What Occupations Do*

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Abstract

Occupations are often seen as key to labor market outcomes, but surprisingly little is known about their relationship with workers' wages and career trajectories. Using worker-occupation fixed effects, we first find that occupations explain only 3% of wage variance in the United States—too little to explain much of inequality, gender wage gaps, or other issues. Second, by introducing a new natural measure of occupational distance, we find that some occupations are consistently *pluripotent*, propelling workers to diverse jobs and allowing them to quickly overcome job loss. Third, we compile our estimates in a form that can inform job seekers as they consider potential career paths.

Keywords: Occupations, Variance decomposition, Earnings growth

JEL Codes: J24, J31, J62, J63

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1 Introduction

It is widely believed that occupations are a key determinant of wages. For example, the governments of both the United States and Canada have websites set up for career advice in which one of the primary pieces of information presented about any occupation is its average pay.[1] On the one hand, this makes sense: people in different occupations, on average, have very different wages. Indeed, in the United States, the difference between occupational averages explains 29% of total wage inequality. However, that statistic does not tell us the full effect of occupations for two reasons.

First, the individuals who go into high-wage jobs are often different from those who go into low-wage jobs. Therefore, differences in occupational average wage could be due to differences in the types of workers who go into those occupations, so that any given worker's wage would not be affected much by choosing a different occupation. Second, occupations could help to determine one's occupational outcomes, including wages, in the future as well as now: for example, working as an accounting clerk could help someone get a higher-paying job as an accountant. However, to our knowledge, no prior research has systematically examined how particular occupations are associated with wages and career trajectories—how much more or less a worker might expect to earn in one occupation compared to another, both in the present and in future jobs.

Two questions motivate the paper. First, *are apparent wage gaps across occupations due to worker sorting or do occupations themselves raise or lower pay?* We find that, once individual heterogeneity and sorting are netted out, occupations account for only about 3% of wage dispersion—and moving one standard deviation up the occupation ladder lifts current earnings by roughly 9%. Second, *even if current premia are small, do today's occupations shape future trajectories?* To probe this channel, we build a novel data-driven distance matrix across occupations and collapse it into what we call a *pluripotency* index——a measure of how widely an occupation can propel workers along diverse career paths. Workers displaced from high-pluripotency jobs re-enter employment sooner, especially among non-college workers and those facing difficult economic circumstances.

To establish these results, we start our analysis with a fixed effect model similar to that proposed by Abowd et al. (1999) [AKM]. AKM proposed estimating whether a firm is high-

[1] See https://www.bls.gov/ooh in the United States and https://www.jobbank.gc.ca in Canada.

wage or low-wage not by its average pay but with the firm's fixed effect (after controlling for the workers' fixed effects): whether workers' pay goes up or down when they move between it and other firms. AKM then decomposed the variance of log pay into a component related to the firm fixed effect, the worker fixed effect (a measure of how much more or less the worker would be paid relative to others at the same firm) and the covariance between them. This model has been used extensively since then to understand these firm or establishment fixed effects—for example, by Card et al. (2013), who use it to examine changes in inequality over time, and Di Addario et al. (2023), who extend the model to show that past firms matter little for future wages. In our fixed effect model, we analyze occupational fixed effects rather than those of employers: the extent to which workers gain or lose when switching from one occupation to another.

A known concern from the literature on AKM-type models is the measurement error in the high-dimensional fixed effects, as noted by Andrews et al. (2008). Although the estimated employer fixed effects are unbiased, they are noisy, which can lead to incorrect analyses related to these fixed effects. To avoid this problem, we follow the leave-out-one correction proposed by Kline et al. (2020).[2] Because we generally see many moves to and from each occupation, this correction makes little difference in the estimated variance of occupational fixed effects, suggesting that our estimated fixed effects are precisely estimated and can therefore be individually reported and analyzed.

A further threat to identification comes from measurement error in the occupation variable itself. Interviewers occasionally assign different census codes to what is essentially the same job (Moscarini and Thomsson, 2007; Fujita et al., 2024). Indeed, a non-trivial share of "occupation switches" recorded in surveys are in fact data-entry noise rather than real mobility. To minimize this error, we restrict the estimation sample to employment spells that begin with a change of employer. Occupation changes in the middle of job spells are often spurious—for example, due to a new interviewer coding the same job in a different way—while changes that occur exactly in the month a new job starts are more likely to be driven by changes in work requirements. As a robustness check, we also estimate fixed effects restricting to observations where a worker reports two occupations in the same interview wave, and the results are similar.

To ensure the validity of our fixed effect research design with this sample, we conduct several

[2] We do not use the correction introduced by Bonhomme et al. (2019) because it would involve grouping together many occupations, which would not allow us to later determine which particular occupations, or characteristics of occupations, are associated with high or low fixed effects.

tests, mostly to verify the assumption of exogenous mobility, which posits that wage changes are independent of unobserved factors among individuals switching occupations. First, we examine wage trends before and after occupational switches to ensure there were no significant pre-trends or post-trends that could bias our results. The absence of such trends supports the idea that wage changes are due to the occupation switch itself. Additionally, we check for systematic errors in wage estimates by comparing actual versus predicted wages across different occupation levels and found no significant variation in residuals. We also verify that occupation fixed effects predict wage changes out of sample—an important consideration given the local nature of our fixed effects, as discussed below. A final concern is asymmetry: wage dynamics for those who go to better jobs may be different from those who are forced to go to a worse job. We present three tests of this idea. We find no asymmetry in wage gains and losses for individuals moving between different quartiles of occupational wage. We also examine whether changes in residuals were symmetric for those moving between occupations with different fixed effects, finding no relationship that would suggest bias. Additionally, we find similar results when restricting to moves up to only higher-wage occupations, or down to only lower-wage occupations.

We use data from the Survey of Income and Program Participation (SIPP), a large, nationally-representative survey in the United States with data from 1983 through 2013.[3] For us, a key feature of that dataset is that it consists of a series of household panels: households are surveyed multiple times over the course of four years, which allows us to observe individuals who change occupations, sometimes multiple times. Many other data sources have some advantages over the SIPP, but would not be sufficient to answer the questions we are addressing. Many other large surveys with panel components, such as the Current Population Survey in the U.S. or the Labour Force Survey in Canada, track dwellings rather than households or individuals, so individuals are dropped if they move for a job; because such moves are likely important aspects of occupational change for many workers, these surveys are not well-suited to this research. Surveys designed as long-term panels studies, such as the Panel Study of Income Dynamics (PSID) or the National Longitudinal Survey of Youth (NLSY), both in the U.S., generally have sample sizes that are an order of magnitude smaller than the SIPP, which would make estimates much less precise. Administrative labor data in many countries (such as the U.S.) do not include occupation. Administrative data in other countries (such as Germany) does not include hours worked; because part-time work is an important feature of certain occupations, ignoring hours

[3]For more information about the SIPP, see https://www.census.gov/programs-surveys/sipp/about.html.

would cause us to erroneously view those occupations as paying especially poorly.

Our first finding is that occupational fixed effects play a relatively small role in accounting for inequality in the United States—only 3%. Because differences in average wages across occupations explain about 29% of overall inequality, this implies that just 10% ($\approx 3/29$) of occupational wage dispersion is due to premia. Put differently—because standard deviation is the square root of variance—on average, around one dollar out of every three that separates a high-pay and a low-pay occupation is attributable to the job itself; the other two dollars reflect who sorts into each occupation. Even so, such a premium is not negligible: moving to an occupation with a one standard deviation higher fixed effect would lead to earnings increasing by around 9%. The much larger share of the differences comes from individual selection (about 67%) and positive sorting: high-wage workers tend to be in high-wage occupations (about 11%).

A key advantage of our framework is that we can identify and discuss the fixed effects of individual occupations. Among larger occupations, the highest fixed effect belongs to electrical engineers: an otherwise average worker would earn about 20% more in that role than in the typical occupation. At the opposite extreme, farm workers display a fixed effect of roughly –19%, so pay would remain well below average even for a highly skilled entrant. While high-effect jobs usually attract high-skill individuals, we document some exceptions. College subject instructors and electricians, for example, rank among the highest observed wage earners even though their occupation effects hover near the mean; their advantage stems mainly from workers' own fixed effects rather than from the job itself. Conversely, insulation workers and management support workers earn wages near the average despite high occupation effects, suggesting that workforce composition rather than occupation-specific rents explain why these occupations do not have high wages.

We interpret these fixed effects—or premia—as *locally* causal. They capture the wage change for workers who can feasibly move between occupations, not a hypothetical effect if any worker were randomly assigned to any occupation. Our estimates thus reflect the expected gains or losses of those at the margin who have both occupations in their choice set, recognizing that barriers like education and licensing limit who can make particular transitions. To be clear, these estimates are not informative about the effect of human capital investments that would change the occupational choice set—for example, a student considering attending medical school. However, once someone has attended medical school and is considering changing occupations, these fixed effects can serve as a guide on expected wage changes. They also cannot tell us about how an occupation might increase human capital, and thereby wages, while someone is on the job. Despite these limitations, these fixed effects represent estimates that are policy-relevant for workers interested in switching careers, or policymakers considering policies that could affect such choices.

We continue by analyzing the characteristics of occupations that have particularly high fixed effects. In general, occupations with high fixed effects require more intellectual skills, such as complex problem solving or directing an activity. Occupations with low fixed effects more often require physical tasks under unpleasant conditions, such as extreme temperatures and exposure to contaminants. Interestingly, this suggests that the fixed effects we find are not driven by compensating differentials: high fixed effect occupations are likely to be more pleasant than low fixed effect occupations.

We also analyze how occupational effects interact with wage gaps across various demographic groups—such as gender wage gaps—where past literature suggests that occupations play a role. In our data, almost half of the male-female wage gap is indeed explained by the average wages across occupations. Yet, occupational fixed effects account for only 7% of the gap. This suggests that redistributing workers across occupations would do little to narrow the gender wage gap. Similarly, more than half of the wage gaps by race and education are explained by occupational average wage, but occupational fixed effects explain less than 20% of these gaps.

While occupation fixed effects only explain a small portion of wage inequality in the U.S., occupations may serve as launchpads that propel workers to different jobs. In fact, though, extending the AKM methodology to incorporate past occupation as in Di Addario et al. (2023), workers' *previous* occupations account for less than 1% of total inequality. However, occupations may still affect career paths by allowing workers to move to a greater variety of other career opportunities. Borrowing from biological terminology, we introduce the concept of *pluripotency*,[4] which refers to the capacity of certain occupations to serve as stepping stones to a wide array of other career opportunities. We estimate the distances between occupations using a Poisson regression model that predicts the expected transitions from one job to another, considering each occupation's characteristics, including required skills and knowledge. These distances provide a basis for our pluripotency index, which gauges how far workers move across the occupational landscape compared to what would be expected given occupations' sizes and similarities.

Beyond their role in constructing the index, these estimated distances are arguably more

[4]In biology, a *pluripotent* cell can develop into any cell in the body.

informative than existing measures of occupational similarity. Traditional approaches either rely on hierarchical classification codes, which reflect how statisticians group occupations rather than how workers actually move between them, or on task distances, which treat all listed skills as equally salient. In contrast, our measure is grounded in observed mobility patterns but still connected to occupational characteristics, allowing the data to reveal which dimensions of similarity matter most for real-world transitions. As such, the distances we measure between occupations are of independent interest to the literature—for example, in studying monopsony power and labor market frictions more broadly.

A higher pluripotency index for an occupation suggests that it offers greater versatility in career progression opportunities than typical. For example, roles such as auto repairers, physical therapists and mail carriers demonstrate high pluripotency, positioning them as flexible entry points into various career trajectories. On the other hand, occupations such as librarians, actors and roofers are characterized by lower pluripotency, suggesting more specialized and stable career paths with fewer opportunities for broader transitions. Further analysis shows that displaced workers from pluripotent occupations are more likely to find new employment quickly. The difference is strongest for declining occupations and for less-educated workers, suggesting that a pluripotent occupation can offset some of the vulnerability normally mitigated by higher education and fast-growing sectors.

1.1 Related Literature

Our study contributes to the existing literature examining the causal relationship between occupations and wages, a topic that intersects with broader debates on human capital, structural wage differentials, and labor market sorting. The dominant views within this literature emphasize either that wages primarily reflect differences in workers' skills, education, and innate ability (Roy, 1951; Heckman and Sedlacek, 1985), or alternatively, that occupation-specific factors such as barriers to entry, rent-sharing, and unionization fundamentally shape wage structures (Acemoglu and Autor, 2011). While prior studies (Acemoglu and Autor, 2011; Autor and Dorn, 2013; Hsieh et al., 2019; Böhm et al., 2024) have documented significant and persistent wage disparities across occupations that are then linked to inequality and polarization, they often stop short of establishing causal relationships, leaving unclear whether occupations directly affect wages or merely attract certain types of workers.

First, in contrast to past literature, we quantify the causal effect of occupations on wages. We use an empirical approach inspired by Abowd et al. (1999) that isolates occupational wage premiums from individual heterogeneity. While much of the literature applying AKM frameworks emphasizes firm-level wage differences (Card et al., 2013; Song et al., 2019; Bonhomme et al., 2019)—and, more recently, locations (Card et al., 2025) and industries (Card et al., 2024)—the independent role of occupations has received comparatively less attention. One exception is Hou and Milsom (2025); though not the focus of their paper, they estimate occupational and individual fixed effects in the United Kingdom, finding a modestly larger variance of occupational effects, but they do not explore which particular occupations (or occupational features) lead to higher earnings, or whether occupations can propel workers to higher earnings in future jobs. Some other papers that do highlight the role of occupations—such as Kambourov and Manovskii (2009), Altonji et al. (2016), and Böhm et al. (2024)—highlight that human capital is largely occupation-specific, implying occupation-level effects on wage trajectories. This paper also informs the literature on the way workers are assigned to occupations. Literature on assignment models dating back at least to Heckman and Scheinkman (1987) recognizes that there can be different returns to workers' skills in different sectors. In this paper, we find evidence confirming these different returns. Further work is needed to use the fixed effects we estimate (along with worker skills, which we do not observe) to determine the implied return to various characteristics in different occupations—and therefore the extent of nonuniform pricing of characteristics. Relatedly, gender wage gap studies have long associated observed disparities with occupational segregation (Fawcett, 1918; Goldin, 2014; Blau and Kahn, 2017). However, our results challenge the magnitude of this relationship by showing that occupation fixed effects account for only a modest portion of wage differentials. Thus, reallocating workers to occupations based solely on average wages may have limited potential for meaningfully reducing aggregate inequality and wage gaps, reinforcing a point made by Autor (2019).

Second, our analysis contributes to the literature on job-to-job transitions by introducing and exploring the concept of occupational pluripotency. Occupational mobility has traditionally been analyzed from two theoretical perspectives. The human capital literature, following Roy (1951), Kambourov and Manovskii (2009, 2013), and Gathmann and Schönberg (2010), views mobility as skill-driven, arguing that workers transition primarily between occupations with similar skill demands due to accumulated task-specific human capital. Alternatively, frictional models emphasize labor market constraints, job ladders, and imperfect transferability of skills, highlighting limited mobility or costly transitions (Moscarini and Postel-Vinay, 2018; Deming and Noray, 2020). While these frameworks provide valuable insights, they do not systematically measure an occupation's versatility in facilitating broad career moves. We bridge this gap by introducing occupational pluripotency—a novel measure that quantifies an occupation's potential to propel workers across diverse job opportunities. Previous empirical studies underscore that occupational transitions influence wage trajectories significantly (Shaw, 1987; Poletaev and Robinson, 2008; Cortes et al., 2024). Our approach advances this literature by providing a structured, quantitative assessment of occupations as stepping stones or bottlenecks in career trajectories. In doing so, we offer new insights into the career implications of occupational choices, especially following layoffs (Jacobson et al., 1993; Couch and Placzek, 2010; Couch et al., 2011; Krolikowski, 2017; Huckfeldt, 2022), and illustrate that pluripotent occupations can enhance resilience to labor market shocks, particularly for less-educated workers and those in declining fields.

Finally, we contribute directly to policy and practice by presenting our findings for each occupation in a form that can be easily used by job seekers and policymakers; that information can be found on the authors' websites. Occupational guidance typically emphasizes average pay as a key piece of information. While insightful, this approach neglects crucial aspects of career trajectories, including mobility opportunities, skill transferability, and resilience to economic shocks. Existing literature has documented broad trends in employment shifts and occupational restructuring, underscoring their relevance for policy interventions and individual decisions.

The remainder of this paper proceeds as follows. Section 2 describes the SIPP data we use. Section 3 presents our methodology, including the two-way fixed effect estimator and our pluripotency measure. Section 4 presents our results on occupational fixed effects; Section 5 presents our results on pluripotency. Section 6 concludes.

2 Data and Descriptive Statistics

2.1 Survey of Income and Program Participation

To measure the occupations' fixed effects and the pluripotency index, we use all the waves of the Survey of Income and Program Participation (SIPP) from National Bureau of Economic Research (2017). We use the panels from 1984 to 2008. Each individual record contains detailed employment histories over a span of up to 4 years, including occupation codes, unique worker-level employer identifiers, average hours worked per week and average monthly earnings. The main outcome of interest in the two-way fixed effects model is the (log) average hourly inflation-adjusted[5] wage during an employment spell. An employment spell is defined as the period of time during which the individual works for the same employer. As earnings are measured at the month level and hours worked at the week level, we measure hourly wages by dividing the average monthly earnings during an employment spell by the product of 4.345—the average number of weeks in a month—and the average number of hours worked during the same employment spell.[6]

To ensure consistency and comparability across all the years of data, we use the occupations classification system developed in Dorn (2009) and Autor and Dorn (2013). This classification offers a standardized way to compare different occupations over time, taking into account variations in occupational titles and functions. It is important to note that there is a literature documenting errors in occupational codes in survey data; see for instance Kambourov and Manovskii (2013). To reduce the probability that an individual has one occupation but is misclassified as switching to another, we restrict our attention to individuals who change employers, as measurement error is less likely when occupation changes coincide with employer changes than when they occur mid-spell. Within this employer-change sample, occupation fixed effects and our pluripotency index are identified by those who also change occupations, while those who keep the same occupation help pin down individual fixed effects and improve precision. There still may be individuals who are erroneously classified as having switched occupations when, in fact, they did not—or, indeed, we may misidentify occupations in other ways, too. However, as long as measurement errors are independent of any errors in measured pay, we should still recover the effect of being in a job that an interviewer would associate with a certain occupation, even if we do not identify the effect of that occupation itself.

As a robustness check, we estimate occupation fixed effects considering all moves between occupations where both occupations are reported in the same interview (each interview covers a 4-month period), regardless of whether the person changed jobs. As discussed in Appendix Section C, this sample is much smaller, so fixed effects are less well-estimated, but they are

[5]We correct for inflation with the Consumer Price Index, from `https://fred.stlouisfed.org/series/CPIAUCSL`. The base year is 2002, around the middle of our dataset.

[6]Using the averages in earnings and hours worked helps in reducing measurement error associated with these variables. As we will detail below, we focus our analysis on individuals who change employers during the survey, and individuals tend to report fewer hours worked and earnings in the month before and after the change. The first and last month of an employment spell are therefore not considered when producing these variables.

substantially similar. This suggests that within-employer occupation changes are similar to those between occupation, and that our results are not driven by misidentification of moves.

As mentioned above, we restrict the sample to all individuals who experience at least one employer change during our observation window. We further limit the data to workers aged 25–65 who average at least 20 hours of work per week and whose spell-average wage exceeds the spell's average statutory minimum wage.[7] To ensure that extreme earners do not drive the dispersion of occupation effects, we trim the top and bottom 1 percent of the pay distribution. These filters yield a core sample of 184,987 employment spells for 74,658 unique workers; when we require information on the previous occupation (and thus at least two changes of employers), the sample contracts to 75,554 spells for 31,209 workers. More details about the sample selections are provided in Appendix E.

Table 1 shows that all workers in the United States share many similarities with those we observe changing employers, and those changing occupations. Our primary sample consists of those changing employers at least once. We additionally present statistics on occupation switchers because this group alone drives occupation fixed effects and pluripotency calculations. These results, and all others unless otherwise noted, are weighted using SIPP individual weights. All groups work around 40-41 hours per week and are 53-54% male. The racial and ethnic compositions are also quite close, with White non-Hispanic individuals comprising roughly 75% of the full sample and 72-73% of switchers, and nearly identical proportions of Black non-Hispanic, and Hispanic individuals. Employer and occupation switchers are slightly younger, with an average age of 39 compared to 41 in the full sample. The primary difference is that the number of jobs is higher for those who switch employer (2.8) and occupation (3.0) than the full sample (1.6).

