Workers' First Jobs and Long-Term Wage Growth: Variation by Gender and Race/Ethnicity

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Abstract

We use data on a large, longitudinal sample of U.S. workers to examine how workers' wage growth varies across early career occupations. We find that wage growth tends to be highest for workers who start in occupations with high average starting wages, a fact that leads to increasing wage inequality. Wage growth varies notably by gender and race and these disparities are not fully explained by initial occupation choices; we see large disparities in wage growth by gender and race within most occupations, even conditional on worker and firm characteristics. Finally, we examine how wage growth and gaps by gender and race vary based on the skills composition of starting occupations.

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1. Introduction

The United States is facing rising economic inequality and declining mobility, with especially large inequality across gender and racial/ethnic groups (Autor, Katz, & Kearney, 2008; Chetty et al, 2022; Piketty & Saez, 2003). The majority of workers' wage growth is concentrated in their first decade in the labor market, so understanding the role of early career experiences is crucial for understanding these trends (Card, 1999; Rubinstein & Weiss, 2006; Von Wachter, 2020). Workers' initial occupation choices are likely to be particularly important in determining career progression and subsequent disparities by gender, race, and ethnicity (Burning Glass & Strada, 2024). However, the lack of large-scale longitudinal data in the United States that tracks individual wage trajectories over time and contains information about initial occupations has meant that the importance of a workers' initial occupation choice for wage growth and gender and racial/ethnic disparities has remained understudied in the United States.[2]

In this paper, we address this gap by constructing a longitudinal database of workers' wages and early career occupations based on data from several U.S. states from 2005 to 2019. Quarterly data on wages and firm characteristics come from the Longitudinal Employer Household Database (LEHD), and we link these records to information on worker demographics and occupations reported in the American Community Survey (ACS) for people ages 18-26. Linking these gives us a dataset on roughly 313,000 individuals who entered the labor market between ages 18 and 26 from 2005 to 2011 and whose employment and earnings we can follow for eight years. This allows us to explore, on a large scale, the relationship between U.S. workers' early career occupations and wage mobility in the United States.

Using this dataset, we uncover three main findings. First, wage growth tends to be highest in occupations where workers have high average starting wages. This is crucial for understanding the role of individuals' initial occupation in economic inequality in the United States, as the positive correlation between occupations' average starting wages and long-term growth rates

[2] There are few other U.S. datasets which contain a worker's occupation and earnings over time for such a broad sample of workers. The Health and Retirement Study follows tracks occupation and earnings but only for workers aged 51 or older. The National Longitudinal Surveys of Youth (NLSY), Panel of Survey Income Dynamics (PSID), and Survey of Income and Program Participation (SIPP) also contact occupation and earnings information over time; however, being surveys they contain much smaller samples and so they cannot be used to estimate variation at the 4-digit occupation-level.

leads to a divergence (rather than a convergence) in workers' average earnings over time. Nevertheless, there are some occupations that have notably higher or lower average wage growth than would be expected given their starting wages. For instance, people who start as registered nurses have high earnings at labor market entry but only moderate wage growth, while people who start as police officers and or accountants have high wage growth relative to their earnings at labor market entry.

Second, we show that the lower wage growth observed for women and Black workers cannot be fully explained by their initial occupation choice. Women and Black workers experience lower wage growth between labor market entry and eight years later than other workers, even conditional on their initial choice of occupation (as well as industry, year and age of labor market entry, and educational attainment). In fact, we find that gaps in wage growth by gender and for Black relative to white[3] workers exist in the majority of occupations. However, some occupations, such as protective services occupations and installation, maintenance, and repair occupations have particularly large gaps in wage growth by gender and for Black workers relative to white workers.

Third, we examine how the skills profile of a worker's occupation is related to observed wage growth. We find that wage growth is highest for workers whose initial occupation has a high concentration of nonroutine analytical skills, deductive and inductive reasoning, and interacting with others. Workers who start in occupations that require number facility skills and coordinating work and teams tend to have lower wage growth. There are also some differences in the returns to skills by gender, race, and ethnicity. Women and Hispanic workers experience larger returns to starting in an occupation with a high concentration of service skills while for Black workers' returns are larger to starting in an occupation that requires information use and coordinating skills.

This work builds on three main literatures. First, we build on the literature which examines how early career experiences influence earnings growth and future labor market outcomes. This literature indicates that workers' initial jobs impact long-run labor market sorting, earnings, human capital accumulation, and future occupational choices (Adda, Dustmann, & Stevens, 2017; Altman, Falk, Jäger, & Zimmermann, 2018; Biewen & Seifert, 2018; Fadlon, Lyngse, &

[3] Throughout this working paper, we define white workers as white non-Hispanic workers and Black workers as Black non-Hispanic workers.

Nielsen, 2020; Härkönen & Bihagen, 2011; Kleven, Landais,& Søgaard, 2019, Card, Cardoso & Kline, 2016). However, most of this literature is based on data from European countries, so it is unclear if these findings extrapolate to the United States (Card, Chetty, Feldstein, and Saez, 2010). Instead, research focused on the U.S. context primarily examines how wages are associated with firms or industries (Song et al., 2019; Bloom et al., 2021) rather than occupations, given that this information is more readily available in existing large-scale datasets.

Some U.S.-based work indicates that initial occupation sorting may be important for future labor market outcomes. Deming (2023) shows wage growth is largely explained by people's first jobs, and that occupational sorting explains much of why wage growth is faster for more educated workers. However, Deming (2023) focuses on the role of occupations and what they mean for returns to education, rather than focusing on how wage growth varies across specific occupations or worker demographics. Staiger (2023) also finds that workers whose first job is at their parent's employer experience larger earnings gains than their peers. The most related work is a study by Escobari et al. (2021) which examines which occupations have the greatest upward mobility; however, they do not measure how wages vary by worker characteristics within occupations. We extend this work by examining how occupations are differentially related to upward mobility by gender, race, and ethnicity.

Second, this paper builds broadly on the literatures examining returns to human capital accumulation and different types of skills. While much evidence indicates premiums associated with attending certain types of colleges, especially for workers from racial/ethnic minority backgrounds (e.g., Chetty et al., 2017; Dale & Krueger, 2014; Zimmerman, 2019), different college majors (Altonji, Kahn, & Speer, 2016; Andrews et al., 2022; Kirkeboen, Leuven & Mogstad, 2016; Deming & Noray, 2020), or from working at different types of establishments (Arellano-Bover, 2024; Goldin, Kerr, Olivetti & Barth, 2017), less is known about how initial occupation choices influence worker trajectories and differences across gender, race, and ethnicity. Similar to educational experiences, these early career jobs may signal something about workers' ability or help them develop skills that are valuable for job mobility or wage growth (Deming & Noray, 2020).

Third, we build on the literature on gender and racial/ethnic disparities in the labor market. This literature shows that women receive a smaller share of firm specific wage premiums (Card, Cardoso, & Kline, 2016), are underrepresented in high-paying professions and managerial occupations (Lordan & Pischke, 2022), and that early labor market experiences have larger impacts on the careers of women than men (Fadlon, Lyngse, & Nielsen, 2020). In addition, female labor force attachment, wages, and earnings growth varies across occupations (Bertrand, Goldin, & Katz, 2010; Goldin, 2014; Denning, Jacob, Lefgren, & Vom Lehn, 2019) indicating that initial occupational sorting may be important for explaining subsequent gender gaps. There is less research on racial/ethnic disparities in occupational sorting. Existing research largely focuses on differences in earnings and education (Bayer & Charles, 2018) though some work indicates that the black-white wage gap in white-collar jobs is larger for jobs with more soft-skills than those focused on hard-skills (Fan, Wei & Zhang, 2016). Jardina et al. (2023) shows that segregation across occupations has significant implications for wage inequality between black and white workers. We extend this literature by examining how gender and racial/ethnic disparities in employment and earnings evolve over people's careers and how sorting into initial jobs is related to subsequent labor market disparities.

The rest of the paper proceeds as follows. Section 2 describes our data and methods and Section 3 discusses our results. Section 4 concludes.

2. Data and Methods

2.1 Data

We use data from the American Community Survey (ACS) and Longitudinal Employer Household Dynamics (LEHD) dataset between 2005 and 2019. Our main sample consists of individuals who were surveyed for the American Community Survey (ACS) at some point between ages 18 and 26 and whom we can link to the Longitudinal Employer Household Dynamics (LEHD) dataset. We focus on people in these datasets who were aged 18-26 between 2005 and 2011 so that we can follow people for eight years (up to 2019). We exclude data after 2019 to avoid capturing changes in earnings and employment during the COVID-19 pandemic and because data collection challenges impacted the 2020 wave of the ACS.

