Old and New Jobs: Understanding Wage Formation, Sorting, and Firm Behavior*

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Abstract

This paper examines how uncertainty about match productivity in newly created roles within firms affects hiring decisions, wage formation, and post-hiring outcomes. Using matched employer-employee data from Sweden covering 1.7 million new hires, I show that firms raise hiring standards by selecting more experienced workers and poaching workers from other firms into these new roles. Workers hired into new roles earn entry wages that are 3 percent higher, conditional on rich sets of worker and firm fixed effects. Tenure in new roles is longer on average, leading to an eight percent earnings premium within a given employment relationship. I shed light on a previously undocumented source of hiring uncertainty - firms' previous employment experience in a particular occupation - which generates wage inequality among similar workers.

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1 Introduction

Hiring decisions are made under uncertainty about worker productivity and match quality. A large literature suggests that this hiring uncertainty is an important determinant of employee selection, entry wages, and subsequent wage growth. This literature, to a large extent, focuses on worker experience as a key source of information about worker productivity. As workers accumulate experience in the labor market, their productivity becomes observable to employers (Farber and Gibbons, 1996; Altonji and Pierret, 2001; Lange, 2007; Fredriksson et al., 2018). However, much less is known about how a firm's employment experience in a given occupation shapes wage inequality among otherwise similar workers.

In this paper, I study how a firm's occupation-specific employment experience affects employee selection, entry wages, and match quality. Using firms' employment history by occupation, I distinguish between hires into occupations the firm has previously employed ("old jobs") and hires into occupations it has not previously employed ("new jobs"). The main argument is that occupation-specific knowledge about job requirements and the match productivity accumulates within firms through employment in that occupation. When a firm hires into an occupation it has not previously employed, it faces greater uncertainty about match productivity, which may have implications for both wage setting and worker sorting. Empirically, I exploit within-firm variation in job novelty at the time of hiring to compare outcomes for entrants into new versus old jobs.

To guide the empirical analysis, I develop a simple model that links occupation-specific experience to entry wages. I extend the stochastic job-matching framework of Pissarides (2000) by allowing incumbent firms to post vacancies in old and new jobs. The main assumption is that match productivity is more uncertain in new jobs. This higher uncertainty changes acceptance behavior on both sides of the market: firms raise their reservation productivity and workers increase their reservation wages in new jobs. The model yields a central prediction that guides the empirical work. Entry wages are higher in new jobs than in old jobs, holding the firm's overall wage-setting environment constant.

I test this prediction using Swedish matched employer–employee data from 1996 to 2013, focusing on 1.7 million new hires. The data allow me to track firms and workers over time and to link each hire to the firm's employment history by occupation. This makes it possible to identify new jobs and to compare hires made by the same firm when an occupation is new versus when it is already established within the firm. I then study how wages evolve as the firm accumulates occupation-specific employment experience.

The main empirical challenge is that new jobs arise when firms expand along a new occupation, whereas hires into old jobs can reflect both expansion and replacement hiring within

existing occupations. This raises two related concerns. First, new jobs may coincide with firm-level changes in productivity, product demand, or wage policies that affect wages. Second, workers may sort differentially into new versus old jobs on observed and unobserved characteristics. I address these concerns by comparing expanding old jobs to new jobs within the same firm-year, controlling for rich worker characteristics and time-varying occupation controls. I further probe selection concerns using specifications with worker fixed effects and tests based on predetermined measures of worker quality.

I document three main findings. First, consistent with the main prediction of the model, the data show a robust entry wage premium for new jobs. Conditional on time-varying firm conditions and occupation-year shocks, workers entering new jobs earn about 3-4% higher entry wages than comparable workers entering old jobs within the same firm-year. Importantly, this premium is present across all skill groups and remains similar after allowing for within-firm, broad occupational wage adjustments and when comparing the same worker across job spells. This *new job wage premium* gradually declines with employment experience within occupation (job age) and becomes statistically indistinguishable from zero after six to eight years, consistent with the theoretical model that job-specific uncertainty resolves as firms accumulate experience in the occupation.

The new job wage premium is comparable in magnitude to the wage gains associated with job-to-job mobility in my data (3.5–4%), a benchmark often viewed as central for life-cycle wage growth (Topel and Ward, 1992; Adda and Dustmann, 2023). This indicates that transitions into new jobs is a quantitatively important and understudied margin of wage growth. Furthermore, across the residual wage distribution, entering a new job moves the median worker up by 15 percentiles.

Second, in line with the mechanisms implied by the model, new jobs are associated with stronger selection on observable worker characteristics such as experience and current labor market status. For example, the probability of poaching the worker from another firm is 2.5 percentage points higher for new jobs than for old jobs. Furthermore, new job entrants are 8.8 percentage points (about 20 percent) more likely to have at least ten years of labor market experience. Contrarily, I find no evidence that new job entrants are positively selected on unobserved abilities.[1]

Third, post-hiring outcomes indicate higher match quality in new jobs. Workers hired into new jobs are 1.2 pp (11 percent) less likely to separate within the first year and 1.6 pp (3

[1]To assess whether unobserved worker ability can explain the new job wage premium, I estimate a two-way fixed effects model following Abowd et al. (1999) (AKM) using pre-dated data (1985–95) to obtain a worker skill measure that is orthogonal to entering a new versus an old job in the analysis sample. This unobserved worker skill (AKM worker fixed effects) cannot explain the new job wage premium.

percent) more likely to remain with the firm for at least three years. These results remain robust even after controlling for entry wages. Conditional on staying three years, wage growth is similar across jobs. The combination of higher entry wages and longer match duration leads to an 8.4 percent higher within-job earnings –equivalent to approximately €4000– for workers entering new jobs compared to those entering old jobs within the same firm.

I perform a range of robustness checks and heterogeneity analysis to validate my findings. First, I show that the results hold under alternative definitions of jobs, such as when occupations are defined at a more granular 4-digit level instead of the 3-digit level. To assess whether the estimated new job wage premium is driven by a subset of firms, I examine heterogeneity by firm age, firm size, and industry. The premium remains positive and economically meaningful across these firm categories, suggesting it is not explained by a narrow group of firms. I further replicate the main wage results using various subsamples, such as firms established after 1996, and obtain very similar findings.

To separate higher uncertainty due to information frictions in new jobs from differences in marginal productivity or broad shifts in the market value of occupations, I exploit variation in how similar a newly introduced occupation is to the firm's existing occupations. Following Gathmann and Schönberg (2010) and Macaluso (2025), I measure occupational similarity using the skill content of occupations drawn from O*NET. I classify new jobs as similar or dissimilar relative to the firm's pre-existing occupations based on the distance between their skill profiles. The new job wage premium is twice as large when the new occupation is more dissimilar to the firm's existing workforce, and firms fill dissimilar new jobs more selectively, drawing more on experienced workers and job-to-job movers while avoiding the long-term unemployed. This evidence is consistent with limited firm experience in an occupation amplifying hiring uncertainty and affecting both wage setting and sorting. While a marginal productivity interpretation can account for higher wages, it does not predict stronger selection on observables for more dissimilar occupations.

Finally, I assess whether the empirical evidence aligns with alternative theories and explanations. The empirical patterns are inconsistent with compensating differentials and monopsonistic competition. First, the theory of compensating differentials is not consistent with the observed differences in worker turnover since new jobs have longer tenure, even conditional on entry wages. Furthermore, the new job wage premium does not vary by job size at entry, suggesting that wage differential is not attributable to monetary compensation for working alone.[2] I also show that the premium is not explained by differential promotion prospects or team-building responsibilities in new jobs. Second, time-varying firm effects hold the hiring rate of

[2]New jobs are of smaller size during the initial year of employment, around 80% of jobs employ a single worker in the first year. One could presume that workers seek compensation if they are expected to work alone.

firms at a given time point constant, which makes it unlikely that monopsonistic competition can explain the wage premium. Relatedly, firm-level event studies show that firms introducing new jobs do not pay higher wages to incumbents or to other entrants into old jobs relative to firms that expand only along old jobs. I conclude that neither of these alternative theories can explain the new job wage premium.[3]

This paper contributes to several strands of literature. The main contribution is to the literature on the role of employer uncertainty on workers' labor market outcomes (Farber and Gibbons, 1996; Altonji and Pierret, 2001; Lange, 2007; Schönberg, 2007; Kahn, 2013; Fredriksson et al., 2018).[4] I show that firms screen on easily observable characteristics such as labor market experience, and current labor market status when they hire into new jobs. While existing research extensively studies how workers' productivity is revealed over time, this paper flips the perspective and examines how workers and firms learn about productivity of newly created roles within firms.[5] Consistent with findings in employer learning literature (Lange, 2007), the new job wage premium declines with firms' employment experience in an occupation, and disappears after approximately 6–8 years.

Second, I contribute to the literature on wage inequality among observably similar workers. A central finding is that wages depend on both where people work—across firms and industries—and what they do—across occupations (Kline, 2024).[6] More recent work highlights information imperfections as an additional source of wage inequality. Workers may have limited knowledge of outside opportunities (Jäger et al., 2024), and employers may be imperfectly informed about prevailing market wages (Cullen et al., 2025). I show that creation of new roles within firms is a previously unexplored driver of wage inequality, generating wage differences both within firms across occupations and across firms within occupations.

An extensive literature documents that hiring is costly and uncertain due to search frictions (Manning, 2011; Oyer and Schaefer, 2011; Le Barbanchon et al., 2023b; Hoffman and Stanton, 2025). Consistent with these frictions, recent studies find that exogenous worker separations generate sizable costs for employers (Ginja et al., 2023; Jäger et al., 2025). Survey evidence

[3]Another plausible theoretical explanation for wage premium is efficiency wages, which would produce empirically identical predictions with compensating differentials in the absence of differences in monitoring cost across new and old jobs (Shapiro and Stiglitz, 1984; Katz, 1986; Schmieder, 2023).

[4]While Schönberg (2007) and Kahn (2013) show that employers differ in the information they hold about workers, I emphasize that employers also differ in the information they hold about occupations, due to differences in employment experience.

[5]While Mansour (2012) shows that employer learning differs across occupations, I identify within-firm variation in occupational experience by comparing the same occupation at different stages of a firm's experience employing workers in that occupation, while absorbing aggregate occupation-level learning with occupation-by-time fixed effects and controlling for life-cycle effects with age fixed effects.

[6]A very large literature documents persistent wage premia by industry (Krueger and Summers, 1988; Thaler, 1989), establishment characteristics such as firm age (Brown and Medoff, 2003; Babina et al., 2019; Schmieder, 2023), and firms more broadly (Abowd et al., 1999; Card et al., 2013).

primarily points to difficulties locating the right skills and to costly screening under imperfect information (Barron et al., 1985; Barron and Bishop, 1985; Bertheau et al., 2023). I contribute to this literature by arguing that hiring frictions are not uniform within firms. Specifically, they vary with the firm's employment experience in a given occupation. This within-firm heterogeneity in hiring frictions is often ignored, but I show that it has significant implications for sorting and match quality. Consistent with the previous findings that hiring practices affect match quality and turnover (Hoffman et al., 2018; Pries and Rogerson, 2022), I show that selection criteria differ in newly created jobs within firms, which increases expected match quality and reduces subsequent turnover.

Lastly, I contribute to the literature on the importance of job matches in workers' careers. Previous studies show that firms and occupations shape lifetime outcomes. For example, employer size at the first job Arellano-Bover (2024), and mismatch at the job and occupation level predicts subsequent earnings (Fredriksson et al., 2018; Guvenen et al., 2020). I add a new dimension which is the newness of the job. While newly established firms often pay wage premia (Babina et al., 2019; Schmieder, 2023; Kim, 2023), I show that even holding firm age fixed, entering a new job is associated with substantially different earnings trajectories among otherwise similar workers.

The remainder of the paper is organized as follows. Section 2 presents a simple framework that illustrates the relationship between job age and entry wages. Section 3 describes the data, the construction of key variables, and the analysis sample. Section 4 outlines the empirical strategy. Section 5 reports the main results, while section 6 discusses alternative models and interpretation of the results. Section 7 concludes.

2 Theoretical framework

To motivate the empirical analysis, I develop a simple job-matching model. The model isolates a single mechanism—how differences in uncertainty about match quality affect accepted wages—while abstracting from worker sorting, occupation-specific demand shocks, and firm heterogeneity, which are addressed in the empirical analysis.

The model builds on a standard matching framework following Jovanovic (1979) and Pissarides (2000). Workers and firms are ex-ante identical and meet through random search. Upon meeting, match-specific productivity y is realized. A match forms if y exceeds a reservation threshold. As a result, even though agents are ex-ante identical, accepted matches differ in realized productivity.

Firms can post vacancies in two types of jobs: occupations they have previously employed

(old jobs, O) and occupations new to the firm (new jobs, N). The key distinction is that workers and firms have less information about the productivity of potential matches in new jobs. When hiring into an existing occupation, both can draw on prior experience and internal benchmarks; when hiring into a new occupation, such information is limited.

I capture this difference by assuming that match productivity in new jobs is more dispersed than in old jobs. Specifically, productivity in old jobs is drawn from a distribution $G(y)$, while productivity in new jobs is drawn from $H(y;\sigma)$, where $H(\cdot;\sigma)$ is a mean-preserving spread of G. Thus, both job types have the same ex-ante mean productivity, but new jobs involve greater uncertainty about match quality. The parameter σ summarizes the degree of uncertainty at the time of hiring.

This simple structure implies that differences in uncertainty can translate into differences in accepted match quality and therefore in entry wages. Importantly, the model isolates this variance-driven selection channel and abstracts from other mechanisms—such as differences in average productivity, firm-level wage policies, or endogenous job creation—that could also generate wage differences across job types. The empirical analysis therefore evaluates whether the patterns in the data are consistent with this mechanism and helps distinguish it from alternative explanations.

Figure 1 illustrates the key intuition. Although ex-ante expected productivity is the same across job types, greater dispersion in new jobs leads to differences in the distribution of accepted matches. Consistent with this mechanism, Appendix Figure A1 shows that entry wages are more dispersed for workers entering new jobs than for those entering expanding old jobs. The next subsection describes the matching technology and equilibrium conditions that determine reservation thresholds and match formation.

2.1 Matching in new and old jobs

Let the matching function be $m = m(u, v)$, where u denotes unemployment and v denotes vacancies. Labor market tightness is $\theta \equiv v/u$. Define the meeting rate for a vacancy as $q(\theta) = \frac{m(u,v)}{v}$, and the meeting rate for an unemployed worker as $\theta q(\theta) = \frac{m(u,v)}{u}$.

After meeting a vacancy of type j, productivity y is drawn from G for an old job and from $H(\cdot;\sigma)$ for a new job, and is observed by both parties. The worker-firm pair forms a match if and only if $y_j \geq y_{R,j}$. Therefore, the acceptance probability in old (new) job is $1 - G_O(y_{R,O})$ $(1 - H_N(y_{R,N}))$. The vacancy filling rate for an old job is $q^f = q(\theta)\left[1 - G_O(y_{R,O})\right]$. Similarly, the worker's job-finding rate into an old job is $q^w = \theta q(\theta)[1 - G_O(y_{R,O})]$.

2.2 Reservation productivity

The central object is reservation productivity, $y_{R,j}$. Intuitively, greater dispersion in match productivity raises the option value of waiting for a better draw, which tends to increase the equilibrium acceptance cutoff for new jobs. In Appendix A4, I show that a marginal increase in dispersion σ increases the reservation productivity:

$$\frac{\partial y_R(\sigma)}{\partial \sigma} \geq 0. \tag{1}$$

The mechanism is that more dispersion increases probability mass in both tails. Since firms and workers can reject low-productivity draws, they optimally accept only matches with $y \geq y_R$. The gains from high-productivity realizations dominate the losses from low draws that would be rejected anyway, implying a higher optimal productivity cutoff y_R.

2.3 Value functions and wage determination

Firms The value of a filled job (J_j) is given by:

$$rJ_j = y_j - w(y_j) - sJ_j \tag{2}$$

where s represents exogenous job separation rate, r denotes discount rate, and $w(y_j)$ the wage. The value of vacancies (V) is given by:

$$rV_j = -c + q_j^f(J_j - V_j) \tag{3}$$

where c is some fixed cost of holding the vacancy open. In equilibrium, $V_j = 0$, the job creation condition is given by:

$$\frac{y_j - w(y_j)}{r+s} = \frac{c}{q_j^f} \tag{4}$$

Equation (4) shows the equilibrium relationship between the expected net return of creating a job and the associated costs. Left-hand side represents the present value of the expected net gain from a job. The term on the right-hand side captures the costs of maintaining a vacancy. The denominator q_j represents the rate at which vacant jobs become filled.

Consider a firm with a vacancy in a new job ($j = N$). If the contact becomes a match, the value to the job will be $J_N = J(y_N)$. If $J(y)$ is an increasing function of y, there is a reservation productivity $y_{R,N}$ such that all $y_N \geq y_R$ are accepted. y_N is defined by the condition: $J(y_{R,N}) = 0$; $\quad y_{R,N} - w(y_{R,N}) = 0$, since $y_{R,N}$ is the threshold value below which firm would not form a match in new jobs.

Workers Workers follow a reservation wage rule to decide which jobs to match and which jobs to reject. A worker randomly faces a new or an old job, and I abstract from on-the-job search. A worker would accept a job if the value of employment exceeds the value of unemployment. Thus, a worker would accept a wage offer w_j if it satisfies $W_j \geq U$.

The net value of unemployment is given by:

$$rU = z + q^w (W^e - U) \tag{5}$$

where q^w is the job finding rate and z represents the value of unemployment. The value of employment to the worker is job-specific and given by:

$$rW_j = w(y_j) + s(U - W) \tag{6}$$

Wage determination According to the standard wage bargaining model, wages depend on match-specific surplus and workers' outside options (Mortensen, 2003; Pissarides, 2000). If the firm and the worker decide to form the match ($y \geq y_R$), the worker enjoys net worth W_j and the firm J_j. Otherwise, the worker has net worth U and the firm V. The wages w_j are determined to maximize the product:

$$w_j(y) \in \arg\max_w \ (W_j(y) - U)^\beta (J_j(y) - V_j)^{1-\beta} \tag{7}$$

where $\beta \in (0, 1)$ denotes the worker's bargaining power, i.e., the share of the total surplus that accrues to the worker. The first-order condition implies the standard surplus-splitting rule

$$(1 - \beta)\big(W_j(y) - U\big) = \beta\big(J_j(y) - V_j\big). \tag{8}$$

Substituting the value of employment (eq. 6), value of job (eq. 2), and value of unemployment (eq. 5) into Nash bargaining (eq. 7), and taking into account in equilibrium $V_j = 0$, we get to the wage equation:[7]

$$w(y_j) = \beta(y_j + \theta c) + (1 - \beta)z \tag{9}$$

The wage rate is a function of match productivity (y_j), vacancy costs (c), market tightness (θ), and workers' outside options (z). Most importantly, I am interested in wage differentials in new versus old jobs. The only dimension along which new and old jobs differ is the reservation productivity, $y_{R(j)}$. I assume outside options, bargaining power, and vacancy costs c are identical across jobs.[8]

[7] See Appendix Section A3 for derivation of the wage equation.

[8] Empirically, I will compare workers who are recruited from unemployment or employment, in the same

In the baseline model with common market conditions (θ, z, c, β), the reservation productivity is common across job types, $y_{R,N} = y_{R,O} = y_R$. Differences between new and old jobs arise from the distribution of realized match productivities among accepted matches.

