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Old and new jobs: Understanding wage formation, sorting and firm behavior

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Old and new jobs: Understanding wage formation, sorting, and firm behavior*

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Abstract

This paper studies hiring and wage setting in new jobs. Using Swedish matched employer-employee data covering 1.7 million new hires, I show that entrants into occupations new to the firm have more labor market experience and are more likely to be hired from other employers. Conditional on entrant characteristics, new jobs have a 3 percent entry-wage premium and exhibit lower turnover than old jobs. The premium declines as firms accumulate occupation-specific employment experience, consistent with hiring uncertainty that resolves as the firm gains experience in the occupation. The new job wage premium is a previously undocumented source of wage dispersion among similar workers.

JEL Classifications: J31, J23, J63, D83

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1 Introduction

Hiring takes place under uncertainty about worker productivity and match quality. A large literature documents that this uncertainty is an important determinant of employee selection, entry wages, and turnover (Farber and Gibbons, 1996; Altonji and Pierret, 2001; Lange, 2007; Schönberg, 2007; Fredriksson et al., 2018). Much of this work examines how information about worker productivity accumulates over the course of a career, with worker experience helping employers resolve uncertainty about productivity. Less is known about the other side of the market: how firms' own experience employing workers in a given occupation shapes labor market outcomes.

In this paper, I study how firms' occupation-specific employment experience affects employee selection, entry wages, and match quality. Using firms' employment histories across occupations, I distinguish between hires into occupations in which the firm has previously employed workers ("old jobs") and hires into occupations that are new to the firm ("new jobs"). The central idea is that firms accumulate occupation-specific knowledge through employment. When firms hire into an occupation that is new to them, they are likely to have less information about match productivity and the worker characteristics that predict success. I exploit within-firm variation in whether an occupation is new or established at the time of hiring to compare entry wages, selection, and match outcomes for workers entering new versus old jobs within the same firm.

To guide the empirical analysis, I develop a simple search model in which firms hire workers into either existing occupations or occupations that are new to them. New jobs involve a one-time entry cost and greater dispersion in match productivity, capturing the firm's lack of information about the occupation. Both raise the firm's reservation productivity threshold and shift accepted matches toward higher-productivity draws. The model predicts that, holding the firm's wage-setting environment fixed, entry wages are higher in new jobs than in old jobs, and that the premium declines as firms accumulate occupation-specific employment experience.

I test this prediction using Swedish matched employer–employee data covering 1.7 million new hires between 1996 and 2013. The data allow me to link each hire to the firm's employment history by occupation, making it possible to identify whether the worker enters an occupation that is new to the firm or one in which the firm already employs workers. This linkage allows me to compare hires made by the same firm when an occupation is new versus old, and to trace how wage differences evolve as firms accumulate occupation-specific experience.

A key challenge is that newly created jobs may differ from existing jobs for reasons unrelated to occupation-specific hiring uncertainty. They may coincide with firm-level shocks that affect wage setting, or they may attract workers who differ systematically in observed and unobserved productivity. I address these concerns by comparing new jobs to expanding old jobs within the same firm-year, controlling for rich worker characteristics, and probing residual selection using worker fixed effects and predetermined measures of worker ability.

I document three main findings. First, consistent with the model's main prediction, new jobs carry a robust entry wage premium. Within the same firm-year and conditional on occupation-by-year fixed effects, entry wages in new jobs are 4.6 percent higher than in expanding old jobs. After controlling for entrant characteristics, the premium remains 3.1 percent. This *new job wage premium* is present across broad skill groups and remains after allowing firms to adjust wages differently across these groups. It declines gradually as firms accumulate employment experience in the occupation and becomes statistically indistinguishable from zero after six to eight years, consistent with occupation-specific uncertainty resolving over time.

The new job wage premium is comparable in magnitude to the wage gain associated with job-to-job mobility in my data, a benchmark often viewed as central to life-cycle wage growth (Topel and Ward, 1992; Adda and Dustmann, 2023). In distributional terms, entering a new job moves the median worker up by about 15 percentiles in the residual wage distribution. These findings indicate that transitions into new jobs are a quantitatively important and understudied margin of wage growth.

Second, in line with the mechanisms implied by the model, new jobs are associated with stronger selection on observable worker characteristics. New job entrants are 2.5 percentage points more likely to be poached from another firm rather than hired from non-employment, and 8.8 percentage points (about 21 percent) more likely to have at least ten years of labor market experience. Together, these observable differences account for about one-third of the entry wage premium (from 4.6 to 3.1 percent). Adding worker fixed effects, which absorb any time-invariant component of worker productivity, leaves the premium unchanged.[1]

Third, post-hiring outcomes are consistent with 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 (3.4 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 old and new jobs. The combination of higher entry wages and longer match duration leads to 8.4 percent higher within-job earnings for workers entering new jobs compared to those entering old jobs within the same firm.