We use the quarterly data from the LEHD to define a worker as first entering the labor market in the year in which we first observe a worker's earnings exceed what they would have earned working full time (2000 hours per year) at a minimum wage job in their state.[4] Since we

[4] We focus on earnings starting at age 18.

cannot observe hours worked in the LEHD, this is our best proxy for estimating whether workers are likely working full time. We define age of labor market entry as the worker's age at the end of the year in which they first entered the labor market (i.e. year – birthyear). We restrict our sample to people whom we observe entering the labor market between ages 18 and 26. We define earnings as those associated with a worker's primary job. This typically corresponds to the job in which a worker had the highest earnings in a given quarter. Appendix B describes the data construction process in more detail.

The ACS contains information about people's occupations, schooling, and demographic characteristics at the point they are surveyed. Since we are interested in how initial occupational sorting relates to later career outcomes, we drop from our sample all people who responded to the ACS before they are classified as entering the labor market. We also drop people who were in school when they responded to the ACS, since their earnings are low and they likely switched occupations when they finished school or entered a full-time job. Unfortunately, we do not observe occupations for everyone in the year they enter the labor market because individuals are not always surveyed for the ACS in the same year they entered the labor market. Thus, we use data on occupations for people in our sample who met the conditions above and responded to the ACS between ages 18-26. For some people, the data on occupations comes from a year after they entered the labor market, however, it is still measured at a point at which individuals are relatively young and thus likely to be employed in their first occupation. (On average, people in our sample responded to the ACS within two years of entering the labor market. Appendix Table 1 shows how much age when surveyed varies across age at entry.)

We focus on people who enter the labor market between ages 18 and 26 because prior work has found that 86 percent of people have their first stable job at this point (Staiger, 2023) and we are interested in how early career earnings vary with initial job placement.[5] People who enter after age 26 may have different career trajectories or they may have entered the labor market in states excluded from our sample. Appendix Figure A.1 summarizes earnings profiles for our sample of people who enter the labor market between 18 and 26. It indicates a sharp increase in earnings in the year in which they start what we classify as their first job. Appendix Table A.1.

[5] Staiger (2023) defines a stable job as one in which someone earns at least 3,300 per quarter (which is roughly equivalent to working 35 hours a week at the federal minimum wage) for three consecutive quarters and is employed by the same employer for all three quarters.

also summarizes the share of workers in our sample who enter the labor market at each age. Twenty-three is the most common age for workers to enter, with 19% of our sample entering at this age, and eighteen is the least common age, with only 2%of our sample entering at that age. Appendix Table A.2. also summarizes the characteristics of our sample. It is important to note that our sample features a relatively low share of Black individuals (6%) relative to the national average. This is because of the sample restrictions imposed and it could impact the generalizability of our findings. Due to these restrictions, our results may not reflect broader trends for all young adults who enter the labor market.

2.2 Methods

All of our analyses are intended to be descriptive. We start by presenting descriptive statistics on earnings for 22 two-digit occupation groups (the first two digits of the six-digit Standard Occupational Classification System from 2010) and roughly 100 four-digit occupations (based on the 2010 census codes).[6] For each group, we compute average and median earnings in the year of labor market entry, as well as the average and median earnings for eight years after entry. We estimate wage growth as the difference between later earnings and initial earnings, divided by initial earnings. We compute wage growth for individual workers and then in some cases report the average wage growth by the occupations in which people started.

Because of how we define first jobs, everyone in our sample is employed at baseline. People who do not have records in our LEHD sample eight years after entry are treated as unemployed (with zero earnings). While some of these people may have moved to one of the states or a type of job not covered by our sample (e.g., federal and self-employed workers), we do not have any way of distinguishing these people from those who are actually unemployed. We chose to keep them in the sample with their earnings as zeros because unemployment (or leaving the labor force) is an important outcome, especially for some of the demographic groups we examine. We also keep earnings records for any individual earning below the minimum wage in their given state and year if these low earnings are observed after the individual first entered the labor market; we do this to obtain a more comprehensive picture of underemployment after labor

[6] Examples of two-digit occupation codes include, for example, “Management Occupations”, whereas four-digit occupation codes include, for example, “Chief Executives”, “Marketing and Sales Managers”, and “Financial Managers”.

market entry. We winsorize all wages, replacing wages above the 99th percentile with those at the 99th percentile for our sample.[7] In addition, we adjust all estimates for inflation to 2019 dollars.

We merge in information about the skill profiles of four-digit occupations from Deming (2017) to estimate how wage trajectories vary with the skills typically associated with a worker's occupation. We use the ten main measures defined by Deming, which include: (1) social skills; (2) nonroutine analytical; (3) routine; (4) service; (5) deductive and inductive reasoning; (6) number facility; (7) information use; (8) require social interaction; (9) coordinate; and (10) interact.[8] Appendix C contains definitions for these skills measures.

We also fit regression models to estimate how wage trajectories vary with worker and firm characteristics. Equation (1) shows how we fit our models.

$$WageGrowth_i = \alpha_0 + \beta_1 Occ_i + \beta_2 FirmType_j + \beta_3 Demos_i + \psi_i \times \eta_i + \epsilon_i \quad (1)$$

Occ_i is a vector with indicators for each occupation category (at the two-digit level), and the coefficient β_1 captures differences in wage growth across initial occupations. As mentioned above, occupations are measured at the first point we see an individual in the ACS (after labor market entry). $FirmType_j$ is a vector which includes the age, size, and industry associated with a worker's main job when they first enter the labor market.[9] $Demos_i$ includes indicators for whether the worker is female, Asian, Black, Hispanic, another race (besides white), attended some college, or had a bachelor's degree or higher (at the point they were surveyed by the ACS). The reference groups are people who are white, male, and did not attend college. In some models we interact our covariates with demographic indicators to understand how relationships vary by gender, race, and ethnicity, and education level. In all models, we include fixed effects for the year of labor market entry (ψ_i) interacted with age of labor market entry (η_i) to account for cyclical shocks to earnings trajectories and variation in earnings profiles by age. We also fit

[7] We winsorize wages separately for each year in sample.

[8] See Deming (2017) for more details on how these are constructed and what each skills category encompasses.

[9] We focus on the two-digit NAICS sector codes (Bureau of Labor Statistics, undated); industry information is from the ACS, measured when the individual was surveyed. Firm characteristics are from the LEHD so they are available for every quarter/year.

models which include a vector, $Skills_i$, that includes measures of the average skill levels associated with the worker's initial four-digit occupation.

Due to census disclosure rules, we are limited in the groups we examine. We focus on analyses by gender (male vs. female), and whether workers are white, Black, or Hispanic. We use the demographic measures and education variable from the ACS, so education is measured at the point someone is surveyed in the ACS. This should be close to when they enter the labor market (and at a point when they are not in school), though some people may have obtained additional education between when they were surveyed and when we measure their later earnings. To estimate how wage gaps vary within occupations we fit a model where we interacted female with the occupational categories. For the wage gaps focused on race and ethnicity, we interact occupational categories with the focal racial or ethnic groups and then report the β_1 coefficients. In these models, we control for the average wage growth in each occupation (in the term $\beta_4 Occ_i$) and the average wage gap by gender and race and ethnicity (in the $\beta_3 Demos_i$ term).

$$WageGrowth_i = \alpha_0 + \beta_1 Occ_i \times \text{Female}_\text{i} + \beta_2 FirmType_j + \beta_3 Demos_i + \beta_4 Occ_i + \psi_i \times \eta_i + \epsilon_i \quad (2)$$

For the occupation analyses focused on four-digit occupations, we limit our analyses to occupations with at least 500 people, including at least 50 men, 50 women, 50 white workers and 50 non-white workers. This provides us a sample of 116 four-digit occupations. We are able to match roughly 90% of these occupations to the skills dataset from Deming (2017). Appendix Table 2 summarizes our sample.

3. Results

3.1 Variation in Wage Growth by Occupations

We find substantial variation in wages and wage growth across occupations. On average, workers in our sample experience a 49% increase in wages from when they enter the labor market to eight years after entry; mean wages at labor market entry are \$29,280 versus \$41,320 eight years later, and the median wages are $25,270 versus $36,610 eight years later (in 2019 dollar terms).

