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THE OCCUPATIONAL LADDER: IMPLICATIONS FOR LIFE-CYCLE WAGE DYNAMICS

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ABSTRACT

Some occupations pay higher wages than others, even conditional on worker characteristics, implying that occupations can be ranked on a ladder. We develop a simple decomposition to study the role this occupational ladder plays in average wage growth and in the fanning out of wages over the life cycle. We present three main findings. First, the distribution of employment shifts towards higher-paying occupations as workers gain experience. This contributes modestly to average life-cycle wage growth, with greatest impact in early career. Second, this upward movement in the occupational employment distribution is not accompanied by increasing dispersion; thus, the occupational ladder does not directly contribute to the fanning out of wages. Third, early-career workers who are well-positioned on the occupational ladder tend to earn wages far below the occupational average. However, by mid-career, workers' relative wages within occupations (their positions on the job ladder) no longer depend on their occupation. This change in the covariance between individuals' positions on the job and occupational ladders is a major contributor to the fanning out of wages over workers' careers.

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1 Introduction

In this paper, we quantify the role of the "occupational ladder" for life-cycle wage dynamics. Specifically, some occupations pay higher wages than others, even conditional on worker-level characteristics. Occupations can thus be ranked on a ladder, with better paying occupations representing higher "rungs" on the ladder (see e.g., Jovanovic and Nyarko, 1997; Groes et al., 2015). In addition, workers make occupational transitions over the life cycle. What role does climbing the occupational ladder play in average life-cycle wage growth? What role does differential climbing—both up and down the ladder—play in the fanning out of wages over the life cycle?

To answer these questions, we develop a simple decomposition of individual-level wages into an *occupational wage* and deviations from the occupational wage. The ranking of occupational wages constitutes the occupational ladder. We implement our decomposition using US data from the American Community Survey (ACS), 2005–2019, to study life-cycle wage patterns, in terms of means and variances. An attractive feature of our approach is the simplicity of the empirical exercise—one that can be implemented on readily available, cross-sectional data.

The life-cycle profile of average earnings and wages in high-income countries is one of the most widely documented patterns in empirical labor economics (see e.g., Ben-Porath, 1967; Mincer, 1974; Murphy and Welch, 1992).[1] An important body of work also documents increasing earnings dispersion over the life cycle (see e.g., Storesletten et al., 2004; Heathcote et al., 2005). Meanwhile, the idea that people can attain earnings and wage gains by moving up rungs on an occupational ladder is ubiquitous in public economics, social policy, and workforce development. An example of this is the *Occupational Mobility Explorer*, created by the Federal Reserve Banks of Philadelphia and Cleveland.[2] This online tool is designed to help workers "expand opportunities for economic mobility," allowing users to "explore career paths and visualize how job skills needed for specific occupations can transfer to higher-paying occupations."

[1] For evidence from low- and middle-income economies, see Lagakos et al. (2018); Jedwab et al. (2023).

[2] https://www.philadelphiafed.org/surveys-and-data/community-development-data/occupational-mobility-explorer.

This paper quantifies the extent to which these opportunities for occupational transitions materialize for the average US worker over their career, and their importance as a driver of the life-cycle profile of wages. We also quantify the extent to which heterogeneity in workers' positions along the occupational ladder at higher potential experience levels accounts for the life-cycle profile of wage inequality. Our approach tracks how residual wages—purged of compositional differences in education, demographics, location, and time—evolve with potential experience and how employment shifts over the life cycle across 674 detailed ACS occupations ranked by their economy-wide residualized wage.

We find that, as potential experience rises, the distribution of employment shifts towards higher-paying occupations. This implies that the average worker climbs the occupational ladder over their life cycle. However, this effect contributes only modestly to total career wage growth. Improvements in the occupational distribution of employment account for about one-quarter of wage gains between the first and the fifth year of potential experience, when wage growth is greatest. The job ladder within occupations becomes increasingly important as workers accumulate experience. These results are robust to allowing for time-varying occupational wage premia, and are broadly observed across geographic areas and time periods. The relative roles of the occupational and job ladders are also very similar among men and women. We further validate our decomposition results from the repeated cross-sectional ACS data by confirming their robustness in other datasets that allow us to track either synthetic or actual cohorts, namely the Current Population Survey's Outgoing Rotation Groups (CPS ORG) and the National Longitudinal Survey of Youth 1979 (NLSY79) samples.

When analyzing the role of the occupational ladder for the fanning out of wages over the life cycle, we find that the distribution of employment across occupations changes with potential experience in such a way that the variance of the occupational wage remains essentially constant. Hence, differential movements along the occupational ladder do not *directly* contribute to the increasing variance of life-cycle wages. However, we document an important *covariance effect*. Specifically, in early career, workers in high-paying occupations tend to be located on particularly low rungs of the job ladder within their occupations. This negative correlation between occupational quality and individual earnings within occupations serves to compress overall wage

dispersion among less experienced workers. Subsequently, over the first 15 years of potential labor market experience, this covariance rises to essentially zero, and that shift plays a central role in the life-cycle widening of wage inequality.

Our results contribute to a number of strands in the labor literature studying life-cycle wage dynamics. First, we contribute to the literature on the increasing and concave life-cycle profile of earnings and wages. Rubinstein and Weiss (2006) discuss the roles of human capital investment, frictional job search, and learning about productivity for wage growth as a function of labor market experience. Lemieux (2006b) and Heckman et al. (2006) offer retrospectives on the voluminous work on the Mincer regression, and highlight the important interaction between experience and education. The seminal work of Topel and Ward (1992) documents how the high degree of job mobility experienced by workers during their first ten years in the labor market accounts for a significant fraction of early-career wage growth. They relate this to learning about one's comparative advantage, via sampling and experiencing a variety of jobs. More recent work using on-the-job search models, such as Altonji et al. (2013), Bagger et al. (2014), and Menzio et al. (2016), emphasizes pay raises in response to outside offers and employer-employer transitions to jobs with better firm fixed effects or match-specific productivity. Our analysis explores the role of occupations and the occupational ladder in accounting for the overall experience profile of wages—a largely understudied dimension in this strand of the literature.

Several papers have considered the role of learning in driving occupational mobility and wage growth. Examples of such papers include Papageorgiou (2014) and Gervais et al. (2016), which feature models in which the ranking of occupations varies across individuals depending on their comparative advantage. Individuals can experience earnings growth by moving from occupations where they earn below-average wages to occupations where they earn above-average wages, i.e., by moving to higher positions along the job ladder *within an occupation*, but with no role for an occupational ladder. Groes et al. (2015) develop a framework in which occupations are vertically differentiated. In their model, it is efficient for high-ability workers to sort into occupations on higher rungs of the occupational ladder; however, workers initially have limited information about their ability. As in the models above, learning leads to occupational mobility, but in this case, a worker's position on the within-occupation job ladder determines the likelihood and direction of switching along the

occupational ladder. Although these papers provide empirical evidence supporting their model predictions, they do not directly investigate the roles of the occupational ladder and job ladder in accounting for life-cycle wage growth.[3]

A distinct body of work documents the increasing dispersion of wages over the life cycle (see e.g. Huggett et al., 2006; Guvenen et al., 2022). Heathcote et al. (2005) and Storesletten et al. (2004) represent important examples that decompose individual wage dynamics into fixed effects (realized at labor market entry), and persistent and transitory shocks (realized over one's career).[4] Both papers find that highly persistent idiosyncratic shocks are critical for accounting for the fanning out over the life cycle. Heathcote et al. (2005) demonstrate that a near-unit-root specification is necessary to match the approximately linear increase in wage inequality. These papers characterize wage dynamics statistically, and the source of persistent shocks is specified as a reduced-form statistical process. Our analysis provides a potential, explicit interpretation: workers' transitions between rungs on an occupational ladder might represent a source of such shocks.[5]

Our paper is also related to the literature that distinguishes between general and specific human capital. Neal (1995) and Parent (2000) argue that an important component of human capital is industry specific, and is lost when a worker switches to a different industry. Kambourov and Manovskii (2009) find that returns to occupational tenure are substantial, and much more important than returns to tenure in an industry or with an employer. Our framework suggests that the ways in which general

[3]A related literature studies the extent to which workers tend to switch occupations over the business cycle, see e.g., Carrillo-Tudela et al. (2016); Carrillo-Tudela and Visschers (2023) show this cyclicality is driven by worker-occupation match quality rather than occupation-wide productivity.

[4]Keane and Wolpin (1997) present a model of schooling, participation, and occupational choice between white-collar, blue-collar, and military occupations. Their estimation results, given their assumption of serially independent skill shocks, emphasize the importance of heterogeneity in (permanent) skill types.

[5]See also Kahn and Lange (2014) who find that the fanning out of wages over the life cycle reflects heterogeneity in the stochastic evolution of productivity. Their work does not speak to the potential role of an occupational ladder, since their data consist of personnel records for only managerial employees, containing both wage and job performance measures. Recent work by Deming (2025) and Erosa et al. (2025) finds that occupations differ in the extent to which they provide learning opportunities (or returns to tenure), which can help explain the rising dispersion of earnings over the life cycle. Carrillo-Tudela et al. (2026) show that cyclical shifts in the quality of idiosyncratic worker-occupation matches, rather than occupation-wide productivity, are the main source of earnings risk over the business cycle, a distinction analogous to our job and occupational ladders.

and (occupation) specific human capital interact may be more complex than traditionally modeled. In particular, experience in an occupation may enable individuals to work in a higher-paying occupation later in life—a type of return to occupational tenure that would not be captured in a specification such as the one estimated by Kambourov and Manovskii (2009).

Recent work by Bayer and Kuhn (2025) uses German matched employer-employee data containing direct measures of "job levels"—a classification based on the complexity, autonomy, and responsibility involved in task execution. Their findings align closely with ours. Empirically, they show that progression across job levels accounts for approximately half of life-cycle wage growth and nearly all of the increase in wage dispersion with age. Moreover, job-level differences alone explain nearly half of cross-sectional wage variation. Movements across occupations contribute relatively little to wage dynamics once job levels are controlled for. The "job levels" in Bayer and Kuhn (2025) correspond to what we term the "job ladder within occupations"; their results corroborate our finding that this margin dominates the occupational ladder in accounting for life-cycle wage patterns. A key advantage of their approach is access to data with encoded job-level information unavailable in most datasets. By contrast, our empirical methodology can be implemented on readily available cross-sectional survey data, making it well-suited for broader application and cross-country comparison. Additionally, our decomposition reveals a covariance mechanism that contributes to the fanning out of wages.

2 Data and Methodology

2.1 Data

Our primary source of data is the American Community Survey (ACS) for the years 2005–2019, as provided by IPUMS (Ruggles et al., 2020). We restrict the sample to non-institutionalized individuals aged 17–66 at the time of the survey who report a non-military occupation. Earnings are measured as total pre-tax wage and salary income for the previous year (i.e., when the individuals were aged 16–65). Individuals who report zero earnings are dropped from the sample. To focus on individuals' post-

schooling careers, we exclude respondents who report attending school or college in the three months prior to the survey.[6] After making those restrictions, the sample includes roughly 18.4 million observations. We use this sample to estimate occupational mean wages and to estimate the regressions that residualize wages, a procedure we describe in more detail in the next section.

We compute hourly wages by dividing individuals' total annual income by their annual hours, where annual hours are constructed as the product of weeks worked last year and usual hours per week.[7] We deflate nominal values to constant 2009 dollars using the Consumer Price Index from the Bureau of Labor Statistics, and winsorize the top and bottom 1% of real hourly wages. Individuals are always weighted using the person weights provided in the dataset.

The ACS is a repeated cross-sectional dataset. We therefore cannot track individual wage profiles. However, we can construct an average life-cycle wage profile by focusing on the evolution of wages across workers at different levels of potential experience.[8] We compute potential experience as current age minus one (since earnings are measured for the year preceding the survey), minus a proxy for the age at which the individual entered the labor market given their level of education. Specifically, this proxy is equal to: 16 for individuals who completed grade 10 or less; 17 for those who completed grade 11; 18 for those who completed grade 12 or have a high school diploma or equivalent; 19 for those with some college but less than one year; 20 for those with one or more years of college credit and those with an associate's degree; 22 for those with a bachelor's degree; 24 for those with a professional or master's degree; and 26 for individuals with a doctoral degree.[9] In all of our life-cycle profiles and decomposition exercises, we restrict the sample to those with 1 to 39 years of potential experience. This leads to a sample of around 16.4 million observations.

