consistently hold longer tenures than their non-college counterparts.

2.5 Fact IV: Career-Match Quality and Human Capital Investment

The evidence presented to this point supports the notion that college graduates enter the labor market with less uncertainty regarding their best career fit and form high-quality career matches. The last component of our hypothesis that requires empirical support is to examine whether there is a relationship between career match quality and human capital investment. The intuition for such a linkage is straightforward. As better matches are associated with a longer tenure, a worker-firm pair in a high-quality match has a stronger incentive to invest in human capital as they can enjoy the benefits over a longer expected duration.

On-the-job human capital investment, broadly defined, is not completely observable. Therefore, we rely on a proxy of human capital investment provided by the NLSY79 in the form of training records. The NLSY79 offers a continuous record of training-related information, covering the duration, type, reason, and generality, among many other characteristics, for each training program received since the last survey year. We identify an individual's training status (i.e., whether they were engaged in training) for each period based on the reported training duration.

We validate the NLSY79 training records' ability to serve as a proxy for on-the-job human capital investment by presenting several facts in Appendix Figure A11. In particular, we find that training is by far the most prevalent type of training reported. Further, the primary reason cited for undertaking training is the desire to maintain and upgrade skills and over 85% of respondents affirmed the applicability of the skills acquired through training to their current or most recent jobs. Finally, these patterns do not differ systematically between college and non-college groups, which reinforces the measure's validity.

We estimate the correlation between match quality and training incidence via the following regression:

$$TRN_{it} = \beta MQ + Age_{it} + \mathbb{X}_i + \mathbf{\Phi} + \epsilon_{it}, \tag{2}$$

where TRN_{it} is an indicator for whether an employed worker i receives training at time t, and MQ is the proxy for match quality, which can be the standardized Euclidean distance or the standardized angular distance of the worker's current job to their expected occupation, or the magnitude of skill mismatch. The regression also controls for education, gender, race, cognitive ability, age, and industry and occupation fixed effects.

The left panel of Table 3 presents the estimation results. The first row shows that a higher match quality, manifested as lower forecast error or skill mismatch, is positively correlated with the likelihood of receiving training. For example, workers whose angular distance is one standard deviation above the mean are 0.8 percentage points less likely to receive training than those one standard deviation below the mean.

Table 3: Training and Career Match Quality

	Training Incidence			Training Timing		
	(1) Euclidean	(2) Angular	(3) Mismatch	(1) Euclidean	(2) Angular	(3) Mismatch
MQ	-0.002***	-0.004***	-0.003***	0.272**	0.377***	0.216*
College	0.014***	0.014***	0.016***	-1.953***	-1.918***	-2.017***
Age	-0.003***	-0.003***	-0.002***			
AFQT	0.022***	0.022***	0.022***	-0.870***	-0.849***	-0.420***
Race	-0.009***	-0.009***	-0.012***	0.984***	0.983***	0.135
Female	0.013***	0.013***	0.008***	0.015	-0.005	-0.185
Constant	0.195***	0.195***	0.183***	7.782***	7.778***	7.245***
Observations	135,887	135,887	212,279	3,355	3,355	5,776
R^2	0.030	0.030	0.027	0.060	0.062	0.042

Notes: The forecast error measures have been standardized to zero mean and unit standard error. In the right panel specification, we control for occupation fixed effects and industry fixed effects as observed at the time of each individual's first training. Data are from the NLSY79 sample, 1978-2018. Levels of statistical significance are indicated by *($p < 0.10$), **($p < 0.05$), ***($p < 0.01$).

An alternative implication concerns the timing of when training was received. If workers have more certainty regarding their best career fit, and consequently are more likely to start out in a good fit, they will tend to begin on-the-job investment earlier in their careers; then we should observe a negative correlation between match quality and the timing of initial training. To empirically examine this, we employ a specification akin to equation (2), wherein we substitute the binary training status with the number of years of work experience at which individual i first receives on-the-job training ($TRNTiming_i$), while retaining the aforementioned set of standard time-invariant demographic controls.

The right panel of Table 3 shows the results. The coefficient in the first row is of primary interest. It indicates that workers with a lower forecast error or a smaller average skill mismatch receive their first training earlier during their career.[12]

[12]Certain jobs require compulsory onboarding training, and firms sometimes provide short-term training that is neither related to genuine human capital accumulation nor match quality considerations (e.g., cybersecurity training). To examine the robustness of our results to this concern, we estimate the regressions using a sample restricted to training programs of sufficient duration. See Appendix A.7.3 for details.

2.6 Summary and Transition to the Model

This section has synthesized the empirical patterns that we argue stand as a rationale for why lower career uncertainty among college graduates explains why, in-part, the college wage premium increases over the life cycle. We have documented that college workers have lower occupational forecast errors, which supports the foundation of our hypothesis, namely that they face lower uncertainty about their best career fit. As a result, college graduates are more likely to be in high-quality career matches. Since high-quality career matches have longer tenures, they also exhibit greater investment in on-the-job human capital accumulation.[13] A corollary to this is that human capital and wage growth are faster among college graduates.

Our remaining primary objective is to quantify the contribution of career uncertainty to the college wage premium. To this end, we proceed to develop a search model with endogenous on-the-job human capital accumulation, separations, and career switching in which workers are uncertain about their best career fit and learn through sampling careers.

3 Model

This section presents a life cycle search model with endogenous on-the-job human capital accumulation, separations, and career switching. Section 3.1 details the economic environment. Section 3.2 presents the recursive formulation and defines a stationary equilibrium. Section 3.3 demonstrates the model's mechanisms and transitions to the quantitative analysis. To simplify the presentation of the model, we write the model without educational attainment as a state variable. Later, in the quantitative analysis, we calibrate the model separately for non-college and college graduates.

3.1 Environment

Time is continuous and goes on forever. The economy is populated by overlapping generations of workers and a large measure of firms. All agents are risk neutral and discount the future at rate $r > 0$.

Workers are heterogeneous in four dimensions. The first is potential experience $x \in \{x_1, \ldots, x_T\}$. Second, each worker is best suited for one career, which we refer to as their good fit, $c^* \in \mathbb{C}$ where $\mathbb{C} \subset \mathbb{Z}_+$ and $N \equiv |\mathbb{C}| > 2$. Third is a worker's history, n, the number of careers the worker has sampled. Fourth is human capital, $h \in \{h_1, h_2, \ldots, h_J\}$. Human capital is general.

[13] The evidence indicating that higher match quality is associated with faster wage growth is well documented in Appendix Section A.6.

Upon entering the labor market, workers are endowed with potential experience x_1, human capital h_1, and are assigned their good fit by nature. Potential experience, human capital, and a worker's history are observable. The good fit is initially unobserved and the worker's initial beliefs are uniform over $\mathbb{C}$: $\Pr(c = c^*) = 1/N$ for all $c \in \mathbb{C}$. 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. A worker's status in each career is observable.

Employed workers with history n and status $s = un$ learn their fit at rate ϕ.[14] Workers who learn that their current career is not their good fit update their beliefs over the careers they have not sampled according to Bayes rule. A type n worker who has learned that $n-1$ careers are not their good fit believes that the n^{th} career is their good fit with probability $p(n)$, where

$$p(n) = \frac{1}{N - (n-1)}. \tag{3}$$

The labor market is segmented by career. That is, there are N distinct labor markets. Firms incur a flow cost k to post and maintain a vacancy. Search is random within each segment of the labor market. The number of meetings between workers and firms is governed by the meeting function $m(u, v)$ where u is the measure of unemployed workers and v is the amount of vacancies in the market. There is no search on the job. The meeting function exhibits constant returns to scale. Denote $\theta = v/u$ as market tightness. The job finding rate is $f(\theta) = m(u, v)/u$ where f: $\mathbb{R}_+ \to [0, \infty)$ is strictly increasing and concave. Firms fill their vacancy at rate $q(\theta) = m(u, v)/v$ where q: $\mathbb{R}_+ \to [0, \infty)$ is strictly decreasing and convex.

A worker with potential experience x and human capital h_j who is employed in a good fit produces a flow output Ah_j where $A > 0$. Workers in a bad fit produce αAh_j units of output, where $\alpha \in (0, 1)$. The output in an unsure match, where the worker has history n, is the expected output $p(n)Ah_j + (1 - p(n))\alpha Ah_j$. Matches between a firm and a worker with human capital h_j are destroyed at an exogenous rate $\delta(h_j)$ where $\partial\delta(h_j)/\partial h_j \leq 0$. Unemployed workers with human capital h_j produce a flow output $bh_j < \alpha Ah_j$.

Employed workers accumulate human capital. Let $\tau \geq 0$ denote effort put into accumulating human capital/learning on the job. The disutility of effort incurred by the worker is $c(\tau)$ where $c(0) = 0$, $c'(0) = 0$, $c'(\cdot) > 0$, and $c''(\cdot) > 0$. Given effort τ and potential experience x_i, a worker increases their human capital from h_j to h_{j^+} at rate $\pi(x_i, \tau)$ where $j^+ = \min\{j + 1, J\}$, $\partial\pi(x_i, \tau)/\partial\tau > 0$, $\partial^2\pi(x_i, \tau)/\partial\tau^2 \leq 0$, and $\partial\pi(x_i, \tau)/\partial x_i \leq 0$ for all x_i.

[14] We interpret the learning rate as a reduced form representation of a signal extraction problem where, with probability ϕ over a short interval of time, dt, the observed match output is perfectly informative of the worker's career fit and with a complementary probability is completely uninformative.

Unemployed workers lose human capital through two channels. The first is the decay of human capital over an unemployment spell: unemployed workers with human capital h_j transition to h_{j^-}, where $j^- = \max\{1, j-1\}$, at rate μ. Second, workers lose human capital in career switches. Unemployed workers can switch careers at any time and workers of human capital h_j who move from career c to c' transition from h_j to $h_{j\lfloor\rfloor}$ with probability γ, where $h_{j\lfloor\rfloor} = \max\{\lfloor \zeta h_j \rfloor, h_1\}$ and $\zeta \in (0,1)$. With probability $1-\gamma$, the worker transitions to $h_{j\lceil\rceil}$ where $h_{j\lceil\rceil} = \max\{\lceil \zeta h_j \rceil, h_1\}$. In words, workers who switch careers experience a proportional decrease in their human capital. The decision to leave a career is irreversible.

The economy is initially populated by a unit measure of workers distributed evenly across all levels of potential experience. A worker of potential experience x_i ages to x_{i^+} at rate σ. Workers with potential experience x_T die at rate σ. To maintain a constant population of workers, a measure σ/T of newborn workers enters the economy at each point in time.

3.2 Equilibrium

We restrict our attention to stationary equilibria and begin characterizing the equilibrium by noting that there is a symmetry across the labor markets for each career $c \in \mathbb{C}$. This is because each career has the same production technology and each market has the same meeting technology and vacancy posting cost. Further, good fits are distributed uniformly over $\mathbb{C}$. This implies that workers with an unsure career fit are indifferent between which career to search for and will be evenly distributed across the N distinct markets. In turn, firms enter each market at the same rate in equilibrium. This is why, in what follows, we do not index any endogenous variables by the specific career, c.

With the symmetric property of the model in mind, we proceed to describe the determination of wages and human capital effort, τ, which we simply refer to as "effort" henceforth. Wages and effort are determined jointly and cooperatively by the worker and firm through Nash bargaining with continuous renegotiation. Let $R(s, n, x_i, h_j)$ denote the lifetime discounted utility of an unemployed worker with status s in their current career, history n, potential experience x_i, and human capital h_j. The value of employment for a given wage and effort is $\tilde{W}(s, n, x_i, h_j; w, \tau)$. The value of a filled job to the firm is $\tilde{J}(s, n, x_i, h_j; w, \tau)$. Denoting $\beta \in [0,1]$ as the worker's bargaining power, the Nash bargaining problem is

$$\max_{w,\tau} \left[\tilde{W}(s, n, x_i, h_j; w, \tau) - R(s, n, x_i, h_j)\right]^{\beta} \left[\tilde{J}(s, n, x_i, h_j; w, \tau)\right]^{1-\beta}, \tag{4}$$

where the value of unemployment is the worker's outside option and the value of the firm's outside option, an unfilled vacancy, is zero through free entry. Let $w^*(s, n, x_i, h_j)$ and $\tau^*(s, n, x_i, h_j)$ denote the solutions to (4). We then define $W(s, n, x_i, h_j)$ and $J(s, n, x_i, h_j)$

as the value of employment for a worker and firm, respectively, at the equilibrium values for wage and effort:

$$W(s,n,x_i,h_j) \equiv \tilde{W}\left(s,n,x_i,h_j;w^*(s,n,x_i,h_j),\tau^*(s,n,x_i,h_j)\right), \tag{5}$$

$$J(s,n,x_i,h_j) \equiv \tilde{J}\left(s,n,x_i,h_j;w^*(s,n,x_i,h_j),\tau^*(s,n,x_i,h_j)\right). \tag{6}$$

Appendix B.2 shows that the first order condition of (4) with respect to the wage gives

$$W(s,n,x_i,h_j) - R(s,n,x_i,h_j) = \beta S(s,n,x_i,h_i), \tag{7}$$

where $S(s,n,x_i,h_j) = W(s,n,x_i,h_j) - R(s,n,x_i,h_j) + J(s,n,x_i,h_j)$ is the match surplus. The first order condition of (4) with respect to effort is

$$c'(\tau) = \frac{\partial \pi(x_i,\tau)}{\partial \tau}\left[S(s,n,x_i,h_{j^+}) - S(s,n,x_i,h_j) + R(s,n,x_i,h_{j^+}) - R(s,n,x_i,h_j)\right]. \tag{8}$$

Appendix B.2 shows that equation (8) corresponds with the first order condition of the match surplus with respect to τ. That is, effort is chosen to maximize the joint surplus of the match. Then, through the surplus sharing rule in equation (7), the wage is set so that workers earn a share β of the match surplus.

We now proceed to the flow Bellman equations for workers and firms. Let $U(s,n,x_i,h_j)$ denote the value of unemployment for a worker who is searching for a career where their status is s. It satisfies the following flow Bellman equation:

$$\begin{aligned} rU(s,n,x_i,h_j) = {} & bh_j + \sigma\left[\mathbb{1}_{\{i<T\}}R(s,n,x_{i^+},h_j) - U(s,n,x_i,h_j)\right] + \\ & \mu\big[R(s,n,x_i,h_{j^-}) - U(s,n,x_i,h_j)\big] + f(\theta)\left[W(s,n,x_i,h_j) - U(s,n,x_i,h_j)\right], \end{aligned} \tag{9}$$

where $\mathbb{1}_{\{i<T\}}$ is equal to one if $i<T$ and $R(s,n,x_i,h_j)$ satisfies

$$R(s,n,x_i,h_j) = \begin{cases} \max\{\overbrace{\mathbb{E}U(u,n+1,x_i,\zeta h_j)}^{\text{Switch careers}}, \overbrace{U(s,n,x_i,h_j)}^{\text{Remain in current career}}\} & \text{if } n < N-1, \\ \max\{\mathbb{E}U(g,N,x_i,\zeta h_j), U(s,n,x_i,h_j)\} & \text{if } n = N-1. \end{cases} \tag{10}$$

From equation (9), unemployed workers produce flow output bh_j, age at rate σ, lose human capital at rate μ, and find a job at rate $f(\theta)$ where θ is the equilibrium value of tightness in market. After an aging or human capital shock, the worker decides whether to switch careers or not. According to equation (10), the option value of switching careers, $R(s,n,x_i,h_j)$, is the maximum of the value of switching careers and remaining in the current career. When

a worker switches careers, their history increases by one to $n+1$ and they lose human capital. The dependence of $R(s,n,x_i,h_j)$ on the worker's history, n, shows that workers with a history $n<N-1$ and who switch careers will enter their next career with an unsure status. Workers with history $n=N-1$ have only one more career to sample and, by process of elimination, will have identified the one remaining career as their good fit. As such, if they switch careers, they enter that career with status $s=g$. Finally, recall that $R(s,n,x_i,h_j)$ is the worker's outside option in the bargaining problem specified in equation (4). That is, a worker always uses the value of searching for a job in their current career or the value of switching careers, whichever is higher, as their outside option.

The value of employment for a worker who is employed in their good fit given their wage and effort, $\tilde{W}(g,n,x_i,h_j;w,\tau)$, satisfies

$$\begin{aligned} r\tilde{W}(g,n,x_i,h_j;w,\tau) &= w-c(\tau)+\pi(x_i,\tau)\big[W(g,n,x_i,h_{j^+})-W(g,n,x_i,h_j)\big]+ \\ &\sigma\big[\mathbb{1}_{\{i<T\}}W(g,n,x_{i^+},h_j)-W(g,n,x_i,h_j)\big]+\delta(h_j)\left[U(g,n,x_i,h_j)-W(g,n,x_i,h_j)\right]. \end{aligned} \tag{11}$$

Equation (11) shows that the worker earns a wage w and incurs effort cost, $c(\tau)$. At rate $\pi(x_i,\tau)$, the worker's human capital increases to h_{j^+}. The worker is hit by an aging shock at rate σ and separates into unemployment at rate $\delta(h_j)$. As workers who have found their good fit will not switch careers, the continuation value upon entering unemployment is $U(g,n,x_i,h_j)$.

The value of employment in a bad fit is given by

$$\begin{aligned} r\tilde{W}(b,n,x_i,h_j;w,\tau) &= w-c(\tau)+\pi(x_i,\tau)\big[Q(n,x_i,h_{j^+})-W(b,n,x_i,h_j)\big]+ \\ &\sigma\left[\mathbb{1}_{\{i<T\}}Q(n,x_{i^+},h_j)-W(b,n,x_i,h_j)\right]+\delta(h_j)\left[R(b,n,x_i,h_j)-W(b,n,x_i,h_j)\right], \end{aligned} \tag{12}$$

where

$$Q(n,x_i,h_j)=\begin{cases} \max\{\overbrace{\mathbb{E}U(u,n+1,x_i,\zeta h_j)}^{\text{Destroy the match}},\overbrace{W(b,n,x_i,h_j)}^{\text{Maintain the match}}\} & \text{if } n<N-1, \\ \max\{\mathbb{E}U(g,N,x_i,\zeta h_j),W(b,n,x_i,h_j)\} & \text{if } n=N-1. \end{cases} \tag{13}$$

From (12), the worker earns their wage and incurs the cost of effort, $c(\tau)$. At rate $\pi(x_i,\tau)$, their human capital increases from h_j to h_{j^+} and the worker is hit by an aging shock at rate σ. Following a human capital gain or aging shock, the worker's continuation value is $Q(n,x_i,h_j)$, which represents the option value to the worker of destroying the match or remaining employed. The last term of (12) captures that the match is destroyed at rate $\delta(h_j)$ and, upon entering unemployment, the worker decides whether to switch careers or

not. As such, their continuation value is given by $R(b, n, x_i, h_j)$.

Before proceeding to the next value function, we will characterize the endogenous job destruction choices in the model. As seen in (12), there are scenarios where a worker may opt to become unemployed and switch careers instead of being employed in a bad career fit. While the preceding value function presents this choice as one made by the worker, a worker and firm will always be aligned on when to destroy a match or not. This is because the worker and firm share the match surplus through the sharing condition, equation (7). To demonstrate, suppose that $n < N - 1$. The continuation value following a human capital gain shock,[15] $Q(n, x_i, h_{j^+})$, can be rewritten as

$$Q(n, x_i, h_{j^+}) = \max\{0, W(b, n, x_i, h_{j^+}) - R(b, n, x_i, h_{j^+})\} = \max\{0, \beta S(b, n, x_i, h_{j^+})\}, \quad (14)$$

where we have used the fact that $R(s, n, x_i, h_{j^+}) = \mathbb{E}U(u, n + 1, x_i, \zeta h_{j^+})$ when the worker wants to switch careers and applied the surplus sharing condition, equation (7), between the second and third terms. From (14), the worker chooses to maintain the match if $S(b, n, x_i, h_{j^+}) > 0$. It will be made clear below that the firm will also opt to maintain the match if the surplus is positive.

Continuing with the value functions, the value of employment in an unsure fit satisfies

$$\begin{aligned} r\tilde{W}(u, n, x_i, h_j; w, \tau) = w - c(\tau) + \pi(x, \tau)\big[W(u, n, x_i, h_{j^+}) - W(u, n, x_i, h_j)\big] + \\ \sigma\left[\mathbb{1}_{\{i<T\}}W(u, n, x_{i^+}, h_j) - W(u, n, x_i, h_j)\right] + \delta(h_j)\left[U(u, n, x_i, h_j) - W(u, n, x_i, h_j)\right] + \\ \phi\left[p(n)\left[W(g, n, x_i, h_j) - W(u, n, x_i, h_j)\right] + (1 - p(n))[Q(n, x_i, h_j) - W(u, n, x_i, h_j)]\right]. \end{aligned} \quad (15)$$

The first two lines of (15) have a similar interpretation to the preceding value functions for good and bad fits. The third line is unique to the unsure state and captures that the worker's fit is revealed at rate ϕ. The conditional probability that the worker is in their good fit is given by their prior, $p(n)$. If the worker is in their good fit, they remain employed and their status updates from $s = un$ to $s = g$. With probability $1 - p(n)$ the worker learns they are in a bad fit and earns the continuation value $Q(n, x_i, h_j)$, as the worker decides whether to enter unemployment in favor of switching careers or to remain employed in a bad fit.

We will now transition to characterizing the behavior of firms. The value of a filled job

[15] The same logic is applicable following an aging shock and, for matches with an unsure career fit, a learning shock.

with a worker who is in their good fit for a given wage and effort, $\tilde{J}(g, n, x_i, h_j; w, \tau)$, satisfies

$$\begin{aligned} r\tilde{J}(g, n, x_i, h_j; w, \tau) = Ah_j - w + \pi(x_i, \tau)\left[J(g, n, x_i, h_{j+}) - J(g, n, x_i, h_j)\right] + \\ \sigma\left[\mathbb{1}_{\{i<T\}}J(g, n, x_{i^+}, h_j) - J(g, n, x_i, h_j)\right] + \delta(h_j)[V - J(g, n, x_i, h_j)], \end{aligned} \tag{16}$$

where $Ah_j - w$ is the flow profit earned by the firm and V is the value of an unfilled vacancy. The value of a filled job with a worker who is in a bad career fit is given by

$$\begin{aligned} r\tilde{J}(b, n, x_i, h_j; w, \tau) = \alpha Ah_j - w + \pi(x_i, \tau)\left[\max\{J(b, n, x_i, h_{j+}), V\} - J(b, n, x_i, h_j)\right] \\ + \sigma\left[\max\{\mathbb{1}_{\{i<T\}}J(b, n, x_{i^+}, h_j), V\} - J(b, n, x_i, h_j)\right] + \delta(h_j)[V - J(b, n, x_i, h_j)]. \end{aligned} \tag{17}$$

From (17), the continuation value following a human capital or aging shock is given by the maximum between the value of a filled job and a vacancy, V. Following our discussion above, applying the surplus sharing condition implies that the firm would choose to maintain the match if the match surplus, following a shock, is positive.

The value of a filled job in an unsure career fit, $\tilde{J}(u, n, x_i, h_j; w, \tau)$, satisfies

$$\begin{aligned} r\tilde{J}(u, n, x_i, h_j; w, \tau) = p(n)Ah_j + (1 - p(n))\alpha Ah_j - w \\ + \pi(x_i, \tau)\left[J(u, n, x_i, h_{j+}) - J(u, n, x_i, h_j)\right] \\ + \sigma\left[\mathbb{1}_{\{i<T\}}J(u, n, x_{i^+}, h_j) - J(u, n, x_i, h_j)\right] + \delta(h_j)\left[V - J(u, n, x_i, h_j)\right] \\ + \phi\left[p(n)J(g, n, x_i, h_j) + (1 - p(n))\max\{J(b, n, x_i, h_j), V\} - J(u, n, x_i, h_j)\right]. \end{aligned} \tag{18}$$

The interpretation of equation (18) mirrors that of the worker's value of employment in an unsure match, equation (15).

To characterize the value of a vacancy, we first introduce notation for the distribution of workers within each market. Let $\omega(s, n, x_i, h_j)$ denote the measure of unemployed workers with status s, history n, potential experience x_i, and human capital h_j. The total measure of unemployed workers is

$$\Omega = \sum_{j=1}^{J}\sum_{i=1}^{T}\sum_{n=1}^{N}\sum_{s\in\{un,b,g\}}\omega(s, n, x_i, h_j). \tag{19}$$

As workers are equally distributed across the markets for each career $c \in \mathbb{C}$, the probability, conditional on meeting a worker, of a firm meeting a worker with characteristics (s, n, x_i, h_j)

is $\omega(s,n,x_i,h_j)/\Omega$. Therefore, the value of a vacancy, V, satisfies

$$rV = -k + q(\theta)\sum_{j=1}^{J}\sum_{i=1}^{T}\sum_{n=1}^{N}\sum_{s\in\{un,b,g\}}\frac{\omega(s,n,x_i,h_j)}{\Omega}\left[J(s,n,x_i,h_j) - V\right]. \tag{20}$$

Firms post vacancies in each market until $V = 0$. Combining (20) with $V = 0$ gives:

$$\frac{k}{q(\theta)} = \sum_{j=1}^{J}\sum_{i=1}^{T}\sum_{n=1}^{N}\sum_{s\in\{un,b,g\}}\frac{\omega(s,n,x_i,h_j)}{\Omega}J(s,n,x_i,h_j). \tag{21}$$

The equilibrium value of tightness in each market, θ, is pinned down by (21) and is the value of tightness where the expected cost to fill a vacancy are equal to the expected value of a filled job. We are now ready to define a stationary equilibrium.