New jobs have higher reservation productivity, following from Equation 1, $(y_{R(N)} > y_{R(O)})$. More dispersed productivity distribution leads to higher reservation productivity, thus resulting in higher wages.

This simple matching process implies that, conditional on market tightness and observables, higher variance in match productivity in new jobs generates higher expected productivity among accepted matches and thus higher expected entry wages.

2.4 Predictions and empirical tests for potential mechanisms

The model delivers one main prediction: conditional on market tightness and observables, entry wages are higher in new jobs. While the model's formal prediction concerns entry wages, the underlying mechanism—more selective matching under greater uncertainty—generates additional testable implications that I evaluate empirically.

1. New job wage premium: The model predicts that new jobs have higher entry wages than old jobs due to higher reservation wage and reservation productivity. Thus, the key test is whether entrants into new jobs earn higher entry wages than entrants into expanding old jobs: $\mathbb{E}[w \mid j = N] > \mathbb{E}[w \mid j = O]$. Empirically, I estimate the new job wage premium conditional on worker and firm characteristics on top of occupation, industry, and labor market status at entry to hold outside options fixed.

2. Hiring standards and worker selection: The model does not generate predictions regarding hiring standards about observable worker characteristics. However, if information frictions are higher in new jobs, firms may rely more on observable proxies for information about workers. In this case, new job hires should be differentially selected on observable characteristics that can be used as a proxy for information. However, I cannot directly observe hiring standards since the pool of applicants is unknown in the data. But I empirically examine the characteristics of the new hires across new and old jobs within firm. If firms are using observable characteristics (e.g., experience, labor market status) as a way of reducing uncertainty, new job entrants are expected to be more experienced and less likely to be coming from unemployment.

3. Turnover and match quality: In the model workers and firms reject low-productivity draws, which raises average reservation match productivity for new jobs. If separations are decreasing in match quality, then lower early-job turnover in new jobs compared to old jobs is

occupation, industry, and location in order to hold outside options constant across new and old job takers.

consistent with a selection mechanism (Pries and Rogerson, 2022). In contrast, if the new job wage premium reflects, for instance, compensating differentials for additional responsibilities rather than selection, turnover may be higher in new jobs. I therefore examine early-tenure turnover as evidence on whether the wage premium reflects higher match quality versus compensation for certain characteristics of new jobs.

4. Wage growth and learning: The model has the simplifying assumption that the match productivity is revealed upon meeting, so wages are determined at entry and there is no additional systematic learning within the match. Under that assumption, wage growth profiles should be similar across new and old jobs. Deviations from this pattern—e.g., steeper wage growth in new jobs—would suggest gradual learning in new jobs that is not captured by the model. I therefore compare wage growth trajectories across jobs as a check on the instantaneous revelation assumption.

5. Earnings within employment relationship: Lastly, new jobs would have earnings premium due to the entry wage premium and longer match duration. If the wage growth/tenure do not differ systematically, then new jobs generate an earnings premium.

3 Data

The data used in this paper cover the entire Swedish working population from 1996 to 2013. These data include linked information on firm- and individual-level information. Below, I describe the main components of the data in detail. Then, I will describe the construction of the main variable of interest used in the analysis.

3.1 Data sources and sample construction

Demographic information: The demographic information (age, sex, municipality of residence, education) is retrieved from Statistics Sweden's LOUISE register data covering the population of Swedish residents between ages 16 and 74.

Wages and occupations: The data on wages and occupations come from Statistics Sweden's Wage Structure Statistics (WSS henceforth). Each year, sampled firms must report wages and occupations (SSYK-96, corresponding to ISCO-88) for each worker who was employed in September. The data cover the entire public sector workforce and approximately 50 percent of the private sector. The sampling procedure of private sector firms is based on firm size, with larger firms having a higher probability of being included.[9] The wage measure reflects the

[9]Sampling of private sector firms in (Wage structure statistics, WSS) is stratified by firm size with the sampling probabilities 3, 12, 41, 70, and 100 percent for the firm size intervals 1–9, 10– 49, 50–199, 200– 499,

employee's full-time monthly equivalent wages.

The occupations are classified according to the Swedish Standard for Occupational Classification, which is based on the international ISCO-88 classification. The classification groups jobs hierarchically by task content and qualification level. Each occupation is placed according to the main tasks performed and the qualification level required. The 1-digit level captures differences in skill and education, while lower levels distinguish functional specializations within these broader groups. As an example, Appendix Table C1 lists occupations that belong to major group 3 (Technicians and associate professionals) and its hierarchy: sub-major group 31 "Physical and engineering science associate professionals," minor group 311 "Physical and engineering science technicians".

Employment registers and earnings: I use linked employer–employee register data that allow tracking of workers and firms over time. These data are collected from tax registers, cover the entire population of workers and firms, and can be matched to WSS data. Each employment spell is observed with its first and last months of the employment relationship. I rely on the employment registers to define new hires, tenure, separations, experience, and earnings (monthly, employer-specific, and annual).[10]

A new hire is defined as a worker who starts working at a firm for the first time. Temporary layoffs and callbacks are not considered new hires; therefore, individuals returning to their previous employer are excluded from the sample.

The employment registers allow me to identify all new hires, as they cover the universe of job spells. However, these registers lack occupational information. Thus, I complement employment registers with the WSS data to distinguish between new and existing occupations at the firm level. Because the WSS is based on firm sampling, not all firms are observed every year. To identify firm-level expansions in new and existing jobs, I restrict the sample to firms observed in at least two consecutive years in the WSS.[11]

I exploit variation in the number of workers within a job cell (firm x occupation x year) to distinguish old and new jobs from each other. Due to the firm-based sampling design of the WSS, some firms may randomly drop out of the sample from one year to the next. Consequently, I apply a set of criteria to categorize new hires into different types of jobs.

First, I impose the restriction that a firm must be sampled for at least two consecutive years in the WSS. This condition allows me to calculate changes in job size.[12] Consequently,

and 500–, respectively.

[10] All monetary values are deflated to 2006 Swedish Kronor (SEK).

[11] Since hires are defined using employment registers that cover the full population, the sampling nature of the WSS does not pose a concern. The restriction to two consecutive years is required to observe occupational information used to calculate job size.

[12] The sampling is conducted at the firm level rather than the worker level. If a firm is sampled in a given year, all workers employed in that firm are included.

this restriction excludes new hires in a firm's first sampling year and newly established firms, as all hires in firm births occur in newly created occupations. As a result, each firm included in the WSS must be observed for a minimum of two consecutive years.

Second, I exclude temporary employment agencies or other recruitment agencies. Such firms act as intermediaries rather than final employers; their employment relationships are short-term and often span multiple client firms. Including them would obscure the link between firms and the jobs actually performed, which is essential for identifying firm-level occupation structure.

3.2 Distinguishing old and new jobs in the data

Below, I sketch the main rule for classifying new hires into new and old jobs, from which I construct the main variable of interest. The main variable of interest is "New Job", which is a categorical variable that includes three groups of hires based on the following rule:

$$\text{New Job}_{jot}\{N,E,R\} = \begin{cases} \text{New job} & \text{if} \quad L_{jot} > 0 \mid L_{jot-m} = 0 \\ \text{Old job} & \begin{cases} (E)xpanding & \text{if} \quad L_{jot} - L_{jot-1} > 0 \mid L_{jot-m} \neq 0 \\ (R)eplacing & \text{if} \quad L_{jot} - L_{jot-1} \leq 0 \mid L_{jot-m} \neq 0 \end{cases} \end{cases}$$

where j, o, and t represent firm, occupation, and year, respectively. The variable L_{jot} represents job size. The grouping of new hires is based on the change in job size from one year to the next.

The first group, new job (N), emerges when a firm hires to an occupation for the first time, given that it has not employed anyone in that occupation in the past m years.[13] All new hires into existing occupations within a firm belong to the *old jobs*, defined as occupations in which the firm has at least one year of prior employment experience. I further divide old jobs based on changes in job size. When employment in an old job increases from one year to the next, $L_{jot} - L_{jot-1} > 0$, I classify all new hires as expansion hires within an existing occupation (E). When employment in an old job decreases, $L_{jot} - L_{jot-1} \leq 0$, I classify all new hires as replacements, (R).

As an illustrative example, assume two workers are hired into the *same existing occupation* in a given year; they are either part of expanding old job (E) or replacing old job (R). There is, however, variation across occupations within a firm. If the employment grew in an existing

[13] m ranges from 1 to 17, corresponding to the first (1996) and last (2013) year of the data, denoting the first year in which the firm was sampled.

occupation from $t-1$ to t, all new hires to this particular occupation at time t are categorized as hires into expanding old jobs. Conversely, newly hired workers are considered replacements in an old job if the firm downsizes between $t-1$ and t in a particular occupation. Thus, new hires into the same job cell are classified as either expansion hires in existing occupations or replacements, not a combination. In summary, new job (N) is the job experiencing employment growth from a base of zero, (E) is the old job that experiences growth from a base of non-zero, and (R) is turnover without employment growth.

Notably, distinguishing hires in this way has the advantage of identifying different types of frictions that may lead to differences in entry wages and other outcomes. First, contrasting expanding old jobs to replacing old jobs shows the effect of expanding a particular job, conditional on having previous hiring experience in both occupations. Second, comparing new jobs (N) to expanding old jobs (E) allows one to identify greater uncertainty in match productivity due to the firm' missing employment experience in a particular occupation.

3.3 Descriptive statistics

Here I analyze sample statistics of workers entering new versus old jobs, and firms creating new versus old jobs. Table 1 presents descriptive statistics for the individual- and firm-level variables used in the main analysis. The columns distinguish between different types of hires—those entering new jobs and those entering old jobs (expansions and replacements). Panel A reports characteristics of newly hired workers, with each hire representing a unit of observation. Panel B summarizes characteristics of the hiring firms, categorized by hire type.[14]

Workers: Workers entering new jobs have higher entry wages (around 8-9 log points), lower separation rates within the first year of employmen"t, and longer tenure. Additionally, they are older and more experienced, measured as the having more than ten years of labor market experience. They are equally likely to hold university degree and slightly more likely to be employed in high-skill occupations.[15] The occupational composition at the 1-digit level is balanced across entrants into expanding versus replacing old jobs. New jobs, however, are more likely to be in managerial and clerical roles, and less likely to be in sales and service roles.

Notably, new jobs make up a considerably smaller share compared to old job expansions (E) and old job replacements (R). Job size in new jobs is also smaller relative to old jobs (see Figure 6). Nevertheless, new jobs account for about 12% of all jobs (10,520 out of 89,307).

[14]Firm-level observations are weighted by the weights provided in the original Wage Structure Statistics data.

[15]Using the ISCO-88 broad skill-group classification (combining managers, professionals, and technicians), 39 percent of new job hires are high-skilled, compared with 35 percent of hires into old jobs.

This implies that, although the number of hires into new jobs is small, the introduction of new jobs by firms is relatively common.

Firms: Panel B of Table 1 compares firms hiring into new versus old jobs. Firms that introduce new jobs are smaller and younger: 43% are young firms (younger than 10 years old) and they employ 36 workers on average. They hire 8 workers in total, of which 1.5 are into new jobs; the bulk of their hiring still goes to expanding existing jobs (5.2) rather than replacement hiring (1.3). In contrast, firms that primarily expand old jobs are larger (62 workers) and less likely to be young (33%). Their hiring is concentrated almost entirely in expanding existing roles (6.7 hires), with very little hiring into new jobs (0.2). Firms that replacement-hire are the largest (71 workers) and least likely to be young (30%), and their hiring reflects both expanding and replacement needs (5 versus 3.6). Overall, new job creation is concentrated among smaller, younger firms, while hiring in existing jobs—especially replacement hiring—characterizes larger, more established employers.[16] Despite these differences, value added per worker is the same across firms that hire for different purposes.

Occupations: Appendix Table C3 shows the distribution of the most common occupations among new hires across three categories. In new jobs, office clerks and store clerks hold the largest shares, at 4.2% and 3.7% respectively, indicating a larger share of administrative roles. For expanding and replacing old jobs, salespersons, personal care workers, and finance and sales associates dominate.

4 Empirical strategy

This section describes the empirical strategy used to estimate differences in outcomes associated with entering new versus old jobs. The goal is to quantify how entry wages, the composition of hires, and subsequent match outcomes differ when a firm hires into an occupation it has not previously employed.

Let i, j, o, and t index workers, firms, occupations, and years, respectively. For a job characterized by (j, o, t), let New Job$_{jot}$ denote an indicator for whether the firm is hiring into a newly created job, as defined in Section 3.2. For worker i matched to (j, o, t), let $y_{ijot}(1)$ and $y_{ijot}(0)$ denote potential outcomes if the worker enters a new or an old job, respectively. The main estimand is the average treatment effect $\tau \equiv \mathbb{E}[y_{ijot}(1) - y_{ijot}(0)]$, where outcomes include entry wages, measures of entrant characteristics, and post-hiring outcomes.

[16] See Appendix Figures B1 and B2 for distributions of firm size and growth, respectively.

Because potential outcomes are not jointly observed, τ cannot be estimated directly. For each worker we observe the outcome under the job type they actually enter (new or old), but not the counterfactual outcome under the alternative job type. Therefore, identifying τ requires assumptions that allow me to use outcomes of comparable workers as counterfactuals. I estimate τ using a regression design that compares entrants into new and old jobs within firm–year and occupation–year cells. The baseline estimating equation is

$$y_{ijot} = \beta \,\text{New Job}_{jot} + \lambda_{jt} + \lambda_{ot} + X_{it}'\delta + \epsilon_{ijot}, \tag{10}$$

where λ_{jt} are firm-by-year fixed effects, λ_{ot} are occupation–by–year fixed effects, X_{it} is a vector of worker characteristics, and ϵ_{ijot} is an idiosyncratic error term. The coefficient β is identified from comparisons of workers entering new versus old jobs within the same firm and year across different occupations, while holding occupation-specific conditions constant through λ_{ot}. Individual covariates are age, gender, education level, and experience. In alternative versions, I replace firm-by-year fixed effects with 3-digit-industry-by-year fixed effects. This specification compares workers across firms within the same industry-year and occupation–year cells, absorbing time-varying industry conditions and product-market demand. To account for systematic differences in wage-setting across firms, I flexibly control for firm age and log firm size.[17]

I estimate Equation (10) for three classes of outcome variables:

(i) *Entry wages:* y_{ijot} is log entry wages, so β captures the entry wage differentials across new and old jobs.

(ii) *Hiring selectivity and sorting:* y_{ijot} is a predetermined entrant characteristic (e.g., job-to-job mobility, long-term unemployment, experience), so β captures differences in the composition of hires across job types.

(iii) *Post-hiring outcomes and match quality:* y_{ijot} captures subsequent outcomes (separation, tenure, wage growth, total earnings), so β summarizes how matches originating in new jobs evolve relative to those originating in old jobs.

Identifying assumption and interpretation A causal interpretation of β as an estimate of τ requires that, conditional on the fixed effects and observed worker characteristics, job type is orthogonal to unobserved determinants of outcomes: $\mathbb{E}[\epsilon_{ijot}\text{New Job}_{jot} \mid \lambda_{jt}, \lambda_{ot}, X_{it}] = 0$. This condition may fail if New Job_{jot} is correlated with, for instance, unobserved worker quality,

[17]Previous research has documented that wages vary with firm age and size—young firms often pay more, although this relationship can reverse once worker and firm selection are taken into account (see, for example, Brown and Medoff (2003); Babina et al. (2019); Schmieder (2023)).

or unobserved job attributes or occupation-specific wage responses within firms. Therefore, in my empirical analysis, I proceed with a set of tighter specifications.

First, I assess worker selection by documenting selection on observable pre-hire characteristics (Section 5.5), testing for sorting on predetermined AKM person effects estimated in a pre-period (Section 5.6), and estimating within-worker specifications with worker fixed effects.

Second, I address job-level unobservables and within-firm occupational heterogeneity by estimating specifications with more granular fixed effects (firm-by-year-by-occupation at the 1- and 2-digit level), so that comparisons are made within narrower occupation groups inside a firm-year (Table 2, Panel B, columns (3)–(4)). I further examine heterogeneity by occupation group and by occupational similarity (Section 5.8) to distinguish job-specific uncertainty from broad shifts in skill demand.

Third, I evaluate endogenous job creation and firm-wide changes by contrasting across-firm and within-firm estimates, adding firm growth and productivity controls in the across-firm specifications, and testing whether the premium varies with firm growth or reflects firm-wide pay changes using firm-level event-study evidence (Section 6.3).

Overall, the baseline estimates should be interpreted as reduced-form differences in outcomes associated with entering newly created roles, conditional on rich firm-year and occupation–year controls. The subsequent analyses assess whether these differences are attributable to the creation of new roles within firms—as in the framework—rather than to sorting, within-firm occupational shocks, or alternative wage-setting channels explored in Section 6.

5 Main results

This section presents the main results. I proceed in five steps. First, I document the entry wage premium associated with new jobs—both across and within firms—and study how it evolves with job age. Second, to shed light on mechanisms, I examine whether firms select different workers into new jobs based on observable pre-hire characteristics. Third, I test whether workers sort into new jobs on unobserved productivity using pre-period AKM person effects. Fourth, I analyze post-hiring outcomes to assess match quality. Finally, I study heterogeneity by occupational similarity to distinguish job-specific uncertainty from broader shifts in skill demand.

5.1 New job wage premium

Table 2 reports the main estimates from two specifications of Equation 10: comparisons of entrants into new and old jobs across firms (Panel A) and within firms (Panel B). Panel B

Column (1) reports the estimated β from Equation 10. Other columns vary by specification and controls.

5.1.1 Across-firm comparison

Panel A compares entry wages of workers hired by different firms, controlling for industry-by-year and occupation-by-year fixed effects, as well as worker characteristics (education, age, experience, and gender). Column (1) shows that workers entering new jobs earn 2.8 percent higher wages than those entering replacing or expanding old jobs. The coefficient on "Old job (Replacing)" is statistically insignificant and economically small. This implies that conditional on prior employment experience in an occupation, entry wages do not differ meaningfully between expanding and replacing hires into existing positions. Taken together, these results suggest that information frictions, rather than factors specific to expansion, are central in driving new job wage premium.

As shown descriptively in Section 3.3, firms that expand into a new occupation differ from those hiring into existing jobs: they are younger and smaller, and tend to hire more workers relative to their size.[18] To account for time-varying firm characteristics, columns (2) and (3) add controls for the symmetric employment growth rate and log value added per capita.[19] Even with these controls, the estimated new job wage premium stays similar to the baseline.

Comparing new and old jobs across firms has a limitation, since unobserved firm-level factors (e.g., idiosyncratic demand conditions or wage-setting practices) might be driving the wage premium. This concern motivates the need for within-firm analysis, which holds firm-level characteristics and overall demand conditions constant at the time of entry.

5.1.2 Within-firm comparison

Table 2, Panel B, columns (1) and (2) show that the new job wage premium persists even when entrants are compared across different occupations within the same firm.[20] As before, entry wages into old jobs do not differ meaningfully between replacing and expanding hires, reinforcing that expansion per se does not drive the premium. Column (2) adds an indicator for being a job-to-job mover. The new job premium and the job-to-job mover premium are comparable in magnitude –3.0 and 3.3 percent, respectively – suggesting that starting a new

[18] See Appendix Figures B1 and B2 for distributions of firm size and growth, respectively. Employment growth rate is measured by the DHS index (Davis et al., 1996) and is defined as $2\frac{L_t - L_{t-1}}{L_t + L_{t+1}}$, with L_t being employment in year t.