The model implies that hiring uncertainty is larger when firms enter occupations that are less similar to their existing workforce. I test this prediction by examining whether wage and selection patterns are stronger in occupations that are more distant from a firm's incumbent

[1] Consistent with this, the AKM person effect (Abowd et al., 1999) estimated using pre-sample data (1985–96) – a measure of permanent unobserved skill that is predetermined with respect to entry into new versus existing jobs in the analysis sample – also cannot account for the remaining premium.

occupational structure. I use occupational dissimilarity as an empirical proxy for this uncertainty, classifying new jobs according to the distance between their skill profiles and those of the firm's pre-existing occupations.[2] The wage premium for newly created jobs is nearly twice as large when the introduced occupation is dissimilar to the firm's existing workforce. Firms also hire more selectively into these positions, relying more heavily on experienced workers and job-to-job movers, and less on the long-term unemployed. The joint increase in wages and selectivity with occupational dissimilarity is consistent with the information frictions mechanism: when firms enter occupations in which prior hiring experience is less transferable, they appear to raise hiring standards and pay higher entry wages.[3]

I further assess whether alternative explanations can account for the patterns observed in the data. First, a compensating wage differentials interpretation is difficult to reconcile with the turnover patterns, since new jobs have longer tenure even conditional on entry wages. Additionally, the premium does not vary with job size at entry, suggesting that it is not related to compensation for working alone.[4] Related explanations based on team-building responsibilities or differential promotion prospects also receive little empirical support: the premium persists after accounting for subsequent growth of the job and workers' realized promotion within three years of hire. Second, firms' monopsony power is also unlikely to explain the effects. 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 expanding only in old jobs. Taken together, these patterns are difficult to reconcile with the alternative theoretical explanations considered and point to hiring uncertainty as the most consistent interpretation.[5]

The main findings are robust to alternative job definitions and sample restrictions, and are similar across firm characteristics. The new job wage premium remains similar when jobs are defined using more granular 4-digit occupations rather than the baseline 3-digit classification. It is also stable across firm age, firm size, and industry groups, suggesting that the result is not driven by a narrow set of firms. Finally, the findings are similar across subsamples designed to address measurement and identification concerns, including restrictions based on firm panel length.

This paper contributes to several strands of literature. First, I contribute to the literature on

[2]Following Gathmann and Schönberg (2010) and Macaluso (2025), I measure occupational similarity using O*NET skill content.

[3]Higher *ex ante* marginal productivity in more dissimilar occupations could also generate a wage gradient. However, this alternative explanation does not predict stronger selection on experience and job-to-job mobility as occupational distance increases.

[4]New jobs are smaller in the initial year of employment; around 80 percent of new jobs employ a single worker. One possible concern is that workers require compensation if they expect to work alone.

[5]Another plausible theoretical explanation for the wage premium is efficiency wages, which would generate empirically similar predictions to compensating differentials in the absence of differences in monitoring costs across new and old jobs (Shapiro and Stiglitz, 1984; Katz, 1986).

how employer uncertainty shapes workers' labor market outcomes (Farber and Gibbons, 1996; Altonji and Pierret, 2001; Lange, 2007; Fredriksson et al., 2018). The employer-learning literature studies how information about a worker's productivity accumulates over tenure within a match or across employers over the worker's career. I study another dimension of employer information: how a firm's information about match productivity in an occupation accumulates as it makes repeated hires into that occupation. Consistent with the speed-of-learning patterns (Lange, 2007), the new job wage premium declines with the firm's occupation-specific employment experience and disappears after six to eight years. Schönberg (2007) and Kahn (2013) study asymmetric information between incumbent and outside employers about individual workers, while Mansour (2012) shows that employer learning varies across occupations. My paper documents a complementary mechanism: firms are better informed about occupations in which they have prior employment experience, so information varies not only across occupations but also across firms within the same occupation.

Second, I contribute to the literature on wage inequality among observably similar workers (Kline, 2024).[6] Recent work points to information imperfections as one source of such wage differences. 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 identify a new source of wage inequality: firms pay differently when they create roles in occupations in which they have limited prior experience. This generates wage differences both within firms across occupations and across firms within occupations. The finding complements evidence that newly established firms pay wage premia (Schmieder, 2023; Kim, 2025), but shows that job newness matters even conditional on firm age.

Third, I contribute to the literature on frictions in hiring. A large body of work shows that hiring is costly and uncertain because firms must search for suitable workers, screen applicants, and assess match quality (Manning, 2011; Oyer and Schaefer, 2011; Le Barbanchon et al., 2023b; Hoffman and Stanton, 2025). Survey evidence points in particular to firms' difficulties in finding workers with the right skills and to the costs of screening under information frictions (Barron et al., 1985; Barron and Bishop, 1985; Bertheau et al., 2023). Consistent with these frictions, recent studies show that exogenous worker separations impose sizable costs on employers (Ginja et al., 2023; Jäger et al., 2025). I add to this literature by showing that hiring frictions vary not only across firms, but also within firms across occupations, depending on firms' prior employment experience in those occupations. This within-firm heterogeneity matters for sorting and match quality: when firms create new roles, they select workers differently in ways that raise expected

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

match quality and reduce subsequent turnover. This interpretation is consistent with evidence that hiring practices shape match quality and turnover (Hoffman et al., 2018; Pries and Rogerson, 2022).