Definition 1. A stationary equilibrium is a wage function, $w^*(s,n,x_i,h_j)$, effort function, $\tau^*(s,n,x_i,h_j)$, value functions for unemployed workers $\{U(s,n,x_i,h_j), R(s,n,x_i,h_j)\}$, value functions for employed workers $\{W(s,n,x_i,h_j;w,\tau), \tilde{W}(s,n,x_i,h_j), Q(n,x_i,h_j)\}$, firm value functions $\{V, \tilde{J}(s,n,x_i,h_j;w,\tau), J(s,n,x_i,h_j)\}$, market tightness θ, and a distribution of workers that satisfies the following conditions. The wage and effort functions satisfy equations (7)-(8). The value functions for unemployed workers satisfy equations (9) and (10). The value functions for employed workers satisfy equations (5) and (11)-(15). The value functions for firms satisfy equations (6), (16)-(18), and (20). Market tightness satisfies (21). Finally, the distribution of workers is such that all inflows and outflows of workers across the states of employment status, career fit status, history, potential experience, and human capital are equal to each other and satisfy the laws of motion specified in Appendix B.3.

3.3 Mechanisms

The goal of this section is to set the foundation for understanding and interpreting the quantitative results in Section 4. In particular, this section explains how some workers become stuck or locked in at a bad career fit, why the model can explain the joint evolution of wages, separations, and career switching over the life cycle observed in the data, and how a reduction in career uncertainty shapes human capital accumulation and wage growth.

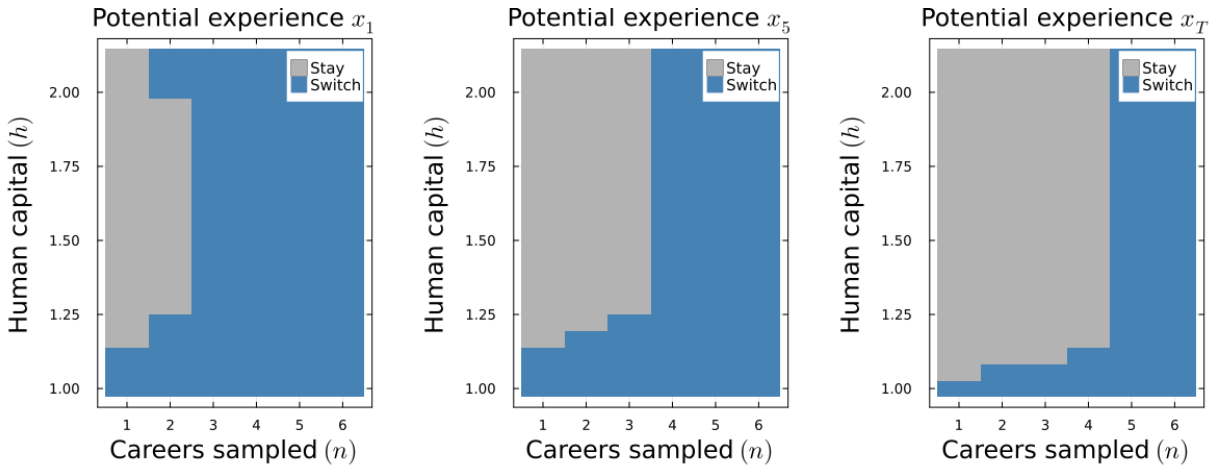


Figure 3: Career Switching Policy Function. *Notes:* This figure represents the career switching choice of an unemployed worker with $s = b$, potential experience x, careers sampled n, and human capital h. Grey regions are where the worker would stay in a bad career fit, while blue regions are where they would switch careers. Produced using the non-college parameter values listed in Table 5.

3.3.1 Career Switching

We begin by analyzing the decision of an unemployed worker to switch careers. Recall from Section 3.2 that an unemployed worker in a bad fit switches careers if

$$\mathbb{E}U(u, n+1, x_i, \zeta h_j) > U(b, n, x_i, h_j). \tag{22}$$

From equation (22), the worker weighs the loss of human capital in a career switch with the increase in their career history from n to $n+1$, which gets them one step closer to finding their good fit. Figure 3 visualizes this tradeoff by plotting the career switching policy function in (n, h_j) space for three different levels of potential experience. Focusing on the left panel, workers with a high h_j and low n typically stay in their current career. This is because workers with a high h_j lose more human capital in a career switch and, if n is low, the next career is unlikely to be a good fit. Therefore, the human capital loss is too large to justify switching careers for these workers. In other words, these workers accumulated enough human capital on the job to make them "stuck" or "locked-in" to a bad fit. Workers with a high h_j and n find it worth it to switch careers, as the large decline in human capital is offset by the fact that their next career is more likely to be their good fit. Further, comparing the three panels in Figure 3 shows that older workers are less likely to switch careers. This is because older workers have a shorter working horizon, and therefore less time to regain the human capital that is lost in a career switch.

The policy functions shown in Figure 3 also allude to a dynamic aspect of the career switching choice over an unemployment spell. A worker who enters unemployment may

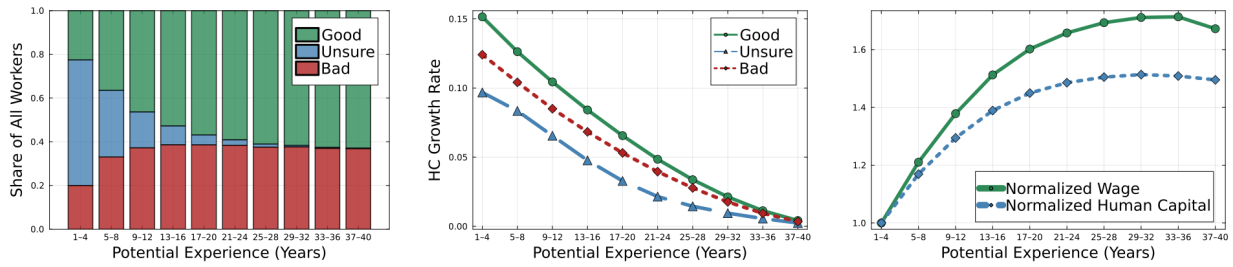
initially remain in a bad career fit. If the worker remains unemployed, they lose human capital through the μ shocks, which lowers the indirect cost of switching careers. Therefore, as the unemployment spell lengthens and human capital decays, workers become more and more likely to switch careers. This is consistent with Carrillo-Tudela and Visschers (2023), who document that occupational switching rates are increasing in unemployment duration.

3.3.2 Life Cycle Dynamics

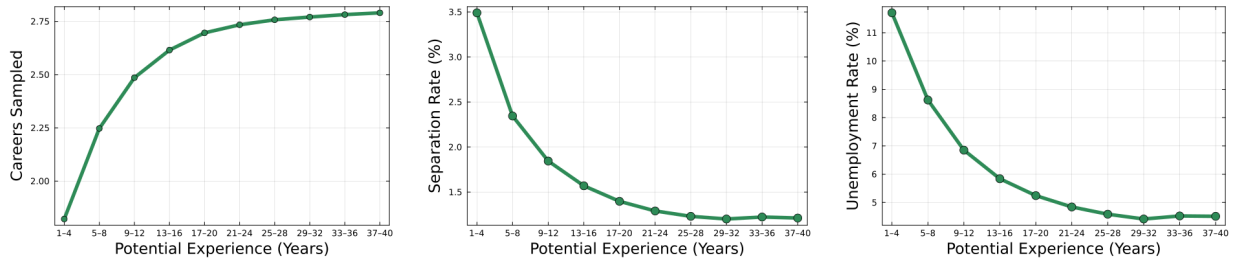
Figure 4 displays several life cycle profiles produced by the model. We start the narrative of a worker's life cycle with Figure 4(a), which displays the career fit composition by potential experience. Workers face the highest amount of career uncertainty early and, over time, sort into a good or bad fit. We can see that many workers are in a bad career fit throughout the life cycle. As discussed in Section 3.3.1, this occurs when the worker accumulates enough human capital to lock the worker into a bad fit. Next, Figure 4(b) displays the average human capital growth rate, $\pi(x_i, \tau)$, by potential experience and status. Human capital growth is decreasing in potential experience as older workers are concentrated along higher rungs on the human capital ladder, where there is less of an incentive to accumulate additional human capital. Further, older workers have a shorter horizon to benefit from human capital growth. Figure 4(b) also shows that good fits exhibit the highest rate of human capital growth. Unsure fits have a lower growth rate because they have a high separation rate, as they face the prospect of being destroyed if/when the worker learns that they are in a bad fit.[16] The high expected separation rate reduces the incentive for the worker and firm to invest in human capital. Figure 4(c) shows as workers' career uncertainty resolves and they sort into career fits that exhibit higher rates of human capital growth, the average level of human capital grows. Moreover, the average wage grows as workers accumulate more human capital and are increasingly employed in a good fit, where they are more productive.

The bottom row displays the number of careers sampled, separations, and unemployment. Figure 4(d) shows that the average number of careers sampled/worked in has a concave shape as the propensity for workers to switch careers decreases over potential experience as they either find their good fit or get stuck in a bad fit. From Figure 4(e), the average separation rate decreases over the life cycle as (i) the rate of endogenous separations associated with learning a bad fit dissipates over potential experience and (ii) the average level of human capital increases, which lowers the average exogenous separation rate $\delta(h_j)$. As the separation rate decreases and all workers face the same job finding rate, $f(\theta)$, the unemployment rate decreases with potential experience, as shown in Figure 4(f).

[16] The average separation rate by fit in this example is $4.70, 1.23$, and 1.33 for unsure, bad, and good, respectively.



(a) Fit Composition (b) Human Capital Growth Rate (c) Human Capital and Wages



(d) Careers Sampled (e) Separation Rate (f) Unemployment Rate

Figure 4: Life Cycle Dynamics. *Notes*: The average human capital growth rate excludes workers who are at the highest human capital level, h_J. Produced using the non-college parameter values listed in Table 5.

3.3.3 Reducing Career Uncertainty

This section demonstrates the effect of reducing career uncertainty on human capital accumulation and wage growth. While there are several parameter changes that can capture a reduction in career uncertainty, the simplest is to reduce the size of the career set, N. Doing so increases the probability that a worker of any history n is in their good fit.

Figure 5 demonstrates the effect of reducing N from 7 to 4.[17] As seen in the left panel, reducing N increases the fraction of workers who are in their good fit at each level of potential experience. The middle panel shows that as more workers are employed in a good fit, where the rate of human capital accumulation is the highest, the average level of human capital increases throughout the life cycle. The right panel shows that wages increase throughout the life cycle. There are several drivers for this, but the primary reason is that more workers are employed in a good career fit where they (i) are more productive and (ii) accumulate more human capital at a higher rate. We will revisit this in Section 4, where we decompose the wage gains following a reduction in career uncertainty.

[17] We choose these values of N for this example as these are the calibrated values of N for non-college and college graduates, respectively. See Sections 4.1 and 4.2 for more details.

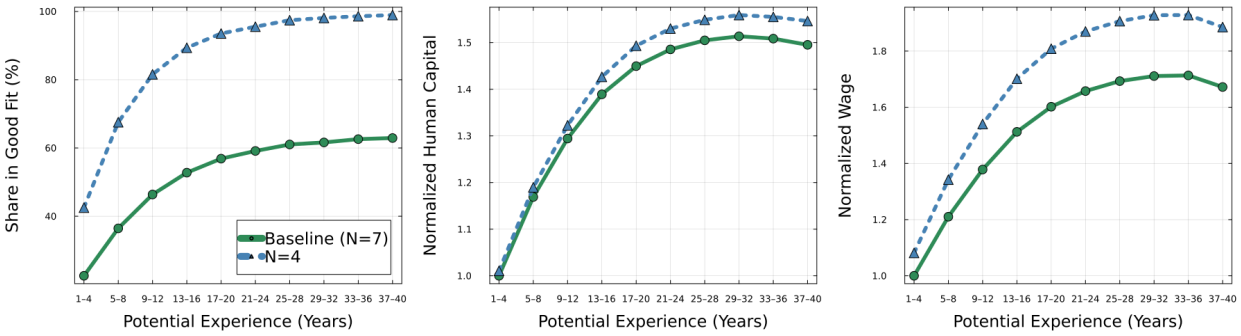


Figure 5: The Effect of Reducing Career Uncertainty. *Notes:* The green solid lines in each plot are produced using the non-college parameter values listed in Table 5. The blue dashed lines are produced using the same parameter values and $N = 4$.

4 Quantitative Analysis

This section calibrates the model and carries out a series of quantitative exercises. Section 4.1 details the calibration. Section 4.2 reports the model's fit. Section 4.3 quantifies the contribution of career uncertainty to wage and earnings inequality. Finally, Section 4.4 applies the model to analyze the implications of (i) an AI-induced shock to career uncertainty and (ii) subsidizing on-the-job learning.

4.1 Calibration

A unit of time is one month. The disutility of effort is $c(\tau) = \frac{\tau^2}{2}$. The meeting function is $m(u, v) = u^{\eta} v^{1-\eta}$. The rate of human capital accumulation is $\pi(x_i, \tau) = d_i \tau$ where $d_i \in \{d_1, \ldots, d_T\}$. We calibrate d_1 and d_T and apply a linear interpolation to fill in the remaining grid points. The exogenous separation rate, $\delta(h_j)$, is a grid $\{\delta_1, \ldots, \delta_J\}$. We calibrate the values of δ_1 and δ_J and apply a linear interpolation between them. The human capital grid, $h \in \{h_1, \ldots, h_J\}$, has 21 grid points and h_1 is set to 1.

The model has 18 parameters. We carry out two calibrations where a subset of parameters vary by educational attainment (non-college and college). The remainder of this section explains how we arrive at each parameter's value. First, we set $\{r, \beta, \eta, \sigma\}$ externally and fix them across the calibrations. The discount rate is $r = 0.045/12$. The elasticity of the meeting function is set to $\eta = 0.5$ following Petrongolo and Pissarides (2001). The bargaining power is set to $\beta = 0.5$. The aging rate is $\sigma = 1/(12 * 4)$ so that workers expect to spend four years at each potential experience bin. The maximum potential experience is set to $T = 10$ in the non-college calibration and $T = 9$ in the college calibration.

The remaining 13 parameters are calibrated separately for non-college and college gradu-

ates to match a set of education-specific moments.[18] As the model has complex interactions, the parameters are not pinned down by a unique moment. However, each parameter is intuitively connected to a particular moment. We now provide a heuristic overview of how the set of 13 parameters are identified.

The productivity of unemployment, b, is chosen so that the ratio of output among unemployed workers, $\mathbb{E}[bh]$, to average labor productivity, $\mathbb{E}[Ah]$, is 0.4 (Shimer, 2005). The rate of human capital loss shocks, μ, is chosen to match the average change in log wages before and after an unemployment spell in which the worker did not switch careers. The proportion of human capital maintained in a career switch, ζ, is chosen to match the average change in log wages before and after an unemployment spell in which the worker exited unemployment employed in a career that was different from the one that preceded the unemployment spell.

The output in a bad fit, α, is chosen to match the evolution of wage dispersion over potential experience bins 1 through 4. Let $p_{i,x}$ denote the i^{th} percentile of the wage distribution among workers at potential experience x. The ratio $p_{50,4}/p_{25,4}$ measures the ratio between the 50^{th} and 25^{th} percentiles in the fourth potential experience bin. We choose α to target $(p_{50,4}/p_{25,4})/(p_{50,1}/p_{25,1})$, which measures how much dispersion in the lower-half of the wage distribution varies between the first and fourth potential experience bins. Intuitively, lowering α reduces the output in bad fits, increasing wage dispersion early in the life cycle.

Total factor productivity, A, is normalized to 1 in the non-college calibration. In the college calibration, TFP is chosen to match the gap in average log wages among workers in the first potential experience bin. The efficiency of human capital accumulation in the first potential experience bin, d_1, highest potential experience bin, d_T, and maximum level of human capital, h_J, are chosen to match the average log wage by potential experience relative to the average log wage among non-college workers in the first potential experience bin.[19]

The exogenous separation rate in matches with the lowest human capital, δ_1, and in matches with the highest human capital, δ_J, are chosen to match the separation rate by potential experience. The maximum number of careers, N, and learning rate, ϕ, target the number of unique careers sampled by potential experience. Finally, the vacancy posting cost targets the average job finding rate across all potential experience bins.

Table 4: Model Fit

Moment	Non-College (Data)	Non-College (Model)	College (Data)	College (Model)
Job finding rate	25.680	25.607	28.320	28.622
Wage ratio	1.083	1.133	1.022	1.011
Wage change (no switch)	-0.016	-0.017	-0.043	-0.042
Wage change (switch)	-0.020	-0.020	-0.062	-0.062
$\mathbb{E}[bh/Ah]$	0.400	0.395	0.400	0.405

Notes: The job finding rate is the average monthly job finding probability across all levels of potential experience. The wage ratio is $(p_{50,4}/p_{25,4})/(p_{50,1}/p_{25,1})$ where $p_{i,x}$ is the i^{th} percentile of the wage distribution among workers in potential experience bin x. Wage change (no switch) is the average change in log wages before and after an unemployment spell in which the worker did not change careers. Wage change (switch) is the average change in log wage before and after an unemployment spell in which the worker did change careers. The last row, $\mathbb{E}[bh/Ah]$, is the ratio of the average production among unemployed workers, bh, to labor productivity among employed workers, Ah. All model moments are generated by simulating labor market histories of 15,000 workers.

4.2 Model Fit

Table 4 reports the model's fit to the targeted point moments, and Figure 6 reports the model's fit to the targeted life cycle profiles. Overall, the model achieves a good fit. Of particular note is the model's ability to match the larger change in average wages, both with and without a career switch, following an unemployment spell for college graduates. Further, the model can match the flattening of the wage profile and even slight decline towards the end of the life cycle. This is because the rate of human capital accumulation decreases in potential experience (see Figure 4(b)). As human capital accumulation slows down and unemployed workers lose human capital during unemployment, the average level of human capital among employed workers decreases, dragging down wages towards the end of the life cycle. Moreover, there is a horizon effect whereby matches with older workers have a shorter expected duration, reducing the match surplus and, therefore, wages.

Table 5 presents the calibrated parameters, where we place each parameter into one of four groups: career uncertainty, human capital dynamics, occupation-specific characteristics, and technology.[20] While the difference in each parameter between the non-college and college calibrations is notable and can merit discussion, we focus on the career uncertainty parame-

[18] Appendix C.1 details how each targeted moment is constructed.

[19] The college wage premium, based on the raw wage profiles targeted in the calibration, increases by 12.5 log points over 36 years of potential experience. Appendix A.3 shows that applying corrections that strip time and cohort effects out of the life cycle wage profiles leads to very similar estimates for the growth in the college wage premium over the life cycle.

[20] The specific grouping of parameters is inconsequential for most of our quantitative analysis. The only exception is that the groups are used in Section 4.3 when we carry out a Shapley-Owen-Shorrocks decomposition of the college wage and earnings premia.

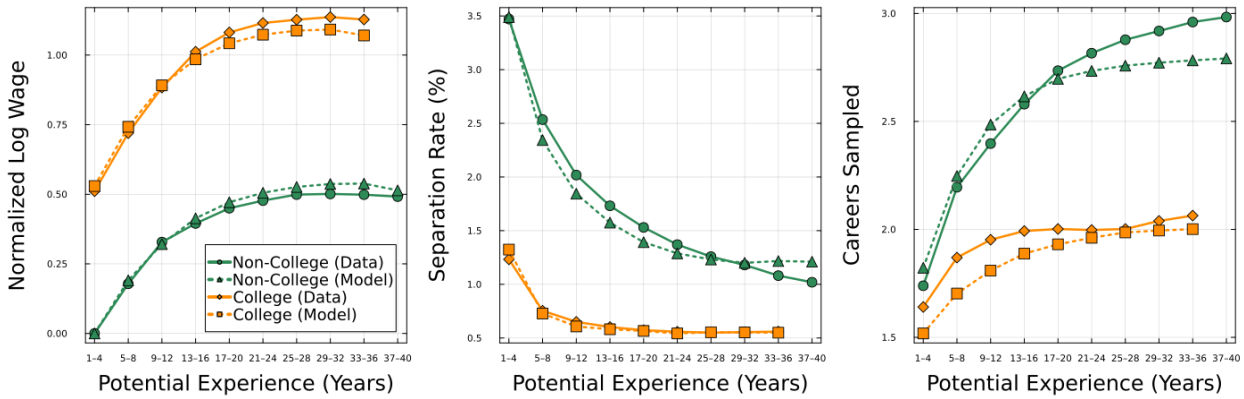


Figure 6: Life Cycle Profiles. *Notes:* Solid lines are the data. Dashed lines are produced by the simulated model. The left panel presents the average log wage by potential experience relative to the average log wage among non-college workers in the first bin of potential experience. The middle panel presents the average monthly separation probability by educational attainment and potential experience. The right panel is the average number of unique careers worked in by potential experience and education.

ters in Panel A. We find that college graduates have a smaller career set and faster learning speed. Recall that these parameters targeted the career sampling profiles and, as seen in Figure 6, college graduates have a smaller number of sampled careers throughout the life cycle. The difference in N implies that college graduates are more likely to be in their good fit at any history n than non-college graduates.[21] The difference in learning rates, ϕ, allows college graduates to resolve their uncertainty and find their good fit at an earlier stage.

We also would like to elaborate on the differences in $\{\zeta, \alpha\}$. The fact that human capital retention in career switches, ζ, is slightly higher for college graduates (0.925 vs. 0.913) indicates that college workers, even when they switch careers, are switching between relatively similar careers where their human capital can be transferred over at a higher rate. Further, the higher productivity in the bad fit output, α, indicates that when a college graduate is in a bad fit, it is not an "excessively" bad fit. In other words, the fit is decent enough and does not cause a steep drop-off in productivity. While these results may appear to challenge the belief that college graduates have more specialized skills, they are consistent with the notion that college graduates enter the labor market having narrowed down the set of careers that are potentially their good fit. The values of $\{\zeta, \alpha\}$ in the non-college calibration indicate that non-college workers are switching between careers where their human capital is not as transferable and that there is a steep drop-off in productivity between their good fit and all other careers.

[21] The calibrated values of N should not be interpreted as non-college graduates being able to work in more careers than college graduates. Instead, this difference implies that college graduates enter the labor market having already narrowed down the set of careers that they deem to be candidates for their good fit.

Table 5: Calibrated Parameters

Parameter	Description	Non-College	College
Panel A: Career Uncertainty			
N	Number of careers	7	4
ϕ	Learning rate	0.055	0.098
Panel B: Human Capital Dynamics			
μ	Human capital loss arrival rate	0.186	0.349
ζ	Human capital retention	0.913	0.925
d_1	Human capital accumulation at x_1	0.129	0.116
d_T	Human capital accumulation at x_T	0.043	0.115
Panel C: Occupation-Specific Characteristics			
δ_1	Separation rate at h_1	0.026	0.008
δ_J	Separation rate at h_J	0.011	0.006
h_J	Maximum human capital	2.118	2.941
Panel D: Technology			
A	TFP	1.000	1.050
α	Bad fit output	0.790	0.913
k	Vacancy posting cost	16.53	30.57
b	Unemployment flow value	0.424	0.486

Notes: There are 21 human capital grid points for each education group. The "Non-College" column refers to the calibration where the listed parameters are chosen to fit non-college targets from the data. The "College" column corresponds to when the parameters are chosen to target college targets. TFP is normalized to one in the non-college calibration. The remaining parameters take the values $r = 0.045/12$, $\beta = 0.5$, $\eta = 0.5$, and $\sigma = 1/48$ in both the non-college and college calibrations.

4.2.1 Validation

This section validates the calibrated model by comparing the model and data along some untargeted moments. Starting with the unemployment rate, Figure 7 demonstrates that the model generates a declining life cycle unemployment pattern for each education group and an education-gap in unemployment that closely track the data. Next, we apply a decomposition as in Pissarides (2009) to compute the proportion of the education-gap in unemployment that is attributable to differences in the job-finding and separations rates.[22] The first row in Table 6 shows that, consistent with the data, the model attributes the bulk of the educational-gap in unemployment rates to differences in separations.

An important feature of learning about career fit is that workers learn their best fit by working and that they can transfer what they have learned about their good fit between matches. Consequently, the expected duration of a worker–firm match should be increasing in the worker's prior experience at the time the match is formed. Following Bover et al.

[22] Appendix C.2.1 describes the decomposition in detail.

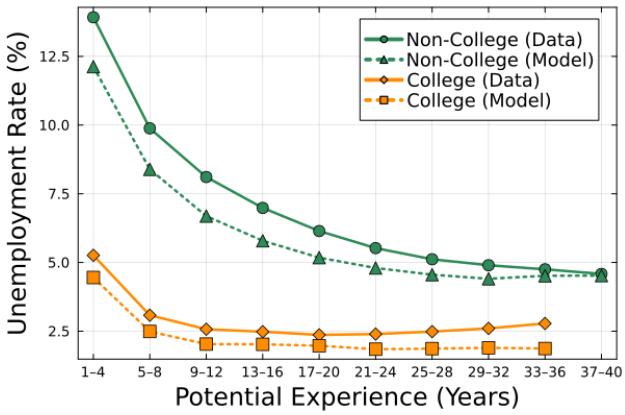


Figure 7: Unemployment Rate Over the Life Cycle. *Notes:* Solid lines are the data. Dashed lines are produced by the simulated model.