In Panel A of Table 1, we summarize the individual characteristics for this sample. The two core stylized facts that we explore in this paper are evident. First, average

[6] Appendix Table A.1 reports the number of observations dropped by each of these restrictions.

[7] For years in which the ACS records weeks worked in intervals, we use the midpoint of each interval.

[8] In Section 3.3 we verify the robustness of our results in longitudinal data.

[9] It is worth noting that *actual* and potential experience may differ due to differences in the timing of educational completion, or due to non-employment spells, for example. The latter tend to be more prevalent in the case of women (Munasinghe et al., 2008). Below we present results from our analysis separately for men and women.

wages follow the familiar concave life-cycle profile, with strong growth in early career and relatively little further growth thereafter. Second, the standard deviation of wages increases with experience, representing the 'fanning-out' of wages over the life cycle. It is also worth noting that the composition of the workforce shifts across potential experience levels. Workers at higher experience levels are less likely to hold a bachelor's degree and more likely to have completed high school or less. The share of women is higher among workers with more than 20 years of potential experience, and the share of the workforce that is white rises with experience. This reflects cohort differences in a repeated cross section, as well as changes over the life cycle in who is employed. These compositional differences motivate our focus on residual wages, which net out these observable characteristics, as well as our subsequent cohort-level analysis, both of which are discussed in further detail below.[10]

In our main decompositions, occupations are defined by the 4-digit ACS occupation codes, which distinguish between 674 occupational categories.[11] Panel B of Table 1 shows that all 674 occupations are observed at every stage of the life cycle, with a median of more than 7,400 observations per occupation overall and a median of at least 1,500 within each 10-year potential experience bin, ensuring that the occupational employment shares underlying our decompositions are precisely measured at every experience level. We also report, in Panel B, the employment shares across broad occupational groups. This provides an initial indication of movements up the occupational ladder at an aggregate level. Between the first ten years and mid-career at 21–30 years of potential experience, the share of workers in management, business, and financial occupations rises from 12.0 to 17.0 percent, while the share in service occupations falls from 18.9 to 14.6 percent.

[10] As we discuss in the next section, our residualization also removes the influence of any aggregate time variation in overall wages. We demonstrate how mean real hourly wages evolve over time in Appendix Figure B.1, which shows that average real wages decline steadily up until 2014, and subsequently recover and surpass their initial levels. This overall pattern is also observed within each potential experience group.

[11] The occupation codes used in the ACS experienced minor revisions in 2010, 2012, and 2018 (see https://usa.ipums.org/usa-action/variables/occ#codes_section). We treat any detailed occupation code that ever exists as its own category. As we discuss below, we characterize each detailed occupation by its mean wage. Since the coding changes involve minor merging and splitting of detailed occupational categories that are likely very similar to each other in terms of their occupational mean wages, we do not expect the revisions to the coding schemes to have a major impact on our results. We have also verified that we obtain nearly identical results for the role of the occupational ladder when using the harmonized occupation codes of Autor and Dorn (2013).

2.2 Decomposing the Average Wage

Our approach is to express an individual's wage (either in levels or in logs) as the sum of an occupation-specific component, measured as the mean wage in the occupation j that the individual works in, and an individual-specific deviation from this mean. In other words, individual i's wage at the time when they have e years of (potential) labor market experience can be written as:

$$w_{ie(j)} = \sum_j D_{ie}^j w^j + \epsilon_{ie}, \tag{1}$$

where D_{ie}^j is an indicator variable which is equal to one for the occupation j that individual i works in at e years of potential experience, and equal to zero for all other occupations. w^j is the economy-wide mean wage of occupation j, and $\epsilon_{ie} \equiv w_{ie(j)} - \sum_j D_{ie}^j w^j$ captures the individual-specific wage deviation from this occupational mean wage.

We interpret w^j, the occupational wage, as a measure of the "quality" of the occupation that the individual works in—their position on an *occupational ladder*.[12] Meanwhile, ϵ_{ie} is a measure of the quality of the *job* that individual i holds at potential experience e *within* occupation j—their position on a *job ladder* within an occupation.

We compute the occupational wage w^j by pooling the entire sample, i.e., averaging over all individuals observed across all years.[13] We use both raw and residualized wages in our decompositions; the quality interpretation of w^j is more meaningful in residual wages, as discussed in more detail below.

Using Equation (1), we can express the average wage across all individuals of

[12] Characterizing occupations by their mean or median income is frequently done in the economic history literature, as many historical datasets lack information on individual wages or education but do provide information on individuals' occupations (see e.g., Sobek, 1995, and the OCCSCORE variable on IPUMS). The sociology literature often focuses on occupational 'prestige', considering occupational characteristics beyond income (see e.g., Hauser and Warren, 1997, and the SEI and PRESGL variables on IPUMS).

[13] In Subsection 3.2, we allow this measure of occupational quality to vary over time, by computing a year-specific occupational (mean) wage, and show that results are insensitive to this change.

potential experience e, $\overline{w}_e$, as:

$$\begin{aligned}\overline{w}_e &\equiv \frac{1}{n_e}\sum_{i\in e} w_{ie(j)} \\ &= \sum_j s_{ej} w^j + \frac{1}{n_e}\sum_{i\in e}\epsilon_{ie}, \end{aligned} \tag{2}$$

where n_e is the total number of individuals of potential experience e, and $s_{ej} = \sum_{i\in e} D^j_{ie}/n_e$ is the share of individuals of potential experience e working in occupation j.[14] Equation (2) shows that the average wage of individuals with e years of potential labor market experience can be expressed as the sum of: (i) their weighted average position on the *occupational ladder*, and (ii) their average position on the *job ladder* within occupations.

The evolution of $\overline{w}_e$ across values of e reveals the life-cycle profile of wages. Given Equation (2), the life-cycle profile can be decomposed into two components. The first is related to climbing the occupational ladder, i.e., changes in $\sum_j s_{ej} w^j$, that are due to changes in the distribution of employment across occupations for individuals with different levels of potential experience. This term increases over the life cycle if more experienced individuals tend to work in occupations with higher w^j's—"better" occupations—than less experienced individuals. The second component is related to climbing the job ladder within occupations, i.e., changes in $(1/n_e)\sum_{i\in e}\epsilon_{ie}$. This term will increase if, on average, individuals obtain wage increases within their occupation as they gain experience (due to tenure on the job, job switches within occupations, etc.). Because the ACS is a repeated cross section, both components are identified from comparisons across different individuals observed at different levels of potential experience, and thus capture net changes rather than the gross occupational or job mobility patterns of specific individuals. We return to this distinction in Section 3.3.

In short, plotting the value of the two components in Equation (2) across different levels of potential experience allows us to understand how much of the life-cycle profile of wages is due to (i) climbing the occupational ladder, and (ii) climbing the job ladder within occupations.

[14] We use $i \in e$ to denote individuals in the sample at potential experience level e.

2.3 Rungs on the Occupational Ladder

We perform our decompositions using both raw and residualized wages. With raw wages, variation in w^j may arise if individuals with specific observable characteristics tend to cluster in specific occupations. For example, high w^j occupations might be those that disproportionately employ highly educated workers. Consequently, to address this issue and obtain a cleaner measure of occupational quality, we perform our analysis using residual wages.

Residual wages are obtained by regressing the natural log of wages on race and ethnicity (non-Hispanic White, non-Hispanic Black, Hispanic, all others), sex (female, male), education (indicators for no schooling, lower primary, upper primary, each of grades 9–12, and each of 1, 2, 4 or 5 plus years of college), as well as year and state fixed effects. This regression is run pooling all observations for all years. We then compute w^j using the economy-wide mean of the residual wage within each occupation. These residualized occupational wages reflect the premia paid by the occupation conditional on observable worker characteristics and are, therefore, a more meaningful measure of occupational quality.

Panel (a) of Figure 1 shows that the mean (raw) log wage is very strongly correlated with the mean residual wage at the occupational level; the weighted correlation between the two is 0.89. This implies that the relative measure of an occupation's quality turns out to be very similar regardless of whether we consider unconditional mean wages or whether we net out observables.

Because we are specifically interested in average life-cycle movements along the occupational ladder, we do not include potential experience as a regressor in our residualization. Nonetheless, the interpretation of the mean occupational residual wage as a measure of occupational quality may be undermined if it primarily reflects the composition of workers in terms of labor market experience. For example, if an occupation primarily hires workers who have recently entered the labor market, it might have a low average wage (in levels or residuals) not because it is "low quality," but because its workers lack experience. Similarly, high w^j occupations might disproportionately employ high-experience workers. To explore whether this is the case, we regress the individual-level residual wages on a full set of potential-experience-level fixed effects. We obtain the residuals from this regression and compute the average

for each occupation. This gives us an alternative measure of mean residual wage in each occupation that is purged of experience.

Panel (b) of Figure 1 shows that there is a very high correlation between the measure of w^j based on residual wages that we use in our analysis, and the alternative measure of w^j that is purged of potential experience. The weighted correlation between the two is 0.99. This implies that it is valid to interpret our measure of w^j based on residual wages as a measure of the occupational wage premium—it is not driven by the composition of workers in each occupation along the experience dimension. Instead, high w^j occupations pay more, even conditional on potential experience.

This result also foreshadows our main findings. The two measures of w^j differ only through the experience composition of each occupation's workforce, and they would diverge if experienced workers were disproportionately clustered in higher-paying occupations, which is precisely what substantial net movement up the occupational ladder would produce. The near-coincidence of the two measures thus points towards the finding of Section 3 that climbing the occupational ladder accounts for a modest share of cumulative life-cycle wage growth. The comparison of the two measures of w^j in Panel (b) of Figure 1, however, concerns the ranking of occupational wage *levels*, and carries no implication about the occupational ladder's role in the fanning out of wages over the life cycle, a margin we return to below.

2.4 Decomposing the Variance of Wages

Equation (2) allows us to study the role of movements along the occupational ladder in accounting for the life-cycle profile of *mean* wages. We can also leverage the simple decomposition of wages from Equation (1) to study the extent to which movements along the occupational ladder contribute to the rising *dispersion* of wages over the life cycle. In particular, the variance of wages among individuals with potential

experience level e can be written as:

$$Var_e(w_{ie(j)}) = Var_e\left(\sum_j D_{ie}^j w^j\right) + Var_e\Big(\epsilon_{ie}\Big) + 2Cov_e\left(\sum_j D_{ie}^j w^j, \epsilon_{ie}\right)$$

$$= \sum_j s_{ej}\left(w^j - \bar{w}_e^j\right)^2 + \frac{1}{n_e}\sum_{i\in e}\left(\epsilon_{ie} - \bar{\epsilon}_e\right)^2 + 2\sum_j s_{ej}\left(w^j - \bar{w}_e^j\right)\left(\bar{\epsilon}_{ej} - \bar{\epsilon}_e\right) \tag{3}$$

where $\bar{w}_e^j$ denotes the average position along the occupational ladder of individuals with e years of potential experience—i.e., the first term on the right-hand-side of Equation (2)—and $\bar{\epsilon}_e$ is the average position along the job ladder within occupations of individuals with e years of potential experience—i.e., the second term on the right-hand-side of Equation (2). The term $\bar{\epsilon}_{ej} \equiv \sum_{i\in e} D_{ie}^j \epsilon_{ie} \big/ \sum_{i\in e} D_{ie}^j$ is the average position on the job ladder among individuals with e years of potential experience working in occupation j.