Finally, I contribute to the literature on the persistent importance of job matches for workers' careers. Previous work shows that both firms and occupations shape workers' lifetime outcomes. Employer size at the first job affects career trajectories (Arellano-Bover, 2024), while match quality at the job and occupation level predicts subsequent earnings (Fredriksson et al., 2018; Guvenen et al., 2020). I show that newly created roles constitute an additional source of match heterogeneity: observably similar workers experience different outcomes depending on whether they are hired into newly created or existing roles.

The remainder of the paper proceeds as follows. Section 2 presents a simple framework that links the newness of jobs within firms to entry wages. Section 3 describes the data, variable construction, and analysis sample. Section 4 outlines the empirical strategy. Section 5 reports the main results. Section 6 discusses alternative models and interpretations of the findings. Section 7 concludes.

2 Theoretical framework

This section introduces a simple model of wage formation in which entry wages depend on a firm's prior employment experience in an occupation. The model emphasizes two features that distinguish new jobs from old jobs. First, hiring into a new job requires an initial setup cost, which increases the reservation productivity. Second, match productivity is more dispersed in new jobs, reflecting greater uncertainty about match quality. Because firms hire only when realized productivity exceeds a reservation threshold, both the higher cutoff and the thicker upper tail shift accepted matches toward higher-productivity draws. The model therefore predicts more selective matching and higher entry wages in new jobs. To isolate the role of greater uncertainty in new jobs, I abstract from worker sorting, occupation-specific demand shocks, and firm heterogeneity, all of which are addressed in the empirical analysis.

2.1 Environment

Time is continuous. Workers and firms meet randomly. Let $m(u, v)$ denote the matching function, with u the measure of unemployed workers and v the measure of vacancies. Labor market tightness is $\theta \equiv v/u$; vacancies meet workers at rate $q(\theta) = m(u, v)/v$ and workers meet vacancies at rate $\theta q(\theta)$. Matches dissolve at an exogenous rate s, and both sides discount the future at rate r.

Firms post vacancies in old (O) and new jobs (N). Upon meeting, match-specific productivity y is drawn and observed by both parties.[7] I assume that match productivity is normally distributed with a common mean and type-specific variance:

$$Y_j \sim \mathcal{N}(\mu, \sigma_j^2), \qquad j \in \{O, N\}, \qquad \sigma_N > \sigma_O > 0. \tag{1}$$

Let F_j denote the CDF of Y_j. Old and new jobs have the same mean productivity μ, but new job productivity is more dispersed; the parameter σ_j captures the degree of uncertainty about match quality in jobs of type j.[8]

When a match forms in a new job, the firm pays a one-time hiring cost $k > 0$, reflecting the cost of entering a new market (occupation). Old job matches have no such cost.[9] A worker-firm contact becomes a match if realized productivity exceeds the reservation threshold, $y \geq y_{R,j}$ for $j \in \{O, N\}$. Let $\pi_j \equiv v_j/v$ denote the share of type-j vacancies among all posted vacancies. The acceptance probability for a type-j meeting is $1 - F_j(y_{R,j})$; the vacancy-filling rate for a type-j vacancy is $q_j^f = q(\theta)[1 - F_j(y_{R,j})]$; and the rate at which an unemployed worker meets and forms a type-j match is $q_j^w = \pi_j \theta q(\theta)[1 - F_j(y_{R,j})]$.

2.2 Value functions and wage determination

Firms. Let $J_j(y)$ denote the value of a filled job of type j with realized productivity y:

$$(r + s)J_j(y) = y - w_j(y), \tag{2}$$

where I assume for simplicity that after a match dissolves, the firm holds an old job vacancy.

Let V_j denote the value of a posted type-j vacancy. Following Pissarides (2000), I write conditional expectations on acceptable matches in shorthand as

$$y_j^e \equiv \mathbb{E}_{F_j}\big[Y \mid Y \geq y_{R,j}\big], \qquad w_j^e \equiv \mathbb{E}_{F_j}\big[w_j(Y) \mid Y \geq y_{R,j}\big], \qquad J_j^e \equiv \mathbb{E}_{F_j}\big[J_j(Y) \mid Y \geq y_{R,j}\big].$$

The firm pays a flow vacancy cost c while unfilled and a one-shot hiring cost k_j (with $k_O = 0$,

[7] The assumption that productivity is observed at the meeting stage is a tractability device. In a richer environment with post-hire learning (Jovanovic, 1979; Pries and Rogerson, 2005), firms would screen workers based on a noisy signal at the meeting stage and update their beliefs over tenure. The selection mechanism behind the new job wage premium would remain: firms would still reject matches with low expected productivity at the meeting stage. Such a setting would also generate additional predictions about turnover and wage growth, which I examine empirically in Section 2.4.