(2002), we estimate the relationship between prior experience and match survival using the following specification:

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

where Survival_{it} indicates whether the match survives to the next period. The additive indicator variable for each monthly duration, Dur_{it}, allows us to flexibly capture the duration dependence in the survival probability. The estimated coefficient on prior experience, $\hat{\beta}_1 = 9 \times 10^{-5}$, indicates that longer prior work experience is associated with a higher survival probability. However, this effect is weaker for college graduates, as estimated by $\hat{\beta}_3 = -4 \times 10^{-5}$.[23] This is consistent with our hypothesis, as non-college workers rely more on experience to find their best fit. The second and third rows of Table 6 present the estimated coefficients in both the NLSY79 and simulated data. The model successfully reproduces the relationship between prior experience, match survival, and educational attainment.

Next, following Deming (2024), we assess the relative contributions of within-career growth versus career-sampling growth by estimating:

$$\ln(wage_{ijt}) = \sum_k \phi_k^{within} Exp_{it} + \zeta_{ij} + \epsilon_{ijt}. \tag{23}$$

where i indexes the individual, j tracks the number of careers sampled by the individual

[23] Full estimation results can be found in Appendix C.2.2.

Table 6: Model Validation

Untargeted Moments	Data	Model
Frac. of U-E gap explained by SP	0.91	0.84
β(PriorExp)	9×10^{-5}	4×10^{-5}
β(PriorExp $\times$ College)	-4×10^{-5}	-2×10^{-5}
% of wage growth explained by CS, non-college	4.84	8.05
% of wage growth explained by CS, college	-0.05	4.09
Training incidence, non-college	0.082	0.084
Training incidence, college	0.139	0.140
Avg. employer tenure if trained vs. not, non-college	[7.09, 3.03]	[5.52, 4.00]
Avg. employer tenure if trained vs. not, college	[8.43, 3.38]	[8.99, 8.84]

Notes: "U-E" refers to the educational gap in unemployment rate, "frac." is fraction, "SP" is separation probability, and "CS" is short for career samplings.

i, and t denotes years.[24] Given that we control for the worker-career fixed effect (ζ_{ij}), the estimated coefficients, $\{\phi_k^{within}\}$, capture the wage growth at k^{th} career stage conditional on having sampled j unique careers so far. This is labelled as the within-career wage growth. We compare these with an analogous specification with individual fixed effect, ζ_i, instead. This yields estimates of $\{\phi_k^{total}\}$ that measure total wage growth, including both growth within the current information status and growth obtained by experimenting with an additional career. Consequently, the wage growth from career samplings, $\{\phi_k^{cross}\}$ is obtained by subtracting the within-career wage growth from total wage growth. Estimating (23) on the NLSY79 sample reveals the cumulative wage growth over potential work experience attributable to career sampling is 4.84% for non-college workers and -0.048% for college workers.[25]

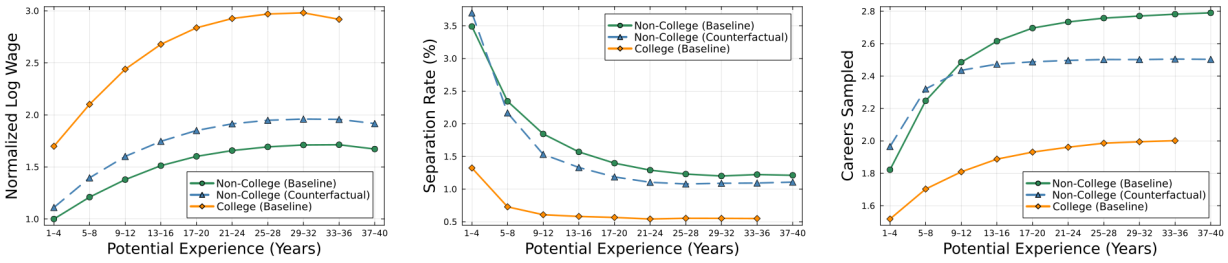
The fourth and fifth rows of Table 6 show that the model can generate a decent fraction of wage growth through career switches for non-college workers. For college workers, however, the fraction of wage growth attributable to career sampling overshoots the data moments. This could be due to skill obsolescence during the late career stage of college workers, which leads to wage losses in later career sampling periods, which is abstracted from our model. Despite that, our model successfully replicates the pattern that the fraction of wage growth explained by career sampling is larger for non-college workers.

The sixth and seventh rows of Table 6 show that the model matches the training incidence by education.[26] From these two rows, we can see that both the data and the model generate

[24]The number of sampled careers is capped at 6 (4) for non-college (college) workers, as only 27 (53) non-college (college) workers sampled more than these thresholds. These caps affect only about 0.13% (1.27%) of employment observations for non-college (college) workers.

[25]Detailed results can be found in Appendix C.2.3.

[26]We define training in the model to be an indicator equal to 1 if an employed worker with status s, human



(a) Wages (b) Separation Rate (c) Career Sampling

Figure 8: Counterfactual Life Cycle Dynamics. *Notes:* The counterfactual assigns college career uncertainty parameters $\{N, \phi\}$ to non-college workers while keeping all other non-college parameters unchanged. All wages are normalized relative to the baseline non-college wage in the first potential experience bin.

the pattern of a higher training incidence among college workers. The last two rows indicate that our model replicates the data pattern that the average employer tenure is higher for matches receiving training than for those without ever receiving training. This is consistent with the linkage between human capital investment, match quality, and expected duration.

4.3 Career Uncertainty and Inequality

In this section, we quantify the contribution of career uncertainty to the college wage and lifetime earnings premia. To begin, we perform a simple counterfactual where we assign non-college workers the values of $\{N, \phi\}$ from the college calibration. Specifically, we reduce N from 7 to 4 and increase ϕ from 0.055 to 0.098 while keeping all other non-college parameters at the values presented in Table 5.

Figure 8 presents the life cycle profiles for wages, separations, and careers sampled for the baseline college (orange curve), baseline non-college (green curve), and counterfactual non-college (blue curve). The reduction in career uncertainty increases wages at every career stage for non-college workers, with an average increase of 14.89%. The increase in wages is accompanied by a reduction in separations and careers sampled. Another way to gauge the effect is through the reduction of the college wage premium. Table 7 reports the fraction of the wage gap that is closed at each potential experience bin. Averaging over potential experience bins 1 through 9, we find that the aggregate wage premium decreases by 19.92%.

capital h, and history n exhibits human capital investment, τ, such that

$$\frac{c(\tau)}{y(s,h,n)} > \bar{\tau},$$

where $y(s,h,n)$ is the output of the match and $\bar{\tau}$ is chosen so that the overall annual training incidence produced by the model matches that observed in the NLSY79. We find $\bar{\tau} = 0.527$ produces an average annual training rate of 9.55% in the model. This closely matches the training incidence in the data of 9.51%.

Table 7: Fraction of Wage Gap Closed by Potential Experience

x	Non-College (Baseline)	Non-College (Counterfactual)	College (Baseline)	Gap (Baseline)	Fraction Closed (%)
1	1.000	1.111	1.699	0.699	15.88
2	1.210	1.395	2.102	0.892	20.76
3	1.378	1.601	2.439	1.061	21.02
4	1.513	1.746	2.679	1.166	20.05
5	1.602	1.850	2.837	1.235	20.12
6	1.658	1.914	2.926	1.269	20.24
7	1.693	1.949	2.970	1.276	20.01
8	1.711	1.960	2.981	1.270	19.61
9	1.713	1.957	2.919	1.205	20.23
Overall					19.92

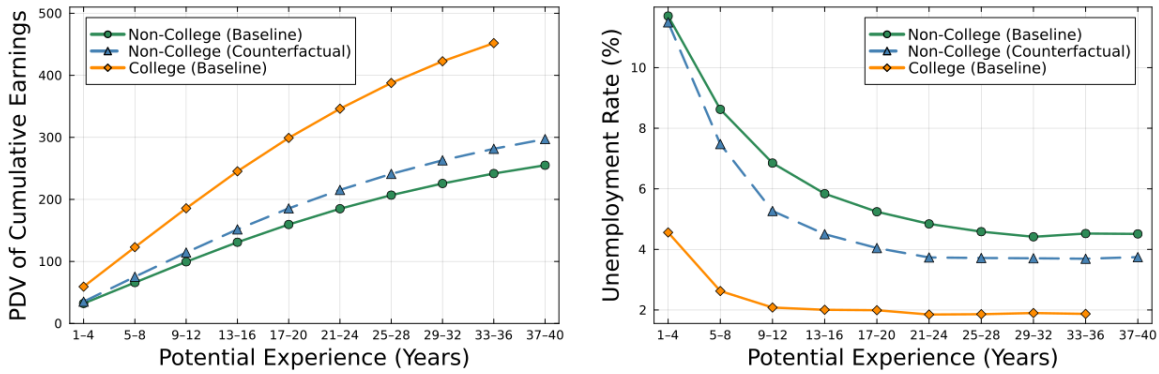
Notes: The first column, x, is the potential experience bin. All wages are normalized relative to the baseline non-college wage in the first experience bin. The counterfactual assigns the college values of $\{N, \phi\}$ to non-college workers while keeping all other non-college parameters unchanged. The fraction closed is computed as $(w^{counter} - w^{NC})/(w^{C} - w^{NC}) \times 100$.

Another additional implication of the reduction in uncertainty among non-college workers concerns lifetime earnings. Figure 9(a) presents the average present discounted value (PDV) of cumulative earnings across the life cycle.[27] Overall, discounted cumulative earnings increase by an average of 18.96% among non-college workers. For context, this represents a 16.49% reduction in the original gap in lifetime earnings between non-college and college workers. This increase is the compound result of two factors: a higher wage rate, as shown in Figure 8(a), and a lower unemployment rate, or equivalently, a higher employment rate, as shown in Figure 9(b). The latter arises primarily because non-college workers settle into their best fit early on, which lowers the probability of endogenous separation and sustains higher employment over the life cycle.

4.3.1 Sources of Wage and Earnings Gains

Next, we decompose the gains in wages and cumulative earnings experienced by non-college workers. Let $\Delta w(x) = w^{new}(x) - w^{base}(x)$ denote the total wage gain in average wages at potential experience level x, with superscripts "*new*" and "*base*" referring to the counterfactual and the baseline case, respectively. We decompose $\Delta w(x)$ into two components. The first component, $\Delta w^{f}(x)$, captures how much of the total wage gains come from a shift in the

[27] For a worker i with history $\{\text{emp}_{it}, w_{it}\}_{t=0}^{T}$, where emp_{it} is an indicator for whether individual i is employed at time t and w_{it} is their wage at time t, the cumulative PDV of earnings at potential experience bin x is $\text{PDV}_i(x) = \sum_{t=0}^{\bar{t}(x)} \text{emp}_{it} w_{it} \cdot (1+r)^{-t}$, where $\bar{t}(x)$ is the last month of experience bin x. We then average $\text{PDV}_i(x)$ across workers to obtain the average cumulative PDV at level of potential experience.



(a) Present Discounted Value of Total Earnings

(b) Unemployment Rate Profile

Figure 9: Cumulative Earnings and Unemployment. *Notes:* The counterfactual assigns the college values of $\{N, \phi\}$ to non-college workers while keeping all other non-college parameters unchanged.

distribution of career fits, holding the within-fit wages fixed at their values in the baseline economy. Therefore, $\Delta w^f(x)$ is given by:

$$\Delta w^f(x) = \sum_{s \in \{un,b,g\}} \left[\pi^{new}(s|x) - \pi^{base}(s|x)\right] \bar{w}^{base}(s,x), \tag{24}$$

where $\pi(s|x)$ is the fraction of employed workers in career fit s at potential experience x and $\bar{w}^{base}(s,x)$ is the average wage among workers with career fit s and potential experience x in the baseline economy.

The second component of the decomposition, $\Delta w^{within}(x)$, measures how much of the total change in wages comes from the change in wages within a career fit, holding the fit distribution fixed at $\pi^{new}(s|x)$. It is given by:

$$\Delta w^{within}(x) = \sum_{s \in \{un,b,g\}} \pi^{new}(s|x) \left[\bar{w}^{new}(s,x) - \bar{w}^{base}(s,x)\right], \tag{25}$$

where $\bar{w}^{new}(s,x)$ is the average wage at career fit s and potential experience x under the counterfactual parameters.

The left panel of Figure 10 presents the decomposition of wage gains, with the black line showing total wage gains for non-college workers at each level of potential experience, the blue bars denoting $\Delta w^f(x)$, and the orange bars denoting $\Delta w^{within}(x)$. The decomposition yields two notable findings. First, the fit composition accounts for the majority of wage gains, 61.2% on average, as the distribution, $\pi^{new}(s|x)$, shifts toward good fits. Second, the contribution of the fit composition declines over the life cycle, whereas the contribution of within-fit wages increases. Notably, the within-fit contribution is even negative early in

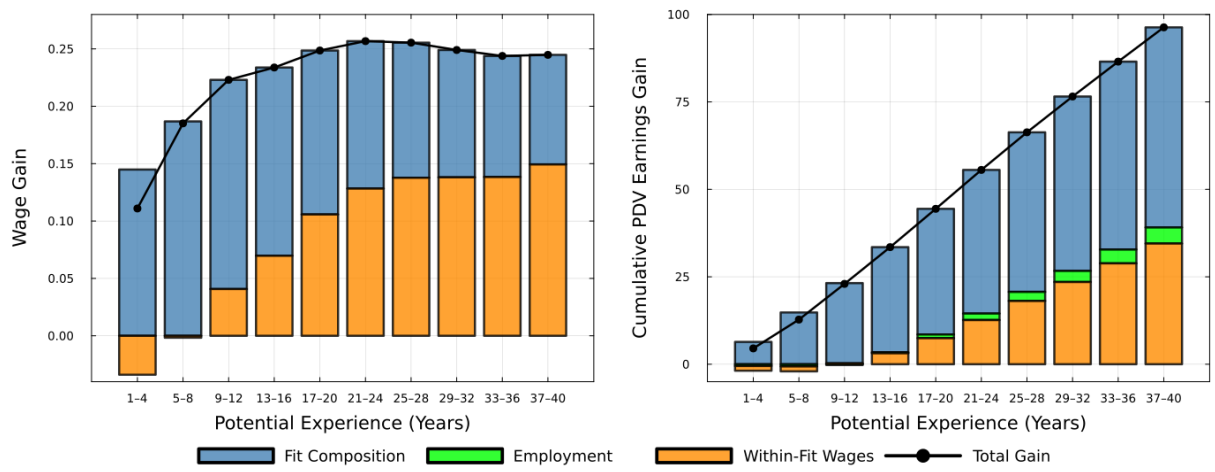


Figure 10: Decomposition of Wage and Earnings Gains. *Notes*: The left panel decomposes the change in average wages at each potential experience bin. The black line is the total wage gain, the blue bars are the contribution of the shift in the distribution of workers across career fits, $\Delta w^f(x)$, and the orange bars are the contribution of changes in wages within each career fit, $\Delta w^{within}(x)$. The right panel decomposes the change in the present discounted value of cumulative earnings through each potential experience bin. The black line is the total earnings gain, and the bars show the contributions of the career fit composition (blue), the employment rate (green), and within-fit wages (orange).

the life cycle, which originates from two sources. On one hand, non-college workers with counterfactually lower initial uncertainty now anticipate faster future human capital growth and are thus willing to accept lower wages initially. On the other hand, accelerated learning during the early career life raises both the separation rate (as seen in Figure 8(b)) and the unemployment rate (Figure 9(b)), which leads to more human capital depreciation and, in turn, lowers the average level of human capital. Together, these forces generate an early decline in within-fit wages.[28]

Similarly, we can decompose the gains in lifetime earnings. Since earnings are a composite outcome of both the employment rate and wages, we therefore decompose the gains in earnings into three components: (i) fit composition, (ii) employment rate, and (iii) within-fit wages.[29] As shown in the right panel of Figure 10, consistent with the decomposition of wage gains discussed above, most of the earnings gains (59.4%) come from the fit composition channel, and its contribution is relatively larger early in the life cycle. Within-fit

[28]Appendix C.4.1 presents a more detailed decomposition of the wage gains. We find that nearly all of the fit composition effect $\Delta w^f(x)$, 57.4 of 61.2 percentage points, reflects the direct productivity gain from being in a good career fit rather than differences in human capital across career fits. Most of the within-fit effect $\Delta w^{within}(x)$, 34.2 of 38.8 percentage points, comes from non-college workers accumulating more human capital within each career fit, rather than from higher wages at a given level of human capital.

[29]The employment component is given by $\sum_s \pi^{new}(s|x)\left[e^{new}(s,x) - e^{base}(s,x)\right]\bar{w}^{base}(s,x)$, where $e(s,x)$ is the employment rate among workers with career fit s and potential experience x. Further, $\pi(s,x)$ denotes the share of all workers with career fit s at potential experience x in the earnings decomposition, not just employed workers as in the wage decomposition.

Table 8: Lifelong Gains from a Strong Start

	Wages			Separation Rate		Unemployment Rate		PDV Earnings		
x	$\{N, \phi\}$	$\{N', \phi'\}$	$\%\Delta$	$\{N, \phi\}$	$\{N', \phi'\}$	$\{N, \phi\}$	$\{N', \phi'\}$	$\{N, \phi\}$	$\{N', \phi'\}$	$\%\Delta$
1	0.9	1.1	26.6	3.5	3.4	11.6	10.6	34.1	55.3	62.5
2	1.1	1.5	35.6	2.3	1.5	8.4	4.9	66.8	97.5	45.9
3	1.3	1.7	31.4	1.8	1.2	6.7	4.2	98.8	137.8	39.5
4	1.4	1.8	28.4	1.5	1.2	5.7	4.0	128.4	174.6	36.0
5	1.5	1.8	26.8	1.4	1.1	5.2	3.8	155.3	208.1	34.1
6	1.5	1.9	24.9	1.3	1.0	4.8	3.4	179.4	237.7	32.5
7	1.6	1.9	23.3	1.2	1.0	4.5	3.4	200.2	263.0	31.4
8	1.6	1.9	22.5	1.2	1.0	4.3	3.4	217.6	284.1	30.5
9	1.6	1.9	22.0	1.2	1.0	4.4	3.4	232.7	302.0	29.8
10	1.5	1.9	22.1	1.2	1.0	4.4	3.5	245.4	317.3	29.3

Notes: This table compares labor market outcomes for non-college workers who do not find their good fit within the first four years of potential experience in the baseline, but do find their good fit within the first four years in the counterfactual. x is the potential experience bin. $\{N, \phi\}$ denotes outcomes under the baseline calibration. $\{N', \phi'\}$ denotes outcomes for the same set of workers after being assigned the college values of N and ϕ. $\%\Delta$ is the percentage change between the counterfactual and baseline outcomes.

wage changes contribute increasingly over the life cycle, accounting for 35.8% of total earnings gains. The remaining 4.8% is attributable to the employment channel, which operates through reductions in separations as non-college workers sort into their good fit and accumulate more human capital.

4.3.2 The Benefits of Finding a Good Fit

We next quantify the gains in wages and earnings for non-college workers who have a "strong start", i.e., find their good fit earlier in their work-life, following the reduction in career uncertainty. To do so, we compare the labor market outcomes for non-college workers who, in the baseline economy and simulation, do not find their good fit within their first four years of potential experience but do find their good fit within the first four years of potential experience in the counterfactual economy.[30]

Table 8 presents the changes in wages, separation rates, unemployment rates, and cumulative earnings for this subset of non-college workers. It shows that their wages increase at each career stage, as they now found their good fit at an early career stage. As such, they exhibit fewer separations and are unemployed less often, driven by both a composition shift toward good fits and increased human capital investment. These wage gains, compounded by the rise in match stability, translate into a 29.3% increase in cumulative lifetime earnings.

[30] 36.7% of workers in the simulated economy fit these criteria.

4.3.3 Shapley Decomposition

To this point, we have quantified the effect of assigning non-college workers the values of $\{N, \phi\}$ from the college calibration, while holding all other parameters fixed at their baseline values. We prefer this exercise and present it as our main decomposition because it addresses a simple and particular question: how much would the college wage and earnings premia change by if we were to lower career uncertainty among non-college workers while not changing any other characteristic of their economic environment? In other words, suppose that non-college workers still operate in an economy with the same technological parameters and work in occupations with the characteristics that are summarized by the parameters presented in Table 5, but enter such an economy with lower career uncertainty. What would be the impact on their wages and lifetime earnings?

While this is our preferred decomposition, it does not paint a complete picture because it represents only one ordering in which the differences in parameters between non-college and college workers can be eliminated. To demonstrate, if instead we assigned all college parameter values to the non-college calibration except $\{N, \phi\}$, only 9.6% (4.3%) of the college wage (earnings) premium remains. Therefore, the impact of reducing career uncertainty on wages and earnings is larger when non-college workers face the same technological, human capital dynamics, and occupation-specific parameters presented in Table 5.

Given that the impact of reducing career uncertainty on inequality is sensitive to the order, or timing, of when the differences in career uncertainty are eliminated, we carry out a Shapley-Owen-Shorrocks decomposition. This decomposition computes the contribution of each parameter to an outcome of interest by first evaluating the marginal contribution of that parameter to the outcome for a particular order in which the factors that contribute to the outcome are eliminated. 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. Appendix C.3 describes the decomposition in greater detail.

Table 9 presents the results.[31] Panel A shows that the career uncertainty parameters account for 13.6% of the college wage premium and 11.8% of the gap in lifetime earnings. Most of this group's explanatory power is attributable to the size of the career set, N. Panel B shows the joint contribution of the human capital dynamic parameters, which turn out to

[31] To reduce the number of permutations we solve the model under, we group several parameters together rather than estimating the contribution of each specific parameter.

Table 9: Shapley-Owen-Shorrocks Decomposition

	Wage Gap (%)	Lifetime Earnings Gap (%)
Panel A: Career Uncertainty		
N	10.3	9.8
ϕ	3.3	2.0
Within-panel total	13.6	11.8
Panel B: Human Capital Dynamics		
μ, ζ, d_1, d_T	-1.9	-3.9
Panel C: Occupation-Specific Characteristics		
h_J	71.3	65.0
δ_1, δ_J	6.6	11.2
Within-panel total	77.9	76.3
Panel D: Technology		
A, α, k, b	12.6	16.6
Total	102.3	100.8

Notes: Each cell is the percentage of the gap between college and non-college workers in average wages (over potential experience bins 1–9) and in lifetime earnings (present discounted value of earnings through bin 9) attributable to a parameter or group of parameters. The contributions of the four parameter groups are Shapley values computed over all 2^4 combinations of groups switched from their non-college to their college values. Each combination is solved in general equilibrium. Totals differ from 100 because the non-college economy has one more potential experience bin than the college economy.

be negative, meaning that these parameters actually lower the wage and earnings gaps. This is primarily because college graduates have a higher rate of skill loss during unemployment, μ. Panel C shows that the occupation-specific characteristics account for slightly more than three-fourths of the wage and earnings premia. The vast majority of this is accounted for by the difference in h_J, the highest human capital value.[32] Finally, panel D shows that the technological parameters account for 12.6% of the wage gap and 16.6% of the earnings gap.

Taken together, the decompositions presented in this section show that career uncertainty accounts for between 9.6 and 19.9% of the college wage premium. For the college earnings premium, the contribution of career uncertainty ranges from between 4.3 and 16.5%. For both outcomes, the impact of career uncertainty is generally increasing in the number of differences in parameters between non-college and college workers. The Shapley decomposition shows that, overall, career uncertainty accounts for slightly more than 10% of the college wage and earnings premia.

[32] We group this parameter with the occupation-specific characteristics because we interpret it as capturing differences in the capacity to advance within a career path (e.g., from entry level, to middle manager, to a high-level executive within a career field).

4.4 Applications

With an understanding of how career uncertainty contributes to the gap in wages and lifetime earnings between non-college and college graduates, we now proceed to apply our model to study the implications of (i) elevated career uncertainty associated with artificial intelligence (AI) and (ii) subsidizing on-the-job learning on wage and earnings inequality.

4.4.1 AI, Uncertainty, and Inequality

We think that our model is well suited to analyze one particular aspect of AI, and that is the elevated level of career uncertainty it appears to have caused among college students and graduates. For example, in a 2025 survey of college students in the US, 47% reported giving at least a fair amount of consideration to changing their major because of the impact AI might have on the job market or a specific industry, while 16% reported having done so already (Lumina Foundation and Gallup, 2026). Further, 25% of employed college graduates reported that AI makes their job feel less secure, compared with 16% of workers without a degree, and about one in four workers reported having considered changing industries because of AI (CNBC and SurveyMonkey, 2026).

To formalize an AI uncertainty shock, we extend the model so that all workers are hit with an uncertainty shock at rate ρ. Workers who are hit with the uncertainty shock have their status, s, and history, n, reset to $s = un$ and $n = 1$. In other words, the uncertainty shock causes workers to "forget" all they have learned about their fit and have their history reset to the level of a newborn worker. The shock does not impact the worker's human capital, h.

Before proceeding to analyze the effects of such a shock, let us first provide an interpretation of it. We think of developments in AI as changing the underlying production technology across different careers. We do not explicitly model these changes. However, if the production technology changes in different ways across careers, then the worker's good fit (where they are most productive) can also change. Hence, we capture this effect through resetting the worker's status and history. A career that a worker knew for sure was their good fit may or may not be after the AI shock (e.g., computer programmers). Similarly, a career that was a bad fit may not be anymore because the worker may be most productive in this career relative to others given the underlying changes to the production technology across careers caused by AI. Finally, we model the uncertainty shock through a Poisson process rather than an aggregate shock because workers may face elevated uncertainty at different times given their current job and the contemporary developments in AI.