[19] The estimate on log(value added per capita) in column (4) implies that a one percent increase is associated with a 3.7 percent increase in entry wages among *new hires*, which is close to estimates in a few studies using firm-level productivity measures and individual-level wages, as reported by Card et al. (2018).

[20] Identification relies on firms that hire for both new and old jobs in a given year. I replicate the results by restricting the sample to such firms and obtain identical estimates (Appendix Table C5).

job within a firm carries a wage advantage similar to the well-documented return to on-the-job search.[21]

As emphasized in the pass-through literature (e.g., Card et al. (2018); Kline et al. (2019); Maibom and Vejlin (2021)), firms may adjust wages differently across skill groups in response to a common shock. In that case, firm-by-year fixed effects may not fully capture within-firm heterogeneity because they apply uniformly across occupations within a firm-year, and occupation-year effects are not firm-specific. Column (3) therefore introduce more granular fixed effects—firm-by-year-by-skill level – absorbing skill-specific shocks within firms. Identification then comes from variation between new and old jobs within the same skill group.[22] The new job wage premium remains robust under these stricter controls, consistent with the interpretation that the effect is tied to the creation of new roles rather than differential occupation-specific responses to firm-level shocks. I next investigate whether new job wage premium reflects sorting of high-ability workers into new jobs.

5.1.3 Worker fixed effects

To assess whether the new job premium reflects unobserved worker productivity or unobserved worker–firm complementarities, I estimate a specification that includes worker and firm fixed effects—while maintaining the same set of controls as in Equation 10:

$$\ln(\text{entry wage})_{ijot} = \beta \text{New Job}_{jot} + \alpha_i + \lambda_j + \lambda_{ot} + X'_{it}\delta + \epsilon_{ijot}, \tag{11}$$

where α_i denotes worker fixed effects, λ_j firm fixed effects, λ_{ot} occupation-by-year fixed effects, and X_{it} worker controls.

Table 2 column (4) reports the estimates. In Panel A, the specification includes industry-by-year fixed effects in place of firm fixed effects, while Panel B incorporates firm fixed effects, effectively estimating an augmented version of the AKM model (Abowd et al., 1999). Worker fixed effects absorb time-invariant worker characteristics, including persistent differences in productivity. The estimated new job wage premium remains identical to the baseline, suggesting that the premium is not driven by time-invariant unobserved differences in worker ability.

[21] Appendix Table C4 restricts the sample to job-to-job movers only and obtains virtually identical estimates, confirming that the new job wage premium exists even when comparing workers with the same labor market status at entry.

[22] Skill groups are defined using the first digit of the ISCO occupation classification. High-skilled occupations comprise managers, professionals, and technicians; all remaining occupation groups are classified as low-skilled.

5.1.4 Heterogeneity by occupation groups

In this section I assess the plausibility that new jobs may be associated with ex ante higher productivity—for example, when firms adopt new technologies—so the new job indicator could partly proxy for high-skill, technology-complementary roles. In addition, an average new job premium could mask heterogeneity across skill groups.[23] To assess these possibilities, I estimate Equation 2 separately by broad 1-digit ISCO occupation groups.

Figure 2 shows that the new job wage premium is present across all of the occupation groups except for the elementary occupations. Point estimates are on the order of 3–4% for managers, professionals, and technicians, and around 2–3% for clerks. The premium is particularly pronounced in sales (roughly 8%) and remains sizable for machine operators (around 5–6%). By contrast, the estimate for elementary occupations is small and imprecise. Overall, these patterns indicate that the new job premium is not concentrated in high-skill occupations, making it unlikely that it is driven solely by technology-related or skill-based compositional differences across jobs. Instead, the presence of a premium in both white-collar and blue-collar groups is consistent with wage-setting differences that arise when firms hire into occupations in which they have limited prior experience.

5.2 When does a job get old?

According to theory outlined in Section 2, the new job wage premium should decrease with firms' hiring experience in an occupation, as job-specific uncertainty is expected to resolve over time. I therefore estimate how the premium evolves with job age. I regress log entry wages on job-age indicators, where job age equals zero for new jobs and old jobs are grouped into job-age categories.

Figure 3 shows that new jobs offer a 4.5% wage premium relative to jobs that have existed within the firm for 13 years or more. The premium declines sharply within the first few years and levels off around year 6. Beyond this point, entry wages in new jobs are statistically indistinguishable from those in old jobs.[24]

These patterns mirror predictions from the employer-learning literature, which emphasizes that uncertainty about productivity declines with experience (Farber and Gibbons, 1996; Al-

[23] The literature finds that firms' search efforts depend on job skill requirements (Barron and Bishop, 1985; Barron et al., 1997; Van Ours and Ridder, 1992, 1993).

[24] This declining pattern also speaks against the possibility that the new job wage premium reflects changes in collective agreement coverage coinciding with firms' entry into new occupations. The occupation-by-year fixed effects absorb any aggregate occupation-specific floor, while the firm-by-year fixed effects absorb any firm-level change in agreement affiliation. Moreover, if the premium reflected a permanent shift in bargaining regime, it should persist for all subsequent hires into that occupation. The gradual decline documented here is inconsistent with a permanent institutional shift and instead matches a transitory friction that resolves with experience.

tonji and Pierret, 2001; Lange, 2007). Consistent with this view, the premium associated with new jobs diminishes as firms learn about productivity at the job level and uncertainty resolves over time. As jobs age, information improves (declining σ in theoretical model), and the premium fades by years 6–8.

5.3 How large is the new job wage premium?

So far, I have documented that there is robust new job wage premium. In order to assess the magnitude of the new job premium, I proceed in two ways. First, I benchmark it against the wage gain from job-to-job mobility. Second, I interpret it as a movement within the within-occupation residual wage distribution.

Returns to job-to-job mobility Prior research identifies job mobility between firms as a key driver of wage growth over the life cycle (Topel and Ward, 1992; Adda and Dustmann, 2023). In my sample, job-to-job movers earn entry wages that are 3.3 percent higher than those of workers entering from non-employment, conditional on worker characteristics and experience at entry. The estimates in Panel B, column (2) of Table 2 show that the new job wage premium is of a comparable magnitude—and the two premia are separately identified in the same specification, so the new job premium is estimated net of the job-to-job mover effect. The comparison is informative because the two premia reflect distinct mechanisms: the job-to-job premium captures returns to on-the-job search and upward mobility along the job ladder, whereas the new job premium reflects the wage gain due to entering a newly created role. That the two are of similar size underscores the economic significance of the new job premium—entering a new job yields a wage gain comparable to one of the most well-documented sources of wage growth in the labor market. This suggests that transitions into new jobs constitute a quantitatively important and previously overlooked margin of wage growth.

Position in the wage distribution To interpret the size of the new job wage premium in distributional terms, I map the new job wage premium onto the residual wage distribution of new hires. I first estimate Equation 10 separately for each one-digit occupation group and obtain an occupation-specific new job wage premium (see Figure 2). Then, I link these estimates to residual wage distribution.[25] For each occupation, I compute the percentile a median worker would reach in the residual wage distribution after entering a new job.

Figure 4 plots, for each broad occupation group, the 10th–90th percentile range and the

[25] I residualize wages on age, experience, gender, education, occupation-by-year, and firm-by-year effects.

inter-quartile range, marks the median, and overlays β_s together with its nearest percentile label. This visualization shows both within-occupation dispersion and the size of the estimated effect. For each occupation, the triangle marker and its percentile label indicate to which percentile a median worker's position in the within-occupation residual wage distribution would shift when moving into a new job.

The results imply that a median worker entering a new job moves up by roughly 15 percentile points—from the 50th to the 65th percentile—equivalent to an increase of one to two deciles. Across occupations, the upward movement ranges from about 12 percentiles (elementary occupations) to 32 percentiles (sales occupations), indicating that the premium is large enough to move a typical worker noticeably up in the wage distribution among comparable new hires.

5.4 Robustness with alternative definition of jobs and sub-samples

The baseline definition of a job is firm × year × occupation at the 3-digit level. As a robustness check, I redefine jobs using 4-digit occupation codes to address a potential aggregation issue: a 3-digit category may bundle several 4-digit occupations that differ in tasks and pay. When a firm hires into a new 4-digit occupation within a 3-digit category it already employs, the 3-digit definition may classify the observation as an "old" job even if the role is new. Using 4-digit occupations creates more homogeneous job cells and limits both (i) misclassification of new roles as existing jobs and (ii) wage changes driven by shifts in the mix of roles within a broad 3-digit category. Appendix Table C6 reports estimates under the 4-digit definition and shows results very similar to the baseline, indicating that the estimated new job wage premium is not driven by the occupational aggregation choice.

A second robustness check restricts the sample to firms established after 1996, the first year in which occupation information is available. This restriction rules out the possibility that a firm employed workers in a given occupation before 1996 but is observed only later due to missing occupation codes; in this subsample, jobs can therefore be interpreted more confidently as "new". Appendix Table C7 shows a larger premium for new jobs (4.5% to 6%), suggesting that the baseline estimates likely represent a lower bound on the true new job wage premium.

Firm-level heterogeneity Younger and smaller firms are more likely to create new jobs (Table 1). I therefore examine whether the new job premium varies by firm age, firm size, and industry. Appendix Table C8 shows comparable estimates across firm age and size categories. Appendix Figure B3 shows that the effect is present across industries. Overall, these patterns suggest that the new job premium is not concentrated in a narrow set of firms.

Taken together, I have documented the evidence that (i) new jobs pay higher entry wages than old jobs both across and within firms and present across all skill groups, (ii) declines with job age, (iii) it is as large as the gain associated with between firm mobility, and (iv) is robust to alternative controls and job definitions. I next examine whether firms fill new jobs by selecting different workers on observables and whether workers sort into new jobs on unobserved productivity, and then test the model's match quality implications.

5.5 Firms' employee selection

To shed light on potential mechanisms and assess whether hiring frictions vary within firms across jobs, I examine how the observable characteristics of hires differ between new and old jobs. Hiring is made under uncertainty because match productivity is not directly observed at the time of hire. If uncertainty is higher when a firm hires into an occupation it has not previously employed, new job entrants could be positively selected on observable signals that are informative about worker quality.

I focus on two sets of signals observed at entry: workers' current labor market status and labor market experience. Labor market status captures whether the worker is currently employed (poached from another firm) or long-term unemployed (unemployed for more than one year). Experience captures the number of years in the spent in the labor market at entry.[26]

Table 3 reports the main results. Column (1) shows that the probability a firm poaches a worker from another firm is 2.5 (2.9) percentage points higher for hires into new jobs than for hires into expanding (replacing) old jobs.[27] Column (2) shows that the probability of being long-term unemployed is 0.66 (1) percentage points lower for hires into new jobs than for hires into expanding (replacing) old jobs. Together, these results indicate that firms recruit relatively more from other firms and relatively less from long term unemployment spells. To the extent that firms view unemployment spells as a negative signal—for example through skill depreciation—these patterns are consistent with more selective hiring for new jobs.[28]

Column (3) provides complementary evidence using labor market experience. Entrants into new jobs are 8.8 percentage points (21 percent) more likely to be experienced than entrants

[26]Survey and field experimental evidence suggests employers screen primarily on prior experience and current labor market status and may assign a negative signal to long-term unemployment (see, e.g., Behrenz (2001); Oberholzer-Gee (2008); Kroft et al. (2013); Eriksson and Rooth (2014); Farber et al. (2019)). Behrenz (2001) reports that 60% of employers view labor market experience as a key selection criterion.

[27]I use the month gap between employment spells as a proxy for non-employment duration and construct a job-to-job mobility indicator equal to one when the gap between consecutive jobs is no more than two months. By this definition, 71% of new entrants are job-to-job movers in my data.

[28]Edin and Gustavsson (2008) present evidence from Sweden that non-employment spells contribute to skill depreciation, whereas Cohen et al. (2025) report no such evidence for Germany.

into old jobs.[29] Experience is an observable proxy for information about the worker: longer employment histories provide additional signals about past performance, which is particularly valuable when the firm has limited occupation-specific information about what predicts success in the role.[30]

Furthermore, I also find differential selection within old jobs: expanding old jobs exhibit different selection patterns than replacing old jobs, implying that hiring frictions related to expansion remain even conditional on prior occupational experience, but they do not generate wage differentials.[31]

The identifying variation in Table 3 comes from comparing hires into new versus old jobs across occupations within the same firm-year. In Appendix Table C9, I relax this restriction by estimating a model without firm-year fixed effects. In this specification, identification comes from across-firm variation among firms hiring into the same occupations in the same year. The results remain qualitatively similar, and the magnitudes are larger.

Since recruiting intensity and selectivity may vary systematically with firms' hiring rates across jobs (Carrillo-Tudela et al., 2023), I repeat the same analysis restricting my sample to firm–occupation–year cells with at most one hire. This restriction reduces mechanical differences related to the number of hires and limits composition shifts driven by multi-hire expansions. Appendix Table C10 shows that new job hires are 4 percentage points more likely to be experienced. Differences in poaching and long-term unemployment have the same sign but are not statistically significant.

5.6 Worker sorting on unobservables

In Section 5.1, I show that the new job wage premium persists after including worker fixed effects (Table 2, column 5). The identification of new job wage premium in that specification relies on individuals who have multiple job spells in different types of jobs during the observation period. In this section, I address the selection question from a different angle by evaluating whether new and old job entrants differ in unobserved quality. While the previous approach accounted for unobserved ability, in this section I aim to quantify the role of selection (if any)

[29] *Experienced* is defined as an indicator equal to one for individuals with more than ten years of labor market experience, given that the data begin in 1985 and a continuous measure of experience cannot be constructed for earlier years.

[30] New jobs within firms may also differ from old jobs because they can involve additional responsibilities, such as establishing new teams; I discuss this alternative channel in Section 6.2.

[31] This is supportive empirical evidence to Elsby et al. (2025); as in their model, expanding firms poach employed workers and job-to-job movers enter expanding positions, whereas replacement hiring is more likely to match with unemployed workers.

in explaining the new job wage premium.[32]

I measure workers' portable human capital using AKM person effects estimated on a pre-analysis period (1985–1996).[33] Estimating worker effects in a pre-period ensures that the skill measure is predetermined relative to subsequent placement into new versus old jobs in the main sample.

Specifically, I estimate:

$$\ln w_{it} = \theta_i + \psi_{j(i,t)} + X'_{it}\gamma + \varepsilon_{it}, \tag{12}$$

where w_{it} is worker i's monthly earnings in year t at firm $j(i,t)$, θ_i is a worker effect. To separately identify age, time, and worker fixed effects, I follow Card et al. (2013) and Card et al. (2018) in restricting the age-wage profile to be flat at age 40. Specifically, X'_{it} includes year fixed effects and education group indicators interacted with quadratic and cubic age polynomials, omitting the linear term.[34]

I then relate the estimated person effects $\hat{\theta}_i$ to entry into new jobs by estimating:

$$\hat{\theta}_i = \phi \text{New Job}_{jot} + \lambda_{jt} + \lambda_{ot} + X'_{it}\delta + \epsilon_{ijot}, \tag{13}$$

where ϕ captures sorting on unobserved worker quality. Because $\hat{\theta}_i$ is on the wage scale, the magnitude of sorting can be benchmarked directly against wage responses (Carlsson et al., 2016).

Figure 5 plots the estimated new job wage premium and the sorting parameter. The left panel ("Across-firms") shows entry wage differentials (β) across firms, and the right panel ("Within-firm") shows the corresponding within-firm estimates. Within each panel, the first two points report the baseline estimate (main sample) and the estimate in the AKM sample, and the third point reports ϕ.

The figure shows that the sorting estimates are much smaller—about one-fifth of β—and statistically indistinguishable from zero (Table C12). Together, these results imply that differences in estimated person effects are negligible relative to the new job premium. Thus, I find no evidence that entrants into newly created roles are positively selected on unobserved productivity. The new job premium cannot be attributed to high-ability workers sorting into

[32]These two approaches are complementary: the analysis in this section directly tests for sorting on unobserved skills allowing for a direct comparison of new and old job entrants, while the within-worker specification provides results after accounting for all unobserved, time-invariant worker characteristics.

[33]Appendix Table C2 presents summary statistics for the sample of workers and firms included in the AKM estimation over 1985–1996. Approximately half of the workers from the original sample (mostly older workers) are retained for the AKM estimation. Firm-level coverage is substantially higher, indicating that most firms were already operating during 1985–1996.

[34]The wage measure used in this regression is monthly earnings. Appendix Table C11 replicates the analysis using monthly full-time-equivalent wages from WSS. Since WSS is a sample of firms, worker and firm fixed effects are identified through moves between sampled firms.

new jobs.

5.7 Post-hiring outcomes and match quality

The hiring patterns documented above suggest that firms fill new jobs with different types of workers. The next question is whether these differences translate to better or worse matches (Lalive, 2007; Nekoei and Weber, 2017; Hoffman et al., 2018). In this section I assess whether match quality differs between new and old jobs using post-hire outcomes, together with entry wages. I study five outcomes: (i) first-year separation, (ii) the probability of remaining in the job for at least three years, (iii) on-the-job wage growth, (iv) within-spell wage dispersion (the standard deviation of wages), and (v) total earnings over the job spell.[35]

I estimate regressions analogous to Equation 10, replacing the outcome with y_{ijot} (one of the match quality measures), and compare workers entering the same firm in the same year while including the same covariates and fixed effects as in the main specification. $\mathbb{1}$(1st-year separation) equals one if the worker leaves the firm within a year, and $\mathbb{1}$(Stay in $t+3$) indicates remaining in the firm after three years. Within-job earnings are total earnings accumulated over the employment relationship. Wage growth is defined as the three-year change in log wages among workers who remain in the same firm.[36]

Table 4 reports the results. Column (1) shows that first-year separation is 1.2 percentage points (11 percent) lower for new job entrants than for expanding old job entrants. Column (2) shows that the probability of remaining at the firm after three years is 1.6 percentage points higher (3.5 percent). Three-year wage growth does not differ systematically across job types, implying that the initial entry wage premium persists over the spell without clear convergence or divergence.

The final column shows that entrants into new jobs earn 8.4 percent more over the job match, corresponding to roughly 40,000 SEK (approximately €4000). Because within-job earnings reflect hours worked, tenure, and hourly wages—and because wage growth is similar across jobs—the combination of higher entry wages and longer tenure yields sizable differences in cumulative earnings. These patterns are consistent with the model's prediction that higher reservation productivity in new jobs leads to higher match quality.

[35]Some commonly used measures of match quality rely on workers' subjective assessments (e.g., job satisfaction), which are typically unavailable in administrative data (Belot et al., 2024).

[36]The sample is reduced to roughly one-quarter of the original size because wage data are sampled, and within-job wage growth is observed only for workers who remain in the same job for three years.

5.8 Heterogeneity by occupational similarity

The theoretical model in Section 2 predicts a new job wage premium arising from information frictions: pre-hire uncertainty about match productivity leads workers and firms to apply different acceptance thresholds in new jobs. A key implication is that both the wage premium and selection on observables should be larger when the new job is in an occupation dissimilar to those the firm already employs, because the firm can draw less on prior experience. In contrast, if the premium primarily reflects differences in marginal productivity or broad shifts in demand for particular worker skills, one would expect similar and dissimilar new jobs to exhibit comparable premia and similar observable composition.