[8] The equal-mean assumption is a benchmark to isolate the role of dispersion. In practice, worker productivity, outside options, and average occupation-specific productivity may differ across jobs; these factors are absorbed by the fixed effects in the empirical design.

[9] Setting $k = 0$ and $\sigma_N = \sigma_O$ nests the standard DMP model. The hiring cost k is paid once at match formation.

$k_N = k$) at the moment a match is formed. The value of vacancy is

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

Free entry drives $V_j = 0$ for each actively posted type, giving a job-creation condition for each job type:

$$\frac{c}{q_j^f} = J_j^e - k_j, \qquad j \in \{O, N\}. \tag{4}$$

The expected filled value of a vacancy must cover its expected posting and hiring costs. For old jobs ($k_O = 0$), equation (4) reduces to the standard Pissarides (2000) job-creation condition; for new jobs, the hiring cost k raises the required expected surplus.

Workers. Let U denote the value of unemployment. An unemployed worker receives flow value z and meets and accepts type-j matches at rate q_j^w, obtaining the expected value of employment conditional on acceptance, $W_j^e \equiv \mathbb{E}_{F_j}[W_j(Y) \mid Y \geq y_{R,j}]$. The value of unemployment is

$$rU = z + \sum_{j \in \{O,N\}} q_j^w \big(W_j^e - U\big). \tag{5}$$

The value of employment in a job of type j with realized productivity y is

$$(r+s)W_j(y) = w_j(y) + sU. \tag{6}$$

For tractability, I take the worker's outside option U and labor market tightness θ as given, and focus on cases in which firms post both old and new job vacancies. This allows me to compare wages across jobs while holding aggregate labor market conditions fixed. The analysis is therefore a partial equilibrium comparison of wages across coexisting job types, rather than a characterization of the equilibrium composition of vacancies.[10]

Wage determination. Wages are determined by Nash bargaining (Mortensen, 2003; Pissarides, 2000), with $\beta \in (0, 1)$ the worker's bargaining power. The hiring cost k_j is sunk by the time bargaining occurs: it is part of the firm's recruitment expenditure captured by the vacancy value (3) and job-creation condition (4), and it does not enter the surplus split. Nash bargaining

[10] In a fully closed model, greater dispersion in match productivity would also affect the worker's outside option by changing the option value of continued search (Mortensen, 1986). I abstract from this channel here. The wage premium therefore operates entirely through firm-side selection: the higher cutoff induced by the hiring cost k and the greater dispersion of accepted productivity draws. This partial equilibrium characterization is sufficient for deriving the new job wage premium and mirrors the empirical design, which compares hires within firm-years and occupation-years.

therefore applies to the surplus of the ongoing match:[11]

$$(1-\beta)\big(W_j(y)-U\big)=\beta\, J_j(y), \qquad j\in\{O,N\}. \tag{7}$$

Substituting the value functions and solving yields the wage equation:

$$w_j(y)=(1-\beta)\, rU+\beta\, y, \qquad j\in\{O,N\}. \tag{8}$$

At any given productivity y, the wages are the same for both job types. I assume that workers receive the same Nash share β of the ongoing match surplus in both jobs. The hiring cost affects entry wages only through selection, by shifting which productivity draws are accepted in new jobs.

2.3 Reservation productivity and the wage premium

A match forms only if both the worker and the firm prefer forming the match to their outside options. The worker accepts a match if $W_j(y)\geq U$. Using the wage equation in (8), this condition is equivalent to $y\geq rU$.

The firm accepts a match if the value of the filled job, net of the hiring cost, is at least as large as the value of keeping the vacancy open: $J_j(y)-k_j\geq V_j$.

Under free entry, $V_j=0$, so the firm's acceptance condition becomes $J_j(y)\geq k_j$. Using

$$J_j(y)=\frac{(1-\beta)(y-rU)}{r+s},$$

this condition can be written as

$$y\geq rU+\frac{(r+s)k_j}{1-\beta}.$$

Thus, the worker is willing to accept any match with productivity at least rU, whereas the firm requires productivity at least $rU+(r+s)k_j/(1-\beta)$. When $k_j>0$, the firm's cutoff is higher and therefore determines the reservation productivity. Since old jobs have $k_O=0$ and new jobs have $k_N=k>0$, the reservation productivities are

$$y_{R,O}=rU, \qquad y_{R,N}=rU+\frac{(r+s)k}{1-\beta}, \tag{9}$$

with

$$y_{R,N}-y_{R,O}=\frac{(r+s)k}{1-\beta}>0. \tag{10}$$

[11] See Appendix A2 for the full derivation.