We now analyze the impact of the uncertainty shock when it is only college workers

Table 10: AI-Induced Career Uncertainty and Labor Market Outcomes

	Baseline ($\rho = 0$)	Once per 40 years ($\rho = 1/480$)	Once per 20 years ($\rho = 1/240$)	Once per 10 years ($\rho = 1/120$)
Panel A: Aggregate and Lifetime Outcomes				
Wage premium	0.544	0.526 (−3.3)	0.519 (−4.6)	0.518 (−4.8)
Earnings premium	0.626	0.619 (−1.1)	0.622 (−0.6)	0.620 (−1.0)
Unemployment rate (%)	2.30	2.21 (−4.1)	1.88 (−18.2)	1.88 (−18.5)
Separation rate (%)	0.665	0.631 (−5.1)	0.565 (−15.0)	0.563 (−15.3)
Career switches	0.995	0.568 (−42.9)	0.064 (−93.6)	0.042 (−95.8)
Panel B: Early Career ($x = 1$)				
Wage premium	0.530	0.545 (+2.9)	0.555 (+4.7)	0.558 (+5.3)
Earnings premium	0.609	0.636 (+4.6)	0.675 (+11.0)	0.681 (+11.9)
Unemployment rate (%)	4.56	4.06 (−11.0)	2.06 (−54.8)	2.02 (−55.7)
Separation rate (%)	1.324	1.134 (−14.3)	0.640 (−51.7)	0.620 (−53.2)
Career switches	0.518	0.382 (−26.3)	0.035 (−93.3)	0.027 (−94.8)
Panel C: Mid-Career ($x = 5$)				
Wage premium	0.572	0.552 (−3.5)	0.543 (−5.1)	0.542 (−5.2)
Earnings premium	0.629	0.628 (−0.1)	0.636 (+1.2)	0.635 (+1.1)
Unemployment rate (%)	1.99	1.94 (−2.8)	1.82 (−8.4)	1.80 (−9.9)
Separation rate (%)	0.566	0.553 (−2.2)	0.553 (−2.2)	0.556 (−1.8)
Career switches	0.934	0.556 (−40.5)	0.055 (−94.1)	0.039 (−95.8)
Panel D: Late Career ($x = 9$)				
Wage premium	0.533	0.502 (−5.8)	0.495 (−7.1)	0.494 (−7.3)
Unemployment rate (%)	1.87	1.87 (0.0)	1.77 (−5.4)	1.83 (−2.1)
Separation rate (%)	0.550	0.548 (−0.3)	0.525 (−4.5)	0.542 (−1.4)

Notes: Each column reports outcomes for college workers when the AI shocks arrive at rate ρ. Numbers in parentheses are percentage changes relative to the baseline ($\rho = 0$). Wage premia are log differences in average wages between college and non-college workers. Earnings premia are log differences in the present discounted value of cumulative earnings through the given potential experience bin. Non-college outcomes are held at their baseline values. Career switches are cumulative through the given potential experience bin. Panel A's wage, unemployment and separation rates are averaged over all experience bins. Lifetime outcomes are measured through potential experience bin $x = 9$.

who are exposed to it.[33] The monthly arrival rate of the shock takes the values $\rho \in \left\{\frac{1}{12*40}, \frac{1}{12*20}, \frac{1}{12*10}\right\}$ so that each worker expects to be hit by the uncertainty shock once every forty, twenty, and ten years, respectively.

Table 10 presents the effect of the uncertainty shock on the wage premium, earnings premium, unemployment and separation rate among college workers, and career switches among college workers over the entire life cycle and at specific stages of the life cycle. Starting with Panel A, we can see that the uncertainty shock reduces the wage and lifetime earnings

[33]While a bit extreme, this is in line with the general sentiment that college graduates work in occupations that stand to gain and lose the most through advancements in AI.

premium. The effect on the wage premium is larger than on the earnings premium, in-part, because the unemployment and separation rates are decreasing in ρ. To understand why, consider the last row in panel A. The number of career switches declines dramatically in the arrival rate of the uncertainty shock. This is because the uncertainty shock generates two effects. The first, a "wait and see" effect, is that workers who are in a bad fit know that the uncertainty shock can reset their status and history without the worker having to switch careers and incur the loss of human capital in the switch. As such, workers opt to wait in a bad fit rather than voluntarily switch careers. The second is a "discouragement" effect, where the returns to finding one's good fit are lower when the uncertainty shock can displace workers from their good fit. These effects switch on between the once per 40 and once per 20 year scenarios, as an arrival rate of $\rho = 1/240$ is frequent enough to induce most workers in a bad fit to wait for the uncertainty shock. Further, the unemployment rate also declines as tightness (and therefore the job-finding rate) is generally increasing in ρ.[34] This effect is driven by the fact that the composition of unemployed workers is comprised more of workers in unsure fit and that the surplus generated by an unsure fit is higher under the uncertainty shock, as the shock improves the value of being in a bad fit.

Panels B through D highlight that the effects of the uncertainty shock are not uniform across the life cycle. In particular, the uncertainty shock increases the wage and earnings premia early in the life cycle, and decreases them at later career stages. This is because workers are most likely to be in an unsure fit early in their career. For these workers, they are likely to learn they are in a bad career fit. The uncertainty shock opens a pathway from a bad to a good career fit without switching careers. Hence, discovering a bad fit is less costly for a currently unsure worker. As such, average wages (and therefore earnings) are higher earlier in the life cycle because more workers are in an unsure fit, the wages earned in an unsure fit increase, and fewer workers switch careers and lose human capital in the process. The effect of the uncertainty shock on wages and earnings later in the life cycle is different because the uncertainty shock also displaces workers from good fits, and it is older workers who are most likely to be in a good career fit.

To understand the driving forces behind the uncertainty shock, we study the effects of an alternative shock that only hits workers in a good career fit. This removes the "wait-and-see" effect described earlier as workers in a bad fit cannot have their fit reset to unsure in this specification. The full table of results is presented in Appendix Table C3. The main findings are that the effects of uncertainty shocks are larger when only workers in a good fit are hit by them. For example, when shocks arrive once every ten years, the wage premium falls by 8.7% as opposed to 4.8%. The lifetime earnings premium decreases by 3.8% as compared to

[34] The values of tightness across the scenarios, from baseline to $\rho = \frac{1}{120}$ are $\{0.115, 0.113, 0.120, 0.121\}$.

1%. We still see large declines in the rate of career switching, but this effect is driven by the "discouragement" effect, i.e., the lower returns to identifying one's good fit. Together, these exercises show that the effect of career uncertainty brought on by advancements in AI on the college wage and earnings premia can be sizeable and will depend on whether AI reshapes career uncertainty among all workers, or just those who have found their good fit.

4.4.2 Subsidizing On-the-Job Learning

Our model points to sorting into a good career fit and accumulating human capital on the job as key drivers of wage growth. An additional takeaway is that these drivers of wage growth have important interactions with the life cycle, as human capital investment is highest among young workers. A natural extension of these results is to evaluate the implications of lowering the cost to accumulate human capital by subsidizing on-the-job learning, and to study how those implications change if the subsidies are indexed to the worker's potential experience. Therefore, we use this section to study the implications of subsidizing on-the-job human capital investment on wage and earnings inequality.[35]

We introduce subsidies by assuming the cost to learn on the job for a worker of potential experience x_i is given by $(1-\gamma_i)c(\tau)$ where

$$\gamma_i = \begin{cases} \bar{\gamma} & \text{for } i < i^*, \\ 0 & \text{for } i \geq i^*. \end{cases} \tag{26}$$

The subsidy policy is summarized by two parameters: $\{\bar{\gamma}, i^*\}$. The first, $\bar{\gamma}$, captures the subsidy amount and i^* determines the eligibility for the subsidies, with workers with potential experience x_i and $i \geq i^*$ not receiving any subsidy. Finally, we assume that the subsidy is financed through non-distortionary lump-sum taxes on firms and workers. With this setup, we compute the model's equilibrium in both the non-college and college calibrations for each combination of $\bar{\gamma}$ and i^* where $\bar{\gamma} \in \{0.1, 0.25, 0.5\}$ and $i^* \in \{2, 3, 5, 11\}$.

Figure 11 presents the change in the wage premium and lifetime earnings premium for each policy. The group of orange lines represents the outcomes when subsidies are only given to college workers, the blue set of lines is when all education groups receive the subsidy, and the green lines correspond to when only non-college workers receive the subsidies. There are four lines within each color, each representing the different values of i^*. For example, the line with circle markers within each group corresponds to $i^* = 2$, i.e., where only workers

[35] As human capital investment, τ, is chosen to maximize the joint surplus of a match, there is no obvious motivation from a normative perspective to subsidize human capital investment. This is why we instead limit our focus to the positive implications of subsidizing human capital investment.

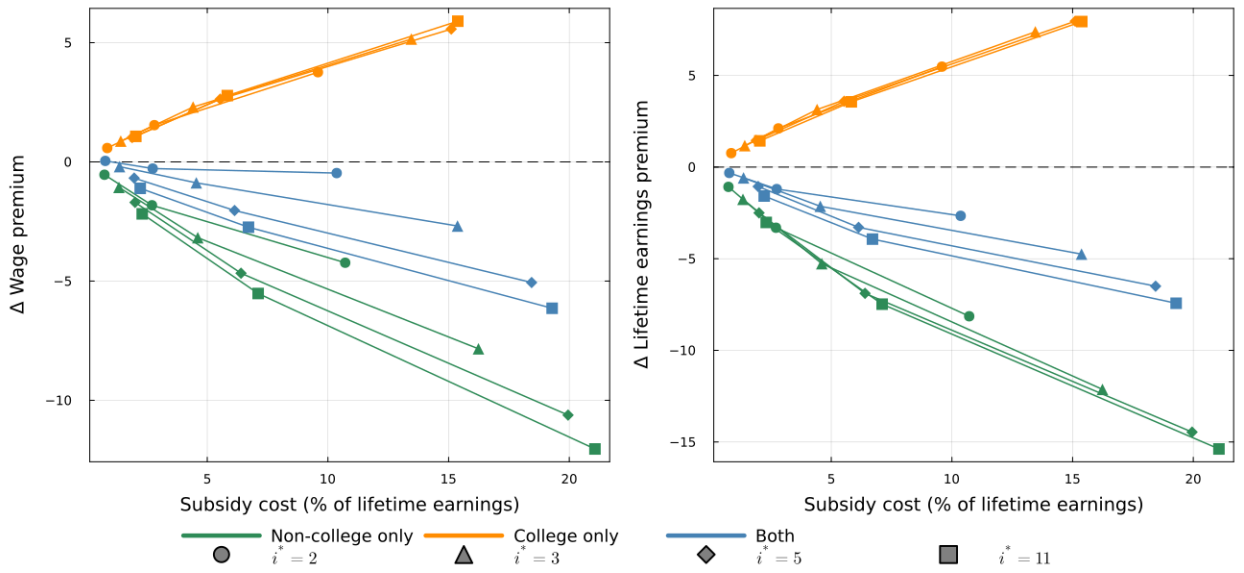


Figure 11: Subsidies for Human Capital Investment and Inequality. *Notes*: Each point is a training subsidy that reduces $c(\tau)$ by a share $\bar{\gamma} \in \{0.10, 0.25, 0.50\}$ for workers with potential experience x_i and $i < i^*$. The colors indicate which education group receives the subsidy. The marker shape indicates the value of i^* and hence the experience bins covered. The lines connect subsidies with the same coverage and recipients as $\bar{\gamma}$ increases. The horizontal axis is the present discounted value of the subsidy amount per worker, expressed as a percentage of baseline lifetime earnings of the subsidized group. The vertical axes report the change in the college wage premium (the log difference in average wages over potential experience bins 1–9) and in the lifetime earnings premium (the log difference in the present discounted value of earnings). Both changes are in log points multiplied by 100.

at potential experience x_1 receive the subsidy. The variation within each line along the horizontal axis corresponds to the different values of $\bar{\gamma}$. As $\bar{\gamma}$ is not straightforward to interpret, we map each value of $\bar{\gamma}$ to the ratio of the average present discounted value of total subsidies received by a worker relative to their lifetime earnings with $\bar{\gamma} = 0$.

Figure 11 shows that subsidizing human capital investment lowers both the wage premium and earnings premium if non-college workers receive the subsidy. The reduction in inequality is largest when non-college workers are the only group to receive the subsidy. Further, the amount that the wage and earnings premia decrease by is generally increasing in both the amount of the subsidy, $\bar{\gamma}$, and the eligibility threshold i^*.

To demonstrate how the effects of subsidizing human capital investment on the wage premium can vary over the life cycle, Figure 12 presents the change in the wage premium by potential experience for $\bar{\gamma} = 0.25$, $i^* \in \{2, 3, 5, 11\}$, and when only non-college workers receive the subsidy. The reduction in the wage premium is generally the largest early in the life cycle, as this is when human capital investment is most responsive to the subsidy. The change in the wage premium generally dissipates over the life cycle. In fact, when only workers at potential experience x_1 receive the subsidy, the subsidy causes the wage premium

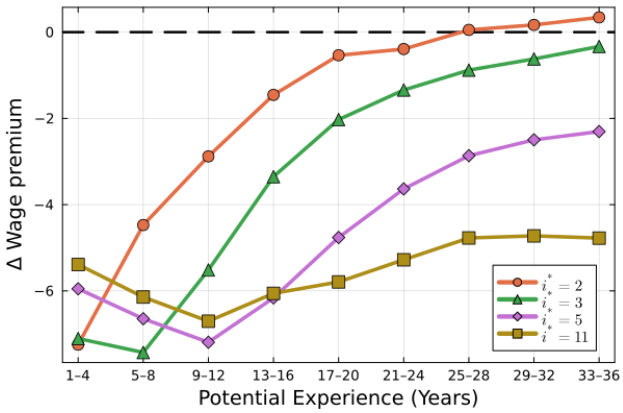


Figure 12: Change in the College Wage Premium by Potential Experience. *Notes*: This figure plots the change in the college wage premium at each potential experience bin when non-college workers receive a training subsidy that reduces $c(\tau)$ by a share $\bar{\gamma} = 0.25$. Each line corresponds to a different value of i^*. The wage premium at each bin is the log difference in average wages between college and non-college workers, and changes are relative to the baseline without a subsidy, in log points multiplied by 100.

to slightly increase towards the end of the life cycle. This is because subsidizing human capital investment also leads some workers to accumulate human capital to the point where switching careers is too costly, thereby leaving them locked-in to a bad career fit. As these workers would have otherwise switched and some would have ultimately found their good fit, their average wages towards the end of the life cycle are slightly lower despite having exhibited higher human capital investment and growth earlier in the life cycle.

Table 11 demonstrates the lock-in effect of the subsidies. When the subsidy is available only for workers with potential experience x_1, it narrows the wage premium sharply early in the life cycle, but this effect reverses by the end of the career, where the premium is slightly wider than in the baseline economy. The reason is that subsidized human capital investment early in the career raises human capital investment, accumulated human capital, and also the amount of human capital a worker would lose by switching careers. Therefore, more workers who discover they are in a bad fit do not switch to a different career. At $\bar{\gamma} = 0.5$, the subsidy for x_1 workers reduces lifetime career switches among non-college workers by 46.9% and lowers the share in a good career fit by 19.6 percentage points. Panel B shows that a subsidy that is available at all levels of potential experience has very different effects. At $\bar{\gamma} = 0.1$, the two policies reduce career switching and the good-fit share by similar amounts. At $\bar{\gamma} = 0.5$, however, the subsidy available at all ages reduces career switches by only 3.0% and the good-fit share by only 3.1 percentage points, and it narrows the premium by a similar amount early and late in the career. This is because when workers are eligible to receive the subsidy throughout the life cycle, workers in a bad fit know that they have plenty of time to rebuild any human capital that is lost in a career transition by investing in human capital at

Table 11: Human Capital Subsidies and Career Lock-In

Subsidy rate ($\bar{\gamma}$)	Δ Wage Premium		Career Fit and Switching	
	$x = 1$	$x = 9$	Δ Good fit share (pp)	% Δ Lifetime career switches
Panel A: Subsidy at x_1 only				
0.10	−2.3	0.2	−2.9	−6.2
0.50	−16.6	0.8	−19.6	−46.9
Panel B: Subsidy at all x_i				
0.10	−1.8	−2.0	−3.0	−6.8
0.50	−11.3	−10.0	−3.1	−3.0

Notes: Each row is a training subsidy given only to non-college workers, which reduces the cost of human capital investment, $c(\tau)$, by a share $\bar{\gamma}$. In Panel A, the subsidy applies only in the first potential experience bin ($i^* = 2$); in Panel B, it applies at all levels of potential experience. The first two columns report the change in the college wage premium at potential experience bins x_1 and x_9, in log points multiplied by 100. The third column reports the change in the share of employed non-college workers in a good career fit, averaged over potential experience bins, in percentage points. The fourth column reports the percentage change in the average number of career switches non-college workers make over their life cycle. All changes are relative to the baseline without a subsidy.

a subsidized rate. Therefore, the subsidy is generous enough to encourage workers to switch despite the human capital that is lost in the transition. In summary, these results highlight a potential tradeoff of concentrating subsidies for on-the-job learning among young workers. That is, subsidies that are given before a worker resolves their career uncertainty can lock workers into a bad career fit.

5 Conclusion

This paper posits differences in career uncertainty upon labor market entry as a novel source of the college wage premium. Using the NLSY79 and CPS, we document a set of facts to support this hypothesis: college graduates form more accurate expectations regarding their future occupation, the college wage premium grows over the life cycle, college graduates are in better quality matches to their careers, and college graduates receive training more frequently and earlier in their work-life. To quantify the contribution of career uncertainty to the college wage premium, we develop a life cycle search model with uncertainty and learning over one's best career fit, endogenous separations and career switches, and endogenous on-the-job human capital accumulation. Our quantitative exercises reveal that career uncertainty explains a meaningful share of the gaps in wages and lifetime earnings between non-college and college graduates. Further, our model indicates that elevated career uncertainty brought

on by advancements in artificial intelligence could decrease the college wage premium by as much as 5% and that subsidizing on-the-job learning, especially early in the life cycle, causes more workers to be locked into a bad career fit. A clear direction for future research is to study the determinants of career uncertainty and to better understand what role education and policy can have in reducing career uncertainty.

References

Acemoglu, D. and D. Autor (2011): "Skills, Tasks and Technologies: Implications for Employment and Earnings," *Handbook of Labor Economics*, 4, 1043–1171.

Aguiar, M. and E. Hurst (2013): "Deconstructing Life Cycle Expenditure," *Journal of Political Economy*, 121, 437–492.

Altonji, J. G., P. Bharadwaj, and F. Lange (2012): "Changes in the Characteristics of American Youth: Implications for Adult Outcomes," *Journal of Labor Economics*, 30, 783–828.

Audoly, R., R. McGee, S. Ocampo-Diaz, and G. Paz-Pardo (2025): "A Practitioner's Note on the Shapley-Owen-Shorrocks Decomposition," FRB of New York Staff Report No. 1163.

Autor, D., D. Dorn, and G. Hanson (2019): "When Work Disappears: Manufacturing Decline and the Falling Marriage Market Value of Young Men," *American Economic Review: Insights*, 1, 161–178.

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

Autor, D. H., L. F. Katz, and A. B. Krueger (1998): "Computing Inequality: Have Computers Changed the Labor Market?" *The Quarterly Journal of Economics*, 113, 1169–1213.

Bagger, J., F. Fontaine, F. Postel-Vinay, and J.-M. Robin (2014): "Tenure, Experience, Human Capital, and Wages: A Tractable Equilibrium Search Model of Wage Dynamics," *American Economic Review*, 104, 1551–1596.

Baley, I., A. Figueiredo, and R. Ulbricht (2022): "Mismatch Cycles," *Journal of Political Economy*, 130, 2943–2984.

Bover, O., M. Arellano, and S. Bentolila (2002): "Unemployment Duration, Benefit Duration and the Business Cycle," *The Economic Journal*, 112, 223–265.

Buera, F. J., J. P. Kaboski, R. Rogerson, and J. I. Vizcaino (2022): "Skill-Biased Structural Change," *The Review of Economic Studies*, 89, 592–625.

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

Card, D. and T. Lemieux (2001): "Can Falling Supply Explain the Rising Return to College for Younger Men? A Cohort-Based Analysis," *The Quarterly Journal of Economics*, 116, 705–746.

Carrillo-Tudela, C. and L. Visschers (2023): "Unemployment and Endogenous Reallocation Over the Business Cycle," *Econometrica*, 91, 1119–1153.

CNBC and SurveyMonkey (2026): "CNBC and SurveyMonkey Quarterly AI & Jobs Survey," https://www.surveymonkey.com/curiosity/cnbc-ai-work-survey-may-2026/, survey conducted April 17–21, 2026.

Deaton, A. (1997): *The Analysis of Household Surveys: A Microeconometric Approach to Development Policy*, World Bank.

Deming, D. J. (2024): "Why Do Wages Grow Faster for Educated Workers?" Tech. rep., National Bureau of Economic Research.

Diamond, P. A. (1982): "Wage Determination and Efficiency in Search Equilibrium," *The Review of Economic Studies*, 49, 217–227.

Doepke, M. and R. Gaetani (2024): "Why Didn't the College Premium Rise Everywhere? Employment Protection and On-the-Job Investment in Skills," *American Economic Journal: Macroeconomics*, 16, 268–309.

Duan, J. and P. Jackson (2026): "Uncertainty, Learning, and the Unemployment-Education Gap Over the Life Cycle," Working paper.

Engbom, N. (2026): "Labor Market Policy, Worker Careers, and Aggregate Productivity," Working paper.

Farber, H. S., D. Herbst, I. Kuziemko, and S. Naidu (2021): "Unions and Inequality over the Twentieth Century: New Evidence from Survey Data," *The Quarterly Journal of Economics*, 136, 1325–1385.

Flinn, C., A. Gemici, and S. Laufer (2017): "Search, matching and training," *Review of Economic Dynamics*, 25, 260–297.

Gathmann, C. and U. Schönberg (2010): "How General is Human Capital? A Task-Based Approach," *Journal of Labor Economics*, 28, 1–49.

Gervais, M., N. Jaimovich, H. E. Siu, and Y. Yedid-Levi (2016): "What should I be when I grow up? Occupations and unemployment over the life cycle," *Journal of Monetary Economics*, 83, 54–70.

Guvenen, F. (2009): "An empirical investigation of labor income processes," *Review of Economic Dynamics*, 12, 58–79.

Guvenen, F., B. Kuruscu, S. Tanaka, and D. Wiczer (2020): "Multidimensional Skill Mismatch," *American Economic Journal: Macroeconomics*, 12, 210–44.

Hall, R. E. (1968): "Technical Change and Capital from the Point of View of the Dual," *The Review of Economic Studies*, 35, 35–46.

Heckman, J. J., L. Lochner, and C. Taber (1998): "Explaining rising wage inequality: Explorations with a dynamic general equilibrium model of labor earnings with heterogeneous agents," *Review of Economic Dynamics*, 1, 1–58.

Heckman, J. J., J. Stixrud, and S. Urzua (2006): "The Effects of Cognitive and Noncognitive Abilities on Labor Market Outcomes and Social Behavior," *Journal of Labor Economics*, 24, 411–482.

Huggett, M., G. Ventura, and A. Yaron (2011): "Sources of Lifetime Inequality," *American Economic Review*, 101, 2923–2954.

Kambourov, G. and I. Manovskii (2009): "Occupational Specificity of Human Capital," *International Economic Review*, 50, 63–115.

Katz, L. F. and K. M. Murphy (1992): "Changes in Relative Wages, 1963–1987: Supply and Demand Factors," *The Quarterly Journal of Economics*, 107, 35–78.

Krusell, P., L. E. Ohanian, J.-V. Ríos-Rull, and G. L. Violante (2000): "Capital-Skill Complementarity and Inequality: A Macroeconomic Analysis," *Econometrica*, 68, 1029–1053.

Lagakos, D., B. Moll, T. Porzio, N. Qian, and T. Schoellman (2018): "Life Cycle Wage Growth across Countries," *Journal of Political Economy*, 126, 797–849.

Lemieux, T. (2006): "Increasing Residual Wage Inequality: Composition Effects, Noisy Data, or Rising Demand for Skill?" *American Economic Review*, 96, 461–498.

Ljungqvist, L. and T. J. Sargent (1998): "The European Unemployment Dilemma," *Journal of Political Economy*, 106, 514–550.

Lumina Foundation and Gallup (2026): "AI in Higher Education: Widespread Use, Unclear Rules," Report, Gallup, Inc., lumina Foundation–Gallup State of Higher Education 2026 study.

McKenzie, D. J. (2006): "Disentangling Age, Cohort and Time effects in the Additive Model," *Oxford Bulletin of Economics and Statistics*, 68, 473–495.

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

Mortensen, D. T. and C. A. Pissarides (1994): "Job Creation and Job Destruction in the Theory of Unemployment," *The Review of Economic Studies*, 61, 397–415.

Obama, B. (2014): "Remarks by the President on Opportunity for All: Making College More Affordable," The White House, Office of the Press Secretary, https://obamawhitehouse.archives.gov/the-press-office/2014/06/09/remarks-president-opportunity-all-making-college-more-affordable. Accessed 2026-07-12.