2.2 Other Data Sources

To characterize each occupation, we use the Occupational Information Network (O*NET) data, a detailed source of information on occupational tasks and attributes, from National Center for O*NET Development (2021). O*NET details both the level and the importance of several factors for every occupation code. We extract the levels and importance of four domains most

[7]For each spell we compute the time-weighted average of the federal minimum wage in force and retain only those spells with mean earnings above that benchmark.

Table 1: Summary Statistics

	All Workers		**Employer Switchers**		**Occupation Switchers**	
	Mean	**SD**	**Mean**	**SD**	**Mean**	**SD**
Ln real wage	2.625	0.496	2.549	0.486	2.519	0.476
Average weekly hours	40.773	7.536	40.721	7.102	40.481	6.747
Number of jobs	1.618	1.038	2.841	1.174	2.953	1.242
Age	41.024	10.307	39.276	10.319	39.021	10.244
Male	0.529		0.544		0.542	
Female	0.471		0.456		0.458	
Ed: Less than high school	0.181		0.165		0.161	
Ed: High school	0.594		0.591		0.604	
Ed: College	0.225		0.244		0.235	
Race/Eth: White non-Hispanic	0.753		0.728		0.723	
Race/Eth: Black non-Hispanic	0.106		0.111		0.115	
Race/Eth: Hispanic	0.092		0.105		0.106	
Race/Eth: Other	0.049		0.055		0.055	
Num. of Individuals	261491		74658		52281	

Notes: Sample statistics from the Survey of Income and Program Participation. "Ln real wage" is the natural log of hourly wage at a worker's main job, adjusted for inflation to 2002 values. "Average weekly hours" is the average hours worked at their main job. "Number of jobs" is the number of distinct main jobs a worker has held. "Age" is average age while in the SIPP sample. Where there is variation, sex, education, and race/ethnicity are based on the modal value in the SIPP sample. "All Workers" includes those whose average age while in the sample is between 25 and 65, whose average wage is above the average federal minimum wage while they are in the sample, who average more than 20 hours per week, and whose wage is not in the top 1% or bottom 1%. "Employer Switchers" includes only those who we observe switching employers at the same time, and who satisfy similar restrictions to the full sample at the time of their move. "Occupation Switchers" is the subset of Employer Switchers who we additionally observe switching occupations. Note that a small number of workers appear in the "Switchers" categories but not in the "All Workers" category if their age or average wage in one job is within the sample range, but that statistic is out of range on average while in the SIPP (for example, if they are 24 on average while in SIPP but 25 when they change jobs).

relevant to career mobility—skills, abilities, knowledge and work styles—and map them to occupations using the crosswalk described above. When several codes merge into a single occupation over time, we assign that occupation the mean of each O*NET item. The result is a vector of task requirements for every occupation in our sample.

Our evidence on how pluripotency protects displaced workers comes from combining two datasets. First, we draw individual outcomes from the Current Population Survey's Displaced Worker Supplement (DWS), using data from Flood et al. (2024), which surveys workers who involuntarily lost a job within the previous five years. We harmonize race, sex, age, and education exactly as in our SIPP dataset. For each of the 78,205 displaced workers, we track weekly earnings before displacement, plus re-employment month by month, coding an indicator equal to one if the person is back in work within t months of separation, for $t = 1, \ldots, 24$.

Second, we construct a long panel of occupations from the 1970-2000 censuses, using data from Ruggles et al. (2025). For every census year and state, we record each occupation's employment share. Comparing the 2000 share with the 1970 share yields a simple growth ratio; we label an occupation in a given state as growing if its 2000 share is at least as large as its 1970 share and shrinking otherwise.

3 Methodology

3.1 Occupational Fixed Effects

To understand how much of the variation in wages can be attributed to occupations, we begin by decomposing individual wages within occupations. For an individual i in occupation j, the log wage y_{ij} can be expressed as:

$$y_{ij} = \underbrace{\bar{y}_j}_{\text{occupation mean}} + \underbrace{(y_{ij} - \bar{y}_j)}_{\text{individual deviation}}, \quad (1)$$

where $\bar{y}_j$ is the average log wage in occupation j.[8] This equation decomposes the total log wage into two components: the average wage within an occupation and the individual deviation from this average.

Using this decomposition, we can further break down the variance of log wages into two

[8]Note that all variables are a function of time t, and occupation j is additionally a function of individual i. Except where they are needed, we suppress these arguments to improve readability.

parts:

$$\underbrace{\mathrm{Var}_i\left(y_{ij}\right)}_{\text{total dispersion}} = \underbrace{\mathrm{Var}_j\left(\bar{y}_j\right)}_{\text{between-occupation dispersion}} + \sum_j \omega_j \times \underbrace{\mathrm{Var}_i\left(y_{ij} | i \in j\right)}_{\text{within-occupation-}j\text{ dispersion}},$$

where $\mathrm{Var}_i(y_{ij})$ represents the total dispersion in log wages, $\mathrm{Var}_j(\bar{y}_j)$ captures the variance between different occupations, and $\mathrm{Var}_i(y_{ij}|i \in j)$ reflects the variance within a given occupation j. The term ω_j represents the weight of each occupation in the overall distribution: $\omega_j = N_j/N$ where N_j is the number of workers in occupation j among the workforce of N individuals.

In our data, the proportion of wage variance explained by the between-occupation component, $\frac{\mathrm{Var}_j(\bar{y}_j)}{\mathrm{Var}_i(y_{ij})}$, is approximately 29%. This suggests that a significant portion of wage dispersion is due to differences between occupations. The key question, therefore, is how large a slice of that 29% reflects true occupational effects as opposed to differences in the composition of workers across occupations.

To separate those channels, we estimate several two-way fixed effects regressions. For an individual i in occupation j, we estimate

$$y_{ijt} = \lambda_i + \lambda_j + \mathbf{x}_{it}'\beta + \epsilon_{ijt}, \tag{2}$$

where y_{ijt} is the log of the average hourly wage during the employment spell. The regression incorporates both individual and occupation fixed effects, represented by λ_i and λ_j, respectively. The individual fixed effect, λ_i, captures time-invariant worker attributes. The occupation fixed effect, λ_j, captures the wage premium or penalty attached to the occupation itself. In our preferred specification, $\mathbf{x}_{it}$ includes year fixed effects (corresponding to the year the worker switched employers) and age.[9] With worker heterogeneity held fixed, the estimated occupation effects $\hat{\lambda}_j$ tell us how much a worker's log wage would change if they moved to occupation j from a job with the sample-average occupation effect.

Estimated fixed effects are of independent interest, but we also perform a variance decomposition exercise as in AKM. While the original model decomposes earnings based on workers' and firms' fixed effects, we use a variation of the AKM decomposition that considers occupations instead. Based on the model specified above, we decompose the variance in wages into three

[9]Individual and year fixed effects cannot be combined with age because of perfect collinearity. We therefore include the terms $\left(\frac{\text{age}-40}{40}\right)^2$ and $\left(\frac{\text{age}-40}{40}\right)^3$ in the regressions.

main components (for now, ignoring components related to $\mathbf{x}'_{it}$ and ϵ_{ijt} for tractability):

$$Var(y_{ij}) = Var(\lambda_i) + Var(\lambda_j) + 2\,Cov(\lambda_i, \lambda_j). \tag{3}$$

$Var(\lambda_i)$ represents the variance due to individual worker effects. This term captures the differences in wages that are due to individual characteristics of the workers, such as their skills and knowledge, and other non-time-varying characteristics. $Var(\lambda_j)$ captures the differences in wages that are due to characteristics of the occupations themselves, such as the industry, required skills, or the level of responsibility. $Cov(\lambda_i, \lambda_j)$, the covariance between the two sets of fixed effects, captures the extent to which the individual worker characteristics are correlated with the occupational characteristics—for instance, the extent to which high-skilled workers tend to be in high-paying occupations.

Occupational fixed effects are estimated based on the wage changes we observe for people who move to or from each occupation. If few workers in our data set move to or from certain occupations, the fixed effects associated with those occupations will be estimated noisily. If that is the case, the estimated variance of occupational fixed effects includes the variance of the true fixed effects, but also includes the variance of this noise. To deal with this limited mobility bias, we use the correction outlined in Kline et al. (2020) and the accompanying package.[10] This method first estimates the occupation fixed effects using the full sample, then applies a leave-one-out correction to obtain unbiased estimates of the variance components.

3.2 Validity of Fixed Effects Assumptions

To ensure that we are estimating unbiased causal effects, we rely on several assumptions. Principal among these is the assumption of exogenous mobility, meaning that match effects are uncorrelated with occupations. Although we cannot test these assumptions directly, we test five implications in this section—four tests from the literature, as well as one we develop ourselves.

First, Appendix Figure B.1 (based on a test in Card et al. (2013)) displays the average log wage trends for individuals across different occupation quartiles in the 12 months leading up to an occupational move. These quartiles categorize occupations based on the average log wages, with the first quartile representing the lowest-paying occupations and the fourth

[10] Available here: `https://github.com/rsaggio87/LeaveOutTwoWay`

quartile representing the highest-paying ones. Each line represents transitions between quartiles, with filled-in symbols for downward moves and hollow symbols for upward moves. The trends generally remain stable, indicating no significant differential pre-trends. Similarly, Appendix Figure B.2 shows the average log wage trends for the 12 months following an occupational move. Post-move trends also remain stable, suggesting no significant differential post-trends across quartiles. Although there are noticeable changes in wages immediately before and after the move, these are likely temporary adjustments related to the transition and are therefore excluded from the computation of the average wage for an occupation.

The second testable implication relates to the symmetry between wage gains and losses for individuals moving between different occupation quartiles. We expect that the average wage gains for individuals moving up to a higher-paying quartile should mirror the average wage losses for those moving down to a lower-paying quartile. In other words, if individuals moving from a lower quartile to a higher one experience a certain increase in their log wages, those moving in the opposite direction should experience a similar decrease in their log wages. Appendix Figure B.3 (based on a test in Card et al. (2013)) shows the average log wage changes for individuals who either move up or down between quartiles before and after the occupational move. In general, the changes in log wages appear to be relatively symmetric for both upward and downward movers.

The third testable implication checks whether the errors in the estimated wages systematically vary with the occupational fixed effects. Figure Appendix B.4 (based on a test in Card et al. (2013)) plots the actual versus predicted log wages across deciles of occupational fixed effects. Each decile represents a range of occupations sorted by their fixed effects, with lower deciles corresponding to lower occupational fixed effects and higher deciles to higher ones. The figure shows that the actual and predicted wages align closely across all deciles, indicating that the residual errors do not systematically vary with the level of occupational fixed effects.

The fourth testable implication examines whether the changes in residuals for individuals who move between occupations are related to the change in their occupations' fixed effects. Figure Appendix B.5 (based on a test in Card et al. (2024)) plots the change in residuals against the change in occupational fixed effects for individuals who switch occupations. The lack of a clear pattern or systematic relationship in the scatter plot suggests that changes in the residuals are not correlated with changes in occupational fixed effects. This indicates that up-movers and down-movers have similar error terms, supporting the assumption that the wage changes due to occupational transitions are not biased by unobserved factors or systematic errors.

Some care is needed in interpreting the coefficients because not all workers can transition into any given occupation. For example, only some workers have the option of becoming electrical engineers—the occupation with the highest fixed effect. However, this is the case for firm fixed effects as well: employment at many electrical engineering firms is only open to a small fraction of the population (including certain electrical engineers and support staff). We should therefore consider any estimated AKM fixed effects—in this or any paper that estimates them—to be local to the workers who could join an occupation, firm, or other group. Thus the difference in fixed effect between any occupations A and B between which no one moves should be thought of as being based on the average of the sums of such differences in all chains of occupations from A to B that do see movement. As a robustness check to test whether restrictions on occupational movement overly affect our results, we re-estimate key outcomes after removing workers in occupations that universally require occupational licensing.

Additionally, the above discussion makes clear that fixed effects are useful only if they are informative about how wages change out of sample. That is, there is no *a priori* reason to believe that the wage change among those going from occupation A to B, plus that among those going from B to C, equals the change among those going from A to C. If few people do move from A to C, fixed effects could then give misleading estimates of how much we expect wages would change among people who are able to make that move. Here, we develop a test of this out-of-sample property, which we describe in more detail in Appendix Section D. First, we divide all occupations into deciles based on their estimated fixed effects. Next, for every non-adjacent pair of deciles D_1 and D_2, we estimate Equation 2 using all occupations in deciles between D_1 and D_2, including those in either decile D_1 or D_2 but not those who move between an occupation in D_1 and an occupation in D_2. Then, for everyone who does make such a move between D_1 and D_2, we calculate two values: the change in the newly-calculated occupation fixed effect, and the change in their actual wage. The average of these two values for each such pair of deciles is plotted in Figure D.2. The points are close to the 45-degree line; an OLS regression using these points cannot rule out the null that the line has an intercept of 0 and a slope of 1. This suggests that fixed effects do correctly predict out-of-sample wage changes.

3.3 Motivation for Distance and Pluripotency

Our goal in calculating pluripotency is to measure how far each occupation propels workers, relative to what we would expect for a similar occupation. For example, we might expect that graduate research assistant is a propelling occupation: although it is low pay, it allows workers to get a variety of jobs later. We could measure this variety directly—for example, with a Herfindahl-Hirschman index of the jobs workers get—but this measure would be dependent on the way government statisticians define occupations, and wouldn't give a sense of the distance workers are propelled. To get a sense of this distance, we need to measure the distance between occupations in a natural, data-driven way. We could use occupation codes for this; for example, if two occupations share a 3-digit code but not a 4-digit code, they would be closer than two occupations that share a 2-digit code but not a 3-digit code. (That is, 1234 would be closer to 1239 than to 1229.) However, these occupational definitions may tell us more about how government statisticians define occupations than about occupations themselves; for example, if one occupational group grows, it might split in two even though the underlying work has not changed.

A data-driven alternative distance measure is to determine the distance between occupations based on their characteristics—for example, using the Euclidean or similar distance in O*NET characteristics, as in Gathmann and Schönberg (2010). However, some characteristics may be more important than others, while this measure would be dependent on O*NET's decision of which measurements to report. Another natural measure of distance in this context is the inverse of how often workers actually move to an occupation. The problem with this is that it leads to occupations propelling workers, on average, the same distance away: workers are more likely to go to an occupation that is measured as "close", by definition. Combining the data-driven O*NET measure with the natural move-based idea leads us to our preferred alternative: to measure how much we expect workers to move, based on the characteristics of the two occupations (as measured by O*NET).

Given the above description, any measure of distance that decreases as moves between occupations increase would be a reasonable distance measure. However, for many such distance measures, some occupations would be particularly close to many others, while some would be particularly far from others. Additionally, people would be expected to be more likely to move to big than small occupations. How can we tell if an occupation sends many workers to distant occupations because it is close to few occupations, or far from big occupations, or because it is propelling them? We need to compare how far it propels them to how far we expect it to propel them. Because the distance is lower when people are expected to move more to an occupation, this distance should be constructed in such a way that distance moved is a constant if people move as expected. The formula that creates this identity is the one we present in Section 3.4.

3.4 Calculating Distance and Pluripotency

To understand how versatile different occupations are, we therefore develop a measure that captures how far workers tend to move in their occupations when they switch jobs. Our goal is to distinguish between occupations that act as launchpads—propelling workers into many diverse roles—and those that lead mostly to similar occupations. To do this, we first define a natural, data-driven way to measure distance between occupations and then use it to calculate each occupation's *pluripotency.* We finish with a numerical example.

Step 1: Predicting how many moves should occur

We start by estimating how many workers we expect to move from one occupation, say A, to another, say B, based on how similar these two occupations are. If A and B require similar skills or share similar attributes, more people are likely to switch between them. We use the characteristics from the O*NET data to compute differences in characteristics and let the data tell us which characteristics are most important. That is, we assume that

$$M_{AB} \sim \text{Poisson}\left[(N_A \times N_B) \times \exp\left(\sum_i \beta_i C_i^{AB}\right)\right] \tag{4}$$

where M_{AB} is the observed number of moves from A to B and C_i^{AB} is the difference in characteristic i between occupations A and B. The terms N_A and N_B represent the number of workers in each occupation. Their multiplication reflects the baseline number of potential transitions between the two occupations: if an occupation is twice as big (holding all else equal), we would expect moves to and from it to be twice as common.

We estimate the β_i coefficients with a Poisson regression, and use the results to calculate $\hat{M}_{AB}$, our estimator for $E[M_{AB}]$. To ensure that actual moves from A do not bias expected distance, we leave out moves from A in estimating the β_i's used to define $\hat{M}_{AB}$. (Note that leaving out these moves makes the distances we measure in the next step asymmetrical: distance from A to B is different from the distance from B to A. Empirically, though, the asymmetry is small.)

Step 2: From expected transitions to distance

Intuitively, if many people are predicted to move from A to B, we consider the occupations to be close. Conversely, if few transitions are expected, we infer that the occupations are distant. To make this relative, we normalize the expected number of transitions from A to B by the average transitions from A to all the other occupations.[11] We then take the inverse of this ratio to define the distance (not similarity) from A to B:

$$\hat{D}_{AB} = \left(\frac{\hat{M}_{AB}}{\frac{1}{317} \sum_{j \neq A} \hat{M}_{Aj}} \right)^{-1} \tag{5}$$

where 317 is the number of occupations other than occupation A. Intuitively, the distance between A and B is the inverse of expected moves, where moves are normalized by the average number of expected moves from A to all other occupations.

Step 3: Defining pluripotency

With our distance measure in hand, we now define the pluripotency of an occupation—that is, how broadly it sends workers across the occupational landscape. To do so, we calculate the average distance that workers in occupation A travel when they switch to another occupation. To make this average meaningful, we need a benchmark: how far would we expect them to move if their transitions were fully explained by the observable characteristics of occupations. This benchmark comes from the model of expected transitions we estimated using Equation 4. Formally, the pluripotency of occupation A is defined as

$$\hat{P}_A = \frac{\sum_B w_{AB} \hat{D}_{AB}}{\sum_B w_{AB}}, \tag{6}$$

where w_{AB} is a weight reflecting the observed rate of transitions from A to B, scaled by the product of the sizes of the two occupations:

$$w_{AB} = \frac{\text{moves from } A \text{ to } B}{N_A \times N_B}.$$

Because we define $\hat{D}_{AB}$ as the inverse of predicted transition rates (normalized to have an

[11] In our data, we have a total of 318 occupations, thus there are 317 *other* occupations.

average of 1), and we weight by the actual transition rate w_{AB}, the pluripotency index $\hat{P}_A$ will equal 1 whenever workers move exactly as predicted. Any deviations from 1 therefore reflect whether an occupation propels workers more broadly or narrowly than its characteristics would suggest. That is,

- if $\hat{P}_A > 1$, workers from A tend to move into occupations that are further away than we would expect given A's characteristics;
- if $\hat{P}_A < 1$, workers from A tend to move into closer occupations than predicted.

Numerical example

Table 2 walks through the pluripotency index computation in a simple setting with 300 workers and four equally sized occupations: the origin occupation A and three possible destinations: B, C, and D. Our goal is to compute the pluripotency of occupation A.

Table 2: Illustration of the Pluripotency Calculation

Transition	**Expected Moves**	**Distance**	**Actual number of moves**		
	$\hat{M}_{AX}$	$\hat{D}_{AX}$	Case 1 (perfect fit)	Case 2 (not pluri.)	Case 3 (pluri.)
$A \to B$	150	0.67	150	240	15
$A \to C$	100	1.00	100	40	100
$A \to D$	50	2.00	50	20	185
Numerator: $\sum w_{AX}\hat{D}_{AX}$			300	240	480
Denominator: $\sum w_{AX}$			300	300	300
Pluripotency: $\hat{P}_A$			1.00	0.80	1.60

Notes: Example of pluripotency calculation based on fictitous data. See Equations 4, 5, and 6 for details.