Firms therefore apply a higher acceptance threshold in new jobs because forming these matches requires paying the hiring cost. At the new job cutoff, the wage is[12]

$$w_N(y_{R,N}) = rU + \frac{\beta(r+s)k}{1-\beta} > rU.$$

Two forces raise expected entry wages in new jobs:

(i) The higher cutoff $y_{R,N} > y_{R,O}$ shifts the truncation point upward, raising the conditional mean of accepted draws.

(ii) Greater dispersion in new jobs ($\sigma_N > \sigma_O$) places more probability mass in the upper tail of the productivity distribution. Because firms accept only matches above a cutoff, this raises the conditional mean of accepted productivities at any common cutoff, following the mean-preserving-spread logic (Mortensen, 1986; Pissarides, 2000).

Because the wage equation (8) is linear in productivity with a common slope β, the expected entry wage gap is proportional to the gap in conditional means of productivity:

$$\Delta w \equiv \mathbb{E}\big[w_N(Y_N) \mid Y_N \geq y_{R,N}\big] - \mathbb{E}\big[w_O(Y_O) \mid Y_O \geq y_{R,O}\big] = \beta\Big(\mathbb{E}[Y_N \mid Y_N \geq y_{R,N}] - \mathbb{E}[Y_O \mid Y_O \geq y_{R,O}]\Big). \tag{11}$$

Since $\sigma_N > \sigma_O$ and $y_{R,N} > y_{R,O}$, both forces raise the bracket in (11) above zero, so $\Delta w > 0$: expected entry wages are strictly higher in new jobs than in old jobs. Figure 1 illustrates the mechanism. Consistent with the main intuition of the model, Appendix Figure A1 shows that entry wages are more dispersed for workers entering new jobs than for those entering expanding old jobs.

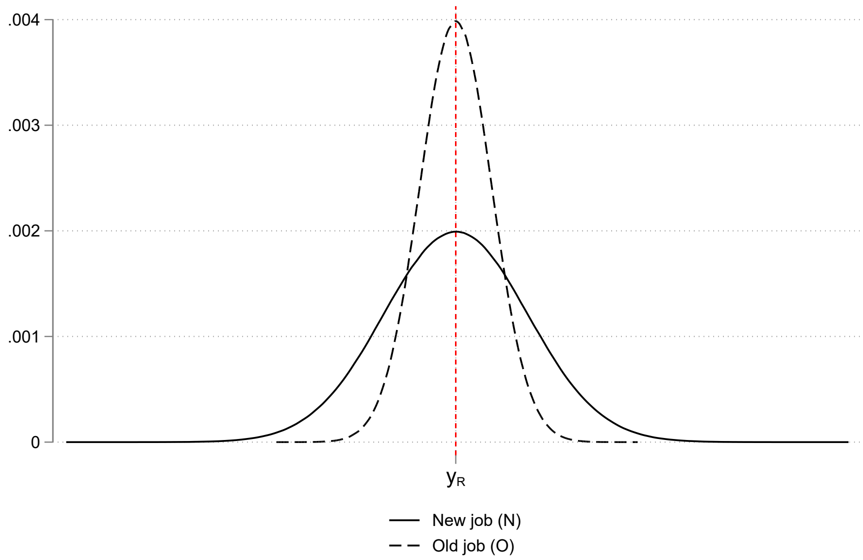
2.4 Predictions and empirically testable implications

The model predicts that entry wages are higher in new jobs than in old jobs (equation 11). The higher reservation productivity induced by the hiring cost and the greater dispersion of new job productivity both push the premium in the same direction. Four additional outcomes are motivated by the model's main mechanism and help distinguish it from alternative explanations.

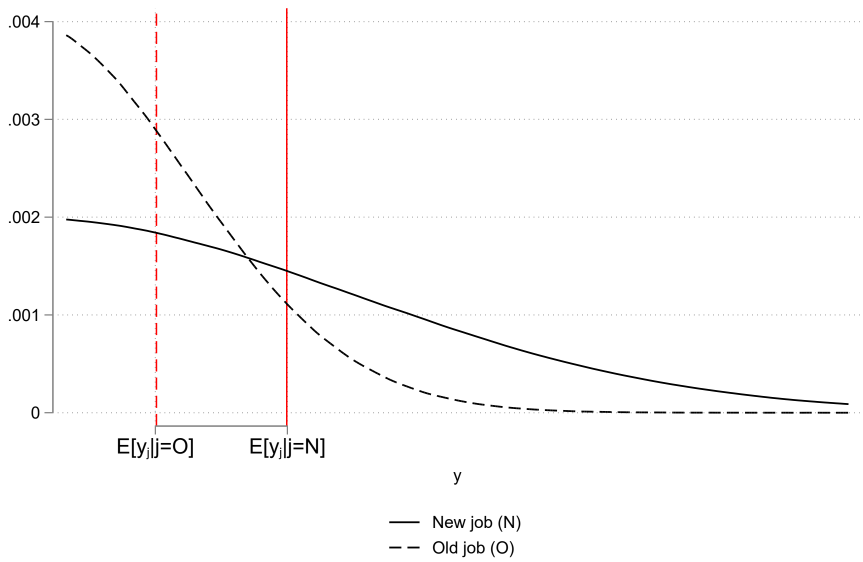
1. **New job wage premium.** $\mathbb{E}[w \mid j = N] > \mathbb{E}[w \mid j = O]$. I estimate this conditional on worker and firm characteristics, together with occupation, industry, and labor market status at entry to hold outside options fixed.

