Why Do Wages Grow Faster for Educated Workers?

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Abstract

The U.S. college wage premium doubles over the life cycle, from 27 percent at age 25 to 60 percent at age 55. Using a panel survey of workers followed through age 60, I show that growth in the college wage premium is primarily explained by occupational sorting. Shortly after graduating, workers with college degrees shift into professional, nonroutine occupations with much greater returns to job tenure. Educated workers are more likely to switch jobs right after completing schooling, but less likely to switch jobs thereafter. As a result, the rising college premium is mostly explained by wage growth within rather than between jobs. To understand these patterns, I develop a model of human capital investment where workers differ in learning ability and jobs vary in complexity. Faster learners sort into complex jobs with greater returns to investment. College acts as a gateway to better jobs, which offer more opportunity for skill development and on-the-job learning.

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1 Introduction

The college wage premium roughly doubles over the life cycle, both in the U.S. and in other developed countries (Lemieux 2006b, Rubinstein and Weiss 2006, Bhuller et al. 2017, Lagakos et al. 2018. Why do wages grow faster for educated workers? Hourly wages grow especially fast early in life. but with wide variability. Annual labor earnings in the U.S. rise by 60 percent from age 25 to 55 for the median worker, but barely at all for workers at the 25th percentile and roughly doubling at the 75th percentile (Guvenen et al. 2021). Life cycle wage growth is potentially as important as schooling in explaining cross-country variation in GDP per worker, with wages growing twice as much in rich countries compared to poor countries (Rossi 2020, Lagakos et al. 2018, Jedwab et al. 2021).

For all these reasons, it is important to understand why wages grow and the relationship between wage growth and human capital accumulation. Yet few studies investigate the determinants of on-the-job learning, especially compared to the vast literature studing the impact of pre-market schooling interventions on earnings (e.g. Rubinstein and Weiss 2006, Sanders and Taber 2012, Deming 2022).

This paper shows how occupational sorting leads to greater wage growth for educated workers. Using a panel of U.S. workers followed through age 60, I first show that the college wage premium increases steadily over the life cycle, more than doubling between the ages of 25 and 55. This basic pattern holds even after controlling for cognitive skill and when using direct measures of labor market experience.[1] Similar to Bhuller et al. (2017), I find that the Mincer earnings function substantially understates the life cycle return to education, and I show that a modified earnings function where education interacts linearly with work

[1] Several other studies have found that earnings increase faster for educated workers, although they are typically limited to shorter panels or cannot separate earnings from wages (e.g. Rubinstein and Weiss 2006, Bhuller et al. 2017, Lagakos et al. 2018). The estimates in this paper use panel data following individual workers, are consistent across both NLSY waves, and are robust to alternative measures of hours and earnings. This finding contrasts with many existing studies that estimate flat or declining returns to potential experience for mid- and late-career workers (e.g. Mincer 1974, Murphy and Welch 1990, Heckman et al. 2006, Lemieux 2006c, Lagakos et al. 2018, Jedwab et al. 2021). I show that wage growth estimates using potential experience are biased downward because educated and higher-wage workers accumulate more hours and are more consistently attached to the labor force.

experience fits the data much better.

I then study the relationship between early career job mobility and wage growth, extending the analyses of Topel and Ward (1992) and von Wachter and Bender (2006) to the 1979 and 1997 cohorts of the National Longitudinal Survey of Youth (NLSY) but focusing on differences in job mobility patterns by education. I exploit detailed employment and wage history data from the NLSY to decompose wage growth into within- and between-job components. I find that job mobility increases net wage growth, but only for college graduates, and only in the first few years after they complete schooling. From mid-career onward, within-job wage growth is *greater* than total wage growth for college graduates, suggesting a net negative effect of job mobility. In contrast, total and within-job wage growth are nearly identical for high school graduates throughout the life cycle.

I find that college graduates switch jobs more frequently in the first two years after completing schooling, but less frequently for the rest of their careers. After graduating, workers with college degrees sort out of administrative support and services occupations and into professional occupations in business, engineering, medicine, education, and related fields. A good summary statistic for occupational sorting is *routineness*, following seminal work by Autor et al. (2003), Goos et al. (2014) and others. College educated workers sort into nonroutine occupations shortly after completing schooling, whereas the occupation mix changes very little for workers after they finish high school.

Using detailed panel data, I estimate wage growth with job tenure and show how it varies by occupation. I find that wage growth is slower in routine occupations. Real wages are more than 20 percent higher after 15 years of job tenure for workers in occupations at the 25th percentile of routineness. In contrast, I find almost no wage growth beyond 4 years of tenure in jobs at the 75th percentile of routineness. These conclusions are robust to controlling for occupation fixed effects and individual fixed effects, which accounts for level differences in wages across occupations and is identified from within-worker job switching.

How much of the life cycle widening of educational wage differentials can be explained by occupational sorting? I approach this question in two ways. First, using data from the March Current Population Survey (CPS), I assign NLSY respondents the average wage at each age for their first post-schooling occupation. This projected college wage premium is about half the size at each age of the actual premium among NLSY respondents. Second, I show that the controlling for occupation-by-tenure fixed effects reduces the life cycle growth in the college wage premium by about 50 percent. Overall, I estimate that early career occupational sorting explains at least half of the life cycle growth in the college wage premium.

To understand these facts, I develop a simple model of human capital investment and on-the-job learning in the spirit of Ben-Porath (1967) and Cavounidis and Lang (2020). Workers vary in their ability to learn on-the-job, and the productivity of on-the-job learning is greater in complex (nonroutine) occupations.[2] Returns to on-the-job learning diminish more rapidly in routine jobs, which are simpler and more predictable (e.g. Autor et al. 2003). Since learning ability and job complexity are complements, faster learners will obtain more schooling and will sort into complex occupations. The college wage premium increases with experience because of sorting, but also because of the greater returns to scale in skill investment afforded by complex occupations. I close the model by introducing imperfect substitution across occupations, which causes wages to adjust until the marginal worker is indifferent between sectors.[3] With reasonable assumptions about the distribution of learning ability and the assignment of workers to tasks, the model delivers a simple characterization of life-cycle college wage premia and occupational wage differentials.

This paper establishes the primary role of occupational sorting in explaining life cycle growth of the college wage premium. It complements a large literature studying the sources of wage growth over workers' careers, including heterogeneity by firm and industry (e.g. Dustmann and Meghir 2005, Gregory 2020, Arellano-Bover and Saltiel 2021, Adda and Dustmann

[2]In Ben-Porath (1967), the human capital production function includes a productivity parameter that augments learning output and a curvature parameter that determines the returns to scale in human capital investment. I interpret the productivity parameter as individual learning ability following Neal and Rosen (2000) and Huggett et al. (2006), and the curvature parameter as occupation complexity (nonroutineness).

[3]The equilibrium of the model is characterized by a threshold learning ability, with sorting below and above into routine and complex occupations respectively.

2023). These studies typically find that general human capital accumulation is the most important source of wage growth (e.g. Connolly and Gottschalk 2006, Schönberg 2007, Bagger et al. 2014). A growing body of work documents sorting of high-wage workers to high-wage firms, which is potentially consistent with occupational sorting given the rise of firm specialization and domestic outsourcing (e.g. Card et al. 2013, Goldschmidt and Schmieder 2017, Song et al. 2019). More broadly, my findings highlight the importance of the school-to-work transition and early career mobility for lifetime wage growth (e.g. Ryan 2001, Oreopoulos et al. 2012, Wachter 2020).

Intuitively, a college degree provides access to better jobs, which allow for more skill development and on-the-job learning. This may seem obvious. Yet it is unexplained by many seminal models of human capital and wage determination.[4] The Mincer (1974) earnings function implies a constant return to schooling over the life-cycle, although more recent evidence suggests otherwise (Lemieux 2006c, Heckman et al. 2006, Bhuller et al. 2017, Lagakos et al. 2018). The most influential model of how human capital affects the wage structure of an economy is the supply-demand-institutions (SDI) framework, or the *canonical model,* which shows how technology increases relative demand for high-skilled labor (Tinbergen 1975, Goldin and Katz 2007, Acemoglu and Autor 2011). In the canonical model and the task framework of Acemoglu and Autor (2011), the college wage premium increases over time because of changes in the economic environment. This paper builds human capital investment and wage dynamics into the structure of the canonical model, which allows workers to respond endogenously to skill-biased technological change.

This paper contributes to our understanding of how routine work affects life cycle wage inequality. The sorting of educated workers into high wage-growth jobs suggests that lifetime

[4] Bagger et al. (2014) develop an equilibrium model with on-the-job learning, heterogeneous employers, and individual shocks. They find faster wage growth for educated workers, and they decompose it into human capital accumulation versus higher returns to job search. They find that job search is an important contributor, but only in the first 10 years of a worker's career. Lise and Postel-Vinay (2020) estimate a structural search-and-matching model with cognitive, manual, and interpersonal skills and find that the return to cognitive skills - but not the other two - increases with work experience. Neither paper explicitly studies heterogeneous returns to experience by job routineness or other dimensions of occupation.

earnings inequality may be larger than cross-sectional comparisons suggest (e.g. Aaberge and Mogstad 2015, Hoffmann et al. 2020, Guvenen et al. 2022). Acemoglu and Restrepo (2018) find that the increasing automation of routine tasks has increased the college wage premium since educated workers are much more likely to hold nonroutine jobs. This paper complements their finding by exploring this occupational sorting directly and developing a model that explains it as an equilibrium phenomenon. Routine jobs require repeated execution of rule-based tasks and are purposely designed to limit worker discretion and on-the-job learning (Lindbeck and Snower 2000, Autor et al. 2003, Bartling et al. 2012).

My findings are also related to the literature on job ladders and knowledge hierarchies, where skilled workers are promoted to positions that increase their decision-making authority and span of control within the firm (Gibbons and Waldman 1999, Garicano and Rossi-Hansberg 2006, Gibbons and Waldman 2006). By allowing for differences in the productivity of on-the-job learning, my model is similar in spirit to Nelson and Phelps (1966), who view education as increasing the ability to learn and adapt to change. Finally, this paper contributes to the macroeconomic literature on human capital investment, learning-by-doing, and earnings dynamics (Rosen 1972, Heckman et al. 1998, 2002, Guvenen 2006, Bowlus and Robinson 2012, Manuelli and Seshadri 2014).

The paper proceeds as follows. Section 3 establishes the empirical pattern of greater life cycle wage growth for educated workers. Section 4 establishes occupational sorting as a key explanation for the life cycle growth in the college wage premium. Section 5 presents the model and develops its implications, and Section 6 concludes.

2 Data

My main data source is the 1979 National Longitudinal Survey of Youth (NLSY79). The NLSY79 is a nationally representative sample of 11,406 youth ages 14 to 22 in 1979.[5] The

[5]The NLSY79 includes a nationally representative sample (n=6,111), an oversample of some geographies in order to obtain higher shares of nonwhite and disadvantaged youth (n=5,295), and an active duty military

survey was conducted yearly from 1979 to 1993 and then biannually from 1994 through 2018, when respondents were ages 53 to 61. Attrition is relatively low, with about 90 percent of participants retained through 1994 and 70 percent retained through 2018.

I supplement the main analysis with data from the 1997 NLSY (NLSY97), a nationally representative sample of 8,984 youth age 12 to 17 in 1997.[6] The survey was conducted yearly from 1997 to 2011 and then biannually from 2011 to 2019, when respondents were ages 34 to 39. Attrition is also low in the NLSY97, with 77 percent retained through 2019. Both the NLSY79 and the NLSY97 surveys include consistent and detailed measures of education and premarket skills, employment, wages and earnings, and occupation and employer history.

I harmonize occupation codes across NLSY waves and years using the "occ1990dd" crosswalk developed by Autor and Dorn (2013) and extended by Deming (2017), and I match these occupation codes to measures of the task content of work from O*NET.[7] I focus on routine occupations, defined here as jobs that score higher on the question "how important is repeating the same physical activities (e.g. key entry) or mental activities (e.g. checking entries in a ledger) over and over, without stopping, to performing this job?", following Deming (2017).[8] Because responses to these questions have no cardinal meaning, I convert them to a 0-10 scale where occupations are given the value that reflects their percentile rank in the labor supply-weighted distribution of employment in the 2017-2019 American Community Survey (ACS).[9]

My main outcome is the inflation-adjusted log hourly wage (indexed to 2018 dollars), trimmed for values below 3 and above 200 following Altonji et al. (2012). I use Armed Forces

sample which was reduced drastically in 1985 (n=1,280 originally, n=186 in 1985). I drop the military sample from all my analyses.

[6]The NLSY97 includes a nationally representative sample (n=6,748) and an oversample of some geographies in order to obtain higher shares of nonwhite and disadvantaged youth (n=2,236),

[7]O*NET is a survey administered by the U.S. Department of Labor to a random sample of workers in each occupation. I use the 1998 O*NET to maximize consistency across sample waves.

[8]This definition differs slightly from Deming (2017), which uses the average of this question and another - "how automated is the job?". I drop this question because of concerns about the consistency of responses across waves, although my main results are robust to including both questions.

[9]For example, if we ordered all workers in the U.S. economy in 2017-2019 according to their occupation's routineness score, the occupation at the 25th percentile would receive a score of 2.5.

Qualifying Test (AFQT) scores to measure cognitive skill, following many other studies, and I employ the age-normed mapping of scores across waves created by Altonji et al. (2012). Both waves of the NLSY include masked employer and job identifiers, enabling me to calculate employer and occupation tenure.

I supplement the NLSY analyses with cross-sectional data from the 1980-2020 March CPS Annual Social and Economic Supplement (ASEC). In the March CPS I compute wages by dividing annual wage and salary income by annual hours worked, following Lemieux (2006a).

2.1 Measurement of Work Experience and Job Spells

A key advantage of the NLSY data is the detailed calculation of work histories and work experience. The work history data include a comprehensive weekly measurement of labor force status, total number of hours worked, and jobs held (if any) covering every week since January 1, 1978, including the years in between surveys or if respondents skip a survey wave.[10] These weekly measurements are then summed up to calculate hours and weeks worked in the last calendar year and since the last survey interview. To account for reporting errors and the different ages at which each survey begins, I disregard work experience prior to age 18 in both surveys, although results are very similar if teenage work experience is included.

I use these variables to create (fractional) measures of yearly work experience, with one year equalling 2,080 hours (52 weeks times 40 hours per week). My baseline measurement of work experience uses the actual hours reported by each respondent in each week, even if it exceeds 40. For respondents age 25 to 54 in the NLSY79, median work experience per year is 0.65 (about 26 hours per week), including non-employed respondents. Among respondents reporting at least some work in a year, 39 percent worked less than full-time, 26 percent worked exactly full-time (2,080 hours), 22 percent worked between 40 and 50 hours per

[10] All weeks are counted, and respondents were unable to recall their activities in a week in less than 5 percent of cases. In cases of missing weeks, I interpolate the average for the rest of the period (e.g. if a respondent was working for 40 weeks of the year, not working for 10, and missing for 2, I code the 2 missing weeks as 0.8 working and 0.2 not working). The results are not sensitive to other reasonable choices.

week, and 13 percent reported working more than 50 hours per week.[11]

To study life-cycle patterns, I convert the NLSY data into panel format, with one observation per respondent-year, and regress work experience on two-year age bins controlling for individual fixed effects. Since there is some attrition, the panel is not perfectly balanced, but the age coefficients are identified only by within-worker differences. Appendix Figure A1 presents hours worked (in fractions of a year) by age and education level, for all NLSY79 respondents. Four-year college graduates work fewer hours initially but quickly catch up, accumulating more total hours worked by their late 20s. Hours peak at age 30 for four-year college graduates and at age 26 for non-college graduates, and then decline steadily through age 60.[12]

The NLSY measures work experience more accurately than most widely-used labor market data sources. The Current Population Survey (CPS) and the American Community Survey (ACS) ask respondents about their "usual" hours worked per week and weeks worked per year, either in general or over a specific period of time such as the last year (Ruggles et al 2022).[13] Respondents are instructed to count weeks in which they worked even a few hours and to count vacation and sick leave as work (Flood et al 2022). Both approaches probably overstate work experience, particularly for employees with irregular hours. This is consistent with Lachowska et al. (2022) who compare administrative records from the Washington state Unemployment Insurance system to the CPS and find that the CPS substantially overstates

[11] To assess the robustness of the results, I create an alternative measure that caps work experience at 2,080 hours per year. I also explore using all data reported since the last interview even if it is several years old, although my preferred approach uses data from only the past year to minimize the impact of recall bias. Finally, I compute returns to work experience in terms of annual earnings rather than wages, to address potential attenuation bias from using hours to compute both wages and work experience. None of these alternative approaches has any substantive impact on the main results.

[12] Four-year college graduates also work longer hours conditional on employment, averaging more than 40 hours per week between the ages of 34 and 56. Workers with either some college or a high school degree peak around 38 hours per week at age 42 and then decline gradually. This broad pattern holds even if I condition on half-time work or more, and suggests that college graduates quickly accumulate more work experience at a given age despite starting later. These findings from the NLSY are consistent with Bick et al. (2022), who show using the Current Population Survey (CPS) Outgoing Rotation Groups that college-educated workers are much more likely to report usual weekly hours worked above 40.

[13] The CPS also asks respondents about their actual hours worked in the last week, but only for "usual" hours farther back.

work hours.[14]

Both waves of the NLSY collect wage, tenure, and hours information for up to 5 jobs between each survey response.[15] This allows me to construct a panel with one observation per respondent-job-year, and to decompose wage changes into within- and between-job components. Over all survey years in the NLSY79, the mean number of jobs between waves is 1.67, and the median respondent holds 12 jobs between 1979 and 2018.

3 Faster Wage Growth for Educated Workers

3.1 College premia by age

I first show that the college wage premium is increasing in age even after conditioning on cognitive skill. I estimate regressions of the form:

$$\ln wage_{it} = \sum_{a}^{A} \beta_a A_{it} + \sum_{a}^{A} \gamma_a * Bach_i A_{it} + \sum_{a}^{A} \delta_a * AFQT_i A_{it} + \pi_i + \varepsilon_{it} \tag{1}$$

where A_{it} indexes two-year age bins and age is interacted with indicators for having a bachelor's degree and the normalized AFQT score. The regression also includes individual fixed effects, which absorbs time-invariant heterogeneity across workers. Standard errors are clustered at the individual level.

Figure 1 plots the γ_a and δ_a coefficients, which measure the marginal impact of education and ability on log wages at each age. I first plot results from a regression that excludes AFQT score, then a second model that includes both jointly.

The college wage premium increases from 22 percent at age 26 to 49 percent at age 40 and 56 percent at age 60. Adding interactions between age and AFQT score lowers the

[14]Lachowska et al. (2022) show that 37 percent of workers in the CPS report exactly 40 hours per week, compared to 17 percent in the Washington state UI data. I find in the NLSY79 that 21 percent of all workers report exactly 40 hours per week (26 percent when restricting to ages 25 to 54).

[15]I eliminate the 3 percent of jobs which are missing either employer IDs or wages. The NLSY97 collects data on more than 5 jobs for the small number of respondents to whom this applies, but I restrict to only the first 5 for consistency across waves.

college wage premium by about 20 percent, but the college wage premium still more than doubles over the life cycle. A one standard deviation increase in AFQT score increases wages by 4.5 percent at age 26, 10 percent at age 40, and 12 percent at age 60. The cognitive skill premium also more than doubles over the life cycle. In terms of relative magnitudes, having a bachelor's degree explains about as much life-cycle wage growth as 1.5 to 2 standard deviations of cognitive skill.