To distinguish between these two channels, I exploit variation in how similar a newly introduced occupation is to the firm's existing occupations, using two measures of occupational similarity. The first is based on the skill content of occupations. I measure similarity using 35 skills from the O*NET database (version 15.1, February 2011) on the *level* scale, which capture the proficiency required in each skill for a given occupation, after mapping O*NET occupations to ISCO-88 via standard crosswalks (Hardy et al., 2018).[37] Each occupation o is characterized by a standardized skill vector $s_o = (s_{o1}, \ldots, s_{oK})$, where s_{ok} denotes the level score of skill k in occupation o. I compute pairwise similarity using the cosine of the angle between skill vectors, following Gathmann and Schönberg (2010):

$$\text{AngSep}_{oo'} = \frac{\sum_{k=1}^{K} s_{ok} \times s_{o'k}}{\left[\left(\sum_{k=1}^{K} s_{ok}^2\right) \times \left(\sum_{k=1}^{K} s_{o'k}^2\right)\right]^{1/2}}, \tag{14}$$

and define occupational distance as $\text{Dis}_{oo'} = 1 - \text{AngSep}_{oo'}$. The measure equals zero for occupations with identical skill profiles, one for occupations with orthogonal profiles, and takes larger values when occupations have negatively correlated skill requirements.[38] For each new job in occupation d, I assign the minimum distance to the firm's closest existing occupation: $\text{skill distance}_d = \min_{o \in \mathcal{O}_{\text{firm}}} \text{Dis}_{od}$. I classify a new job as *similar* if its skill distance falls below the median among all new jobs, and as *dissimilar* otherwise. The measure is set to zero for hires into existing occupations.

Table 5 reports results using the skill-based measure, classifying new jobs as *similar* (below median skill distance) or *dissimilar* (above median) relative to the firm's closest existing

[37] Appendix Table C14 shows the list of skills. I use version 15.1 (February 2011) because my sample period ends in 2013. Twelve SSYK-96 3-digit codes lack a direct O*NET counterpart due to gaps in the O*NET–SOC crosswalk coverage. These codes are mapped to the nearest ISCO-88 occupation based on the classification hierarchy. Results are robust to excluding these observations.

[38] Results are robust to using Euclidean and Manhattan distance metrics on the same skill vectors (Macaluso, 2025), and to computing distance separately on O*NET work activities and work context domains.

occupation. Column (1) shows that both similar and dissimilar new jobs are associated with an entry wage premium, but the premium is nearly twice as large for dissimilar new jobs (4.2 percent versus 2.3 percent). A Wald test rejects the equality of these two coefficients (p-value = 0.003). Columns (2)–(4) document that dissimilar new jobs exhibit substantially stronger selection: they are 4 percentage points more likely to be filled by job-to-job movers (compared to 1.3 for similar), 11 percentage points more likely to hire experienced workers (compared to 7.3 for similar), and 1 percentage point less likely to draw from long-term unemployment. The differences between similar and dissimilar new jobs are statistically significant for entry wages, job-to-job hiring, and experience selection (p-values below 0.01), though not for long-term unemployment (p-value = 0.27). These patterns confirm that when the skill content of the new occupation is more distant from the firm's existing workforce, both the wage premium and the selectivity increase, consistent with the information frictions interpretation.[39]

The second measure is based on observed worker transitions between occupations, following Belot et al. (2019) and Le Barbanchon et al. (2023a). Using Swedish administrative data from 1996 to 2013, I compute destination-normalized transition shares $\tau_{od} = \frac{N_{od}}{\sum_{o'} N_{o'd}}$, which capture the fraction of inflows into occupation d coming from origin o. For each new job, I assign a best-match distance to the firm's pre-existing occupational structure: best match distance $= 1 - \max_{o \in \mathcal{O}_{\text{firm}}} \tau_{od}$. I classify a new job as *similar* if the best-match distance is at most 0.75, and as *dissimilar* otherwise.[40] This transition-based measure captures revealed proximity between occupations—two occupations are similar if workers frequently move between them—which plausibly reflects overlap in underlying skill requirements. However, unlike the skill-based measure, it may also be influenced by labor market conditions such as the geographic co-location of industries or institutional features of career ladders.

Table C15 reports results using the transition-based measure. The patterns are consistent with those from the skill-based measure: the entry wage premium is larger for dissimilar new jobs, and dissimilar new jobs exhibit stronger selection on job-to-job status and experience.

The fact that both measures—one based on the intrinsic skill content of occupations and the other on revealed worker mobility patterns—yield consistent results strengthens the interpretation that occupation-specific uncertainty drives the observed patterns. These findings support the view that it is not merely the newness of the occupation to the firm that matters, but the degree of skill novelty the firm faces when introducing the role.

[39] Using a continuous measure of skill novelty yields consistent results (Appendix Table C16). Skill novelty is defined as one minus the cosine similarity between the new occupation and the firm's closest prior occupation, so higher values indicate lower similarity. The distribution of the measure has a median of 0.19 and an interquartile range of approximately 0.09 to 0.36. In column (1), the estimated coefficient implies that a 0.1 increase in skill novelty is associated with about 0.5 percent higher entry wages.

[40] The cutoff is guided by the distribution of transition shares: across destination occupations, the mean top-origin share is about 0.26, so $\tau_{\text{best}} \geq 0.25$ captures a typical dominant transition pathway.

6 Alternative theories and interpretations of results

In this section, I consider alternative theories and mechanisms that could generate the new job wage premium. The first is compensating wage differentials: if newly created jobs bundle unobserved disamenities that are not absorbed by firm or occupation fixed effects, higher entry wages could reflect compensation. The second is promotion dynamics and team-building responsibilities: early hires may receive higher wages because they are expected to build teams or because their promotion prospects differ. The third is monopsonistic competition: if wages increase with firms' hiring rates, the premium may be explained by firm growth. And the last one is regarding the possibility of task reallocation within firms.

6.1 Compensating wage differentials

Jobs differ along many dimensions, and wages can partly reflect compensation for non-wage attributes (Rosen, 1986; Lavetti, 2023; Mas, 2025). This raises the possibility that the new-job wage premium reflects compensating differentials. If newly created jobs bundle disamenities that are not observable in the register data and are not absorbed by firm or occupation fixed effects, then the new job wage premium could reflect compensation rather than higher match productivity. I assess this possibility using turnover and other job characteristics.

The turnover results is difficult to reconcile with the theory of compensating differentials. Table 4 shows that entrants into new jobs have longer tenure than comparable entrants into old jobs. This difference persists even after conditioning on entry wages (Appendix Table C13). If the premium merely compensates workers for job-specific disamenities, turnover should not be systematically lower among new-job entrants, especially conditional on wages.

A salient feature of new jobs is, however, the low number of workers during the first year of employment. Figure 6 shows that new jobs are more likely to employ single worker. Approximately 80% of new jobs consist of a single worker in their first year. Working in small teams may be an undesirable job feature because, e.g., due to weaker peer support. It may also increase firms' costs of worker absences when there are few internal substitutes (Hensvik and Rosenqvist, 2019). To assess whether small job size can account for the new job wage premium, I examine heterogeneity by job size at entry. If the premium is compensation for being in a small job, it should decline as job size at entry increases.

Table 6 reports the results. Column (1) shows that conditioning on job size at entry leaves the new job wage premium essentially unchanged. Moreover, the interaction term between the new job indicator and job size at entry is economically small and statistically insignificant, implying that the premium does not vary systematically with initial team size. Column (2)

shows the coefficients how entry wages differ when a new hire enters a newly created job cell of size 1–5 relative to expanding old jobs. Even though single-worker new jobs do earn a positive wage premium, the premium is of similar magnitude for new jobs that begin with multiple workers, and it does not decline systematically with initial job size. The absence of such gradient suggests that uniqueness is unlikely to be the primary driver of the new job wage premium (Azmat et al., 2025).

I also examine whether contract types differ between old and new jobs. Column (3) in Table 6 tests for differences in full-time status. The coefficient on the new job indicator is positive but small and statistically insignificant, indicating no meaningful difference in the likelihood of being hired into a full-time position across job types. Finally, column (4) examines differences in overtime work. New job entrants are 2.7 percentage points (13 percent) less likely to work overtime than entrants into old jobs. If anything, this finding runs counter to a compensating differentials interpretation based on job intensity as they appear to be less demanding in terms of overtime work.

6.2 Role content, team-building, and promotion dynamics

A leading alternative interpretation of the new job wage premium is that the first hire into a new occupation performs a different role than later hires under the same occupation code. When a firm introduces a new role, the first hire may be expected to build the team and responsibilities from scratch: establishing routines, designing processes, and coordinating with other departments. This would make the role *different* than subsequent hires into the same occupation, generating both higher wages and more selective hiring without any appeal to information frictions. Since occupation codes, even at the 3- or 4-digit level, cannot fully capture within-occupation variation in task content, the data cannot directly rule out this possibility. However, the broader pattern of results is difficult to reconcile with a pure role-content explanation.

First, if the premium reflects a difference in responsibilities between the first hire and later hires, it should decline sharply once the job is established—most plausibly after the first or second year. Figure 3 shows that the premium instead declines gradually with job age and does not become statistically indistinguishable from zero until years six to eight. This time profile is more consistent with a process of uncertainty resolution than with a difference in task content.

Second, Table 6 shows that the premium does not vary with initial job size. If the "founder" interpretation were correct, single-worker new jobs would represent the purest case of a founding role, and the premium should decline as initial team size increases and founding responsibilities

are shared across multiple entrants. No such gradient is observed.

Third, the occupational similarity results in Table C15 show that the premium is larger when the new occupation is more dissimilar to the firm's existing workforce. The role-content interpretation does not have a clear prediction here: establishing routines for an accounting function should not be inherently more demanding when the firm previously had no similar occupations. By contrast, the information frictions interpretation predicts this pattern directly, because dissimilar occupations are precisely those where the firm's prior employment experience is least transferable.

Alternatively, newly created roles could offer different promotion prospects or entail team-building responsibilities. I examine two proxies for the team-building and promotion channels directly. First, I proxy team-building responsibilities with subsequent job growth. If early hires are compensated for establishing and staffing a new role, the entry premium should be driven by jobs that expand in subsequent years. I therefore estimate regressions that include indicators for (i) promotion to a managerial position within the firm during any of the first three years and (ii) whether the job expands in subsequent years (i.e., employment in the same firm–occupation job increases after entry). All specifications continue to compare new jobs to expanding old jobs within the same firm and year, conditional on occupation-by-year effects.

Table 7 shows that conditioning on whether the worker is subsequently promoted to a managerial position within the firm does not attenuate the new job wage premium. If early hires into new jobs were compensated for taking on managerial-type founding responsibilities, the premium should be at least partly absorbed by this control. Similarly, conditioning on whether the job expands in subsequent years—a proxy for whether the initial hire was expected to build a team—has no effect on the estimated premium.

Taken together, these results suggest that while some degree of task differentiation between first and later hires is plausible, the overall constellation of findings—a gradually declining premium, no job-size gradient, a similarity gradient, and no absorption by promotion or expansion controls—is difficult to generate from role content alone. The patterns are instead consistent with information frictions that resolve as firms accumulate occupation-specific employment experience.

6.3 Monopsony

Schmieder (2023) shows that higher entry wages at newly established firms are largely explained by faster employment growth, consistent with monopsonistic competition.[41] In line

[41] Under monopsonistic competition, firms face an upward-sloping labor supply curve, implying a positive relationship between wages and hiring rates (Manning, 2003).

with his main finding, Table 2, Panel A, column (3) shows that firm growth is positively associated with entry wages. However, Panel B of the same table shows that entrants into new jobs earn more than entrants into expanding old jobs within the same firm-year. Since time-varying firm effects absorb firm-level hiring conditions in a given year, monopsony may help explain cross-firm differences in entry wages but cannot account for the new job wage premium.

To further assess the plausibility of the monopsony channel, I examine whether firms that introduce new jobs pay higher wages to all of their workers compared to other expanding firms, following the approach used in Schmieder (2023). If new job creation reflects solely an increase in desired employment, one expects higher wage offers for marginal hires—including hires into old jobs (Kline, 2025). I test this using a firm-level event study:

$$ln\, w_{jt} = \sum_{\tau=-3}^{3} \gamma_\tau \mathbb{1}(\text{New Job}_{j,t+\tau}) + \alpha_j + \lambda_t + \varepsilon_{jt}, \tag{15}$$

where the term $\sum_{\tau=-3}^{3} \gamma_\tau \mathbb{1}(\text{New Job}_{j,t+\tau})$ captures the effect of introducing a new job within the firm, where (τ) indicates different time periods relative to the event. $\mathbb{1}(\text{New Job}_{j,t+\tau})$ represents an indicator function which takes value one if the firm introduces a new job in year t. Firm fixed effects α_j absorb time-invariant firm heterogeneity and year fixed effects λ_t capture aggregate trends. The coefficients (γ_τ) measure how the average wage changes τ periods before and after. Finally, ε_{jt} is the idiosyncratic error term, capturing unexplained variation in average wages within firms.

Panel (a) and (b) in Figure 7 show the event study estimates where the outcome is the average wages per worker of all and incumbent workers only, respectively. Firms that introduce new jobs do not differ in average pay from other firms. Panel (c) and Panel (d) of the same figure shows the evolution of average wages firms pay to newly hired workers including and excluding new jobs, respectively. Panel (c) shows that firms that create new jobs pay new hires on average 2 percent higher wages. Since new hires include new job entrants as well as old job entrants, this finding is not surprising and consistent with the new jobs wage premium estimates documented in Table 2.

A more direct test is to examine whether firms pay other hires to old jobs more compared to other firms. Figure 7 Panel (d) shows no such difference: firms that introduce new jobs offer comparable wages to new hires into old jobs. Moreover, the event study reveals no differential trends in wages in the pre- or post-periods relative to firms that expand only along existing occupations. Overall, the event-study evidence provides limited support for an explanation based on monopsonistic competition operating through firm-level hiring intensity or firm-wide

pay differences. Instead, the evidence is more consistent with a premium that is specific to entrants into newly created jobs.

6.4 Task reallocation within firms

The within-firm design compares newly created roles to existing roles within the same firm-year. A natural concern is that introducing a new occupation may reallocate tasks across jobs, altering the composition of the comparison group. The estimated coefficient therefore reflects the wage difference between new and existing roles after any reallocation within the firm, and should be interpreted as an equilibrium object rather than a pure ceteris paribus comparison.

Two pieces of evidence suggest that such reallocation is limited. First, the firm-level event studies in Figure 7 show that neither incumbent wages (Panel b) nor entry wages into existing occupations (Panel d) respond when a new occupation is introduced. While task reallocation need not mechanically translate into wage changes, the absence of any systematic wage response suggests that large shifts in responsibilities are unlikely. Second, within-job wage growth does not differ systematically between new and old jobs (Table 4, column 3). If firms were actively reorganizing task assignments after introducing new roles, one would expect divergence in wage growth trajectories, which is not observed.

More broadly, newly created roles may function as complements, substitutes, or largely independent additions to existing roles. The absence of wage adjustments among incumbents is most consistent with new roles being either weak complements or largely independent expansions, rather than strong substitutes that would reallocate core tasks across jobs. Taken together, the evidence suggests that the estimated premium primarily reflects differences in the task content of new roles rather than changes in the comparison group.

7 Conclusion

Previous research has documented that workers experience diverse labor market outcomes influenced by firm and individual job match characteristics. However, the precise mechanisms that drive these differences are largely unknown. In particular, no prior research has explored how information frictions due to limited employment experience in a particular occupation lead to differential match outcomes and cause earnings inequality among similar workers.

In this paper, I introduce a new perspective on hiring frictions by studying how firms make their first hire into newly created roles within firms, and what this implies for match outcomes. I provide the first evidence on the impact of firms' employment experience in a particular occupation on firms' employee selection, wages, and match outcomes. My findings underline

that hiring frictions lead to diverse labor market outcomes among equally productive workers, highlighting the critical role of information frictions in shaping workers' labor market outcomes.

My findings reveal several key insights. I demonstrate that these information frictions affect firms' hiring decisions which has implications for wage setting, worker reallocation and match quality. Firms select workers based on observables (job movers and more experienced) to reduce the inherent uncertainty associated with new jobs. Match quality is higher in new jobs and workers entering new jobs obtain better labor market outcomes which are not attributable to unobserved differences across workers. Workers who are employed in the same occupation and industry are paid differently across firms because of different employment histories within firms. The paper contributes to our understanding of one the mechanisms that leads to wage inequality by emphasizing the importance of demand-side information frictions.

The mechanisms I document imply additional frictions associated with expanding a firm's occupational structure. Thus, my paper also sheds light on the hiring uncertainties related to the structural change in the economy (Autor et al., 2024). If firms want to move in a new direction—such as through technological change or growth—they must hire new types of workers and offer higher wages, making labor adjustments more costly. These adjustment costs can, in turn, slow down the pace of structural transformation. It is reasonable to expect that the mechanisms I highlight are going to be important given the change in technological advances is becoming more prevalent.