Equation (3) decomposes the variance of wages at potential experience level e into three terms. The first represents the variance of occupational mean wages within an experience level, capturing the degree of concentration or dispersion on the occupational ladder among workers with potential experience level e. Changes in the employment distribution that shift weight towards the tails of the occupational wage distribution cause this term to increase. The second term is the variance of within-occupation wage deviations at potential experience e. This captures the degree of concentration or dispersion on the job ladder within occupations among workers with potential experience e. The final term is (two times) the covariance between the occupational mean wage and the within-occupation residual wage. This term captures the extent to which workers in higher-paying occupations (relative to their peers with the same level of potential experience) achieve better positions on the job ladder within those occupations (given their experience).

Plotting the value of the three components in Equation (3) across different levels of potential experience allows us to understand how much of the life-cycle evolution of the wage variance is due to (i) differential movements along the occupational ladder, (ii) differential movements along the job ladder within occupations, and (iii) the extent

to which individuals' position on the occupation ladder relates to their position on the job ladder.

3 Results: Life-Cycle Wage Growth

3.1 Decomposition Results

We begin by plotting the well-known patterns of life-cycle wage growth as a function of potential labor market experience. Panels (a) and (b) of Figure 2 display the evolution of hourly and log hourly wages, respectively, from the first year up to 39 years of potential experience. The profiles are concave and mildly hump-shaped, peaking at around 30 years of potential experience.[15] At their peak, hourly wages are approximately twice as high as (or 64 log points higher than) in the first year of experience. Wages increase most rapidly early in the career—a well-established feature of life-cycle profiles. The average worker experiences a 39% increase after 5 years of experience. More than two-thirds of lifetime wage gains are accrued within the first 10 years in the labor market.

Panel (c) of Figure 2 plots the evolution of residual wages over the life cycle. By construction, residual wages are mean zero, so, not surprisingly, they are negative on average at the start of workers' careers and become positive later on. Interestingly, as Panel (d) shows, the cumulative growth in residual wages is only very slightly lower than the growth in (non-residualized) log wages. This indicates that compositional changes in observable characteristics of the working population at different levels of potential experience are not an important driver of the profile documented in Panel (b), with the exception of the (slight) late-career decline in log wages that is muted in residual wages.

We now implement the decomposition from Equation (2) to determine how much of this life-cycle pattern is due to climbing the occupational ladder, versus climbing the job ladder within occupations. Panel (a) of Figure 3 displays the evolution of each

[15] Note that the late-career decline is very modest; this is consistent with Rupert and Zanella (2015), who find hourly wages in the PSID show little tendency to decline before workers reach their mid-60s.

component of the decomposition, based on residual wages. The black line replicates the pattern shown in Panel (c) of Figure 2. This corresponds to the left-hand side of Equation (2). The blue line represents the first term on the right hand side of Equation (2), capturing the evolution along the occupational ladder. The red line corresponds to the second term in our decomposition and captures the evolution along the job ladder.

Both the occupational ladder and the job ladder components are negative in early career, and positive in late career: on average, individuals start their career in below-average occupations (in terms of their occupational wages), and also earn below-average wages within their occupations. The blue line indicates that, by around 10 years of potential experience, the occupational employment distribution is close to the average overall distribution, in terms of average wages. Meanwhile, the red line shows that, from around 15 years of labor market experience onwards, workers tend to earn wages that are higher than the occupational mean.

To more easily visualize the contribution of the two ladders, Panel (b) of Figure 3 displays analogous information to Panel (a), but represented as cumulative changes over the life cycle. This is done by normalizing, at each point of the life cycle, the average residual wage and its decomposition components by their value in the first year of labor market experience. The figure confirms that climbing the occupational ladder plays a small, but important, role in life-cycle wage growth, particularly in early career. Improvements in the occupational distribution of employment account for about 28% of wage gains between the first and the fifth year of potential labor market experience. The job ladder within occupations becomes increasingly important as workers accumulate experience. At 25 years of potential experience, the contribution of the occupational ladder to wage growth is about 21%.

The contribution of movements along the occupational ladder to average wage growth reflects shifts in the distribution of employment towards higher-paying occupations over the life cycle. To show where in the distribution those shifts occur, Panel (a) of Figure 4 presents kernel densities for the occupational employment distribution among workers with 1, 15 and 30 years of potential experience, respectively; Panel (b) shows the changes in the densities relative to 1 year of experience. There is a clear rightward shift in mass between low- and high-experience workers, with growth

in the share of workers in all occupations with above-average residual wages between 1 and 15 years of experience, and relatively little change thereafter. The declines in mass occur in occupations with mean residual wages that are ten log points or more below average. We have labeled the occupational mean wages of selected occupations along the distribution where the largest shifts in mass occur. In the lower tail of the distribution, workers substantially shift away from occupations like cashiers and retail salespersons over their life cycles. By 15 years of potential experience, employment growth in occupations such as miscellaneous managers and executive occupations is especially evident; we return to a discussion of managers and supervisors shortly.

In summary, our benchmark decomposition indicates that climbing the occupational ladder accounts for around one-quarter of early-career wage gains, when wage growth is greatest. The relative contribution of the job ladder within occupations to wage growth is greater and increases over the life cycle.

3.2 Additional Results

We next investigate the robustness of our findings across alternative specifications and explore how they vary across groups of workers.

Varying the Level of Occupational Aggregation The level at which occupations are aggregated affects how much wage growth is attributed to the occupational ladder. At the extreme, if all employment were aggregated into one occupational category, there would be no scope for the occupational ladder to contribute to life-cycle wage growth. By contrast, very narrowly defined occupations leave less scope for the role of the job ladder. To gauge how our results vary across different levels of aggregation, we decompose movements along the occupational ladder into two components: changes that occur between 12 broad occupational categories, and changes that occur between narrowly defined 4-digit occupations within those categories; see Appendix B.2 for details.

The results are presented in Panel (a) of Figure 5. The cumulative life-cycle profile (black line) and job ladder component (red line) are the same as in Panel (b) of Figure 3. The orange and green lines sum to the total contribution of the occupational ladder

(i.e., the blue line in Panel (b) of Figure 3), and capture changes in employment composition *across* the 12 broad occupational categories (orange line), and across 4-digit occupations *within* these categories (green line). We find that even at the highest level of aggregation, movements across broad occupational categories are meaningful, accounting for around 40% of the occupational ladder's contribution, while movements across detailed occupations within categories account for the remaining 60%.[16]

Transitions into Managerial and Supervisory Roles Advancement into management and supervisory roles, which have more responsibility and pay better than closely related entry-level occupations involving similar tasks, is arguably a distinct occupational ladder, which is potentially different in nature from one involving transitions across less related occupations. To explore the importance of transitions into leadership roles, we decompose movements along the occupational ladder into a component driven by changes in the share of workers in management and supervisory occupations (the "leadership" ladder), and a component driven by changes in the share of workers in different 4-digit occupations *within* management, supervisory, and non-leadership roles; see Appendix B.3 for details.

The results are reported in Panel (b) of Figure 5. The blue line with short dashes represents the "leadership" ladder, and the blue line with long dashes is the occupational ladder within leadership categories. Moving into leadership positions accounts for only a small portion of life-cycle wage growth. This is due to the fact that the share of employment in supervisory and management occupations peaks at only around 20% after 25 years of potential experience, as shown in Appendix Figure B.2. This makes it unsurprising that climbing the leadership ladder accounts for very little of average lifetime wage gains.

Time-Varying Occupational Wages The rungs on the occupational ladder in our decomposition, defined in Equation (2), are based on the overall mean wage of occupation j, w^j, pooling all available years of data in the ACS. Occupational wages,

[16]Panel (a) also reveals what we would obtain if we instead performed the decomposition directly at the level of the 12 broad categories. The occupational ladder component would be exactly the orange (short-dashed) line, while the movements across detailed occupations within broad categories captured by the green (long-dashed) line would be absorbed into the job ladder.

however, may change over time during our sample. To quantify the importance of time-varying occupational mean wages, we extend our decomposition by expressing the wage of individual i, whose potential experience level is e, and who is observed in occupation j in year t as:

$$w_{iet(j)} = \sum_j D^j_{iet} w^j + \sum_j D^j_{iet} \left(w^j_t - w^j \right) + \left(w_{iet(j)} - \sum_j D^j_{iet} w^j_t \right) \tag{4}$$

where w^j_t is the mean wage of occupation j in year t, and the other terms are as defined in Section 2 (with the added time sub-index to make clear which terms vary over time). Averaging this expression across individuals with a given experience level, we obtain a similar decomposition to Equation (2):

$$\overline{w}_e = \sum_j s_{ej} w^j + \sum_j \sum_t s_{ejt} \left(w^j_t - w^j \right) + \frac{1}{n_e} \sum_{i \in e} \left(w_{iet(j)} - \sum_j D^j_{iet} w^j_t \right), \tag{5}$$

where $s_{ejt} = \sum_{i \in e} D^j_{iet} / n_e$ is the share of individuals of potential experience e who are observed working in occupation j in year t, so that $\sum_t s_{ejt} = s_{ej}$.

In this decomposition, we have an additional term that is related to the period-specific deviation of the occupational mean wage from the global occupational average. The job ladder—the final term in Equation (5)—now captures individual-specific deviations from the occupational mean wage in the year in which the individual is working in the occupation, rather than deviations from the global occupational mean wage.

Panel (c) of Figure 5 displays the results from this analysis, once again reporting cumulative growth in residual wages. The green line represents the life-cycle evolution of the time-varying component of occupational wages. As it turns out, the year-specific deviations of occupational mean wages are not quantitatively important in accounting for the life-cycle profile of wages.

Heterogeneity across Groups An attractive feature of our decomposition is that it can be applied to any subgroup of workers observable in the data. Holding the economy-wide occupational wages fixed, we compute group-specific employment

shares and group-specific average deviations from the occupational means at each level of potential experience.

We begin by exploring heterogeneity across geographic areas and time periods, implementing the decomposition separately by Census region and by five-year time period. As Appendix Figures B.3 and B.4 show, the results are remarkably stable, with the relative contributions of the occupational and job ladders essentially unchanged across regions and periods.

We also apply the decomposition separately by sex. If women are promoted into managerial occupations at lower rates, or move towards higher-paying occupations more slowly, the female profile for the occupational ladder would be flatter. If women fall behind within occupations because career interruptions and weaker job attachment (Munasinghe et al., 2008) slow wage progression within jobs or because pay in some occupations disproportionately rewards long and inflexible hours (Goldin, 2014), the female profile for the job ladder would be flatter. As Figure 6 shows, the profiles for men and women have the same qualitative shape. The main difference across the sexes is in the magnitude of total growth, with cumulative life-cycle wage growth being substantially lower for women than for men. The relative roles of the occupational and job ladders are very similar across the two groups: the occupational ladder contributes most in early career and the job ladder becomes increasingly dominant with experience. At 25 years of potential experience, climbing the occupational ladder accounts for slightly more than 20 percent of cumulative wage growth for both sexes, in line with our benchmark estimate for the pooled sample.

3.3 Cohort Analysis

One might be concerned that the patterns presented so far are driven by differences in occupational composition *across* cohorts, rather than changes in the occupational composition within a cohort over the life cycle. In our data, the most recent cohorts are only observed at low levels of experience, while the earliest cohorts are only observed later in their careers. If early cohorts systematically started in better occupations than recent cohorts, our results would reflect those cohort differences rather than occupational movements within a cohort, over their life cycle.

To demonstrate that our results are robust to following cohorts of workers, we turn to two additional datasets: the Current Population Survey's Outgoing Rotation Groups (CPS ORG) and the National Longitudinal Survey of Youth 1979 (NLSY79) samples.

The CPS ORG data allow us to track the outcomes among a synthetic cohort of workers over a relatively long time span, 1989–2019. We obtain the CPS ORG data from IPUMS (Flood et al., 2020). Since multiple occupation classification systems are used in the CPS over time, we crosswalk all occupation codes to the harmonized codes of Autor and Dorn (2013), which distinguish between 330 occupational categories.[17] We focus on individuals who entered the labor market during the 1989–1991 period. Their outcomes can be observed over the subsequent 28 years (until 2017–2019). Appendix B.5 provides further details on our CPS sample restrictions, and Table A.3 provides descriptive statistics for this synthetic cohort.