The first step involves using a Poisson regression to predict the number of moves from A to the other occupations, $\hat{M}_{AX}$ (with $X \in \{B, C, D\}$), as in Equation 4. Occupation pairs that look very similar ($A \to B$ in this example) are predicted to exchange many workers (150), while very different pairs ($A \to D$) are predicted to exchange few (50). This is reflected in the distance measures, which can be computed using Equation 5. For instance, for $A \to B$, we have

$$\hat{D}_{AB} = \left(\frac{150}{\frac{1}{3}(\hat{M}_{AB} + \hat{M}_{AC} + \hat{M}_{AD})} \right)^{-1} = 0.67.$$

Large predicted flows therefore translate into small distances (0.67 for $A \to B$) while small predicted flows translate into large distances (2.0 for $A \to D$).

We next consider three cases. In Case 1, occupation A is neither pluripotent nor non-pluripotent: workers move exactly as expected. Multiplying each flow by its distance and adding up gives a weighted sum of distances—the numerator of the pluripotency index in Equation 6—of 300. Because the sum of flows is also 300, the ratio $\hat{P}_A$ is exactly one.

In Case 2, occupation A is not pluripotent because workers overwhelmingly choose the nearest destination: 240 moves go to B, only 20 to the remote D. The weighted sum of distances shrinks to 240, driving the index down to $\hat{P}_A = 0.80$. The interpretation is straightforward: given what the observable data tell us about A, its departing workers choose occupations that are closer than expected—A offers relatively narrow onward options.

In Case 3, the pattern is different: more workers (185) leap to the distant occupation D. This pushes the weighted-average distance up to 480 and the pluripotency index increases to 1.6. Here, A acts as a launchpad: it sends its workers further than its characteristics alone would predict.

4 Results on Occupational Fixed Effects

4.1 Occupational Fixed Effects

We estimate Equation 2 using OLS, and report the distribution of the estimated occupational fixed effects (denoted by λ_j) in Appendix Figure B.6. The distribution is fairly symmetrical and clustered around around zero, but some fixed effects are economically significant: about 10% of workers are in occupations with fixed effects above 0.15 (indicating their occupations pay them at least 15% more than an average occupation would), while 10% of workers are in occupations with fixed effects below -0.12. A strength of our setting is that we can report precisely-estimated fixed effects for each occupation (we further discuss precision below). Therefore, Table 3 lists the ten occupations with the highest and lowest occupational fixed effects.[12] The left side of the table shows the high fixed-effect occupations, which are associated with higher wages after controlling for individual characteristics. At the top of this list are electrical and industrial engineers, with

[12]This and most other figures and tables that describe particular occupations are restricted to the largest 50% of occupations, where 93% of people are employed and estimates are most precise. All fixed effects, including those of smaller occupations, are shown in Appendix Tables A.4, A.5, A.6, and A.7.

Table 3: Occupations with High and Low Fixed Effects Among Large Occupations

High Fixed Effect Occupations	**Fixed Effect**	**Low Fixed Effect Occupations**	**Fixed Effect**
Electrical engineers	0.203	Cooks	-0.135
Industrial engineers	0.201	Bakers	-0.146
Operations and systems researchers, analysts	0.193	Guards and police, except public service	-0.149
Mechanical engineers	0.190	Waiters and waitresses	-0.151
Chief execs, public admin, legislators	0.184	Gardeners and groundskeepers	-0.155
Engineers and other professionals, n.e.c.	0.182	Cashiers	-0.157
Computer software developers	0.175	Food preparation workers	-0.162
Computer systems analysts, computer scientists	0.172	Misc food preparation, service workers	-0.169
Chemists	0.170	Personal service occupations, n.e.c	-0.185
Physical therapists	0.163	Farm workers, incl. nursery farming	-0.193

Notes: Occupational fixed effects are calculated using Equation 2. Fixed effects for the occupations with the ten highest and lowest values are listed here. Only occupations above the median size are included.

fixed effects above 0.2. Other high fixed-effect occupations include chief executive officers and other types of engineers. The right side of the table lists low fixed-effect occupations. These occupations include farm workers and a variety of food service workers. Generally, we see high-skill occupations with high fixed effects, and vice versa; we return to this point below.

Figure 1 shows that these fixed effects are relatively stable over time.[13] Fixed effects along the x-axis are calculated using only data from the 1980s and 1990s, while those along the y-axis use data from the 2000s and 2010s. Each point corresponds to an occupation, with most clustered along the diagonal, for a correlation of 76%. Despite the overall stability, pharmacists and CEOs now see substantially higher recent fixed effects. On the other hand, structural metal workers and postal service mail carriers have seen their fixed effects decline since 2000. Although fixed effects changed little, these changes explain much of the between-occupation change in average wages. Occupation fixed effects increasing by 1 between the two periods is associated with occupation average wages increasing by 0.609 (robust standard error .086), with an R^2 of .24.

To further understand the factors driving these wage disparities, we regress the estimated fixed effects on various skill requirements from the O*NET database. Figure 2 illustrates the regression coefficients for different skills, with positive coefficients indicating that skills generally associated with “high-skill” work, like “Time Management”, “Complex Problem Solving”, and “Critical Thinking”, are associated with higher occupational fixed effects. Conversely, skills such as “Operation and Control”, “Equipment Maintenance”, and “Repairing” are linked to

[13] A similar graph for all occupations is shown in Appendix Figure B.7.

Figure 1: How Stable are Occupations' Fixed Effects?

Notes: One observation per occupation. Occupational fixed effects are calculated using Equation 2 two times: once including all observations through 1999 (as shown on the x-axis), and once including all observations in 2000 and later (y-axis). Only occupations above the median size are included. The red line indicates values where occupational fixed effects are unchanged (that is, the 45-degree line). Selected occupations are labeled.

occupations with lower fixed effects.

Notably, these patterns likely run counter to compensating differentials, if we believe the skill requirements associated with high fixed effects in Figure 2 are those that would make a job interesting and therefore desirable. A desire for "interesting" work, of course, may reflect our bias as economists. However, we also note that high fixed effects are associated with physically unpleasant work contexts, such as extreme temperatures, exposure to contaminants, and risk of minor burns and cuts. This suggests the labor market compounds rather than compensates for poor working conditions, with unpleasant occupations offering both worse amenities and lower wage premia.

4.2 Wages and Fixed Effects

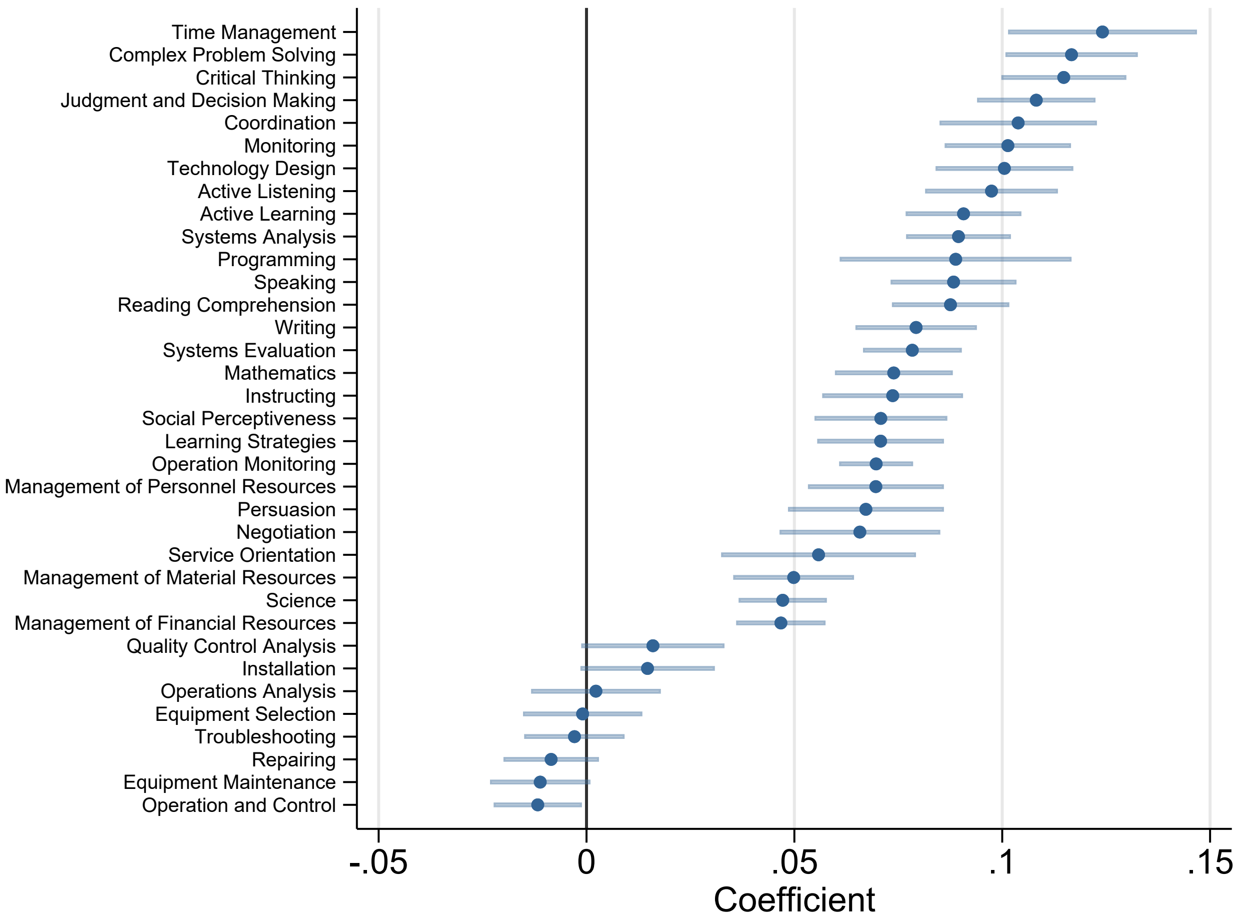
We have seen that high-skill occupations generally have high fixed effects; as we might expect, then, high fixed-effects occupations are associated with higher pay. The scatter plot in Figure 3 shows the strong positive relationship between an occupation's fixed effects and the occupation-wide average log real wage. However, note that variation in occupation fixed effect is substantially smaller than variation in log wages, and that high-wage occupations are also more likely to employ workers with high average individual fixed effects (red squares) than low average fixed effects (blue circles); we return to this point in Section 4.3.

Despite the strong relationship between occupational fixed effects and wages, some occupations have average wages that are either above or below what would be predicted based on their fixed effects alone. Building on this variation, Panel A from Table 4 lists occupations with relatively high average wages but low fixed effects, such as surveyors and college instructors, showing that some occupations pay well despite having lower fixed effects. In other words, workers in these fields are paid well, but could likely earn even more elsewhere. Conversely, Panel B highlights occupations with relatively low wages but high fixed effects, like insulation workers.

4.3 Variance Decomposition

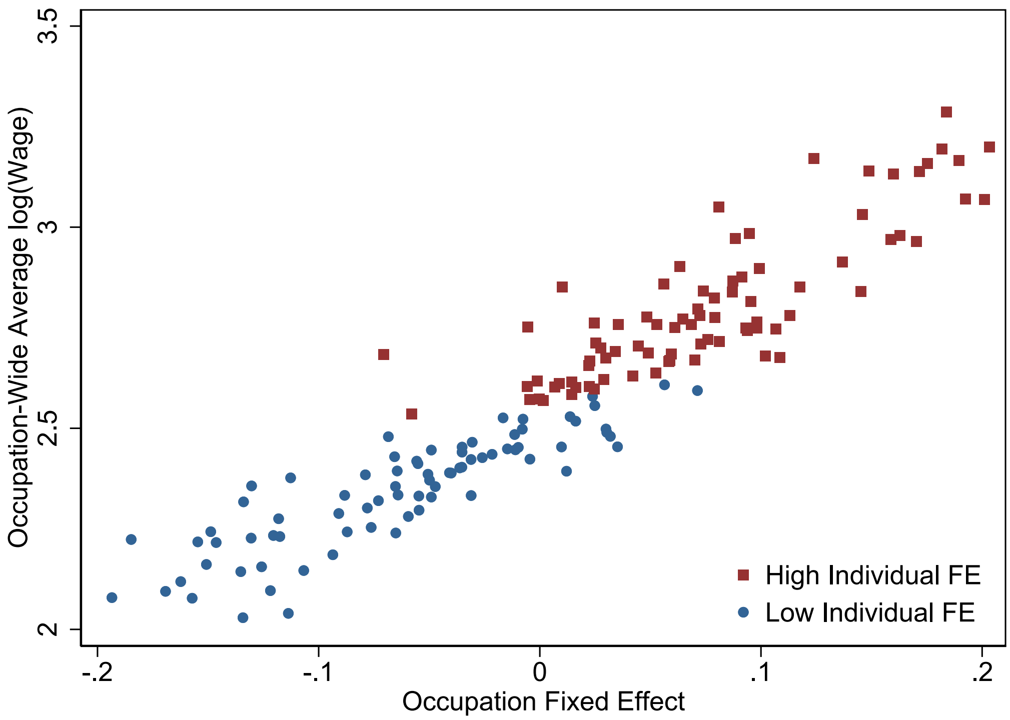
To isolate the respective roles of occupations and individual ability in determining wages, we run a simple decomposition exercise by estimating Equation 3. The variance in wages is decomposed into four main terms: one related to the dispersion of individual fixed effects, one related to the

Figure 2: Relation between Various Skills and Occupation Fixed Effects



Notes: Each point represents the coefficient from a simple regression with one observation per occupation. The dependent variable is the occupation's fixed effect; the independent variable is a standardized measure of an O*NET skill. Bars represent heteroskedasticity-robust 95% confidence intervals. Regressions are weighted by size of the occupation.

Figure 3: Correlation of Wages with Occupation Fixed Effects



Notes: One observation per occupation. The x-axis measures the occupation's occupational fixed effect; the y-axis measures the average log real wage in the occupation. Red squares are occupations in which average individual fixed effects are above the average of all occupations; blue circles are occupations in which it is below average. Only occupations above the median size are included.

Table 4: Differences between Fixed Effects and Average Wages

Occupation	Average ln(Wage)	Wage Rank	Fixed Effect	FE Rank	Diff
Panel A: High Wage, Low Fixed Effect					
Surveryors, cartographers, mapping scientists/techs	2.684	58	-0.071	129	71
Subject instructors, college	2.851	26	0.010	83	57
Fire fighting, fire prevention, and fire inspection occs	2.752	43	-0.005	92	49
Auto body repairers	2.536	86	-0.058	121	35
Electricians	2.762	39	0.025	72	33
Automobile mechanics and repairers	2.479	96	-0.068	128	32
Purchasing managers, agents, and buyers, n.e.c.	2.859	24	0.056	53	29
Financial service sales occupations	2.903	20	0.063	47	27
Recreation facility attendants	2.357	123	-0.130	146	23
Management analysts	3.050	12	0.081	35	23
Panel B: Low Wage, High Fixed Effect					
Supervisors of food preparation and service	2.333	128	-0.031	104	-24
Actors, directors, and producers	2.747	47	0.107	21	-26
Administrative support jobs, n.e.c.	2.498	91	0.030	65	-26
Payroll and timekeeping clerks	2.490	93	0.030	64	-29
Correspondence and order clerks	2.480	95	0.032	63	-32
Machine operators, n.e.c.	2.393	116	0.012	82	-34
Management support occupations	2.594	79	0.071	43	-36
Roofers and slaters	2.454	98	0.035	61	-37
Postal clerks, exluding mail carriers	2.680	59	0.102	22	-37
Insulation workers	2.676	60	0.109	20	-40

Notes: Only the 159 occupations above the median size are included in this analysis. For each occupation in the table, we present, for the workers in that occupation in our sample, the average of the natural log of real hourly wage; the rank of that wage, where 1 indicates the highest wage; the occupation's fixed effect; the rank of that effect, where 1 indicates the highest effect; and the difference between wage rank and fixed effect rank. All 159 occupations are sorted by this difference; the top 10 and bottom 10 are included in this table.

dispersion of occupational fixed effects, one related to the sorting of high-ability workers into high-effect occupations, and one capturing other variation, including noise. The results from four specifications are provided in Table 5.

Panel A shows that, as expected, wages are fairly consistent over time for individuals: individual fixed effects, by themselves, explain 79% of overall wage variance. Occupations by themselves also have important explanatory power, explaining 29% of total variance. However, controlling for individual effects, occupations are much less important: in Panel C, we find that occupation effects only explain around 3.2% of the variance. The sorting component, which captures the selection of individuals into high and low-paid occupations, explains a further 11.6%. Panel D shows that including control variables—our preferred specification—does not substantially change this result: occupations explain 3.1%, while sorting explains 11.3%. Overall, these results indicate that individual characteristics are the primary drivers of wage variance, including between occupations. In Appendix Table A.1, we find that occupation fixed effects also explain little of the increase in inequality over the past few decades. We may worry that occupational licensing can restrict which occupations workers can enter, thereby biasing our results; however, in Appendix Table A.2, we find that removing occupations that require licensing barely changes our estimates. Comparing our results to those of Bonhomme et al. (2023), we find that occupational fixed effects explain substantially less variation than do firm fixed effects in the United States (around 5 or 6%).

Table 5: Variance Decomposition

	Var(Wages) =	Var(Ind. FE)	+ Var(Occ. FE)	+ 2 × Cov(Ind. FE, Occ. FE)	+ Other terms
			Panel A: Individual Fixed-Effects		
Component	.2513	.1978			.0535
Proportion	1	.7871			.2129
			Panel B: Occupations Fixed-Effects		
Component	.2513		.0727		.1787
Proportion	1		.2891		.7109
			Panel C: All (without controls)		
Component	.2513	.1629	.0079	2 × .0145	.0515
Proportion	1	.6482	.0315	2 × .0578	.2047
			Panel D: All (with full set of controls)		
Component	.2513	.1643	.0077	2 × .0142	.0509
Proportion	1	.6536	.0308	2 × .0565	.2026

Notes: Results of a variance decomposition based on Equation 3. "Var(Wages)" measures the overall variance of log real wages, with one observation per person, per employer. "Var(Ind. FE)" measures the variance of individual fixed effects. Var(Occ. FE) measure the variance of occupation fixed effects. "2 × Cov(Ind. FE, Occ. FE)" measures twice the covariance between individual and occupation fixed effects. "Other terms" includes the variance of the error term, as well as all terms related to other covariates, if they are included. All results weighted using SIPP weights. Panel A is based on a regression including only individual fixed effects. Panel B includes only occupational fixed effects. Panel C includes both types of fixed effects. Panel D adds year fixed effects, as well as controls for age^2 and age^3.

Limited mobility bias arises in variance decomposition analyses when there is insufficient movement of individuals between occupations or firms. As highlighted by Andrews et al. (2008), this lack of mobility can lead to biased estimates of the variances associated with fixed effects because the data does not capture enough variation in worker transitions. Because we see many movers in and out of most occupations, we would not expect limited mobility bias to be a major issue. Indeed, in Appendix Figure B.8 we plot the occupational fixed effect variance, as well as twice its covariance with individual effects, restricting to occupations of various sizes; these terms vary little with this restriction.

To more formally adjust for limited mobility bias, we apply the unbiased estimator proposed by Kline et al. (2020). The results of this correction are displayed in Table 6. Panel A shows the decomposition using the usual OLS ("plug-in") approach without any controls, while Panel B shows results after applying the unbiased estimator.[14] Although the variance of individual effects is substantially lower with the unbiased estimator (48%) than with the plug-in estimator (63%), our primary outcomes of interest are similar: variance of occupation fixed effects is around 3% and 2 times covariance is around 12% using both methodologies. This suggests that each occupation fixed effect—particularly that for larger occupations—is estimated precisely enough to be reported individually, as we do above.

Table 6: Comparison with the Unbiased Approach

	Var(Wages) =	Var(Ind. FE)	+ Var(Occ. FE)	+ 2 × Cov(Ind. FE, Occ. FE)	+ Other terms
Panel A: No controls, plug-in approach, unweighted					
Component	.2540	.1608	.0081	2 × .0149	.0555
Proportion	1	.6329	.0318	2 × .0585	.2183
Panel B: No controls, unbiased approach, unweighted					
Component	.2540	.1209	.0075	2 × .0152	.0952
Proportion	1	.4760	.0295	2 × .0598	.3749

Notes: See notes for Table 5. All results are unweighted, with no additional control variables. Panel A is based on an OLS regression; Panel B is based on variances and covariances estimated following Kline et al. (2020).