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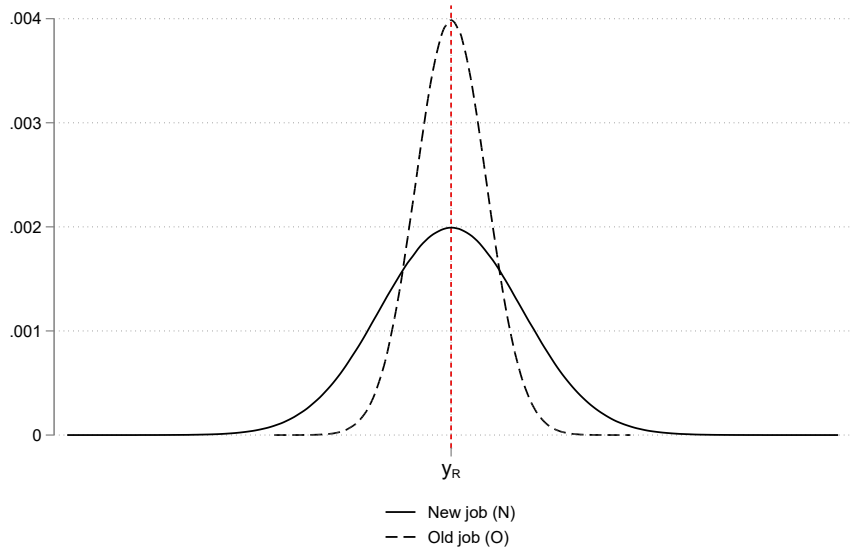
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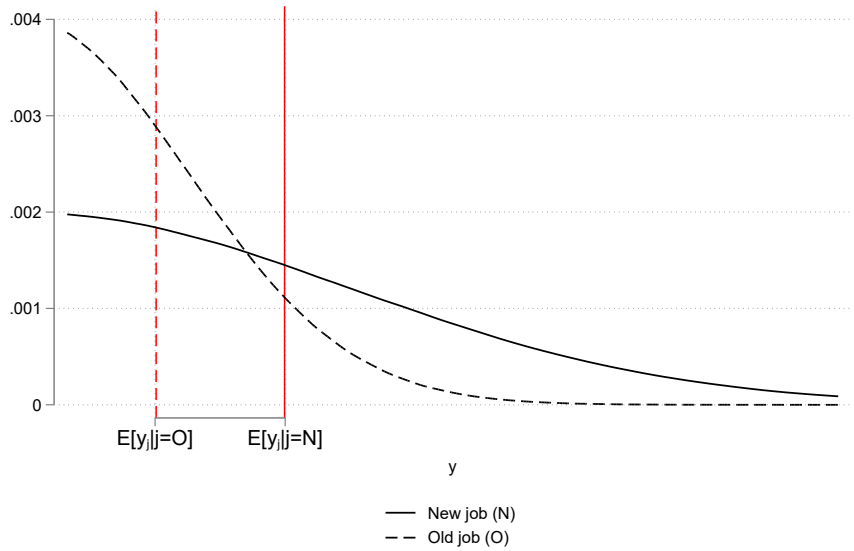
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8 Figures and Tables

Figure 1: Ex-ante and ex-post match productivity distributions



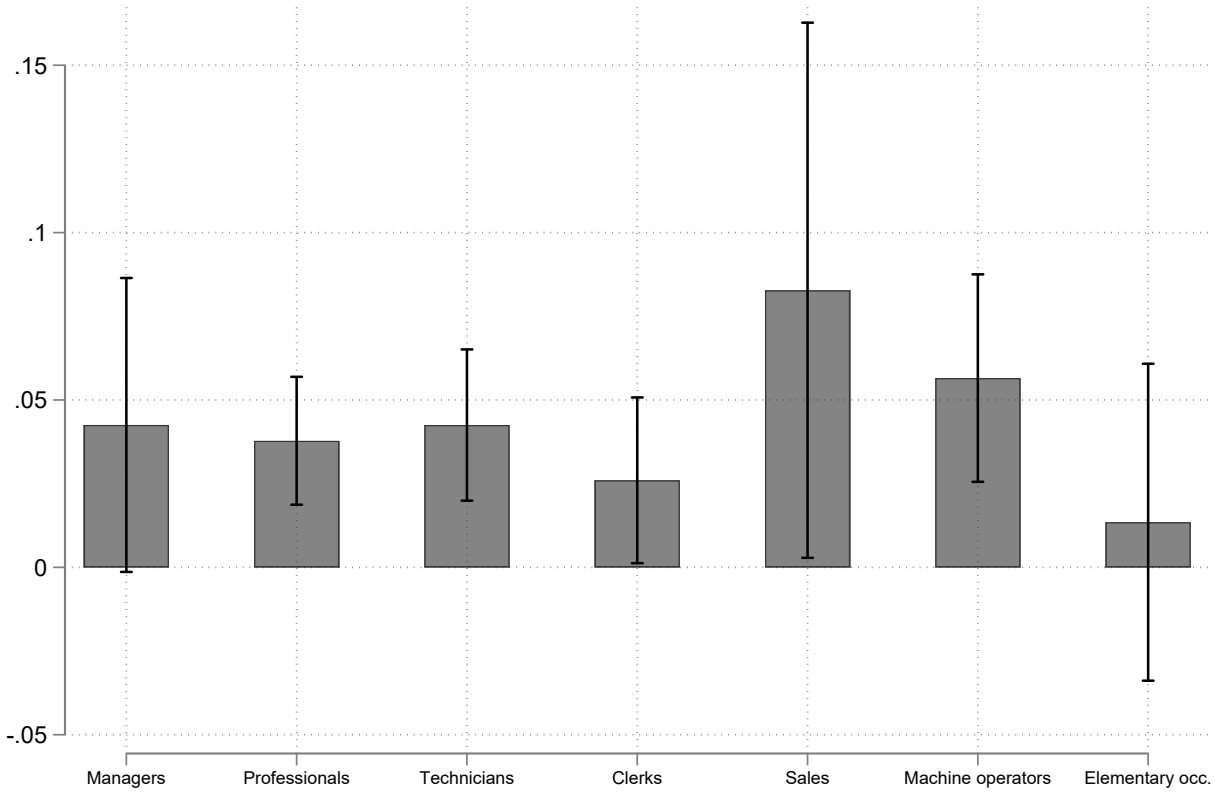
(a) Ex-ante productivity distribution



(b) Ex-post productivity distribution

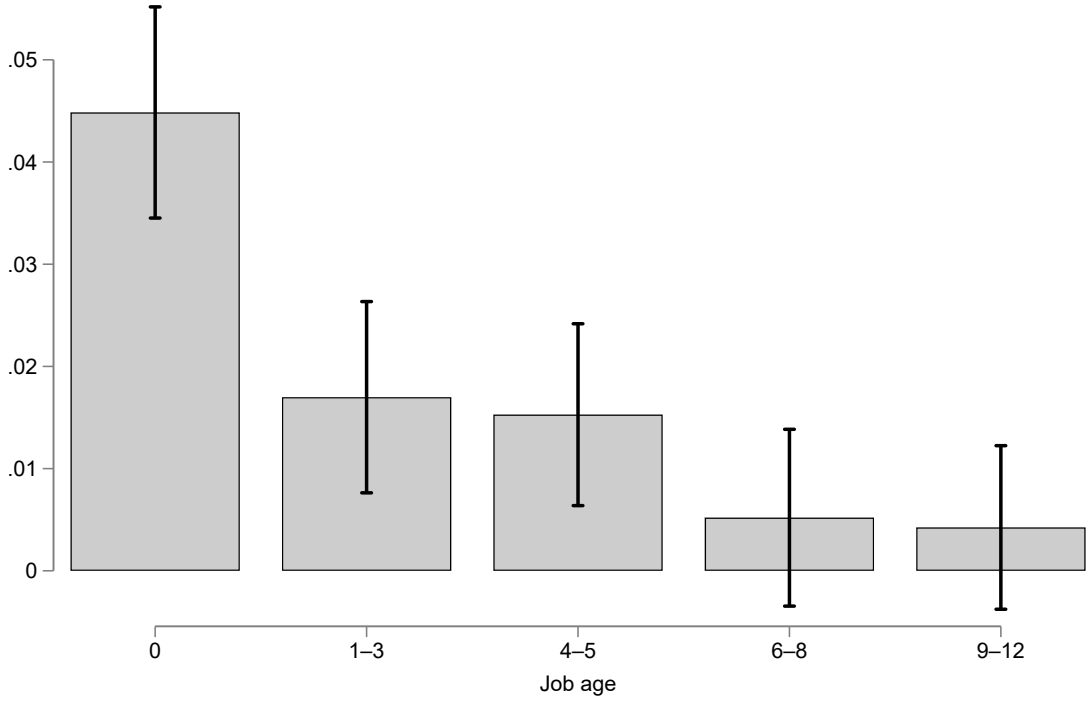
Notes: This figure illustrates the key intuition of the model, ex-ante and ex-post match productivity distributions for new and old jobs (shown by solid and dashed lines, respectively). Panel (a) shows that ex-ante, expected productivities are the same across new and old jobs. Panel (b) presents ex-post match productivities conditional on match formation. The dashed red line depicts match productivity in the old job, while the solid red line represents match productivity in new jobs.

Figure 2: New job wage premium: Heterogeneity by occupation



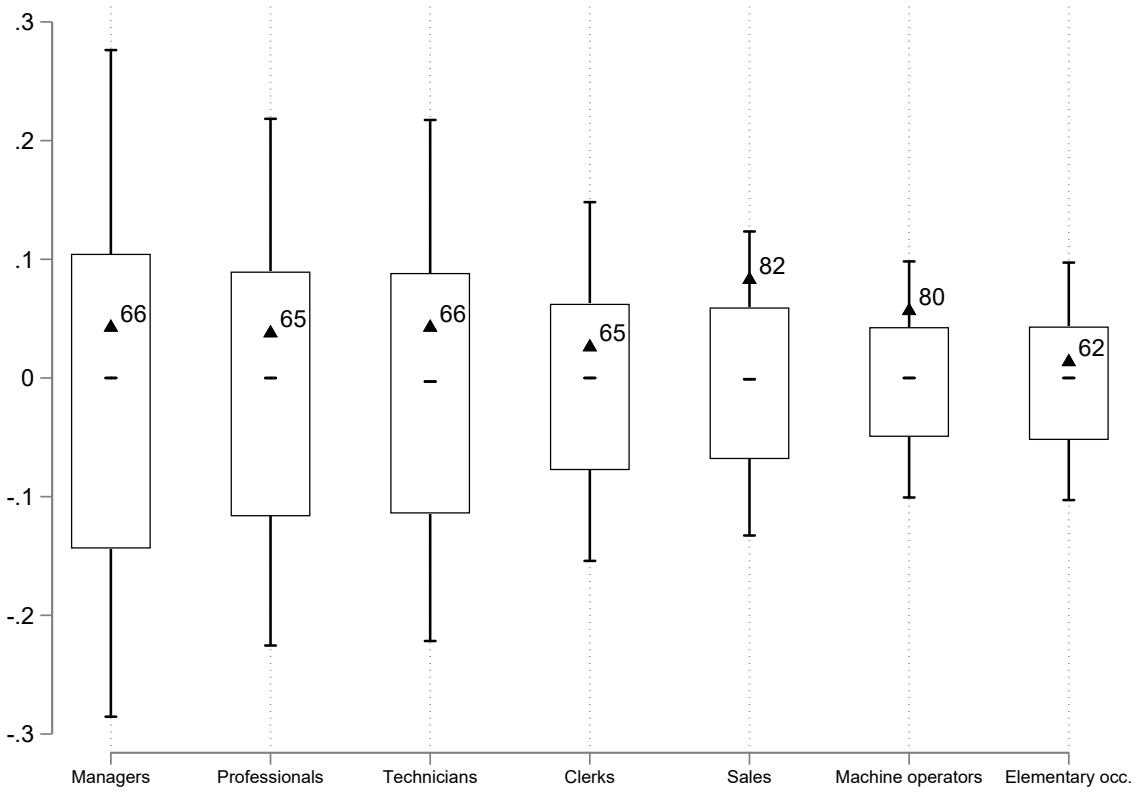
Notes: This figure shows new job wage premium across broad occupation groups. I group workers according to ISCO (International Standard Classification of Occupations) codes. I then estimate Equation (10) separately for each occupation. Each regression controls for occupation-by-year fixed effects, firm-by-year fixed effects, age fixed effects, experience, nine education level fixed effects, and gender. Whiskers indicate 95% confidence intervals. Standard errors are clustered by firm. I do not have sufficient data on workers in the military (ISCO 10), in agricultural occupations (ISCO 6), and in craftsmen (ISCO 7).

Figure 3: Job age-wage profile



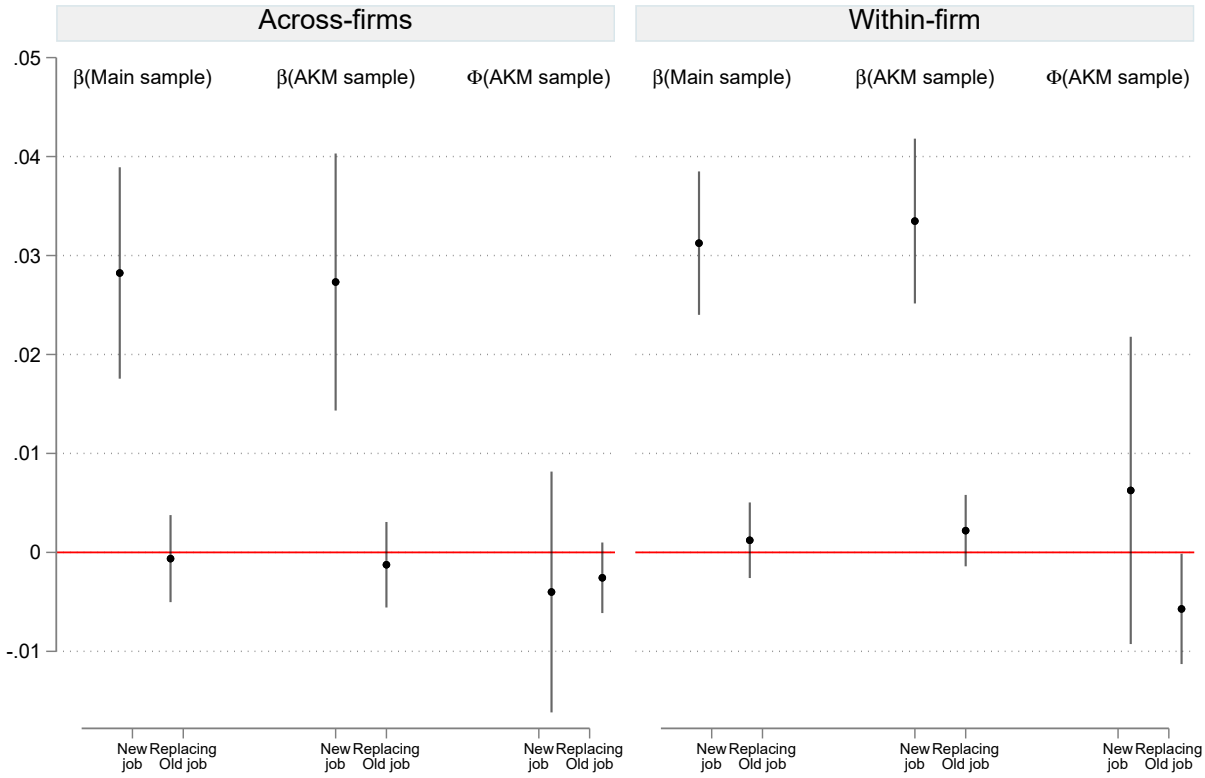
Notes: This figure plots coefficients from a regression of log wages on job age categories where job age is defined as the number of years since a given firm–occupation pair is first observed, computed as the current year minus the first year that firm–occupation appears in the data. I group job age into six bins (0; 1–3; 4–5; 6–8; 9–12; 13+) and estimate the main specification omitting the last job age category. The estimation sample is identical to the one reported in Table 2 where job age 0 corresponds to a new job in the main specification and old jobs are grouped into job-age bins based on the number of years the firm–occupation pair has existed. The omitted (reference) category is job age with 13+ years. Bars report the estimated wage differentials relative to this reference group; whiskers denote 95% confidence intervals. I cluster standard errors at the firm–year–occupation level.

Figure 4: Residual wage dispersion and the distributional magnitude of the new job wage premium



Notes: This figure shows the residual wage dispersion for each occupational group and the size of the new job wage premium in distributional terms. The vertical whiskers span the 10th to the 90th percentile, while the box covers the inter-quartile range from the 25th to the 75th percentile. The short horizontal dash in the middle of each box marks the median. Triangles and adjacent numbers. For each occupation, the triangle marker and its percentile label indicate to which percentile a median worker's position in the within-occupation residual wage distribution would shift when moving into a new job.

Figure 5: Estimates of new job wage premium and sorting parameter



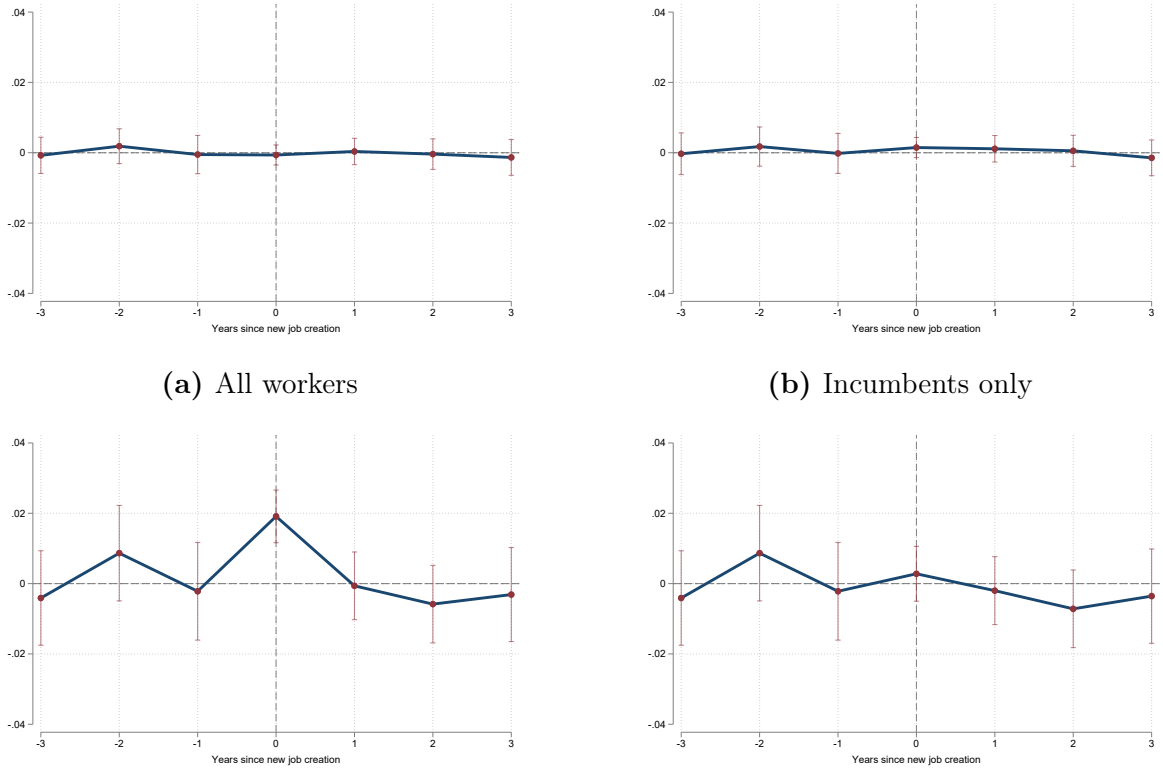
Notes: The figure plots entry-wage differentials from both the baseline and AKM samples, together with ϕ estimates from Equation 13. The left panel reports β estimates across firms; the right panel reports β estimates within firms. In each panel, the first two set of points correspond to β estimated on the main sample and on the pre-dated AKM sample, respectively. The third set of points show ϕ from Equation 13, based on the pre-dated AKM sample. All regressions include the same individual- and firm-level controls as in the main specification. Standard errors are clustered at the 3-digit industry level for the across-firm estimates and at the firm level for the within-firm estimates.

Figure 6: Job employment size distribution at entry



Notes: The figure shows job employment size distribution among new hires (workers with tenure=0). A "job" is defined at the firm × occupation × entry-year level. Job size is the number of workers employed in that firm–occupation cell in the entry year, grouped into the size bins shown in the x axis. Bars report the fraction of new hires entering jobs of each size, separately for (i) new jobs (newly created firm–occupation cells), (ii) old jobs (expansion) (hires into pre-existing cells that are expanding at entry), and (iii) old jobs (replacement) (hires into pre-existing cells without net expansion at entry). Fractions are computed within each job types.

Figure 7: Firm-level event studies - wage per worker



(a) All workers

(b) Incumbents only

(c) New hires only

(d) New hires excluding new jobs

Notes: The figure shows the event study estimates of the γ_τ parameters in Equation (15), together with the 95% confidence intervals. The regressions control for industry-by-time fixed effects and firm size categories. Standard errors are clustered at the firm level. The treatment is the introduction of new job at the firm. The control group consists of firms that expand along an old job. Sub-panels (a)-(d) show changes in log wages per worker among a) all workers, b) incumbents, c) new hires including new and old jobs, and d) new hires excluding new jobs, before and after the introduction of the new job, respectively.