Figure 1 shows that baseline wages and wage growth vary significantly across the four-digit occupations in which workers start their careers. For instance, people who start as software engineers, police officers or accountants have average wage growth over 100%, while there is almost no wage growth for people who start as cosmetologists, maids or childcare workers.[10] Figure 1 also indicates that wage growth is positively correlated with baseline wages. For example, police officers have average baseline wages of $36,510 and average wages of $72,610 eight years later, representing 126% wage growth. Conversely, nursing, psychiatric, and home health aides have average baseline wages of $23,460 and average wages of $25,110 eight years after entry, representing only a 10% increase in wage growth. This indicates that earnings inequality is likely to grow the longer people are in the labor market.

Nevertheless, there are several occupations whose wage growth may not be easily predicted by their average baseline wages. For instance, people who entered the labor market as registered nurses had high baseline wages but low wage growth relative to other occupations with similar baseline wages. Conversely, workers entering as police officers and accountants had high wage growth relative to their baseline wages.

[10]Some of the low wage growth in these occupations may be due to people leaving the labor force.

Figure 1. Correlation Between Baseline Wages and Wage Growth by Initial Four-Digit Occupation

Source: This figure is based on data from the American Community Survey and Longitudinal Employer Household Database. The research was performed at a Federal Statistical Research Data Center under FSRDC Project Number 2759. (CBDRB-FY25-P2759-R11726)
Notes: This figure shows, for each four-digit occupation code from the 2010 census, the average wages at labor market entry for workers who started in that occupation, and those workers' average wage growth over eight years after labor market entry. All estimates are in 2019 dollars. The bubbles are proportional to the size of the occupation. Only occupations with at least 500 workers (including 50 men, 50 women, 50 white workers and 50 non-white workers) in our sample are shown. Select occupations are labeled.

It is important to note that these trajectories do not necessarily represent within occupation wage growth, as our analysis does not constrain one's occupation eight years after entry to be the same as their initial occupation. Additionally, the trajectories we present may be impacted by other factors, such as some initial occupations having workers who are disproportionately more (or less) likely to leave the labor force or to transition to other low (or high) wage occupations.

3.2 Variation in Wage Growth Across Demographic Groups

The wage growth documented in the previous section differs significantly by gender, race, and ethnicity (Appendix Table A.3). In particular, average wage growth is largest for men (63%), Asian workers (71%), white workers (52%), and workers with a bachelor's degree or higher (85%). Conversely, wage growth is smaller for women (32%), Hispanic workers (43%), Black workers (28%) and those with no college experience (29%). Thus, we examine whether differences in the types of occupations in which people from different racial/ethnic backgrounds or genders start working can explain wage growth gaps by gender, race, and ethnicity. Due to smaller sample sizes when looking at subgroups, we focus on two-digit occupations.

Figure 2 shows that occupations with high wage growth for men also tend to have high wage growth for women. However, across every occupation, women experience lower average wage growth than men. For example, women experience the largest wage growth in architecture and engineering (78%), but men still experience much higher wage growth, 107%, in this occupation. (see Appendix Table A.3).[11] On average, women's wage growth is roughly half of men's (32% relative to 63%).

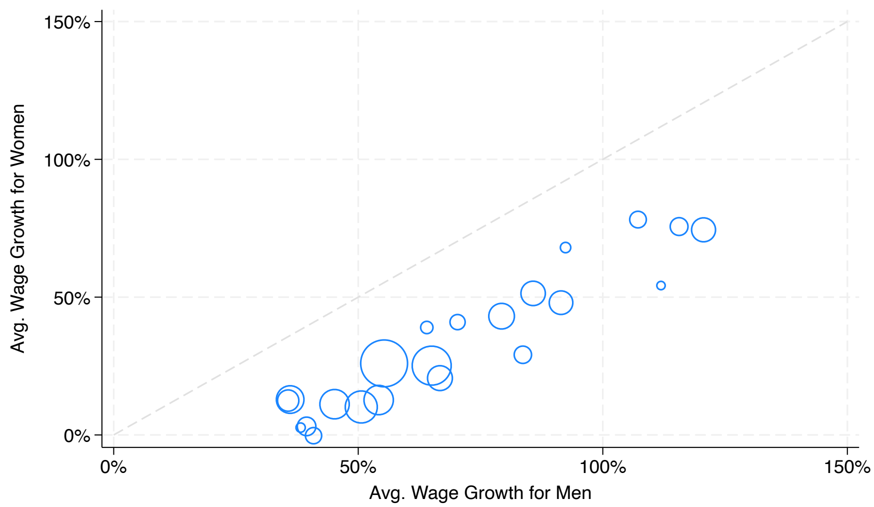
Panel B of Figure of 2 shows similar patterns for Black relative to white workers. In particular, occupations that have high wage growth for white workers also tend to have high wage growth for Black workers, but Black workers have lower average wage growth than white workers for nearly every occupation. For example, computer and mathematical occupations have the highest average wage growth for Black and white workers, but it is 113% for white workers versus only 66% for Black workers (see Appendix Table A.3). Gaps are much smaller, and in many occupations non-existent when comparing average wage growth for white (non-Hispanic) workers to Hispanic workers (Appendix Figure A.3).

Some of these differences in wage growth may be due to other relevant demographic differences in workers, such as age of labor market entry or educational attainment. Thus, we also fit the regression models specified in equation (1) in section two. In these models we regress workers' wage growth on indicators for their initial occupation and worker and firm characteristics (including age and year of labor market entry, educational attainment, race, ethnicity, gender, initial industry of employment, firm size and firm age).

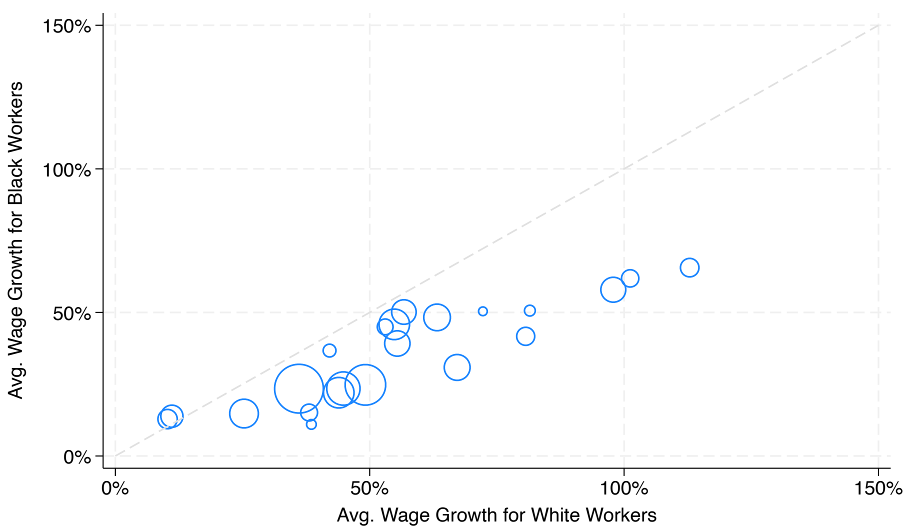
[11] Appendix Table 3 provides more detail by listing the mean earnings at entry and wage growth for each two-digit occupation by gender and race/ethnicity.

Figure 2. Average Wage Growth by Demographic groups for each Initial Two-Digit Occupation

(A) Average Wage Growth by Occupation and Gender



(B) Average Wage Growth by Occupation for Black and White Workers



Source: This figure is based on data from the American Community Survey and Longitudinal Employer Household Database. The research was performed at a Federal Statistical Research Data Center under FSRDC Project Number 2759. (CBDRB-FY25-P2759-R11726)

Notes: This figure shows, for each two-digit occupation code from the Bureau of Labor Statistics major occupation profiles, the average wage growth between labor market entry and eight years later workers who started in that occupation. In panel A the x-axis represents average wage growth for women and the y-axis represents wage growth for men. In panel B the x-axis represents average wage growth for white workers and the y-axis represents average wage growth for Black workers. The dashed line indicates the 45 degree line. Bubbles below this line indicate that women (or black workers) have lower wage growth than men (or white workers) and vice versa for bubbles above the line. The bubbles are proportional to the size of the occupation.