[12] Derivations are provided in Appendix A3.

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. It plots 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 vertical dashed red line depicts expected match productivity in the old job, $E[y_j \mid j = O]$, while the vertical solid red line represents expected match productivity in new jobs, $E[y_j \mid j = N]$.

2. **Hiring standards and worker selection.** The model does not include observable worker characteristics. The higher reservation productivity in new jobs is not observed directly. I therefore interpret differences in observable worker characteristics – such as experience and prior employment status – as reduced-form evidence of differential selection. Empirically, I examine whether entrants into new jobs are differentially selected along these dimensions.

3. **Turnover and match quality.** The model has exogenous separation at rate s and therefore does not predict differential turnover across jobs. However, accepted matches in new jobs start with higher productivity. A natural extension in which matches also face idiosyncratic productivity shocks and dissolve endogenously when productivity falls below a continuation threshold (Jovanovic, 1979; Pries and Rogerson, 2005) would predict lower early-tenure turnover for matches that start further above the threshold. I use early-tenure separation and tenure as proxies for match quality.

4. **Wage growth.** The model assumes productivity is revealed at the time of meeting and does not predict differential wage growth across job types. Steeper wage growth in new jobs would point to gradual learning within the match, which is not captured by the model. Similar wage growth across job types would be consistent with the model's simplifying assumption.

5. **Cumulative earnings.** If new jobs combine higher entry wages with longer match duration and similar wage growth, they generate higher cumulative earnings over the employment relationship. I report this as a summary measure of the combined wage and tenure differences.

3 Data

The data used in this paper cover the entire Swedish working population from 1996 to 2013. These data include linked information on firms and workers. Below, I describe the main components of the data in detail. Then, I 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-October. 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.[13] The wage measure reflects the 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 finer levels (2-, 3-, and 4-digit) distinguish functional specializations within these broader groups. As an example, Appendix Table C1 lists occupations in major group 3 (Technicians and associate professionals) and its nested subgroups: 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).[14]

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 new hire 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 old jobs, I restrict the sample to firms observed in at least two consecutive years in the WSS.[15]

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. Thus, I impose the

[13] Sampling of private sector firms in (Wage structure statistics, WSS) is stratified by firm size.

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

[15] 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.

restriction that a firm must be sampled for at least two consecutive years in the WSS so that I can calculate *changes* in job size.[16] Consequently, 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. I also exclude temporary employment and 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 "New Job", a categorical variable with three groups of hires:

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

where j, o, and t denote firm, occupation, and year, respectively. The variable L_{jot} denotes employment in occupation o at firm j in year t. The grouping of new hires is based on the firm's previous employment history in a given occupation and on the change in job size from one year to the next.

The first group, new jobs (N), arises when a firm hires into an occupation in year t after having employed no one in that occupation during the previous m years, that is, when $\sum_{k=1}^{m} L_{jo,t-k} = 0$.[17] All new hires into occupations with positive prior employment within the previous m years, that is, when $\sum_{k=1}^{m} L_{jo,t-k} > 0$, are classified as hires into *old jobs*. I further divide old jobs according to changes in job size. When employment in an old job increases from $t-1$ to t, such that $L_{jot} - L_{jo,t-1} > 0$, I classify all new hires into that occupation as expansion hires within an existing occupation (E). When employment in an old job does not increase, such that $L_{jot} - L_{jo,t-1} \leq 0$, I classify all new hires as replacements (R).

As an illustrative example, suppose two workers are hired into the *same existing occupation* in a given year. Both are classified either as hires into an expanding old job (E) or as hires into a replacing old job (R). The classification varies across occupations within a firm, not across

[16] 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.