Table 1: Sample statistics of new hires

Panel A. Workers	All entrants (1997-2013)			
	New job (N)	Old job (E)	Old job (R)	All
ln(entry wage)	10.0	9.92	9.91	9.92
1st-year separation	0.088	0.11	0.13	0.11
Age	39.4	34.1	32.6	33.7
Female	0.41	0.44	0.47	0.45
Experienced	0.65	0.43	0.38	0.42
Tenure (months)	61.0	55.0	48.8	53.3
Education				
Compulsory or less	0.16	0.14	0.13	0.14
High school	0.52	0.52	0.52	0.52
College	0.33	0.34	0.35	0.34
Occupations				
Managers	0.073	0.036	0.040	0.038
Professionals	0.14	0.15	0.12	0.14
Technicians and associate professionals	0.18	0.16	0.17	0.16
Clerks	0.17	0.11	0.12	0.11
Service workers and shop sales workers	0.058	0.20	0.23	0.20
Skilled agricultural and fishery workers	0.014	0.0043	0.0067	0.0051
Craft and related trades workers	0.11	0.078	0.077	0.078
Plant machine operators and assemblers	0.16	0.13	0.12	0.13
Elementary occupations	0.099	0.13	0.11	0.13
# of distinct jobs (firm x occupation)	10520	47971	30816	
Observations	22298	1236817	506397	1765512
Panel B. Firms				
Young firm (<10y)	0.43	0.33	0.30	0.42
Firm size	35.9	62.5	70.9	60.3
log(value added per worker)	13.1	13.1	13.1	13.1
# of 3-digit occupations	5.03	5.33	5.67	6.56
# of new hires	8.09	8.71	8.80	13.6
# of new hires to new jobs	1.48	0.23	0.19	1.68
# of new hires to expanding old jobs	5.24	6.72	4.94	9.43
# of new hires to replacing old jobs	1.36	1.76	3.66	2.45
Observations	9486	48199	44468	7805

Notes: Panel A shows mean statistics at the worker-year level of new hires in the estimation sample. Columns 1–4 in Panel A represent new hires in a new job, in an expanding old job, in replacing old jobs, and all hires, respectively. The observations are at the firm-year level. Columns 1–4 in Panel B represent firm characteristics among firms that hire into new jobs, expanding old jobs, replacing old jobs, and firms that hire both to new and old jobs, respectively.

Table 2: New job wage premium

Dependent var: ln(Entry Wage)				
Panel A. Across-firms	(1)	(2)	(3)	(4)
Omitted category: Expanding old jobs				
New job	0.028***	0.027***	0.030***	0.028***
	(0.0055)	(0.0054)	(0.0050)	(0.0044)
Old job (Replacing)	-0.00053	0.0015	0.0043**	-0.0011
	(0.0023)	(0.0021)	(0.0015)	(0.0011)
log(Firm size)	-0.00082	-0.00084	0.00071	-0.00081
	(0.0016)	(0.0016)	(0.0013)	(0.00080)
Firm growth rate (DHS index)		0.0088**	0.0074**	0.0032
		(0.0030)	(0.0028)	(0.0017)
log(value added per capita)			0.037***	0.014***
			(0.0037)	(0.0015)
Observations	1765512	1765512	1523783	1523783
Adjusted R^2	0.746	0.746	0.763	0.780
Occupation x LLM x Year FE	✓	✓	✓	✓
Industry x Year	✓	✓	✓	✓
Worker FE				✓
Panel B. Within-firm	(1)	(2)	(3)	(4)
Omitted category: Expanding old jobs				
New job	0.031***	0.030***	0.038***	0.029***
	(0.0038)	(0.0037)	(0.0041)	(0.0061)
Old job (Replacing)	0.0012	0.0014	0.00042	-0.0019*
	(0.0020)	(0.0020)	(0.0025)	(0.00093)
J2J mover		0.033***		
		(0.0011)		
Observations	1765512	1765512	1765512	1765512
Adjusted R^2	0.783	0.784	0.791	0.805
Occupation x LLM x Year FE	✓	✓	✓	✓
Firm x Year FE	✓	✓		
Firm x Year x Skill FE			✓	
Firm FE				✓
Worker FE				✓

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. This table presents baseline estimates of new job wage premium. Dependent variable is log entry wages. The estimates of "New Job" shows the difference in entry wages between new job entrants and expanding old job entrants. Each column represents a separate regression and all regressions flexibly control for age, gender, labor market experience, and education. Standard errors clustered at 2-digit industry level for regressions in Panel A, and at firm level for regressions in Panel B. There are fewer observations in panel A column 3 and 4 than in columns 1-2 because the value added is only available for non-financial corporations in Sweden (in real SEK for the base year 2006).

Table 3: Firms' differential employee selection

Dependent variable:	**1**(J2J Mover)	**1**(Long-term Unemployed)	**1**(Experienced)
	(1)	(2)	(3)
Omitted category: Expanding old jobs			
New job	0.025***	-0.0066**	0.088***
	(0.0049)	(0.0032)	(0.0062)
Old job (Replacing)	-0.0040**	0.0036***	0.00094
	(0.0017)	(0.0010)	(0.0026)
Observations	1765512	1765512	1765512
Adjusted R^2	0.205	0.081	0.346
Mean dependent variable	.71	.12	.42
Occupation x LLM x Year FE	✓	✓	✓
Firm x Year FE	✓	✓	✓

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. This table shows differences in labor market status and experience at the time of hiring between new and old job entrants in the private sector, spanning the years 1997 to 2013. The outcome variables *J2J Mover* and *Long-term Unemployed* are binary indicators where the former equals one for individuals who are job-to-job movers, whereas the latter equals one for individuals who have been unemployed for more than one year. *Experienced* is defined as a binary indicator that takes the value one for individuals with more than ten years of labor market experience. Columns (1) and (2) show the estimation results flexibly controlling for age, experience, gender, and 9-education level controls in addition to occupation-by-year and firm-by-year fixed effects. Column (3) excludes age and experience controls. Standard errors clustered at the firm level. The estimates of "New Job" shows the difference in outcome variables between new job entrants and old expanding job entrants at the time of hiring.

Table 4: Post-hiring outcomes

Dependent variable:	**1**(1st-year separation)	**1**(Stay in t+3)	3-year wage growth	sd(wage)	Within-job earnings$_{ij}$
	(1)	(2)	(3)	(4)	(5)
Omitted category: Expanding old jobs					
New job	-0.012***	0.016**	0.00012	-0.0026	0.084***
	(0.0032)	(0.0063)	(0.0013)	(0.0022)	(0.023)
Old job (Replacing)	0.00027	-0.0011	0.00025	0.00031	0.0017
	(0.0012)	(0.0021)	(0.00046)	(0.00070)	(0.0073)
Observations	1765512	1765512	474353	474353	1765512
Adjusted R^2	0.245	0.274	0.293	0.329	0.451
Mean dependent variable	.11	.47	.04	.09	13.09
Occupation x LLM x Year FE	✓	✓	✓	✓	✓
Firm x Year FE	✓	✓	✓	✓	✓

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. This table presents differences in post-hiring outcomes among entrants into new and old jobs. *1st-year separation* is a binary indicator for whether an entrant separates from the firm within the first twelve months of employment. *Stay in* $t + 3$ indicates whether the entrant remains with the firm for at least three years. *3-year wage growth* and *sd(wage)* capture the average wage growth and the standard deviation of wages within the match, respectively. *Within-job earnings* represents the total earnings accumulated within a given match. Note that Columns (3) and (4) have fewer observations, as they focus on employees who stayed for at least three years. All regressions include the same set of fixed effects and individual-level covariates as in the main specification, and standard errors are clustered at the firm level.

Table 5: New job outcomes by skill similarity: Angular distance

	Entry wages	**1**(J2J Mover)	**1**(Long-term Unemployed)	**1**(Experienced)
	(1)	(2)	(3)	(4)
Omitted category: Expanding old jobs				
New job – **1**[Similar]	0.023***	0.013**	-0.0036	0.073***
	(0.0051)	(0.0063)	(0.0040)	(0.0077)
New job – **1**[Dissimilar]	0.042***	0.040***	-0.010**	0.11***
	(0.0049)	(0.0068)	(0.0048)	(0.0089)
Observations	1765512	1765512	1765512	1765512
p-value (Similar = Dissimilar)	0.0034	0.0024	0.27	0.0019
Mean dependent variable		.71	.12	.42
Fixed effects				
Occupation x LLM x Year FE	✓	✓	✓	✓
Firm x Year FE	✓	✓	✓	✓

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. The table reports results for the new job wage premium and employee selection separately for *similar* and *dissimilar* new jobs. Similarity is measured using the angular separation (Gathmann and Schönberg, 2010) between standardized O*NET skill vectors (level scale, 35 dimensions). New jobs are classified as *similar* (below median distance) or *dissimilar* (above median distance) relative to the firm's closest existing occupation. The omitted category is expanding old jobs. The regressions include the same control variables as in Equation 10.

Table 6: Job characteristics and the role of compensating differentials

Dependent variable:	ln(entry wage)		**1**(Full-time)	**1**(Over-time)
	(1)	(2)	(3)	(4)
Omitted category: Old jobs				
New Job	0.032***		0.0082	-0.027***
	(0.0036)		(0.0053)	(0.0052)
New job - Unique worker		0.036***		
		(0.0025)		
New job - 2 workers		0.042***		
		(0.0051)		
New job - 3 workers		0.023***		
		(0.0071)		
New job - 4 workers		0.036***		
		(0.0096)		
New job - 5 workers		0.059***		
		(0.011)		
New Job x Job size$_{jot}$	-0.000078			
	(0.00012)			
Observations	1765512	1757439	1765512	1765512
Adjusted R^2	0.783	0.784	0.504	0.291
Mean dependent variable			.75	.2
Occ x LLM x Year FE	✓	✓	✓	✓
Firm x Year FE	✓	✓	✓	✓

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. This table shows the new job wage premium conditional on job size at entry, and job characteristics that may help explain differences in job characteristics between old and new jobs. The dependent variables in columns (1) and (2) are log entry wages, while columns (3) and (4) use indicators for full-time employment and working overtime, respectively. Job size$_{jot}$ refers to the number of workers at entry. Column (1) shows the new jobs wage premium estimates in the full sample, conditional on job size, while column (2) excludes new jobs with more than five employees. All regressions include the same set of individual-level controls and fixed effects for occupation × local labor market × year and firm × year. Standard errors are clustered at the firm level.

Table 7: New-job wage premium conditional on promotion and job growth dynamics

Dependent variable: ln(entry wage)	(1)	(2)	(3)
Omitted category: Old job (Expanding)			
New job	0.034***	0.031***	0.036***
	(0.0049)	(0.0048)	(0.0056)
1(Subsequent within-firm promotion)		0.16***	
		(0.0066)	
1(Job continues to grow)			-0.0084
			(0.0098)
Observations	1030148	1030148	1030148
Adjusted R^2	0.779	0.782	0.779
Occupation x LLM x Year FE	✓	✓	✓
Firm x Year FE	✓	✓	✓

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. This table reports estimates of the new job wage premium conditional on subsequent within-firm career outcomes. The dependent variable is log entry wages. The estimation sample is restricted to jobs with non-missing occupation information in subsequent years. Column (1) reports the baseline estimates of the new job wage premium. Column (2) augments the specification with an indicator for whether the worker is subsequently promoted to a managerial position within the same firm. Column (3) instead conditions on whether the job grows within three years. All regressions include the same set of individual-level controls and fixed effects. Standard errors are clustered at the firm level.

Online Appendix

Old and New Jobs: Understanding Wage Formation, Sorting, and Firm Behavior

Dogan Gülümser[†]

A. Theory appendix

B. Figure appendix

C. Tables appendix

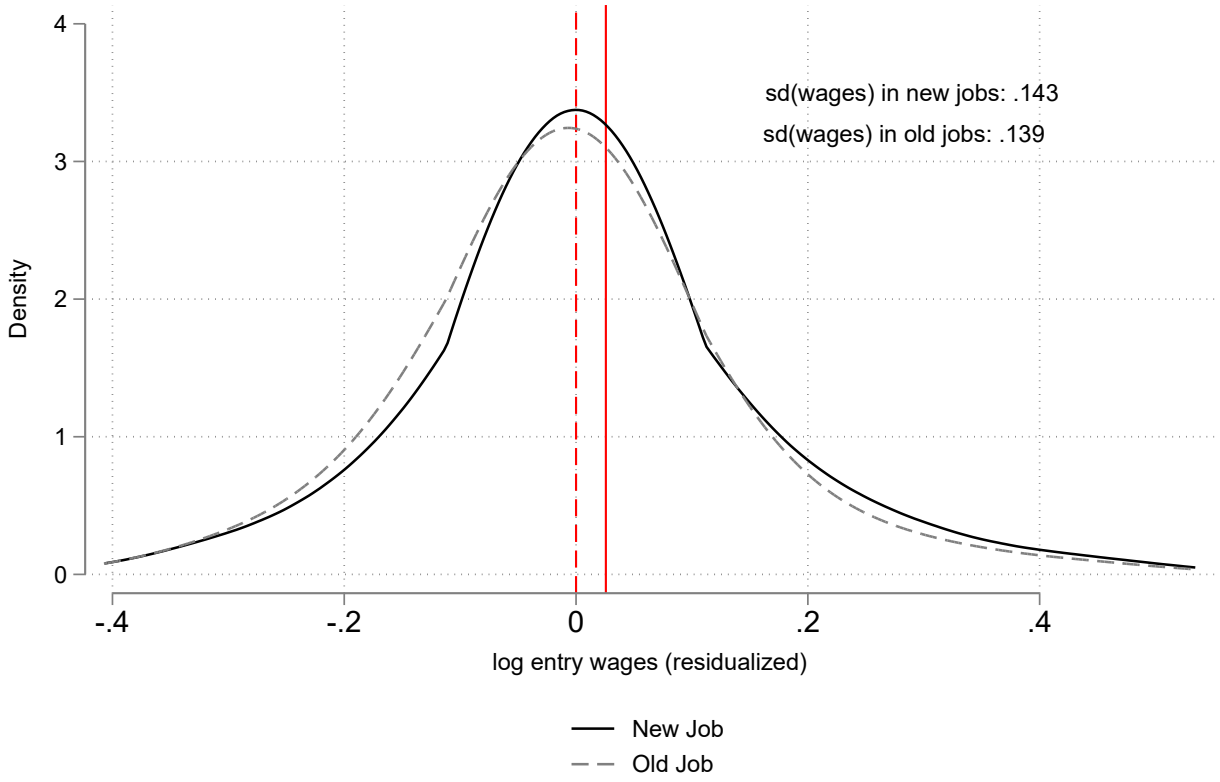
[†] Rockwool Foundation Berlin, ESMT Berlin, BSoE, and UCLS. d.gulumser@rfberlin.com.

A Theory Appendix

A1 Empirical wage dispersion among old and new jobs

The central assumption in the theoretical model is that new jobs are associated with greater heterogeneity in match productivity. Empirically, I observe only realized matches—that is, worker-firm contacts where expected productivity exceeds the reservation productivity ($y \geq y_R$), and result in a match. I provide empirical evidence consistent with this assumption: both residual wage dispersion and mean wages are higher in new jobs, where the wage gap is 3%, and the standard deviation of wages is 0.143 compared to 0.139 in expanding old jobs. This greater wage dispersion among realized matches substantiates the theoretical model's prediction.

Figure A1: Wage dispersion in old and new jobs in the data



Notes: This figure presents kernel density estimates of residualized log entry wages for workers in new jobs (solid line) and expanding old jobs (dashed line). Residual wages are obtained by regressing log wages on the controls and fixed effects from the main specification (Equation 10). The plotted distributions are based on residuals from this regression, winsorized at the 1st and 99th percentiles, for visualization purposes. Vertical solid and dashed lines indicate the mean residual wages of new and old job entrants, respectively. The text reports the standard deviation of residual wages as a measure of wage dispersion.

A2 Reservation wage

A worker accepts an offer if $W \geq U$. The reservation wage w_r is defined by indifference $W(w_r) = U$. From (6), setting $W = U$ implies

$$w_r = rU. \tag{16}$$

Solving (6) for W gives

$$W = \frac{w + sU}{r + s}. \tag{17}$$

Taking expectations yields

$$W^e = \frac{w^e + sU}{r + s}, \tag{18}$$

where $w^e \equiv E[w|w \geq w_r]$ denotes the expected wage relevant for W^e.

Substituting (18) into (5) and using $rU = w_r$ from (16) gives

$$rU = z + q^w \left(\frac{w^e + sU}{r + s} - U \right) = z + q^w \frac{w^e - rU}{r + s}.$$

Rearranging,

$$rU = \frac{(r + s)z + q^w w^e}{r + s + q^w}. \tag{19}$$

Combining (16) and (19) yields the reservation wage:

$$w_r = \frac{(r + s)z + q^w w^e}{r + s + q^w}. \tag{20}$$

A3 Wage equation

This subsection derives the wage equation using the Nash bargaining condition (8) together with the value equations for workers and firms, (6), (5), and (2), and imposing free entry $V_j = 0$ as in (3). Dropping the job-type subscript j for ease of notation, Nash bargaining implies the worker receives share β of total match surplus:

$$W - U = \beta \, (J + W - U - V).$$

With free entry $V = 0$, this becomes

$$W - U = \frac{\beta}{1 - \beta} \, J. \tag{21}$$

From (6),

$$(r+s)W = w + sU \quad \Rightarrow \quad (r+s)(W-U) = w - rU \quad \Rightarrow \quad W - U = \frac{w - rU}{r+s}.$$

From (2) with $V = 0$ and the implied law of motion $rJ = y - w - sJ$,

$$(r+s)J = y - w \quad \Rightarrow \quad J = \frac{y-w}{r+s}.$$

Substituting into (21) gives

$$\frac{w - rU}{r+s} = \frac{\beta}{1-\beta}\frac{y-w}{r+s} \quad \Rightarrow \quad rU = \frac{w - \beta y}{1-\beta}.$$

Next, under the standard free-entry condition in the main text, (4),

$$J = \frac{c}{q(\theta)}.$$

Using $q^w = \theta q(\theta)$ (as defined in Section 2) together with (5) and (21) yields

$$rU = z + q^w(W-U) = z + \theta q(\theta)\frac{\beta}{1-\beta}J = z + \theta q(\theta)\frac{\beta}{1-\beta}\frac{c}{q(\theta)} = z + \frac{\beta}{1-\beta}\theta c.$$

Equating the two expressions for rU and solving for w gives

$$w(y) = (1-\beta)z + \beta\,(y + \theta c), \tag{22}$$

A4 Main comparative statics

Match productivity in old jobs is drawn from $G(y)$ on $y > 0$ with mean μ. Match productivity in new jobs is drawn from $H(y;\sigma)$, where $\sigma \geq 0$ indexes dispersion and $H(\cdot;0) = G(\cdot)$. Let y denote a realization and let Y be the corresponding random variable with CDF $H(\cdot;\sigma)$.

Assumptions Assume $H(y;\sigma)$ is continuously differentiable in σ for all $y > 0$, and has constant mean $E[Y \mid \sigma] = \mu$ for all σ (so $\frac{d}{d\sigma}E[Y \mid \sigma] = 0$). Moreover, assume monotone dispersion:

$$\int_0^y H_\sigma(x;\sigma)\,dx \;\geq\; 0 \qquad \forall\, y > 0,\ \forall\, \sigma \geq 0, \tag{23}$$

where $H_\sigma(x;\sigma) \equiv \partial H(x;\sigma)/\partial\sigma$. (With $H(\cdot;0) = G(\cdot)$, (23) implies that $H(\cdot;\sigma)$ is a mean-preserving spread of G for each σ.)