The results of these models are presented in Appendix Figure A.2 and Table 1 below. Column 1 of Table 1 indicates that, as above, wage growth varies across occupations, even conditional on the characteristics of the workers and firms in which they are employed. Wage growth is highest in computer and mathematical occupations and business and financial operations occupations, while lowest in community and social service occupations and personal care and service occupations.

We also find that gender gap in wage growth is slightly *larger* conditional on starting occupations and these other characteristics. Appendix Figure A.2. indicates that the conditional gender gap in wage growth is 37% while the unconditional gap was 32% (Table A.3). Thus, initial occupational sorting does not appear to explain much of the gender gap in wage growth. The Black-White gap in wage growth is slightly smaller in these models, but it is not clear if this is due to occupational sorting or differences in educational attainment.

Finally, we examine how wage growth varies across demographic groups within specific occupations using regression models which interact the initial occupation vector with worker demographics. Table 1 shows that the gender gap in wage growth is smaller than average in healthcare support and larger than average in protective services, business and financial operations, and education and instructional services. Black workers experience the highest relative wage growth within educational instruction and library occupations and healthcare support occupations, and lower relative wage growth in installation, maintenance and repair occupations. Hispanic workers experience the largest advantage in community and social service occupations, and lower relative wage growth within business and financial operations. It is important to note that some of these patterns may be due to the broadness of the two-digit occupations that we examine, which do not allow us to as precisely control for one's very specific occupation. For example, if female workers hold relatively low-skill jobs versus men within the more broadly defined two-digit occupation, this could be driving some of the observed wage growth differences.

Table 1: Variation in Wage Growth Across Occupations by Gender, Race, and Ethnicity

	Overall	Female Workers	Black Workers	Hispanic Workers
Computer and Mathematical	0.173***	-0.0984*	-0.173	-0.0425
	(0.0232)	(0.0497)	(0.102)	(0.0751)
Business and Financial Operations	0.145***	-0.107**	-0.113	-0.117*
	(0.0186)	(0.0371)	(0.0682)	(0.0464)
Architecture and Engineering	0.0563*	-0.0297	-0.156	0.0621
	(0.0236)	(0.0535)	(0.129)	(0.0754)
Installation, Maintenance, and Repair	0.0466**	-0.140*	-0.165*	-0.00504
	(0.0166)	(0.0650)	(0.0655)	(0.0351)
Healthcare Practitioners and Technical	0.0481**	-0.0443	0.0783	0.0458
	(0.0176)	(0.0408)	(0.0560)	(0.0402)
Legal	0.0230	-0.145	-0.0845	-0.189
	(0.0433)	(0.115)	(0.218)	(0.103)
Educational Instruction and Library	-0.118***	-0.110**	0.252***	0.147***
	(0.0200)	(0.0384)	(0.0600)	(0.0407)
Art, Design, Entertainment, Sports, and Media	-0.152***	-0.0482	0.115	0.0797
	(0.0235)	(0.0457)	(0.108)	(0.0654)
Healthcare Practitioners and Technical	0.0481**	-0.0443	0.0783	0.0458
	(0.0176)	(0.0408)	(0.0560)	(0.0402)
Protective Service	-0.00820	-0.206***	-0.00179	0.000567
	(0.0212)	(0.0412)	(0.0570)	(0.0470)
Life, Physical, and Social Science	-0.0466	0.0351	-0.0307	0.120
	(0.0328)	(0.0644)	(0.165)	(0.111)
Sales and Related	-0.0373**	-0.0653*	0.0254	-0.0101
	(0.0144)	(0.0264)	(0.0391)	(0.0260)
Office and Administrative Support	-0.0904***	0.0287	0.0840*	0.0436
	(0.0129)	(0.0255)	(0.0355)	(0.0232)
Production	-0.117***	-0.0707*	0.0419	0.0181
	(0.0158)	(0.0282)	(0.0442)	(0.0278)
Educational Instruction and Library	-0.118***	-0.110**	0.252***	0.147***
	(0.0200)	(0.0384)	(0.0600)	(0.0407)
Food Preparation and Serving Related	-0.120***	0.0610*	0.0969*	0.0287
	(0.0152)	(0.0280)	(0.0432)	(0.0289)
Construction and Extraction	-0.120***	-0.117	0.121	-0.0232
	(0.0193)	(0.0628)	(0.0755)	(0.0307)
Healthcare support	-0.138***	0.112**	0.225***	0.154***
	(0.0170)	(0.0404)	(0.0431)	(0.0308)
Transportation and Material Moving	-0.140***			
	(0.0153)			
Building and Grounds Cleaning and Maintenance	-0.147***	-0.0374	0.0216	-0.0370
	(0.0190)	(0.0379)	(0.0602)	(0.0371)
Art, Design, Entertainment, Sports, and Media	-0.152***	-0.0482	0.115	0.0797
	(0.0235)	(0.0457)	(0.108)	(0.0654)
Farming, Fishing, and Forestry	-0.181***	-0.0845	-0.0181	-0.0721
	(0.0392)	(0.0672)	(0.194)	(0.0556)
Personal Care and Service	-0.223***	-0.00946	0.208***	0.0175
	(0.0178)	(0.0395)	(0.0526)	(0.0386)
Community and Social Service	-0.241***	0.0158	0.188**	0.310***
	(0.0249)	(0.0584)	(0.0720)	(0.0667)
Average Gap for Demographic Group		-0.333***	-0.180***	0.0122
		(0.0228)	(0.0308)	(0.0200)

Source: This table is based on data from the American Community Survey and Longitudinal Employer Household Database. The research was performed at a Federal Statistical Research Data Center under FSRDC Project Number 2759. (CBDRB-FY25-P2759-R11726)

Notes: Robust standard errors are in parentheses (*p<0.05 .**p<0.01. ***p<0.001). N=313,000. Estimates are from regression models which include entry year by entry age fixed effects, as well as industry fixed effects. They also control for worker gender, education, race, and ethnicity, as well as firm size. The coefficients in columns 2-4 are from the interaction between the demographic group and the occupation vector. These models also control for the occupations, so that the coefficients represent the differential relationship between the occupation and wage growth for the noted demographic group. The last row indicates the average gap in wage growth for women relative to men (in column 2), for black workers relative to white workers (in column 3) and Hispanic workers relative to white workers (in column 4).

3.3 Skills Associated with Wage Growth

Finally, we examine how the skills composition of a worker's occupations relates to observed wage growth. Appendix C defines each of the skills we examine (based on Deming, 2017). Table 2 shows that nonroutine analytical skills are most predictive of positive wage growth (column 1). The magnitude of this coefficient is reduced when we control for worker demographics (column 2) but still remains significant.[12] In the model with controls, deductive and inductive reasoning are most predictive of wage growth, but nonroutine analytical skills remains a strong predictor. Wage growth is lowest among occupations that require number facility skills and coordinating work and teams. These patterns are relatively consistent with the literature which has found that wage growth is faster in occupations involving nonroutine tasks (e.g., Deming, 2023; Deming, 2021; Autor et al., 2003) and social skills (Deming, 2017).

The subsequent columns of Table 2 also show that the relationships between skills and wage growth vary by gender, race, and ethnicity. These estimates are from a model which regresses wage growth on the interaction between the focal demographic characteristics (e.g., an indicator for female) and the skill vector. Thus, the coefficients indicate the relative difference in the relationship between the skill and wage growth for women relative to men or for Black or Hispanic workers relative to white workers. Wage growth for women is largest in occupations that include service skills and lower in occupations that require social skills and social interactions. For Black workers, wage growth is larger in occupations that require information use and coordinating skills, while it is lower in occupations requiring social skills. Wage growth is largest for Hispanic workers within occupations with service skills.

[12] For these analyses, we regress a worker's wage growth on the vector of skills, and condition on worker and firm characteristics, age and year of labor market entry, and industry of initial employment but not the worker's initial occupation.