Before presenting the synthetic cohort results, we first verify that our main results using the CPS are similar to those obtained from our benchmark ACS analysis. Appendix Figure B.5 replicates our main decomposition results from Panel (b) of Figure 3, but using data from the CPS for the same set of years (2005–2019). The life-cycle profiles estimated in the CPS feature less cumulative growth. This is likely due to the difference in the earnings measure across the two datasets, as well as the different restrictions used to exclude students (see Appendix B.5 and Table A.2). Nevertheless, our key results are robust: the occupational ladder plays a relatively important role for early-career wage growth. At 5 years of potential experience, climbing the occupational ladder accounts for 32% of cumulative residualized wage growth in the CPS (versus 28% in the ACS). At 25 years of potential experience, the occupational and job ladders account for 21% and 79% of cumulative residualized wage growth, respectively, which is nearly identical to our result in the ACS.

Panel (a) of Figure 7 presents results of our decomposition following the synthetic cohort of workers who entered the labor market during the 1989–1991 period. The figure shows a pattern that is quantitatively very similar to that in Appendix Figure

[17] We have also verified that if we perform our analysis in the ACS data using the harmonized Autor-Dorn occupation codes, we obtain essentially identical results regarding the role of the occupational ladder for life-cycle wage growth. In other words, the aggregation from 674 detailed ACS codes to 330 Autor-Dorn categories does not meaningfully impact our findings.

B.5. This indicates that our main findings indeed reflect changes occurring within cohorts as they gain experience and, in particular, that the occupational ladder component captures changes in occupational composition occurring within cohorts over the course of their life cycle, rather than differences between cohorts.

Next, we turn to data from the NLSY79, allowing us to compare our results to those obtained from longitudinal data following a specific (as opposed to synthetic) cohort. The NLSY79 tracks a sample of individuals born between 1957 and 1965, interviewed annually from 1979 to 1994 and biennially thereafter. Because it follows the same individuals over their careers rather than drawing new individuals from a repeated cross section, the NLSY79 lets us assess whether our findings are shaped by changing sample composition in the ACS and CPS.

Consistent with our ACS restrictions, we exclude person-year observations in which the respondent reports being enrolled in school at the time of the interview, and we require positive labor earnings in the prior calendar year. Residual wages are obtained by regressing log real hourly wages on sex, race and ethnicity, and education, with adjustments that reflect the NLSY79's single-cohort design. Education is measured as the highest level attained by age 29 and is interacted with birth year. Birth year fixed effects take the place of calendar year fixed effects, since calendar year is not separately identified from potential experience in a sample spanning only nine birth cohorts. Region fixed effects take the place of state fixed effects. The residualization uses all person-year observations in our NLSY79 sample, prior to imposing the balance restrictions described below.

We construct two samples that impose different restrictions on how consistently an individual must be observed working over the survey period. Given the biennial interview schedule after 1994, workers are observed at every second level of potential experience over most of their careers. We therefore restrict the analysis to odd levels of potential experience between 1 and 27, so the NLSY79 profiles are measured at two-year intervals.[18] We construct a partially-balanced panel, consisting of workers observed at experience levels 1 and 27, plus at least eight of the intervening odd levels, for a total of 1,443 individuals. We also construct a fully-balanced panel, consisting

[18]In Appendix B.6, we repeat this exercise using even levels of experience to show that the key patterns do not depend on this sample restriction.

of workers observed at all fourteen odd levels, for a total of 549 individuals.[19] The number of occupations is large relative to the number of observations, so we do not estimate occupational mean wages from the NLSY79. Instead, we import those estimated from the ACS and merge them in at the level of the harmonized occupational codes of Autor and Dorn (2013). It is worth noting that the benefits of working with this type of longitudinal data—which enable us to observe the same individuals at labor market entry as well as at high experience levels—come at the cost of working with dramatically smaller (and potentially non-randomly selected) samples.

Panels (b) and (c) of Figure 7 present the decomposition results for the partially- and fully-balanced panels of the NLSY79, respectively. The life-cycle profile is slightly less concave and displays slightly greater total growth relative to our benchmark analysis. This is, perhaps, not surprising if individuals who satisfy the balance restrictions (remaining in the survey and reporting positive earnings at most or all of the odd experience levels over a 27-year span) are positively selected with respect to labor market outcomes. Nevertheless, the takeaways of the decomposition exercise for average wage growth are largely unchanged. Climbing the occupational ladder plays a relatively small role in accounting for total life-cycle wage growth; as before, its contribution levels off after approximately 15 years of potential experience. The role of climbing the job ladder within occupations is greater and increases over the life cycle.

The movements along the occupational ladder that we have documented through our decomposition analysis capture net occupational mobility over the life cycle: as workers gain potential experience, the tendency is towards employment in occupations on higher rungs of the ladder. This does not shed light on the nature of gross occupational mobility and its change over the life cycle. A net change that is positive could reflect different combinations of positive and negative occupational moves.[20] The longitudinal nature of the NLSY79 data, however, allows us to consider the life-cycle patterns of gross occupational mobility.

The top row of Figure 8 presents the probability of occupational switches that

[19] Appendix Table A.3 provides descriptive statistics for these two samples.

[20] Net positive change is consistent with, for example, an increasing likelihood of downward occupational mobility over the life-cycle that is more than offset by an increasing likelihood of upward mobility; a constant likelihood of upward occupational mobility with a decreasing likelihood of downward mobility, etc.

represent upward (solid line) *and* downward (dashed line) moves on the occupational ladder, over a two-year horizon. This is shown in Panel (a) for the partially-balanced sample and in Panel (b) for the fully-balanced sample. As is evident, the probability of an occupational switch, in either direction, is initially high and declines dramatically with potential experience. Movements up the ladder are more likely than movements down early in the career, and become about equally likely at higher experience levels. This is consistent with our result of the flattening of the occupational ladder with experience. The bottom row of Figure 8 presents the "size" of occupational ladder moves (conditional on switching). At low levels of experience, switches into better occupations entail a larger change in occupational wage than switches into lower-paying occupations. Movements across rungs become smaller with potential experience, as the magnitude of the occupational wage change declines. Again, this is consistent with our headline result regarding the diminishing role of climbing the occupational ladder over the career in accounting for the shape of life-cycle wage change.

4 Results: Wage Inequality over the Life Cycle

We now analyze the evolution of the variance of wages over the life cycle. Figure 9 illustrates the "fanning out" of the wage distribution as workers gain labor market experience, by plotting the variance of real hourly wage levels in Panel (a), log real hourly wages in Panel (b), and residual wages in Panel (c). Panel (d) plots the cumulative change in the variance of log real hourly wages in the solid line, and the cumulative change in the variance of residual wages in the dashed line. The variance of (log) real hourly wages increases steeply over the first 15 years of potential experience and then is relatively flat. When computing the variance of residual wages, we see an initial decrease, followed by a continuous increase after around 5 years of potential experience. This implies that the rise in the variance of raw wages during the first 5 years of potential experience is driven by changes in the composition of the workforce. Compositional changes are important again in late career, although in the opposite direction. After around 25 years of potential experience, the flattening of the variance of raw wages masks continued increases in wage heterogeneity after accounting for observable characteristics.

We now implement the decomposition from Equation (3), as described in Section 2.4, based on residual wages. Panel (a) of Figure 10 displays the evolution of each component of the decomposition, in levels. The black line shows the overall residual wage variance, corresponding to the left-hand side of Equation (3). The blue line represents the first term on the right hand side of Equation (3), which captures the role of movements along the occupational ladder. The red line corresponds to the second term in our decomposition, capturing the role of movements along the job ladder. The orange line corresponds to the third term, the covariance between individuals' positions on the occupational ladder and their positions on the job ladder (relative to others with the same level of experience). To ease visualization, Panel (b) of Figure 10 displays the cumulative changes over the life cycle for each component, thus decomposing the cumulative change in the residual wage variance from Figure 9, Panel (d).

The fact that the blue line is essentially flat indicates that there is very little change in the dispersion of occupational mean wages over the life cycle. While our earlier results showed that workers tend to move to higher-paying occupations as they gain experience, the pattern in Figure 10 implies that high-experience workers are not more spread out across the occupational wage landscape. This is consistent with the pattern illustrated in Figure 4, which shows that the occupational employment distribution shifts upwards with experience, but does not become more dispersed.[21]

The red line in Figure 10 shows that the variance of individuals' positions along the job ladder within occupations starts to rise sharply after around 5 years of potential experience. Hence, this is a contributor to the fanning out of residual wages between 5 and 15 years of potential experience and, critically, accounts for nearly all of the increase in dispersion from 15 years of experience onwards. As documented in Section 3, individuals move to higher-paying occupations as they gain experience. Hence, one might be led to think that the increase in job ladder variance is driven, at least in part, by the fact that higher-paying occupations might inherently feature higher levels of within-occupation wage dispersion. However, this is not the case. As we show in Appendix Figure B.7, while high-wage occupations are indeed high-

[21]The finding that the variance of occupational mean wages is approximately constant over the life cycle is robust to performing the analysis at a more aggregated occupational level (i.e., using the 12 broad occupational categories discussed above).

variance occupations in terms of wage *levels* (in dollar terms), this is not the case when considering wages in logarithmic terms, or when considering residual wages (in approximately percentage terms) as in the analysis of Figure 10.

Finally, the orange line in Figure 10 displays the covariance between individuals' positions on the occupational ladder and their positions on the job ladder within their occupation (conditional on their potential experience level). It is negative in early career, increases quickly especially during the first 10 years, and is near zero by around 15 years of potential experience and until the end of the life cycle. This increase in the covariance early on is an important contributor to the fanning out of residual wages over the first third of the career, as is evident from Panel (b).

We use Figure 11 to shed further light on this life-cycle evolution. The covariance, represented as the third term from Equation (3), can be simplified as follows:

$$\sum_j s_{ej} \left(w^j - \bar{w}_e^j\right) \left(\bar{\epsilon}_{ej} - \bar{\epsilon}_e\right) = \sum_j s_{ej} \left(\bar{\epsilon}_{ej} - \bar{\epsilon}_e\right) w^j.$$

This representation makes it clear that the covariance is a share-weighted sum across occupations. Each occupation contributes the deviation of its workers' average job-ladder position from the experience-e average ($\bar{\epsilon}_{ej} - \bar{\epsilon}_e$), weighted by its employment share (s_{ej}) and multiplied by its mean wage (w^j).

Focus first on the blue circles in Figure 11. The size of each circle represents the number of workers with one year of potential experience in a particular occupation, s_{1j}. Occupations are arranged along the horizontal axis according to their residual occupational wage, w^j. The vertical placement of the blue circles represents the average deviation from the occupational mean among one-year-experience workers in that occupation, i.e., their average position on the within-occupation job ladder, $\bar{\epsilon}_{1j}$. Among workers with one year of experience, the average deviation from the occupational mean is negative for all occupations—early-career workers tend to be on low rungs of the job ladder. The blue line in Figure 11, which is the line of best fit, makes it clear that early career workers employed in higher-wage occupations tend to be even lower on the job ladders within their occupations. The negative slope of this line represents the negative covariance at experience level one in Panel (a) of Figure 10.

The covariance among workers with 30 years of potential experience is represented by the red line. On average, these peak-career workers have reached levels on the job ladder above the occupational mean, and this is true regardless of whether they are in high- or low-paying occupations. In fact, the average position on the job ladder within occupations is similar across all occupations: this is why the red line is virtually flat and why the covariance term is close to zero for high-experience workers in Panel (a) of Figure 10.

Finally, the black line shows the analogous correlation among workers with 10 years of potential experience (for visual clarity, we do not plot the circles for individual occupations for this experience level). While the correlation is still negative, the black line is substantially flatter than the corresponding line of best fit for workers with one year of potential experience. This is consistent with the correlation term being only slightly negative at 10 years of experience in Panel (a) of Figure 10, again indicating that the increase in covariance occurs relatively quickly over the life cycle, and flattens out thereafter.[22]

In short, workers who are well-positioned on the occupational ladder in early career tend to earn wages far below the occupational mean (compared to the wages earned by their peers in lower-paying occupations). This negative correlation between workers' positions on the occupational ladder and their positions on the job ladder dampens the overall variance of wages in early career. By mid-career, this is no longer the case: workers' positions on the occupational and job ladders are essentially uncorrelated. This change in the covariance is a major contributor to the fanning out of wages over the first 10–15 years of workers' careers.