Rearranging the value of employment from (6), and given the condition that a worker

accepts a match iff $W(y) \geq U$, equivalently $w(y) \geq rU$. Define reservation productivity $y_R(\sigma)$ by indifference:

$$W(y_R(\sigma)) = U \quad \Longleftrightarrow \quad w(y_R(\sigma)) = rU. \tag{24}$$

If $w'(y) > 0$, the acceptance set is $[y_R(\sigma), \infty)$.

Cutoff condition Define the job-finding rate as

$$q^w(\theta, \sigma) \equiv \theta q(\theta) \Pr(Y \geq y_R(\sigma)) = \theta q(\theta)\big(1 - H(y_R(\sigma); \sigma)\big), \tag{25}$$

and define

$$W^e(\sigma) \equiv E[W(Y) \mid Y \geq y_R(\sigma)]\,. \tag{26}$$

Then (5) implies

$$rU = z + q^w(\theta, \sigma)\big(W^e(\sigma) - U\big). \tag{27}$$

Using $W(Y) - U = (w(Y) - rU)/(r + s)$ and evaluating $w(\cdot)$ using the wage equation (9),

$$w(Y) - rU = \beta\big(Y - y_R(\sigma)\big), \qquad W(Y) - U = \frac{\beta}{r+s}\big(Y - y_R(\sigma)\big).$$

Therefore

$$W^e(\sigma) - U = \frac{\beta}{r+s}\, E[Y - y_R(\sigma) \mid Y \geq y_R(\sigma)]\,.$$

Substituting into (27) gives

$$rU = z + q^w(\theta, \sigma)\, \frac{\beta}{r+s}\, E[Y - y_R(\sigma) \mid Y \geq y_R(\sigma)]\,.$$

By definition of the cutoff, (24) and (9) also imply

$$rU = (1 - \beta)z + \beta\big[y_R(\sigma) + \theta c\big].$$

Combining the last two equations and simplifying yields the cutoff condition

$$(r + s)\, y_R(\sigma) = (r + s)\big[z - \theta c\big] + q^w(\theta, \sigma)\, E[Y - y_R(\sigma) \mid Y \geq y_R(\sigma)]\,. \tag{28}$$

Note that $\Pr(Y \geq y)\, E[Y - y \mid Y \geq y] = E[(Y - y)^+]$ and use (25) to write

$$q^w(\theta, \sigma)\, E[Y - y_R(\sigma) \mid Y \geq y_R(\sigma)] = \theta q(\theta)\, E\big[(Y - y_R(\sigma))^+\big]\,.$$

For $Y \geq 0$ with CDF $H(\cdot;\sigma)$,

$$E[Y \mid \sigma] \;=\; \int_0^\infty \big(1 - H(x;\sigma)\big)\, dx.$$

Partitioning at y and rearranging yields

$$E\big[(Y-y)^+ \mid \sigma\big] = \int_y^\infty \big(1 - H(x;\sigma)\big)\, dx = E[Y \mid \sigma] - y + \int_0^y H(x;\sigma)\, dx. \tag{29}$$

From (25), we have $q^w(\theta,\sigma) = \theta q(\theta)\Pr\big(Y \geq y_R(\sigma)\big)$, which implies

$$q^w(\theta,\sigma)\, E[Y - y_R(\sigma) \mid Y \geq y_R(\sigma)] = \theta q(\theta)\, E\big[(Y - y_R(\sigma))^+\big]. \tag{30}$$

Setting $y = y_R(\sigma)$ in (29) and substituting into (28) using (30) gives

$$(r+s)\, y_R(\sigma) = (r+s)\big[z - \theta c\big] + \theta q(\theta)\Big(E[Y \mid \sigma] - y_R(\sigma) + \int_0^{y_R(\sigma)} H(x;\sigma)\, dx\Big).$$

Rearranging,

$$(r + s + \theta q(\theta))\, y_R(\sigma) = (r+s)\big[z - \theta c\big] + \theta q(\theta)\, E[Y \mid \sigma] + \theta q(\theta) \int_0^{y_R(\sigma)} H(x;\sigma)\, dx. \tag{31}$$

The impact of σ on reservation productivity Differentiating (31) with respect to σ (and using $\frac{d}{d\sigma}E[Y \mid \sigma] = 0$), conditional on θ, yields

$$\frac{d}{d\sigma}\int_0^{y_R(\sigma)} H(x;\sigma)\, dx = \int_0^{y_R(\sigma)} H_\sigma(x;\sigma)\, dx + H\big(y_R(\sigma);\sigma\big)\, y_R'(\sigma).$$

Collecting terms in $y_R'(\sigma)$ gives

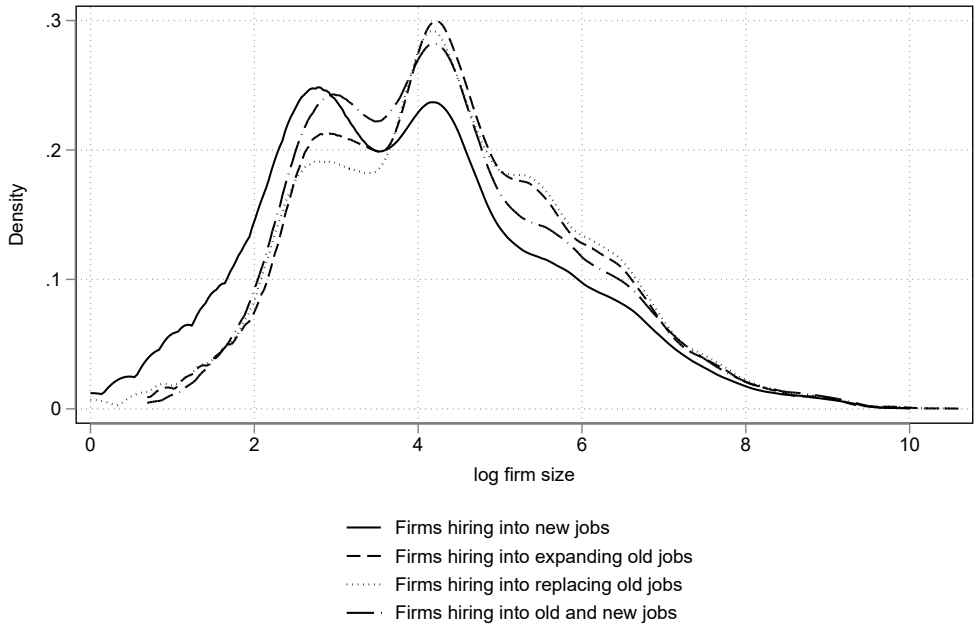
$$\big(r + s + \theta q(\theta)\big(1 - H(y_R(\sigma);\sigma)\big)\big)\, y_R'(\sigma) = \theta q(\theta) \int_0^{y_R(\sigma)} H_\sigma(x;\sigma)\, dx,$$

and therefore

$$\frac{\partial y_R(\sigma)}{\partial \sigma} = \frac{\theta q(\theta) \displaystyle\int_0^{y_R(\sigma)} H_\sigma(x;\sigma)\, dx}{r + s + \theta q(\theta)\big(1 - H(y_R(\sigma);\sigma)\big)} \geq 0. \tag{32}$$

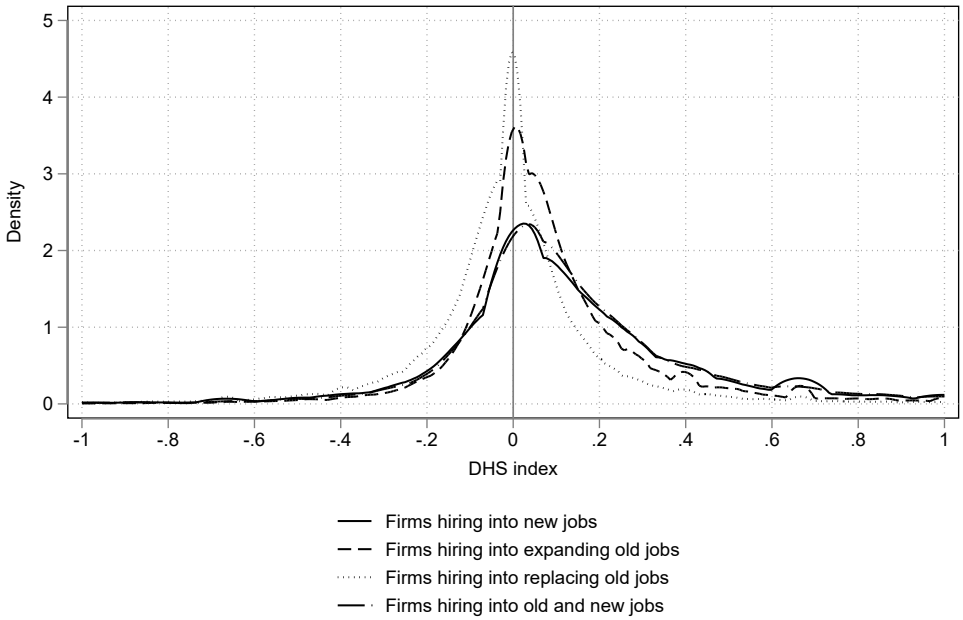
A1 Appendix Figures

Figure B1: Firm size distribution by types of hires



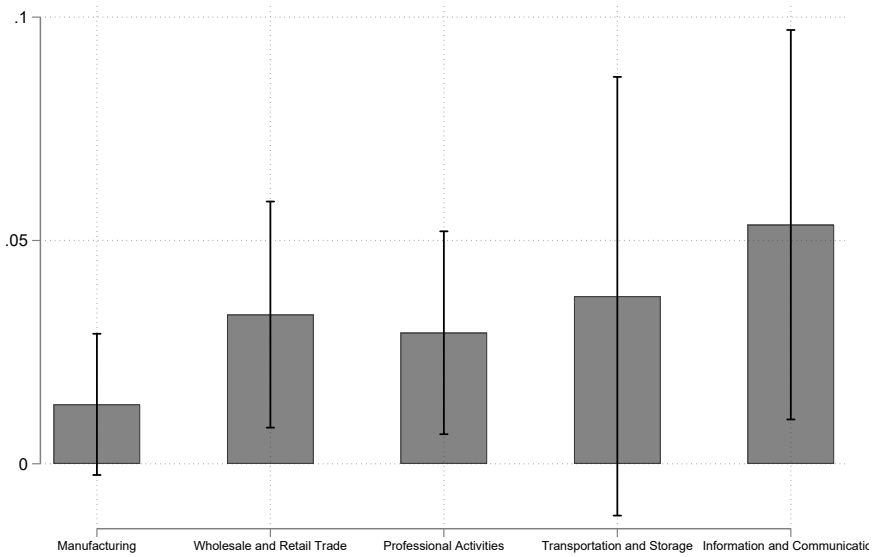
Notes: This figure plots kernel density estimates of log firm employment size in firm-years with different types of hiring. Firm size is measured as total employment in the sampling month (in logs). The solid line corresponds to firms hiring into new jobs, the dashed line to firms hiring into expanding old jobs, the dotted line to firms hiring into replacing old jobs, and the dash-dotted line to firms hiring into both new and old jobs in the same year.

Figure B2: Firm growth rate distribution by types of hires



Notes: This figure plots kernel density estimates of firm employment growth rates (DHS index) in firm-years with different types of hiring. The solid line corresponds to firms hiring into new jobs, the dashed line to firms hiring into expanding old jobs, the dotted line to firms hiring into replacing old jobs, and the dash-dotted line to firms hiring into both new and old jobs in the same year. The vertical line marks zero employment growth.

Figure B3: New job wage premium: Heterogeneity by industry



Notes: This figure shows how the new job wage premium varies across the five largest industry groups, which together account for about 70% of total employment in the data. Industries are defined using Sweden's industry classification (SNI), which is based on NACE. I estimate Equation (10) separately within each 1-digit SNI industry. The dependent variable is log entry wages. Each regression includes occupation-by-year fixed effects, firm-by-year fixed effects, age fixed effects, labor market experience, nine education-level fixed effects, and gender. Whiskers indicate 95% confidence intervals. Standard errors are clustered at the firm level.

C1 Appendix Tables

Table C1: Occupation structure for major group 3: Technicians and associate professionals

3	MAJOR OCUPATION GROUP: Technicians and Associate Professionals
31	Science and Engineering Associate Professionals
311	Physical and engineering science technicians
3111	Chemical and physical science technicians
3112	Civil engineering technicians
3113	Electrical engineering technicians
3114	Electronics and telecommunications engineering technicians
3115	Mechanical engineering technicians
3116	Chemical engineering technicians
3117	Mining and metallurgical technicians
3118	Draughtspersons
3119	Physical and engineering science technicians not elsewhere classified
312	Computer associate professionals
3121	Computer assistants
3122	Computer equipment operators
3123	Industrial robot controllers
313	Optical and electronic equipment operators
3131	Photographers and image and sound recording equipment operators
3132	Broadcasting and telecommunications equipment operators
3133	Medical equipment operators
3139	Optical and electronic equipment operators not elsewhere classified
314	Ship and aircraft controllers and technicians
3141	Ships' engineers
3142	Ships' deck officers and pilots
3143	Aircraft pilots and related associate professionals
3144	Air traffic controllers
3145	Air traffic safety technicians
315	Safety and quality inspectors
3151	Building and fire inspectors
3152	Safety, health and quality inspectors

Notes: This table lists occupations included under Major Group 3, Technicians and Associate Professionals, and specifically under Subgroup 31, Physical and Engineering Science Associate Professionals, following the International Standard Classification of Occupations (ISCO-88). The listed subcategories cover a range of technical fields such as civil, electrical, mechanical, and chemical engineering, as well as computer operations, optical and electronic equipment, and safety inspection roles. For further details, see the official ISCO-88 documentation provided by the International Labour Organization (ILO):
https://ilostat.ilo.org/methods/concepts-and-definitions/classification-occupation/

Table C2: Akm sample statistics

Panel A. Workers	All entrants (1997-2013)			
	New job (N)	Old job (E)	Old job (R)	All
ln(entry wage)	10.0	9.99	10.00	9.99
1st-year separation	0.075	0.090	0.11	0.095
Age	42.0	39.0	38.1	38.8
Female	0.41	0.41	0.45	0.42
Experienced	0.77	0.64	0.62	0.64
Tenure (months)	63.7	61.7	55.4	60.1
Education				
Compulsory or less	0.16	0.13	0.11	0.13
High school	0.51	0.50	0.50	0.50
College	0.33	0.36	0.39	0.37
Occupations				
Managers	0.083	0.052	0.063	0.055
Professionals	0.14	0.17	0.16	0.17
Technicians and associate professionals	0.18	0.19	0.21	0.20
Clerks	0.16	0.10	0.11	0.10
Service workers and shop sales workers	0.051	0.15	0.17	0.15
Skilled agricultural and fishery workers	0.014	0.0046	0.0074	0.0055
Craft and related trades workers	0.12	0.088	0.087	0.088
Plant machine operators and assemblers	0.16	0.13	0.12	0.13
Elementary occupations	0.083	0.11	0.077	0.10
# of distinct jobs (firm x occupation)	10520	47971	30816	42781.5
Observations	18530	803447	298501	1120478
Panel B. Firms				
Young firm (<10y)	0.41	0.33	0.29	0.41
Firm size	39.7	71.5	83.2	61.7
log(value added per worker)	13.1	13.1	13.1	13.1
# of 3-digit occupations	5.30	5.75	6.24	6.63
# of new hires	8.92	9.92	10.3	13.8
# of new hires to new jobs	1.53	0.27	0.23	1.69
# of new hires to expanding old jobs	5.87	7.60	5.95	9.66
# of new hires to replacing old jobs	1.52	2.06	4.11	2.50
Observations	9112	45364	41616	7696

Notes: The table reports descriptive statistics for observations that appear in the pre-period AKM estimation sample (1985–1996). Panel A reports worker-year means for new hires in the analysis sample who are also present in the AKM sample. Columns 1–4 in Panel A correspond to hires into new jobs, old expanding jobs, old replacing jobs, and all hires, respectively. Panel B reports firm-year means. Columns 1–4 in Panel B correspond to firms that hire into new jobs, old expanding jobs, old replacing jobs, and firms that hire into both new and old jobs, respectively.

Table C3: Most common occupations in new and old jobs

New Jobs		Old Jobs (Expanding)		Old Jobs (Replacing)	
Occupations	**Share(%)**	**Occupations**	**Share(%)**	**Occupations**	**Share(%)**
Office clerks	4.2	Salespersons	8.5	Salespersons	12.4
Store clerks	3.7	Personal care w.	7.9	Personal care	6.8
Client info clerks	3.5	Finance and sales	5.2	Finance and sales	6.8
Finance and sales	3.3	Engineering sci. techs	4.3	Engineering sci. techs	3.8
Machine operators	3.1	Computing professionals	4.1	Helpers in restaurants	3.7
Numerical clerks	3.1	Motor-vehicle drivers	3.8	Motor-vehicle drivers	3.5
Helpers and cleaners	3	Helpers in restaurants	3.5	Helpers and cleaners	3.4

Notes: This table lists the most common occupations among new hires, separately by job type: new jobs (newly created firm–occupation cells), expanding old jobs, and replacing old jobs. Occupations are defined at the 3-digit ISCO level and labels are abbreviated for readability. Shares are computed within each job type and sum to less than 100 percent because only the top occupations are shown.

Table C4: New job wage premium: Restricting sample to job-to-job movers

Dependent var: ln(Entry Wage) **Panel A. Across-firms**	(1)	(2)	(3)
Omitted category: Expanding old jobs			
New job	0.028***	0.029***	0.026***
	(0.0059)	(0.0053)	(0.0055)
Old job (Replacing)	-0.00020	0.0044**	-0.0017
	(0.0024)	(0.0016)	(0.0014)
log(Firm size)	-0.0017	-0.00015	-0.0022**
	(0.0016)	(0.0013)	(0.00079)
Firm growth rate (DHS index)		0.0052	0.0015
		(0.0030)	(0.0025)
log(value added per capita)		0.036***	0.012***
		(0.0039)	(0.0018)
Observations	1249420	1069931	1069931
Adjusted R^2	0.742	0.760	0.212
Occupation x LLM x Year FE	✓	✓	✓
Industry x Year	✓	✓	✓
Worker FE			✓
Panel B. Within-firm	(1)	(2)	(3)
Omitted category: Expanding old jobs			
New job	0.034***	0.042***	0.030***
	(0.0041)	(0.0047)	(0.0082)
Old job (Replacing)	0.0013	0.00012	-0.0020
	(0.0021)	(0.0027)	(0.0012)
Observations	1249420	1249420	1249420
Adjusted R^2	0.777	0.784	0.556
Occupation x LLM x Year FE	✓	✓	✓
Firm x Year FE	✓		
Firm x Year x Skill FE		✓	
Firm FE			✓
Worker FE			✓

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. This table replicates the baseline specification in Table 2 restricting the sample to job-to-job movers, defined as entrants with less than two months of intervening non-employment between the previous job and the new job. The dependent variable is log entry wages. The coefficient on *New Job* measures the difference in entry wages between new-job entrants and entrants into expanding old jobs (the omitted category). Panel A reports across-firm estimates; Panel B reports within-firm estimates. Standard errors are clustered at the 3-digit industry level in Panel A and at the firm level in Panel B.