Overall, Figure 1 shows clear evidence that wages grow faster with age for more skilled and more educated workers. Appendix Figure A2 plots analogous estimates of equation (1) using the NLSY97 sample. This yields very similar results, with rising returns to education and cognitive skill through age 38. Education is also strongly correlated with AFQT scores. In both NLSY waves, the difference in AFQT scores between respondents with a high school degree or less and a bachelor's degree or more is about 1.3 standard deviations.

My findings are consistent with Bhuller et al. (2017), who find using administrative data from Norway that the Mincer model understates life-cycle returns to education even after controlling for cognitive skill. They also find similar results using a twin fixed effects design and an instrumental variables (IV) approach using the staggered adoption of compulsory schooling laws. Several other studies find suggestive evidence of steeper experience-earnings profiles for college-educated workers (e.g. Rubinstein and Weiss 2006, Lagakos et al. 2018).

To show the generalizability of this finding in the U.S., I study the evolution of the college wage premium across birth cohorts using the March CPS. I create synthetic birth cohorts for workers born between 1941 and 1990 and compute the log wage difference between workers in the CPS with and without a college degree at each age.

Figure 2 plots three-year moving averages of the college wage premium by age, separately for ten year cohort groups (1941-1950, 1951-1960, etc.) and also controlling for birth cohort fixed effects. While the intercepts differ across groups, the college wage premium increases substantially over the life cycle for all birth cohorts between 1941 and 1990.

3.2 College premia by work experience

Most of the existing literature studies life-cycle wage growth using *potential experience*, calculated as age minus years of education minus six (e.g. Mincer 1974, Murphy and Welch 1990). Unlike the results shown in Figure 1, these studies typically find that wage growth levels off after 20 years of potential experience (eg Murphy and Welch 1990, Lagakos et al. 2018). Potential experience assumes that all workers accumulate exactly one year of experience per calendar year, and it can be calculated in cross-sectional data without any direct information on hours worked. Yet if educated and higher-paid workers stay more attached to the labor force over time and work longer hours, potential experience may understate the wage premium to actual work experience.[16]

Appendix Figure A3 quantifies the bias of potential experience by plotting the difference between potential and actual experience by age and education level in the NLSY79 data. The bias is increasing in age and much greater for less-educated workers. By age 40, potential experience overstates actual experience by 11.1 years for high school graduates, 7.5 years for workers with some college, and 3.6 years for four-year college graduates.

Figure 3 examines life cycle wage growth by actual work experience. I compare estimates from a traditional Mincerian regression against a non-parametric version that allows returns to education to vary by work experience:

$$\ln wage_{it} = \alpha_i + \sum_{w}^{W} \beta_w W_{it} + \sum_{w}^{W} \gamma_w * Bach_i W_{it} + \delta X_{it} + \varepsilon_{it} \tag{2}$$

where two-year work experience bins (as above) are interacted with indicators for whether workers have a bachelor's degree ($Bach_i$) and X_{it} is a vector of demographic covariates such

[16] O'Neill and Polachek (1993) and Antecol and Bedard (2004) show that lower labor force attachment among women and nonwhite workers respectively leads to biased estimates of gender and racial wage gaps when using potential rather than actual experience. Blau and Kahn (2013) compare the CPS Tenure Supplement to survey data with retrospective measures of actual work experience, and show that they play an important role in explaining the growth of the gender wage gap over the life course. Braga (2018) argues that potential experience understates life-cycle returns to education because it is highly collinear with age and year. Ashworth et al. (2021) find that potential experience overstates the early-career return to education relative to actual experience.

as race, gender, age, and year. I restrict the sample to age 22 and above to make the education coefficients interpretable. I also estimate a panel regression version of equation (2), with an individual fixed effect (ζ_i) added and the intercept and covariates removed.[17]

The solid line in Figure 3 shows the constant term from a Mincerian earnings regression, which imposes the restrictions that all the γ_w coefficients are the same, and that work experience W_{it} takes a quadratic form. The coefficient on $Bach_i$ is 0.401, consistent with many studies finding that the return to an additional year of postsecondary schooling is around 10 percent (Card 2001, Deming 2022). The dashed line shows estimates of equation (2), with returns to education that vary by work experience. The dotted line presents results from the panel regression version of equation (2). Both tell a very similar story. The college wage premium roughly doubles over the course of a worker's career, from 0.3 after 4 years of experience to 0.6 after 38 years of experience.

Overall, Figure 3 shows that the college wage premium is roughly linear in work experience. To demonstrate this directly, I estimate an alternative form of the Mincer earnings function, where education is interacted with actual work experience:

$$\ln wage_{it} = \alpha_i + \beta_1 Bach_i + \beta_2 W_{it} + \beta_3 (Bach_i * W_{it}) + \delta X_{it} + \varepsilon_{it} \tag{3}$$

The dash-dotted line in Figure 3 plots the implied values from the coefficients in equation (3). With the exception of the first 3 years, where wage growth is faster than the model predicts, this specification is an excellent fit. The estimates of β_1 and β_3 are 0.277 and 0.0092, implying that the college wage premium increases from 0.29 to 0.63 over the lifecycle. The actual estimates implied by the panel regression version of equation (2) are 0.15 and 0.62.[18]

[17] This estimates separate slopes for individuals with different levels of education and then compares them in a single model. In principle I could leave age and year in the panel regression, but I exclude them because they are so highly collinear with work experience when individual fixed effects are included.

[18] Appendix Figure A4 presents a parallel set of results in the NLSY97. The patterns are overall very similar, with the college wage premium increasing steadily with work experience and the interacted Mincer model providing an excellent fit to the data.

Appendix Figure A5 plots wage growth per year of actual work experience separately by education level.[19] Wages grow fastest early in life for workers at all levels of education. However, they also continue to grow throughout the life cycle, just at different rates. Among respondents with ten or more years of work experience, real wages grow by an average of 0.9, 1.5, and 1.8 percent per year for workers with a high school degree, some college, and a bachelor's degree or more respectively. This differs importantly from cross-sectional comparisons using data such as the CPS, which are confounded by endogenous labor force participation later in life.

4 Why do wages grow faster for educated workers?

4.1 Early Career Mobility

The early years of young workers' careers are characterized by high job mobility and high earnings growth (e.g. Topel and Ward 1992, von Wachter and Bender 2006). Does education improve job mobility and increase access to better-paying jobs? Education might increase life cycle wage growth by improving "search capital", e.g. helping workers transition to better occupations and employers (Keane and Wolpin 1997, Bagger et al. 2014).

I extend the analysis of early career mobility in Topel and Ward (1992) and von Wachter and Bender (2006) by studying job transitions among young workers in the NLSY cohorts. I make two main modifications to their approach. First, I study differences in job mobility by education. Second, rather than studying job transitions over a certain age, I time a worker's career by coding as year zero the last survey wave in which they reported attending school full-time.[20]

[19] I estimate panel regression versions of equation (2) with wages in levels, only the work experience indicators, and individual fixed effects, and I estimate separate models for respondents with a high school degree or less, some college but no degree, and a bachelor's degree or more. I then compute percent changes per year of actual work experience and plot five-year moving averages for each education group in Appendix Figure A5.

[20] 80 percent of workers with a high school degree or less finish schooling by age 19 and 92 percent finish by age 25. The end of schooling is even more spread out for college-educated workers. Only 53 percent finish by

Table 1 presents summary statistics on job mobility by education. To account for sample attrition, I estimate simple regressions of the form:

$$outcome_{it} = \sum_{w}^{W} \beta_w C_{it} + \zeta_i + \varepsilon_{it} \tag{4}$$

where i indexes individuals, t indexes survey years, C_{it} measures years since the end of full-time schooling (with $C_{it} = 0$ as the left-out category) and ζ_i is an individual fixed effect. Columns 1 and 2 show estimates of equation (4) with the cumulative number of unique jobs as the outcome. Workers with a high school degree or less have held an average of 2.7 total jobs by the time they finish full-time schooling, compared to 5.9 for workers with at least a bachelor's degree. College graduates also have higher job mobility early in their career, holding an average of 1.5 additional jobs in the first two years of their career compared to 0.9 for less educated workers. However, this trend soon reverses sharply. From year 2 to year 10, college graduates hold an average of only 2.3 additional jobs compared to 4 for workers with a high school degree or less. Overall, college graduates have higher job mobility in the first two years after full-time schooling but lower job mobility from years 2 to 30.

I find similar patterns for job tenure. Ten years post-schooling, employed college graduates have been in their current job for an average of 5.1 years, compared to 3 years for workers with a high school degree or less. The tenure gaps grows from 2.1 in year 10 to 3.5 by year 30.

These broad patterns also hold when accounting for differences in non-employment across groups. One year after the end of full-time schooling, 71 percent of currently employed college graduates are working for a different employer than in the previous survey wave, compared to 75 percent for less educated workers. This share falls rapidly for both groups but moreso for college graduates. By year 10, only 26 percent of employed college graduates work for a

age 23 compared to 86 percent by age 30. This is consistent with Bhuller et al. (2017), who identify working during school as a major source of bias in Mincerian estimates of the return to schooling. As a robustness check I also condition career start on the end of half-time or full-time schooling, rather than only full-time. This less restrictive definition of career start yields broadly similar results.

new employer, compared to 40 percent of workers with a high school degree or less.

Columns 7 and 8 of Table 1 present real wages by education and years post-schooling. Wages grow steadily for both groups but faster for college graduates. The college wage premium grows from 43 percent in year zero (the last year of full-time schooling) to 75 percent in year 1, and then steadily by 3-5 percentage points per year. Real wages grow by 55 percent over the first 10 years of the careers of college graduates and 62 percent for less educated workers.[21]

Appendix Table A1 shows analogous results for the NLSY97 sample. The number of jobs at career start is almost identical to the NLSY79 for both education groups.[22] However, job mobility is lower overall in the more recent sample, especially for less educated workers. Real wages are modestly higher, especially for more educated workers. These patterns are broadly consistent with Molloy et al. (2014), who find declining job mobility across NLSY cohorts and argue that this explains decreased interstate migration.

How much of the rising life cycle college wage premium can be explained by job mobility? To answer this question, I convert the NLSY into a worker-year-job panel, with wage and employer data for up to 5 jobs between each survey year as discussed in Section 2.1. I then estimate regressions of log wages on worker-by-job fixed effects:

$$\ln wage_{ijt} = \sum_{w}^{W} \beta_w C_{it} + \zeta_{ij} + \varepsilon_{ijt} \tag{5}$$

where i indexes individuals, j indexes jobs, t indexes survey years. I define a "job" as a

[21] Both of these figures are less than what is reported by Murphy and Welch (1990) and others, who find that 80 percent of wage growth occurs in the first 10 years of potential experience. The difference is that potential experience assumes full labor force participation after age 18 for high school graduates and age 22 for college graduates, even though most young workers stay enrolled in school for longer. Measuring career starts as the end of full-time schooling for each individual increases the average starting wage, which lowers the share of estimated wage growth that happens in the first 10 years. I find that 76 percent of lifetime wage growth occurs in the first 10 years of *potential* experience, consistent with Murphy and Welch (1990).

[22] I find very similar levels of job mobility in the NLSY79 compared to the sample in Topel and Ward (1992). They find that male workers hold an average of 4.56 and 6.96 jobs 5 after 5 and 10 years of potential experience respectively, compared to 4.66 and 6.77 jobs in my sample. Thus the main difference between Table 1 and Topel and Ward (1992) comes from timing careers based on completed schooling rather than potential experience. Topel and Ward (1992) also find that 60 percent of lifetime wage growth occurs in the first 10 years, which is very similar to my results.

unique employer-by-occupation pairing. C_{it} is either years since the end of full-time schooling (e.g. "Career"), or actual work experience as in equation (3) above.

Equation (5) yields an estimate of within-job wage growth at different parts of the life cycle. I compare these estimates to versions of equation (5) that only include individual fixed effects (e.g. ζ_i), which measures total individual wage growth, both within and across jobs.

Panel A of Figure 4 presents estimates of cumulative wage growth by years since completed schooling, separately by education. There are 3 main takeaways from Panel A of Figure 4. First, wage growth is substantially greater for college graduates compared to less educated workers, with the biggest differences in the first five years of their careers. Second, early career wage growth for college graduates is much higher overall than within-job, which suggests an important role for job mobility. In contrast, total and within-job wage growth are nearly identical for high school graduates throughout the life cycle. Third, within-job wage growth is *greater* than total wage growth for college graduates from career year 10 onward. The two lines nearly converge by year 30, and within-job wage growth is about 90% of total wage growth over 30 years of college educated workers' careers. Appendix Figure A6 shows analogous results in the NLSY97, which yields broadly similar results.

The net impact of job mobility on wage growth combines the impact of job-to-job switches with the impact of transitions to and from nonemployment. The former are usually positive, while the latter are usually negative (von Wachter and Bender 2006). Wage growth may be higher mechanically for job stayers in Panel A since they remain more consistently employed than job switchers.

To address this, Panel B of Figure 4 presents cumulative wage growth by actual work experience rather than years since full-time schooling.[23] Life cycle wage growth is still much higher early in life and for college graduates compared to less educated workers. However,

[23]The net impact of job mobility could still be downward biased when using actual work experience if unemployment spells cause persistent wage losses through scarring. However, von Wachter and Bender (2006) find that young job losers in Germany experience initially large wage losses that fully recover after 5 years, and that persistent negative effects of displacement found in other studies are mostly due to negative selection.

the contribution of job mobility is greater for both groups after accounting for nonemployment and part-time work. About two-thirds of early career wage growth occurs within-job for college graduates, and about 80 percent for workers with a high school degree or less. However, those figures increase to 90 percent and 85 percent respectively after thirty or more years of work experience. Within-job wage growth becomes much more important later in life, especially for college graduates. This is consistent with Bagger et al. (2014), who find using Danish administrative data that search and matching contributes to educational wage differentials, but only in the first 10 years of workers' careers, with human capital accumulation being the dominant factor later in life.

Figure 5 shows this more clearly by plotting five-year moving averages of wage growth per year of actual work experience (2,080 hours). The difference in overall wage growth by education is about 4.4 percentage points after 2 years of work experience. Since the within-job difference by education is only 1.3 percentage points, one interpretation is that job mobility accounts for about 70 percent of the difference in wage growth between less and more educated workers. However, after 10 years of work experience, total wage growth and within-job wage growth are nearly identical for both education groups. In the next section I explore the role of occupational sorting in explaining differences in wage growth by education.

4.2 Occupational Sorting by Education

Figure 6 studies occupational sorting by education. I estimate versions of equation (4) above, where the outcomes are different occupation categories. As in Table 1 I use the last year of school enrollment as the left-out category, but I also report results for one and two years prior to school enrollment. I group occupations into four broad categories - managerial, other professional, sales and administrative support, and services and blue collar occupations.[24]

[24]Professional, sales and administrative support, and services and blue collar categories correspond to occ1990dd codes 23-235, 243-399, and 400 and above respectively. Mangement includes codes 4-22, and also a series of codes indicating supervisors of workers in the other categories (e.g. retail store managers, construction foremen, etc.). These supervisory codes are 243, 303, 413-415, 433, 448, 450, 470, 503 558, 628, 803 and 823.

Panel A shows results for high school graduates. The share of high school workers holding managerial occupations increases from 1.5 percent to 16.5 percent over the life cycle. Professional occupations increase from 2 percent to 7 percent. Sales and adminstrative support jobs go from 25 percent to 19 percent, and services or blue collar jobs decline from 72 percent to 58 percent. These differences emerge gradually, with little change in the occupation mix of less educated workers in the first five years after completing school.

Panel B of Figure 6 shows results for four-year college graduates. One year prior to graduation, the mix of jobs held by college graduates is about one-third each of managers and professional occupations, sales and administrative support, and services or blue collar occupations. The occupation mix for college graduates changes dramatically right after they complete schooling. The share of college graduates working in professional occupations increases from 28 percent to 50 percent from the year before graduation to two years after, and then remains roughly constant for the next 30 years. The share of college graduates working in sales and adminstrative support and services or blue collar occupations drops by 10 and 18 percentage points respectively over the same period. The share of college graduates holding management jobs more than triples over the life cycle, from 8 percent to 28 percent, but the increase is gradual. By career year 30, 78 percent of college grads are in managerial or professional jobs compared to only 24 percent of HS grads.

Appendix Figure A7 presents an analogous set of results for the NLSY97 sample. The patterns are very similar overall. The share of college graduates working in professional occupations in the NLSY97 increases from 30 percent to 50 percent from the year before to two years after graduation, while the occupation mix changes very little for less educated workers over the same period. Overall, the evidence suggests that high school graduates hold similar types of jobs before and after they complete schooling, whereas college graduates quickly shift into professional occupations after completing school. Working in management becomes gradually more common for all types of workers.

I study occupational sorting more systematically by studying a single dimension that is widely used in the literature - *routineness.* Autor et al. (2003) define a job task as "routine" if it can be accomplished by following simple, explicit rules. Several studies find that computers and information and communication technology (ICT) replace routine tasks but leave more complex, unpredictable work to human decision-makers (Autor et al. 2002, Bresnahan et al. 2002, Bartel et al. 2007). Bayer and Kuhn (2019) show that wage growth with tenure is greater in occupations with higher levels of complexity, autonomy, and responsibility. This suggests that routineness might predict differences in wage growth across occupations.

Figure 7 plots the change in the average routineness of a respondent's occupation around the time they complete schooling. The average routineness of jobs held by college graduates declines by more than 12 percentile points (about one third of a standard deviation) from the year before to two years after they finish schooling. In contrast, there is no change in the average routineness of jobs held by less educated workers. Routineness then declines gradually for all workers throughout the rest of their careers, a trend that is explained entirely by sorting into management occupations.

Overall, the evidence shows that college graduates sort into professional, nonroutine occupations immediately after finishing schooling, whereas high school educated workers hold similar types of jobs before and after graduating. Moreover, Table 1 shows that college graduates have lower mobility and higher job tenure after making the transition into professional occupations. The next section explores variation across occupations in the wage returns to job tenure.

4.3 Slower Wage Growth in Routine Occupations

How does the tenure premium vary by occupation? To study this, I estimate models of the form:

$$\ln wage_{ikt} = \sum_{o}^{O} \beta_o OccTenure_{ikt} + \sum_{w}^{W} \beta_w W_{it} + \delta X_{ikt} + \eta_k + \lambda_t + \varepsilon_{ikt} \tag{6}$$

with k indexing occupations and $OccTenure_{ikt}$ grouped into two-year bins. I restrict the sample to age 19 and above, and I include both NLSY waves in the regression. I also include controls for work experience, which accounts for overall differences in seniority across occupations. Age, education, AFQT score, race and gender, and employer tenure are included in the X_{ikt} vector. I control for employer tenure to offset firm or establishment-specific wage premia, which are particularly important in some jobs and industries (e.g. Dustmann and Meghir 2005). Importantly, equation (6) controls for occupation fixed effects to account for level differences in wages, so the β_o coefficients yield only the *slope* of wage growth with respect to occupation tenure.

Figure 8 presents separate estimates of equation (6) for professional occupations compared to services and blue collar occupations. After accounting for level differences in wages, the tenure premium grows equally for both groups for the first two years of job tenure but then diverges. From year 2 to year 20, the tenure premium rises by 20 log points in professional occupations but only 4 log points in services and blue collar occupations. This difference of 16 log points is roughly half the size of the total life-cycle growth in the college wage premium.

Appendix Figure A8 shows estimates of equation (6) where occupation tenure is interacted separately with education. About half of the difference in wage growth across occupations remains after looking within education groups. These results hold equally in the NLSY79 and NLSY97, and are broadly robust to different specifications and covariates.