[22]The patterns in Figure 11 are consistent with the evidence in Erosa et al. (2025), who show that in higher-wage occupations, there is a larger wage difference between older and younger workers (as compared to lower-wage occupations). In Figure 11, this is reflected in the fact that, for high-wage occupations, the average deviation from the occupational mean changes substantially as workers gain experience (i.e., the distance between the blue and the red circles for high-wage occupations is large), whereas the deviation is much smaller for low-wage occupations.

5 Conclusion

We present a decomposition of an individual worker's wage into an occupation's mean wage and the deviation from that occupational wage. This allows us to quantify how much of average life-cycle wage growth is attributable to changes in the distribution of employment across better- and worse-paying occupations—climbing an occupational ladder—or to wage differentials within an occupation—climbing a job ladder. It also allows us to quantify the contribution of the occupational ladder to the fanning out of wages over the life cycle.

We find that climbing the occupational ladder accounts for 28% of wage growth in early career, when the life-cycle profile is steepest. Later in life, climbing the job ladder becomes more important so that, by retirement age, it is the dominant factor accounting for cumulative wage growth. We show that the relative contributions of the job and occupational ladders are very similar across geographic areas and time periods, and among men and women. Although our results are based on repeated cross-sectional data from the American Community Survey, we obtain very similar findings when implementing our decomposition on synthetic cohort data from the Current Population Survey, as well as on partially- or fully-balanced panels from the National Longitudinal Survey of Youth.

Turning to the fanning out of wages over the life cycle, we find that the increasing variance of wages is primarily driven by differential rates of climbing the job ladder—within-occupation wage inequality. The variance of occupational mean wages remains essentially constant across experience levels. As workers shift toward higher-paying occupations, moving up the occupational ladder, they do not become more dispersed across the occupational wage distribution.

On its face, this implies that occupations have little impact on the stylized fact that wage inequality increases with experience. However, we uncover an important role for occupations in driving the increasing variance of wages over the life cycle: the increasing covariance between individuals' positions on the occupational ladder and their positions on the job ladder (relative to their peers with the same level of experience). Specifically, we document that young workers in high-paying occupations tend to be positioned on particularly low rungs of the job ladder within those occupations.

This negative correlation compresses overall wage dispersion among less experienced workers. As this negative covariance rises toward zero over the first 10 to 15 years of potential labor market experience, it contributes substantially to the widening of wage inequality during this phase of the life cycle.

Our results provide insights into the role of occupations for life-cycle wage dynamics in the US. The straightforward nature of our empirical framework implies that a similar exercise could be readily implemented on other cross-sectional datasets, lending itself to future cross-country analysis and comparison. Additional analysis using longitudinal data could provide further insights into the determinants of individual-level movements along the occupational and job ladders over the life cycle. In particular, panel data on employer transitions would make it possible to separate movements along the job ladder into wage growth accumulated with a single employer and gains obtained by switching employers within an occupation. Longitudinal data would also allow researchers to identify the occupations in which within-occupation wage growth is steepest, and thus which occupations account for the dominant role of the job ladder in life-cycle wage growth.

The existence of an occupational ladder in early career does not neatly fit into traditional empirical models that distinguish between general and (occupation-)specific human capital, as it suggests that experience in certain occupations may enable individuals to work in higher-paying occupations later in life. While more recent work has used information on the task content of occupations in order to construct task distance measures (e.g., Gathmann and Schönberg, 2010; Cortes and Gallipoli, 2017)—thus allowing human capital built up in one occupation to be partially transferable to other occupations that share similar tasks—these task distance measures normally do not differentiate between increases and decreases in task usage. Moreover, these task measures tend to be based on occupational averages and do not necessarily reflect individual-level task usage (Cassidy, 2017). Investigating the extent to which movements up the occupational ladder involve a deepening of task usage over the life cycle, or the extent to which certain tasks (e.g., managerial ones) can only be performed by individuals who have enough general labor market experience, remains promising avenues for future work.

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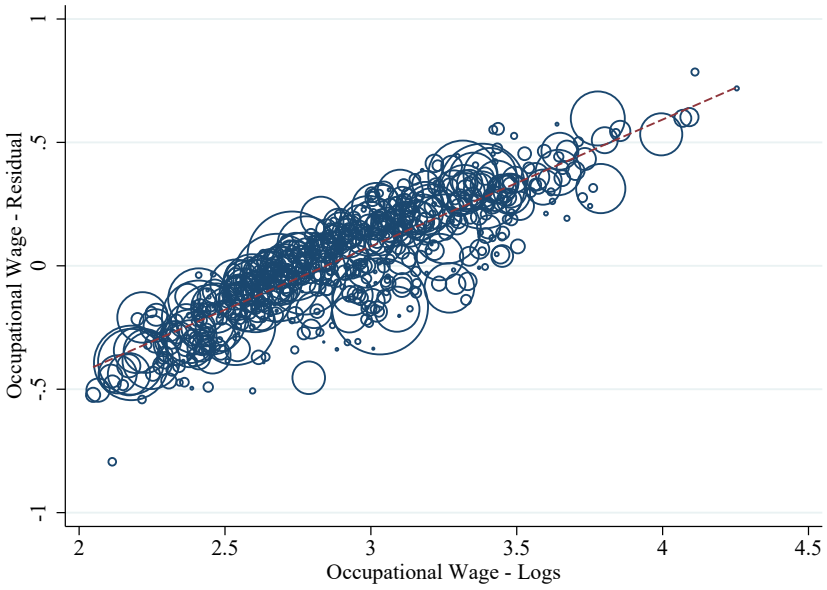
Table 1: Descriptive Statistics

		By potential experience			
	All	1–10	11–20	21–30	31–39
Panel A: Worker characteristics					
Real hourly wage (2009 dollars)					
Mean	23.33	17.72	24.14	25.91	25.77
Median	17.44	13.73	18.06	19.45	19.29
S.D.	21.59	15.61	21.84	23.48	23.61
S.D. of log hourly wage	0.744	0.696	0.738	0.744	0.741
S.D. of residual log wage	0.646	0.598	0.622	0.640	0.659
Female (percent)	46.8	46.5	45.5	47.3	48.0
Race/ethnicity (percent)					
White	64.8	60.8	60.6	66.5	72.7
Black	11.3	11.9	11.8	11.2	10.1
Hispanic	16.1	18.5	18.9	15.1	11.1
Other	7.7	8.7	8.7	7.1	6.1
Education (percent)					
Less than high school	7.9	6.6	8.4	8.4	8.3
High school graduate	28.4	28.8	25.8	28.3	31.3
Some college or associate degree	29.5	27.9	29.1	30.0	30.9
Bachelor's degree	21.6	24.8	22.6	20.6	17.8
Graduate or professional degree	12.6	11.9	14.0	12.6	11.8
Mean age	40.8	26.7	36.7	46.5	55.6
Mean potential experience	19.8	5.6	15.5	25.5	34.7
Panel B: Occupation information					
Number of detailed occupations	674	674	674	674	674
Median observations per occupation	7,441	1,561	1,743	1,965	1,719
S.D. of occupational mean residual wage	0.241	0.242	0.240	0.238	0.236
Employment share by broad group (percent)					
Management, business, and financial	15.3	12.0	16.1	17.0	16.1
Computer, engineering, and science	5.9	6.4	6.4	5.7	4.8
Education, legal, community service, arts, media	10.5	10.7	10.8	10.2	10.3
Healthcare practitioners and technical	5.8	5.7	6.1	5.7	5.6
Service	15.9	18.9	15.6	14.6	14.2
Sales and related	9.9	11.3	9.5	9.3	9.3
Office and administrative support	13.3	12.8	12.0	13.3	15.2
Farming, fishing, and forestry	0.8	0.8	0.8	0.7	0.7
Construction and extraction	5.7	5.7	6.4	5.7	5.1
Installation, maintenance, and repair	3.5	3.2	3.4	3.6	3.7
Production	6.8	5.9	6.5	7.2	7.6
Transportation and material moving	6.7	6.3	6.3	6.9	7.3
Observations	16,387,989	3,700,736	4,011,369	4,612,990	4,062,894

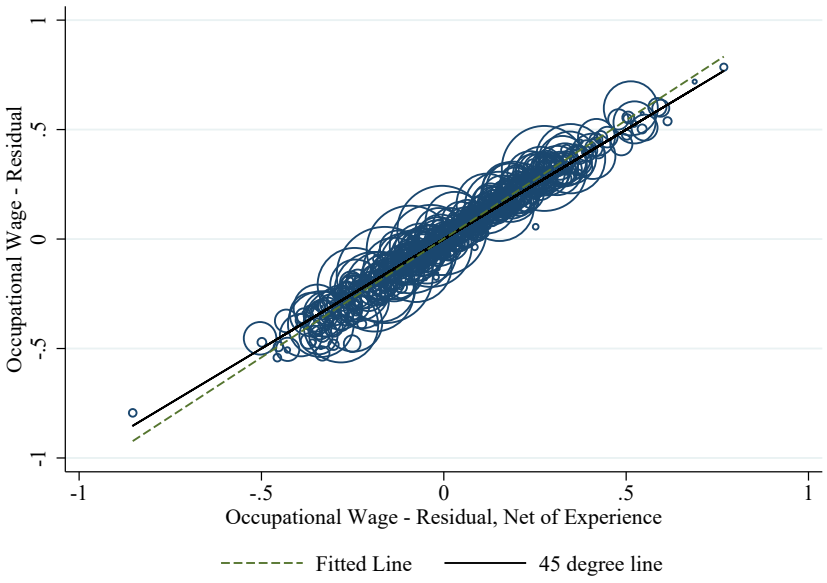
Note: The table reports summary statistics for the ACS analysis sample for 2005–2019. Statistics are weighted using ACS person weights. Real hourly wages are in 2009 dollars, winsorized at the top and bottom 1 percent. Residual wages control for race and ethnicity, sex, education, and year and state fixed effects. Occupations in Panel B are the 674 detailed 4-digit ACS codes, and broad groups are the 12 ACS major occupational categories.