Table 2: Relationship between Skills and Wage Growth Overall and by Gender, Race, and Ethnicity

	Overall	Overall	Female Workers	Black Workers	Hispanic Workers
Require social interaction	-0.0242***	-0.0108***	-0.0127*	0.0111	-0.00210
	(0.00264)	(0.00281)	(0.00621)	(0.0116)	(0.00625)
Number facility	-0.0997***	-0.0510***	0.00732	0.0514	-0.0133
	(0.00738)	(0.00784)	(0.0164)	(0.0316)	(0.0188)
Nonroutine analytical	0.0786***	0.0473***	0.0241	-0.0373	0.0119
	(0.00893)	(0.00940)	(0.0186)	(0.0370)	(0.0226)
Routine	0.0199***	0.0112***	-0.00696	-0.00988	0.00387
	(0.00222)	(0.00232)	(0.00468)	(0.00934)	(0.00564)
Social skills	0.0347***	-0.00647	-0.0237**	-0.0459**	-0.00454
	(0.00419)	(0.00443)	(0.00852)	(0.0164)	(0.0105)
Service	-0.0187***	-0.00975**	0.0193**	0.0443***	0.0265***
	(0.00288)	(0.00364)	(0.00657)	(0.0104)	(0.00772)
Deductive and inductive reasoning	0.0556***	0.0378***	-0.0121	-0.0358	-0.00565
	(0.00588)	(0.00601)	(0.0123)	(0.0239)	(0.0157)
Information use	0.0547***	-0.00819	-0.0210	0.0640*	0.00770
	(0.00714)	(0.00780)	(0.0152)	(0.0288)	(0.0190)
Coordinate	-0.0280***	-0.0226***	0.00587	0.0564***	0.00897
	(0.00305)	(0.00325)	(0.00607)	(0.0113)	(0.00764)
Interact	0.0276***	0.0603***	0.0188	-0.0740**	-0.0124
	(0.00585)	(0.00638)	(0.0134)	(0.0273)	(0.0150)
Includes Worker/Firm Controls	no	yes	yes	yes	yes

Source: This table is based on data from the American Community Survey and Longitudinal Employer Household Database. The research was performed at a Federal Statistical Research Data Center under FSRDC Project Number 2759. (CBDRB-FY25-P2759-R11726)
Notes: Robust standard errors are in parentheses (*p<0.05 .**p<0.01. ***p<0.001). N=313,000. Models include entry year by entry age fixed effects. In columns 2-5 they also control for worker gender, education, race, and ethnicity, as well as firm size and industry fixed effects. The coefficients in columns 3-5 are from the interaction between the demographic group and the skill vector. These models also control for the skills, so that the coefficients represent the differential relationship between the skill and wage growth for the noted demographic group. Definitions of the skills categories are in Appendix C.

4. Discussion

This research indicates that workers' first jobs can play an important role in shaping career trajectories. Initial wages in a worker's first occupation are highly correlated with wage growth eight years later after labor market entry. However, there is notable variation across occupations in wage growth, even conditional on baseline earnings. We also see notable disparities in wage growth by gender, race, and ethnicity. These gaps persist even when looking within occupations and conditioning on worker and firm characteristics. We also find that wage growth, and the magnitude of gender, race, and ethnicity gaps, vary across the skill profiles of workers' initial occupations.

Our results suggest that people's initial occupation choices can have important implications for their longer-term labor market trajectories, earnings inequality, and for gender, racial, and ethnicity wage gaps. While there may be benefits to individual workers moving to occupations with higher baseline wages or smaller wage gaps, the prevalence of gaps across occupations suggests the need for broad efforts to address disparities by gender, race, and ethnicity. Future research on potential mechanisms for disparities in wage growth may be helpful for identifying ways to reduce gender, race, and ethnicity gaps within occupations.

References

Altonji, J. G., Kahn, L. B., & Speer, J. D. (2016). Cashier or consultant? Entry labor market conditions, field of study, and career success. *Journal of Labor Economics*, *34*(S1), S361-S401.

Andrews, R. J., Imberman, S. A., Lovenheim, M. F., & Stange, K. M. (2022). *The returns to college major choice: Average and distributional effects, career trajectories, and earnings variability* (No. w30331). National Bureau of Economic Research.

Arellano-Bover, Jaime. (2024). "Career consequences of firm heterogeneity for young workers: First job and firm size." *Journal of Labor Economics* 42, no. 2 : 549-589.https://www.journals.uchicago.edu/doi/epdf/10.1086/723500

Autor, David H., Frank Levy, and Richard J. Murnane, "The Skill Content of Recent Technological Change: An Empirical Exploration," *Quarterly Journal of Economics*, Vol. 118, No. 4, November 2003.

Autor, D. H., Katz, L. F., & Kearney, M. S. (2008). Trends in US wage inequality: Revising the revisionists. *Review of Economics and Statistics*, *90*(2), 300-323.

Bayer, P., & Charles, K. K. (2018). Divergent paths: A new perspective on earnings differences between black and white men since 1940. *Quarterly Journal of Economics*, *133*(3), 1459-1501.

Bertrand, M., Goldin, C., & Katz, L. F. (2010). Dynamics of the gender gap for young professionals in the financial and corporate sectors. *American Economic Journal: Applied Economics*, *2*(3), 228-255.

Biewen, M., & Seifert, S. (2018). Potential parenthood and career progression of men and women–a simultaneous hazards approach. *The BE Journal of Economic Analysis & Policy*, *18*(2), 20170154.

Bloom, N., Ohlmacher, S. W., Tello-Trillo, C. J., & Wallskog, M. (2021). *Pay, productivity and management* (No. w29377). National Bureau of Economic Research.

Burning Glass Institute and Strada Institute for the Future of Work, Talent Disrupted: Underemployment, College Graduates, and the Way Forward, 2024: https://static1.squarespace.com/static/6197797102be715f55c0e0a1/t/65fb306bc81e0c239fb4f6a9/1710960749260/Talent+Disrupted+03052024.pdf

Card, D. (1999). The causal effect of education on earnings. *Handbook of Labor Economics*, *3*, 1801-1863.

Card, D., Cardoso, A. R., & Kline, P. (2016). Bargaining, sorting, and the gender wage gap: Quantifying the impact of firms on the relative pay of women. *Quarterly Journal of Economics*, *131*(2), 633-686.

Card, D., Chetty, R., Feldstein, M. S., & Saez, E. (2010). Expanding access to administrative data for research in the United States. *American economic association, ten years and beyond: Economists answer NSF's call for long-term research agendas*.

Chetty, R., Friedman, J. N., Saez, E., Turner, N., & Yagan, D. (2017). *Mobility report cards: The role of colleges in intergenerational mobility* (No. w23618). National Bureau of Economic Research.

Chetty, R., Jackson, M. O., Kuchler, T., Stroebel, J., Hendren, N., Fluegge, R. B., ... & Wernerfelt, N. (2022). Social capital I: measurement and associations with economic mobility. *Nature*, *608*(7921), 108-121.

Dale, S. B., & Krueger, A. B. (2014). Estimating the effects of college characteristics over the career using administrative earnings data. *Journal of Human Resources*, *49*(2), 323-358.

Deming, D. J. (2017). The growing importance of social skills in the labor market. Q*uarterly Journal of Economics*, *132*(4), 1593-1640.

Deming, D. J. (2023). *Why Do Wages Grow Faster for Educated Workers?* (No. w31373). National Bureau of Economic Research.

Deming, D. J., & Noray, K. (2020). Earnings dynamics, changing job skills, and STEM careers. *Quarterly Journal of Economics*, *135*(4), 1965-2005.

Denning, J. T., Jacob, B., Lefgren, L., & Vom Lehn, C. (2019). *The return to hours worked within and across occupations: Implications for the gender wage gap* (No. w25739). National Bureau of Economic Research.

Escobari, M., Seyal, I., & Daboin, C. (2021). Moving up: Promoting workers' upward mobility using network analysis. *Brookings*. Accessed on August 29, 2024 at https://www.brookings.edu/articles/moving-up-promoting-workers-upward-mobility-in-a-time-of-change/

Fadlon, I., Lyngse, F. P., & Nielsen, T. H. (2020). *Early Career Setbacks and Women's Career-Family Trade-Off* (No. w28245). National Bureau of Economic Research.

Fan, C. S., Wei, X., & Zhang, J. (2017). Soft skills, hard skills, and the black/white wage gap. *Economic Inquiry*, *55*(2), 1032-1053.

Goldin, C. (2014). A grand gender convergence: Its last chapter. *American Economic Review*, *104*(4), 1091-1119.

Goldin, C., Kerr, S. P., Olivetti, C., & Barth, E. (2017). The expanding gender earnings gap: Evidence from the LEHD-2000 Census. *American Economic Review*, *107*(5), 110-114.

Härkönen, J., & Bihagen, E. (2011). Occupational attainment and career progression in Sweden. *European Societies*, *13*(3), 451-479.