I study differences in wage growth across occupations systematically by estimating versions of equation (6) where occupation tenure is interacted with routineness:

$$\ln wage_{ikt} = \sum_{o}^{O} \beta_o OccTenure_{ikt} * Routine_k + \sum_{o}^{O} \gamma_o OccTenure_{ikt} + \sum_{w}^{W} \gamma_w W_{it} + \delta X_{ikt} + \eta_k + \lambda_t + \varepsilon_{ikt} \tag{7}$$

As discussed in Section 2.1, the routineness measure comes from the 1998 O*NET but is rescaled to range from 0 to 10 where 5 is the routineness of the median job in the 2017-2019 ACS. I also estimate versions of equation (7) that omit time-invariant controls but include an individual fixed effect (ζ_i), which identifies tenure effects only from within-worker job changes.

Table 2 present four different estimates of equation (7) - cross-sectional and panel regressions, with and without the interactions with routineness (the β_o coefficients). For ease of interpretation, Figure 9 plots the implied values from the regression coefficients for occupations at the 25th and 75th percentile of routineness. The solid lines plot coefficients from the cross-section model, while the dashed lines are from panel regressions. The tenure premium increases substantially for occupations in the 25th percentile of routineness, with wage growth of more than 20 percent after 20 years in the cross-sectional model. However, I find almost no wage growth beyond 4 years for occupations at the 75th percentile of routineness.

Results from panel regressions are very similar, with substantial tenure premia in nonroutine occupations but no growth at all in routine occupations. Since these estimates are identified only from within-worker switching, they strongly suggest that nonroutine jobs offer much greater opportunities for workers to earn higher wages as they gain experience.[25]

4.4 Explaining Life Cycle Growth in the College Wage Premium

The results above show that college graduates are highly sorted into nonroutine, professional occupations with higher returns to job tenure, and that this sorting happens almost immediately after they complete schooling. How much of the life cycle growth in the college wage premium can be explained by occupational sorting? I answer this in two ways. First, I project future wages based on NLSY79 respondents' first post-schooling occupation. Specifically, I compute average wages by occupation and age for the NLSY birth cohorts (1958 to 1965) using the March CPS, and then I compare the actual path of log wage growth to projected

[25] This complements a large literature studying the returns to job tenure and seniority (e.g. Abraham and Farber 1987, Dustmann and Meghir 2005, Bagger et al. 2014). Lagakos et al. 2018 find flatter wage growth in manual occupations compared to "cognitive" occupations.

wages from the CPS.

Figure 10 compares the actual college wage premium by age (and work experience) to a projection of the expected college wage premium based on the wage path by age of a respondent's first post-schooling occupation. The projected wage path assumes that workers keep the first job they held after completing full-time schooling and that they receive the wage by age in that occupation from the March CPS. The projected college wage premium still more than doubles over the life cycle despite these restrictions, from 0.09 at age 28 to 0.23 at age 58. The actual college wage premium in the NLSY79 grows from 0.16 at age 28 to 0.44 at age 58. Thus, about half of the total growth in the college wage premium can be explained only by first occupation.

Second, I estimate versions of the non-parametric Mincer model in equation (2), augmented with occupation-by-tenure fixed effects. This specification compares college graduates to less educated respondents working in the same occupation for the same amount of time. The results are in Figure 11. The solid line shows the same estimates from Figure 3, while the dashed line adds occupation-by-tenure fixed effects.

Figure 11 presents the results from Figure 3 next to an augmented version of equation (2) that also includes occupation-by-tenure fixed effects. This reduces the college wage premium at 10 years of experience from 42 percent to 24 percent, and from 57 percent to 33 percent at 30 years of experience. Overall, adding occupation-by-tenure fixed effects to equation (3) explains about half of the life cycle growth in the college wage premium. Appendix Figure A9 shows qualitatively similar results when also adding AFQT scores interacted with two-year work experience bins. Overall, occupational sorting explains about half of the growth in the college wage premium according to both approaches above.

5 Model

Why do wages grow faster for educated workers? The evidence presented above shows that a key reason is occupational sorting. Soon after completing schooling, college graduates sort into professional, nonroutine occupations with high returns to job tenure. Less educated workers hold routine jobs with lower returns to tenure, both before and after completing high school. As a result, the educational wage differentials grow steadily throughout the life cycle. Overall, occupational sorting explains about half of the life cycle growth in the college wage premium.

These facts are difficult to reconcile with existing economic models of human capital and wage determination. In the pioneering work of Mincer (1974), workers maximize the present discounted value of lifetime earnings by working and investing in human capital, and the rate of return to investment is constant over time for individuals (Heckman et al. 2006, Lemieux 2006c).[26] In the influential supply-demand-institutions (SDI) framework, low- and high-skilled labor groups are taken as given, and the college wage premium is determined by the race between growing relative supply of college graduates and growing relative demand from skill-biased technology (Tinbergen 1975, Goldin and Katz 2007, Acemoglu and Autor 2011).[27] How does educational investment affect the growth of human capital over a worker's career? If some jobs are "dead ends" with little opportunity for advancement but others foster learning and skill development, how does the aggregate economy sort workers into jobs of each type?

The goal of this section is to develop a parsimonious model of human capital investment

[26]Heckman et al. (2006) show that Mincer (1974) approximates a Ben-Porath (1967) model where learning investment on-the-job declines linearly in years of experience. Mincer (1974) allows for individual heterogeneity in the rate of return to schooling investment, but assumes that schooling levels are exogenous. The quadratic in work experience emerges from the constant rate of return assumption plus the fact that the horizon over which investments can pay off decreases linearly with age. In Mincer (1958), agents are identical, occupations require different amounts of training, and the return to schooling is a compensating differential that is balanced against foregone earnings.

[27]The task framework of Acemoglu and Autor (2011) adds occupational sorting to the SDI framework, and Vogel (2023) adds the minimum wage, although in both papers the college wage premium does not evolve over time for an individual worker.

and wage dynamics that explains these patterns. I begin with Ben-Porath (1967), which treats human capital investment as an intertemporal optimization problem. Workers maximize the present discounted value of lifetime consumption by allocating time between human capital investments and market work. Current skill investment augments future productivity. The incentive to invest declines throughout the life cycle, because there are fewer years left to recoup lost time work time.

I add occupational sorting to an otherwise standard Ben-Porath (1967) model. Workers vary in their ability to learn, and jobs vary in complexity. Faster learners endogenously complete more schooling and sort into complex jobs, which have greater returns to scale in learning investment. The college wage premium increases with labor market experience because of sorting, but also because of greater scope for on-the-job learning in complex occupations. This helps explain why the wage premia to cognitive skill and education are both increasing over the life cycle, and also why occupational sorting explains a substantial share, but not all, of the growth in relative wages for college graduates.

I close the model by nesting human capital investment into a CES production function with imperfect substitution across occupations as in Katz and Murphy (1992) and Goldin and Katz (2007). The structure of the aggregate economy is isomorphic to their SDI model, except with wages adjusting until the marginal workers is indifferent between routine and complex occupations rather than low- and high-skilled worker groups. I also show how the baseline model can be generalized to incorporate leisure, task-specific human capital, learning-by-doing, multiple occupations, and other extensions.

The model is deliberately simple and abstracts away from task-specific human capital, imperfect competition, asymmetric information, and other realistic features of labor markets. I discuss how some of these features could be incorporated into the baseline model in Section 5.4.

5.1 Setup

I begin with a standard Ben-Porath (1967) model and extend it to allow for heterogeneous learning ability and job complexity. The worker's problem is:

$$\max_{s} \sum_{t=1}^{T} \beta^{t-1} w_{kt} \left(1 - s_t\right) \tag{8}$$

$$s.t.\ s_t = 1 - l_{kt}\,;\ 0 \leq l_{kt} \leq 1; 0 \leq s_t \leq 1 \tag{9}$$

$$w_{kt} = w\left(h_t, A_{kt}, \overrightarrow{L_{kt}}, \sigma\right) \tag{10}$$

where k indexes occupations and t indexes years, and β is a discount factor.[28] Workers retire exogenously at time $T > t$ and choose skill invesment s to maximize the present discounted value of lifetime earnings (wages w_{kt} times labor supply l_{kt}), subject to a time allocation constraint. Wages depend on human capital h_t, but also on occupation skill prices A_{kt}, total labor supplied in the aggregate economy to each occupation type $\overrightarrow{L_{kt}}$, and the elasticity of substitution between occupations σ.

Time at work increases earnings, but skill investment increases earnings potential. The production function for human capital is:[29]

$$h_{kt+1} = h_{kt} + \alpha \left(s_t h_{kt}\right)^{\theta_k} \tag{11}$$

with $0 < \theta_k < 1$ and $h_{k1} > 0$ by assumption. Future human capital is a function of current human capital and time spent investing (s_t). The scale parameter $\alpha > 0$ represents the worker's learning ability following Neal and Rosen (2000) and Huggett et al. (2006),

[28] $\beta = \frac{1}{1+r}$, where r is the economy-wide interest rate (e.g. individuals can borrow and lend freely at rate r).

[29] The human capital production function in Ben-Porath (1967) also includes market goods, and sometimes includes a depreciation term δ, e.g. $h_{t+1} = (1-\delta)\, h_t + \alpha \left(s_t h_t\right)^{\theta_k}$. I omit market goods for simplicity, and I omit the depreciation term because the empirical results in Section 4 show no evidence of wage declines through age 60.

with individual subscripts suppressed for notational convenience. Faster learners acquire more human capital per unit of time invested. The share parameter θ_k represents the output elasticity of investment in human capital, and is specific to occupation k. Jobs with higher θ_k allow for greater returns to scale in human capital investment.

5.2 Equilibrium with one occupation

With only one occupation (e.g. $\theta_k = \theta$), the model has a standard solution that involves transforming equations (8) through (11) into a dynamic programming problem (e.g. Heckman et al. 1998, Neal and Rosen 2000, Huggett et al. 2006, Sanders and Taber 2012).[30] Appendix Figure A10 presents simulated wage growth and optimal human capital investment over the life-cycle for individuals with different values of α and θ_k.[31]

Workers with the same learning ability have higher wages in complex occupations, and the gap grows with work experience. Moreover, higher learning ability leads to higher wages even among workers in the same occupation, and again the gap grows with work experience. This is because α and θ_k are complements in equation (11). Optimal human capital investment is increasing in θ_k because of greater returns to scale, and wage growth is greater for workers who spend more time in formal schooling.[32]

The empirical analog of learning ability is the AFQT score, which has been used in many studies as a measure of innate or pre-market ability (e.g. Neal and Johnson 1996, Altonji

[30]Rewrite the model as a Bellman equation with human capital as the only state variable $V_t\left(h_t\right) = \max_s \left(1 - s_t\right) h_t + \beta V_{t+1}(h_{t+1})$, normalizing $w_t = h_t$ for simplicity. Since human capital investment is concave in s and the problem for the last period is just $V_T\left(h_T\right) = \max_s \left(1 - s_T\right) h_T$, s_T must equal 0, and then iterate backward from there to find the optimal investment path. When $0 < s_t^* < 1$, it must be true that $h_t s_t^* = \left[\alpha\beta\left(\frac{\partial V_{t+1}(h_{t+1})}{\partial h_{t+1}}\right)\right]^{\frac{1}{1-\theta}}$, which implies that human capital investment $h_t s_t$ is decreasing in t (since the value of future investment declines over time and eventually reaches zero at $t = T$). Investment is increasing in α, β, and θ but not initial skill h_1 (e.g. Ben-Porath neutrality).

[31]For simplicity I assume that $w_{kt} = h_t$ as in the case where occupations are perfect substitutes, and I set wages equal to zero in years where individuals are not working (e.g. $s_t = 1$). The parameter values in Appendix Figure A10 are $\beta = 0.95$, $h_0 = 1$, $\alpha = 0.4$ and $\alpha = 0.5$ for low and high learning ability respectively, and $\theta_k = 0.4$ and $\theta_k = 0.5$ for routine and nonroutine occupations respectively.

[32]Following the literature (e.g. Ben-Porath 1967, Sanders and Taber 2012), I assume that $s = 1$ corresponds to formal schooling whereas values of s between 0 and 1 represent on-the-job training and skill investment. Also, note that earnings growth is higher than wage growth, because workers spend less time investing as t approaches the final period $\widehat{t}$.

et al. 2012). Several studies model schooling as a signal of productivity and AFQT as *true* productivity, which is unobserved initially and has to be learned by employers (Farber and Gibbons 1996, Altonji and Pierret 2001, Lange 2007, Aryal et al. 2022) Empirically, these studies find a positive interaction between AFQT and potential experience and a negative interaction with schooling, suggesting that the schooling "signal" becomes less important as employers learn about productivity.[33] A key assumption is that worker productivity is a static object to be learned over time. In contrast, I model AFQT as the *ability to learn*, which has a dynamic impact on schooling decisions and productivity throughout the life cycle.[34]

The empirical analog of θ_k is complexity, or non-routineness. Conceptually, returns to investment diminish more rapidly in routine jobs because they are simpler and more predictable, so there is less to learn (Autor et al. 2003). Bayer and Kuhn (2019) study the importance of "job levels", with the levels corresponding to increasing complexity, autonomy, and responsibility within an occupation. However, variation in average job level *across* occupations positively predicts life cycle wage growth. θ_k could also vary across firms - Gregory (2020) and Arellano-Bover and Saltiel (2021) find wide variation in wage growth across firms using matched employer-employee data. A final useful comparison is to the θ parameter in Deming (2017), which indexes the scope for comparative advantage in team production. Intuitively, the gains from learning - either from one's own experience or from others - should be smaller when there is a well-established correct way to perform many of the tasks required in a job.

[33]However, Castex and Kogan Dechter (2014) find that this pattern only holds in the NLSY79, not the NLSY97, where the coefficients on both interactions are not statistically distinguishable from zero. The results here are consistent with signaling and human capital both contributing to estimated returns in equilibrium.

[34]Aryal et al. (2022) modify the employer learning model by allowing the returns to skill to vary with experience. But their model assumes that ability and schooling are separable, whereas they are complements in the human capital production function in (11) and learning ability has a direct impact on the schooling investment decision.

5.3 Equilibrium with two occupations

In the standard Ben-Porath (1967) model, there is only one occupation in the economy (e.g. $\theta_k = \theta$) and wages are equal to human capital times some exogenous skill price (e.g. $w_{kt} = Ph_{kt}$, or $w_{kt} = h_{kt}$ with P normalized to 1). As I show below, the model nests this as a special case where $\sigma \to \infty$ and skill supplies do not matter because occupations are perfect substitutes. To close the model and gain some intuition for occupational sorting, we need some additional assumptions and an expression for wages.

For simplicity, I assume that workers are hired by identical firms at $t = 1$ into one of only two occupations - routine or complex (R and C respectively), with $L_{kt} = L(R_t, C_t)$ and $\theta_c > \theta_r$ by assumption. Workers then accumulate human capital according to (11) until they retire exogenously at time T. All workers begin with $h_{k1} = \widetilde{h}$. With perfect information and competitive markets, workers simultaneously choose their occupation (R or C) and the implied income-maximizing skill investment, labor supply, and leisure schedules for all future years from $t = 1$ to $t = T$, subject to the annual time constraints in equation (9).

Notice that wages for any given worker with learning ability α are always higher in complex occupations. Thus if $w_{kt} = h_{kt}$, all workers would sort into the complex occupation and the model would collapse to the standard Ben-Porath (1967) framework. If the economy requires some routine output, however, wages should adjust until some workers benefit from working in routine jobs.

I formalize this by assuming that the aggregate economy operates with a constant elasticity of substitution (CES) production function, which combines inputs from workers in routine and complex jobs to produce a single composite good Y:

$$Y = \left[A_r \left(\overline{H_r} R\right)^{\frac{\sigma-1}{\sigma}} + A_c \left(\overline{H_c} C\right)^{\frac{\sigma-1}{\sigma}}\right]^{\frac{\sigma}{\sigma-1}} \tag{12}$$

where $\sigma \in [1, \infty)$ is the elasticity of substitution between routine (R) and complex (C) task output, $\overline{H_r}$ and $\overline{H_c}$ are the average human capital stock of workers in each occupation category, and A_r and A_c are exogenous market prices for each occupation type.[35] R and C are the total labor supplied to each occupation, which are simply "added up" across workers (e.g. workers are perfect substitutes in task output, $R = \sum_r l_r$ and $C = \sum_c l_c$).[36] I also assume that workers with the same human capital are perfect substitutes (e.g. no cohort effects) and that aggregate labor supply and the distribution of learning ability across workers $f(\alpha)$ are stationary.[37]

Wages are equal to marginal products in each occupation. Differentiating equation (12) with respect to C and R, computing the ratio and taking logs yields the following expression for relative wages:

$$\ln\left(\frac{w_c}{w_r}\right) = \ln\left(\frac{A_c}{A_r}\right) + \frac{\sigma-1}{\sigma}\ln\left(\frac{\overline{H_c}}{\overline{H_r}}\right) - \frac{1}{\sigma}\ln\left(\frac{C}{R}\right) \tag{13}$$

Wages depend on relative productivity but also on skill supplies, according to σ. As $\sigma \to \infty$, occupation types become perfect substitutes. In that case, relative wages equal relative skill prices plus relative human capital, skill supplies don't matter and all workers will enter the complex sector θ_c where they are most productive.

However, if occupations are imperfect substitutes, the economy needs some routine jobs and wages will adjust through the third term in equation (13) to make the marginal worker indifferent between sectors. In the limiting case of $\sigma = 1$ the production function is Cobb-Douglas, with fixed shares paid to each occupation type. More generally, equation (13) shows that an increase in the relative supply of complex occupations reduces the wage premium in complex occupations with an elasticity of $\frac{1}{\sigma}$. Imperfect substitution compresses relative wages through a labor supply effect, which makes some marginal workers switch into routine

[35]The aggregate production function in equation (12) applies in every period, so I suppress time subscripts for notational convenience.

[36]I assume away the case of $\sigma < 1$ (routine and nonroutine occupations as gross complements) because it is not intuitive (it implies, for example, that an increase in the relative productivity of nonroutine occupations will *decrease* relative wages of workers in these occupations), and because the literature nearly always estimates values of σ between 1 and 2 (e.g. Acemoglu and Autor 2011).

[37]The impact of changes in aggregate labor supply over time depends on the degree of substitutability across age cohorts with the same amount of completed schooling and/or human capital - see Card and Lemieux (2001) for a model of imperfect substitution across birth cohorts.

occupations.

The equilibrium of the model is characterized by a learning ability threshold α^*, with sorting into routine and complex occupations below and above α^* respectively. Equilibrium wage differences and relative labor supplies across occupations are determined by the parameters of the model $(\beta, \theta_r, \theta_c, A_r, A_c, \sigma)$.