Ortego-Marti, V. (2016): "Unemployment history and frictional wage dispersion," *Journal of Monetary Economics*, 78, 5–22.

Petrongolo, B. and C. A. Pissarides (2001): "Looking into the Black Box: A Survey of the Matching Function," *Journal of Economic Literature*, 39, 390–431.

Pissarides, C. A. (1992): "Loss of Skill During Unemployment and the Persistence of Employment Shocks," *The Quarterly Journal of Economics*, 107, 1371–1391.

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

Qiu, X., J. Wedewer, and R. Wu (2026): "The Worker and Firm Origins of Life-Cycle Wage Inequality," Tech. rep.

Rubinstein, Y. and Y. Weiss (2006): "Chapter 1 Post Schooling Wage Growth: Investment, Search and Learning," Elsevier, vol. 1 of *Handbook of the Economics of Education*, 1–67.

Schulhofer-Wohl, S. (2018): "The age-time-cohort problem and the identification of structural parameters in life-cycle models," *Quantitative Economics*, 9, 643–658.

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

Shorrocks, A. F. (2013): "Decomposition procedures for distributional analysis: A unified framework based on the Shapley value," *The Journal of Economic Inequality*, 11, 99–126.

Wasmer, E. (2006): "General versus Specific Skills in Labor Markets with Search Frictions and Firing Costs," *American Economic Review*, 96, 811–831.

Appendix

A Empirical Appendix

A.1 Sample Creation

NLSY79 Starting with the weekly basis data, we identify the main job in each year as the job with the highest working hours. In cases where multiple jobs have identical hours, we first select the job with complete occupation and industry records. If ties persist, we retain the job with a non-missing employer ID; remaining ties are resolved by selecting the earliest reported job (i.e., the smallest job code). For years without civilian employment, we assign status codes as follows: employed but missing employer periods is prioritized over unemployed, followed by out of the labor force, non-working with ambiguous status, military, and finally no information.

To address missing wages, we impute values using valid wages from adjacent years for the same employer, occupation, and industry. All hourly wages are deflated using the PCE2000 index and trimmed to the interval $[3, 200]$. After implementing the sample restrictions described in Table A1, we obtain a final annual sample of 10,278 workers and 265,119 observations.

Table A1: Sample Selection, NLSY79

Criteria	**No. Individuals**	**No. Observations**
Original year sample, 1978-2018	12,686	404,253
Post graduation	12,664	315,126
Drop workers who served in military	10,922	285,885
Valid AFQT score	10,289	272,464
Non-college ages 18–57, while college ages 22–57	10,278	265,119

ASEC For consistency with the NLSY sample, we restrict the data to employment observations from 1978 to 2018 and exclude military samples. Hourly wages are imputed as the ratio of wage and salary income to total working hours in the previous year. These wages are then deflated using the PCE index and trimmed to a range of 3 to 200. The final sample consists of 2,871,016 employment observations with valid wage records out of 3,557,482 observations.

NLSY97 We now turn to the NLSY97 sample, which comprises 8,984 respondents initially interviewed in 1997 when they were 12-17 years old. As a result, most of them entered the

Table A2: Sample Selection Process

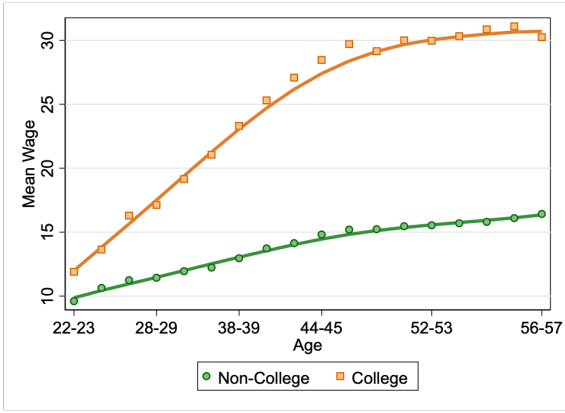
Criteria	No. Individuals	No. Observations
NLSY97 weekly sample	8,984	13,440,064
With identified graduation year	8,867	13,265,032
Prior to Covid year 2020	8,867	11,988,184
Enter labor market after graduation	8,601	6,793,728
Restrict to cross-sectional sample	6,490	5,071,988
Drop respondents who ever served in military	6,269	4,897,932
No more school enrollment	5,786	3,948,060
Drop observations below age 18	5,786	3,936,021

labor market around the 2000s. Our sample selection process for the NLSY97 is detailed in Table A2. In total, we have 3,668 non-college workers and 2,118 college workers. For consistency, all wages were first deflated using the Personal Consumption Expenditures 2000 (PCE2000) index and then top-coded to range between \$3 and \$200.

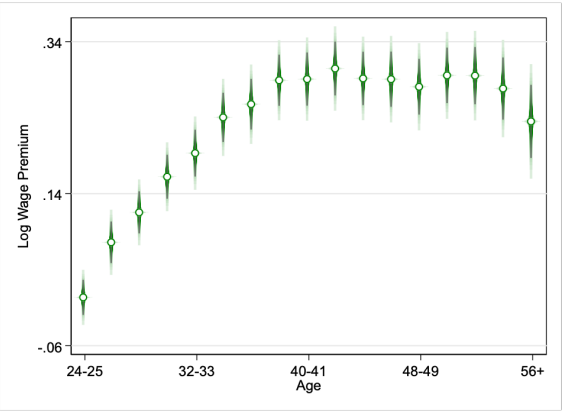
A.2 Life Cycle Pattern of College Premium

Supplementary in NLSY79 We additionally examine NLSY79 wage profiles over age (Figure A1) and actual work experience (Figure A2). The left figure depicts unconditional mean wages, while the right displays conditional college premium estimates. Consistent with the patterns observed for potential experience profiles, college workers earn higher average wages throughout. For example, the mean wage surges by about 150% (58%) for college (non-college) workers between age 22 and 42, and concurrently, the wage gap widens from \$2.30 at age 22 to \$14.51 at age 42, and eventually tapers off to \$13.83 by age 56. If we discount each age at 4 percent per year, the average height of discounted lifetime wage gains amounts to \$10.58 (\$6.17) for college (non-college) workers. Notably, wage growth is most pronounced in the early career life, and college workers experience substantially steeper gains during their initial years of work experience. For instance, the conditional college premium rises from near zero at ages 24–25 to 30% by ages 42–43, stabilizing thereafter.

Replication in ASEC Sample The life cycle wage pattern is replicable in the ASEC sample. Figure A3 shows average wages across ages or potential work experience. First, college workers consistently earn higher wages than non-college workers. Pairwise comparisons at each career stage show statistically significant differences, with the null hypothesis of zero difference rejected at the 99% confidence level. Second, wage growth for college workers is steeper than for non-college workers over time. This is evident from the slope comparison

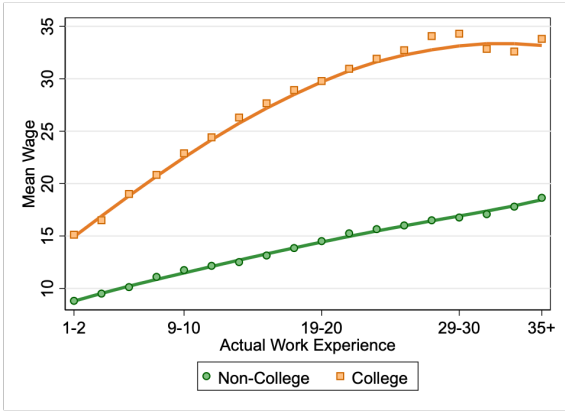


(a) Descriptive Pattern

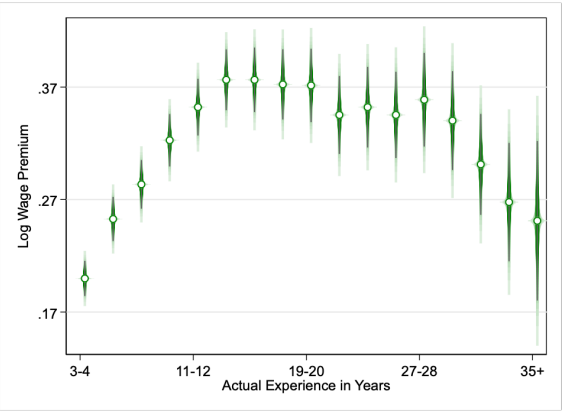


(b) Conditional Estimation

Figure A1: Wage Premium Over Ages. *Notes:* NLSY79 Sample. In the left panel, each pairwise t-test yields a p-value of 0.0000, which rejects the null hypothesis of zero difference. The right panel displays point estimates with 90% confidence intervals; standard errors are clustered at the individual level.



(a) Descriptive Pattern

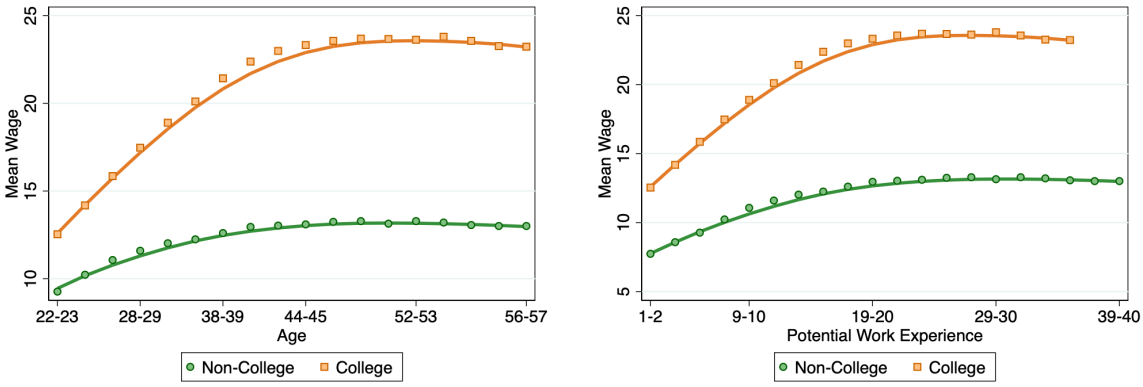


(b) Conditional Estimation

Figure A2: Wage Premium Over Actual Work Experience. *Notes:* NLSY79 Sample. In the left panel, each pairwise t-test yields a p-value of 0.0000, which rejects the null hypothesis of zero difference. The right panel displays point estimates with 90% confidence intervals; standard errors are clustered at the individual level.

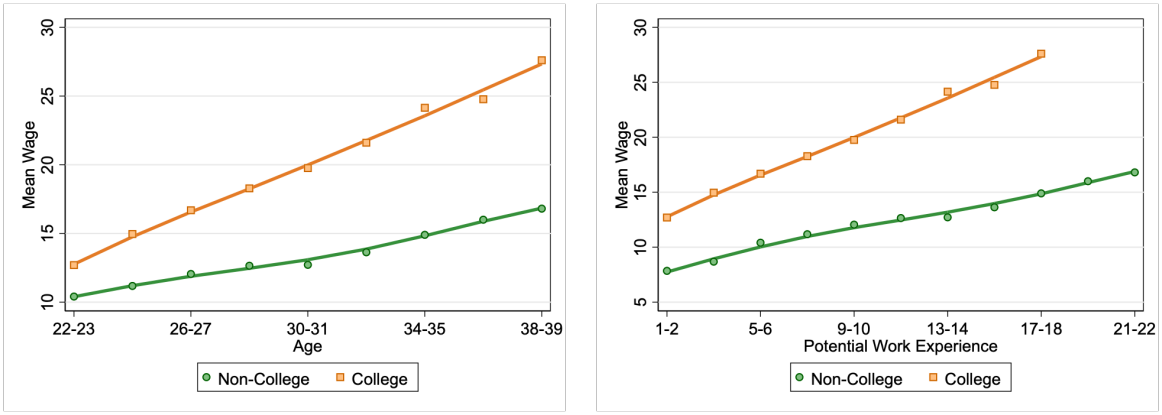
between the red curve for college workers and the green curve for non-college workers. Third, and most notably, the majority of wage growth occurs during early career stages. For instance, the average wage for college workers rises from \$12.54 at age 22 to \$23.56 by age 42, while non-college workers see an increase from \$9.27 to \$13.24 over the same period. After age 42, wages remain relatively stable for both groups.[36]

[36]We also estimate the conditional college wage premium across the life cycle, controlling for race, gender, year, region, marital status, job type, and birth year cohorts. The resulting pattern closely resembles the unconditional results presented above. These detailed results are available upon request.



(a) Age (b) Potential Work Experience

Figure A3: Mean Wage Over Life Cycle. *Notes:* ASEC Sample. Each pairwise t-test yields a p-value of 0.0000, which rejects the null hypothesis of zero difference.



(a) Age (b) Potential Work Experience

Figure A4: Mean Wage Over Life Cycle. *Notes:* Constructed using the NLSY97 sample.

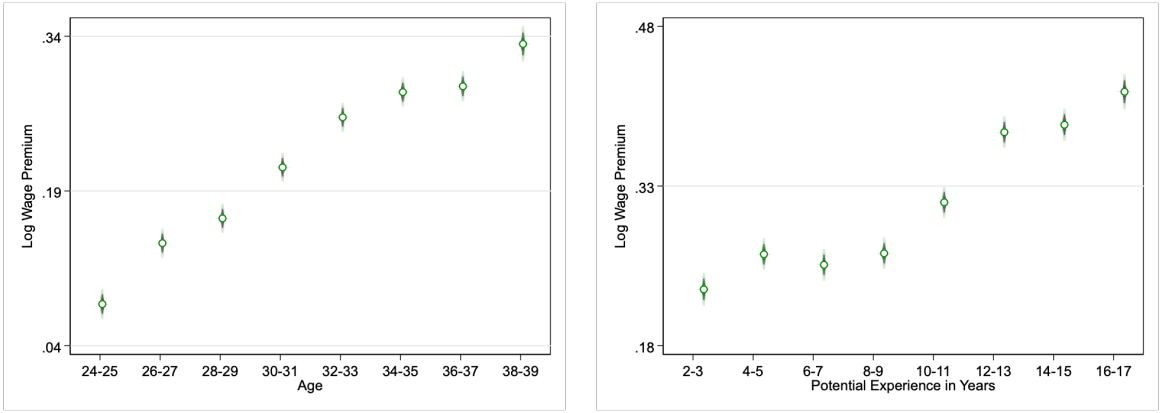
Replication in NLSY97 We first examine the descriptive pattern of the college premium in the NLSY97 sample. Figure A4 demonstrates a consistent increase in the wage premium throughout the observed periods, a finding that resonates with the growing wage premium observed in the NLSY79 during their early careers.

For robustness, we estimate the conditional college premium using the following specification:

$$\ln(wage_{it}) = \alpha College_i + \sum_k Exp_{it} + \sum_k \gamma_k College_i \times Exp_{it} + Urate_{it} + \mathbb{X}_i + \mathbf{\Phi} + \epsilon_{it},$$

where $\mathbb{X}_i$ includes individual-level characteristics like gender, race, and ASVAB, while $\mathbf{\Phi}$ represents industry and occupation fixed effects. Figure A5 confirms that these conditional

estimates closely mirror the descriptive patterns documented above, namely a rising college wage premium over the early career years.



(a) Age (b) Potential Work Experience

Figure A5: Estimated Wage Premium Over Life Cycle. *Notes:* Constructed using the NLSY97 sample.

A.3 Identification of Experience Effects in Wage Growth

The fundamental challenge in estimating wage growth for each education group is that the effects of experience, birth cohort, and time cannot be separately identified due to collinearity. Specifically, the experience effect denotes wage growth attributable to the accumulation of labor market experience. The cohort effect captures wage growth arising from differences across birth cohorts, such as later born cohorts exhibiting better health and thus higher productivity. Likewise, the time effect reflects wage growth resulting from fundamental changes over time, including technological progress. As a result of this collinearity, any estimate of wage growth attributed to experience effects will be biased unless the wage growth due to time effects and cohort effects can be identified in isolation.

In this section, we detail the strategies used to isolate experience effects from cohort and time effects when estimating wage growth by education, following the methodologies of Lagakos et al. (2018). Specifically, we implement both the **Heckman-Lochner-Taber approach** (Heckman et al., 1998; McKenzie, 2006; Huggett et al., 2011; Schulhofer-Wohl, 2018) and the **Deaton-Hall approach** (Hall, 1968; Deaton, 1997; Aguiar and Hurst, 2013). The subsequent subsections outline the identification strategy, implementation details, and present the wage growth attributable to potential work experience by educational attainment, stripped of cohort and time effects.

A.3.1 Heckman-Lochner-Taber Approach

This method is motivated to separate the contributions of time effect, cohort effect, and experience effect to wage dynamics, relying on the theoretical prediction that a worker's wage growth should be little during the final years of their career.

To illustrate this identification strategy, consider two cohorts in the year 2000: a young cohort with 1–4 years of experience and an old cohort with 37–40 years of experience. Suppose that between 2000 and 2005, the young cohort experiences a 5% wage growth, while the old cohort experiences a 1% increase. Given that the old cohort has reached the final years of their career, their one percent growth entirely reflects time effects. Consequently, the young cohort's remaining four percent wage growth ($5\% - 1\%$) is attributed to the experience effect. Iterating this logic across multiple cohorts identifies the full sequence of time effects, allowing for the subsequent estimation of cohort and experience profiles.

To implement the HLT approach, we require two identifying assumptions. First, the parameter y defines the number of periods at the end of the life cycle during which experiential wage growth becomes negligible, as it either ceases or declines due to depreciation of skills or of match quality. Following Huggett et al. (2011) and Lagakos et al. (2018), we consider $y = 1$, i.e., little human capital dynamics during the final 4-year potential work experience. Second, the parameter d specifies the human capital depreciation rate during our selected window for the final years. We consider the scenario $d = -0.005$, which represents 0.5% human capital depreciation in the final work experience years.[37]

The estimation follows an iterative procedure to achieve this. The process begins by guessing an initial trend for the time effects, which is then used to deflate each individual's observed wages across all sample years. Using these deflated wages, the experience and cohort effects are isolated by estimating the following specification:

$$\ln(wage_{it}) = \sum_k \phi_k Exp_{it} + \sum_j \psi_j Cohort_i + Race_i + Gender_i + Region_{it} + Marital_{it} + Type_{it} + \epsilon_{it}, \tag{A.27}$$

where $\ln(wage_{it})$ denotes the log of the time deflated wage for individual i at year t, Exp_{it} is a vector of work experience intervals of every four years of potential experience, and $Cohort_i$ is a vector of birth cohort intervals. This specification controls for time-invariant individual characteristics, including race and gender, alongside time-varying controls for geographic

[37] As a robustness check, we consider alternative values of $d \in \{0.000, -0.010\}$, corresponding to 0 and 1 percent human capital depreciation over the final years of work experience, respectively. The estimated wage growth profiles are similar to those obtained under $d = -0.005$. More importantly, the implied college wage premium increases by 9.9%-16.9% over the first 36 years of potential work experience under these three alternative scenarios. Our wage profile used for calibration features exactly a 12.5% growth in the wage premium, which falls well within this range.

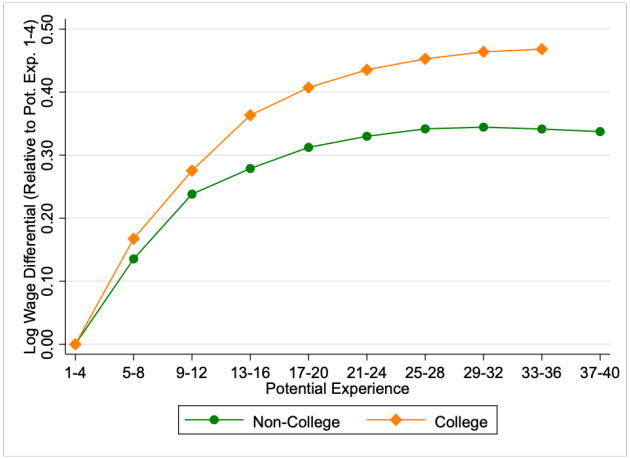


Figure A6: Estimated Wage Growth by Education, Stripped of Time and Cohort Effects *Notes:* ASEC Sample.

region, marital status, and whether a full-time job.

Following this estimation, we evaluate whether the estimated experience profile satisfies the identifying restriction, i.e., we check if it declines on average by d percent over the final y years of the career. If this condition is met within the tolerance level, the procedure stops. Otherwise, the trend in the time effects is adjusted, and the steps are repeated. At the end, we arrive at separate estimates of the cohort, time, and experience effects.

Figure A6 presents the estimated wage growth over potential work experience for each education group, stripped of the cohort and time effects. It can be clearly observed that the wage fully attributable to experience remains growing faster for college workers, particularly during the early years, which aligns with the potential work experience profile of raw wages in the main text. Zooming in on the wage premium, we find that it grows by 12.7% over the first 36 years of potential work experience, which closely matches the fact that the wage profile we use for calibration features a wage premium of 12.5%. The estimated cohort and time effects are reported in Table A3. It is evident that both the time and cohort effects favor the college group more, which is consistent with the classic literature view that college graduates benefit more from technological growth.

A.3.2 Deaton-Hall Approach

This section outlines the conceptual framework and implementation of the Deaton-Hall approach used to identify cohort and time effects. Basically, this method imposes one additional linear restriction on the vector of cohort and time effects to isolate the underlying sources of

Table A3: Estimated Time and Cohort Effects by Education

	Non-College	**College**
Time Effect	0.0067	0.0200
Cohort Effect:		
Cohort 1: Birth prior to 1949	-	-
Cohort 2: Birth during 1950 to 1960	0.0747	0.0937
Cohort 3: Birth during 1961 to 1970	0.0448	0.1658
Cohort 4: Birth during 1971 to 1980	0.0394	0.2086
Cohort 5: Birth later 1981	0.0327	0.2029

aggregate wage growth. We begin by considering total wages in year t as:

$$W_t = \sum_{c \in C_t} \sum_{i=1}^{N_{ct}} w_{ict}$$

where C_t denotes the set of cohorts active in year t, N_{ct} represents the number of individuals in cohort c working in year t, and w_{ict} is the wage of individual i with birth cohort c in year t. Wages are assumed to satisfy:

$$log(w_{ict}) = \alpha + \sum_{x \in X} \phi_x D_{ict}^x + \gamma_t + \chi_c + \underbrace{Race_{ic} + Gender_{ic} + Region_{ict} + Marital_{ict} + Type_{ict}}_{\mathbb{X}} + \epsilon_{ict}, \tag{A.28}$$

where D_{ict}^x is an indicator variable for experience group x, γ_t is the time effect, and χ_c is a vector of cohort fixed effects. The vector $\mathbb{X}$ controls for race, gender, geographic region, marital status, and job type (full-time or part-time). The total wages, W_t, thus can be re-written as:

$$W_t = \Gamma_t \bar{X}_t \bar{F}_t \equiv \Omega_t \bar{F}_t.$$

It implies that total wages are decomposed into three components: (i) $\Gamma_t \equiv \exp(\gamma_t)$ captures wage growth driven by time effects; (ii) $\bar{X}_t \equiv \sum_{c \in C_t} \exp(\chi_c) \frac{F_{ct}}{\bar{F}_t}$ captures growth attributable to cohort effects; and (iii) $\bar{F}_t \equiv \sum_{c \in C_t} F_{ct}$ accounts for changes in the composition of experience with the cohort-year measure $F_{ct} = \sum_{i=1}^{N_{ct}} exp(\sum_{x \in X} \phi_x D_{ict}^x + \mathbb{X} + \epsilon_{ict})$. Accordingly, the aggregate term $\Omega_t \equiv \Gamma_t \bar{X}_t$ defines year-specific aggregate labor productivity, with its growth driven by either cohort-neutral changes (Γ_t) or changes in the cohort composition of the workforce ($\bar{X}_t$).

To separate the time and cohort effects, we decompose the time series of aggregate productivity, Ω_t, into trend and cyclical components, and then impose restrictions on the source of the secular trend. To implement that, it is convenient to work in logs: $\omega_t = \log \Omega_t =$

$\gamma_t + \bar{\chi}_t$, where $\bar{\chi}_t \equiv \log \bar{X}_t$. We then normalize the time periods and fixed effects to deviate from their respective sample means, such that $\sum_{t=1}^{T} t = 0$, $\sum_{t=1}^{T} \gamma_t = 0$, and $\sum_{t=1}^{T} \bar{\chi}_t = 0$. This yields:

$$\omega_t = \bar{\omega} + \gamma_t + \bar{\chi}_t$$

Next, the time and cohort series are partitioned into a trend component and a cyclical component:

$$\gamma_t = g_\gamma t + u_{\gamma,t}, \quad \bar{\chi}_t = g_\chi t + u_{\chi,t}.$$

Substituting these into the log aggregate productivity equation gives:

$$\omega_t = \bar{\omega} + (g_\gamma + g_\chi)t + (u_{\gamma,t} + u_{\chi,t}) = \bar{\omega} + g_M t + u_{M,t},$$

Because g_M is directly estimable from the data, identifying γ_t and $\bar{\chi}_t$ requires an attribution rule to distribute the aggregate trend g_M between g_γ and g_χ. We consider three alternative identifying restrictions:

Restriction 1 Assume aggregate labor productivity growth is entirely explained by cohort effects, implying:

$$g_M = g_\chi, \ g_\gamma = 0.$$

Restriction 2 Assume aggregate labor productivity growth is entirely explained by year effects, implying:

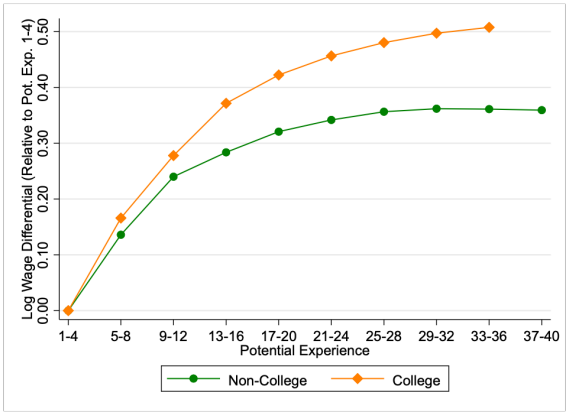
$$g_M = g_\gamma, \ g_\chi = 0.$$

Restriction 3 Assumes both cohort and time effects contribute to productivity growth, where a fraction β of the aggregate growth is attributable to time effects:

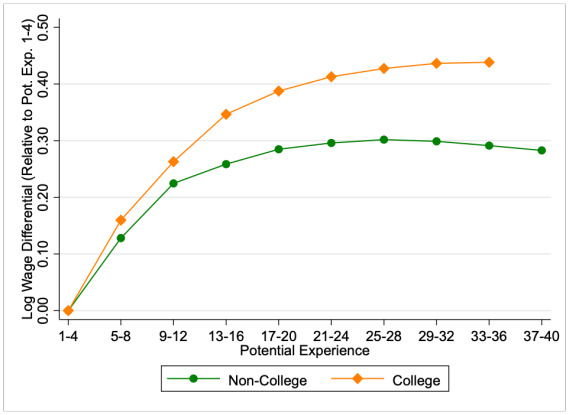
$$g_\gamma = \beta g_M, \ g_\chi = (1 - \beta) g_M.$$

In particular, we consider $\beta = 1/2$.