[17] m ranges from 1 to 17, corresponding to the first (1996) and last (2013) year of the data, and therefore reflects the number of years for which the firm can be observed prior to year t.

workers within the same firm-occupation-year cell. If employment in a given occupation grows from $t-1$ to t, all newly hired workers in that occupation at time t are categorized as expansion hires. Conversely, if employment in that occupation stagnates or declines over the same period, all newly hired workers in that occupation are categorized as replacements. Thus, all new hires into the same firm-occupation-year cell receive the same classification: either expansion hires in existing occupations or replacements, but not a mixture of both. In summary, (N) denotes employment growth from a base of zero, (E) denotes employment growth in an occupation with prior employment, and (R) denotes turnover without net employment growth in an occupation with prior employment.[18]

Distinguishing hires in this way helps identify different types of frictions that may generate differences in entry wages and other outcomes. First, contrasting expanding old jobs (E) with replacing old jobs (R) isolates the effect of expanding a particular occupation conditional on the firm having prior employment experience in that occupation. Second, comparing new jobs (N) with expanding old jobs (E) isolates the role of the firm's lack of occupation-specific employment experience.

3.3 Descriptive statistics

This section analyzes sample statistics of new hires 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.[19]

Workers: Workers entering new jobs have higher entry wages (around 8-9 log points), lower separation rates within the first year of employment, and longer tenure. Additionally, they are older and more experienced (defined as having more than ten years of labor-market experience). They are equally likely to hold a university degree and slightly more likely to be employed in high-skill occupations.[20] The occupational composition at the 1-digit level is balanced across

[18]The three categories are mutually exclusive at the firm–occupation–year level: N requires the occupation to have no prior employment at the firm, while E and R are defined only for occupations with positive prior employment. Occupations that are new to the firm but already contain incumbent workers – for instance, when workers are internally reallocated from other occupations within the same firm – are classified as E rather than N, since the cell is not entirely composed of first-time entrants in that occupation.

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

[20]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.

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 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 7). Nevertheless, new jobs account for about 12 percent of all jobs (10,520 out of 89,307). This implies that, although the flow of hires into new jobs is small relative to old-job hires, 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 percent 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 percent). 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 percent), 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.[21] Despite these differences, value added per worker is broadly similar 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 percent and 3.7 percent, 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

The model outlined in section 2 predicts that entry wages are higher in new jobs than in old jobs because firms apply a higher reservation productivity threshold when hiring into occupations in which they have no prior employment experience. The empirical object of interest is the reduced-form counterpart of this prediction: the entry wage premium associated with entering a new job.

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

The parameter γ from the regression specified below provides a reduced-form measure of the wage premium implied by the model.

$$\Delta w = E[w_N(Y_N) \mid Y_N \geq y_{R,N}] - E[w_O(Y_O) \mid Y_O \geq y_{R,O}].$$

In the data, I estimate the analogous conditional difference in entry wages between workers hired into new jobs and workers hired into expanding old jobs within the same firm-year.

The empirical strategy is designed to compare hires into new and old jobs while accounting for the wage setting environment that could otherwise confound this comparison. I do so by exploiting variation across occupations within the same firm-year, while controlling for aggregate occupation-specific wage conditions and entrant characteristics.

4.1 Specification

The baseline regression is

$$y_{ijot} = \gamma \, \text{New Job}_{jot} + \lambda_{jt} + \lambda_{ot} + X_{it}'\delta + \varepsilon_{ijot}, \tag{12}$$

where i, j, o, and t index workers, firms, occupations, and years, respectively. The variable New Job_{jot} is a categorical variable, defined in Section 3.2, that distinguishes hires into new jobs from hires into expanding and replacing old jobs. The terms λ_{jt} and λ_{ot} denote firm-by-year and occupation-by-year fixed effects, respectively.[22] The vector X_{it} includes worker characteristics measured at entry: age, gender, education, and labor-market experience. Standard errors are clustered at the firm level.

The coefficient of interest, γ, captures the conditional entry wage premium for new jobs relative to expanding old jobs. I estimate equation (12) for two classes of outcomes. First, when y_{ijot} is log entry wages, γ captures the entry wage difference between workers entering new jobs and workers entering expanding old jobs. This is the central object of interest. Second, when y_{ijot} is a post-hire outcome – such as first-year separation, retention after three years, on-the-job wage growth, or cumulative within-spell earnings – γ captures the corresponding difference in subsequent match outcomes between workers who entered new jobs and workers who entered expanding old jobs at the same firm in the same year.

The identifying assumption is that, conditional on firm-by-year effects, occupation-by-year effects, and worker characteristics, new job status is orthogonal to unobserved determinants of

[22] In all specifications, λ_{ot} is implemented at the occupation $\times$ local-labor-market (municipality) $\times$ year level, so that aggregate occupational wage trends are absorbed within commuting zones rather than only nationally. I refer to these as "occupation-by-year" fixed effects throughout for brevity.

entry wages:

$$\mathbb{E}\big[\varepsilon_{ijot} \cdot \text{New Job}_{jot} \mid \lambda_{jt}, \lambda_{ot}, X_{it}\big] = 0. \tag{13}$$

This assumption may fail if newly created jobs differ from existing jobs in ways that affect wages but are not captured by the fixed effects or worker controls. Two concerns are central. First, workers entering new jobs may be positively selected on unobserved productivity. Second, firms may create new occupations in response to within-firm occupation-specific demand or productivity shocks that also raise wages in those occupations. The next sections present main results and further empirical exercises designed to assess these concerns.