5.4 Mapping the Model to the Data

In equilibrium the marginal worker with $\alpha = \alpha^*$ earns the same lifetime wage in each sector. In that case, from equation (13) we have:

$$\ln\left(\frac{C}{R}\right) = \sigma \ln\left(\frac{A_c}{A_r}\right) + (\sigma - 1)\ln\left(\frac{\overline{H_c}}{\overline{H_r}}\right) \tag{14}$$

Equation (14) shows that the relative size of the complex sector is increasing in $\frac{A_c}{A_r}$ and σ. Thus "routine-biased" technological change decreases the optimal size of the routine sector by causing some marginal workers to sort into complex occupations, which shifts α^* upward (Acemoglu and Autor 2011, Goos et al. 2014). The same thing also happens in response to an increase in the distribution of learning ability $f(\alpha)$. A higher distribution of pre-market skills endogenously increases the size of the complex sector, because learning ability and job complexity are complements. This model for the aggregate economy is isomorphic to the supply-demand-institutions (SDI) framework in Katz and Murphy (1992) and Goldin and Katz (2007), except with complex and routine occupations rather than low- and high-skilled labor groups.[38]

The model yields two explanations for growing life cycle returns to cognitive skill and education. The first reason is *sorting* - workers with higher learning ability α will spend more time in school regardless of their occupation, and wage growth is increasing in learning

[38] The model could also explain job polarization simply by adding a third occupation group and changing either relative technology terms or relative values of θ_k. This differs from the mechanism in the task framework of Acemoglu and Autor (2011), which assumes three exogenous worker skill groups (low, middle, and high), a continuum of tasks arranged by complexity, and a Ricardian comparative advantage structure governing the assignment of skill groups to tasks.

ability. We can see this in Appendix Figure A10, which shows how α affects optimal schooling investment for any given θ. This could be interpreted as "ability bias" in the estimated return to schooling (e.g. Griliches 1977, Blackburn and Neumark 1993, Lang 1993).

The second reason is *returns to scale in learning* - wages grow faster in complex jobs even after conditioning on learning ability and completed schooling. Appendix Figure A10 also shows the impact of increasing θ holding α constant. This captures the causal college wage premium for a worker with any given learning ability, and can be computed in the model by comparing workers with $\alpha \approx \alpha^*$ who are right on the margin of working in a routine or complex occupation. The total college wage premium is the sum of these two mechanisms.

In the model, the causal return to education is increasing in $\frac{A_c}{A_r}$ and decreasing in σ. The impact of skill bias is obvious, because it augments the relative productivity of complex occupations. To see why the return to education is decreasing in σ, consider the limiting cases when $\sigma = 1$ and $\sigma \to \infty$. When $\sigma = 1$, $\frac{w_c}{w_r} = \left(\frac{A_c}{A_r}\right)\left(\frac{R}{C}\right)$, and equilibrium requires that wages be equal across sectors. Otherwise workers would switch to the less abundant occupation to increase their lifetime wages regardless of the impact on their human capital h_{kt}. Thus there is no incentive to invest in schooling. When $\sigma \to \infty$, $\frac{w_c}{w_r} = \left(\frac{A_c}{A_r}\right)\left(\frac{H_c}{H_r}\right)$, relative skill supplies don't matter, and workers capture the full return on their human capital investment.[39]

The model can be extended to incorporate leisure, with workers maximize lifetime utility rather than wages (Neal and Rosen 2000, Guvenen et al. 2014, Blandin 2018, Fillmore and Gallen 2019) With standard assumptions, it delivers the result that workers of any given learning ability α^* will take less leisure in complex occupations.[40] This is because the marginal

[39] The literature studying skill-biased technological change in the U.S. finds values of σ between 1 and 2 (e.g. Katz and Murphy 1992, Autor et al. 1998, Goldin and Katz 2007, Acemoglu and Autor 2011). More recent work using cross-country data finds a higher elasticity of substitution between less- and more-educated workers, with values between 4 and 8 (Hendricks and Schoellman 2018, Bils et al. 2022).

[40] Following Guvenen et al. (2014), assume that preferences for leisure are identical across individuals and that period utility can be expressed as $u(c, l) = \log(c) + \psi\left(\frac{l^{1-\gamma}}{1-\gamma}\right)$ with ψ representing the utility weight on leisure and γ as the Frisch elasticity of labor supply, which governs the degree of diminishing returns. With this functional form we have $\frac{\partial u}{\partial l} = \frac{\psi}{l^{\gamma}}$, so that the marginal utility of leisure diminishes from infinity to the utility weight ψ as the share of time allocated to leisure ranges from 0 to 1. Fillmore and Gallen (2019) use hours data from the NLSY79 to estimate a Ben-Porath model with heterogeneous tastes for leisure and find that more than half of adult earnings variation arises from variation in taste. With leisure, the model does

return to both skill investment and market work (but not leisure) is increasing in θ_k. Consider the limiting case of the most routine job, e.g. where $\theta_k = 0$ so there is no return to skill investment and thus no wage growth. In that case the shadow price of leisure is very low, because wages are the same regardless of accumulated experience. This is consistent with several studies showing that high-wage, college-educated adults are more attached to the labor force and work longer hours, and that employment inequality has increased along with wage inequality (Bick et al. 2018, Coglianese 2018, Wolcott 2021, Mantovani 2022).

The model assumes that all post-schooling human capital is sector-specific (e.g. h_{kt}). However, one natural extension would allow for task-specific rather than occupation-specific human capital, which permits on-the-job learning to transfer partly across jobs that share similar tasks (e.g. Gathmann and Schönberg 2010). Similarly, I could allow for differences across workers in initial human capital. Workers with higher initial human capital would have higher lifetime earnings, but would choose *less* schooling over the life-cycle because of diminishing returns (Ben-Porath 1967, Neal and Rosen 2000). This justifies the choice to treat AFQT scores as learning ability rather than human capital, since they are positively correlated with earnings growth and completed schooling.

The Ben-Porath model treats skill investment and market work as substitutes. An alternative approach is learning-by-doing (LBD), where market time l_t directly increases human capital and there is no work-schooling tradeoff (e.g. Rosen 1972, Jovanovic and Nyarko 1996, Heckman et al. 2002, Stantcheva 2015). Blandin (2018) compares the predictions of Ben-Porath (1967) to a model with learning-by-doing and concludes that the Ben-Porath model fits the data better. I assume away human capital depreciation based on empirical estimates of the Ben-Porath model, which conclude that depreciation must be modest based on the flatness of wages at the end of working life (e.g. Heckman et al. 1998, Guvenen 2006, Bowlus and Robinson 2012, Manuelli and Seshadri 2014, Blandin 2018).

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not have a closed form solution but can be solved numerically by searching over all possible schooling/labor supply combinations in each year (Blandin 2018, Fillmore and Gallen 2019).

6 Conclusion

This paper shows that the college wage premium doubles over the life cycle because of occupational sorting. Shortly after graduating, workers with college degrees obtain jobs in professional, nonroutine occupations with much greater scope for on-the-job learning and wage growth. Less educated workers hold jobs in similar occupations before and after completing schooling. Occupational sorting causes relative wages to grow especially rapidly for college graduates in the initial phase of their careers. However, after a few years, educated workers are less likely to switch jobs, yet their wages still grow relatively faster. The return to job tenure is much greater in professional, nonroutine occupations, which are disproportionately held by college graduates. I estimate that occupational sorting explains at least half of the life cycle growth in the college wage premium.

I explain these empirical patterns with a simple model of human capital investment and on-the-job learning. I show that a straightforward extension of the classic Ben-Porath (1967) model with heterogeneous learning ability and job complexity does a good job of explaining the facts described above. The key mechanism is complementarity between learning ability and job complexity. Faster learners obtain more education and sort into complex (nonroutine) jobs which have greater returns to learning investment. The model shows how to naturally build human capital investment and wage dynamics into the canonical supply-demand-institutions (SDI) framework of Katz and Murphy (1992) and Goldin and Katz (2007).

This paper highlights the crucial role of human capital accumulation on-the-job for understanding life-cycle earnings inequality. While some jobs are "dead ends" with little opportunity for learning, others afford greater opportunities for skill development. The sorting of educated workers into complex occupations contributes greatly to life-cycle earnings disparities by education. Understanding how to design jobs so that workers can develop expertise and increase their productivity with experience is an important priority for future work.

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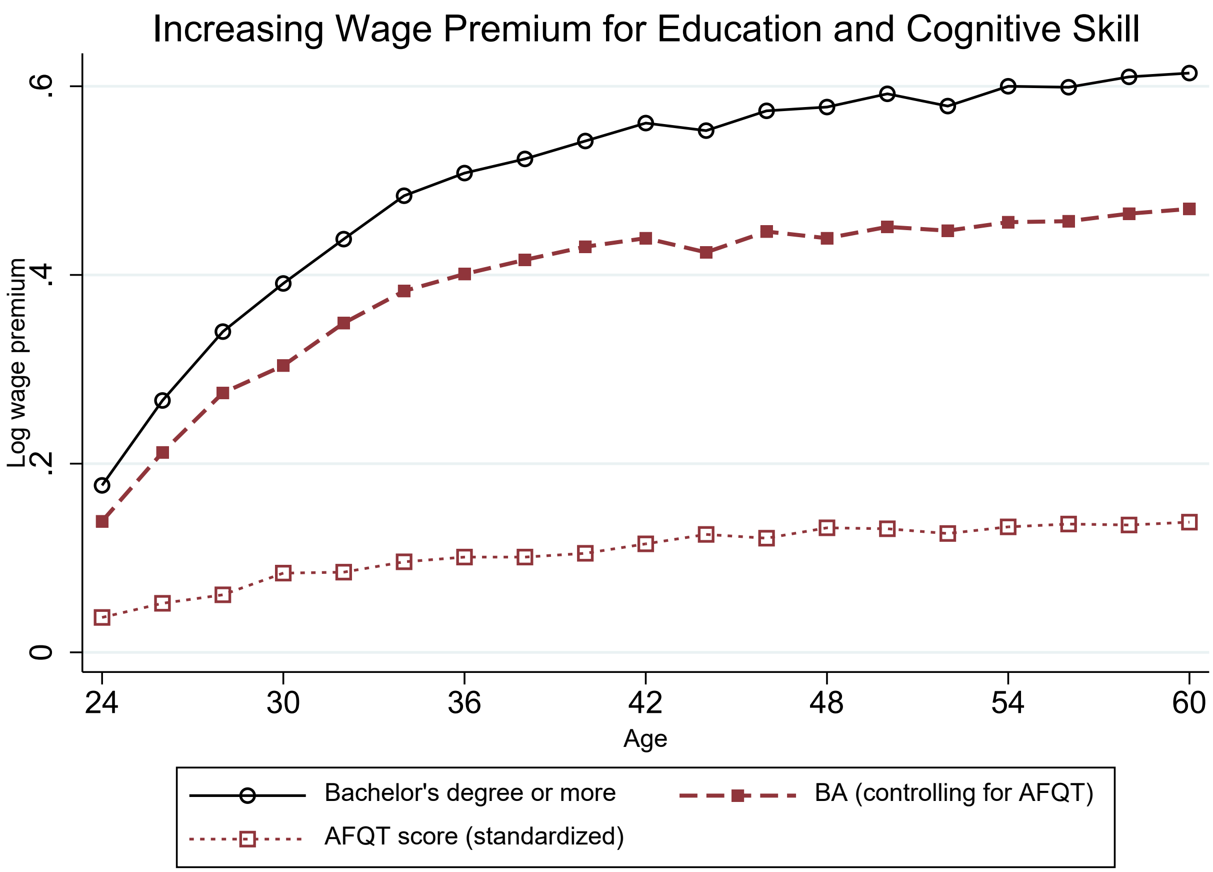
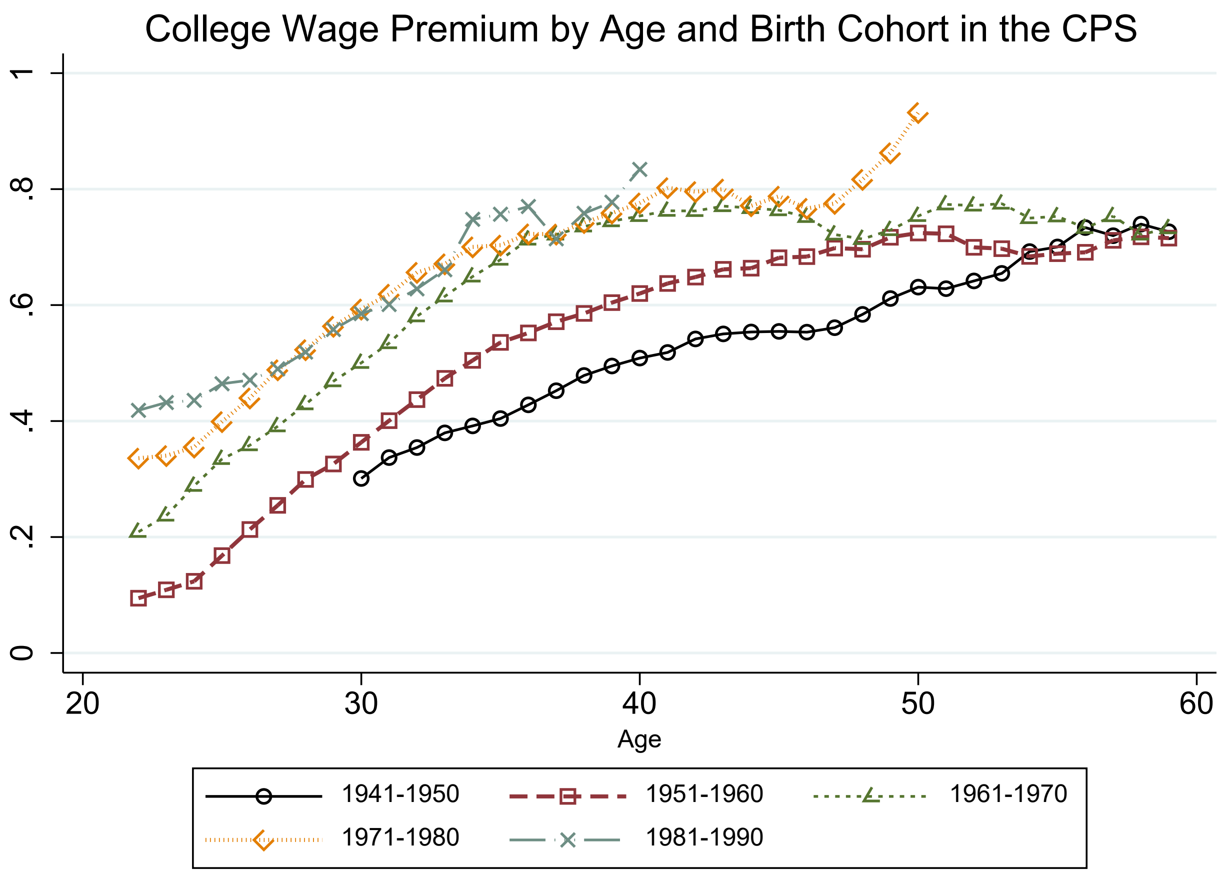
Figure 1



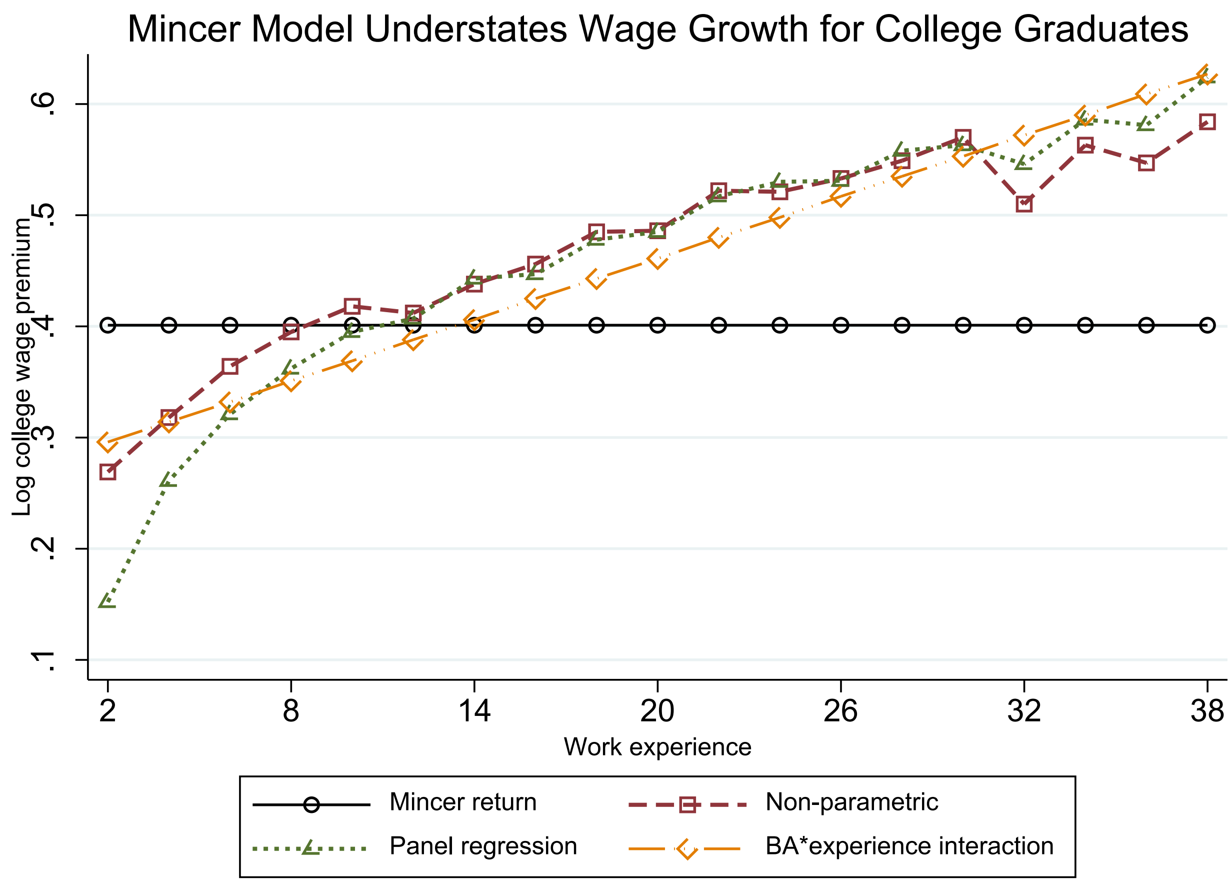
Notes: Figure 1 presents estimates of equation (1) in the paper - separate regressions of log hourly wages on two-year age bins and individual fixed effects. The solid line adds interactions of age with an indicator for having a bachelor's degree or more. The dashed line plots education by age interactions, also controlling for interactions between age and the respondent's Armed Forces Qualifying Test (AFQT) score (the dotted line), which is normalized to have mean zero and standard deviation one. The data come from the NLSY79, ages 22-60.

Figure 2



Notes: Figure 2 presents results from separate regressions of the log wage difference between workers with a bachelor's degree or more and workers without a college degree on indicators for age and birth cohort fixed effects for each ten year grouping of birth cohorts in the 1980-2020 March CPS. The regression is labor supply-weighted and includes ages 21 to 59.