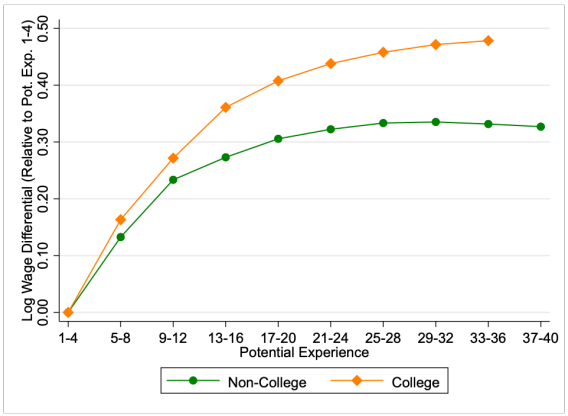
Figure A7 presents estimated wage growth over potential work experience by education level under the three alternative identifying restrictions. Regardless of the identifying restriction imposed, it is obvious that wage growth for college workers is consistently higher than that for non-college workers. More importantly, while the estimated wage levels vary across specifications, the educational wage gap expands by an identical 14.7% during the first 36 years of potential experience under all three restrictions. This is close to the identified wage premium growth from both the original wage profile used for calibration (12.5%) and the



(a) $g_M = g_\chi$



(b) $g_M = g_\gamma$



(c) $g_\gamma = g_\chi = 1/2 g_M$

Figure A7: Estimated Wage Growth by Education, Deaton-Hall Approach *Notes:* ASEC Sample.

estimates obtained via the Heckman-Lochner-Taber approach (12.7%).

A.4 Career Definition

We define the concept of career and then identify the career sampling. Following Baley et al. (2022), we conceptualize careers as sets of occupations requiring a similar mix of skills, a departure from conventional occupation- or industry-based classifications.[38] To quantify skill composition similarities or differences between jobs, we need to characterize the skill vector for each occupation. To achieve this, we first measure the verbal, math, and social skill requirements for each occupation as in Guvenen et al. (2020). To capture lower-order skills that are intensively used in non-college jobs, we measure an occupation's routine and manual task intensity (Autor and Dorn, 2013). This produces a five-dimensional

[38]For example, economists, actuaries, and financial managers share nearly identical skill profiles and are thus identified as one career, despite belonging to distinct occupational classifications.

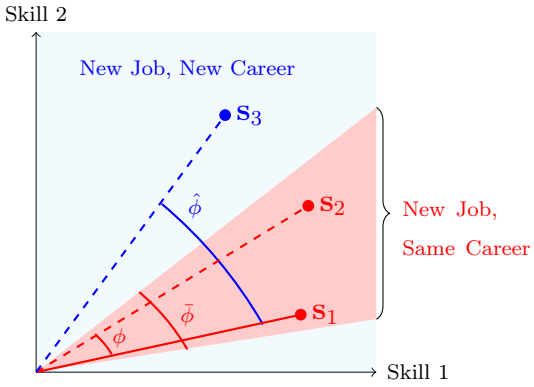


Figure A8: Career Switch

vector, with each element representing the required level of a particular type of skill to perform that job. Second, we quantify skill composition differences using angular distance ϕ: $\mathbb{R}^5 \times \mathbb{R}^5 \to [0, \pi/2]$ between the vector of requirements for individual i's current occupation, $\mathbf{s}_{ik}$, and prior occupation, $\mathbf{s}_{ik-1}$ by:

$$\phi(\mathbf{s}_{ik}, \mathbf{s}_{ik-1}) = \cos^{-1}\left(\frac{\mathbf{s}_{ik} \cdot \mathbf{s}'_{ik-1}}{\|\mathbf{s}_{ik}\|\|\mathbf{s}_{ik-1}\|}\right). \tag{A.29}$$

Accordingly, we define a career transition as an occupation switch where the angular distance between the current and previous job (ϕ) exceeds a threshold, $\bar{\phi}$. The threshold is chosen so that the average correlation in occupational requirements is zero in career switches.[39] Intuitively, a career switch occurs when the worker transitions between occupations with very different compositions of skill requirements. This is depicted in Figure A8. A worker switching from occupation 1 to 2, with the angle between the skill requirements $\mathbf{s}_1$ and $\mathbf{s}_2$ is $\phi < \bar{\phi}$, changes jobs within the same career. By contrast, a move from occupation 1 to 3, with distance $\hat{\phi} > \bar{\phi}$, constitutes a career switch.

To establish that our skill-based career transitions reflect search and matching for best fit rather than natural promotions such as managerial advancement, we examine the direction of occupational mobility following a switch. For each month identified as a career switch, we record the worker's origin and destination occupations at the 1-digit level, which allows us to explicitly identify the direction of mobility.

The first two rows of Table A4 show that switches from non-managerial to managerial occupations account for only 12.26% of the sample, while a roughly equal fraction flow out of managerial occupations. This indicates that managerial roles are not necessarily a terminal stage in career sampling for the best fit, as a considerable share of workers transition out

[39] We find $\bar{\phi} = 23.077$ yields an average correlation of 0.0076 among the 60,189 occupational transitions in our NLSY79 sample.

Table A4: Career Switches Relating to Managerial Promotion

	Non-College	College	Aggregate
Non-Managerial → Managerial	3,201 10.90%	1,108 19.19%	4,309 12.26 %
Managerial → Non-Managerial	2,529 8.61%	902 15.62%	3,431 9.76 %
Non-Managerial → Non-Managerial	23,530 80.13%	3,614 62.59%	27,144 77.25%

of them. Conversely, the third row shows that most career switches, particularly among non-college workers, are unrelated to managerial jobs. Our identified career switches are therefore unlikely to be driven or shaped by conventional career ladder progression.

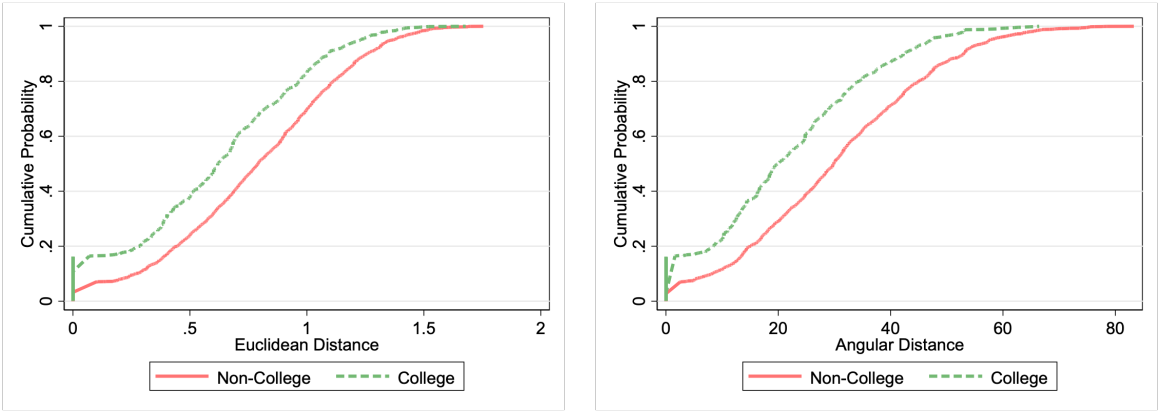
With this skill-based identification strategy, we can track the sequence of careers each individual samples over time. In particular, we identify a new unique career as one that has been sampled by comparing the angular skill distance between the current occupation and all previously held occupations. If this distance is greater than or equal to the predefined threshold, the current job is classified as a new and unique career sampled. In the end, we can keep track of the number of unique careers sampled by a specific time point. In our sample, non-college (college) workers on average sampled 2.79 (2.00) unique careers during their whole career life.

A.5 Comparison of Match Quality

We employ three different metrics for match quality. The first indicator is forecast error, which measures how accurately workers predict their future occupation. We draw upon the NLSY79, where respondents were asked in their initial interview about their expected occupation at age 35 and in 5 years. Among our sample of $10,278$ respondents, $4,243$ ($3,428$) listed an expected occupation at age 35 (in 5 years) and had a realized occupation at that point in time.

Forecast error is quantified by computing the dissimilarity in skill and task requirements between the realized and expected occupation. To gauge this, we calculate the distance in skill and task requirements between the realized occupation ($\mathbf{s_i}$) and the expected occupation ($\hat{\mathbf{s}}_\mathbf{i}$) for each individual i. Specifically, the divergence in skill composition is quantified using the angular distance as Equation (A.29), while the distance in both skill composition and magnitude is derived via the Euclidean distance: $\psi(\mathbf{s}_i, \hat{\mathbf{s}}_i) = \sqrt{\sum_k (s_{i,k} - \hat{s}_{i,k})^2}$. Beyond the

notable educational differences in average forecast errors reported in Table 1, Figure A9 shows that these differences are present at all other percentiles.



(a) Euclidean Distance

(b) Angular Distance

Figure A9: Cumulative Distribution Function of Forecast Error

The second measure is skill mismatch, which is defined as the distance between a worker's abilities and the skill requirements of their job. To quantify this, we need to characterize both worker and job attributes across multiple aptitudes: verbal, math, and social skills.

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

Social skills are measured similarly using the Rotter Locus of Control and Rosenberg Self-Esteem scales, adjusting for age effects, extracting the first PCA component and transforming into percentile ranks.

We characterize each occupation by its skill requirements, represented as a vector of verbal, mathematical, and social skill levels needed for performing a job. Following established methodologies from Guvenen et al. (2020) and Autor and Dorn (2013), we construct these occupational skill profiles by initially selecting relevant O*NET descriptors, subsequently constructing parallel ASVAB components, and then transforming these into verbal, math, and social skill measures for each occupation using PCA.

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

$$m_{i,j,o} = \left| q(A_{i,j}) - q(s_{o,j}) \right|, \tag{A.30}$$

where $q(A_{i,j})$ represents the percentile rank of worker i in skill j, and $q(s_{o,j})$ denotes the requirement percentile of occupation o in skill j. The aggregate mismatch is then defined as:

$$m_{i,o} = \sum_{j} \{\omega_j \left| q(A_{i,j}) - q(s_{o,j}) \right|\}, \tag{A.31}$$

where ω_j represents the weights assigned to each skill j, reflecting the relative importance of the difference in that skill to the aggregate skill mismatch. These weights are determined by factor loadings obtained from the normalized first principal component analysis. In particular, the respective weights for verbal, math, and social are $(0.43, 0.43, 0.14)$, which is similar to the weights in Guvenen et al. (2020).

Table A5: Comparison of Tenure across Education Groups

	Non-College	College
Employer Tenure	3.79	4.99
Occupational Tenure	3.78	4.73
Industry Tenure	4.28	5.53

Notes: The null hypothesis of no difference was rejected for all pairwise comparisons ($p < 0.0001$). In the NLSY79 yearly sample, there are 45,445 (9,986) employer spells, 45,207 (10,598) occupation spells, and 39,300 (8,900) industry spells for the non-college (college) groups, with spell counts accumulated cumulatively, i.e., if a code is left and later resumed, the count picks up where it left off, without restarting.

Career tenure serves as our third ex-post indicator of match quality and is inversely associated with career switching probability. As in Appendix Table A5, our comparison of employer, occupation, and industry tenures across the two educational groups demonstrates that, irrespective of the tenure type, college workers consistently hold longer tenures than their non-college counterparts. This result is congruent with the pattern of lower employer, occupation, and industry mobility observed among the college workers in our companion paper (Duan and Jackson, 2026).

A.6 Wage Growth and Match Quality

To examine whether higher career match quality fosters faster wage growth, we estimate the following specification:

$$\ln(\text{wage}_{it}) = \alpha + \beta_1 \text{Exp}_{it} + \beta_2 \text{Quality} + \gamma(\text{Exp}_{it} \times \text{Quality}) + \mathbf{X}_i'\boldsymbol{\delta} + \theta \text{Urate}_t + \boldsymbol{\Phi} + \epsilon_{it}, \quad \text{(A.32)}$$

where Exp_{it} denotes potential work experience, and Quality measures career match quality. To isolate this mechanism from individual heterogeneity, the control vector $\mathbf{X}_i$ includes standard demographics (race, gender, and education) alongside standardized AFQT scores to account for cognitive ability. The annual unemployment rate, Urate_t, controls for aggregate macroeconomic conditions, while $\boldsymbol{\Phi}$ absorbs a comprehensive set of fixed effects. Our parameter of interest is γ, which captures how returns to experience vary by match quality.

Table A6: Wage Growth and Match Quality

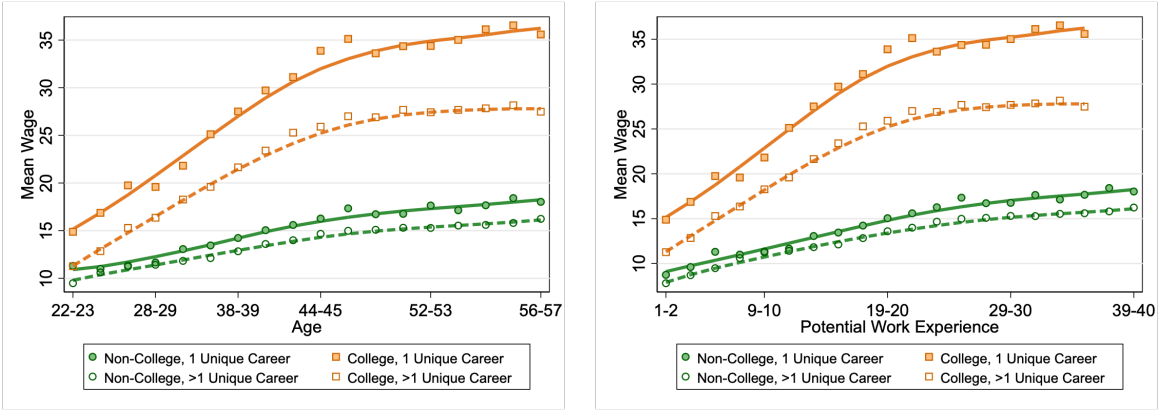
	Forecast Error		**Mismatch**	**Tenure**			
	Euclidean	Angular		Employer	Occupation	Industry	Career
PotExp × Quality	-0.0048***	-0.0001***	-0.0004***	0.0002***	0.0001***	0.0002***	0.0003***
Quality	-0.0150**	-0.0006***	-0.0222***	0.0101***	0.0124***	0.0093***	0.0056***
PotExp	0.0183***	0.0181***	0.0150***	0.0100***	0.0103***	0.0086***	0.0065***
Race	-0.0082**	-0.0082**	-0.0223***	-0.0253***	-0.0205***	-0.0239***	-0.0123***
Female	-0.1882***	-0.1862***	-0.2076***	-0.1926***	-0.1902***	-0.1899***	-0.1790***
AFQT	0.1513***	0.1497***	0.1500***	0.1377***	0.1380***	0.1371***	0.1313***
Urate	-0.0201***	-0.0202***	-0.0188***	-0.0175***	-0.0180***	-0.0192***	-0.0182***
College	0.2767***	0.2755***	0.2676***	0.2832***	0.2643***	0.2737***	0.2830***
Constant	2.3281***	2.3332***	2.3434***	2.2251***	2.2289***	2.2333***	2.2210***
Occupation FE	✓	✓	✓	✓	✓	✓	✓
Industry FE	✓	✓	✓	✓	✓	✓	✓
N	117,686	117,686	205,917	205,917	205,917	205,917	205,917
R^2	0.401	0.402	0.393	0.427	0.420	0.425	0.417

Notes: Robust standard errors are in parentheses. *($p < 0.10$), **($p < 0.05$), ***($p < 0.01$). Match quality is measured by the forecast error in the first two columns, by mismatch magnitude in the third column, and by tenure duration in the last four columns.

Table A6 reports the complete set of estimates for wage growth and match quality. Across the columns, match quality is proxied by forecast error (columns 1–2), mismatch magnitude (column 3), and tenure duration (columns 4–7). As the first row of estimates demonstrates, wage growth over potential work experience is positively associated with better match quality.

Recall that workers have an incentive to initiate career sampling when their current match turns out to be a poor fit. Consequently, workers who remain in a single career, or more precisely, who sample only one unique career throughout the entire sample period, are

argued to be well matched and thus have no incentive to sample further. Building on that, we examine whether wage growth differs between workers who sampled more often and those with only one unique career.



(a) Age

(b) Potential Work Experience

Figure A10: Wage Profiles of Workers with a Single Unique Career

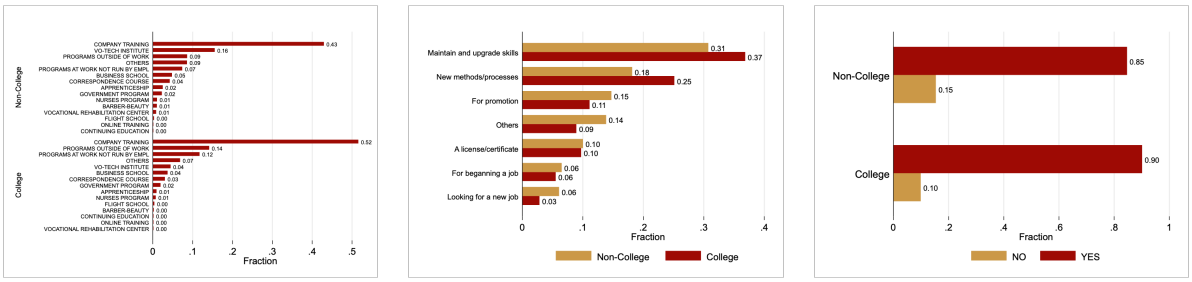
From Figure A10, we can clearly see that workers (1,182 non-college and 900 college workers) with only one unique career exhibit a consistently higher average wage than those with more than one unique career over the survey period, as workers with only one unique career are likely to find their best-fit job earlier in their careers and are less likely to incur productivity losses, which in turn leads to higher wages. Meanwhile, workers with only one unique career are also more likely to begin human capital investment early, resulting in faster wage growth.

A.7 Human Capital Investment: Training

The NLSY79 survey collected information on the training in all survey years, except for 1987. In each interview, respondents were asked to report on up to three (before 1987) or four (since 1988) training programs they had participated in since the last interview. For each reported program, a core set of variables was collected, including the type of provider, start and end dates (month and year), completion status, and the usual weekly hours spent in training, among other details.

A.7.1 An Overview of Training Variables

We examine the characteristics of training programs within the entire NLSY79 database. Figure A11 presents these characteristics across training type, the reported reason for under-



(a) Type (b) Reason (c) Usefulness

Figure A11: Characteristics of Training Programs *Notes:* Constructed using the NLSY79.

taking the training, and the perceived applicability of the acquired skills to the respondent's current or most recent job.

First, looking at training types, nearly half of all training programs reported are directly company training (43% for non-college and 52% for college workers). Second, examining the reasons for training, we find that the majority of training is closely tied to job-related skill enhancement. Among non-college workers, 31% report training for maintaining and upgrading skills, and 18% for new methods or processes, together accounting for nearly half of all reported reasons. For college respondents, these figures are even higher at 37% and 25%, respectively. In contrast, training for beginning a new job or looking for a new job each account for only 6% or less across both education groups, suggesting that the vast majority of training is intended to enhance current job performance rather than facilitate job transitions. Third, the perceived applicability of training to current jobs is remarkably high. In particular, over 85% of non-college respondents and 90% of college respondents report that the skills learned in training are applicable to their current or most recent job.

Overall, these patterns lead to a clear conclusion: the training programs reported in the NLSY79 survey represent highly job-related human capital investments. The dominance of company-provided training, the prevalence of job-enhancement reasons, and the overwhelmingly high perceived applicability all point to training being a strategic tool for improving productivity. This conclusion should become even more pronounced when we restrict our focus to on-the-job training programs within our selected sample, as the link between training and immediate workplace productivity is likely to be more direct and salient.

A.7.2 Transitions and Training

As a complementary exercise to the relationship between tenure length and training receipt, we alternatively explore the correlation between the probability of an individual switching out of their current job and whether they have ever received training from that employer,

Table A7: Switching Probability and Training

	(1) Employer	(2) Occupation	(3) Industry	(4) Career
Receive TRN	-0.03542***	-0.06308***	-0.03899***	-0.08347***
College	-0.10718***	-0.12532***	-0.09545***	-0.11887***
Age	-0.00859***	-0.01496***	-0.01310***	-0.00763***
College × Age	0.00289***	0.00295***	0.00236***	0.00279***
Female	0.01670***	0.01340***	0.00913***	0.01886***
Race	-0.01218***	-0.00840***	-0.00881***	0.00245
AFQT	-0.00885***	-0.00272**	-0.00273**	-0.00037
Constant	0.55835***	0.89260***	0.75591***	0.44845***
N	203,516	203,300	203,235	203,300
R^2	0.071	0.130	0.125	0.093
Occupation FE	✓	✓	✓	✓
Industry FE	✓	✓	✓	✓

Notes: Robust standard errors are in parentheses. *($p < 0.10$), **($p < 0.05$), ***($p < 0.01$).

using the following specification:

$$Switch_{it} = \beta TrnEver_{it} + \text{College}_i + \text{Age}_{it} + \text{College}_i \times \text{Age}_{it} + \mathbb{X}_i + \Phi_{Ind90} + \Phi_{Occ90} + \epsilon_{it},$$

where $Switch_{it}$ is a binary variable indicating whether individual i switched jobs at time t, and $TrnEver_{it}$ is a dummy variable equal to one if the worker has ever received training.[40] Alongside these key variables, we include a standard set of controls for individual demographics, as well as industry and occupation fixed effects. Therefore, the coefficient β captures the correlation between receiving training and the probability of switching jobs.

Table A7 reports the estimates. These show that the probability of switching employer, occupation, industry, or careers becomes statistically significantly lower if the worker has ever received training.

A.7.3 Training Evidence with Selected Training Programs

Not all training is motivated by match fit considerations. For example, many workplace training programs, such as routine company onboarding or mandatory cybersecurity modules, are institutionally required rather than discretionary investments in a worker's productivity or

[40]The training indicator is set to one for a particular employer, occupation, industry, or career if the individual ever received training from that specific employer, occupation, industry, or career. This means that if they transition from other jobs to a job for which they once received training, their training status still counts as one.

human capital, and thus are universally administered to all employees regardless of their underlying match fit. Consequently, our estimated correlation between training incidence, timing, and match quality may be biased due to the inclusion of those mandatory training programs that are largely orthogonal to match fit.

To address this concern, we exploit the training duration variable to select programs that last a sufficiently long period, as the aforementioned perfunctory training programs are typically short-term. By restricting estimation to a selected subsample of programs with at least a certain duration, we can isolate the variation in training incidence and timing that is more plausibly linked to match fit considerations.

Specifically, we select training programs lasting at least one month or 40 training hours in total. For training programs reported prior to 1986, no selection is imposed, as all such programs in the dataset are already one month or longer; otherwise, respondents would not have reported their training programs to the dataset. For training histories since 1988, we select programs of at least one month (identified using start and end dates), or at least four weeks (using the number of weeks attended for the program), or at least 40 training hours (using weeks attended and hours per week). Ultimately, we arrive at 19,273 programs satisfying the duration requirement out of 35,436 originally reported training programs.

Table A8 presents the estimations in (2) within the sample containing only selected training programs. It is clear that matches of higher quality, in terms of a lower distance to the expected occupation or a lower skill mismatch between workers' skills and jobs' skill requirements, are associated with a higher likelihood of receiving training or an earlier timing of training initiation during the career. This pattern mirrors what we observed in the sample that includes all training programs, suggesting that our training evidence is not driven by bias from certain types of training programs.

A.8 Training, Match Quality, and Wage Growth

Table A9 presents the complete regression results for wage growth before and after receiving training, disaggregated by the match quality. The odd-numbered columns detail the estimates for low-quality matches, while the even-numbered columns present those for high-quality matches. Notably, the coefficients in the first row represent the estimates of α, and their positive signs indicate wage growth over the life cycle. Likewise, the coefficients in the second row represent the value of β, and their positive signs suggest a faster rate of wage growth upon receiving training. Critically, a comparison across match quality groups reveals that the magnitude of this training-induced wage growth acceleration is greater for high-quality matches.