Figure 1: Correlation of Occupational Wage Measures

(a) Mean Occupational Wage: Logs versus Residuals

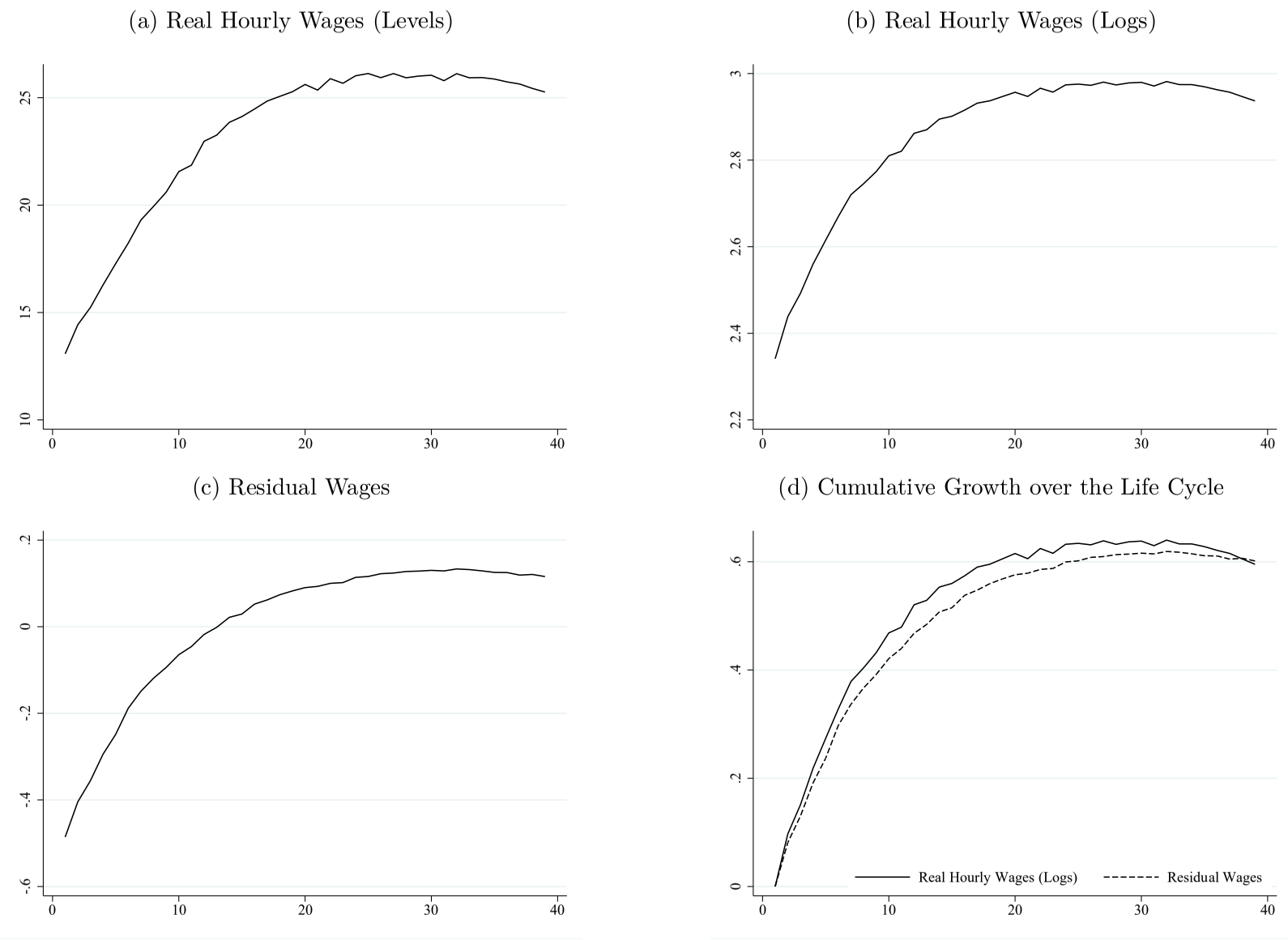


(b) Mean Residual Wage: Gross versus Net of Experience



Note: Panel (a) plots the mean log wage on the x-axis, and the mean residual wage on the y-axis for each occupation. Residual wages control for race and ethnicity, sex, education, and year and state fixed effects. Panel (b) plots the same residual wage on the y-axis, and a measure purged of experience effects on the x-axis. See text for details. The analysis uses data from the American Community Survey for the years 2005–2019.

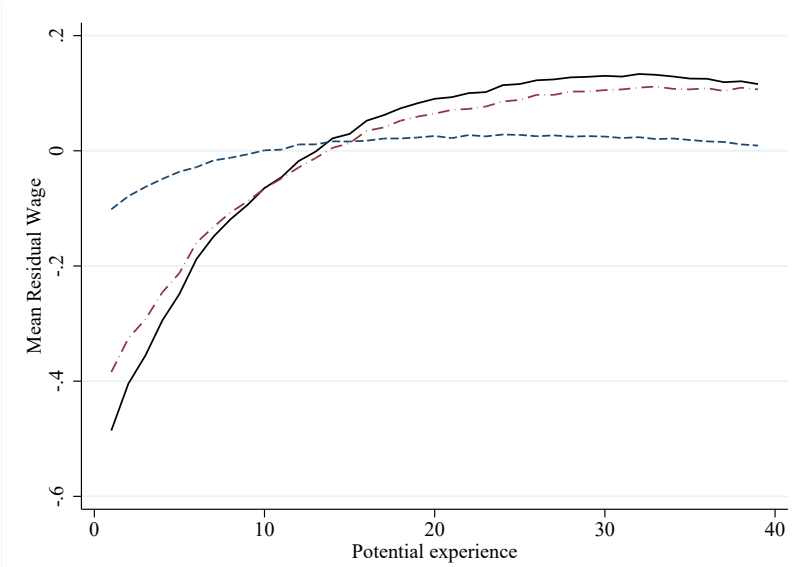
Figure 2: Life-Cycle Profile of Wages



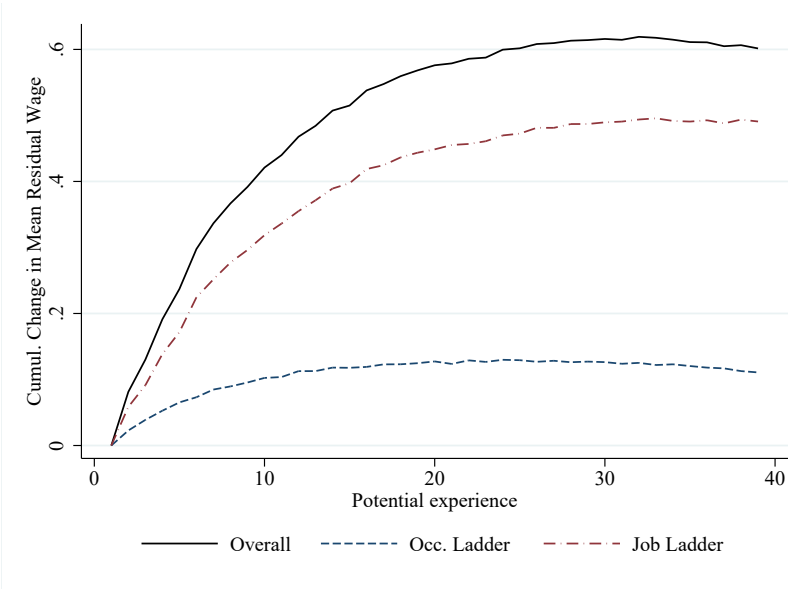
Note: The figure plots the life-cycle profile of wages across years of potential labor market experience, using data from the American Community Survey for the years 2005–2019. Nominal values have been converted to real 2009 dollars. Residual wages are obtained from a regression of individual log real hourly wages on education (indicators for no schooling, lower primary, upper primary, each of grades 9–12, and each of 1, 2, 4 or 5 plus years of college), race/ethnicity (White, Black, Hispanic, all others), sex (female, male), and state and year fixed effects.

Figure 3: Decomposition of the Life-Cycle Profile of Residual Wages

(a) Components of the Decomposition from Equation (2)

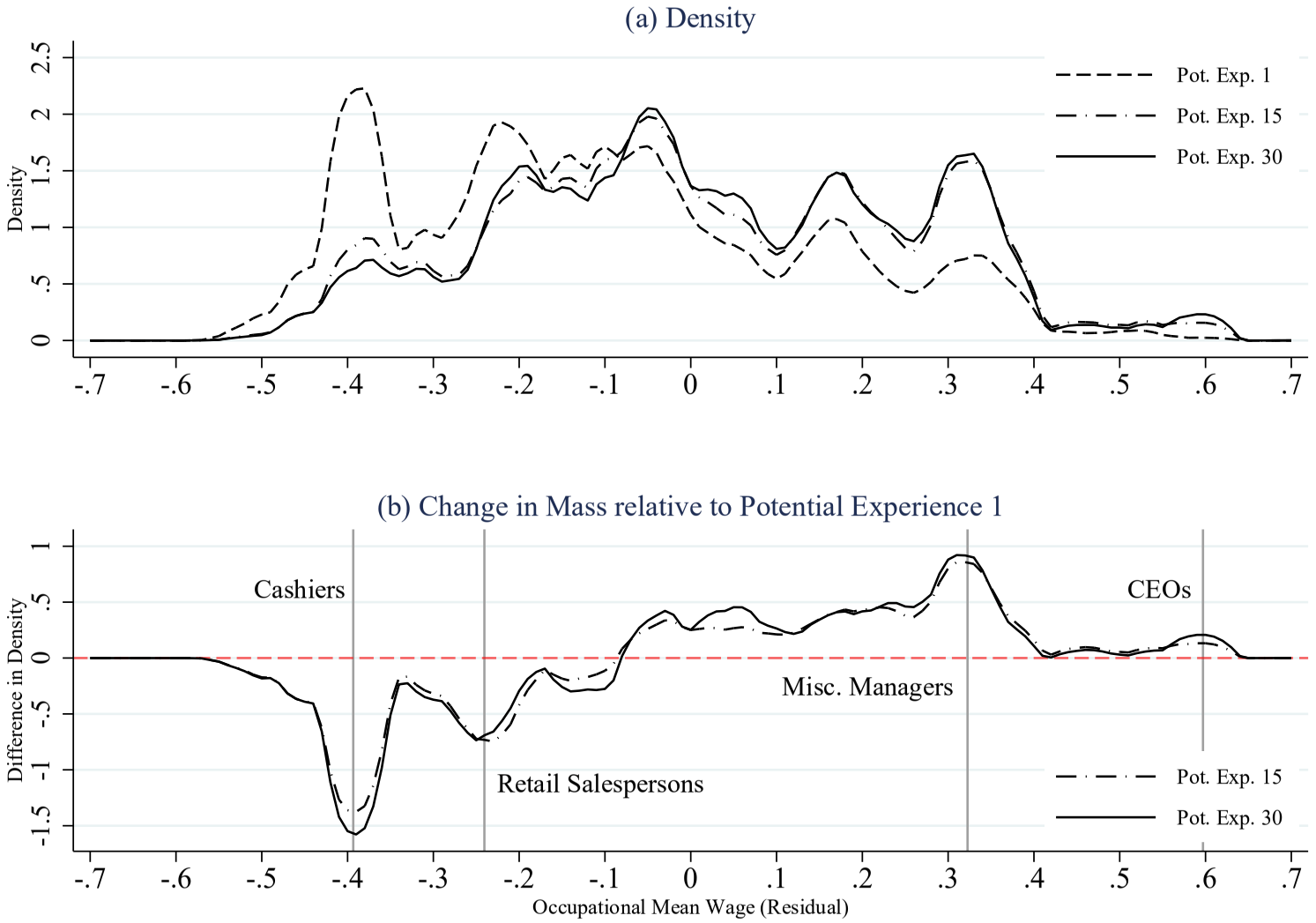


(b) Cumulative Changes



Note: The figure plots the components of the decomposition analysis in Equation (2) for residual wages. Panel (a) shows each component in levels, while Panel (b) expresses these as cumulative changes relative to one year of potential experience. The analysis uses data from the American Community Survey for the years 2005–2019. Residual wages are obtained from a regression of individual log real hourly wages on education (indicators for no schooling, lower primary, upper primary, each of grades 9–12, and each of 1, 2, 4 or 5 plus years of college), race/ethnicity (White, Black, Hispanic, all others), sex (female, male), and state and year fixed effects.