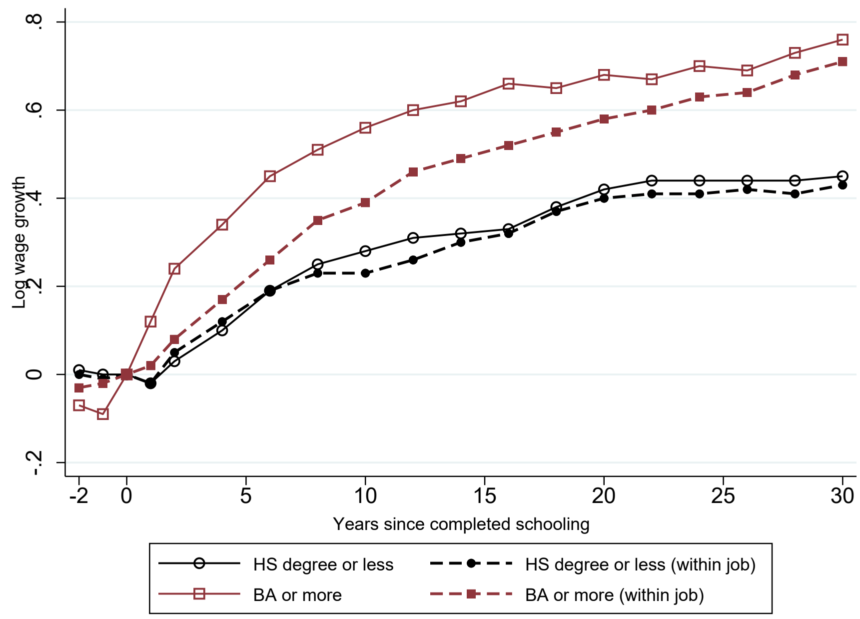
Figure 3



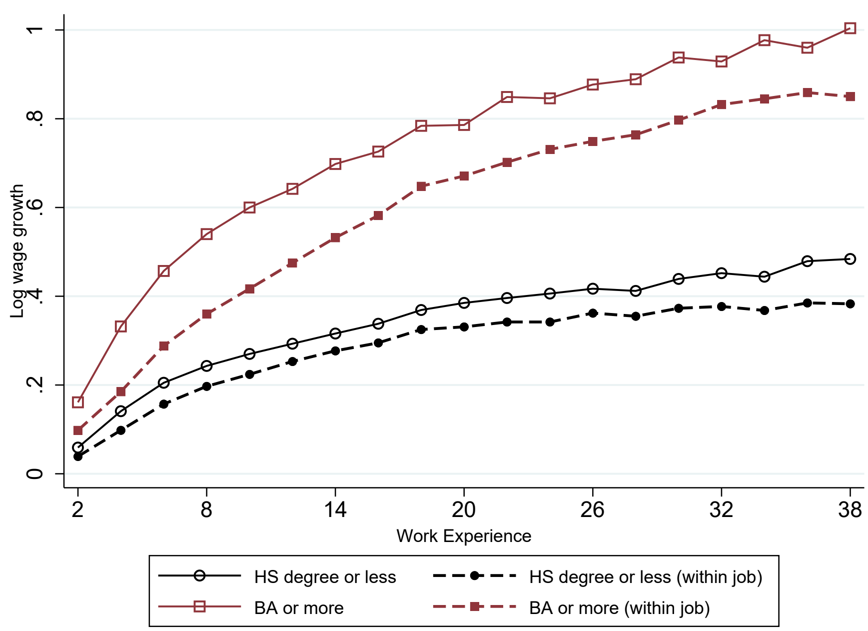
Notes: Figure 3 presents estimates of equations (2) and (3) in the paper, with log hourly wages regressed on education and actual experience (one year = 2,080 hours). The line labeled "Mincer return" is the (constant) coefficient on an indicator for having a bachelor's degree in a Mincerian earnings regression. The line labeled "Non-parametric" is the coefficients from an estimate of equation (2), with BA interacted with two-year work experience bins plus controls for race, gender, year, and age. The panel regression adds individual fixed effects. The line labeled "BA*Exp interaction" presents implied values from an estimate of equation (3), which modifies the Mincer model with a linear interaction between BA and work experience. The data come from the NLSY79, ages 22-60.

Figure 4

Panel A – Wage Growth by Years since Completed Schooling

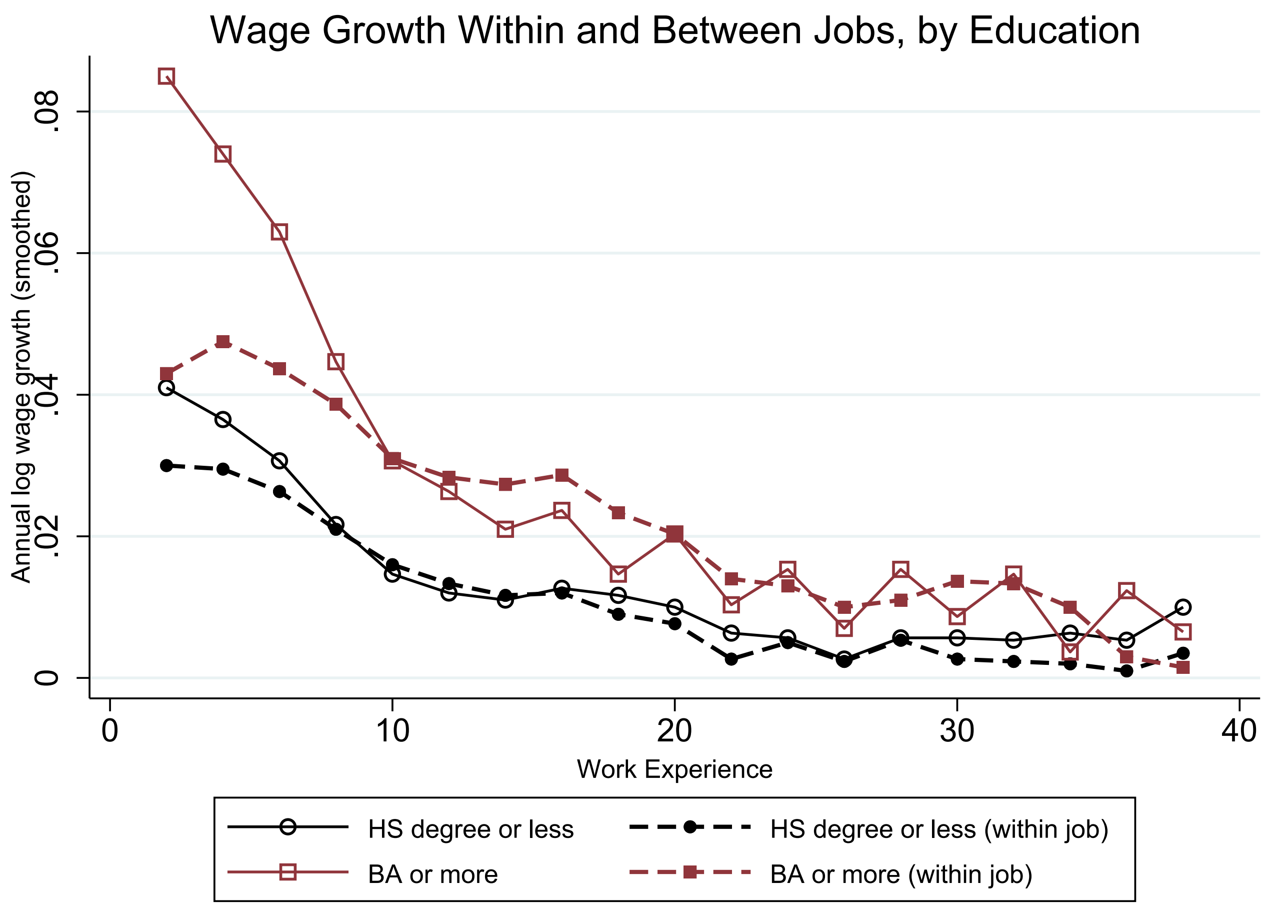


Panel B – Wage Growth by Years of Actual Work Experience



Notes: Figure 4 presents estimates of equation (5) in the paper, with log hourly wages regressed on indicators for years since the last survey wave in which a respondent is enrolled full-time in school (Panel A) or two-year bins of actual work experience (one year = 2,080 hours), plus individual fixed effects (the solid lines) or individual-by-job fixed effects (the dashed lines). The regressions are estimated separately for workers with a high school degree or less (black lines, circle markers) and with a bachelor's degree or more (red lines, square markers). The data come from the NLSY79, ages 19-60.

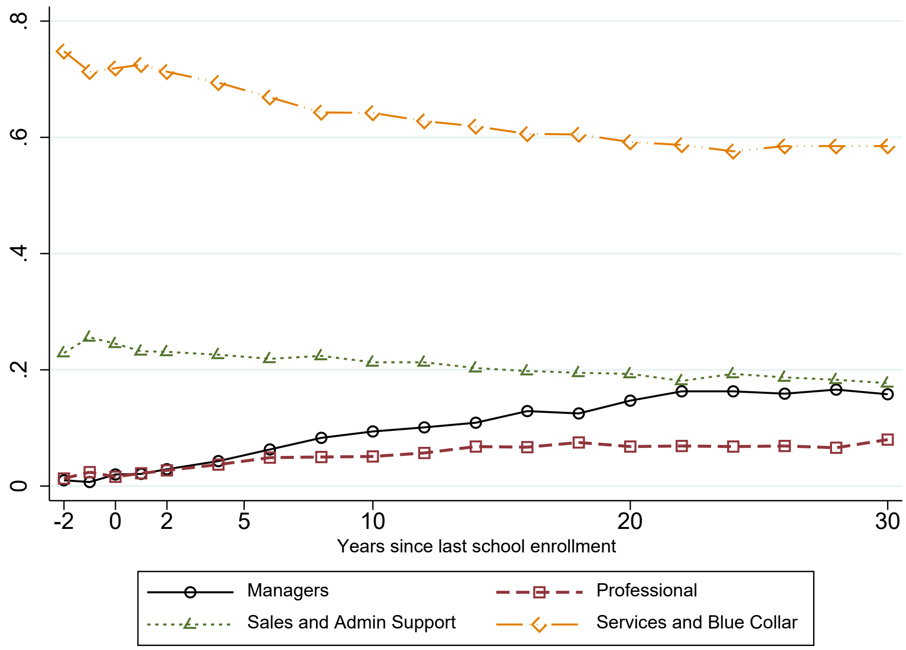
Figure 5



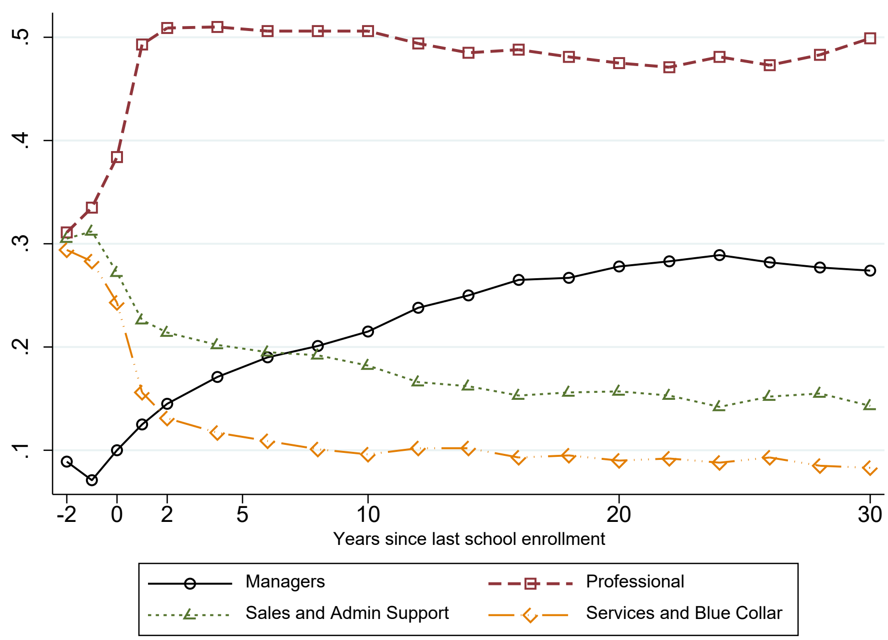
Notes: Figure 5 presents results from four separate estimates of equation (5) in the paper, with log hourly wages regressed on two-year bins of actual work experience plus individual fixed effects (the solid lines) or individual-by-job fixed effects (the dashed lines). The regressions are estimated separately for workers with a high school degree or less (black lines, circle markers) and with a bachelor's degree or more (red lines, square markers). After obtaining the estimates, I convert them into annual growth measures and then smooth them using a five-year moving average. The data come from the NLSY79, ages 19-60 for workers with a HS degree or less and ages 23-60 for workers with a BA or more.

Figure 6

Panel A – Occupations Held by Workers with a HS Degree or Less

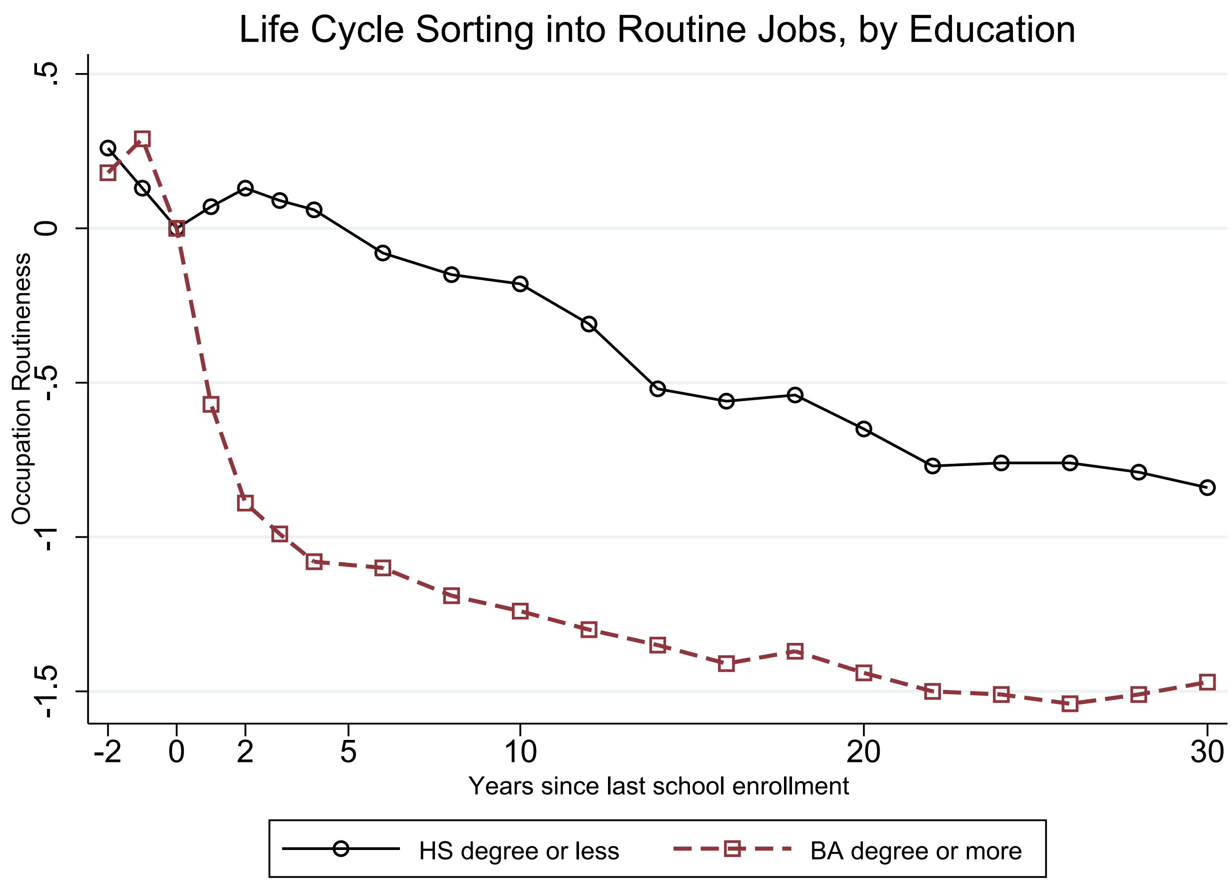


Panel B – Occupations Held by Workers with BA Degree or more



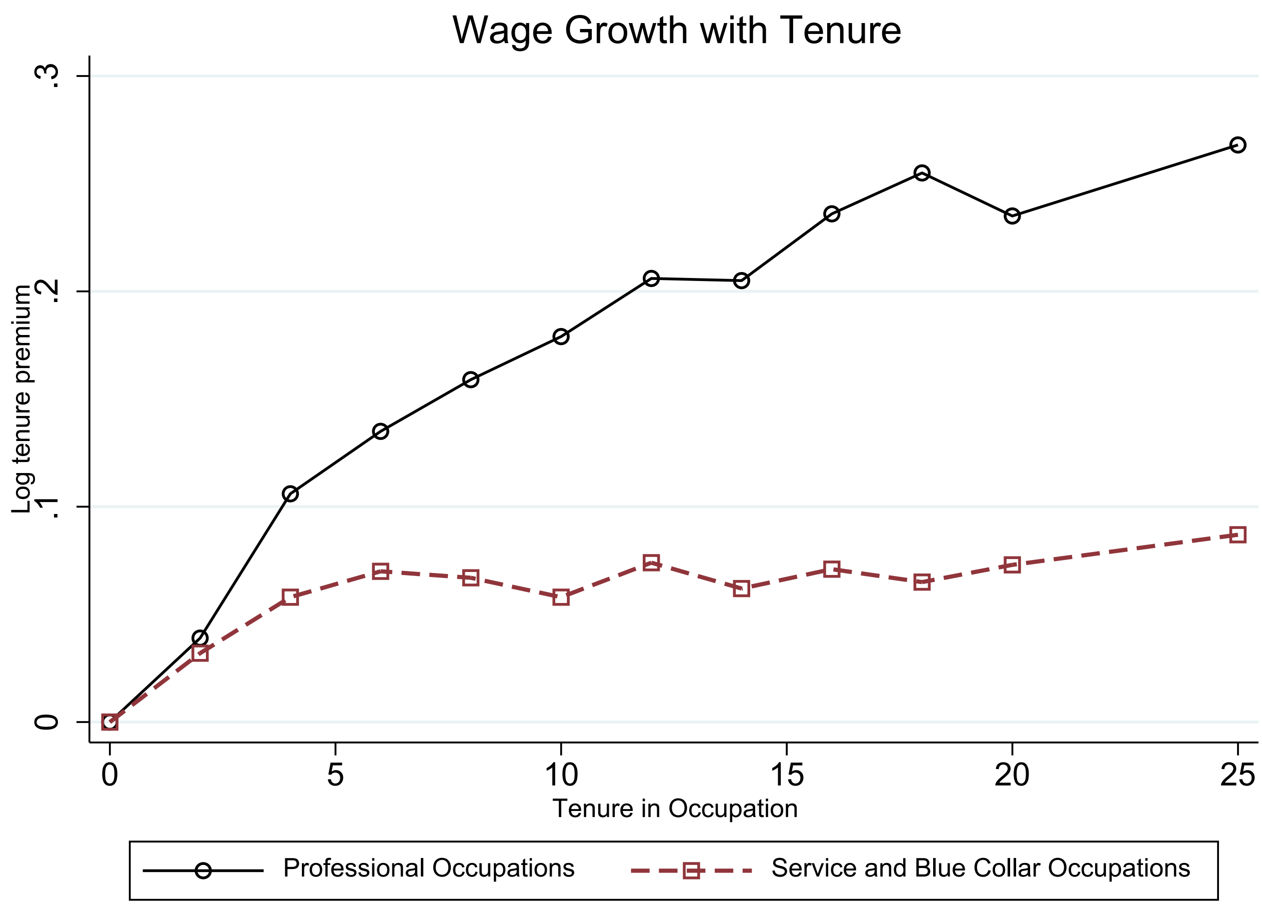
Notes: Figure 6 presents estimates of equation (4) in the paper, with occupation categories regressed on indicators for years since the last time a respondent is enrolled full-time in school and individual fixed effects. Professional, sales/admin support, and services/blue collar correspond to occ1990dd codes 23-235, 243-399, and 400 and above respectively. Mangement includes codes 4-22, and also a series of codes indicating supervisors of workers in the other categories. The data come from the NLSY79, ages 19-60.