Table A8: Training and Match Quality W/ Selection on Training Duration

	Training Incidence			Training Timing		
	(1) Euclidean	(2) Angular	(3) Mismatch	(1) Euclidean	(2) Angular	(3) Mismatch
X	-0.00060	-0.00158**	-0.00157***	0.38655***	0.38914***	0.24157
College	0.00183	0.00159	0.00517***	-1.00932**	-0.99112**	-0.95994***
Age	-0.00245***	-0.00245***	-0.00221***			
AFQT	0.01397***	0.01388***	0.01371***	-0.63929***	-0.62281***	-0.43893***
Race	-0.00961***	-0.00967***	-0.00903***	0.66526**	0.64953**	-0.20520
Female	0.00284*	0.00296*	0.00121	0.14775	0.13560	-0.21247
Constant	0.14934***	0.14930***	0.14104***	7.96727***	7.97205***	7.41225***
Occupation FE	✓	✓	✓	✓	✓	✓
Industry FE	✓	✓	✓	✓	✓	✓
N	135,887	135,887	212,279	2,702	2,702	4,560
R^2	0.020	0.020	0.019	0.052	0.052	0.039

Notes: Robust standard errors are in parentheses. *($p < 0.10$), **($p < 0.05$), ***($p < 0.01$). The forecast error measures have been standardized to zero mean and unit standard error. In the right panel specification, we control for occupation fixed effects and industry fixed effects as observed at the time of each individual's first training.

Table A9: Wage Growth Before and After Training in a Career by Match Quality

	Age		Potential Work Experience		Actual Work Experience	
	Low Quality	High Quality	Low Quality	High Quality	Low Quality	High Quality
X	0.00997***	0.00969***	0.01005***	0.00997***	0.00968***	0.01022***
TRN × X	0.00124***	0.00409***	0.00105***	0.00346***	0.00087**	0.00321***
TRN	0.08125***	-0.03429**	0.10734***	0.05273***	0.10079***	0.05661***
College	0.18837***	0.23445***	0.23073***	0.28260***	0.21127***	0.26450***
AFQT	0.11606***	0.18959***	0.11602***	0.18923***	0.10761***	0.18046***
Race	-0.00988**	-0.01787***	-0.00988**	-0.01783***	-0.00925**	-0.02084***
Female	-0.20557***	-0.21151***	-0.20555***	-0.21164***	-0.19273***	-0.19705***
Year: 1990-1999	0.05296***	0.07203***	0.05251***	0.07071***	0.07082***	0.08705***
Year: 2000-2009	0.11032***	0.13384***	0.10994***	0.13282***	0.15113***	0.17010***
Year: 2010-	0.04426***	0.06300***	0.04410***	0.06277***	0.10449***	0.11778***
Constant	2.07443***	2.11057***	2.24233***	2.26902***	2.28458***	2.30798***
Observations	95,782	96,131	95,782	96,131	95,782	96,131
R^2	0.313	0.449	0.313	0.449	0.317	0.454
Occupation FE	✓	✓	✓	✓	✓	✓
Industry FE	✓	✓	✓	✓	✓	✓

Notes: Robust standard errors are in parentheses. *($p < 0.10$), **($p < 0.05$), ***($p < 0.01$). Low- and high-quality matches are defined as those with a mismatch value above or below the full-sample mean, respectively. The life cycle indicator, X, is measured by age in the first two columns, potential work experience in years in the middle two columns, and actual work experience in years in the last two columns.

B Theory Appendix

B.1 Match Surpluses

This section derives the match surpluses for good, bad, and unsure career fits. Recall that the surplus between a firm and worker with characteristics (s, n, x_i, h_j) is defined as

$$S(s, n, x_i, h_j) = W(s, n, x_i, h_j) - R(s, n, x_i, h_j) + J(s, n, x_i, h_j), \tag{B.1}$$

where $W(s, n, x_i, h_j)$ and $J(s, n, x_i, h_j)$ are given by equations (5) and (6). The value of unemployment, $R(s, n, x_i, h_j)$ is given by equation (10). We begin with the surplus for a good career fit. As workers do not switch careers once they have identified their good fit, $R(g, n, x_i, h_j) = U(g, n, x_i, h_j)$. Combining equations (11) and (16) gives the following flow Bellman equation that defines $S(g, n, x_i, h_j)$:

$$\begin{aligned} rS(g, n, x_i, h_j) &= Ah_j - c(\tau^*) - rU(g, n, x_i, h_j) \\ &+ \pi(x_i, \tau^*)\left[S(g, n, x_i, h_{j+}) - S(g, n, x_i, h_j) + U(g, n, x_i, h_{j+}) - U(g, n, x_i, h_j)\right] \\ &+ \sigma\left[S(g, n, x_{i^+}, h_j) - S(g, n, x_i, h_j) + U(g, n, x_{i^+}, h_j) - U(g, n, x_i, h_j)\right] \\ &- \delta(h_j)S(g, n, x_i, h_j), \end{aligned} \tag{B.2}$$

where $\tau^* = \tau^*(g, n, x_i, h_j)$ is the effort determined through the bargaining problem, equation (4). According to equation (B.2), the match produces a flow output Ah_j net of the disutility, $c(\tau^*)$ and the worker's reservation wage, $rU(g, n, x_i, h_j)$. At rate $\pi(x_i, \tau^*)$, the worker's human capital grows and generates the additional surplus $S(g, n, x_i, h_{j^+}) - S(g, n, x_i, h_j)$ and the additional value of unemployment at the higher level of human capital, $U(g, n, x_i, h_{j^+}) - U(g, n, x_i, h_j)$. The match surplus is lost following an exogenous destruction shock, which occurs at rate $\delta(h_j)$. Finally, notice from (B.2) that the match surplus is independent of the equilibrium wage, $w^*(s, n, x_i, h_j)$ as the wage is a transfer from the firm to the worker.

Now we proceed to the surplus of a match between a firm and worker who is in a bad career fit. Combining equations (12) and (17) gives:

$$\begin{aligned} rS(b, n, x_i, h_j) &= \alpha Ah_j - c(\tau^*) - rR(b, n, x_i, h_j) \\ &+ \pi(x_i, \tau^*)\big[\max\{0, S(b, n, x_i, h_{j+})\} - S(b, n, x_i, h_j) + R(b, n, x_i, h_{j+}) - R(b, n, x_i, h_j)\big] \\ &+ \sigma\left[\max\{0, S(b, n, x_{i^+}, h_j)\} - S(b, n, x_i, h_j) + R(b, n, x_{i^+}, h_j) - R(b, n, x_i, h_j)\right] \\ &- \delta(h_j)S(b, n, x_i, h_j), \end{aligned} \tag{B.3}$$

where $R(b, n, x_i, h_j)$ is the value of unemployment to reflect that workers who are in a bad career fit may switch careers upon becoming unemployed. Another difference between the surplus in a bad and good career fit is that a bad fit may be destroyed following a human capital or aging shock. This is captured in the second and third lines of (B.3) by the $\max\{0, S(b, n, x_i, h_j)\}$. If the match surplus is positive following either shock, then the match survives. If the match surplus turns negative, then it is destroyed.

Lastly, combining equations (15) and (18) gives the flow surplus in an unsure career fit:

$$\begin{aligned} rS(u, n, x_i, h_j) &= p(n)Ah_j + (1 - p(n))\alpha Ah_j - c(\tau^*) - rU(u, n, x_i, h_j) \\ &+ \pi(x, \tau^*)\left[S(u, n, x_i, h_{j+}) - S(u, n, x_i, h_j) + U(u, n, x_i, h_{j+}) - U(u, n, x_i, h_j)\right] \\ &+ \sigma\left[S(u, n, x_{i^+}, h_j) - S(u, n, x_i, h_j) + U(u, n, x_{i^+}, h_j) - U(u, n, x_i, h_j)\right] \\ &+ \phi\big[p(n)\left[S(g, n, x_i, h_j) + U(g, n, x_i, h_j)\right] + \\ &(1 - p(n))\left[R(b, n, x_i, h_j) + \max\{0, S(b, n, x_i, h_j)\}\right] - S(u, n, x_i, h_j) - U(u, n, x_i, h_j)\big] \\ &- \delta(h_j)S(u, n, x_i, h_j), \end{aligned} \tag{B.4}$$

where $U(u, n, x_i, h_j)$ is the value of unemployment for the worker as a worker with an unsure career fit has no incentive to switch careers. The first three lines of (B.4) have a similar interpretation to the surpluses for good and bad fits. The fourth and fifth lines capture the continuation value following the reveal of the worker's career fit, which occurs at rate ϕ. If the worker is in a good fit, the continuation value is $S(g, n, x_i, h_j) + U(g, n, x_i, h_j)$. If the worker learns they are in a bad fit, the continuation value of the match is $R(b, n, x_i, h_j) + \max\{0, S(b, n, x_i, h_j)\}$ to reflect that the option value of switching careers is the relevant value of unemployment for workers in a bad career fit and that the match is destroyed following the reveal of the worker's fit if the surplus becomes negative.

B.2 Bargaining

This appendix presents the derivation of the conditions which, together, jointly determine the equilibrium wage, $w^*(s, n, x_i, h_j)$, and effort, $\tau^*(s, n, x_i, h_j)$. We first rewrite the Nash bargaining problem defined by equation (4) by taking logs:

$$\max_{w,\tau} \beta \ln\left[\tilde{W}(s, n, x_i, h_j; w, \tau) - R(s, n, x_i, h_j)\right] + (1 - \beta)\ln\left[\tilde{J}(s, n, x_i, h_j; w, \tau)\right]. \tag{B.5}$$

Taking the first order condition of (B.5) with respect to w gives

$$\frac{\beta\frac{\partial[\tilde{W}(s,n,x_i,h_j;w,\tau)-R(s,n,x_i,h_j)]}{\partial w}}{\tilde{W}(s,n,x_i,h_j;w,\tau)-R(s,n,x_i,h_j)}+\frac{(1-\beta)\frac{\partial\tilde{J}(s,n,x_i,h_j;w,\tau)}{\partial w}}{\tilde{J}(s,n,x_i,h_j;w,\tau)}=0. \tag{B.6}$$

From the flow Bellman equations, we have

$$\frac{\partial[\tilde{W}(s,n,x_i,h_j;w,\tau)-R(s,n,x_i,h_j)]}{\partial w}=-\frac{\partial\tilde{J}(s,n,x_i,h_j;w,\tau)}{\partial w}. \tag{B.7}$$

Combining (B.7) with (B.6) and rearranging gives

$$\begin{aligned}\tilde{W}(s,n,x_i,h_j;w,\tau)-R(s,n,x_i,h_j)=\\ \beta\left[\tilde{W}(s,n,x_i,h_j;w,\tau)-R(s,n,x_i,h_j)+\tilde{J}(s,n,x_i,h_j;w,\tau)\right].\end{aligned} \tag{B.8}$$

Evaluating (B.8) at $w^*(s,n,x_i,h_j)$ and $\tau^*(s,n,x_i,h_j)$ gives the surplus sharing rule:

$$W(s,n,x_i,h_j)-R(s,n,x_i,h_j)=\beta S(s,n,x_i,h_j). \tag{B.9}$$

Next, taking the first order condition of (B.5) with respect to τ gives

$$\frac{\beta\frac{\partial[\tilde{W}(s,n,x_i,h_j;w,\tau)-R(s,n,x_i,h_j)]}{\partial \tau}}{\tilde{W}(s,n,x_i,h_j;w,\tau)-R(s,n,x_i,h_j)}+\frac{(1-\beta)\frac{\partial\tilde{J}(s,n,x_i,h_j;w,\tau)}{\partial \tau}}{\tilde{J}(s,n,x_i,h_j;w,\tau)}=0. \tag{B.10}$$

Multiplying (B.10) by $\tilde{J}(s,n,x_i,h_j;w,\tau)$ and evaluating the value functions at w^* and τ^* gives

$$\frac{\beta J(s,n,x_i,h_j)\frac{\partial[\tilde{W}(s,n,x_i,h_j;w,\tau)-R(s,n,x_i,h_j)]}{\partial \tau}}{W(s,n,x_i,h_j)-R(s,n,x_i,h_j)}+(1-\beta)\frac{\partial\tilde{J}(s,n,x_i,h_j;w,\tau)}{\partial\tau}=0. \tag{B.11}$$

Applying the surplus sharing rule, equation (B.9), allows (B.11) to be simplified to

$$\frac{\partial\tilde{W}(s,n,x_i,h_j;w,\tau)-R(s,n,x_i,h_j)}{\partial\tau}+\frac{\partial\tilde{J}(s,n,x_i,h_j;w,\tau)}{\partial\tau}=0. \tag{B.12}$$

From the flow Bellman equations detailed in Section 3.2, we have

$$\frac{\partial[\tilde{W}(s,n,x_i,h_j;w,\tau)-R(s,n,x_i,h_j)]}{\partial\tau}=$$

$$-c'(\tau^*)+\begin{cases}\frac{\partial\pi(x_i,\tau)}{\partial\tau}\Big|_{\tau=\tau^*}[W(s,n,x_i,h_{j^+})-W(s,n,x_i,h_j)] & \text{if } s\in\{g,un\},\\ \frac{\partial\pi(x_i,\tau)}{\partial\tau}\Big|_{\tau=\tau^*}[Q(n,x_i,h_{j^+})-W(b,n,x_i,h_j)] & \text{if } s=b.\end{cases} \tag{B.13}$$

and

$$\frac{\partial\tilde{J}(s,n,x_i,h_j;w,\tau)}{\partial\tau}=$$

$$\begin{cases}\frac{\partial\pi(x_i,\tau)}{\partial\tau}\Big|_{\tau=\tau^*}[J(s,n,x_i,h_{j^+})-J(s,n,x_i,h_j)] & \text{if } s\in\{g,un\},\\ \frac{\partial\pi(x_i,\tau)}{\partial\tau}\Big|_{\tau=\tau^*}[\max\{J(b,n,x_i,h_{j^+}),0\}-J(b,n,x_i,h_j)] & \text{if } s=b.\end{cases} \tag{B.14}$$

Substituting (B.13) and (B.14) into (B.12) and using the fact

$$W(s,n,x_i,h_j)+J(s,n,x_i,h_j)=S(s,n,x_i,h_j)+U(s,n,x_i,h_j) \tag{B.15}$$

gives

$$c'(\tau^*)=\frac{\partial\pi(x_i,\tau)}{\partial\tau}\Big|_{\tau=\tau^*}\times$$

$$\begin{cases}S(s,n,x_i,h_{j^+})+U(s,n,x_i,h_{j^+})-S(s,n,x_i,h_j)-U(s,n,x_i,h_j) & \text{if } s\in\{g,un\},\\ \max\{0,S(b,n,x_i,h_{j^+})\}+R(b,n,x_i,h_{j^+})-S(b,n,x_i,h_j)-R(b,n,x_i,h_j) & \text{if } s=b,\end{cases} \tag{B.16}$$

as the equilibrium condition that determines effort, τ^*. Finally, notice that (B.16) is the same condition that one would obtain when taking the first order condition of the match surpluses defined in equations (B.2)-(B.4) with respect to τ.

B.3 Laws of Motion

This section contains the laws of motion for workers across the states of employment status, career status, history, potential experience, and human capital. The laws of motion gov-

ern the stationary distribution of workers which impacts the expected value of meeting a worker and therefore, as seen in the free entry condition, equation (21), has a central role in determining the entry of firms in equilibrium.

Let $\omega(s, n, x_i, h_j)$ be the measure of unemployed workers with career status s, history n, potential experience x_i, and human capital h_j. Further, $\varepsilon(s, n, x_i, h_j)$ is the measure of employed workers with characteristics (s, n, x_i, h_j). We begin with the laws of motion for workers in a good career fit ($s = g$). The law of motion for unemployed workers with $s = g$ and history $n < N$ is given by

$$\begin{aligned}\dot{\omega}(g, n, x_i, h_j) = &\mathbb{1}_{\{i>1\}}\sigma\omega(g, n, x_{i^-}, h_j) + \mathbb{1}_{\{j<J-1\}}\mu\omega(g, n, x_i, h_{j^+}) + \\ &\delta(h_j)\varepsilon(g, n, x_i, h_j) - \left(f(\theta) + \sigma + \mathbb{1}_{\{j>1\}}\mu\right)\omega(g, n, x_i, h_j),\end{aligned} \tag{B.17}$$

where $\mathbb{1}_{\{x\}}$ is an indicator equal to one if x is true. From (B.17), there are flows into unemployment from workers who age from x_{i-1} to x_i if $i > 1$, drop down the human capital ladder from h_{j+1} to h_j if $j < J - 1$, and separate from employment. The last term captures the outflows of unemployed workers that come from workers finding a job, aging/death, or, if $j > 1$, losing human capital.

To write the law of motion for unemployed workers in a good fit with history $n = N$, we need to introduce a few definitions and notations that will be used to capture the fact that there are additional inflows into unemployment with history $n = N$ that come from workers who switch careers, increase their history from $n = N - 1$ to N and, by virtue of having sampled N careers, will have identified their good fit. Recall that workers who switch careers exhibit a decrease in their human capital. To write the law of motion for unemployment at human capital h_j, we need to define the set of origin human capital levels where, after switching careers, the worker has human capital h_j. Let us define $\mathcal{F}(h_j)$ as:

$$\mathcal{F}(h_j) = \{h_k \in \{h_1, h_2, \ldots, h_J\} : \max\{\lfloor \zeta h_k \rfloor, h_1\} = h_j\}. \tag{B.18}$$

The set $\mathcal{F}(h_j)$ captures the levels of human capital such that, after switching careers, a worker has human capital h_j with probability γ. Similarly, we have the set $\mathcal{C}(h_j)$:

$$\mathcal{C}(h_j) = \{h_k \in \{h_1, h_2, \ldots, h_J\} : \max\{\lceil \zeta h_k \rceil, h_1\} = h_j\}. \tag{B.19}$$

The set $\mathcal{C}(h_j)$ is the origin human capital levels where, after switching careers, a worker ends with human capital h_j with probability $1 - \gamma$. Now, we define the expectation operator

$\mathbb{E}_j^{\zeta}[f(h)]$ as

$$\mathbb{E}_j^{\zeta}[f(h)] = \gamma \sum_{h_k \in \mathcal{F}(h_j)} f(h_k) + (1-\gamma) \sum_{h_k \in \mathcal{C}(h_j)} f(h_k), \tag{B.20}$$

which captures the expected value of $f(h)$ given the post-career switch human capital h_j.

Next, we denote $\bar{\omega}^{\varphi}(s, n, x_i, h_j)$ as the measure of unemployed workers who switch careers following a "φ" shock. That is,

$$\bar{\omega}^{\varphi}(s, n, x_i, h_j) = \omega(s, n, x_i, h_j) \mathbb{1}^{\varphi}(s, n, x_i, h_j), \tag{B.21}$$

where $\mathbb{1}^{\varphi}(s, n, x_i, h_j)$ is an indicator function capturing whether an unemployed worker with characteristics (s, n, x_i, h_j) switches careers following a "φ" shock. For example, in the context of an aging shock, $\mathbb{1}^{\sigma}(s, n, x_i, h_j)$ equals 1 if $R(s, n, x_{i^-}, h_j) = \mathbb{E}U(u, n+1, x_{i^-}, \zeta h_j)$. Further, we use $\bar{\varepsilon}^{\varphi}(s, n, x_i, h_j)$ to denote the measure of employed workers who switch careers following a φ shock. Next, we denote $\hat{\varepsilon}^{\varphi}(s, n, x_i, h_j)$ as the measure of employed workers who destroy their match following a φ shock and switch careers. More precisely, we have

$$\hat{\varepsilon}^{\varphi}(s, n, x_i, h_j) = \varepsilon(s, n, x_i, h_j) \mathbb{D}^{\varphi}(s, n, x_i, h_j), \tag{B.22}$$

where $\mathbb{D}^{\varphi}(s, n, x_i, h_j)$ is an indicator function capturing whether an employed worker's match is destroyed following a φ shock. In the context of an aging shock, $\mathbb{D}^{\sigma}(s, n, x_i, h_j) = 1$ if $Q(n, x_{i^+}, h_j) = \mathbb{E}U(u, n+1, x_{i^-}, \zeta h_j)$. With this notation in hand, we are now ready to write the law of motion for $\omega(g, N, x_i, h_j)$. It is given by

$$\begin{aligned}
\dot{\omega}(g, N, x_i, h_j) = \; & \mathbb{1}_{\{i>1\}} \sigma \omega(g, N, x_{i^-}, h_j) + \mathbb{1}_{\{j<J-1\}} \mu \omega(g, N, x_i, h_{j^+}) \\
& + \delta(h_j) \varepsilon(g, N, x_i, h_j) - \left(f(\theta) + \sigma + \mathbb{1}_{\{j>1\}} \mu\right) \omega(g, N, x_i, h_j) \\
& + \mathbb{1}_{\{i>1\}} \sigma \mathbb{E}_j^{\zeta}[\bar{\omega}^{\sigma}(b, N-1, x_{i^-}, h_k)] + \mathbb{1}_{\{j<J-1\}} \mu \sum_{t \in \{j+1, \ldots, J\}} \mathbb{E}_j^{\zeta}[\bar{\omega}^{\mu}(b, N-1, x_i, h_{t^-})] \\
& + \mathbb{E}_j^{\zeta}[\delta(h_k) \bar{\varepsilon}^{\delta}(b, N-1, x_i, h_k)] + \mathbb{1}_{\{i>1\}} \sigma \mathbb{E}_j^{\zeta}[\hat{\varepsilon}^{\sigma}(b, N-1, x_{i^-}, h_k)] \\
& + \sum_{t \in \{1, \ldots, J-1\}} \pi(x_i, \tau^*(b, N-1, x_i, h_t)) \mathbb{E}_j^{\zeta}\left[\hat{\varepsilon}^{\pi}(b, N-1, x_i, h_{t^+})\right] \\
& + \phi \left(1 - p(N-1)\right) \mathbb{E}_j^{\zeta}\left[\hat{\varepsilon}^{\phi}(u, N-1, x_i, h_k)\right].
\end{aligned} \tag{B.23}$$

The first two lines of (B.23) capture the same inflows and outflows described below equation (B.17). The remaining terms capture inflows from workers who, after a shock, end up with $s = g$ and $n = N$ after switching careers. The first term of the third line of (B.23) captures

workers who are in a bad fit, hit with an aging shock, and switch careers. The second term of the third line are unemployed workers with human capital h_t in a bad fit who are hit with a skill loss shock, drop to human capital h_{t^-}, switch careers, and end with human capital h_j. Proceeding to the fourth line, the first term are workers employed in a bad fit who are hit with an exogenous job destruction shock and switch careers upon entering unemployment. The second term of the fourth line are workers who are employed in a bad fit, hit with an aging shock, destroy their match, and switch careers upon entering unemployment. The fifth line captures workers who are employed in a bad fit, increase their human capital from h_t to h_{t^+}, destroy their match, switch careers upon entering unemployment, and end with human capital h_j. Finally, the last line captures the inflows of workers who are employed in an unsure fit, learn that they are in a bad fit, destroy their match, and switch careers upon entering unemployment.

The law of motion for employment in a good fit, $\varepsilon(g, n, x_i, h_j)$ is given by

$$\begin{aligned}\dot{\varepsilon}(g, n, x_i, h_j) = {} & f(\theta)\omega(g, n, x_i, h_j) + \mathbb{1}_{\{j>1\}}\pi(x_i, \tau^*(g, n, x_i, h_{j^-}))\varepsilon(g, n, x_i, h_{j^-}) \\ & + \mathbb{1}_{\{i>1\}}\sigma\varepsilon(g, n, x_{i^-}, h_j) + \phi p(n)\varepsilon(u, n, x_i, h_j) \\ & - \left(\delta(h_j) + \sigma + \pi(x_i, \tau^*(g, n, x_i, h_j))\right)\varepsilon(g, n, x_i, h_j).\end{aligned} \tag{B.24}$$

The first line of (B.24) captures the inflow of unemployed workers who find a job and employed workers with human capital h_{j^-} who experience a human capital gain shock. The second line shows the inflows of employed workers with potential experience x_{i^-} who age and workers who are employed with $s = un$ who learn they are in a good career fit. The last line shows the outflows from employment at states (g, n, x_i, h_j) come from exogenous job destruction shocks, aging shocks, and when the worker's human capital increases.

We now proceed to the laws of motion for workers who are in a bad career fit. To make writing these more convenient, we introduce notation to capture when a worker does not switch careers following a shock. Here, we use $\underline{\omega}^{\varphi}(s, n, x_i, h_j)$ to denote the measure of workers who, following a φ shock, do not switch careers. More specifically,

$$\underline{\omega}^{\varphi}(s, n, x_i, h_j) = \omega(s, n, x_i, h_j)(1 - \mathbb{1}^{\varphi}(s, n, x_i, h_j)), \tag{B.25}$$

where, as described below equation (B.21), $\mathbb{1}^{\varphi}(s, n, x_i, h_j)$ is an indicator function equal to 1 if a worker with characteristics (s, n, x_i, h_j) switches careers following a φ shock. Similarly, we use $\underline{\varepsilon}^{\varphi}(s, n, x_i, h_j)$ to denote employed workers who do not switch careers following a

shock. With this notation, we have the law of motion for unemployed workers in a bad fit:

$$\begin{aligned}\dot{\omega}(b,n,x_i,h_j) = &\mathbb{1}_{\{i>1\}}\sigma\underline{\omega}^{\sigma}(b,n,x_{i^-},h_j) + \mathbb{1}_{\{j<J-1\}}\mu\underline{\omega}^{\mu}(b,n,x_i,h_{j^+}) + \\ &\delta(h_j)\underline{\varepsilon}^{\delta}(b,n,x_i,h_j) - \left(f(\theta)+\sigma+\mathbb{1}_{\{j>1\}}\mu\right)\omega(b,n,x_i,h_j).\end{aligned} \tag{B.26}$$

The interpretation of equation (B.26) is similar to that of unemployed workers in a good fit, equation (B.17). The substantive difference between the two is that the inflows into unemployment in a bad career fit account for whether a worker would remain in a bad fit or switch careers.