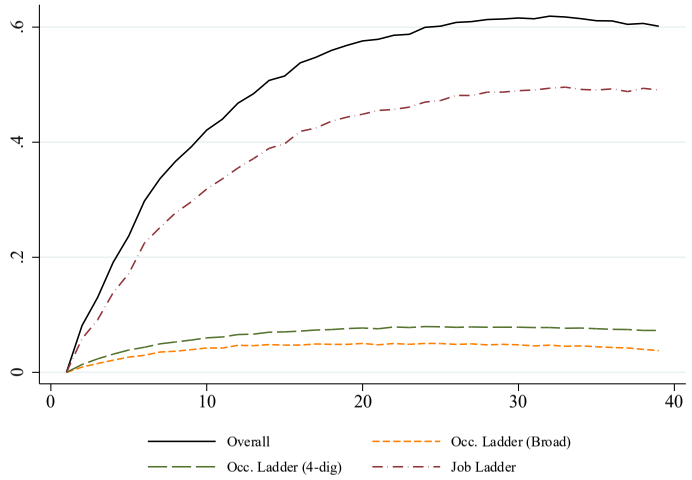
Figure 4: Changes in the Occupational Employment Distribution



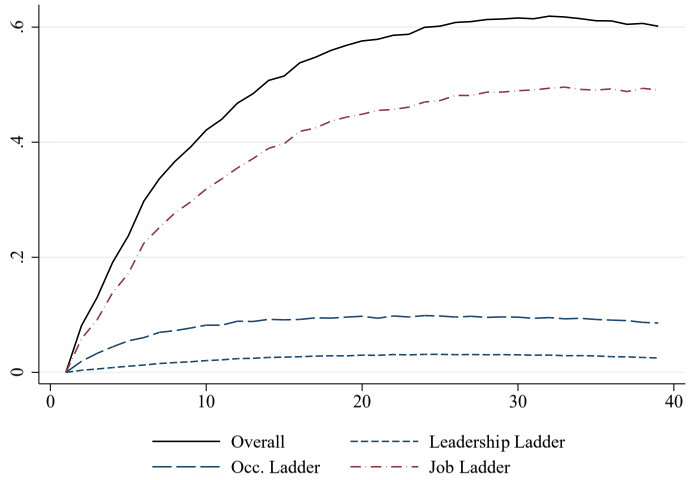
Note: Smoothed kernel densities of occupational employment are plotted for 1, 15 and 30 years of potential experience in Panel (a). Occupations are ranked along the horizontal axes by their mean residual wage. Panel (b) plots the difference in the 15- and 30-year densities, relative to the 1-year density. This analysis uses data from the American Community Survey for the years 2005–2019. Residual wages are obtained from a regression of individual log real hourly wages on education (indicators for no schooling, lower primary, upper primary, each of grades 9–12, and each of 1, 2, 4 or 5 plus years of college), race/ethnicity (White, Black, Hispanic, all others), sex (female, male), and state and year fixed effects.

Figure 5: Additional Results

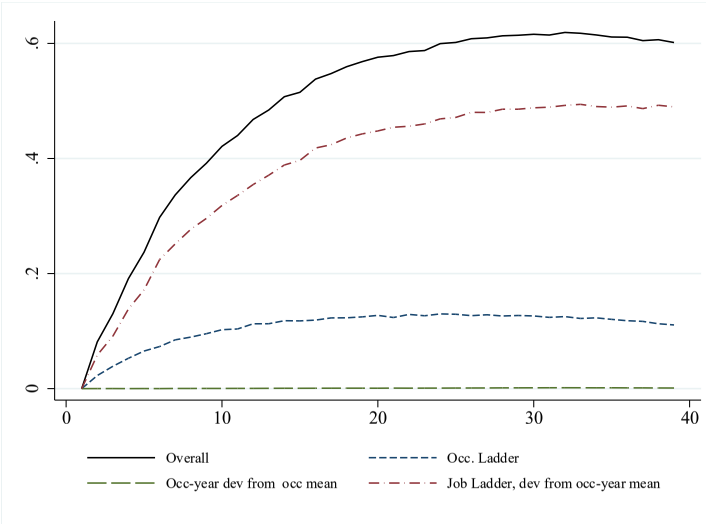
(a) Different Levels of Aggregation



(b) Leadership Ladder



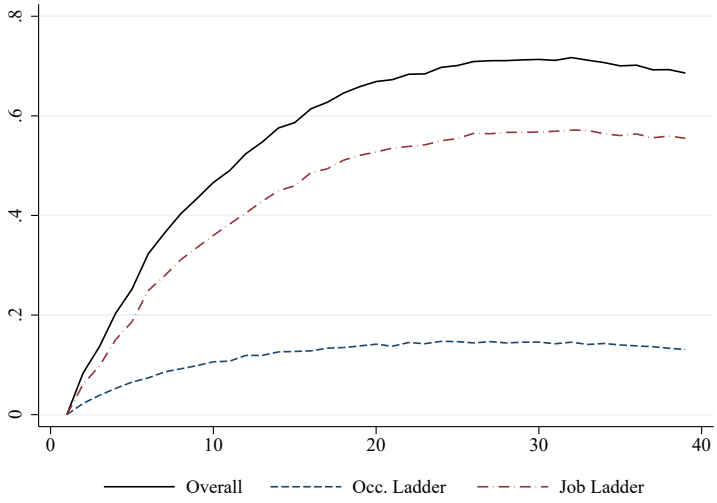
(c) Time-Varying Occupational Mean Wages



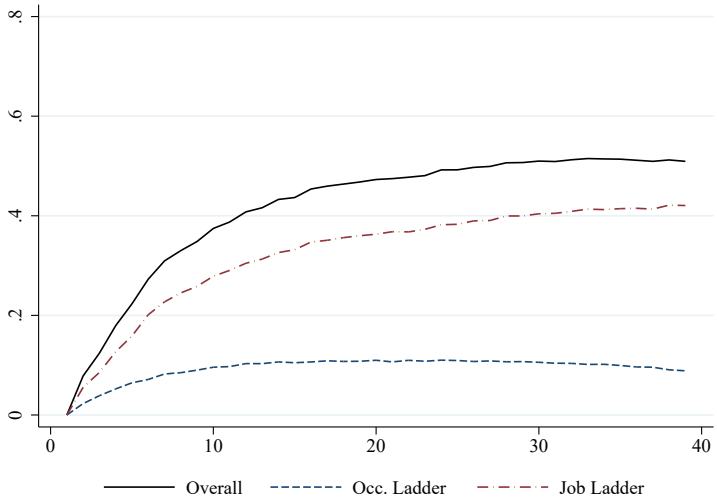
Note: Cumulative changes in residual wages relative to one year of potential experience are shown in all three panels. Panel (a) plots the components of the decomposition analysis in Equation (B.2). Panel (b) plots the components of the decomposition analysis in Equation (B.2) where the first component of the decomposition refers to the leadership ladder. Panel (c) plots the components of the decomposition analysis in Equation (5). The analysis uses data from the American Community Survey for the years 2005–2019.

Figure 6: Heterogeneity by Sex

(a) Males



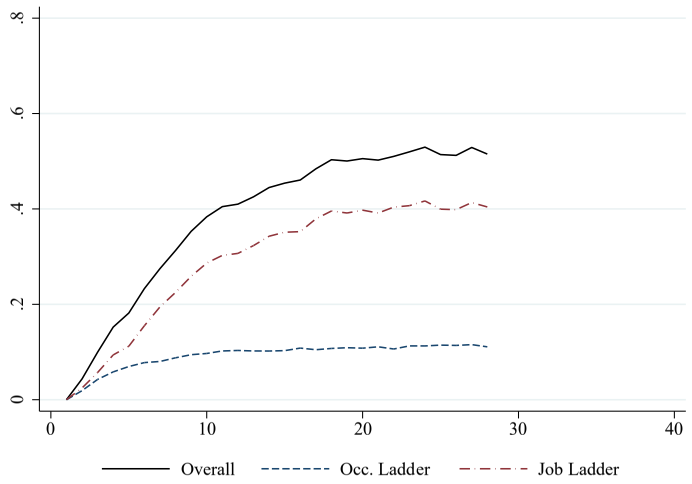
(b) Females



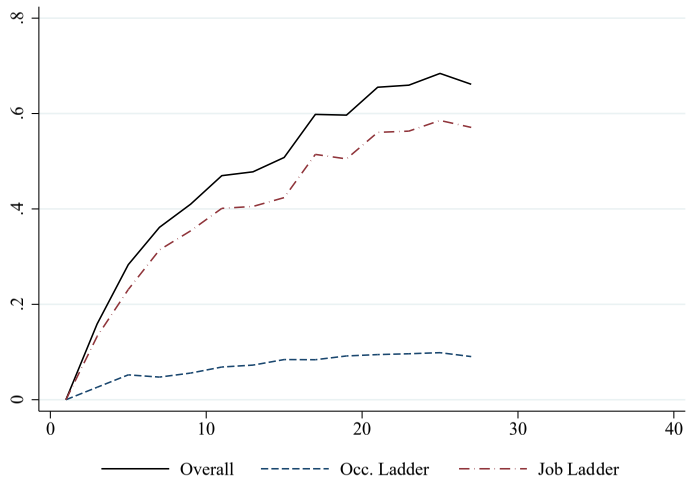
Note: The figure plots the components of the decomposition analysis in Equation (2) for residual wages, expressed as cumulative changes relative to one year of potential experience, separately for men and women. The analysis uses data from the American Community Survey for the years 2005–2019. Occupational mean wages are computed from the pooled sample of both sexes. See text for details.

Figure 7: Cohort Analysis

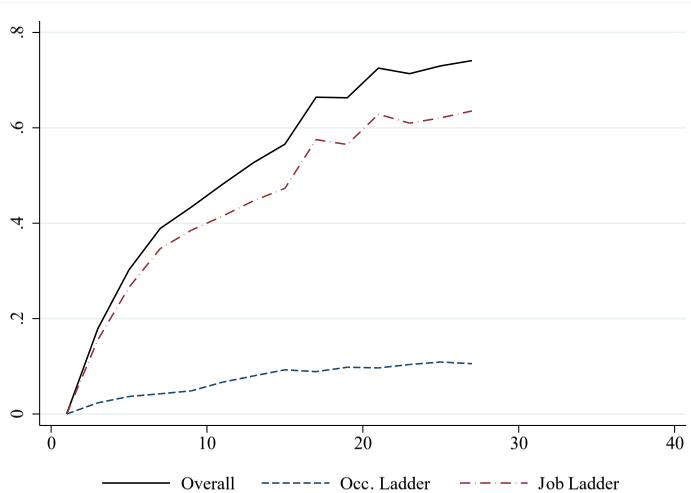
(a) 1989–1991 Labor Market Entry Cohort (CPS)



(b) NLSY79 — Partially-balanced panel



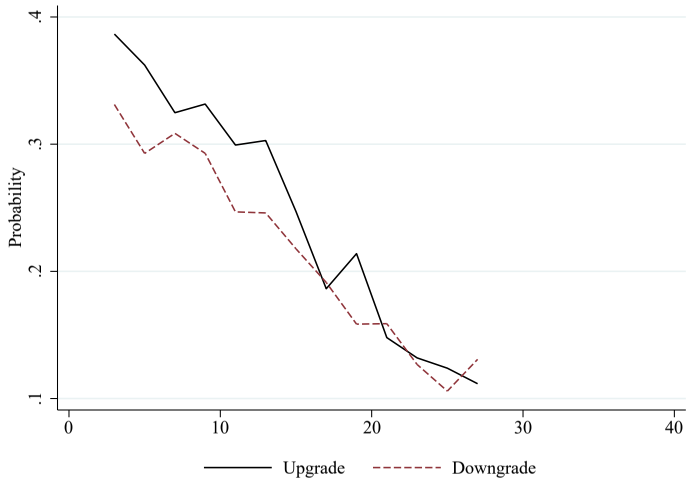
(c) NLSY79 — Fully-balanced panel



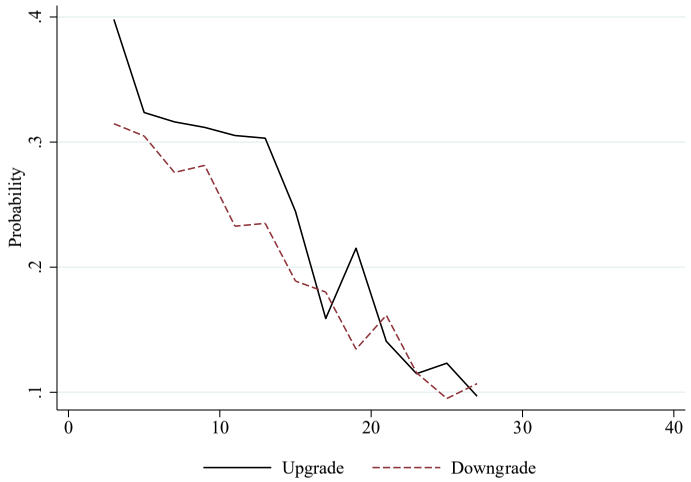
Note: Cumulative changes in residual wages relative to one year of potential experience are shown in all three panels. Panel (a) plots the components of the decomposition analysis in Equation (2) for a synthetic cohort constructed using the Current Population Survey's Outgoing Rotation Groups for the years 1989–2019. Panels (b) and (c) plot the components of the decomposition analysis in Equation (2) for a partially- and a fully-balanced panel of workers from the National Longitudinal Survey of Youth 1979. See text for details.