Figure 7



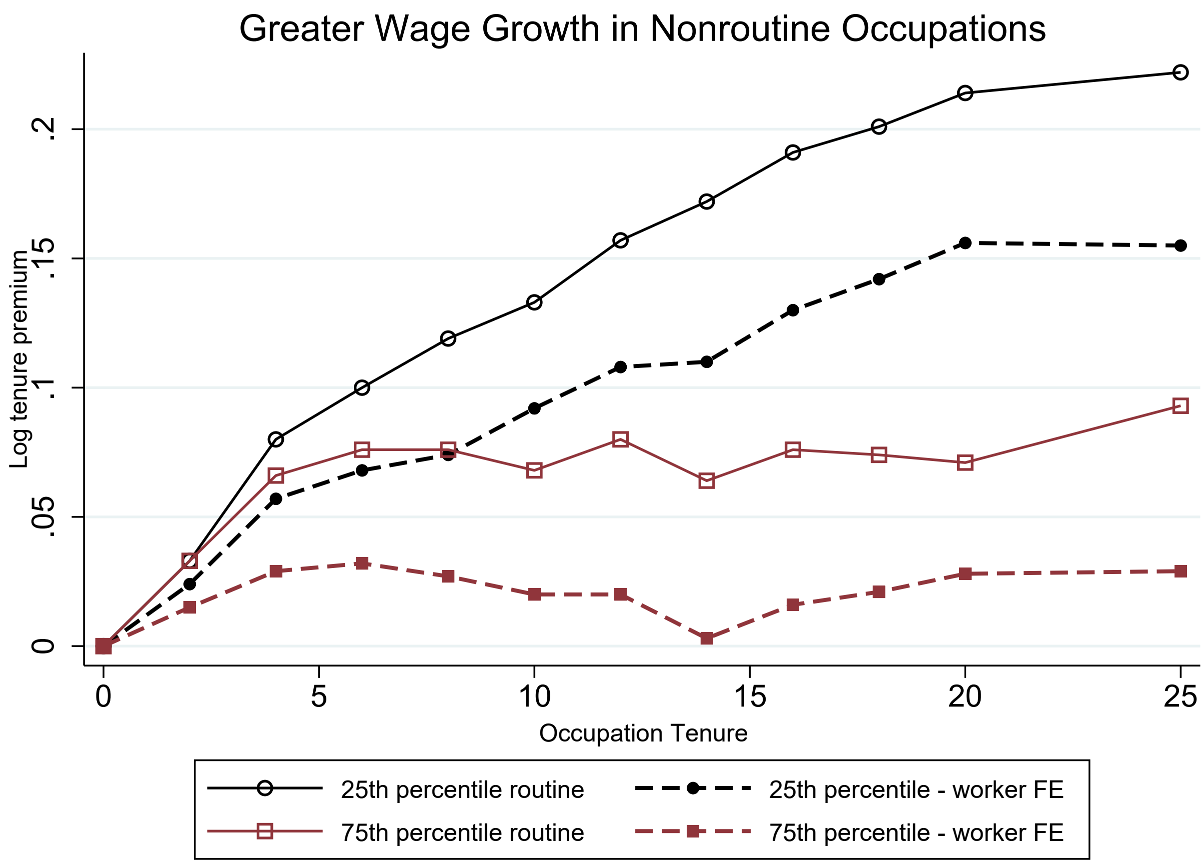
Notes: Figure 7 presents estimates of equation (4) in the paper, with occupation routineness regressed on indicators for years since the last time a respondent is enrolled full-time in school and individual fixed effects. The routineness measure comes from the 1998 O*NET, rescaled to take values between 0 and 10 representing each job's percentile rank in the labor supply-weighted distribution of employment in the 2017-2019 American Community Survey. The data come from the NLSY79, ages 19-60.

Figure 8



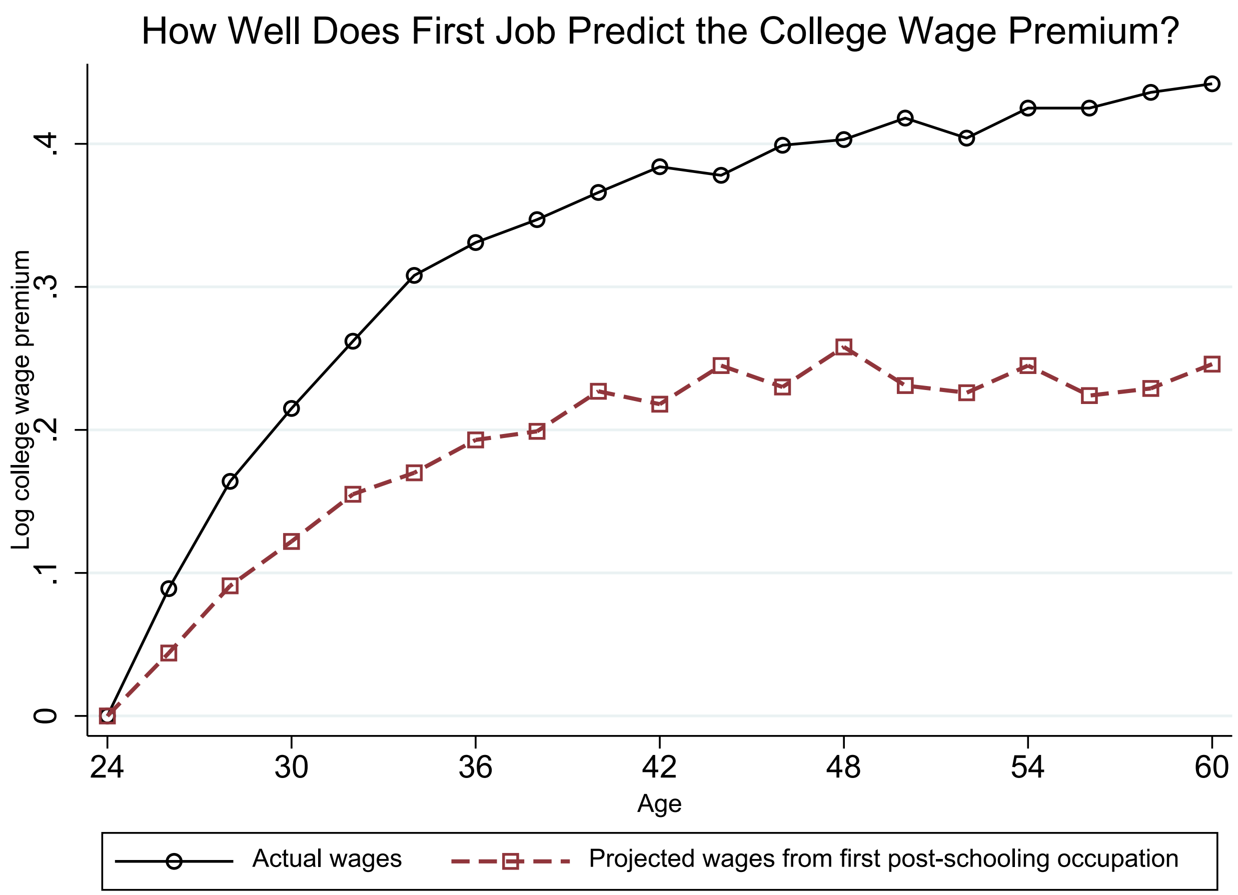
Notes: Figure 8 presents separate regressions by occupation category of equation (6) in the paper, with log wages regressed on indicators for 2-year bins of occupation tenure plus controls for work experience, age, education, AFQT score, race and gender, employer tenure, and occupation fixed effects (which removes level differences in wages and focuses only on the slope with tenure). Professional and services/blue collar correspond to occ1990dd codes 23-235 and 400 and above respectively. The data come from the NLSY79, ages 19-60 and from the NLSY97, ages 19-40.

Figure 9



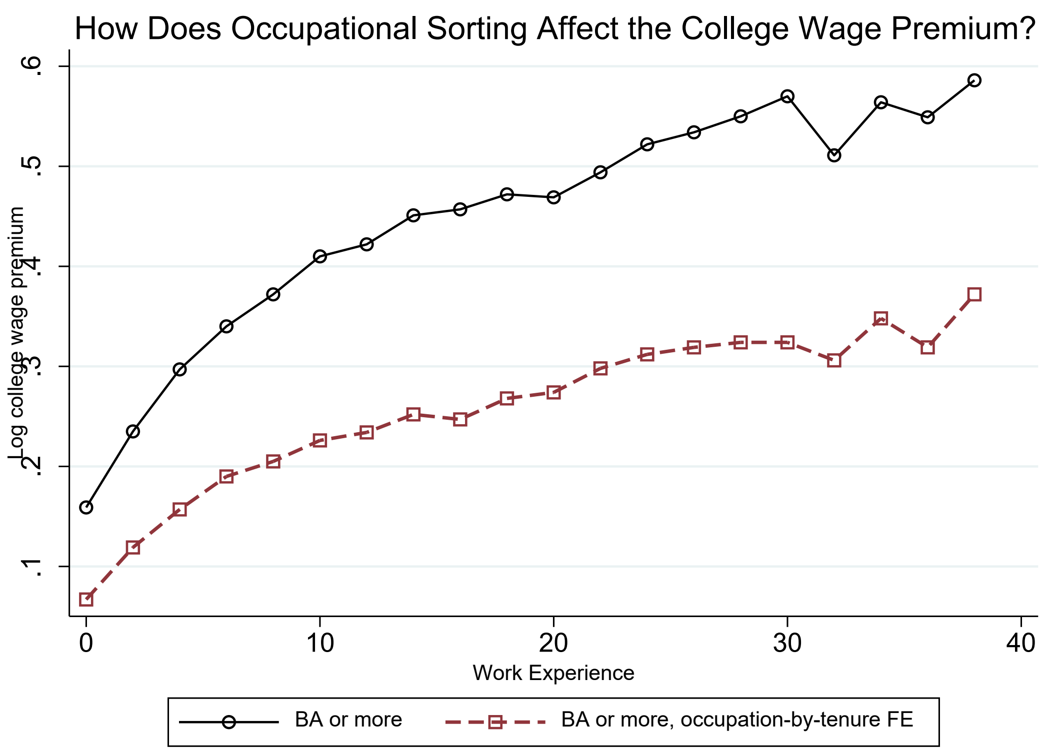
Notes: Figure 9 presents implied values for occupations at the 25th and 75th percentile of routineness from an estimate of equation (6) in the paper, with log wages regressed on indicators for 2-year bins of occupation tenure interacted with job routineness, plus controls for work experience, age, education, AFQT score, race and gender, employer tenure, and occupation fixed effects (which removes level differences in wages and focuses only on the slope with tenure). The dashed lines include individual fixed effects, which identify the coefficients only from within-worker job switching. Regression results with standard errors are in Table 2. The routineness measure comes from the 1998 O*NET data and is rescaled to range from 0 to 10 where 5 is the routineness of the median job in the pooled 2017-2019 American Community Survey. The data come from the NLSY79, ages 19-60 and the NLSY97, ages 19-40.

Figure 10



Notes: Figure 10 presents estimates of a regression of log hourly wages for NLSY79 respondents (the solid line) and mean log hourly wages by occupation and age in the March CPS for the same birth cohorts (the dashed line) on two-year age bins interacted with an indicator for having a bachelor's degree. The dashed line projects the expected college wage premium based on mean hourly wages by age of a respondent's first occupation after completing full-time schooling. The sample is NLSY79 respondents age 21-60.

Figure 11



Notes: Figure 11 presents estimates of equation (2) in the paper, with hourly log wages regressed on indicators for having a bachelor's degree education interacted with two-year actual work experience bins (one year = 2,080 hours) plus controls for race, gender, year, and age. The dashed line present coefficients from the same models as above but adding occupation-by-tenure fixed effects. The data come from the NLSY79, ages 22-60.

Table 1 - Employment Outcomes by Years Since the End of Full-Time Schooling, NLSY79

	Number of Jobs Held		*Average Job Tenure*		*New Employer*		*Real Wages*	
	HS or less	BA or more	HS or less	BA or more	HS or less	BA or more	HS or less	BA or more
Career year	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
0	2.7	5.9	0.6	1.7	0.74	0.56	10.72	15.35
1	3.2	6.8	0.8	1.4	0.75	0.71	10.82	18.95
2	3.8	7.4	1.0	1.9	0.62	0.47	11.49	20.61
4	4.7	8.0	1.4	2.6	0.54	0.36	12.64	23.23
6	5.8	8.7	1.9	3.4	0.50	0.31	14.41	26.22
8	6.9	9.2	2.5	4.3	0.47	0.27	15.87	29.09
10	7.8	9.7	3.0	5.1	0.40	0.26	16.32	31.01
12	8.5	10.1	3.5	5.8	0.37	0.28	16.55	33.62
14	9.2	10.4	4.1	6.6	0.38	0.28	17.04	35.00
16	9.8	10.8	4.6	7.3	0.41	0.30	16.96	36.87
18	10.3	11.1	5.2	8.0	0.42	0.29	18.31	37.64
20	10.8	11.4	5.8	8.7	0.40	0.25	19.36	38.69
22	11.1	11.7	6.5	9.4	0.36	0.27	19.51	39.39
24	11.5	12.0	7.1	10.2	0.34	0.26	19.59	40.74
26	11.8	12.3	7.5	10.8	0.32	0.26	19.59	40.67
28	12.1	12.5	8.2	11.7	0.29	0.24	19.42	41.78
30	12.4	12.8	9.0	12.5	0.27	0.22	19.73	44.05

Notes: Table 1 presents results from a regression of the outcomes in italics above on years since the last survey wave in which a respondent was enrolled full-time in schooling (which I define as career year zero) and individual fixed effects. The odd numbered columns restrict the sample to respondents with a high school degree or less, while the even numbered columns restrict the sample to respondents with a four-year college degree or more. Number of jobs held is the number of unique employers. Job tenure is measured in years. New employer is an indicator variable equal to one if the respondent is working for a new employer in that survey year, conditional on working at all. Real wages are inflation-adjusted to 2016 dollars. The sample is the NLSY79, ages 18-60.

Table 2 - Tenure Premia by Occupation Routineness

	(1)	(2)	(3)	(4)
Occ Tenure - 1 to 2 years	0.037	0.048	0.023	0.040
	[0.002]	[0.005]	[0.002]	[0.005]
* Routineness (0-10 scale)		-0.002		-0.003
		[0.001]		[0.001]
Occ Tenure - 3 to 4 years	0.084	0.119	0.049	0.091
	[0.003]	[0.007]	[0.003]	[0.006]
* Routineness (0-10 scale)		-0.006		-0.008
		[0.001]		[0.001]
Occ Tenure - 5 to 6 years	0.099	0.142	0.054	0.105
	[0.004]	[0.009]	[0.003]	[0.008]
* Routineness (0-10 scale)		-0.008		-0.009
		[0.001]		[0.001]
Occ Tenure - 7 to 8 years	0.107	0.176	0.057	0.122
	[0.005]	[0.011]	[0.004]	[0.009]
* Routineness (0-10 scale)		-0.013		-0.012
		[0.002]		[0.001]
Occ Tenure - 9 to 10 years	0.109	0.201	0.059	0.148
	[0.006]	[0.012]	[0.005]	[0.010]
* Routineness (0-10 scale)		-0.017		-0.016
		[0.002]		[0.001]
Occ Tenure - 11 to 12 years	0.121	0.224	0.064	0.168
	[0.007]	[0.014]	[0.005]	[0.011]
* Routineness (0-10 scale)		-0.019		-0.019
		[0.002]		[0.002]
Occ Tenure - 13 to 14 years	0.120	0.254	0.057	0.176
	[0.008]	[0.017]	[0.006]	[0.013]
* Routineness (0-10 scale)		-0.024		-0.022
		[0.002]		[0.002]
Occ Tenure - 15 to 16 years	0.131	0.269	0.067	0.197
	[0.008]	[0.018]	[0.007]	[0.015]
* Routineness (0-10 scale)		-0.025		-0.023
		[0.003]		[0.002]
Occ Tenure - 17 to 18 years	0.126	0.279	0.066	0.204
	[0.009]	[0.020]	[0.008]	[0.017]
* Routineness (0-10 scale)		-0.028		-0.025
		[0.003]		[0.003]
Occ Tenure - 19 to 20 years	0.132	0.296	0.073	0.216
	[0.010]	[0.022]	[0.009]	[0.019]
* Routineness (0-10 scale)		-0.030		-0.026
		[0.003]		[0.003]
Occ Tenure - 20+ years	0.144	0.291	0.072	0.216
	[0.010]	[0.022]	[0.009]	[0.018]
* Routineness (0-10 scale)		-0.026		-0.025
		[0.003]		[0.003]
Individual Fixed Effects			X	X

Notes: This table presents results from an estimate of equation (7) in the paper, with log wages regressed on indicators for 2-year bins of occupation tenure interacted with job routineness, plus controls for work experience, age, education, AFQT score, race and gender, employer tenure, and occupation fixed effects (which removes level differences in wages and focuses only on the slope with tenure). Columns 3 and 4 also include individual fixed effects, which identifies the coefficients only from within-worker job switching. The routineness measure comes from the 1998 O*NET data, and is rescaled to range from 0 to 10 where 5 is the routineness of the median job in the pooled 2017-2019 American Community Survey.