Finally, we test whether our fixed effects estimates are driven by asymmetric selection patterns. Specifically, we conduct the variance decomposition separately for two subsamples: (1) workers who moved to an occupation with higher average wages ("upward movers"), and (2) workers who moved to an occupation with lower average wages ("downward movers"). We would expect these samples to yield different results if our estimates were driven by, for example, only high-ability workers successfully moving up, and if moves for successful workers are associated with gains that are not the opposite of the losses experienced by those who must move down. We find that occupation fixed effects explain 4.4% of wage variance among upward movers, compared to 2.3% among downward movers; our main result seems to be an average between the two. From this result, changing the proportion of upward versus downward moves in our data could modestly change some fixed effects. Yet even in this selected sample, occupa-

[14] We display these results separately from Table 5 because our usual procedures weight estimates using the SIPP's individual weights, while the Kline et al. (2020) does not allow for weights. We therefore do not use weights in either panel of that table.

tion fixed effects explain less than 5% of wage variance. The full decomposition is available in Appendix Table A.3.

4.4 Wage Gaps

To examine how occupational differences account for various wage gaps, we consider several observable characteristics that are often associated with wage disparities: as gender (men vs. women), education level (college degree or higher vs. high school or less), age group (45-65 vs. 25-44), and race/ethnicity (White non-Hispanic vs. Black or Hispanic). By comparing wage differences across these groups, we can gain insight into the extent to which occupations themselves contribute to overall wage inequality. Results are shown in Table 7. The first row of that table shows the raw log wage differences, which are substantial across all categories (for example, 0.177 for men vs. women, 0.417 for college vs. high school education).

In the second row, we calculate the average log wage for each worker's occupation; we then compare the average of that statistic between groups and report both the occupational wage gap and the fraction of the total wage gap explained by these averages. These gaps are substantial, except in the case of age; it is these gaps that previous literature has measured to suggest that occupations have important explanatory power for wage gaps. For example, men's wages are about 19.4% ($= e^{0.177} - 1$) higher than than women's; 42% of this gap is accounted for by average occupational wages, because men are in occupations that pay about 7.7% more than women's occupations. Naively, one could therefore argue that the gender wage gap would be cut in half if men and women worked in the same occupations. However, as we have shown above, workers switching to a different occupation might not gain the difference in average wages. Thus, in the third row, we compare the average fixed effect for occupations held by each group and report both the gap in fixed effects and the percent of the total wage gap explained by fixed effects. (This final row essentially measures what Card et al. (2016) refer to as sorting in the context of firms and gender wage gaps.) These gaps are all substantially smaller than the difference in average log wage. Thus, for example, switching men and women to be in the same occupations would reduce their wage gap by approximately 1.2 percentage points, or 6.8% of the total gap. Similarly, occupational averages explain more than half of the wage gap by education and race/ethnicity, but occupational fixed effects account for less than 20% of each gap.

Some care is needed in interpreting these gaps, because worker fixed effects include anything fixed about the worker. This includes their underlying skill level, but also their education, any discrimination they face, and so on. For example, our results imply that moving men and women to the same occupations would have little effect on the wage gap if these moves are restricted to those workers may actually make. However, it is possible that the effect would be greater if there were changes in the occupations available to different types of workers, such as due to changing education patterns or a reduction in discrimination.

Table 7: Comparison of Wage Gaps Across Different Groups

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Male vs Female		**College vs ≤HS**		**Age 45-65 vs 25-44**		**White NH vs Black, Hisp.**	
	Gap	%	Gap	%	Gap	%	Gap	%
1. Wage gap	0.177	100.0	0.417	100.0	0.120	100.0	0.196	100.0
2. Occupation wage gap	0.074	42.0	0.243	58.3	0.010	7.9	0.135	68.7
3. Occupation FE gap	0.012	6.8	0.071	17.1	0.003	2.2	0.039	19.8

Notes: Each odd-numbered column reports gaps in wage between two demographic groups: men versus women; those with a college degree versus those with no more than high school; those aged 45-65 versus those aged 25-44; and non-Hispanic White workers versus Black and Hispanic workers. Row 1 shows the raw difference in average log wage between the groups. Row 2 shows the difference between the average log wage in occupations held by each group. Row 3 shows the difference between the average fixed effect for the occupations held by each group. Even-numbered columns report the percent of the total wage gap (from row 1) that is explained by the wage gap reported in the previous column of the same row.

4.5 Incorporating Past Occupations

To explore whether past occupations influence current wages, we perform a decomposition that incorporates both current and previous occupation fixed effects. The results are presented in Table 8; each panel uses a sample that is restricted to those who are observed changing employers twice to allow for computation of both current and previous occupation fixed effects. Panel A shows that in this sample, similar to our main one, current occupation alone explains about 26% of wage variation; Panel B shows that previous occupation has a similar explanatory power, explaining over 20% of variation. However, in Panel C, we see that past occupation essentially proxies for individual attributes: including individual effects reduces the explanatory power of previous occupations to below 1% of the variation. Inclusion of past occupation fixed effects has little influence on our baseline results: in Panel D, current occupation explains around 3% of variation, while past occupation still explains under 1%. In all, the effect of past occupations on current wages is quite marginal compared to the impact of the current occupation. However, as we will show in Section 5, past occupation can have other important effects.

Table 8: Variance Decomposition with Previous Occupations

	Var(Wages) =	Var(Ind. FE)	+ Var(Occ. FE)	+ Var(Prev. Occ. FE)	+ Other terms
Panel A: Occupations Fixed-Effects					
Component	.2459		.0637		.1822
Proportion	1		.259		.741
Panel B: Previous Occupations Fixed-Effects					
Component	.2459			.0503	.1956
Proportion	1			.2046	.7954
Panel C: Previous Occupations + Individual Fixed Effects					
Component	.2459	.2228		.0019	.0212
Proportion	1	.9058		.0077	.0862
Panel D: All					
Component	.2459	.1839	.0082	.0016	.0522
Proportion	1	.7478	.0334	.0064	.2123

Notes: See notes for Table 5. "Var(Prev. Occ. Fe)" measures the variance of the fixed effect for previous occupation. "Other terms" includes all covariance terms, terms related to other covariates, as well as the variance of the error term. Panel A includes only the current occupation fixed effect. Panel B includes only the previous occupation fixed effect. Panel C includes both individual fixed effects and previous occupation fixed effects. Panel D includes individual fixed effects as well as fixed effects for both current and previous occupation. All results only include those included in the sample for Panel D—that is, those with non-missing current and previous occupation, in a connected set including both variables.

5 Results on Pluripotency

5.1 Characteristics Predictive of Moving

When we estimate expected moves between occupations in Equation 4, we determine which characteristics of occupations best predict whether a worker moves between two occupations. To understand what is generating this measure of expected moves, and to understand more generally how workers choose to move between occupations, we also estimate a simple Poisson regression based on Equation 4 once for each characteristic in O*NET; results showing the characteristics that are most and least predictive of moving are in Table 9. For this table, O*NET variables are standardized; thus to help interpret the table, note that for the most-predictive variable (multilimb coordination), we find that two occupations being an additional one standard deviation apart leads us to predict that the natural logarithm of moves would be 0.703 lower—or, that moves would be only 50% ($= e^{-.703}$) as common. (We are careful not to use causal language here, as there are likely many reasons such occupations would have fewer moves.) Note that almost all of the most-predictive characteristics are physical abilities; this suggests that workers rarely move between occupations requiring high and low physical ability levels. On the other hand, differences in requirements for managerial skills and knowledge do not seem to substantially discourage worker moves—likely because workers often switch into managerial roles as they gain experience.

Table 9: O*NET Characteristics Most and Least Predictive of Moving

Most Predictive Characteristics	**Coef.**	**Least Predictive Characteristics**	**Coef.**
Ability: Multilimb Coordination	-0.703	Knowledge: Telecommunications	-0.130
Ability: Extent Flexibility	-0.680	Knowledge: Foreign Language	-0.110
Ability: Manual Dexterity	-0.662	Skill: Management of Financial Resources	-0.100
Ability: Static Strength	-0.659	Knowledge: Food Production	-0.091
Ability: Reaction Time	-0.636	Ability: Time Sharing	-0.089
Ability: Control Precision	-0.629	Ability: Perceptual Speed	-0.069
Ability: Arm-Hand Steadiness	-0.617	Knowledge: Personnel, Human Resources	-0.067
Ability: Response Orientation	-0.617	Ability: Selective Attention	-0.059
Ability: Written Expression	-0.613	Skill: Management of Material Resources	-0.047
Ability: Stamina	-0.612	Knowledge: Administration, Management	-0.046

Notes: Characteristics of occupations are taken from O*NET. We estimate a simple Poisson regression following Equation 4 for each characteristic separately. The highest and lowest estimated coefficients are shown in this table. Strongly negative values indicate that increased distance between occupations in that characteristic is highly predictive of moves being rare; values close to zero indicate that distance in that characteristic matters less.

5.2 Occupational Distance

In Equation 5, we calculate the distance between every pair of occupations; that distance may be of independent interest to researchers and policymakers. Table 10 shows the closest and furthest pairs of occupations, and data on the distances between every pair of occupations is in a dataset posted on both authors' websites. (Empirically, distance is usually close to symmetrical—that is, the distance from occupation A to B is close to the distance from B to A—so for clarity, Table 10 shows the average of the two distances between any pair of occupations.) Distances generally seem reasonable. Medical professions are often among the most similar professions to each other.[15] Thus, for example, we find that, given only their occupational characteristics,

[15]Medical professions are also more likely to require licensing, which could affect the frequency of actual moves; we return to this point in Section 5.7.

we would expect that pharmacists would be about 13 (=1/0.075) times more likely to become physical therapists (and vice versa) than we would expect based on the size of those occupations alone. On the other hand, physicians and pharmacists are far from many other occupations; for example, given the occupational characteristics, we would expect that pharmacists are about 23 times less likely to become construction laborers (and vice versa) than we would expect based on the occupations' size alone. It is not surprising that the same occupations appear in both panels: distance from each occupation averages 1, so if many occupations are close, many others must be far.

Table 10: Close and Far Pairs of Occupations

Occupation 1	Occupation 2	Distance
Panel A: Closest Pairs		
Pharmacists	Physical therapists	0.075
Vocational and educational counselors	Social workers	0.088
Primary school teachers	Secondary school teachers	0.093
Radiologic technologists and technicians	Licensed practical nurses	0.102
Physicians	Registered nurses	0.104
Kindergarten and earlier school teachers	Special education teachers	0.105
Registered nurses	Physical therapists	0.105
Financial managers	Other financial specialists	0.112
Industrial engineers	Engineers and other professionals, n.e.c.	0.118
Subject instructors, college	Primary school teachers	0.121
Panel B: Furthest Pairs		
Pharmacists	Bus, truck, and stationary engine mechanics	16.913
Physicians	Carpenters	17.955
Physicians	Bus, truck, and stationary engine mechanics	18.031
Physicians	Industrial machinery repairers	19.692
Pharmacists	Concrete and cement workers	20.469
Physicians	Structural metal workers	20.972
Physicians	Concrete and cement workers	21.110
Physicians	Other metal and plastic workers	21.516
Pharmacists	Operating engineers of construction equipment	22.261
Pharmacists	Construction laborers	22.551

Notes: Distance between each pair of occupations is calculated following Equation 5. Because distance depends on direction (that is, distance from occupation A to B is not equal to distance from B to A), we take the average of the two distances. Lowest distances and highest distances are shown in this table. Higher values suggest that we expect fewer workers to transition between that pair of occupations. Only occupations above the median size are included.

5.3 Pluripotency

In Equation 6, we define our pluripotency measure, and we find substantial variation in it in Table 11.[16] Auto body repairers end up moving to occupations that are 3 times further away than we would expect if moves were random; on the other hand, librarians end up moving about half as far as we would otherwise expect. Further work is needed to better understand the origin of pluripotency. It may be driven in part by training (either the training required for a job, which might restrict who can join, or any generalizable training workers get on a job, which might help propel workers in their future careers), licensing (which we discuss below), or other aspects of a job. Additionally, some occupations might attract pluripotent workers—that is, workers who like to move to a diverse set of jobs—such that the pluripotency of the jobs we measure is actually due to the workers, not the jobs themselves. Regardless of what drives these measures, it is also important for us to examine whether pluripotency is good or bad for workers. High pluripotency might suggest that workers can move to any job they like, or that workers want to get as far away from that occupation as they can.

5.4 Relation to Wages and Other Characteristics

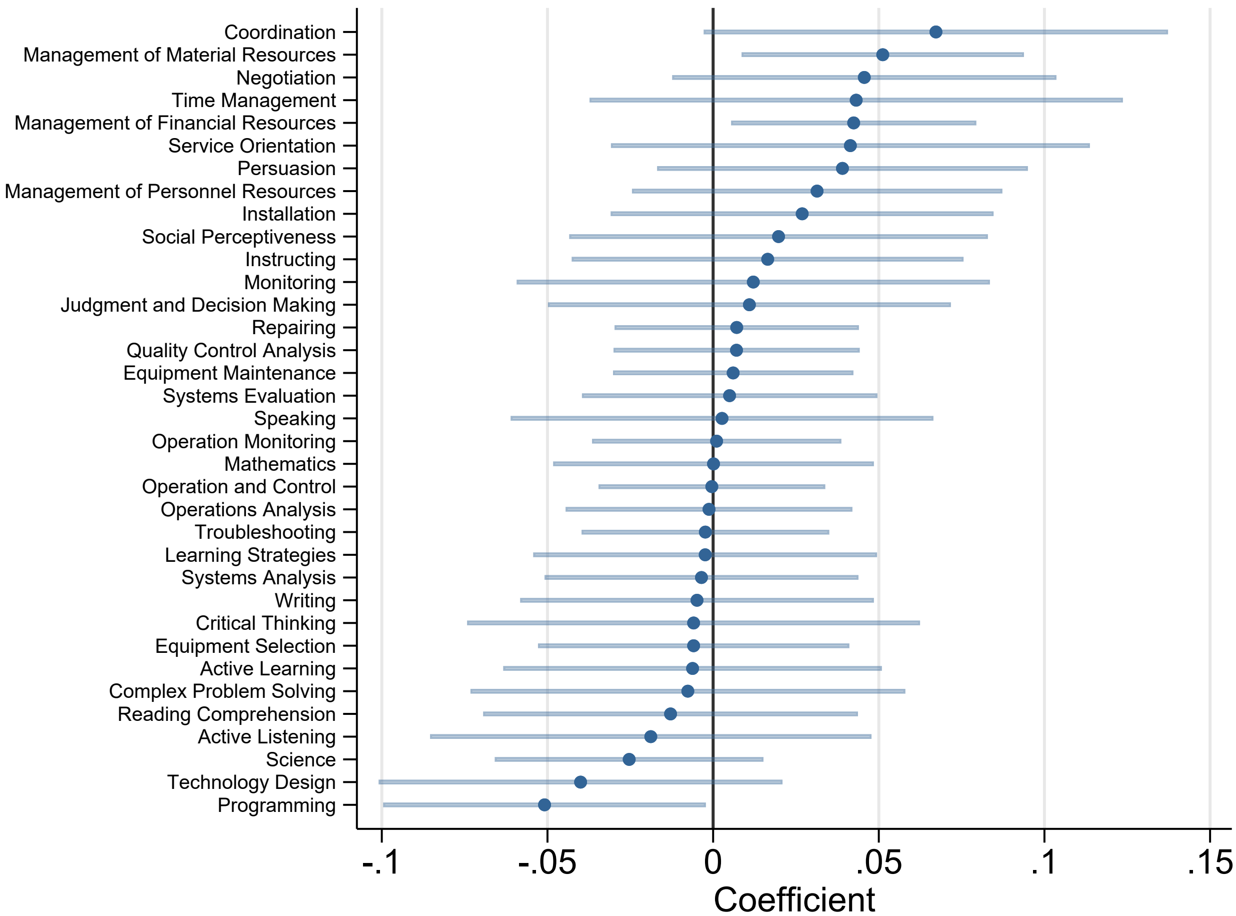
Pluripotency is uncorrelated with many other important occupational characteristics, suggesting that it may be of independent interest. This fact also suggests that its correlation with employment outcomes, as in Section 5.7, is less likely to be spurious. In Table 12, we see that occupations with higher pluripotency do not have significantly higher wages, or higher occupational fixed effects. In Figure 4, we find that only 3 of 35 O*NET skills are associated with significant differences in pluripotency—barely more than what we would expect to find by chance.

5.5 Relation to Wages at Destination Occupations

We believe that occupational distance and pluripotency are of interest for economists even if they are orthogonal to other occupational characteristics, such as average wages. Workers may prefer occupations that set them up to change to different jobs (or those that do the opposite) even if there is no pecuniary benefit to those jobs; our measure can give them information about which occupations have this characteristic. However, it may be of interest whether occupations

[16] Pluripotency for all occupations are shown in Tables A.4, A.5, A.6, and A.7.

Figure 4: Relation between Various Skills and Occupation Pluripotency



Notes: Each point represents the coefficient from a simple regression with one observation per occupation. The dependent variable is the occupation's pluripotency; the independent variable is a standardized measure of an O*NET skill. Bars represent heteroskedasticity-robust 95% confidence intervals. Regressions are weighted by size of the occupation.

Table 11: High and Low Pluripotency

Occupation	Pluripotency
Panel A: Highest Pluripotency	
Auto body repairers	3.01
Other metal and plastic workers	2.75
Pharmacists	2.62
Physical therapists	1.85
Mail carriers for postal service	1.84
Correspondence and order clerks	1.72
Repairers of data processing equipment	1.65
Management support occupations	1.60
Housekeepers, maids, butlers, and cleaners	1.54
Health technologists and technicians, n.e.c.	1.51
Panel B: Lowest Pluripotency	
Engineers and other professionals, n.e.c.	0.66
Roofers and slaters	0.65
Civil engineers	0.65
Laundry and dry cleaning workers	0.63
Operating engineers of construction equipment	0.62
Psychologists	0.61
Slicing, cutting, crushing, grinding machine operators	0.58
Actors, directors, and producers	0.56
Structural metal workers	0.54
Librarians	0.47

Notes: Pluripotency is calculated following Equation 6. Highest and lowest values are shown in this table. Higher values indicate that workers tend to move further away than we would otherwise expect; low values indicate the opposite. Only occupations above the median size are included.

that propel workers to new jobs also propel them to high-wage jobs. In this section, we ask whether, for a given occupation, moving to a distant job is associated with moving to a high-wage job. We find that this is true for some occupations, while the opposite is true for others, highlighting that pluripotency may be helpful for only some types of jobs.

To answer this question, it is important to note a mechanical effect. If someone is in a low-wage job, and they move to a very different job, that job is likely to pay more: similar jobs generally pay similar wages. Similarly, if someone is in a high-wage job, and they move to a very different job, that job is likely to pay less. To explore this relationship, we first measure, for each origin occupation, the weighted correlation between wages in and distance to each destination occupation. That is, we calculate

$$\hat{Corr}_A = \frac{\sum_B w_{AB} \hat{D}^*_{AB} y^*_B}{\sum_B w_{AB}}, \tag{7}$$

where weights w_{AB} are defined as in Equation 6, $\hat{D}^*_{AB}$ is the standardized distance from A to B (that is, the distance defined in Equation 5, minus its mean and divided by its standard

Table 12: Wages and Pluripotency

Variables	(1) Avg Wage	(2) Occ FE
Pluripotency	0.00145	-0.0111
	(0.0696)	(0.0208)
Constant	2.559***	0.0118
	(0.0761)	(0.0223)
Observations	318	318

Notes: *** p<0.01, ** p<0.05, * p<0.1. Robust standard errors in parentheses. One observation per occupation. The dependent variables are the average log wage (in column 1) and the occupation fixed effect (in column 2). The independent variable is occupational pluripotency. The regressions are weighted by the number of workers in each occupation.

deviation), and y^*_B is the standardized average log of the wage in occupation B. As expected, in Appendix Figure B.9a, we see that high-wage occupations tend to have a higher correlation, while low-wage occupations have a low correlation (that is, a strongly negative correlation).

To remove this mechanical effect, we can calculate a version of Equation 7 that uses predicted moves as weights rather than actual moves (where predicted moves are based on the Poisson regression in Equation 4). The correlation based on predicted moves is closely related to the correlation based on actual moves; see Appendix Figure B.9b. The confidence interval for the slope includes one and the confidence interval for the intercept includes zero. This need not be the case. For example, the intercept would be non-zero if workers only go to distant jobs if those jobs were particularly well-paid, in which case moving to a distant job would be associated with getting higher wages than we expect.