Isenberg, E., Landivar, L.C., & Mezey, E. (2013). *A comparison of person-reported industry to employer-reported industry in survey and administrative data.* Center for Economic Studies Working Paper CES 13-47.

Jardina, A., Blair, P. Q., Heck, J., & Debroy, P. (2023). *The Limits of Educational Attainment in Mitigating Occupational Segregation Between Black and White Workers* (No. w31641). National Bureau of Economic Research.

Kirkeboen, L. J., Leuven, E., & Mogstad, M. (2016). Field of study, earnings, and self-selection. *Quarterly Journal of Economics*, *131*(3), 1057-1111.

Kleven, H., Landais, C., & Søgaard, J. E. (2019). Children and gender inequality: Evidence from Denmark. *American Economic Journal: Applied Economics*, *11*(4), 181-209.

Lordan, G., & Pischke, J. S. (2022). Does Rosie like riveting? Male and female occupational choices. *Economica*, *89*(353), 110-130.

McKinney, K., Green, A.S., Vilhuber, L., & Abowd, J.M. (2017). *Total Error and Variability Measures with Integrated Disclosure Limitation for Quarterly Workforce Indicators and LEHD Origin Destination Employment Statistics in OnTheMap.* Center for Economic Studies Working Paper CES 17-71.

Mincer, J. (1974). Schooling, Experience, and Earnings. *Human Behavior & Social Institutions* No. 2.

Piketty, T., & Saez, E. (2003). Income inequality in the United States, 1913–1998. *The Quarterly journal of economics*, *118*(1), 1-41.

Rubinstein, Y., & Weiss, Y. (2006). Post schooling wage growth: Investment, search and learning. *Handbook of the Economics of Education*, *1*, 1-67.

Song, J., Price, D. J., Guvenen, F., Bloom, N., & Von Wachter, T. (2019). Firming up inequality. *Quarterly Journal of Economics*, *134*(1), 1-50.

Staiger, M. (2023). The intergenerational transmission of employers and the earnings of young workers. *Working paper.* https://matthewstaiger.github.io/matthewstaiger.com/The%20Intergenerational%20Transmission%20of%20Employers%20and%20the%20Earnings%20of%20Young%20Workers.pdf

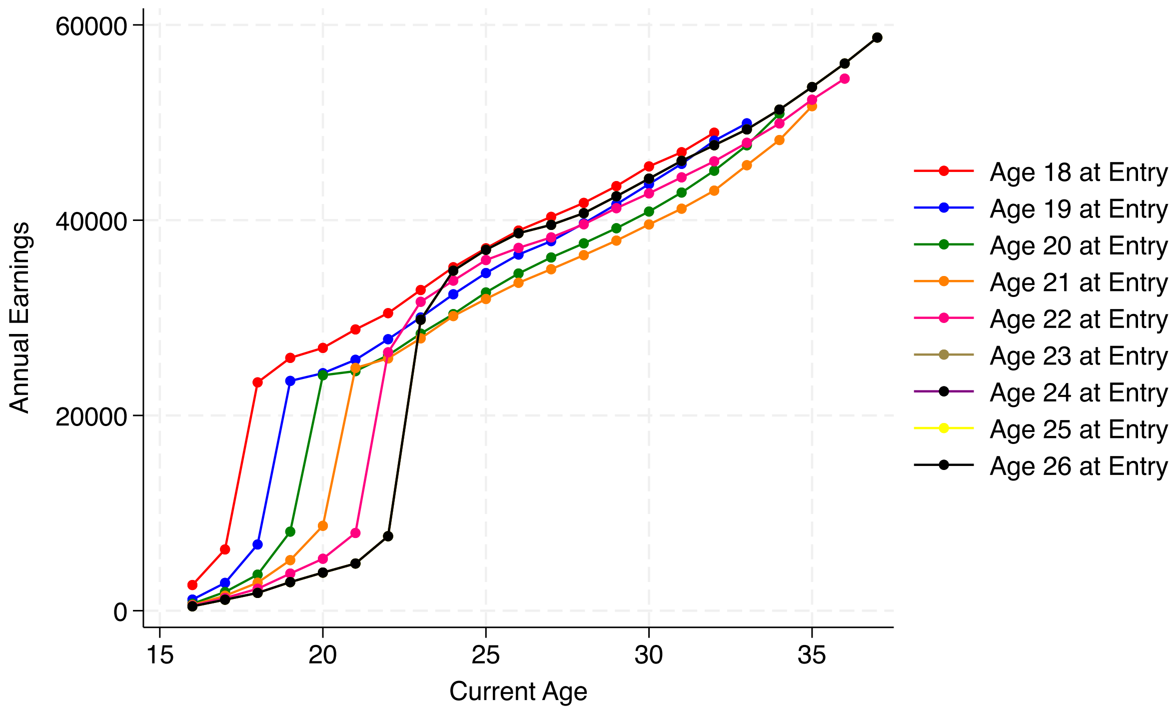
von Wachter, T. (2020). The persistent effects of initial labor market conditions for young adults and their sources. *Journal of Economic Perspectives*, *34*(4), 168-194.

Wagner, D., & Layne, M. (2014). *The Person Identification Validation System (PVS): Applying the Center for Administrative Records Research and Applications (CARRA) Record Linkage Software.* Center for Administrative Records Research and Applications' Working Paper 2014-01.

Zimmerman, S. D. (2019). Elite colleges and upward mobility to top jobs and top incomes. *American Economic Review*, *109*(1), 1-47.

Appendix A. Additional Tables and Figures

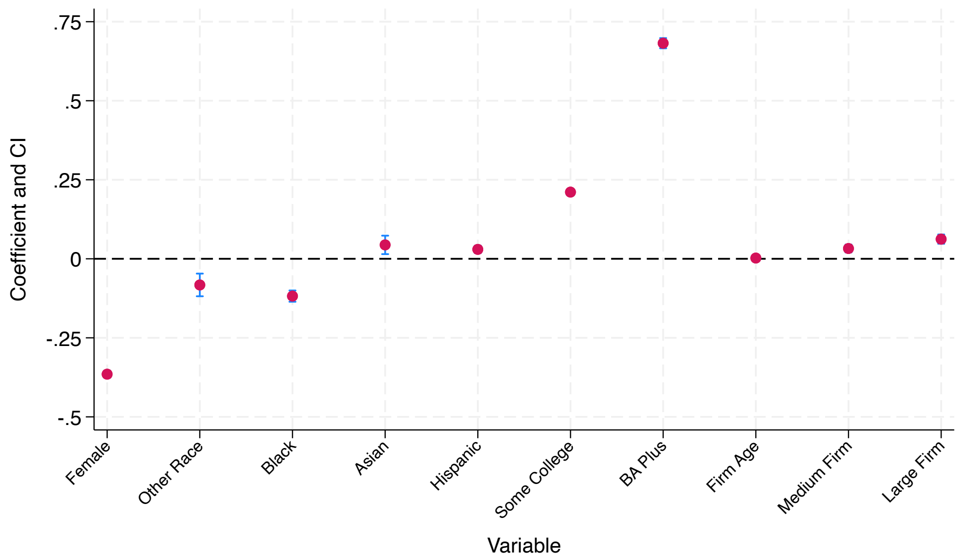
Figure A.1. Earnings by age and labor market entry age



Source: This figure is based on data from the American Community Survey and Longitudinal Employer Household Database. The research was performed at a Federal Statistical Research Data Center under FSRDC Project Number 2759. (CBDRB-FY25-P2759-R11726)