Table C5: New job wage premium: Restricting sample to firms that contribute to the identification of main effects (firms that introduce old and new jobs)

Dependent var: ln(Entry Wage) **Panel A. Across-firms**	(1)	(2)	(3)
Omitted category: Expanding old jobs			
New job	0.028***	0.027***	0.027***
	(0.0042)	(0.0040)	(0.0044)
Old job (Replacing)	0.0032	0.0070	0.0083
	(0.0046)	(0.0046)	(0.0049)
log(Firm size)	0.000093	-0.000016	-0.00033
	(0.0019)	(0.0019)	(0.0019)
Firm growth rate (DHS index)		0.017**	0.014*
		(0.0059)	(0.0054)
log(value added per capita)			0.031***
			(0.0061)
Observations	452487	452487	399088
Adjusted R^2	0.779	0.779	0.793
Occupation x LLM x Year FE	✓	✓	✓
Industry (3-digit) x Year	✓	✓	✓
Panel B. Within-firm	(1)	(2)	(3)
Omitted category: Expanding old jobs			
New job	0.035***	0.035***	0.047***
	(0.0045)	(0.0044)	(0.0051)
Old job (Replacing)	0.0011	0.0014	0.0062
	(0.0039)	(0.0038)	(0.0046)
J2J mover		0.038***	
		(0.0022)	
Observations	452487	452487	452487
Adjusted R^2	0.798	0.799	0.803
Occupation x LLM x Year FE	✓	✓	✓
Firm x Year FE	✓	✓	
Firm x Year x Skill FE			✓

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. This table replicates the baseline specification in Table 2 restricting the sample to "identifying firms", defined as firms that hire into both new jobs and old jobs (expanding or replacing) and therefore contribute to the within-firm identification. The dependent variable is log entry wages. The coefficient on *New Job* measures the difference in entry wages between new-job entrants and entrants into expanding old jobs (the omitted category). Panel A reports across-firm estimates; Panel B reports within-firm estimates. Worker fixed effects are not included in this restricted sample because identification would require multiple observations per worker within identifying firms, which substantially reduces the usable sample. Standard errors are clustered at the 3-digit industry level in Panel A and at the firm level in Panel B.

Table C6: New job wage premium: Job defined at 4th-digit occupation (instead of 3-digit)

Dependent var: ln(Entry Wage)				
Panel A. Across-firms	(1)	(2)	(3)	(4)
Omitted category: Expanding old jobs				
New job	0.032***	0.031***	0.033***	0.030***
	(0.0050)	(0.0050)	(0.0045)	(0.0042)
Old job (Replacing)	-0.00067	0.0011	0.0033*	-0.0017
	(0.0023)	(0.0021)	(0.0015)	(0.0010)
log(Firm size)	0.00023	0.00020	0.0014	-0.00095
	(0.0015)	(0.0015)	(0.0014)	(0.00088)
Firm growth rate (DHS index)		0.0078*	0.0065*	0.0027
		(0.0031)	(0.0026)	(0.0016)
log(value added per capita)			0.035***	0.014***
			(0.0040)	(0.0016)
Observations	1765512	1765512	1523783	1523783
Adjusted R^2	0.762	0.762	0.776	0.434
Occupation x LLM x Year FE	✓	✓	✓	✓
Industry x Year	✓	✓	✓	✓
Panel B. Within-firm	(1)	(2)	(3)	(4)
Omitted category: Expanding old jobs				
New job	0.034***	0.034***	0.041***	0.029***
	(0.0030)	(0.0030)	(0.0034)	(0.0048)
Old job (Replacing)	0.0016	0.0018	0.0015	-0.0020*
	(0.0016)	(0.0016)	(0.0019)	(0.0010)
J2J mover		0.032***		
		(0.0011)		
Observations	1765512	1765512	1765512	480467
Adjusted R^2	0.796	0.797	0.803	0.901
Occupation x LLM x Year FE	✓	✓	✓	✓
Firm x Year FE	✓	✓		
Firm x Year x Skill FE			✓	
Firm FE				✓
Worker FE				✓

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. This table replicates the baseline specification in Table 2 using an alternative definition of a job, where jobs are defined at the firm × 4-digit occupation level (rather than the firm × 3-digit occupation level in the baseline). The dependent variable is log entry wages. The coefficient on *New Job* measures the difference in entry wages between new-job entrants and entrants into expanding old jobs (the omitted category). Panel A reports across-firm estimates; Panel B reports within-firm estimates. Standard errors are clustered at the 3-digit industry level in Panel A and at the firm level in Panel B.

Table C7: New job wage premium: Firms established after 1996

Dependent var: ln(Entry Wage)			
Panel A. Across-firms	(1)	(2)	(3)
Omitted category: Expanding old jobs			
New job	0.044*	0.043*	0.032
	(0.022)	(0.023)	(0.029)
Old job (Replacing)	0.0019	0.0040	0.0029
	(0.0043)	(0.0034)	(0.0039)
log(Firm size)	-0.00018	-0.000068	0.0020
	(0.0048)	(0.0048)	(0.0065)
Firm growth rate (DHS index)		0.017	0.0054
		(0.024)	(0.031)
log(value added per capita)			0.034**
			(0.016)
Observations	97202	97202	80400
Adjusted R^2	0.817	0.817	0.821
Occupation x LLM x Year FE	✓	✓	✓
Industry x Year	✓	✓	✓
Panel B. Within-firm	(1)	(2)	(3)
Omitted category: Expanding old jobs			
New job	0.061***	0.061***	0.079***
	(0.022)	(0.022)	(0.026)
Old job (Replacing)	0.000060	0.00031	-0.0027
	(0.0059)	(0.0060)	(0.0075)
J2J mover		0.029***	
		(0.0043)	
Observations	97202	97202	97202
Adjusted R^2	0.823	0.824	0.825
Occupation x LLM x Year FE	✓	✓	✓
Firm x Year FE	✓	✓	
Firm x Year x Skill FE			✓

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. This table replicates the baseline specification in Table 2 restricting the sample to firms established after 1996, the first year occupations can be observed in the data. The dependent variable is log entry wages. The coefficient on *New Job* measures the difference in entry wages between new job entrants and entrants into expanding old jobs (the omitted category). Panel A reports across-firm estimates; Panel B reports within-firm estimates. Worker fixed effects are not included because they require multiple observations per worker over time and substantially reduce the sample in this subsample. Standard errors are clustered at the 3-digit industry level in Panel A and at the firm level in Panel B.

Table C8: New job wage premium heterogeneity by firm size and firm age

	By firm size				By firm age	
	(1)	(2)	(3)	(4)	(5)	(6)
	1-250	251-500	501-1000	1000+	Young	Old
Omitted category: Expanding old jobs						
New job	0.029***	0.068***	0.058***	0.050***	0.040***	0.033***
	(0.0052)	(0.013)	(0.015)	(0.011)	(0.0085)	(0.0044)
Old job (Replacing)	0.0095***	0.0077**	0.0033	-0.0016	0.0089**	0.00044
	(0.0023)	(0.0039)	(0.0033)	(0.0033)	(0.0038)	(0.0023)
Observations	375108	188089	274320	927995	353846	1411666
Fixed effects						
Occupation x LLM x Year FE	✓	✓	✓	✓	✓	✓
Firm x Year FE	✓	✓	✓	✓	✓	✓

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. This table reports estimates of the new job wage premium from Equation 10, estimated separately by firm-size and firm-age categories. The omitted group is workers entering expanding existing jobs; accordingly, the coefficient on the *New job* indicator measures the difference in entry wages relative to entrants into expanding existing jobs within each category. All specifications include the same controls as in the baseline regression, including occupation-by-year fixed effects and firm-by-year fixed effects. Standard errors are clustered at the firm level. Firm age is defined as the number of years since 1985 (the first year of the matched employer–employee data) in which the firm employed at least one worker; firms with at least 10 such years are classified as "old." Firm size is measured as total employment in the sampling month.

Table C9: Firms' differential employee selection - Comparison across firm

Dependent variable:	**1**(J2J Mover)	**1**(Long-term Unemployed)	**1**(Experienced)
	(1)	(2)	(3)
Omitted category: Expanding old jobs			
New job	0.036***	-0.011***	0.12***
	(0.0070)	(0.0034)	(0.0089)
Old job (Replacing)	-0.018***	0.011***	-0.017***
	(0.0025)	(0.0012)	(0.0023)
Observations	1765512	1765512	1765512
Adjusted R^2	0.187	0.071	0.310
Mean dependent variable	.71	.12	.42
Occupation x LLM x Year FE	✓	✓	✓
Industry x Year FE	✓	✓	✓

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. This table shows differences in labor market status and experience at the time of hiring between new and old job entrants across different firms, replicating the baseline specification in Table 3. The outcome variables *J2J Mover* and *Long-term Unemployed* are binary indicators. The former equals one for individuals who transition directly from another job, whereas the latter equals one for individuals who have been unemployed for more than one year. *Experienced* is defined as a binary indicator that takes the value one for individuals with more than ten years of labor market experience. Columns (1) and (2) show the estimation results flexibly controlling for age, experience, gender, and 7-education level controls in addition to occupation-by-year and industry-by-year fixed effects. Column (3) excludes age and experience controls. Standard errors clustered at the industry level. The estimates of "New Job" shows the difference in outcome variables between new job entrants and old expanding job entrants at the time of hiring.

Table C10: Firms' differential employee selection among single hires within jobs

Dependent variable:	**1**(J2J Mover)	**1**(Long-term Unemployed)	**1**(Experienced)
	(1)	(2)	(3)
Omitted category: Expanding old jobs			
New job	0.020	-0.010	0.040***
	(0.013)	(0.010)	(0.015)
Old job (Replacing)	0.0057	-0.010**	0.00044
	(0.0066)	(0.0047)	(0.0074)
Observations	38952	38952	38952
Adjusted R^2	0.127	0.048	0.211
Mean dependent variable	.79	.09	.6
Occupation x LLM x Year FE	✓	✓	✓
Firm x Year FE	✓	✓	✓

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. This table shows differences in labor market status and experience at the time of hiring between new and old job entrants in the private sector, spanning the years 1997 to 2013, focusing on jobs with a single hire. The outcome variables *J2J Mover* and *Long-term Unemployed* are binary indicators where the former equals one for individuals who are job-to-job movers, whereas the latter equals one for individuals who have been unemployed for more than one year. *Experienced* is defined as a binary indicator that takes the value one for individuals with more than ten years of labor market experience. Columns (1) and (2) show the estimation results flexibly controlling for age, experience, gender, and 9-education level controls in addition to occupation-by-year and firm-by-year fixed effects. Column (3) excludes age and experience controls. Standard errors clustered at the firm level. The estimates of "New Job" shows the difference in outcome variables between new job entrants and old expanding job entrants at the time of hiring.

Table C11: Sorting - AKM (Using wages as outcome from WSS sample)

	Across Firms			Within Firm		
	(1) $\ln(\text{Entry Wage}_{ijot})$	(2) $\ln(\text{Entry Wage}_{ijot})$	(3) $\hat{\theta}_i$	(4) $\ln(\text{Entry Wage}_{ijot})$	(5) $\ln(\text{Entry Wage}_{ijot})$	(6) $\hat{\theta}_i$
Omitted category: Expanding old jobs						
New job	0.028***	0.030***	0.0059	0.031***	0.039***	0.0018
	(0.0055)	(0.0039)	(0.0055)	(0.0038)	(0.0063)	(0.0043)
Old job (Replacing)	-0.00063	-0.00027	-0.0012	0.0012	0.0032	-0.0020
	(0.0023)	(0.0011)	(0.0014)	(0.0020)	(0.0027)	(0.0017)
Observations	1765512	500551	500551	1765512	500551	500551
Adjusted R^2	0.746	0.748	0.400	0.783	0.780	0.407
Occupation x LLM x Year FE	✓	✓	✓	✓	✓	✓
Industry x Year	✓	✓	✓			
Firm x Year FE				✓	✓	✓

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. The table reports estimates of the new job wage premium and the sorting parameter from Equation 13. Columns 1 and 4 report baseline estimates of the entry wage premium from Equation 10 in the main sample (across firms and within firms, respectively). Columns 2 and 5 re-estimate Equation 10 using workers who were present in the pre-dated AKM estimation sample (1985–1996). Columns 3 and 6 report estimates of the sorting parameter ϕ from Equation 13 using the AKM sample (with log wages as the outcome). All specifications include the same individual- and firm-level covariates. Standard errors are clustered at the 2-digit industry level in Columns 1–3 and at the firm level in Columns 4–6.

Table C12: Sorting - AKM (Using earnings as outcome)

	Across Firms			Within Firm		
	(1) ln(Entry Wage$_{ijot}$)	(2) ln(Entry Wage$_{ijot}$)	(3) $\hat{\theta}_i$	(4) ln(Entry Wage$_{ijot}$)	(5) ln(Entry Wage$_{ijot}$)	(6) $\hat{\theta}_i$
Omitted category: Expanding old jobs						
New job	0.028***	0.027***	-0.0043	0.031***	0.033***	0.0063
	(0.0055)	(0.0024)	(0.0063)	(0.0038)	(0.0044)	(0.0082)
Old job (Replacing)	-0.00053	-0.0012**	-0.0026	0.0012	0.0022	-0.0057*
	(0.0023)	(0.00060)	(0.0019)	(0.0020)	(0.0019)	(0.0029)
Observations	1765512	1120478	1120478	1765512	1120478	1120478
Adjusted R^2	0.746	0.754	0.300	0.783	0.787	0.304
Occupation x LLM x Year FE	✓	✓	✓	✓	✓	✓
Industry x Year	✓	✓	✓			
Firm x Year FE				✓	✓	✓

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. The table reports estimates of the new job wage premium and the sorting parameter from Equation 13. Columns 1 and 4 report baseline estimates of the entry wage premium from Equation 10 in the main sample (across firms and within firms, respectively). Columns 2 and 5 re-estimate Equation 10 using workers who were present in the pre-dated AKM estimation sample (1985–1996). Columns 3 and 6 report estimates of the sorting parameter ϕ from Equation 13 using the AKM sample (with log earnings as the outcome). All specifications include the same individual- and firm-level covariates. Standard errors are clustered at the 2-digit industry level in Columns 1–3 and at the firm level in Columns 4–6.

Table C13: Turnover results conditional on entry wages

Dependent variable:	**1**(1st-year separation)	**1**(Stay in t+3)
	(1)	(2)
Omitted category: Expanding old jobs		
New job	-0.011***	0.013**
	(0.0032)	(0.0062)
Old job (Replacing)	0.00032	-0.0012
	(0.0012)	(0.0020)
ln(Entry Wage$_{ijot}$)	-0.044***	0.097***
	(0.0038)	(0.0075)
Observations	1765512	1765512
Adjusted R^2	0.245	0.275
Mean dependent variable	.11	.47
Occupation x LLM x Year FE	✓	✓
Firm x Year FE	✓	✓

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. This table presents turnover outcomes for entrants into new vs. old jobs conditional on entry wage. *1st-year separation* is a binary indicator for whether an entrant separates from the firm within the first twelve months of employment. *Stay in* $t+3$ indicates whether the entrant remains with the firm for at least three years. All regressions include the same set of individual-level covariates, and standard errors are clustered at the firm level.

Table C14: O*NET Skill Categories

No.	Skill
1	Reading Comprehension
2	Active Listening
3	Writing
4	Speaking
5	Mathematics
6	Science
7	Critical Thinking
8	Active Learning
9	Learning Strategies
10	Monitoring
11	Social Perceptiveness
12	Coordination
13	Persuasion
14	Negotiation
15	Instructing
16	Service Orientation
17	Complex Problem Solving
18	Operations Analysis
19	Technology Design
20	Equipment Selection
21	Installation
22	Programming
23	Operation Monitoring
24	Operation and Control
25	Equipment Maintenance
26	Troubleshooting
27	Repairing
28	Quality Control Analysis
29	Judgment and Decision Making
30	Systems Analysis
31	Systems Evaluation
32	Time Management
33	Management of Financial Resources
34	Management of Material Resources
35	Management of Personnel Resources

Notes: This table lists the 35 skill descriptors from the O*NET database (version 15.1, February 2011) used to construct the skill-based occupational distance measure. Each skill is measured on the level scale (1–7), which captures the proficiency required for a given occupation. O*NET occupations are mapped to ISCO-88 3-digit codes via SOC 2010 → ISCO-08 → ISCO-88 crosswalks (Hardy et al., 2018). Pairwise occupational distances are computed using the angular separation metric of Gathmann and Schönberg (2010).

Table C15: New job wage premium and employee selection by occupation similarity

	Entry wages	**1**(J2J Mover)	**1**(Long-term Unemployed)	**1**(Experienced)
	(1)	(2)	(3)	(4)
New job – **1**[Similar]	0.023**	0.0095	-0.0025	0.072***
	(0.0099)	(0.012)	(0.0079)	(0.016)
New job – **1**[Dissimilar]	0.032***	0.027***	-0.0072**	0.090***
	(0.0039)	(0.0051)	(0.0034)	(0.0064)
Observations	1765512	1765512	1765512	1765512
p-value (Similar = Dissimilar)	0.34	0.15	0.58	0.27
Mean dependent variable		.71	.12	.42
Fixed effects				
Occupation x LLM x Year FE	✓	✓	✓	✓
Firm x Year FE	✓	✓	✓	✓

Notes: The table reports results for the new job wage premium and employee selection separately for *similar* and *dissimilar* new jobs. Similarity is measured using observed occupational transitions. For each origin–destination pair (o, d), I compute inflow shares $\tau_{od} = N_{od}/\sum_{o'} N_{o'd}$, and assign each new job in destination occupation d a "best-match" distance to the firm's pre-existing occupations as $1 - \max_{o \in \mathcal{O}_{\text{firm}}} \tau_{od}$. A new job is classified as *similar* if $\max_{o \in \mathcal{O}_{\text{firm}}} \tau_{od} \geq 0.25$ (equivalently, best-match distance ≤ 0.75), and *dissimilar* otherwise. The cutoff is guided by the distribution of transition shares. Across destination occupations, the mean top-origin (largest inflow) share is about 0.26, so $\tau_{\text{best}} \geq 0.25$ captures a typical transition pathway. The omitted category is expanding old jobs. The regressions include the same control variables as in Equation 10.

Table C16: New job outcomes and continuous skill novelty: Angular distance

	Entry wages	**1**(J2J Mover)	**1**(Long-term Unemployed)	**1**(Experienced)
	(1)	(2)	(3)	(4)
Omitted category: Expanding old jobs				
Skill novelty (continuous)	0.051***	0.076***	-0.013	0.17***
	(0.018)	(0.012)	(0.0090)	(0.017)
Observations	1765512	1765512	1765512	1765512
Mean dependent variable		.71	.12	.42
Fixed effects				
Occupation x LLM x Year FE	✓	✓	✓	✓
Firm x Year FE	✓	✓	✓	✓

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. The table reports results using a continuous measure of skill novelty. For each new hire, skill novelty equals the angular separation (Gathmann and Schönberg, 2010) between the new occupation's standardized O*NET skill vector and the firm's closest existing occupation; the measure ranges from zero (identical skill profiles) to one (maximally different) and is set to zero for hires into existing occupations. The omitted category is expanding old jobs. The regressions include the same control variables as in Equation 10.