However, there are meaningful differences between predicted and actual correlation; Table 13 shows occupations with particularly large discrepancies. For example, auto body repairers have a much higher correlation than we would expect based on predicted moves. That means that when workers in the job move to distant occupations, they gain more in wages than we would expect, and when they move to close occupations, they lose more than we would expect. In Table 11, we saw that auto body repairers had one of the highest levels of pluripotency; this result on correlations suggests that moving to a distant job—essentially, pluripotency—is especially valuable for these workers. On the other hand, for pharmacists, the actual correlation is much lower than we would expect; that occupation also has high pluripotency, but pluripotency may be much less valuable for this group.

Table 13: High and Low Difference between Actual and Expected Correlation between Destination Distance and Destination Average Ln(Wage)

Occupation	Actual Correlation	Predicted Correlation	Difference
Panel A: Highest Difference			
Other metal and plastic workers	0.721	0.140	0.581
Auto body repairers	0.829	0.269	0.560
Timber logging and forestry workers	0.759	0.308	0.451
Surveryors cartographers mapping scientists/techs	-0.019	-0.447	0.428
Dental Assistants	0.243	-0.180	0.424
Real estate sales occupations	0.182	-0.117	0.300
Physical therapists	0.060	-0.234	0.294
Chemists	-0.173	-0.459	0.286
Messengers	0.692	0.411	0.281
Data entry keyers	0.393	0.118	0.275
Panel B: Lowest Difference			
Structural metal workers	-0.113	0.169	-0.282
Misc. construction and related occupations	-0.110	0.174	-0.285
Supervisors of mechanics and repairers	-0.282	0.010	-0.292
Painters sculptors craft-artists and print-makers	-0.384	-0.069	-0.315
Welders solderers and metal cutters	-0.038	0.299	-0.338
Mail carriers for postal service	0.075	0.453	-0.379
Insulation workers	-0.183	0.225	-0.408
Speech therapists	-0.677	-0.257	-0.420
Postal clerks exluding mail carriers	0.108	0.573	-0.465
Pharmacists	-0.794	-0.306	-0.488

Notes: For each origin occupation shown, we calculate the correlation between distance to each other (destination) occupation and average log wage at that destination occupation. The actual correlation weights this value using actual moves; predicted correlation weights this value using predicted moves. Highest and lowest values of the difference between these two correlations are shown. Higher values indicate that moving to a distant job is especially valuable for a given origin occupation; lower values indicate the opposite. Only occupations above the median size are shown.

5.6 Consistency of Pluripotency

Regardless of the mechanism, pluripotency does seem to be a consistent trait: occupations that propel workers to one distant occupation tend to propel them to others as well. To test this, we construct a dataset with one observation per pair of occupations A and B. We wish to estimate β_1 in

$$\hat{D}_{AB} = \beta_0 + \beta_1 \hat{P}_A + \epsilon, \tag{8}$$

where $\hat{D}_{AB}$ is the estimated distance (see Equation 5), and $\hat{P}_A$ is pluripotency (see Equation 6). That regression would be weighted by the number of moves from A to B. However, two complications arise. First, if $\hat{D}_{AB}$ is high, then $\hat{P}_A$ will mechanically be high as well, since it

Table 14: Consistency of Pluripotency

Variables	(1) Distance
Avg Other-Occ Dist	0.167**
	(0.0728)
Constant	0.971***
	(0.0233)
Observations	17,689

Notes: *** p<0.01, ** p<0.05, * p<0.1. Standard errors in parentheses are clustered by origin occupation. One observation per pair of occupations. The dependent variable is distance from origin to destination. The independent variable is the move-weighted average distance workers in the origin moved, leaving out those who moved to the destination; minus the expected move-weighted average distance moved. (See Equation 9 for details.) The regression is weighted by the number of moves.

is an average that includes $\hat{D}_{AB}$. To solve this, we could replace $\hat{P}_A$ with L_{AB}, the average distance from occupation A, leaving out the distance to occupation B. However, using this as an independent variable would also lead to bias: because distance from any occupation is defined to average to one if all workers move as expected, leaving out a high value of $\hat{D}_{AB}$ would make the leave-out average, L_{AB}, likely to be low. To correct for this, we also estimate L^e_{AB}, the average distance between A and all occupations other than B, where the average is based on expected moves rather than actual moves. We then use OLS to estimate

$$\hat{D}_{AB} = \beta_0 + \beta_1 (L_{AB} - L^e_{AB}) + \epsilon, \tag{9}$$

weighting the regression by the number of moves from A to B. The results are shown in Table 14; the positive coefficient shows that, when an occupation propels people far to some occupations, it also tends to propel them far to others.

5.7 Displaced Workers

Pluripotency may have important economic implications. For displaced workers—those who involuntarily lose their jobs—pluripotent occupations may serve as crucial stepping stones, facilitating faster reentry if pluripotency opens the door to a wide variety of different jobs, including those that may be more in demand. Conversely, high versatility could instead dilute the usefulness of job experience, making it harder for employers to match workers to specific roles.

In this section, we investigate the relationship between the pluripotency of a worker's pre-displacement occupation and the time it takes to find new employment using data from the Displaced Workers Supplement, a nationally representative dataset that provides detailed information on employment histories and reemployment outcomes. We estimate regressions of the form:

$$T_i^k = \alpha^k + \lambda^k \text{Pluripotency}_i + \mathbf{x}_i' \beta^k + \epsilon_i^k, \tag{10}$$

where T_i^k is a binary indicator equal to 1 if individual i managed to find work within k months of displacement, and 0 otherwise. The term Pluripotency_i represents the standardized pluripotency index of individual i's pre-displacement occupation. The coefficient λ^k measures the association between occupational pluripotency and the probability of finding work within k months. The vector $\mathbf{x}_i$ includes the log of pre-displacement earnings, age, sex, and fixed effects for year, race, education, and state.

We estimate the regression with OLS for multiple values of k (from 1 to 24 months), allowing us to examine how the association between occupational pluripotency and employment outcomes evolves over time. Standard errors are clustered at the occupation level to account for estimation noise in the pluripotency measure. A positive and significant λ^k would suggest that workers from pluripotent occupations are more likely to find reemployment quickly.

The results, shown in Figure 5, show that the coefficients on Pluripotency_i are positive and statistically significant for most time horizons considered, especially so after 5 months following job displacement. However, the magnitude of these effects tends to decrease as the time horizon k increases, suggesting that the benefits of pluripotency are strongest in the immediate aftermath of displacement.

Figure 6a suggests that any effects of occupational pluripotency are primarily driven by non-college-educated individuals. For this group, the coefficients on Pluripotency_i are larger, whereas the coefficients are centered around zero for the group of college-educated workers. Although the coefficients for each month are not statistically different from each other, the point estimates suggest that pluripotency may especially enhance reemployment prospects for non-college-educated workers. For these individuals, the versatility offered by pluripotent oc-

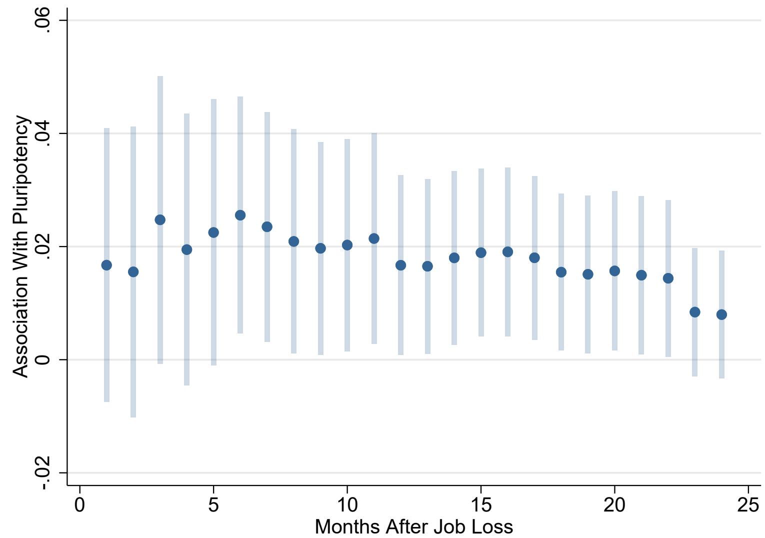
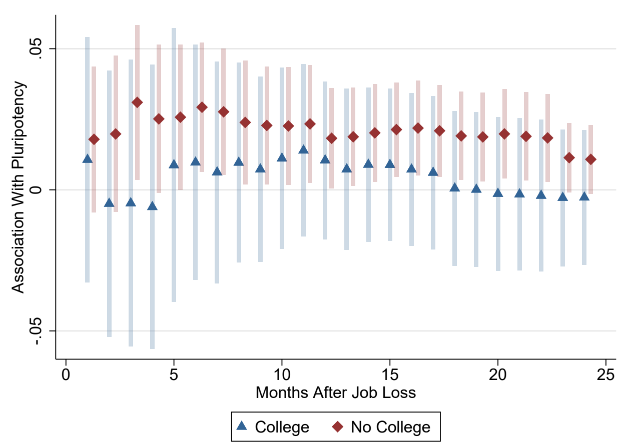


Figure 5: Association Between Pluripotency and Reemployment Outcomes

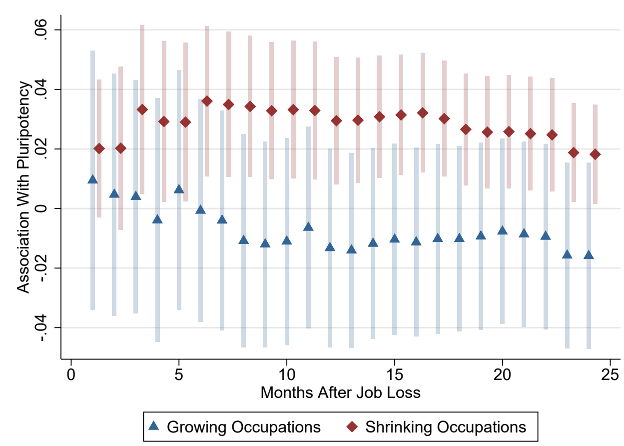
Notes: Each point represents the coefficient from a regression that includes one observation per person in the Displaced Workers Supplement. For the regression shown at k months after job loss, the dependent variable is an indicator for the person being reemployed after k months. The coefficient shown is on the pluripotency of the worker's job before the layoff; the regression also controls for log of prior earnings, age, sex, and fixed effects for year, race, education, and state. Bars represent 95% confidence intervals, clustered at the occupation level.

Figure 6: Association Between Pluripotency and Reemployment Outcomes in Subgroups

(a) Education Level



(b) Growing vs. Shrinking Occupations



Notes: See details in notes for Figure 5. Panel (a) shows results from separate regressions for those with a college education and those with no college education. Panel (b) shows results from separate regressions for those in growing occupations and those in shrinking occupations.

cupations may compensate for the lack of formal qualifications, enabling them to access a broader range of job opportunities. In contrast, the effects of pluripotency are less pronounced for college-educated workers, perhaps because their education already broadens employment opportunities.

Next, we classify each occupation as shrinking or growing according to its change in employment within a state, as a fraction of total state-level employment, between 1970 and 2000. We then re-estimate our reemployment regressions separately for each group. As shown in Figure 6b, for displaced workers whose previous occupations have contracted, the pluripotency coefficient is both positive and statistically significant—indicating faster job-finding—whereas for those from expanding occupations, the coefficients are small and never statistically different from zero. Importantly, this divergence between the effect for shrinking and growing occupations remains statistically significant across most monthly horizons. These results suggest a protective dimension of pluripotency: in contracting fields, a broader set of transferable skills may facilitate transitions into alternative lines of work. By contrast, in expanding fields—where ability to change occupations is less important—the return to additional occupational breadth is attenuated.

As noted above, occupational licensing restricts movement between occupations and therefore may make our pluripotency measure harder to interpret. For this reason, we rerun the displacement analyses after dropping occupations that Johnson and Kleiner (2020) identify as requiring licensing throughout the United States. Results, shown in Appendix Figures B.10, B.11a, and B.11b, are generally similar to the baseline.

6 Discussion

What do occupations do? We find they do little to explain wage inequality, though moving from one occupation to another can predictably raise or lower one's wage. They also appear to shape where workers go next.

Applying a two-way fixed-effects model to panel data, we find that occupation-level premia explain only about 3% of overall wage dispersion. In other words, differences in workers' skills and characteristics account for the vast majority of wage variation. Nevertheless, the remaining occupational effect is economically meaningful: a one-standard-deviation increase in an occupation's fixed effect corresponds to roughly a 9% wage gain, indicating that certain occupations systematically pay more even after controlling for individual traits.

Building on this, we introduce the concept of occupational pluripotency—an index of how readily a job equips workers for a broad array of future roles, which appears to be a consistent trait of some occupations. Occupations with high pluripotency confer both immediate and longer-term advantages. In particular, among displaced workers, those whose former occupations score high on pluripotency reenter employment significantly faster, especially within the first six months after job loss. This protective benefit is driven entirely by workers from shrinking occupations: for those coming from contracting fields, a broader skill set accelerates reemployment, whereas for displaced workers from growing occupations pluripotency has no detectable effect. Moreover, this advantage is most pronounced for non-college-educated workers, for whom transferable skills serve as an essential buffer when formal credentials offer less leverage; by contrast, college-educated workers—whose qualifications already facilitate moves between related roles—derive relatively smaller reemployment gains from additional occupational breadth.

Future work is needed to extend our analysis in several directions. Why do some occupations systematically pay more than others, even after controlling for worker characteristics? Given that more desirable occupations tend to have higher fixed effects, the answer likely goes beyond compensating differentials. Similarly, the origins of pluripotency—why some occupations open more divergent doors than others—warrant further study. More work is also needed to understand other ways that pluripotent jobs might affect workers. Finally, the measures of occupational distance developed here may prove useful in other contexts, including recent work on monopsony and labor market power: the size of a labor market depends on the options workers have, which is what our distance measure estimates. Such work can help researchers, policymakers, and workers have a better understanding of what occupations do.

References

Abowd, J., F. Kramarz, and D. Margolis (1999). High wage workers and high wage firms. *Econometrica 67*(2), 251–333.

Acemoglu, D. and D. Autor (2011). Skills, tasks and technologies: Implications for employment and earnings. In *Handbook of labor economics*, Volume 4, pp. 1043–1171. Elsevier.

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

Andrews, M. J., L. Gill, T. Schank, and R. Upward (2008). High wage workers and low wage firms: negative assortative matching or limited mobility bias? *Journal of the Royal Statistical Society. Series A (Statistics in Society) 171*(3), 673–697.

Autor, D. H. (2019). Work of the past, work of the future. *AEA Papers and Proceedings 109*, 1–32.

Autor, D. H. and D. Dorn (2013). The growth of low-skill service jobs and the polarization of the U.S. labor market. *American Economic Review 103*(5), 1553–1597.

Blau, F. D. and L. M. Kahn (2017). The gender wage gap: extent, trends, and explanations. *Journal of Economic Literature 55*(3), 789–865.

Böhm, M. J., H.-M. von Gaudecker, and F. Schran (2024). Occupation growth, skill prices, and wage inequality. *Journal of Labor Economics 42*(1), 201–243.

Bonhomme, S., K. Holzheu, T. Lamadon, E. Manresa, M. Mogstad, and B. Setzler (2023). How much should we trust estimates of firm effects and worker sorting? *Journal of Labor Economics 41*(2), 291–322.

Bonhomme, S., T. Lamadon, and E. Manresa (2019). A distributional framework for matched employer employee data. *Econometrica 87*(3), 699–739.

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

Card, D., J. Heining, and P. Kline (2013). Workplace heterogeneity and the rise of West German wage inequality. *The Quarterly Journal of Economics 128*(3), 967–1015.

Card, D., J. Rothstein, and M. Yi (2024). Industry Wage Differentials: A Firm-Based Approach. *Journal of Labor Economics 42*(S1), 11–59.

Card, D., J. Rothstein, and M. Yi (2025). Location, location, location. *American Economic Journal: Applied Economics 17*(1), 297–336.

Cortes, G. M., K. Foley, and H. E. Siu (2024). The occupational ladder: implications for wage growth and wage gaps over the life cycle. Working paper.

Couch, K. A., N. A. Jolly, and D. W. Placzek (2011). Earnings losses of displaced workers and the business cycle: an analysis with administrative data. *Economics Letters 111*(1), 16–19.

Couch, K. A. and D. W. Placzek (2010). Earnings losses of displaced workers revisited. *American Economic Review 100*(1), 572–589.

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

Di Addario, S. L., P. M. Kline, R. Saggio, and M. Sølvsten (2023). It ain't where you're from, it's where you're at: Hiring origins, firm heterogeneity, and wages. *Journal of Econometrics 233*(2), 340–374.

Dorn, D. (2009). *Essays on inequality, spatial interaction, and the demand for skills.* Ph. D. thesis, University of St. Gallen.

Fawcett, M. G. (1918). Equal pay for equal work. *The Economic Journal 28*(109), 1–6.

Flood, S., M. King, R. Rodgers, S. Ruggles, J. R. Warren, D. Backman, A. Chen, G. Cooper, S. Richards, M. Schouweiler, and M. Westberry (2024). Integrated Public Use Microdata Series, Current Population Survey: Version 12.0 [dataset]. Minneapolis, MN: IPUMS.

Fujita, S., G. Moscarini, and F. Postel-Vinay (2024). Measuring employer-to-employer reallocation. *American Economic Journal: Macroeconomics 16*(3), 1–51.

Gathmann, C. and U. Schönberg (2010, January). How general is human capital? A task-based approach. *Journal of Labor Economics 28*(1), 1–49.

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

Heckman, J. and J. Scheinkman (1987). The importance of bundling in a gorman-lancaster model of earnings. *The Review of Economic Studies 54*(2), 243–255.

Heckman, J. J. and G. Sedlacek (1985). Heterogeneity, aggregation, and market wage functions: an empirical model of self-selection in the labor market. *Journal of political Economy 93*(6), 1077–1125.

Hou, S. and L. H. Milsom (2025). The role of firms and occupations in wage inequality. Economics Series Working Papers 939, University of Oxford, Department of Economics.

Hsieh, C.-T., E. Hurst, C. I. Jones, and P. J. Klenow (2019). The allocation of talent and U.S. economic growth. *Econometrica 87*(5), 1439–1474.

Huckfeldt, C. (2022). Understanding the scarring effect of recessions. *American Economic Review 112*(4), 1273–1310.

Jacobson, L. S., R. J. LaLonde, and D. G. Sullivan (1993). Earnings losses of displaced workers. *American Economic Review 83*(4), 685–709.

Johnson, J. E. and M. M. Kleiner (2020). Is occupational licensing a barrier to interstate migration? *American Economic Journal: Economic Policy 12*(3), 347–373.

Kambourov, G. and I. Manovskii (2009). Occupational specificity of human capital. *International Economic Review 50*(1), 63–115.

Kambourov, G. and I. Manovskii (2013). A cautionary note on using (March) Current Population Survey and Panel Study of Income Dynamics data to study worker mobility. *Macroeconomic Dynamics 17*(1), 172–194.

Kline, P., R. Saggio, and M. Sølvsten (2020). Leave-out estimation of variance components. *Econometrica 88*(5), 1859–1898.

Krolikowski, P. (2017). Job ladders and earnings of displaced workers. *American Economic Journal: Macroeconomics 9*(2), 1–31.

Moscarini, G. and F. Postel-Vinay (2018). The cyclical job ladder. *Annual Review of Economics 10*, 165–188.

Moscarini, G. and K. Thomsson (2007). Occupational and job mobility in the US. *The Scandinavian Journal of Economics 109*(4), 807–836.

National Bureau of Economic Research (2017). Survey of Income and Program Participation (SIPP). Cambridge, MA.

National Center for O*NET Development (2021). O*NET 26.1 Database. O*NET Resource Center.

Poletaev, M. and C. Robinson (2008). Human capital specificity: evidence from the Dictionary of Occupational Titles and Displaced Worker Surveys, 1984-2000. *Journal of Labor Economics 26*(3), 387–420.

Roy, A. D. (1951). Some thoughts on the distribution of earnings. *Oxford economic papers 3*(2), 135–146.

Ruggles, S., S. Flood, M. Sobek, D. Backman, G. Cooper, J. A. R. Drew, S. Richards, R. Rogers, J. Schroeder, and K. C. Williams (2025). IPUMS USA: Version 16.0 [dataset]. Minneapolis, MN: IPUMS.