Appendix Exhibits

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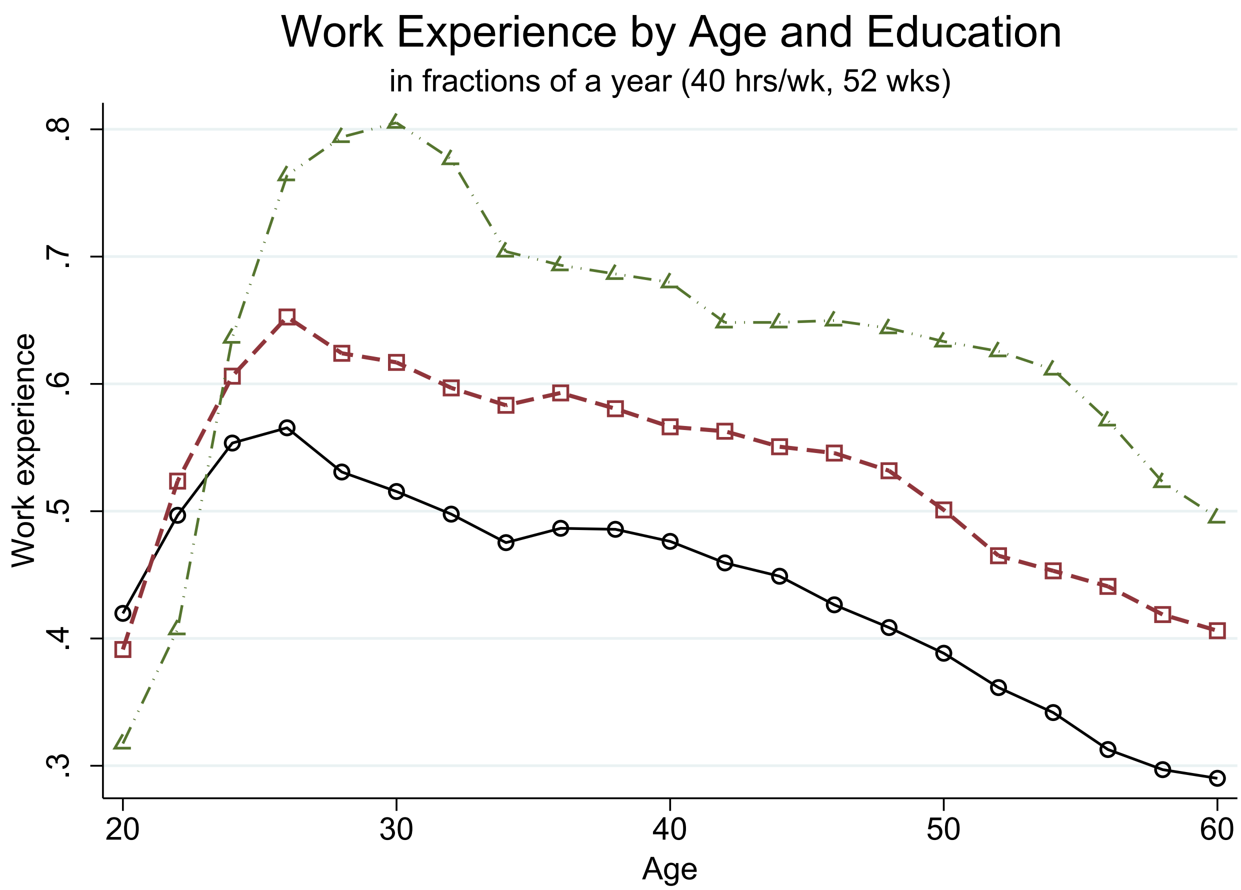
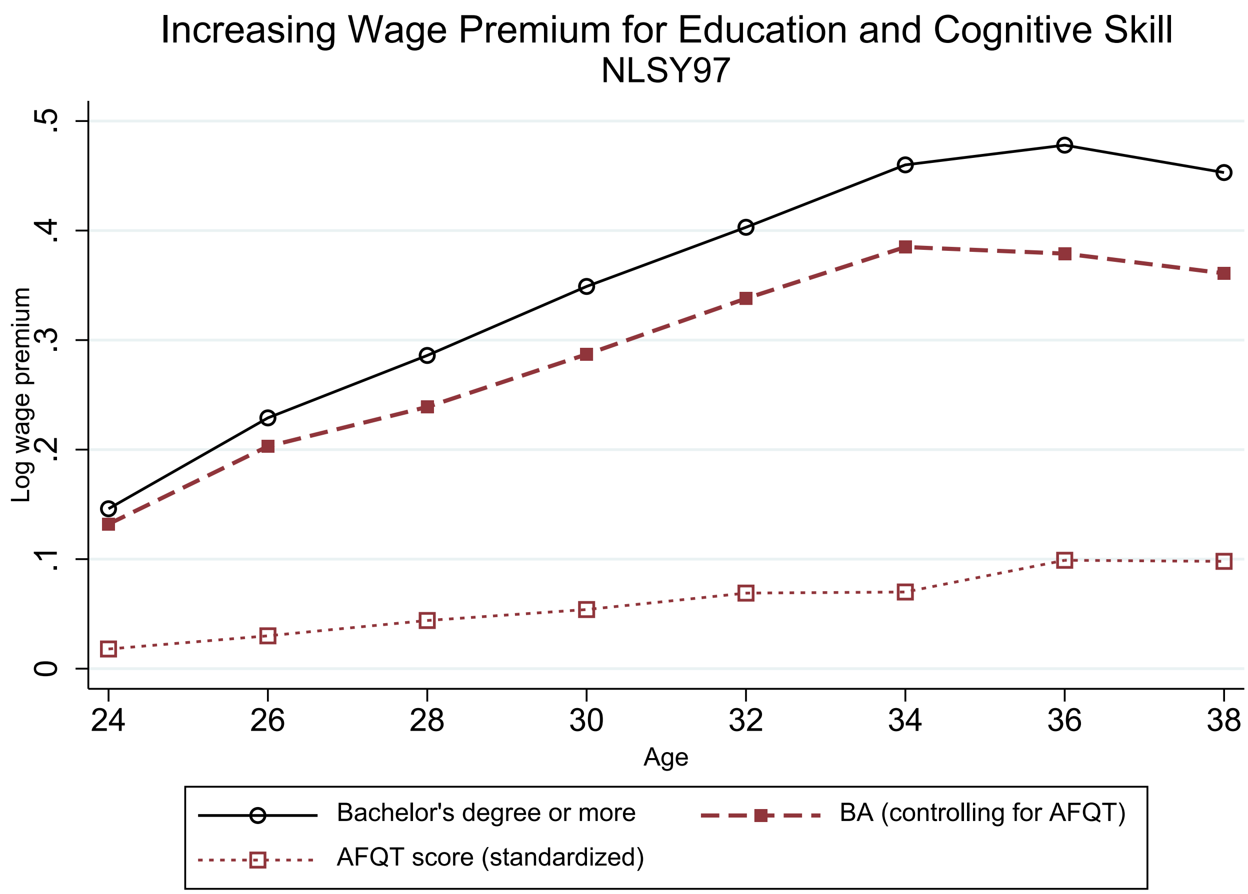
Figure A1



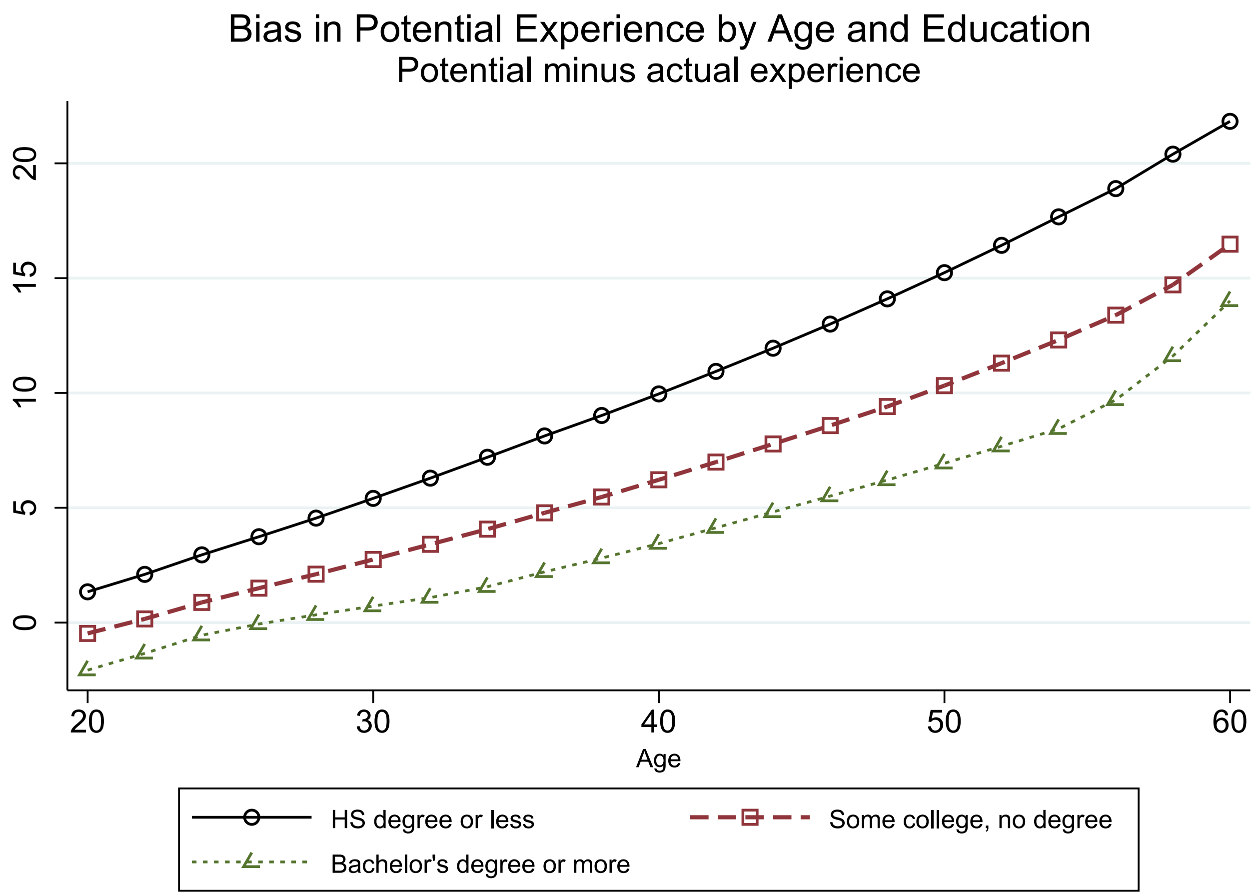
Notes: Figure A1 presents a regression of hours worked on age by education group controlling for individual fixed effects. Experience is scaled to fractions of a year where one year is 2,080 hours. The data come from the NLSY79, ages 19-60.

Figure A2



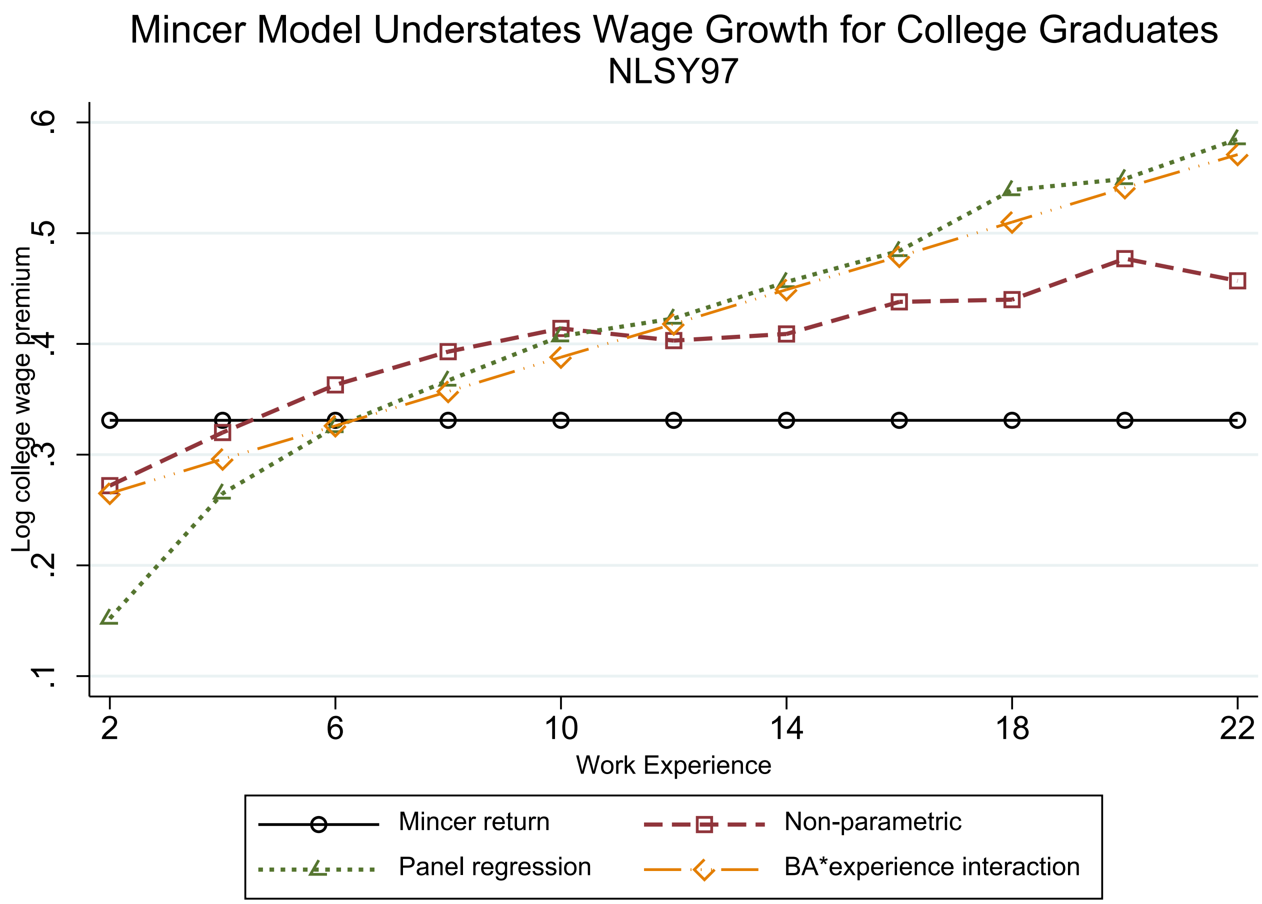
Notes: Figure A2 presents separate regressions of log hourly wages on two-year age bins and individual fixed effects. The solid line adds interactions of age with an indicator for having a bachelor's degree or more. The dashed line plots education by age interactions, also controlling for interactions between age and the respondent's Armed Forces Qualifying Test (AFQT) score (the dotted line), which is normalized to have mean zero and standard deviation one. The data come from the NLSY97, ages 22-38.

Figure A3



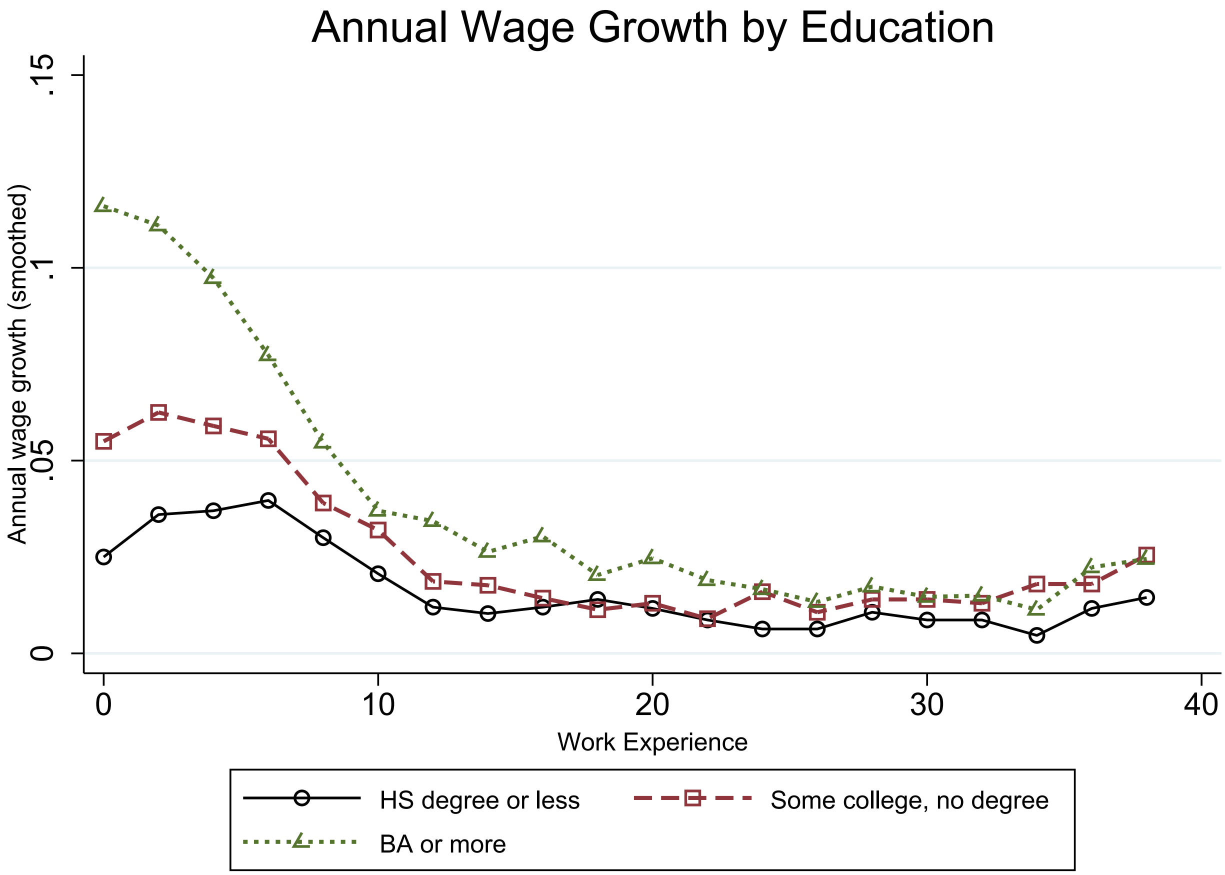
Notes: Figure A3 computes potential experience (age minus years of education minus six) and actual work experience (one year = 2,080 hours) by age and plots the former minus the latter at each age. The data come from the NLSY79, ages 19-60.

Figure A4



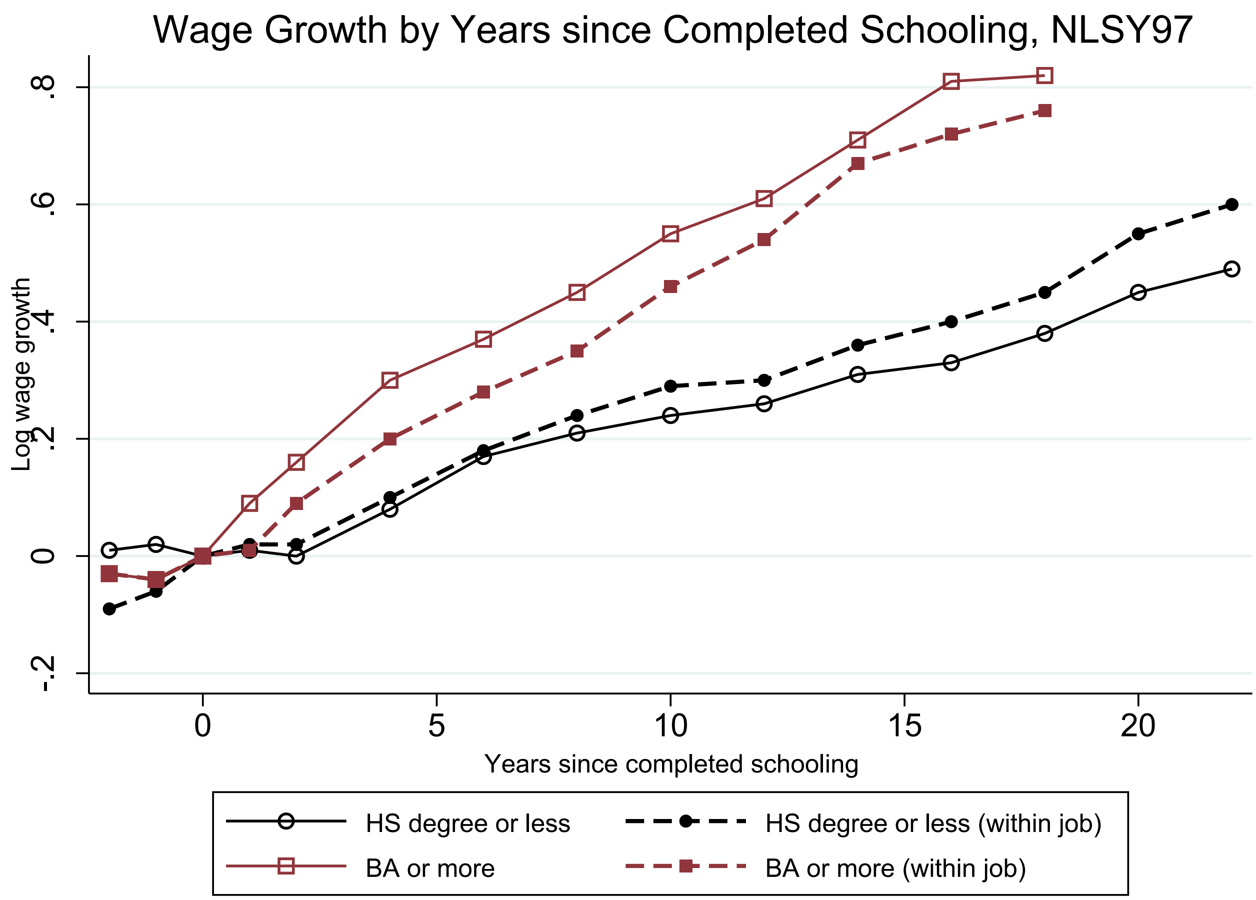
Notes: Figure A4 presents estimates of equations (2) and (3) in the paper, with log hourly wages regressed on education and actual experience (one year = 2,080 hours). The line labeled "Mincer return" is the (constant) coefficient on an indicator for having a bachelor's degree in a Mincerian earnings regression. The line labeled "Non-parametric" is the coefficients from an estimate of equation (2), with BA interacted with two-year work experience bins plus controls for race, gender, year, and age. The panel regression adds individual fixed effects. The line labeled "BA*Exp interaction" presents implied values from an estimate of equation (3), which modifies the Mincer model with a linear interaction between BA and work experience. The data come from the NLSY97, ages 22-38.