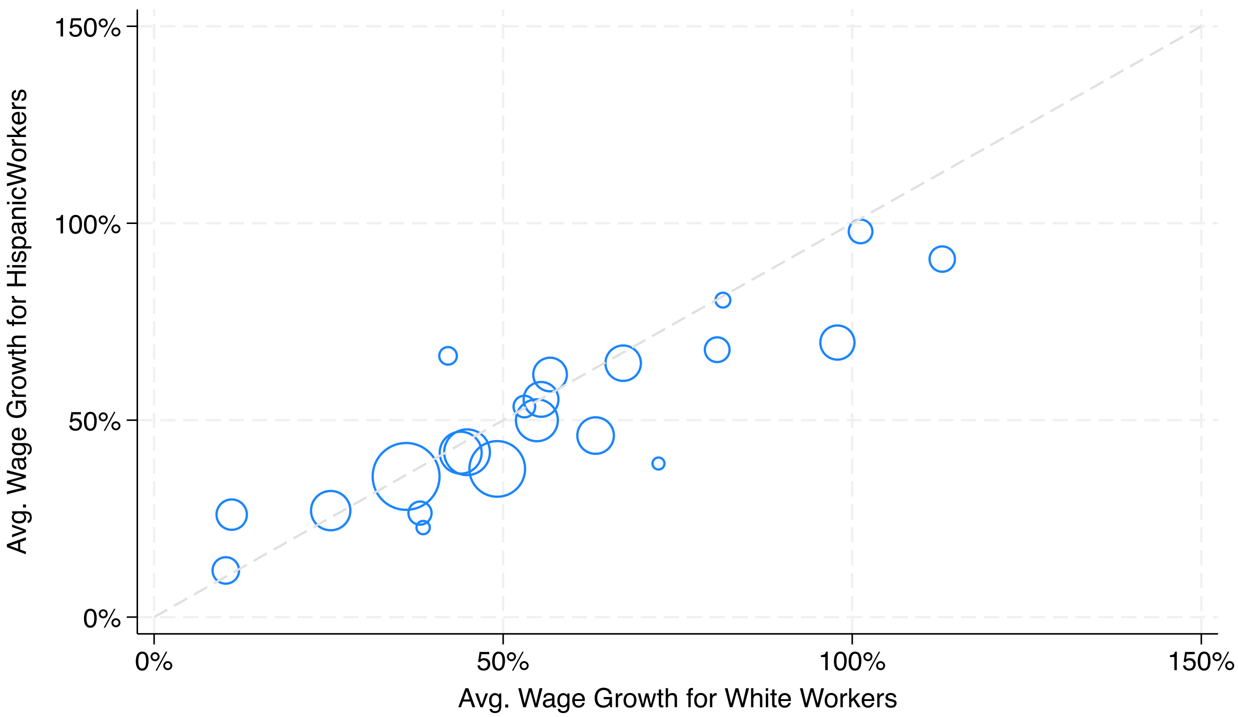
Notes: This figure shows how workers annual earnings change as they age. Each data series (and color) represents a different age at which a set of workers entered the labor market. It shows how earnings increase sharply in the year we define workers to enter the labor market and then continue to increase onward.

Figure A.2. Regression coefficients for wage growth by worker and firm characteristics



Source: This is based on data from the American Community Survey and Longitudinal Employer Household Database. The research was performed at a Federal Statistical Research Data Center under FSRDC Project Number 2759. (CBDRB-FY25-P2759-R11726)
Notes: This figure shows coefficient estimates from a regression of wage growth on the worker and firm characteristics in the figure as well as fixed effects for industry, two-digit occupation and the interaction of year and age of labor market entry. The blue bars indicate the 95% confidence intervals.

Figure A.3. Wage growth for Hispanic and White Workers by Initial Two-Digit Occupation



Source: This figure is based on data from the American Community Survey and Longitudinal Employer Household Database. The research was performed at a Federal Statistical Research Data Center under FSRDC Project Number 2759. (CBDRB-FY25-P2759-R11726)
Notes: This figure shows, for each two-digit occupation code from the Bureau of Labor Statistics major occupation profiles, the average wage growth between labor market entry and eight years later workers who started in that occupation. In panel A the x-axis represents average wage growth for women and the y-axis represents wage growth for men. In panel B the x-axis represents average wage growth for white workers and the y-axis represents average wage growth for Black workers. The dashed line indicates the 45-degree line. Bubbles below this line indicate that women (or black workers) have lower wage growth than men (or white workers) and vice versa for bubbles above the line. The bubbles are proportional to the size of the occupation.

Table A.1 – Average age when occupation is reported relative to labor market entry age

Age Entered Labor Market	Age for ACS Survey	Share of Sample	N
18	21.7	2%	13,500
19	22.0	8%	58,000
20	22.6	13%	94,500
21	23.3	14%	104,000
22	23.9	16%	121,000
23	24.4	19%	139,000
24	25.0	15%	112,000
25	25.5	9%	68,500
26	26.0	4%	30,500

Source: This table is based on data from the American Community Survey and Longitudinal Employer Household Database. The research was performed at a Federal Statistical Research Data Center under FSRDC Project Number 2759. (CBDRB-FY25-P2759-R11726)
Notes: This table indicates the average age in the year people were surveyed by the ACS, separated by the age in which they entered the labor market as well as the share of our sample who entered the labor market at each age. The Ns are rounded per U.S. Census disclosure rules.

Table A.2 – Summary statistics

	Full Sample	Followed for 8 Years	4 Digit Occupations	Skills Sample
Female	45%	46%	50%	49%
Asian	4%	4%	4%	4%
Black	6%	6%	6%	6%
Hispanic	18%	16%	17%	17%
White	69%	72%	71%	71%
HS degree or less	39%	41%	41%	42%
Some College	32%	32%	33%	32%
BA or More	30%	27%	27%	26%
Age in ACS	24	24	24	24
Small Firm	25%	26%	24%	24%
Medium Firm	42%	41%	41%	41%
Large Firm	33%	33%	35%	35%
N	742,000	313,000	234,000	216,000

Source: This table is based on data from the American Community Survey and Longitudinal Employer Household Database. The research was performed at a Federal Statistical Research Data Center under FSRDC Project Number 2759. (CBDRB-FY25-P2759-R11726)

Notes: Column (1) shows the full sample of LEHD records linked to the ACS for individuals who entered the labor market between ages 18 and 25. Column (2) is restricted to the individuals for whom we are able to follow for at least eight years because they entered the labor market by 2011. Column (3) is restricted to the people in column 2 for whom we are able to identify a valid four-digit occupation code based on the 2010 occupation classifications. Column (4) is restricted to the people in column 3 for whom we are able to link information about the typical skill profile of their occupation.

Table A.3 – Average wages and wage growth for 2 digit occupations by subgroup

	Everyone		Female		Male		Black		Hispanic		Asian		White	
Initial Occupation	Baseline Wages	Wage Growth	Baseline Wages	Wage Growth	Baseline Wages	Wage Growth	Baseline Wages	Wage Growth	Baseline Wages	Wage Growth	Baseline Wages	Wage Growth	Baseline Wages	Wage Growth
Management	$32,480	61%	$31,250	43%	$33,800	79%	$29,850	48%	$30,070	46%	$37,110	76%	$32,730	63%
Business and Financial Operations	$35,350	94%	$34,380	74%	$36,690	121%	$33,240	58%	$31,760	70%	$40,040	110%	$35,380	98%
Computer and Mathematical	$39,780	107%	$38,260	76%	$40,220	116%	$35,170	66%	$36,210	91%	$46,880	97%	$38,810	113%
Architecture and Engineering	$41,090	101%	$40,670	78%	$41,200	107%	$40,540	62%	$37,730	98%	$45,640	122%	$40,880	101%
Life, Physical, and Social Science	$34,340	79%	$34,160	68%	$34,550	92%	$33,980	51%	$31,460	80%	$38,720	76%	$34,070	81%
Community and Social Service	$29,220	45%	$29,240	39%	$29,150	64%	$28,410	37%	$29,430	66%	$31,990	67%	$29,190	42%
Legal	$32,520	68%	$31,480	54%	$35,760	112%	$30,420	50%	$31,280	39%	$34,970	91%	$32,590	72%
Educational Instruction and Library	$29,870	57%	$29,600	48%	$30,960	91%	$26,720	50%	$27,850	62%	$32,210	63%	$30,280	57%
Art, Design, Entertainment, Sports, and Media	$31,460	54%	$30,380	41%	$32,790	70%	$34,880	45%	$30,660	53%	$37,160	81%	$31,040	53%
Healthcare Practitioners and Technical	$34,230	57%	$34,440	51%	$33,190	86%	$30,300	39%	$31,210	55%	$39,900	100%	$34,470	55%
Healthcare support	$24,430	15%	$24,280	12%	$25,580	36%	$23,530	14%	$24,770	26%	$26,360	54%	$24,390	11%
Protective Service	$30,850	73%	$29,790	29%	$31,110	84%	$26,800	42%	$30,170	68%	$32,420	75%	$31,660	81%
Food Preparation and Serving Related	$22,940	24%	$22,520	13%	$23,380	36%	$22,100	15%	$23,800	27%	$24,930	28%	$22,690	25%
Building and Grounds Cleaning and Maintenai	$25,110	32%	$23,060	0%	$25,640	41%	$23,460	15%	$25,310	26%	$25,370	25%	$25,250	38%
Personal Care and Service	$24,710	11%	$24,170	3%	$26,560	39%	$22,970	13%	$24,890	12%	$27,960	40%	$24,600	10%
Sales and Related	$28,010	45%	$26,410	25%	$29,610	65%	$25,340	25%	$26,270	38%	$31,240	50%	$28,560	49%
Office and Administrative Support	$26,740	35%	$26,450	26%	$27,340	55%	$25,810	23%	$26,570	36%	$30,640	50%	$26,670	36%
Farming, Fishing, and Forestry	$26,850	34%	$25,000	3%	$27,120	38%	$26,600	11%	$26,390	23%	$27,780	40%	$27,120	39%
Construction and Extraction	$30,790	53%	$28,330	13%	$30,840	54%	$28,340	46%	$30,460	50%	$31,370	40%	$30,980	55%
Installation, Maintenance, and Repair	$30,700	66%	$29,790	21%	$30,720	67%	$28,720	31%	$30,050	64%	$31,160	64%	$30,920	67%
Production	$28,910	43%	$25,850	10%	$29,640	51%	$26,630	24%	$27,990	42%	$28,930	40%	$29,310	45%
Transportation and Material Moving	$27,440	41%	$24,620	11%	$27,790	45%	$25,470	22%	$27,440	42%	$26,420	40%	$27,680	44%
Overall	*$29,280*	*49%*	*$28,100*	*32%*	*$30,270*	*63%*	*$26,460*	*28%*	*$27,680*	*43%*	*$35,110*	*71%*	*$29,590*	*52%*