Shaw, K. L. (1987). Occupational change, employer change, and the transferability of skills. *Southern Economic Journal 53*(3), 703–719.

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

What Occupations Do

Online Appendix

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A Additional Tables

Table A.1 presents a fixed effect variance decomposition separately for data before 2000, and for data in 2000 and later. Table A.2 presents a fixed effect variance decomposition after dropping observations with an occupation identified as universally licensed by Johnson and Kleiner (2020). Tables A.4, A.5, A.6, and A.7 present average wage, fixed effect, and pluripotency for each occupation.

In addition, an Excel file is posted on the authors' websites with the following tables:

- Statistics on each occupation, as in Tables A.4, A.5, A.6, and A.7.
- For each occupation, the top few destination occupations for workers in that occupation, as well as, for each such destination, (1) the fraction of workers from the origin going to that destination (2) the expected gain or loss in wage (based on difference in fixed effect), and (3) the destination occupation's pluripotency.
- Distance between each pair of occupations.

Table A.1: Variance Decomposition: Different Time Periods

	Var(Wages) =	Var(Ind. FE)	+ Var(Occ. FE)	+ 2 × Cov(Ind. FE, Occ. FE)	+ Noise
Panel A: All (with full set of controls)—before 2000					
Component	.2358	.1582	.0079	2 × .0124	.0448
Proportion	1	.6708	.0337	2 × .0527	.1901
Panel B: All (with full set of controls)—2000 and later					
Component	.264	.1653	.0095	2 × .0152	.0587
Proportion	1	.6263	.0361	2 × .0575	.2225

Notes: See notes for Table 5. Panel A includes only observations from before 2000; Panel B includes only observations from 2000 and later.

Table A.2: Variance Decomposition Without Universally Licensed Occupations

	Var(Wages) =	Var(Ind. FE)	+ Var(Occ. FE)	+ 2 × Cov(Ind. FE, Occ. FE)	+ Noise
Panel A: Excluding universally licensed occupations					
Component	.2496	.1627	.0074	2 × .014	.0515
Proportion	1	.6519	.0297	2 × .056	.2063

Notes: See notes for Table 5. Occupations identified as universally licensed by Johnson and Kleiner (2020) are not included in this analysis.

Table A.3: Variance Decomposition For Upward and Downward Movers

	Var(Wages) =	Var(Ind. FE)	+ Var(Occ. FE)	+ 2 × Cov(Ind. FE, Occ. FE)	+ Noise
			Panel A: Upward movers		
Component	.2428	.1516	.0108	2 × .0135	.0535
Proportion	1	.6245	.0444	2 × .0554	.2202
			Panel B: Downward movers		
Component	.2496	.1751	.0059	2 × .0103	.0481
Proportion	1	.7015	.0235	2 × .0412	.1926

Notes: See notes for Table 5. Panel A includes only upward movers (individuals who move to occupations with strictly higher average wages); Panel B includes only downward movers (individuals who move to occupations with strictly lower average wages).

Table A.4: Statistics on Each Occupation, Part 1

Code	Occupation Title	Average Wage	Fixed Effect	Pluri-potency
4	Chief executives, public administrators, and legislators	3.286	0.184	1.109
7	Financial managers	3.031	0.146	1.276
8	Human resources and labor relations managers	2.900	0.093	0.916
13	Managers and specialists in marketing, advert., PR	2.972	0.088	1.079
14	Managers in education and related fields	2.866	0.087	1.085
15	Managers of medicine and health occupations	2.913	0.137	1.484
18	Managers of properties and real estate	2.579	0.024	1.151
19	Funeral directors	2.779	0.098	1.046
22	Managers and administrators, n.e.c.	2.824	0.079	1.144
23	Accountants and auditors	2.841	0.074	1.215
24	Insurance underwriters	2.883	0.104	1.017
25	Other financial specialists	2.876	0.091	1.081
26	Management analysts	3.050	0.081	0.760
27	Personnel, HR, training, and labor rel. specialists	2.709	0.073	0.868
28	Purchasing agents and buyers of farm products	2.601	-0.048	0.925
29	Buyers, wholesale and retail trade	2.601	0.016	1.346
33	Purchasing managers, agents, and buyers, n.e.c.	2.859	0.056	1.313
34	Business and promotion agents	2.466	-0.067	1.544
35	Construction inspectors	2.847	0.048	0.806
36	Inspectors and compliance officers, outside	2.745	0.058	0.839
37	Management support occupations	2.594	0.071	1.602
43	Architects	2.970	0.159	1.162
44	Aerospace engineers	3.319	0.237	1.085
45	Metallurgical and materials engineers	3.092	0.168	1.035
47	Petroleum, mining, and geological engineers	3.263	0.188	1.316
48	Chemical engineers	3.160	0.200	0.371
53	Civil engineers	3.132	0.160	0.651
55	Electrical engineers	3.199	0.203	0.695
56	Industrial engineers	3.069	0.201	0.725
57	Mechanical engineers	3.166	0.190	0.705
59	Engineers and other professionals, n.e.c.	3.194	0.182	0.656
64	Computer systems analysts and computer scientists	3.138	0.172	0.877
65	Operations and systems researchers and analysts	3.070	0.193	0.677
66	Actuaries	3.229	0.022	0.462
68	Mathematicians and statisticians	2.872	0.242	0.565
69	Physicists and astronomers	3.078	0.111	1.136
73	Chemists	2.964	0.170	0.741
74	Atmospheric and space scientists	2.907	0.292	0.748
75	Geologists	3.023	0.062	0.742
76	Physical scientists, n.e.c.	3.016	0.204	0.613
77	Agricultural and food scientists	2.604	-0.044	1.068
78	Biological scientists	2.769	-0.037	0.798
79	Foresters and conservation scientists	2.820	-0.038	0.789
83	Medical scientists	2.946	0.035	0.626
84	Physicians	2.984	0.095	0.677
85	Dentists	3.329	0.091	0.445
86	Veterinarians	3.029	0.276	1.192
87	Optometrists	2.982	0.025	0.659
88	Podiatrists	2.823	-0.068	0.000
89	Other health and therapy occupations	3.025	0.312	1.417
95	Registered nurses	2.852	0.118	1.280
96	Pharmacists	3.171	0.124	2.623
97	Dietitians and nutritionists	2.710	0.023	1.456
98	Respiratory therapists	2.794	0.062	1.454
99	Occupational therapists	3.091	0.239	0.636
103	Physical therapists	2.979	0.163	1.852
104	Speech therapists	2.937	0.203	0.675
105	Therapists, n.e.c.	2.648	0.089	0.475
106	Physicians' assistants	2.747	0.033	0.679
154	Subject instructors, college	2.851	0.010	0.846
155	Kindergarten and earlier school teachers	2.386	-0.051	0.858
156	Primary school teachers	2.705	0.045	0.926
157	Secondary school teachers	2.743	0.094	0.975
158	Special education teachers	2.758	0.068	1.088
159	Teachers, n.e.c.	2.667	0.058	1.105
163	Vocational and educational counselors	2.685	0.059	1.045
164	Librarians	2.691	0.034	0.471
165	Archivists and curators	2.567	-0.026	1.384
166	Economists, market and survey researchers	2.997	0.106	1.162
167	Psychologists	2.758	0.053	0.608
169	Social scientists and sociologists, n.e.c.	2.771	0.062	1.749
173	Urban and regional planners	3.095	0.148	0.585
174	Social workers	2.638	0.053	0.818
176	Clergy and religious workers	2.569	0.001	1.236
177	Welfare service workers	2.241	-0.107	1.535
178	Lawyers and judges	3.140	0.149	1.263
183	Writers and authors	2.828	0.058	1.140
184	Technical writers	2.997	0.223	0.683
185	Designers	2.712	0.025	0.804
186	Musicians and composers	2.667	0.126	1.085

Notes: Statistics presented for all occupations, regardless of occupation size. "Code" and "Occupation Title" are based on codes created by Autor and Dorn (2013). All statistics based on our primary sample. "Average Wage" is the average log real hourly wage for each occupation. "Fixed Effect" and "Pluripotency" are the occupation's fixed effect and pluripotency, calculated as described in the text.

Table A.5: Statistics on Each Occupation, Part 2

Code	Occupation Title	Average Wage	Fixed Effect	Pluri-potency
187	Actors, directors, and producers	2.747	0.107	0.555
188	Painters, sculptors, craft-artists, and print-makers	2.700	0.044	0.750
189	Photographers	2.571	0.043	0.904
193	Dancers	2.598	0.203	3.499
194	Art/entertainment performers and related occs	2.517	-0.026	1.301
195	Editors and reporters	2.840	0.145	0.790
198	Announcers	2.401	0.078	1.829
199	Athletes, sports instructors, and officials	2.601	0.071	1.093
203	Clinical laboratory technologies and technicians	2.630	0.042	0.740
204	Dental hygienists	2.890	0.114	0.962
206	Radiologic technologists and technicians	2.781	0.072	1.079
207	Licensed practical nurses	2.529	0.014	1.106
208	Health technologists and technicians, n.e.c.	2.465	-0.031	1.510
214	Engineering technicians	2.721	0.076	0.862
217	Drafters	2.749	0.093	0.896
218	Surveyors, cartographers, mapping scientists/techs	2.684	-0.071	1.174
223	Biological technicians	2.446	-0.035	0.880
224	Chemical technicians	2.729	-0.000	1.230
225	Other science technicians	2.593	0.122	1.025
226	Airplane pilots and navigators	2.914	-0.069	1.379
227	Air traffic controllers	3.025	0.008	0.978
228	Broadcast equipment operators	2.727	0.153	0.978
229	Computer software developers	3.158	0.175	1.029
233	Programmers of numerically controlled machine tools	2.758	0.003	0.922
234	Legal assistants and paralegals	2.670	0.070	0.782
235	Technicians, n.e.c.	2.764	0.098	1.046
243	Sales supervisors and proprietors	2.603	0.022	1.354
253	Insurance sales occupations	2.656	0.022	1.012
254	Real estate sales occupations	2.751	0.061	1.005
255	Financial service sales occupations	2.903	0.063	1.047
256	Advertising and related sales jobs	2.668	0.059	0.830
258	Sales engineers	3.068	0.078	0.696
274	Salespersons, n.e.c.	2.758	0.036	1.210
275	Retail salespersons and sales clerks	2.377	-0.113	1.100
276	Cashiers	2.078	-0.157	1.040
277	Door-to-door sales, street sales, and news vendors	2.355	-0.047	1.428
283	Sales demonstrators, promoters, and models	2.309	-0.113	0.852
303	Office supervisors	2.688	0.049	1.281
313	Secretaries and stenographers	2.447	-0.011	0.910
315	Typists	2.329	-0.049	1.396
316	Interviewers, enumerators, and surveyors	2.389	-0.041	1.255
317	Hotel clerks	2.078	-0.138	0.910
318	Transportation ticket and reservation agents	2.526	-0.017	0.816
319	Receptionists and other information clerks	2.281	-0.059	0.928
326	Correspondence and order clerks	2.480	0.032	1.716
328	Human resources clerks, excl payroll and timekeeping	2.518	0.011	0.768
329	Library assistants	2.366	-0.075	0.636
335	File clerks	2.334	-0.064	0.784
336	Records clerks	2.441	-0.035	0.903
337	Bookkeepers and accounting and auditing clerks	2.454	0.010	0.960
338	Payroll and timekeeping clerks	2.490	0.030	0.849
344	Billing clerks and related financial records processing	2.423	-0.004	0.790
346	Mail and paper handlers	2.770	0.092	3.625
347	Office machine operators, n.e.c.	2.311	-0.046	0.913
348	Telephone operators	2.352	-0.072	0.773
354	Postal clerks, excluding mail carriers	2.680	0.102	0.802
355	Mail carriers for postal service	2.749	0.098	1.836
356	Mail clerks, outside of post office	2.302	-0.078	1.254
357	Messengers	2.384	-0.079	0.993
359	Dispatchers	2.446	-0.049	0.732
364	Shipping and receiving clerks	2.389	-0.040	1.019
365	Stock and inventory clerks	2.333	-0.088	1.050
366	Meter readers	2.473	-0.036	0.883
368	Weighers, measurers, and checkers	2.436	-0.014	1.116
373	Material recording, sched., prod., plan., expediting cl.	2.598	0.025	1.172
375	Insurance adjusters, examiners, and investigators	2.615	0.014	0.734
376	Customer service reps, invest., adjusters, excl. insur.	2.498	-0.008	1.164
377	Eligibility clerks for government prog., social welfare	2.560	0.101	1.390
378	Bill and account collectors	2.427	-0.026	1.277
379	General office clerks	2.403	-0.035	1.194
383	Bank tellers	2.254	-0.076	0.845
384	Proofreaders	2.310	-0.063	0.561
385	Data entry keyers	2.355	-0.065	0.963
386	Statistical clerks	2.401	0.023	0.735
387	Teacher's aides	2.231	-0.118	0.932
389	Administrative support jobs, n.e.c.	2.498	0.030	1.179
405	Housekeepers, maids, butlers, and cleaners	2.096	-0.122	1.539
408	Laundry and dry cleaning workers	2.029	-0.134	0.632
417	Fire fighting, fire prevention, and fire inspection occs	2.752	-0.005	0.964
418	Police and detectives, public service	2.815	0.095	1.001

Notes: See notes for Table A.4.

Table A.6: Statistics on Each Occupation, Part 3

Code	Occupation Title	Average Wage	Fixed Effect	Pluri-potency
423	Sheriffs, bailiffs, correctional institution officers	2.608	0.056	1.031
425	Crossing guards	2.302	-0.242	1.541
426	Guards and police, except public service	2.243	-0.149	0.914
427	Protective service, n.e.c.	2.374	-0.189	1.012
433	Supervisors of food preparation and service	2.333	-0.031	1.035
434	Bartenders	2.227	-0.131	1.092
435	Waiters and waitresses	2.162	-0.151	1.177
436	Cooks	2.144	-0.135	0.975
439	Food preparation workers	2.119	-0.162	1.120
444	Miscellaneous food preparation and service workers	2.095	-0.169	1.104
445	Dental Assistants	2.394	-0.064	1.074
447	Health and nursing aides	2.242	-0.087	0.933
448	Supervisors of cleaning and building service	2.412	-0.055	1.271
450	Superv. of landscaping, lawn service, groundskeeping	2.435	-0.022	0.816
451	Gardeners and groundskeepers	2.218	-0.155	1.224
453	Janitors	2.234	-0.120	1.149
455	Pest control occupations	2.338	-0.218	1.045
457	Barbers	2.212	-0.133	2.789
458	Hairdressers and cosmetologists	2.275	-0.118	0.798
459	Recreation facility attendants	2.357	-0.130	1.085
461	Guides	2.238	-0.095	0.820
462	Ushers	2.336	-0.134	0.668
464	Baggage porters, bellhops and concierges	2.379	-0.124	0.729
466	Recreation and fitness workers	2.422	-0.031	0.998
468	Child care workers	2.156	-0.126	0.935
469	Personal service occupations, n.e.c	2.224	-0.185	1.065
470	Supervisors of personal service jobs, n.e.c	2.407	0.001	1.067
471	Public transportation attendants and inspectors	2.753	-0.025	1.822
472	Animal caretakers, except farm	2.274	-0.197	0.988
473	Farmers (owners and tenants)	2.403	0.001	0.997
479	Farm workers, incl. nursery farming	2.079	-0.193	1.010
488	Graders and sorters of agricultural products	2.146	-0.053	0.739
489	Inspectors of agricultural products	2.645	0.008	0.665
496	Timber, logging, and forestry workers	2.402	-0.036	1.328
503	Supervisors of mechanics and repairers	2.797	0.071	0.820
505	Automobile mechanics and repairers	2.479	-0.068	1.041
507	Bus, truck, and stationary engine mechanics	2.573	-0.000	1.065
508	Aircraft mechanics	2.776	0.079	1.094
509	Small engine repairers	2.378	0.004	1.089
514	Auto body repairers	2.536	-0.058	3.010
516	Heavy equipment and farm equipment mechanics	2.603	-0.006	0.753
518	Industrial machinery repairers	2.667	0.023	1.397
519	Machinery maintenance occupations	2.589	0.019	0.844
523	Repairers of industrial electrical equipment	2.571	-0.005	0.902
525	Repairers of data processing equipment	2.776	0.048	1.651
526	Repairers of household appliances and power tools	2.443	-0.104	0.863
527	Telecom and line installers and repairers	2.780	0.113	1.202
533	Repairers of electrical equipment, n.e.c.	2.612	0.021	1.046
534	Heating, air conditioning, and refrigeration mechanics	2.617	-0.001	0.723
535	Precision makers, repairers, and smiths	2.467	-0.006	0.998
536	Locksmiths and safe repairers	2.514	-0.013	0.565
539	Repairers of mechanical controls and valves	2.504	-0.074	0.914
543	Elevator installers and repairers	2.879	0.149	2.007
544	Millwrights	2.727	0.000	1.201
549	Mechanics and repairers, n.e.c.	2.523	-0.008	1.357
558	Supervisors of construction work	2.839	0.087	0.857
563	Masons, tilers, and carpet installers	2.556	0.025	0.826
567	Carpenters	2.603	0.007	1.270
573	Drywall installers	2.621	0.029	0.842
575	Electricians	2.762	0.025	1.089
577	Electric power installers and repairers	2.776	0.065	1.259
579	Painters, construction and maintenance	2.449	-0.015	0.841
583	Paperhangers	2.661	-0.013	0.920
584	Plasterers	2.589	0.043	1.028
585	Plumbers, pipe fitters, and steamfitters	2.771	0.065	1.173
588	Concrete and cement workers	2.484	-0.011	0.856
589	Glaziers	2.602	-0.125	0.693
593	Insulation workers	2.676	0.109	0.692
594	Paving, surfacing, and tamping equipment operators	2.506	0.003	0.901
595	Roofers and slaters	2.454	0.035	0.655
597	Structural metal workers	2.898	0.099	0.544
598	Drillers of earth	2.572	0.094	0.358
599	Misc. construction and related occupations	2.518	0.016	0.677
614	Drillers of oil wells	2.472	0.039	0.495
615	Explosives workers	2.645	-0.001	1.366
616	Miners	2.683	0.050	0.470
617	Other mining occupations	2.509	0.042	0.562
628	Production supervisors or foremen	2.716	0.081	1.071
634	Tool and die makers and die setters	2.785	0.053	0.711
637	Machinists	2.612	0.009	0.915

Notes: See notes for Table A.4.