We denote $\check{\varepsilon}^{\varphi}(s,n,x_i,h_j)$ as the measure of employed workers who do not destroy their match following a shock where:

$$\check{\varepsilon}^{\varphi}(s,n,x_i,h_j) = \varepsilon(s,n,x_i,h_j)(1-\mathbb{D}^{\varphi}(s,n,x_i,h_j)), \tag{B.27}$$

where $\mathbb{D}^{\varphi}(s,n,x_i,h_j)$ is an indicator function capturing whether an employed worker's match is destroyed following a shock. The law of motion for $\varepsilon(b,n,x_i,h_j)$ is given by

$$\begin{aligned}\dot{\varepsilon}(b,n,x_i,h_j) = &f(\theta)\omega(b,n,x_i,h_j) + \mathbb{1}_{\{j>1\}}\pi(x_i,\tau^*(b,n,x_i,h_{j^-}))\check{\varepsilon}^{\pi}(b,n,x_i,h_{j^-}) \\ &+ \mathbb{1}_{\{i>1\}}\sigma\check{\varepsilon}^{\sigma}(b,n,x_{i^-},h_j) + \phi(1-p(n))\check{\varepsilon}^{\phi}(u,n,x_i,h_j) \\ &- \left(\delta(h_j)+\sigma+\pi(x_i,\tau^*(b,n,x_i,h_j))\right)\varepsilon(b,n,x_i,h_j).\end{aligned} \tag{B.28}$$

The interpretation of equation (B.28) follows that of (B.24), except that the inflows into employment in a bad career fit account for the possibility of an endogenous separation following an aging, human capital, or learning shock.

Next, we have the law of motion for unemployed workers with an unsure career fit and $n=1$:

$$\begin{aligned}\dot{\omega}(u,1,x_i,h_j) = &\mathbb{1}_{\{i=1,j=1\}}\frac{\sigma}{T} + \mathbb{1}_{\{i>1\}}\sigma\omega(u,1,x_{i^-},h_j) + \mathbb{1}_{\{j<J-1\}}\mu\omega(u,1,x_i,h_{j^+}) \\ &+ \delta(h_j)\varepsilon(u,1,x_i,h_j) - \left(f(\theta)+\sigma+\mathbb{1}_{\{j>1\}}\mu\right)\omega(u,1,x_i,h_j),\end{aligned} \tag{B.29}$$

where the inflows and outflows are the same as in equation (B.17), except the first term, which captures the inflow of newborn workers into the economy who begin with potential experience x_1 and human capital h_1. Notice that for $n=1$, there are no inflows from career switchers. This is because career switchers will have sampled at least two careers.

Relying on the same notation we introduced above for characterizing inflows from career switchers, we can write the law of motion for unemployment with an unsure career fit and

$n > 1$ as:

$$\begin{aligned}
\dot{\omega}(u,n,x_i,h_j) = {} & \mathbb{1}_{\{i>1\}}\sigma\omega(u,n,x_{i^-},h_j) + \mathbb{1}_{\{j<J-1\}}\mu\omega(u,n,x_i,h_{j^+}) \\
& + \delta(h_j)\varepsilon(u,n,x_i,h_j) - \left(f(\theta)+\sigma+\mathbb{1}_{\{j>1\}}\mu\right)\omega(u,n,x_i,h_j) \\
& + \mathbb{1}_{\{i>1\}}\sigma\mathbb{E}_j^{\zeta}[\bar{\omega}^{\sigma}(b,n-1,x_{i^-},h_k)] + \mathbb{1}_{\{j<J-1\}}\mu\sum_{t\in\{j+1,\ldots,J\}}\mathbb{E}_j^{\zeta}[\bar{\omega}^{\mu}(b,n-1,x_i,h_{t^-})] \\
& + \mathbb{E}_j^{\zeta}[\delta(h_k)\bar{\varepsilon}^{\delta}(b,n-1,x_i,h_k)] + \mathbb{1}_{\{i>1\}}\sigma\mathbb{E}_j^{\zeta}[\hat{\varepsilon}^{\sigma}(b,n-1,x_{i^-},h_k)] \\
& + \sum_{t\in\{1,\ldots,J-1\}}\pi(x_i,\tau^*(b,n-1,x_i,h_t))\mathbb{E}_j^{\zeta}\left[\hat{\varepsilon}^{\pi}(b,n-1,x_i,h_{t^+})\right].
\end{aligned} \tag{B.30}$$

The interpretation of (B.30) is essentially the same as with equation (B.23). The only differences are (i) workers with a history $n < N-1$ who switch careers will enter their next career with an unsure fit (instead of $s = g$) and (ii) the last term in equation (B.23) is not present for workers with an unsure fit as the last term of (B.23) captured the inflow of workers who destroyed their match after learning they were in a bad career fit.

Finally, the law of motion for employment in an unsure career fit, $\varepsilon(u,n,x_i,h_j)$ is given by

$$\begin{aligned}
\dot{\varepsilon}(u,n,x_i,h_j) = {} & f(\theta)\omega(u,n,x_i,h_j) + \mathbb{1}_{\{j>1\}}\pi(x_i,\tau^*(u,n,x_i,h_{j^-}))\varepsilon(u,n,x_i,h_{j^-}) \\
& + \mathbb{1}_{\{i>1\}}\sigma\varepsilon(u,n,x_{i^-},h_j) - \left(\delta(h_j)+\sigma+\pi(x_i,\tau^*(u,n,x_i,h_j))+\phi\right)\varepsilon(u,n,x_i,h_j).
\end{aligned} \tag{B.31}$$

The first line of (B.31) captures the inflow of unemployed workers who find a job and workers who experience a human capital gain shock. The first term of the second line captures the inflow of workers who are hit by an aging shock. The last term captures the outflows of workers, which come from separation shocks, aging shocks, human capital gain shocks, and when the worker learns whether they are in a good or bad fit.

C Quantitative Appendix

C.1 Targeted Moments

In this section, we describe the calculation of the data moments used for calibration and present the corresponding results.

Normalized Log Wage We construct hourly wages by dividing total pre-tax wage and salary income from the previous calendar year by total annual hours worked, and we adjust for inflation using the CPI (base year 2000). As in Altonji et al. (2012), we censor wages below 3 and above 200. We then compute the average real wage within each education and potential experience bin, take the natural logarithm, and normalize the profile by subtracting the mean log wage of non-college workers in the first experience bin. We use the unconditional wage profile for calibration, as the education gap in wage growth implied here (12.5%) is nearly identical to the estimates obtained after isolating cohort and time effects (12.7% or 14.7%). The corresponding wage profiles are presented in the first panel of Table C1.

The ratio of the median-to-25th-percentile wage at the fourth potential experience bin to that at the first bin, denoted by $(p_{50,4}/p_{25,4})/(p_{50,1}/p_{25,1})$, is derived directly from the percentile wage profiles by potential experience and education group.

Transition Probabilities We compute the transition probability, including both job finding and separation probabilities, for each education group over the life cycle.

We start with employment status of individuals who belong to age cohort i and education group j in consecutive months from January 1978 through November 2019, we construct time-series for the gross flow of workers $(F(XY)_t)$ between unemployment (U), employment (E), inactivity (I) and with missing record (M), denoted by $F(XY)_t = \frac{N(XY)_t}{\sum_{Z\in\{U,E,I,M\}} N(XZ)_t}$, where $N(XY)_t$ represents the number of workers who transition from X to Y in period t. Based on that, we can compute the original monthly transition probability between different labor force status by $n(AB)_t = \frac{F(AB)_t}{\sum_{M\in\{U,E,I\}} F(AM)_t}$, where $A, B \in \{U, E, I\}$. In particular, n is a 3×3 matrix that governs the full month transition probability between labor force status.

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

ratio, where the base ratio is the mean of the average ratio in 1998. Finally, we can obtain the seasonally adjusted transition probability by dividing the raw value by the ratio from the previous step.

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

Next, we can construct the unbiased full month transition probability between labor force states A and B for subgroup with age cohort i and education attainment j as $\Lambda_t^{ij}(AB) = 1 - exp(-\lambda_t^{ij}(AB))$, that is interpreted as the probability that a worker who starts the period in state A transitions to state B during the month conditional on not experiencing a transition to state C. Lastly, we compute the average transition probabilities with correction of time aggregation bias for each subgroup of age i and education attainment j by taking the mean value of $\Lambda_t^{ij}(AB)$ across different periods. We thus obtain time-aggregation-corrected separation probabilities for each education group and experience bin, displayed in the second panel of Table C1.

Following the same approach, we obtain aggregate job-finding probabilities of 25.68% and 28.32% for non-college and college workers, respectively.

Careers Sampled We identify the sequence of unique careers an individual i has held over their lifetime by comparing the angular skill distance between their current occupation and all previously held occupations. If this distance between the current job and any prior job equals or exceeds the threshold $\bar{\phi} = 23.077$, we classify the current job as a new and unique career. This allows us to track the cumulative number of unique careers sampled by each career stage. We then compute the average number of sampled careers up to each potential experience bin for each education group, and the results are shown in the third panel of Table C1.

Wage Change We calculate log wage changes by taking the difference between the log wage immediately after an employer switch and the log wage immediately before it. These changes are then averaged separately for employer switches that lead to a new career and those that do not. The results are reported in the second and third rows from the bottom of Table C1.

Table C1: Data Moments for Calibration

Moment	Potential Experience	Non-College	College
Normalized log wage	1	0.000	0.511
	2	0.178	0.720
	3	0.328	0.883
	4	0.395	1.012
	5	0.450	1.081
	6	0.477	1.115
	7	0.499	1.127
	8	0.501	1.137
	9	0.499	1.128
	10	0.491	—
Separation Rate	1	3.471	1.233
	2	2.535	0.754
	3	2.018	0.650
	4	1.732	0.602
	5	1.530	0.573
	6	1.370	0.558
	7	1.258	0.550
	8	1.180	0.555
	9	1.081	0.560
	10	1.019	—
Careers Sampled	1	1.739	1.641
	2	2.195	1.869
	3	2.397	1.952
	4	2.580	1.992
	5	2.735	2.002
	6	2.816	1.997
	7	2.878	2.002
	8	2.919	2.039
	9	2.960	2.062
	10	2.983	—
Job-Finding Rate		25.680	28.320
Wage Ratio		1.083	1.022
Wage Change (No Switch)		-0.016	-0.043
Wage Change (Switch)		-0.020	-0.062
$\mathbb{E}[bh/Ah]$		0.400	0.400

C.2 Untargeted Moments

C.2.1 U-E Gap Decompositions

We employ the method by Pissarides (2009) to decompose the U-E gap into differences in the job finding and separation probabilities. Denoting s_j and f_j as the job separation and finding probabilities with educational attainment j, the steady-state unemployment rate for this subgroup is given by:

$$u_j = \frac{s_j}{s_j + f_j}. \tag{C.1}$$

Taking first differences of (C.1) between education levels j and j' gives

$$1 = \underbrace{\frac{(1-u_j)u_{j'}\frac{(s_j - s_{j'})}{s_{j'}}}{\Delta u}}_{\text{Fraction explained by SP}} + \underbrace{\frac{-u_j(1-u_{j'})\frac{(f_j - f_{j'})}{f_{j'}}}{\Delta u}}_{\text{Fraction explained by JFP}}. \tag{C.2}$$

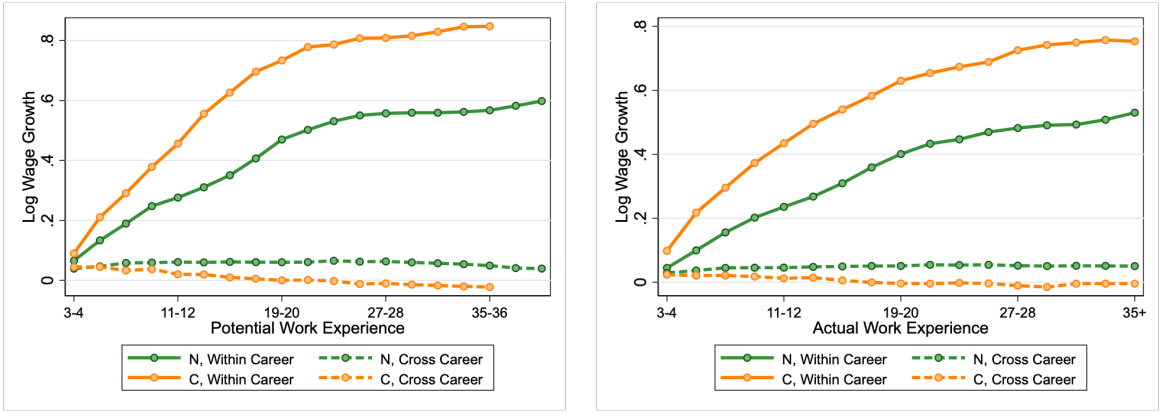
C.2.2 Labor Market Learning

Table C2 shows that prior experience is associated with a higher survival probability, 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 C2: Prior Experience and Match Survival

	(1)	(2)	(3)
Prior Exp.	0.00013***	0.00008***	0.00009***
Log(Dur) × Prior Exp.	-0.00002***	-0.00002***	-0.00002***
Prior Exp. × College		-0.00005***	-0.00004***
Log(Dur) * College		-0.00385***	-0.00353***
Log(Dur) * White		0.00403***	0.00150***
Observations	2,265,922	2,265,922	2,161,989
R^2	0.019	0.022	0.018
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) Potential Experience

(b) Actual Experience

Figure C1: Estimates of Cumulative Wage Growth *Notes:* Constructed using the NLSY79.

C.2.3 Decomposition of Wage Growth

Figure C1 presents estimations of cumulative wage growth as a function of potential or actual work experience. The solid curves depict the within-career wage growth for individuals, as estimated by Equation (23), while the dashed curves illustrate the implied cross-career component of aggregate wage growth, derived by subtracting within-career growth from total wage growth. These results indicate that the cumulative wage growth over potential work experience attributable to career sampling is 4.84% for non-college workers, but -0.048% for college workers. Similar patterns hold when examining the decomposition of wage growth over actual work experience.

C.3 Shapley-Owen-Shorrocks Decomposition

This section details the Shapley-Owen-Shorrocks decomposition used in Section 4.3.3.[41]

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 average wages, $\{x_1, x_2, \ldots, x_n\}$ 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

[41] 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.

(2013) shows that the contribution of x_j can be expressed as:

$$C_j = \sum_{k=0}^{n-1} \frac{(n-k-1)!k!}{n!} \left(\sum_{s \subseteq S_k \setminus \{x_j\}: |s|=k} [f(s \cup \{x_j\}) - f(s)] \right), \tag{C.3}$$

where $k \in \{0, 1, \ldots, n-1\}$. We will now explain each term in (C.3). 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, the learning speed, then the number of careers N, 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.3), 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 $f(s \cup \{x_j\}) - f(s)$. 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.3). 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 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.

C.4 Additional Results

C.4.1 Detailed Decomposition of Wage Gains

This appendix carries out a more detailed decomposition of the wage gains than was presented in Section 4.3.1 into two further components. We start with breaking down the contribution of changes in the career fit composition, $\Delta w^f(x)$ detailed in equation (24). The average baseline wage in career fit s, $\bar{w}^{base}(s, x)$, differs across career fits for two reasons: (i) workers, for the same level of human capital, are more productive in a good fit than a bad fit and (ii) workers in different career fits have different levels of human capital due to there being differences in the optimal human capital investment, τ, across fits. To separate these components, let $\tilde{w}^{base}(s, x)$ denote the baseline wage in career fit s evaluated at a common

level of human capital, $\bar{h}(x)$, equal to the average human capital among all employed workers at potential experience x in the baseline economy. We can then break $\Delta w^f(x)$ into two components and write it as $\Delta w^f(x) = \Delta w^{f,prod}(x) + \Delta w^{f,hc}(x)$, where

$$\Delta w^{f,prod}(x) = \sum_s \left[\pi^{new}(s|x) - \pi^{base}(s|x)\right] \tilde{w}^{base}(s,x), \tag{C.4}$$

$$\Delta w^{f,hc}(x) = \sum_s \left[\pi^{new}(s|x) - \pi^{base}(s|x)\right] \left[\bar{w}^{base}(s,x) - \tilde{w}^{base}(s,x)\right]. \tag{C.5}$$

The first term, defined by (C.4), is the gain from shifting workers toward more productive career fits, having equalized the level of human capital across each career fit. The second term defined in equation (C.5), captures the differences in the level of human capital that workers in each career fit have relative to the population average of $\bar{h}(x)$.

Next, we decompose the within-fit wage gains, $\Delta w^{within}(x)$ defined by equation (25) into two components. Let $\pi(h|s,x)$ denote the distribution of human capital among employed workers with career fit s at potential experience x, and $w(h,s,x)$ be the average wage of employed workers at human capital level h in that career fit. We can then define the total within fit wage gains as $\Delta w^{within}(x) = \Delta w^{w,hc}(x) + \Delta w^{w,fn}(x)$, where

$$\Delta w^{w,hc}(x) = \sum_s \pi^{new}(s|x) \sum_h \left[\pi^{new}(h|s,x) - \pi^{base}(h|s,x)\right] w^{base}(h,s,x), \tag{C.6}$$

$$\Delta w^{w,fn}(x) = \sum_s \pi^{new}(s|x) \sum_h \pi^{new}(h|s,x) \left[w^{new}(h,s,x) - w^{base}(h,s,x)\right]. \tag{C.7}$$

The first term, equation (C.6) is the gain from workers within each career fit accumulating more human capital. The second, equation (C.7), is the change in the equilibrium wage function at a given level of human capital, career fit, and potential experience.

Figure C2 reports the four components by potential experience. Averaged over the life cycle, 57.4% of the wage gain comes from the productivity component of fit composition, $\Delta w^{f,prod}(x)$, and 3.9% from the human capital advantage component, $\Delta w^{f,hc}(x)$. The human capital advantage is positive early in the life cycle, when workers in a good fit hold more human capital than average, and turns negative later in the life cycle. This is likely due to the fact that, in the baseline, workers who remain in a bad fit late in their careers are selected on high human capital, since they would lose a large amount of it by switching. Next, we see that 34.2% of the wage gains come from the human capital composition within each career fit, $\Delta w^{w,hc}(x)$, and this component grows steadily over the life cycle. Finally, 4.6% of the wage gains come from changes in the equilibrium wage function, $\Delta w^{w,fn}(x)$.

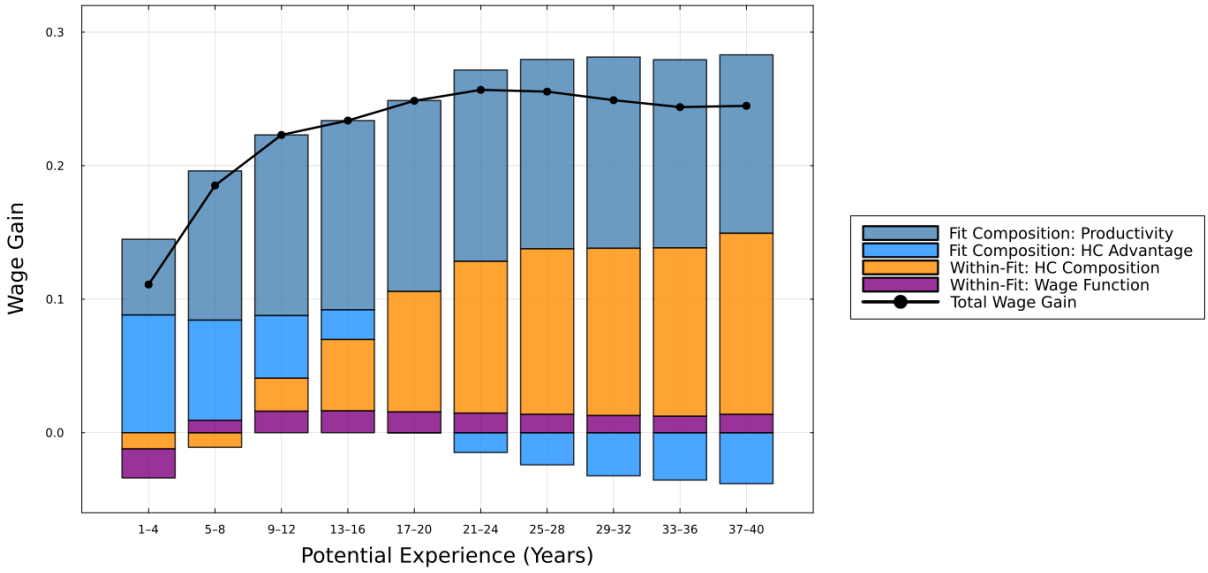


Figure C2: Detailed Decomposition of Non-College Wage Gains. *Notes*: This figure decomposes the change in average wages of non-college workers at each potential experience bin when they are assigned the college values of N and ϕ, keeping all other non-college parameters unchanged. The black line is the total wage gain. The dark blue and light blue bars are the productivity and human capital advantage components of the fit composition effect, $\Delta w^{f,prod}(x)$ and $\Delta w^{f,hc}(x)$. The orange and purple bars are the human capital composition and wage function components of the within-fit effect, $\Delta w^{w,hc}(x)$ and $\Delta w^{w,fn}(x)$.

C.4.2 AI Uncertainty Shocks on Good Fits Only

In the main text, we presented results from when the AI uncertainty shock hits all workers, regardless of their career fit status, s. This appendix presents the results to an alternative specification of the AI uncertainty shocks. In particular, we assume here that only workers in a good career fit ($s = g$) are hit with the uncertainty shock. Table C3 presents the same set of outcomes for the same values of ρ as presented in Table 10, except it is only workers in a good fit who are hit with the uncertainty shock.

Table C3: AI-Induced Career Uncertainty and Labor Market Outcomes (Good Fits Only)

	Baseline ($\rho = 0$)	Once per 40 years ($\rho = 1/480$)	Once per 20 years ($\rho = 1/240$)	Once per 10 years ($\rho = 1/120$)
Panel A: Aggregate and Lifetime Outcomes				
Wage premium	0.544	0.524 (−3.7)	0.511 (−6.1)	0.499 (−8.2)
Earnings premium	0.626	0.615 (−1.7)	0.606 (−3.1)	0.602 (−3.8)
Unemployment rate (%)	2.30	2.21 (−4.1)	2.21 (−4.2)	1.92 (−16.8)
Separation rate (%)	0.665	0.637 (−4.3)	0.631 (−5.2)	0.571 (−14.2)
Career switches	0.995	0.816 (−18.0)	0.559 (−43.8)	0.068 (−93.2)
Panel B: Early Career ($x = 1$)				
Wage premium	0.530	0.539 (+1.7)	0.543 (+2.5)	0.551 (+3.9)
Earnings premium	0.609	0.630 (+3.6)	0.638 (+4.9)	0.674 (+10.8)
Unemployment rate (%)	4.56	4.09 (−10.3)	4.04 (−11.5)	2.03 (−55.4)
Separation rate (%)	1.324	1.169 (−11.7)	1.136 (−14.2)	0.636 (−52.0)
Career switches	0.518	0.441 (−14.8)	0.361 (−30.3)	0.035 (−93.3)
Panel C: Mid-Career ($x = 5$)				
Wage premium	0.572	0.551 (−3.6)	0.537 (−6.1)	0.523 (−8.6)
Earnings premium	0.629	0.626 (−0.4)	0.621 (−1.3)	0.621 (−1.2)
Unemployment rate (%)	1.99	1.92 (−3.5)	1.91 (−3.9)	1.89 (−5.4)
Separation rate (%)	0.566	0.562 (−0.8)	0.561 (−1.0)	0.565 (−0.3)
Career switches	0.934	0.739 (−20.9)	0.528 (−43.5)	0.069 (−92.7)
Panel D: Late Career ($x = 9$)				
Wage premium	0.533	0.500 (−6.2)	0.482 (−9.4)	0.472 (−11.4)
Unemployment rate (%)	1.87	1.82 (−2.6)	1.83 (−2.0)	1.83 (−2.2)
Separation rate (%)	0.550	0.534 (−2.9)	0.533 (−3.0)	0.546 (−0.7)

Notes: Each column reports outcomes for college workers when AI shocks arrive at rate ρ and hit only workers in a good career fit, whether employed or unemployed; workers in a bad or unsure fit are unaffected. Numbers in parentheses are percentage changes relative to the baseline ($\rho = 0$). Wage premia are log differences in average wages between college and non-college workers; earnings premia are log differences in the present discounted value of cumulative earnings through the given potential experience bin. Non-college outcomes are held at their baseline values. Career switches are cumulative through the given potential experience bin. Panel A's wage, unemployment and separation rates average over all experience bins; lifetime outcomes are measured through potential experience bin $x = 9$. The baseline column is identical to that in Table 10.