Source: This table is based on data from the American Community Survey and Longitudinal Employer Household Database. The research was performed at a Federal Statistical Research Data Center under FSRDC Project Number 2759. (CBDRB-FY25-P2759-R11726) Notes: This shows the average baseline wages at labor market entry and wage growth between labor market entry and eight years later for each two-digit occupation. This is based on occupation at labor market entry. The columns are separated by workers' demographic characteristics. The last columns include only non-Hispanic white workers.

Appendix B. Details on Data Construction.

Our starting analytic dataset consists of all LEHD records over the 2005-2019 period for anyone who we could link to an American Community Survey response over the 2005-2019 period. The LEHD covers all private sector workers covered by those states' unemployment insurance systems. Workers who are employed in other states, self-employed or federal government employees are excluded.

We made a few key restrictions when constructing this analytic file. First, we limited the ACS respondents to those aged 16 or older when surveyed and those with a job based on the employment status recode variable and the class of worker variable. Then, the dataset was matched to Protected Identification Keys (PIK) file. This process was not a perfect match because the PIK is probabilistic and not deterministic (Wagner and Layne 2014); we removed records with a blank PIK and records whose PIKs match to multiple households or whose PIKs match to multiple people within the same household. We also removed duplicate records within a given ACS year. This procedure resulted in the creation of the ACS-PIK file.

Next, the ACS-PIK dataset was matched to the Employment History File (EHF) of the LEHD to identify the primary job (identified by the firm id or SEIN) and corresponding earnings. The EHF reflects quarterly earnings for a given individual for each firm and quarter. We matched these records based on the PIK and the quarter of the ACS primary job reference week. (We do not match on year because respondents' whose ACS interview was in early of January could have a reference week in the previous year). Instead, we match on PIK within the range of possible reference weeks. More specifically, in all cases, we identified jobs (defined by SEIN) that took place within a week of the ACS interview. When there was no such job within a week of the ACS interview, we looked as far back as 30 days before the ACS interview date to identify the most likely job that corresponded with the ACS primary job reference week, following methods described in Isenberg, Landivier & Mezey (2013). Additionally, when the reference week crossed a quarter or year boundary, we considered all jobs in both of the reference week's quarters or years.

Once we identified all jobs (identified by SEIN) and the corresponding earnings worked during (or near) the reference week, we determined the most likely job associated with the ACS primary job. For those with one job during (or near) the reference week, the selection process was trivial. For those with two or more jobs during (or near) the reference week, the selection process was as follows: we selected the job with the highest quarterly earnings; then, if quarterly earnings are the same, we selected the job with highest annual earnings; then, if annual earnings are the same, we selected the job randomly. This procedure resulted in the creation of the ACS-PIK-EHF file.

Next, we merged in the appropriate individual-level characteristics, establishment ID (the sub-unit level of the firm), and the firm-level and establishment-level characteristics. We first merged the ACS-PIK-EHF file to the Individual Characteristics File (ICF) at the PIK level. We examined how individual demographic variables in the ICF compared to the same or similar variables in the ACS, notably date of birth, place of birth, sex, race, ethnicity, and education. In general, these variables in the ACS aligned well with the same or similar variables in the ICF, except for education, which is imputed in the ICF for the vast majority of records (McKinney, Green, Vilhuber & Abowd 2017); an additional discrepancy is that education in the ACS represents education at the point of the interview, whereas education in the ICF represents an individual's highest level of education obtained. Because education is imputed in the ICF, we use the education measure from the ACS. We also use the demographic measures from the ACS. This procedure resulted in the creation of the ACS-PIK-EHF-ICF file.

Next, we merged the ACS-PIK-EHF-ICF file with the Job History File (JHF) to obtain the appropriate establishment ID (SEINUNIT) for each record. The matching was done at the PIK-SEIN level. The JHF is organized at the spell-level: each person has a record per spell per firm (SEIN) and each spell has dates of first-accession and last-separation. We selected the establishment ID from any spells that have the primary job's employment dates for that year inside of the spell period.[13] Establishments are imputed so we pick the first of the ten establishment implicates. This procedure resulted in the creation of the ACS-PIK-EHF-ICF-JHF file.

Finally, we linked the ACS-PIK-EHF-ICF-JHF file with the Employer Characteristics file (ECF) to pick up firm and establishment characteristics, specifically size and age. Firm location and industry characteristics were obtained by matching the records at the SEIN-state-year level. Firm age and size were obtained by matching the records at the SEIN-state-year-quarter level.

13 When the year includes multiple rows of the spell (in other words, when a firm's identifiers changed during the spell that year), we selected the establishment associated with the record that corresponds to either (a) the quarter of the ACS reference week, or (b) the first matching record for ACS respondents in non-survey years.

Establishment location, industry, age, and size were obtained by matching the records at the SEIN-SEINUNIT-state-year-quarter level. This procedure resulted in the creation of the ACS-PIK-EHF-ICF-JHF-ECF file.

The last step of the data construction was repeating the aforementioned steps for LEHD records which did not have a corresponding ACS match in the given year, but belonged in the sample because of an ACS match in another year (i.e., earnings in 2006-2019 for a worker surveyed in the 2005 ACS). For these LEHD records, in the absence of an ACS reference week, we identified the primary job from the EHF as the one that had the highest quarterly earnings (or the highest annual earnings if quarterly earnings were the same for two or more jobs). After this selection, we matched the primary job to the ICF, SEIN, and SEINUNIT files as described above.

Appendix C. Skills Definitions

The skills variables and definitions come directly from Deming (2017). They are as follows.

- The *social skills* measure is based on the extent to which the occupation involves social perceptiveness, adjusting in accordance with others' actions, persuasion and negotiation.
- The *nonroutine analytical* measure is based on the mathematical competence that an occupation requires – including mathematical reasoning ability, mathematical knowledge, and mathematics skills.
- The *routine* measure is based on the occupation's degree of automation and importance of repeating physical or mental tasks.
- *Service* is a measure o the extent to which the occupation involves assisting and caring for others and looking for ways to help people.
- *Deductive and inductive reasoning* is a measure of written comprehension, capacity to apply general rules to specific problems, and ability to synthesize separate sources of information to form general conclusions.
- *Number facility* is a measure of people's ability to perform basic mathematical functions (addition, subtraction, multiplication and division) quickly and accurately.
- *Information* use is a measure of the extent to which the occupation involves obtaining the information needed for the job, identifying information received, processing information, and analyzing data or information.
- *Require* social interaction is a measure of how much the job requires the worker to be in contact with others.
- *Coordinate* is a measure of the extent to which the job requires the worker coordinate others and develop and build teams.
- *Interact* is a measure of how much the job involves interpreting information for others, communicating with people inside and outside the organization, and building and sustaining relationships.