Table A.7: Statistics on Each Occupation, Part 4

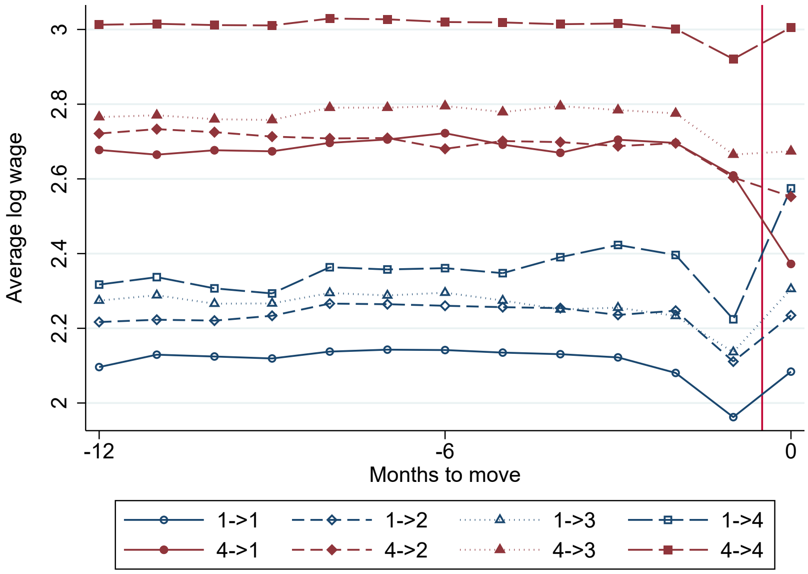
Code	Occupation Title	Average Wage	Fixed Effect	Pluri-potency
643	Boilermakers	2.827	0.109	0.526
644	Precision grinders and fitters	2.573	-0.225	0.501
645	Patternmakers and model makers	2.739	-0.037	0.443
649	Engravers	2.561	-0.093	1.714
653	Other metal and plastic workers	2.700	0.028	2.747
657	Cabinetmakers and bench carpenters	2.413	-0.105	0.780
658	Furniture/wood finishers, other prec. wood workers	2.232	-0.092	0.643
666	Dressmakers, seamstresses, and tailors	2.198	-0.098	0.670
668	Upholsterers	2.560	0.053	1.843
669	Shoemakers, other prec. apparel and fabric workers	2.513	0.056	0.415
675	Hand molders and shapers, except jewelers	2.253	-0.019	1.050
677	Optical goods workers	2.390	-0.029	0.703
678	Dental laboratory and medical appliance technicians	2.467	-0.001	0.923
679	Bookbinders	2.294	-0.097	1.585
686	Butchers and meat cutters	2.320	-0.073	0.784
687	Bakers	2.216	-0.146	0.718
688	Batch food makers	2.198	-0.147	0.981
694	Water and sewage treatment plant operators	2.540	-0.084	0.886
695	Power plant operators	3.160	0.323	1.210
696	Plant and system operators, stationary engineers	2.778	0.075	1.536
699	Other plant and system operators	2.822	0.234	0.418
703	Lathe, milling, and turning machine operatives	2.427	-0.027	0.430
706	Punching and stamping press operatives	2.429	-0.066	0.819
707	Rollers, roll hands, and finishers of metal	2.290	-0.006	2.670
708	Drilling and boring machine operators	2.592	0.018	0.608
709	Grinding, abrading, buffing, and polishing workers	2.376	-0.011	1.205
713	Forge and hammer operators	2.437	-0.043	0.661
719	Molders and casting machine operators	2.370	-0.046	1.667
723	Metal platers	2.374	-0.036	1.807
724	Heat treating equipment operators	2.563	-0.046	0.518
727	Sawing machine operators and sawyers	2.263	-0.027	0.845
729	Nail, tacking, shaping and joining mach ops (wood)	2.395	-0.003	1.555
736	Typesetters and compositors	2.416	-0.083	1.056
738	Winding and twisting textile and apparel operatives	2.200	-0.059	2.567
739	Knitters, loopers, and toppers textile operatives	2.176	-0.030	1.390
743	Textile cutting and dyeing machine operators	2.288	-0.015	3.913
744	Textile sewing machine operators	2.040	-0.114	0.751
745	Shoemaking machine operators	2.068	0.003	0.372
747	Clothing pressing machine operators	2.022	-0.160	0.943
753	Cementing and gluing machine operators	2.066	-0.070	0.489
754	Packers, fillers, and wrappers	2.240	-0.065	1.232
755	Extruding and forming machine operators	2.337	-0.058	3.296
756	Mixing and blending machine operators	2.447	-0.002	1.576
757	Separating, filtering, and clarifying machine operators	2.736	0.151	0.718
763	Food roasting and baking machine operators	2.436	-0.120	0.647
764	Washing, cleaning, and pickling machine operators	2.450	0.003	1.000
765	Paper folding machine operators	2.407	-0.127	2.733
766	Furnace, kiln, and oven operators, apart from food	2.542	0.060	0.841
769	Slicing, cutting, crushing and grinding machine	2.296	-0.055	0.581
774	Photographic process workers t	2.302	-0.035	1.308
779	Machine operators, n.e.c.	2.393	0.012	0.810
783	Welders, solderers, and metal cutters	2.585	0.014	0.960
785	Assemblers of electrical equipment	2.332	-0.055	0.921
789	Painting and decoration occupations	2.419	-0.016	0.929
799	Production checkers, graders, and sorters in	2.453	-0.010	1.194
803	Supervisors of motor vehicle transportation	2.636	0.033	1.068
804	Truck, delivery, and tractor drivers	2.418	-0.056	1.062
808	Bus drivers	2.371	-0.050	1.019
809	Taxi cab drivers and chauffeurs	2.317	-0.134	1.114
813	Parking lot attendants	2.168	-0.207	0.849
823	Railroad conductors and yardmasters	2.830	0.119	0.744
824	Locomotive operators: engineers and firemen	2.845	0.179	0.674
825	Railroad brake, coupler, and switch operators	2.778	0.236	0.541
829	Ship crews and marine engineers	2.594	-0.021	0.847
834	Miscellaneous transportation occupations	2.851	0.118	1.221
844	Operating engineers of construction equipment	2.675	0.030	0.620
848	Crane, derrick, winch, hoist, longshore operators	2.609	0.056	0.485
853	Excavating and loading machine operators	2.564	0.024	0.707
859	Stevedores and misc. material moving occupations	2.551	0.006	0.792
865	Helpers, constructions	2.289	-0.054	0.651
866	Helpers, surveyors	2.283	-0.048	0.941
869	Construction laborers	2.453	-0.035	1.018
873	Production helpers	2.286	-0.111	0.552
875	Garbage and recyclable material collectors	2.438	-0.094	0.794
878	Machine feeders and offbearers	2.237	-0.053	0.579
887	Vehicle washers and equipment cleaners	2.186	-0.094	1.061
888	Packers and packagers by hand	2.146	-0.107	1.008
889	Laborers, freight, stock, and material handlers, n.e.c.	2.288	-0.091	1.362

Notes: See notes for Table A.4.

B Additional Figures

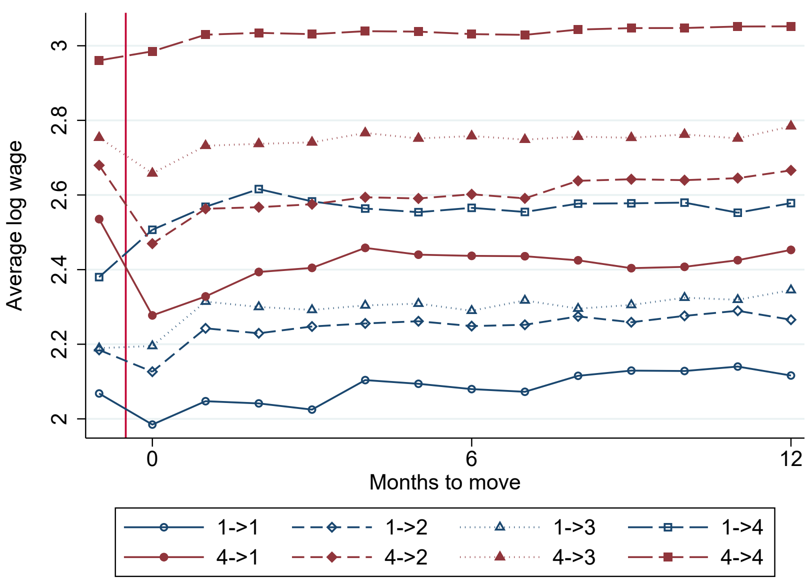
Figures B.1 and B.2 display trends before and after (respectively) moves between occupations that have high and low average wages. Figure B.3 shows average earnings before and after moves between high and low average-wage occupations. Figure B.4 divides the sample into 100 groups—10 deciles of individual fixed effects, and 10 deciles of occupational fixed effects—and presents the average predicted and average actual log real wage in each group. Figure B.5 divides occupations into 20 ventiles based on their occupational fixed effect; for workers moving between each pair of ventiles, the graph plots average change in occupational fixed effect (on the x-axis) and average change in AKM residual (on the y-axis). Figure B.6 is a histogram of occupation fixed effects. Figure B.7 displays occupational fixed effects both in the 20th century (x-axis) and the 21st century (y-axis) for all occupations, regardless of size. Figure B.8 displays the variance of occupational fixed effects, and twice their covariance with individual fixed effects, restricting the analysis to progressively larger occupations. Figure B.10 presents results on displaced workers and pluripotency after dropping observations with an occupation identified as universally licensed by Johnson and Kleiner (2020); Figures B.11a and B.11b present similar results for subgroups by education and growth of occupational labor market.

Figure B.1: No differential pretrends



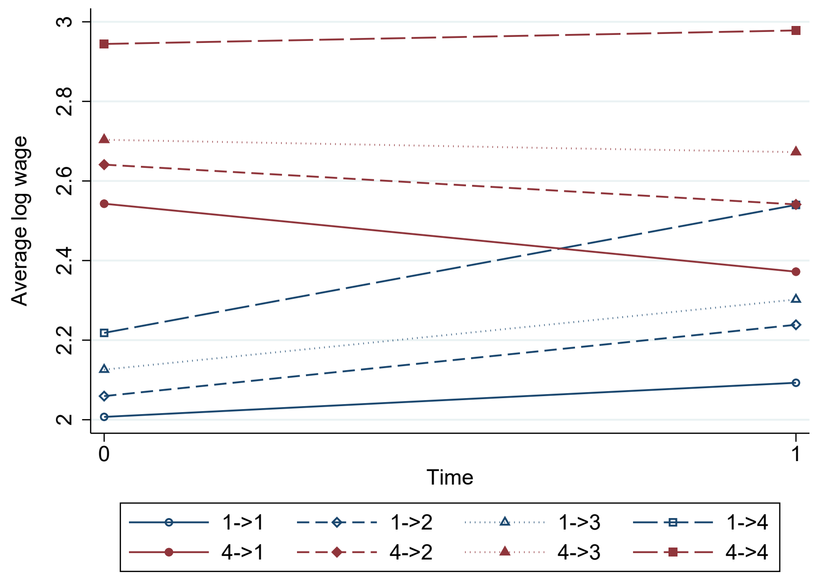
Notes: Occupations are divided into four quartiles on the basis of their average log wage. For selected origin-destination pairs of quartiles, we plot the average log wage of everyone who makes such a move, in the 12 months before the move, among all movers who have data for all 12 months. Post-move log wage, plotted at time 0, is the average wage at the destination occupation.

Figure B.2: No differential posttrends



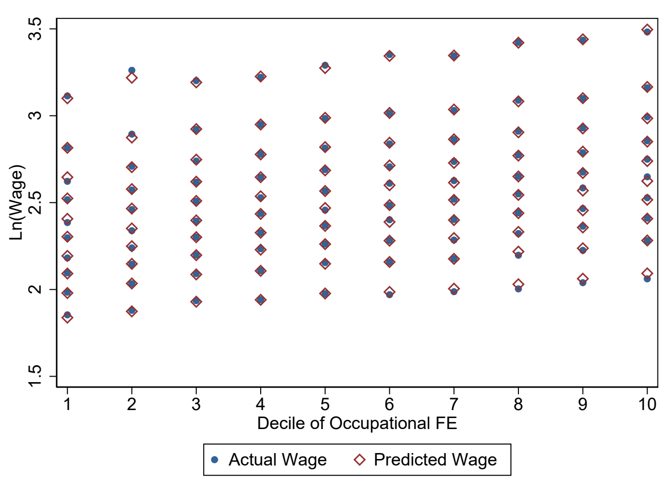
Notes: Occupations are divided into four quartiles on the basis of their average log wage. For selected origin-destination pairs of quartiles, we plot the average log wage of everyone who makes such a move, in the 12 months after the move, among all movers who have data for all 12 months. Pre-move log wage, plotted at time -1, is the average wage at the origin occupation.

Figure B.3: Symmetry between upward and downward movers



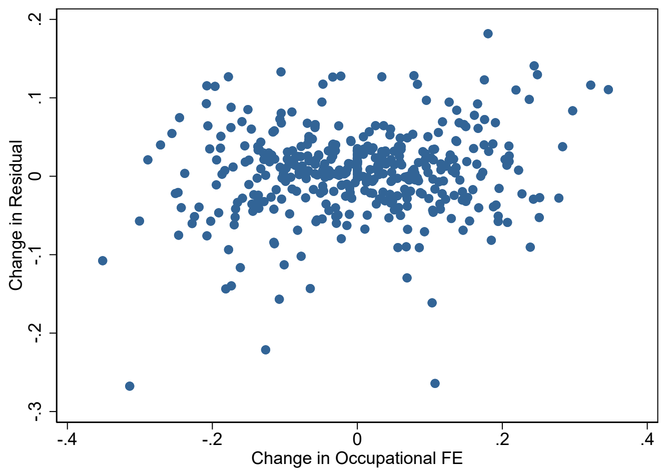
Notes: Occupations are divided into four quartiles on the basis of their average log wage. For selected origin-destination pairs of quartiles, we plot the average log wage at the origin (in time 0) and average log wage at the destination (in time 1).

Figure B.4: Estimated errors



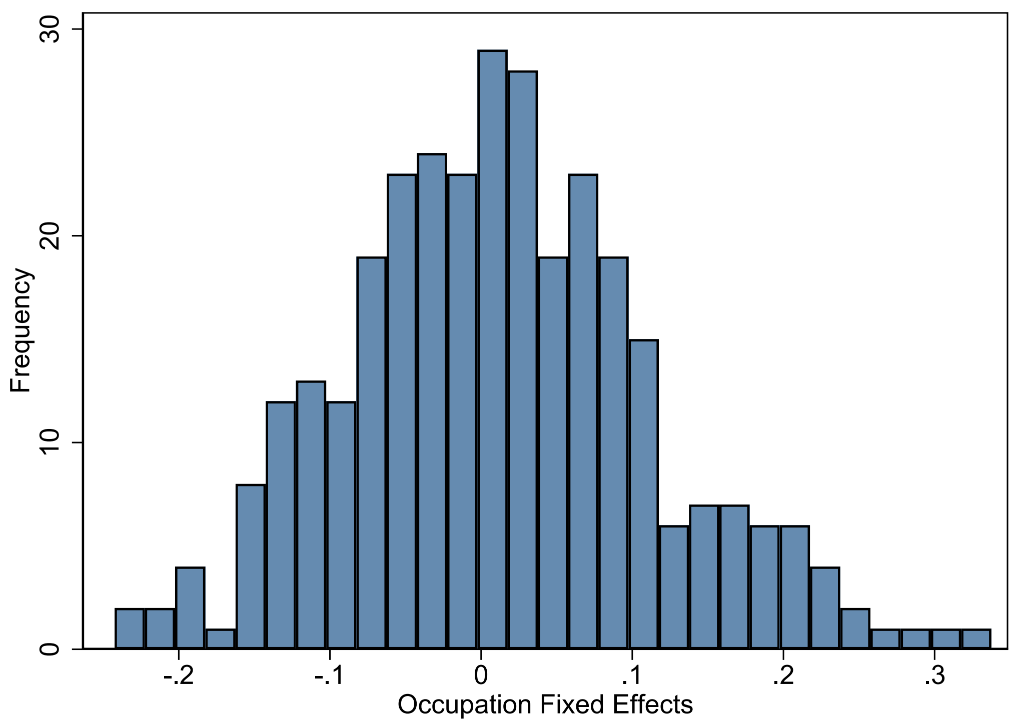
Notes: Individuals are divided into 10 deciles based on individual fixed effect, and occupations are divided into 10 deciles based on occupational fixed effect. The graph shows one point for each of the 100 decile pairs. The x-axis shows the ordinal occupational fixed effect, with 1 indicating occupations with the lowest fixed effect and 10 the highest. The y-axis for solid blue circles shows the average log wage within each decile pair; the y-axis for empty red diamonds shows the predicted log wage, if wage was equal to the sum of individual and occupational fixed effects.

Figure B.5: Error terms for upward and downward movers



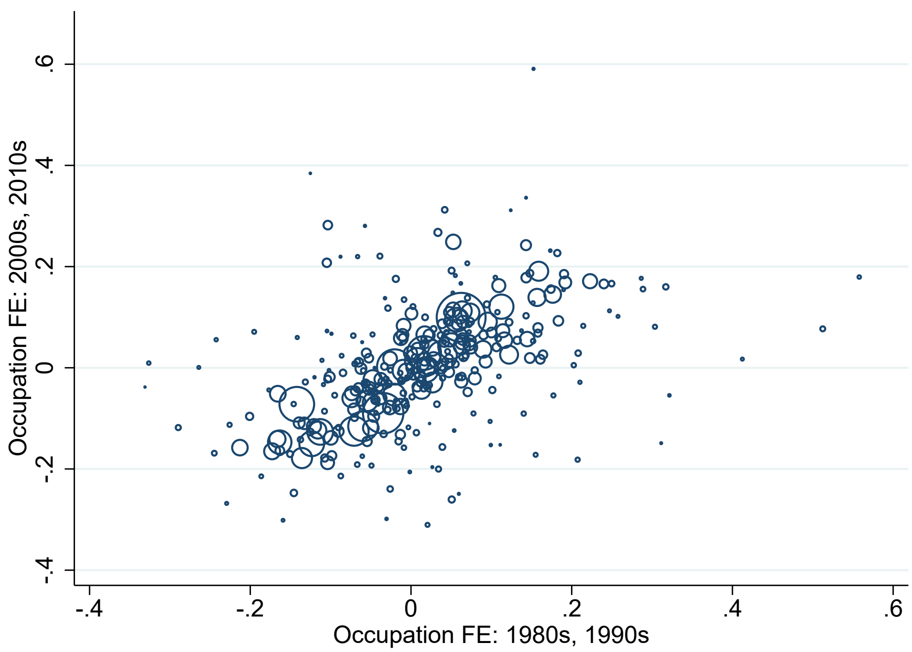
Notes: Occupations are divided into 20 ventiles based on their occupational fixed effect. For each origin-destination pair of occupational ventiles, the x-axis shows the difference between the destination ventile's average fixed effect and the origin ventile's average fixed effect. The y-axis shows the difference between the average AKM residual among workers in the destination ventile minus residual among those in the origin ventile.

Figure B.6: Distribution of the Occupations Fixed Effects



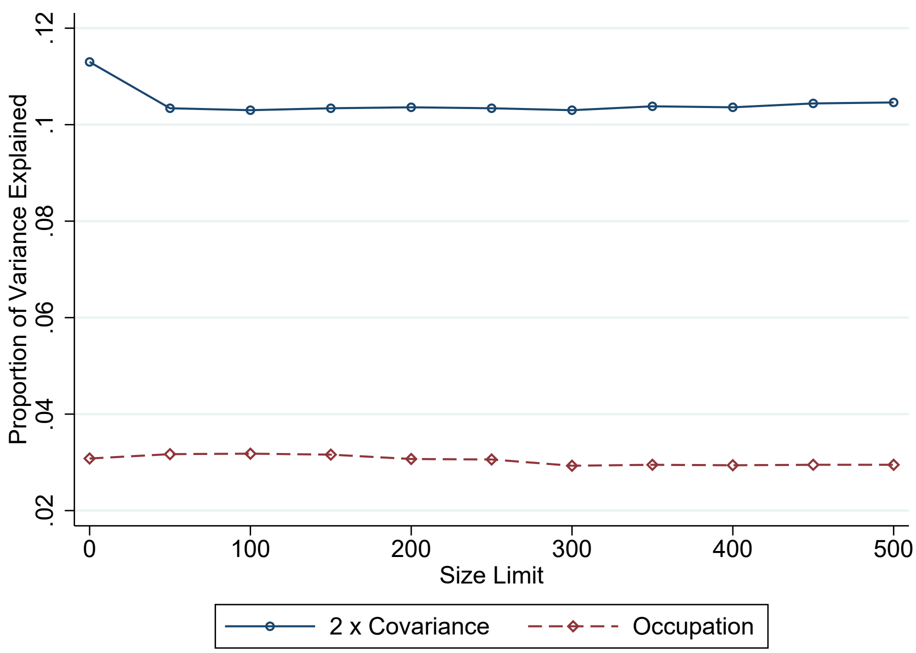
Notes: This histogram shows the distribution of occupational fixed effects. There is one observation per occupation, regardless of occupation size.

Figure B.7: How Stable are Occupations' Fixed Effects? All Occupations



Notes: Occupational fixed effects are calculated using Equation 2 two times: once including all observations through 1999 (as shown on the x-axis), and once including all observations in 2000 and later (y-axis). All occupations are included. Symbol size is proportional to occupation size.

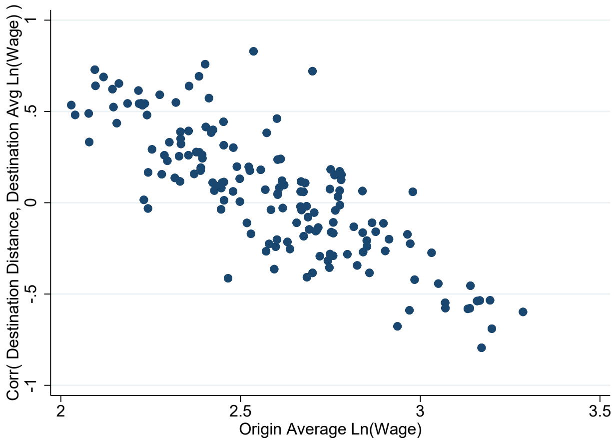
Figure B.8: Do Fixed Effects Vary When Dropping Small Occupations?