Figure A5



Notes: Figure A5 presents separate regressions by education groups of hourly wages (in levels) on two-year bins of actual work experience (one year = 2,080 hours) and individual fixed effects. After obtaining results in levels, I calculate the annual percent change and then smooth the series using a five-year moving average. The data come from the NLSY79, ages 19-60 (starting at age 21 for the some college group and age 23 for the BA or more group).

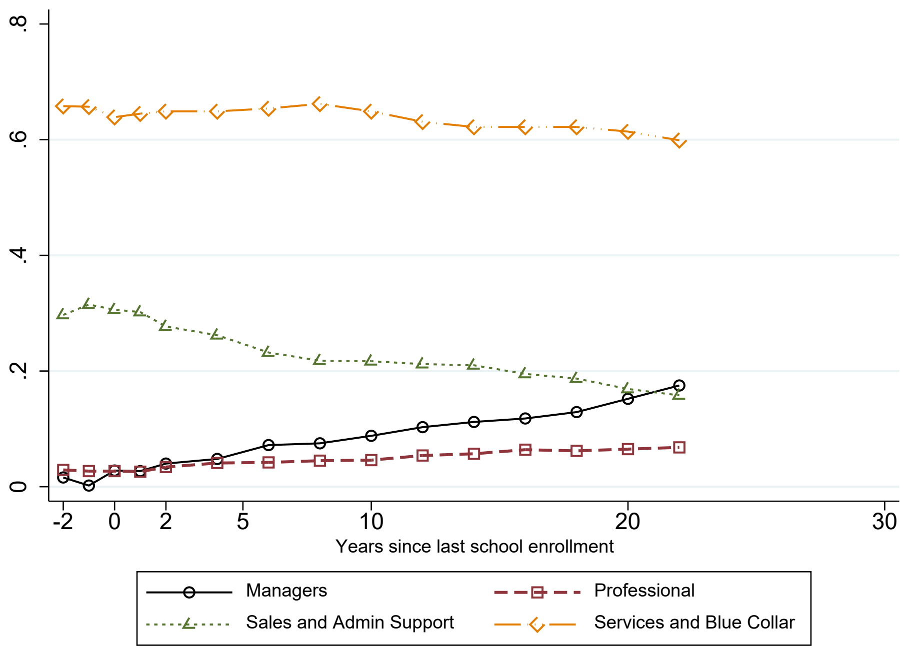
Figure A6



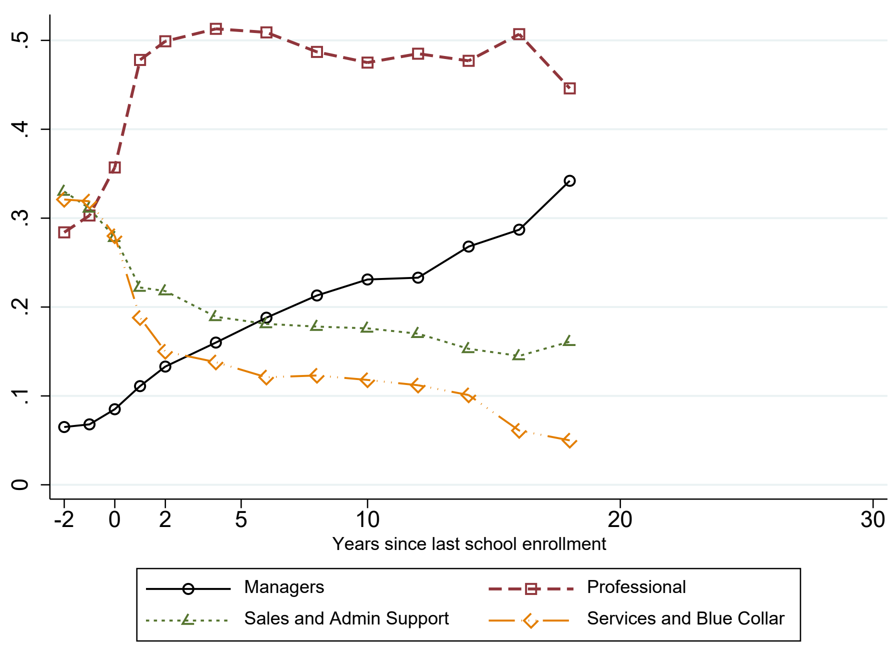
Notes: Figure A6 presents estimates of equation (5) in the paper, with log hourly wages regressed on indicators for years since the last survey wave in which a respondent is enrolled full-time in school plus individual fixed effects (the solid lines) or individual-by-job fixed effects (the dashed lines). The regressions are estimated separately for workers with a high school degree or less (black lines, circle markers) and with a bachelor's degree or more (red lines, square markers). The data come from the NLSY97, ages 19-40.

Figure A7

Panel A – Occupations Held by Workers with a HS Degree or Less

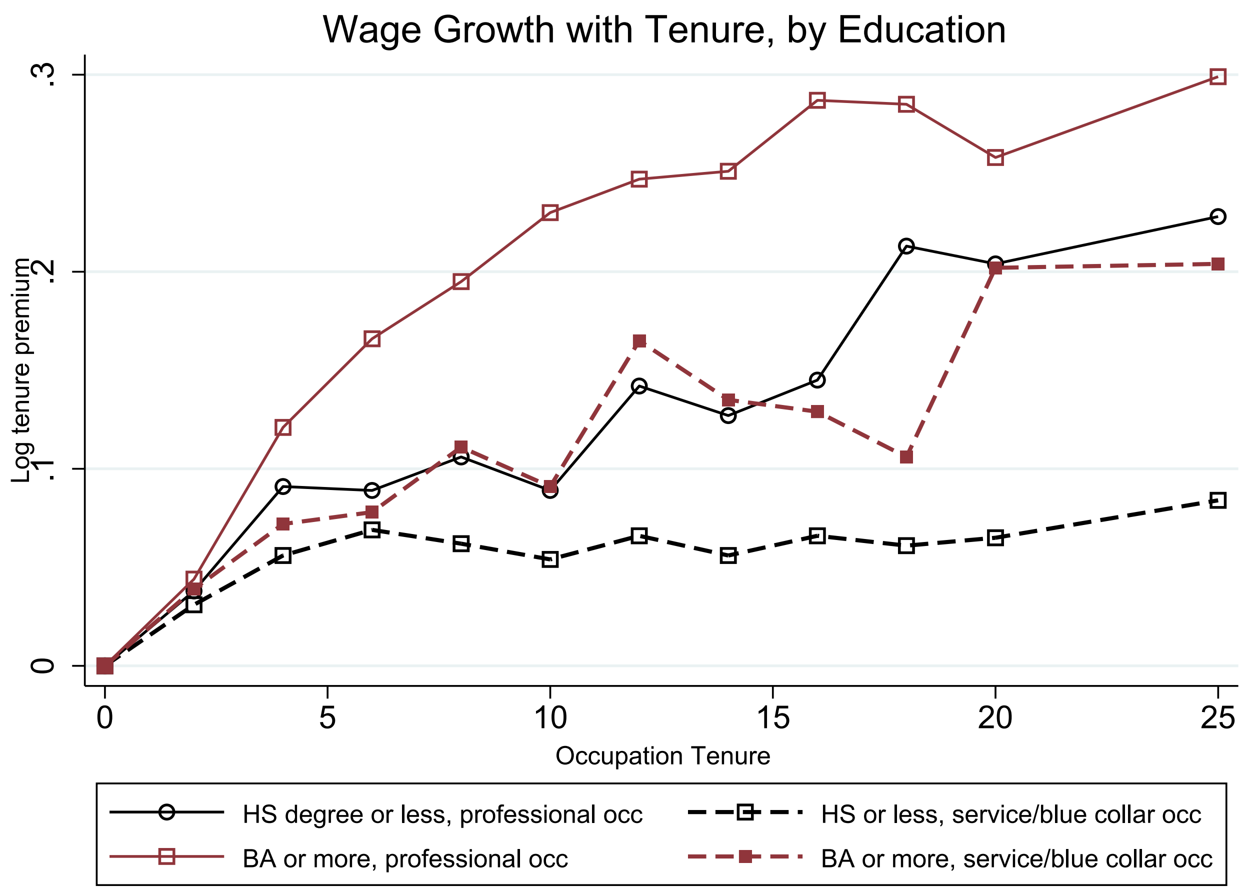


Panel B – Occupations Held by Workers with BA Degree or more



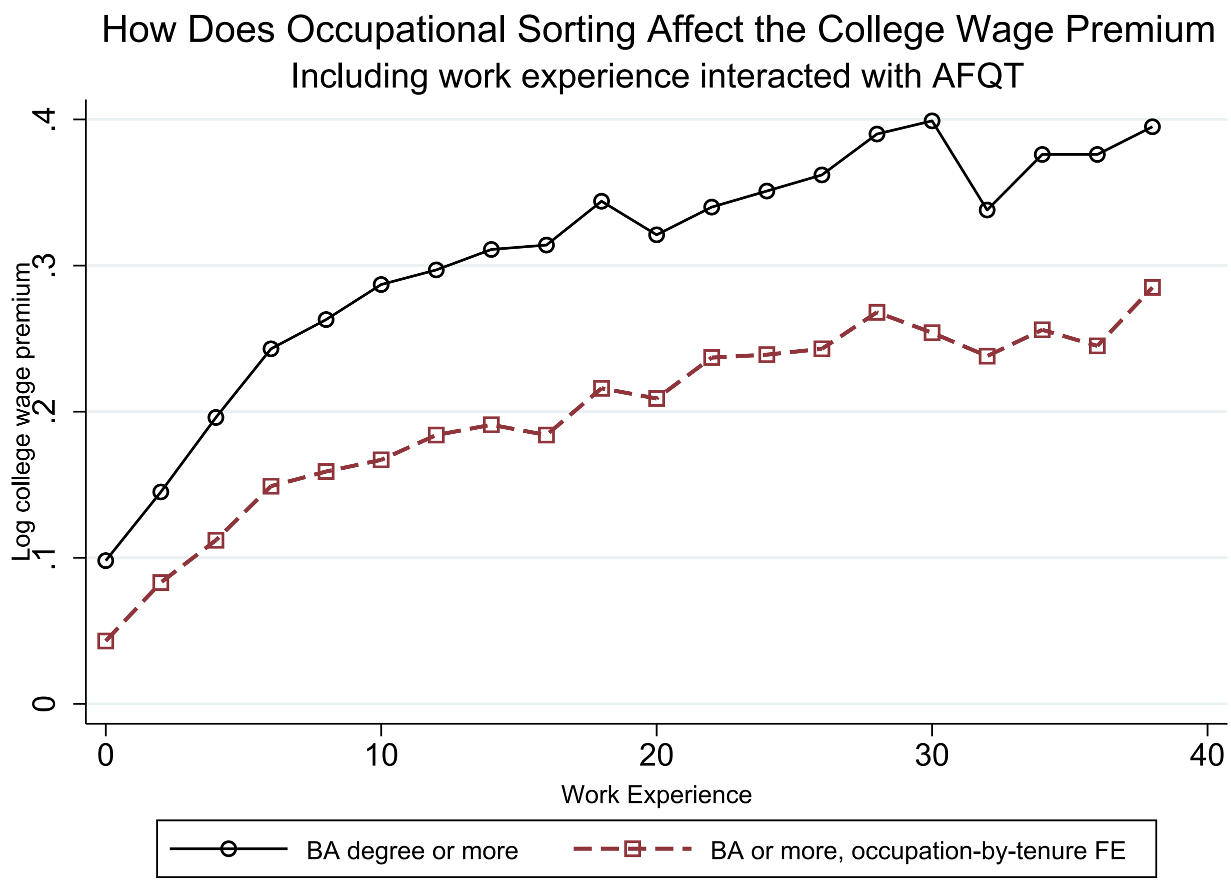
Notes: Figure A7 presents estimates of equation (4) in the paper, with occupation categories regressed on indicators for years since the last time a respondent is enrolled full-time in school and individual fixed effects. Professional, sales/admin support, and services/blue collar correspond to occ1990dd codes 23-235, 243-399, and 400 and above respectively. Mangement includes codes 4-22, and also a series of codes indicating supervisors of workers in the other categories. The data come from the NLSY97, ages 19-40.

Figure A8



Notes: Figure A8 presents separate regressions by occupation category and education of equation (6) in the paper, with log wages regressed on indicators for 2-year bins of occupation tenure plus controls for work experience, age, education, AFQT score, race and gender, employer tenure, and occupation fixed effects (which removes level differences in wages and focuses only on the slope with tenure). Professional and services/blue collar correspond to occ1990dd codes 23-235 and 400 and above respectively. The data come from the NLSY79, ages 19-60 and from the NLSY97, ages 19-40.

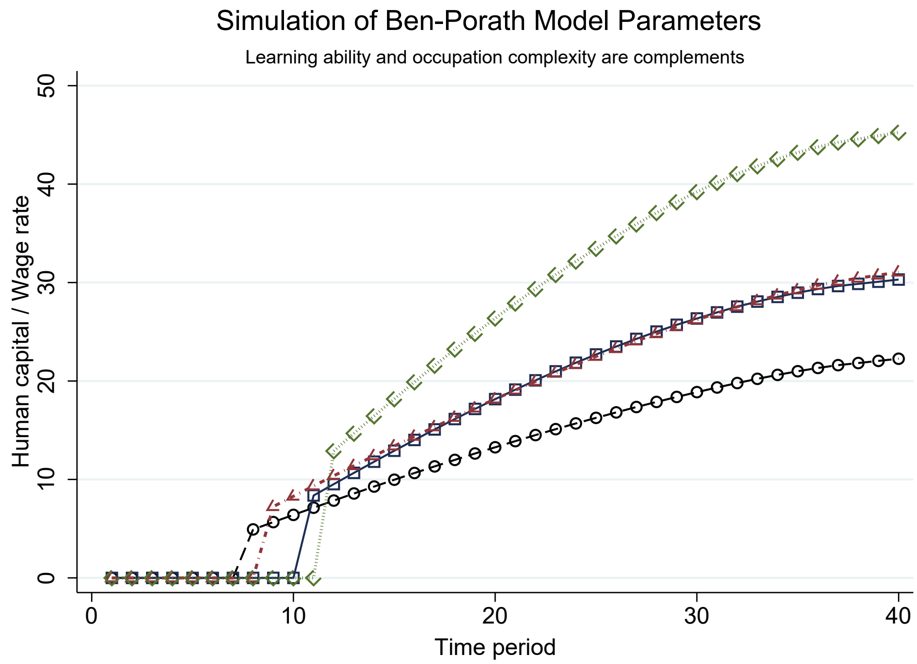
Figure A9



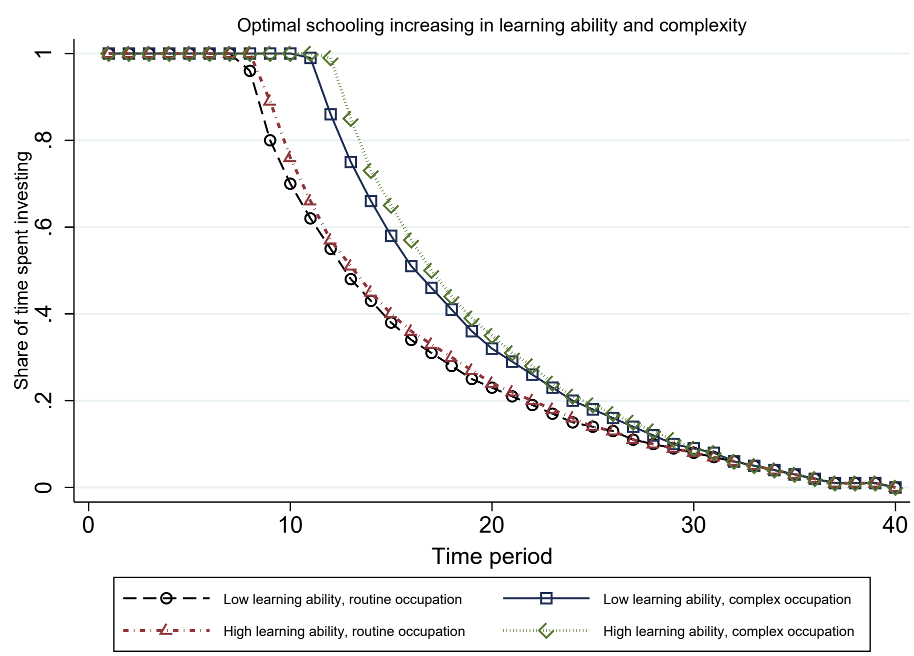
Notes: Figure A9 presents estimates of equation (2) in the paper, with hourly log wages regressed on indicators for having a bachelor's degree education interacted with two-year actual work experience bins (one year = 2,080 hours), AFQT score interacted with work experience, and controls for race, gender, year, and age. The dashed line present coefficients from the same models as above but adding occupation-by-tenure fixed effects. The data come from the NLSY79, ages 22-60.

Figure A10

Panel A



Panel B



Notes: Figure A10 presents simulations of the optimal wage and schooling investment paths from the modified Ben-Porath model in Section 4, with different calibrations of model parameters. Low/high learning ability are $\alpha = 0.4/0.5$, and routine/complex occupation are $\theta = 0.4/0.5$. I assume the discount rate $\beta = 0.95$, $h_1 = 1$, $T = 40$, and $w(t) = h(t)$ in all calibrations. Wages set to zero when $s^* = 1$.

Table A1 - Employment Outcomes by Years Since the End of Full-Time Schooling, NLSY97

	Number of Jobs Held		*Average Job Tenure*		*New Employer*		*Real Wages*	
Career year	HS or less	BA or more	HS or less	BA or more	HS or less	BA or more	HS or less	BA or more
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
0	2.8	6.6	0.6	2.0	0.63	0.42	13.21	18.24
1	3.2	7.2	0.6	1.8	0.69	0.59	11.5	21.4
2	3.8	7.6	0.9	2.1	0.63	0.45	12.8	22.7
4	4.6	8.2	1.3	2.8	0.55	0.35	14.3	25.7
6	5.6	8.7	1.7	3.6	0.46	0.30	15.8	28.1
8	6.4	9.1	2.2	4.4	0.41	0.32	16.4	30.8
10	7.1	9.5	2.7	5.3	0.34	0.32	17.2	35.0
12	7.6	9.9	3.3	6.0	0.32	0.32	17.1	37.6
14	8.0	10.2	4.0	6.7	0.34	0.29	17.8	40.3
16	8.4	10.6	4.5	7.7	0.41	0.24	18.7	44.2
18	8.7	10.9	5.0	8.5	0.37	0.21	19.4	44.9
20	9.1		5.5		0.36		21.1	
22	9.4		5.9		0.34		21.4	

Notes: Table A1 presents results from a regression of the outcomes in italics above on years since the last survey wave in which a respondent was enrolled full-time in schooling (which I define as career year zero) and individual fixed effects. The odd numbered columns restrict the sample to respondents with a high school degree or less, while the even numbered columns restrict the sample to respondents with a four-year college degree or more. Number of jobs held is the number of unique employers. Job tenure is measured in years. New employer is an indicator variable equal to one if the respondent is working for a new employer in that survey year, conditional on working at all. Real wages are inflation-adjusted to 2016 dollars. The sample is the NLSY97, ages 18-40.