Figure 8: Gross Occupational Mobility over 2-year Horizons, NLSY79 Data

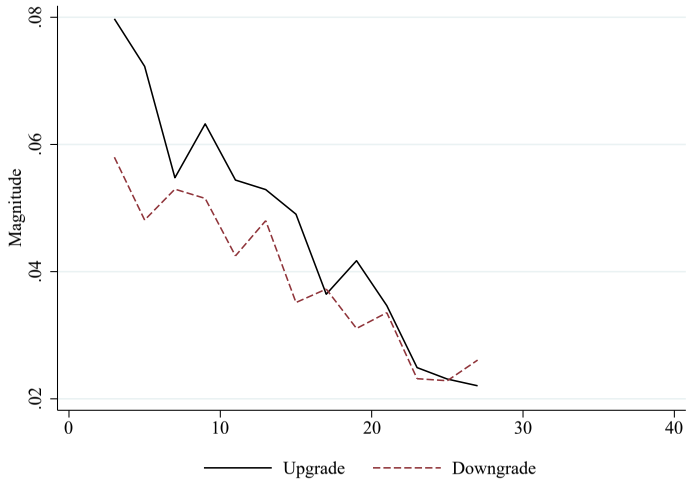
(a) Occ. transition prob. — Partially-balanced panel



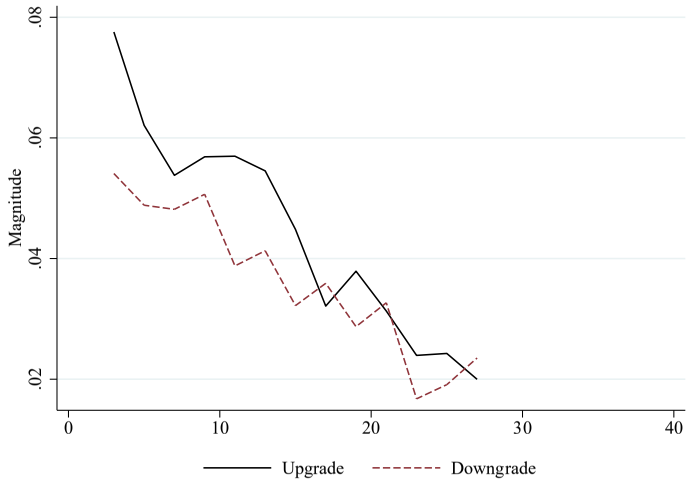
(b) Occ. transition prob. — Fully-balanced panel



(c) Occ. change magnitude — Partially-balanced panel

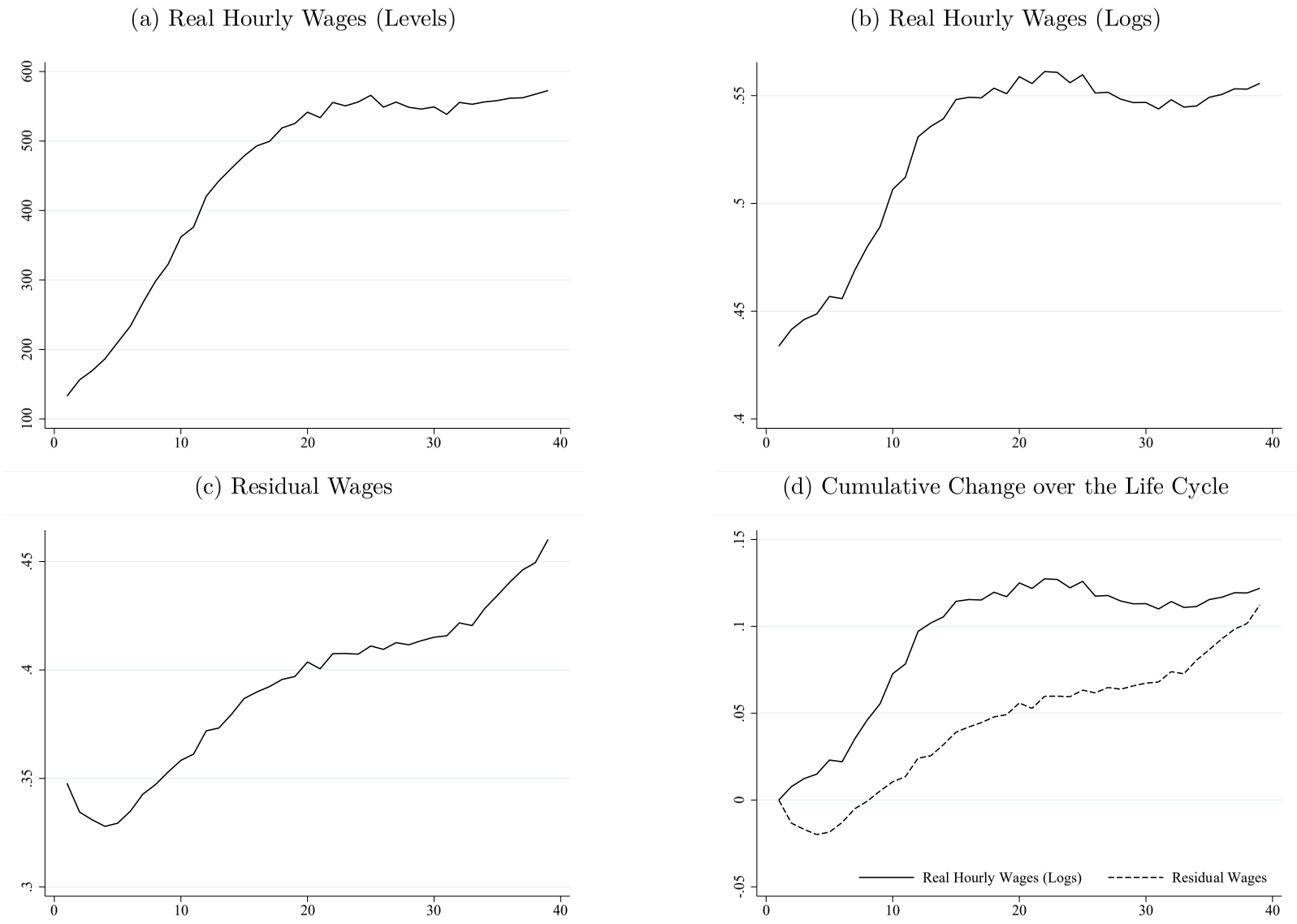


(d) Occ. change magnitude — Fully-balanced panel



Note: Panels (a) and (b) plot individual occupational transition probabilities over 2-year horizons in the National Longitudinal Survey of Youth 1979 data, across different levels of potential experience. The solid lines (Upgrade) represent transitions to occupations that are on higher rungs of the occupational ladder (i.e., have higher average residual wages). The dashed lines (Downgrade) represent transitions to occupations that are on lower rungs of the occupational ladder (i.e., have lower average residual wages). Panels (c) and (d) plot the magnitude of the occupational change, conditional on switching. This is equal to the average absolute value of the difference in mean residual wages between the source and the destination occupations. Panels (a) and (c) are based on a partially-balanced panel of workers, while Panels (b) and (d) are based on a fully-balanced panel. See text for details on the sample construction. Mean occupational residual wages are estimated using data from the American Community Survey, 2005–2019.

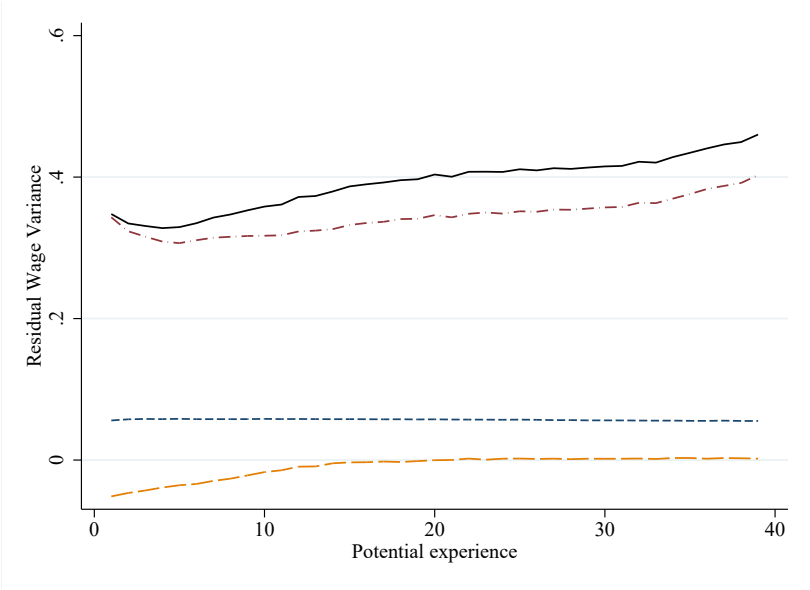
Figure 9: Variance of Wages over the Life Cycle



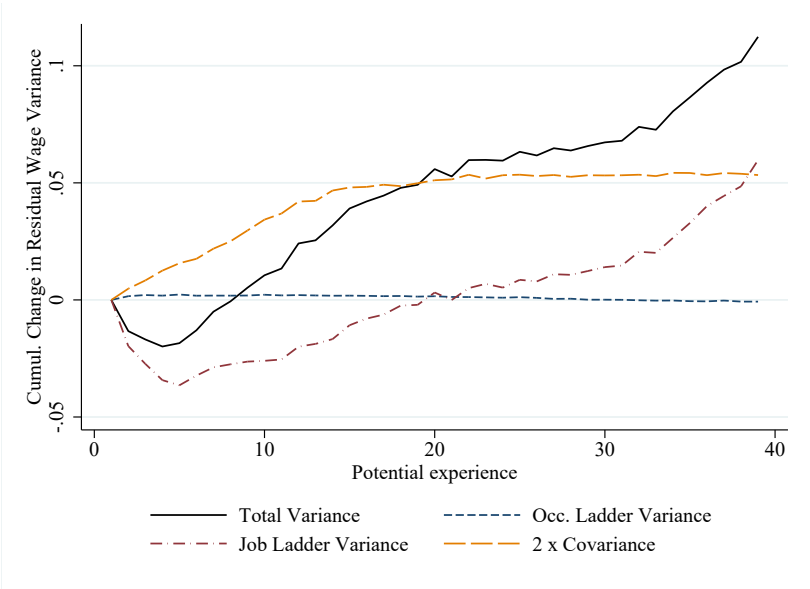
Note: The figure plots the variance of wages across years of potential labor market experience, using data from the American Community Survey for the years 2005–2019. Residual wages are obtained from a regression of individual log real hourly wages on education (indicators for no schooling, lower primary, upper primary, each of grades 9–12, and each of 1, 2, 4 or 5 plus years of college), race/ethnicity (White, Black, Hispanic, all others), sex (female, male), and state and year fixed effects.

Figure 10: Decomposition of the Variance of Residual Wages over the Life Cycle

(a) Components of the Decomposition from Equation (3)



(b) Cumulative Changes



Note: The figure plots the components of the decomposition analysis in Equation (3) for residual wages. Panel (a) shows each component in levels, while Panel (b) expresses these as cumulative changes relative to one year of potential experience. The analysis uses data from the American Community Survey for the years 2005–2019. Residual wages are obtained from a regression of individual log real hourly wages on education (indicators for no schooling, lower primary, upper primary, each of grades 9–12, and each of 1, 2, 4 or 5 plus years of college), race/ethnicity (White, Black, Hispanic, all others), sex (female, male), and state and year fixed effects.

Figure 11: Understanding the Changing Covariance



Note: This figure shows the relationship between occupational mean wages (horizontal axis) and the average deviation from the occupational mean (vertical axis) for workers with one (blue line), ten (black line), and 30 (red line) years of potential experience. Each circle represents an occupation, with circle size proportional to the number of workers in that occupation at one year of potential experience (blue) or 30 years of potential experience (red). We do not plot occupation-specific circles for workers with 10 years of experience. The analysis uses data from the American Community Survey, 2005—2019.