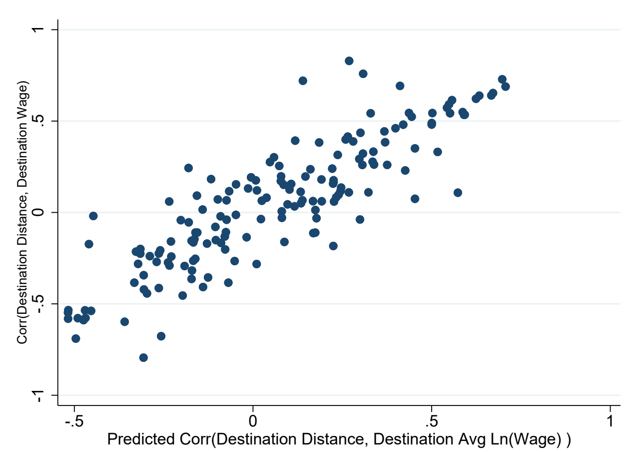
Notes: Each point plots variance of occupational fixed effects (red diamonds) and twice the covariance of that with individual fixed effects (blue circles) in an AKM regression that includes control variables. At each value along the x-axis, the analysis is restricted to occupations for which our sample includes at least that many observations as the origin occupation, and also that many observations as the destination occupation.

Figure B.9: Distance and Wage Correlations

(a) Wages versus Correlation between Destination Average Distance, Wage



(b) Predicted versus Actual Destination Distance and Wage Correlations



Notes: Each point represents one occupation (called the origin in this graph). Only occupations above the median size are shown. In panel (a), the x-axis plots the average of the natural log of wages for workers in that origin occupation; the y-axis plots the correlation between distance to each other (destination) occupation and average log wage at that destination occupation, weighted by number of moves from the origin to the destination, as defined by Equation 7. In panel (b), the y-axis plots the correlation between distance to each other (destination) occupation and average log wage at that destination occupation, weighted by the number of moves from the origin to the destination, as defined by Equation 7; the x-axis plots the same correlation, but weighted by the actual number of moves from the origin to the destination.

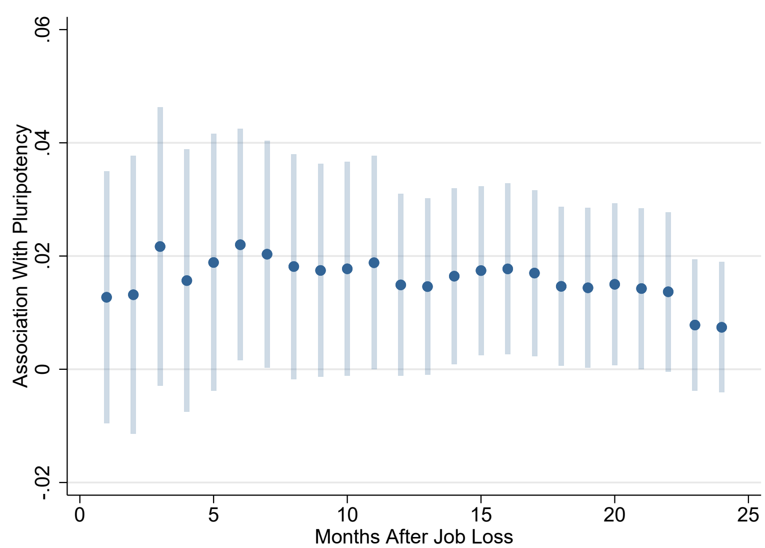


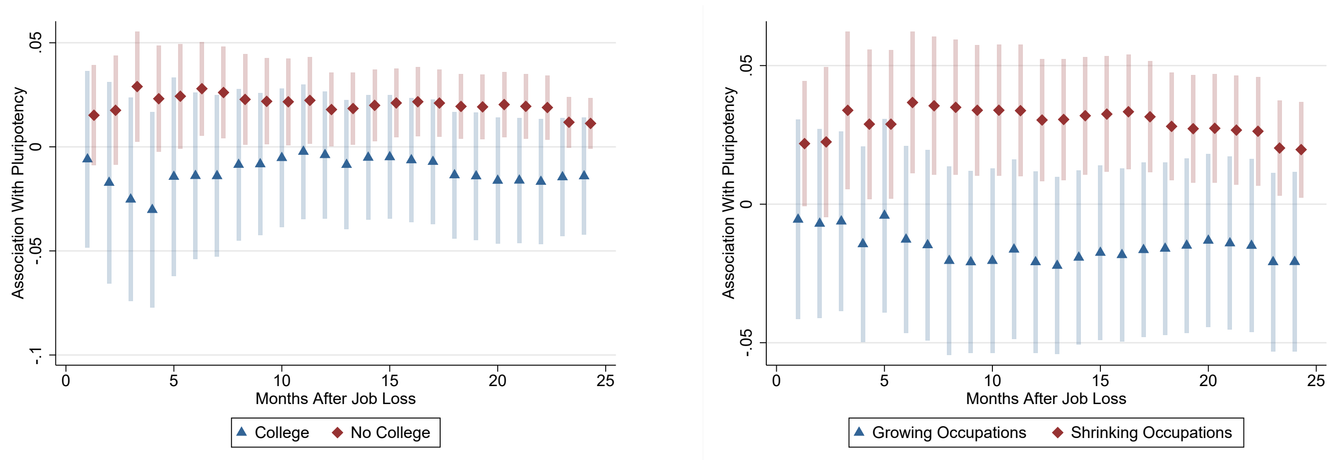
Figure B.10: Association Between Pluripotency and Reemployment Outcomes: No Licensed Occupations

Notes: See details in notes for Figure 5. Workers in occupations identified as licensed by Johnson and Kleiner (2020) are not included.

Figure B.11: Association Between Pluripotency and Reemployment Outcomes in Subgroups: No Licensed Occupations

(a) Education Level

(b) Growing vs. Shrinking Occupations



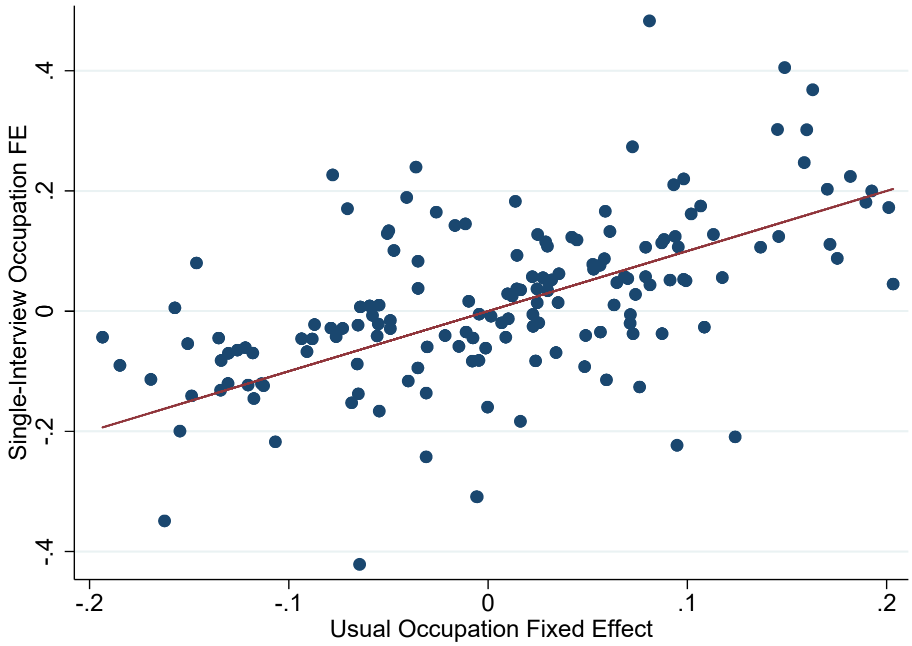
Notes: See details in notes for Figure 6. Workers in occupations identified as licensed by Johnson and Kleiner (2020) are not included.

C Within-Interview Fixed Effects

As discussed in the main text, the literature has found that—in survey data like the SIPP—many occupation moves are spurious. In our main specification, we address this by only considering occupation changes that occur at the same time as employer changes. However, this has two possible drawbacks. First, occupation moves within a firm may be different from those occurring between firms, leading to different fixed effects. Second, some occupation moves that occur at the same time as employer moves may still be spurious, leading to noise in the estimation.

To address both points, we introduce a new sample on which we will estimate fixed effects using Equation 2. We begin by noting that each time someone is interviewed for the SIPP, they report their work history over the previous 4 months. Thus, months 1 through 4 in the data are from one interview, months 5 through 8 on the next, and so on. In theory, we could use any within-interview change in occupation to help estimate fixed effects. However, recall that the first and last month in a job often see lower wages than other months. We therefore restrict attention to interviews that begin in month t where the person works at the same occupation A in month t and $t+1$, switches to a new occupation B in month $t+2$, and stays at occupation B in $t+3$. This greatly limits our sample: only moves with no break in employment are included, and only one quarter of such moves will happen to occur after the second month of an

Figure C.1: Fixed Effects: Usual vs. Within-Interview



Notes: One observation per occupation. The x-axis is the usual occupation fixed effect. The y-axis is the occupation fixed effect calculated by including only occupation moves that occur within a single interview, as described in Section C. Only occupations above the median size are included. The red line is the 45-degree line.

interview. After adding our usual sample restrictions on age, hours worked, and outlier wages, we have 3,466 pairs of observations where the same individual is observed at two occupations in the same interview. This is an order of magnitude smaller than our usual employer-switcher sample, which is why we prefer that sample in our main analysis.

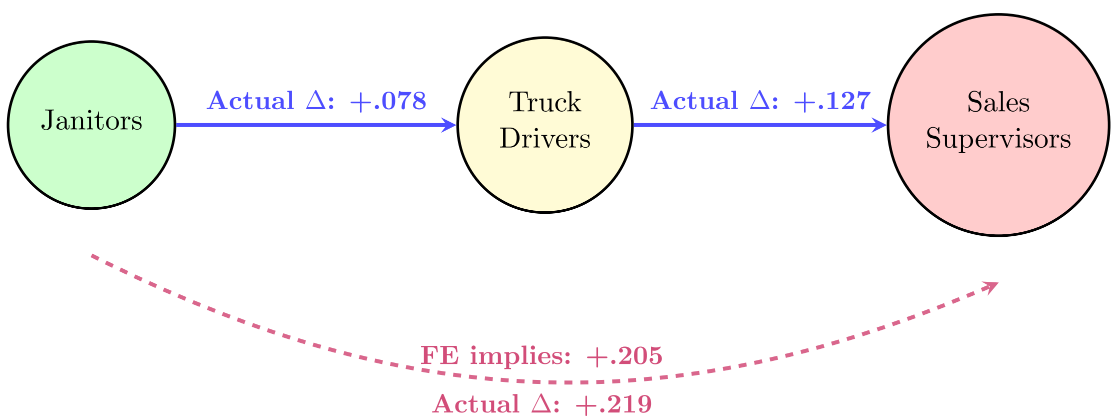
Once we estimate Equation 2 with the Kline et al. (2020) bias correction, the within-interview occupation fixed effects explain 2.5% of total log wage variation—similar to our baseline results. (The Kline et al. (2020) correction is particularly important here since there is more scope in this smaller sample than in our usual estimates for an elevated variance due to limited mobility bias.) In Figure C.1, we compare usual occupation fixed effects to within-interview occupation fixed effects. Using a simple OLS regression of the within-interview occupation fixed effects on the usual fixed effects, weighted by occupation size in the usual data, we estimate a coefficient on the usual fixed effect of .755 (robust standard error .076). This suggests that within-interview occupation fixed effects are substantially similar to the usual fixed effects. (If usual occupation fixed effects are precisely estimated, so there is no attenuation bias, this estimate being less than one means that within-interview fixed effects may be slightly smaller than the usual ones.)

D Out-of-Sample Fixed Effects

A key assumption in our analysis is that these fixed effects represent the effect of changing occupation on wage among those for whom these occupations are in their choice set. However, note that the difference in fixed effect between any pair of occupations A and C is based not just on moves between A and C, but also on moves from A to another occupation B, plus moves from B to C. That is particularly true for pairs of occupations between which there are few or no moves. In order to argue that the fixed effect difference estimates how much workers' wages would change if they were able to make a move, then, it must be that fixed effect differences predict changes in wages out of sample. In this section, we describe our test of this out-of-sample prediction.

Figure D.1 illustrates our approach using three occupations: janitors, truck drivers, and sales supervisors. Among workers who are, at different times, both janitors and truck drivers, their log wage averages .078 higher as truck drivers; among those who are both truck drivers and sales supervisors, their log wage averages .127 higher as sales supervisors. Therefore, if we estimated Equation 2 using only these movers, we would find that the fixed effect for sales supervisors is .205 (=.078+.127) higher than that for janitors. In fact, those who have both jobs have average log wages a similar .219 higher as sales supervisors. Therefore, for this triplet, estimates of Equation 2 predicts out-of-sample wage difference well.

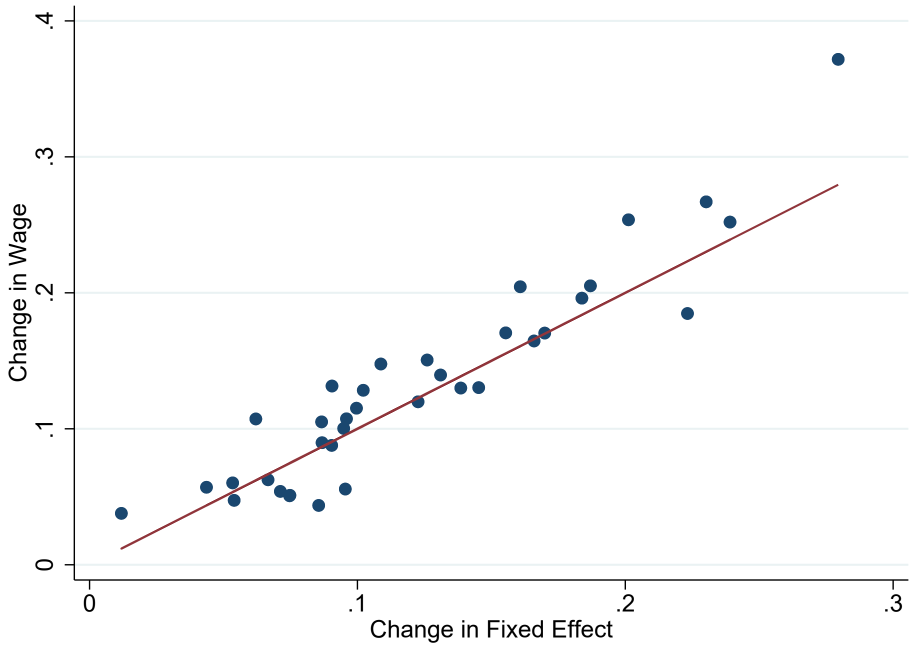
Figure D.1: Intuition for the Out-of-Sample Test



Notes: This figure shows the difference in log wage among those who held two of the listed occupations: those who were both janitors and truck drivers had log wages .078 higher as truck drivers; those who were truck drivers and sales supervisors had .127 higher as sales supervisors; and those who were both janitors and sales supervisors had .219 higher as sales supervisors. The first two differences imply that an AKM analysis involving only the first two types of moves would estimate a fixed effect difference between sales supervisors and janitors of .205.

The above example was chosen such that the math works well; our samples are too small for two pairwise comparisons to reliably estimate fixed effects. To make this test systematic, we extend it to all occupations in the data. We first divide all occupations into deciles by their estimated fixed effect. For every pair of deciles with an least one decile between them (for example, deciles 1 and 3, but not deciles 1 and 2), new occupational fixed effects are calculated using Equation 2 including only observations of occupations between those deciles—including observations of those deciles, but not for workers who are observed at both the top and bottom endpoint. Then, for workers who are observed at both the top and bottom endpoints, we calculate the change in this newly-calculated fixed effect, along with the actual change in their wage. (For example, for the pair of deciles $\{3, 6\}$, we estimate Equation 2 using only observations of occupations in deciles 3, 4, 5, and 6, and only among people who are not, at some point, in occupations in both deciles 3 and 6. Therefore, the change in this fixed effect experienced when moving from 3 to 6 is based only on the moves others make between those groups.) The change in fixed effect and change in wage are plotted in Figure D.2; points lie mostly along the 45-degree line, and a the 95% confidence interval of regression on the points cannot rule out a slope of 1.

Figure D.2: Do fixed effects predict wage changes?



Notes: Occupations are split into 10 deciles by occupational fixed effect. Each point represents a pair of deciles with at least one decile in between. For each such pair, new fixed effects are calculated that include all occupations between this pair, including the endpoints but not workers who move between the endpoints. The x-axis plots the average change in the newly calculated fixed effects for those moving from the lowest to the highest decile in the pair (and the negative of that for those moving in the opposite direction); the y-axis plots the change in average wage for the same group. The red line is the 45-degree line.

E Cleaning Procedure

Occupations. Because occupational classifications change through time, occupations are harmonized and some are merged using a crosswalk mapping various occupational classifications to consistent occupational codes using data from Autor and Dorn (2013).[17] To integrate the O*NET variables, a comprehensive crosswalk was created to link the 1990 Census classification[18] with the Standard Occupational Classification (SOC) and O*NET codes.[19]

*O*NET variables.* In our final occupational classification, some occupations were merged to ensure consistency. When a single occupation, as defined by the Autor and Dorn (2013) classification, corresponded to multiple occupations in the O*NET framework, the O*NET variables were averaged across the corresponding occupations to create a unified representation.

Demographic variables. Demographic variables are harmonized using a standardized coding scheme. In both the SIPP and the Displaced Workers Supplement, education levels are categorized into two groups: high school or less, and college or more, based on respondents' highest reported educational attainment at the time of the questionnaire. Racial and ethnic classifications are consolidated into four mutually exclusive groups: White (non-Hispanic), Black (non-Hispanic), Hispanic, and Other, using reported race and ethnicity identifiers.

Individual weights. Individual weights are used as provided by the SIPP data to reflect the population-level representation of each observation. These weights are normalized where necessary, such as when computing occupation-level averages or aggregating across spells, to avoid double-counting individuals in repeated observations. For specific analyses, like the estimation of occupational fixed effects, adjusted weights are applied to observations from the second period of employment spells after a change in employer.

Calculating wages. Wages are calculated by dividing monthly earnings from the primary occupation by the product of weekly hours worked and the average number of weeks per month (4.345). Adjustments for inflation are made using the Consumer Price Index, with 2002 as the base year, resulting in inflation-adjusted wages. The average wage for an given employment spell is calculated over the entire spell, excluding the first and last months to avoid temporary fluctuations.

Employment spells. Employment spells are defined as continuous periods of employment with

[17] Available at `https://www.ddorn.net/data.htm#Occupation%20Codes`.
[18] Available at `https://www2.census.gov/programs-surveys/demo/guidance/industry-occupation/`.
[19] Available at `https://www.onetcenter.org/taxonomy/2019/soc/`.

a single employer, identified using unique employer identifiers. A new spell begins whenever an individual switches employers. If an individual has multiple occupations within a spell, the spell's last occupation (leaving out the final month of data) is used. To avoid overcounting transitions, gaps between periods of employment with the same employer—whether due to temporary unemployment or unavailability to respond to the survey—are treated as part of the same continuous spell, provided the individual returned to the same employer or occupation.

Final selection. The final estimation sample for the AKM regression and pluripotency analysis is built from an harmonized panel of the Survey of Income and Program Participation (SIPP) from 1984 and 2008, covering individuals observed between the ages of 25 and 65. We retain only employment spells that begin with a change of employer, which helps ensure that occupational codes reflect genuine transitions rather than survey inconsistencies. Within each spell, we restrict to full-time work by requiring an average of at least 20 hours worked per week and exclude spells in which the average hourly wage falls below the inflation-adjusted federal minimum wage. Observations with wages above the 99th percentile and below the 1st percentile are dropped. The resulting dataset comprises 184,987 individual-employer spell observations, corresponding to 74,658 unique individuals.