5 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 as firms gain employment experience in an occupation. Second, 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-hire outcomes to assess match quality. Finally, I study heterogeneity by occupational similarity to assess whether the patterns are stronger when firms enter occupations further from their existing employment experience.

5.1 New job wage premium

Table 2 reports estimates of the new job wage premium under across-firm and within-firm comparisons. Panel A compares workers hired into new and old jobs across firms, while Panel B compares workers hired into new and old jobs within the same firm-year. Panel B, column (2), is the baseline implementation of Equation (12). The remaining columns vary the set of controls and fixed effects.

Across-firm comparison. Panel A compares entry wages of workers hired into new jobs with those of workers hired into old jobs across firms. These specifications control for industry-by-year and occupation-by-year fixed effects, firm size, and, in some columns, worker characteristics. The omitted category is hires into expanding old jobs. Column (1) reports the specification without worker controls; column (2) adds age, gender, education, and labor-market experience. Adding worker controls reduces the estimated new job premium from 5.3 to 2.8 percent, indicating that observable worker composition accounts for a sizable share of the new job wage premium. This attenuation is consistent with the descriptive evidence that new job entrants differ from old job entrants along pre-hire characteristics. The coefficient on "Old job (Replacing)" is small and statistically insignificant, suggesting that, conditional on prior employment experience in an occupation, entry wages do not differ meaningfully between expansion and replacement hires into existing occupations.

As shown descriptively in Section 3.3, firms that introduce new occupations differ from firms hiring only into existing occupations: they are younger and smaller, and they tend to hire more workers relative to their size.[23] To account for these differences, columns (3) and (4) add controls for the symmetric employment growth rate and log value added per worker.[24] The estimated new job wage premium remains close to the across-firm estimate in column (2) after adding these controls.

Across-firm comparisons may nevertheless confound the new job wage premium with unobserved differences in firm-level demand conditions, growth opportunities, or wage-setting practices. Panel B addresses this concern by introducing firm-by-year fixed effects. These fixed effects absorb all wage determinants common to hires at the same firm in the same year, so identification comes from comparing workers hired into new and old jobs within the same firm-year.

Within-firm comparison. Table 2, Panel B, shows that the new job wage premium persists when entrants are compared across occupations within the same firm-year.[25] Column (1) reports the within-firm specification without worker controls; column (2) adds age, gender, education, and labor-market experience. The estimated premium falls from 4.6 to 3.1 percent after adjusting for worker composition. Thus, observable worker characteristics explain around one-third of the within-firm wage difference, but a sizable premium remains among workers with similar observed characteristics. I examine differences in entrant composition directly in Section 5.2.

As in Panel A, entry wages into old jobs do not differ meaningfully between replacement and expansion hires. This suggests that expansion within an existing occupation, by itself, does not account for the premium. Column (3) adds an indicator for job-to-job movers. Entering a new job within a firm carries a wage premium similar in magnitude to the wage gain associated with job-to-job mobility (3 vs. 3.3 percent).[26]

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

[24]The estimate on log value added per worker in column (4) implies that a one percent increase in value added per worker is associated with a 0.037 percent increase in entry wages among *new hires*. This magnitude is close to estimates in studies using firm-level productivity measures and individual-level wages, as reported by Card et al. (2018).

[25]Identification relies on firms that hire into both new and old jobs in a given year. I replicate the results by restricting the sample to these identifying firms and obtain very similar estimates (Appendix Figure B4, *Identifying firms*).

[26]Appendix Figure B4 (*JJ movers*) restricts the sample to job-to-job movers only and obtains virtually identical estimates, showing that the new job wage premium also appears among workers with the same labor-market status

Table 2: New job wage premium

Dependent var: ln(Entry Wage)					
Panel A. Across-firms	(1)	(2)	(3)	(4)	(5)
Omitted category: Expanding old jobs					
New job	0.053***	0.028***	0.027***	0.030***	0.028***
	(0.0063)	(0.0055)	(0.0054)	(0.0050)	(0.0044)
Old job (Replacing)	-0.0039	-0.00053	0.0015	0.0043**	-0.0011
	(0.0025)	(0.0023)	(0.0021)	(0.0015)	(0.0011)
log(Firm size)	-0.0010	-0.00082	-0.00084	0.00071	-0.00081
	(0.0017)	(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	1765512	1523783	1523783
Adjusted R^2	0.685	0.746	0.746	0.763	0.780
Occupation x LLM x Year FE	✓	✓	✓	✓	✓
Industry x Year	✓	✓	✓	✓	✓
Worker controls		✓	✓	✓	✓
Worker FE					✓
Panel B. Within-firm	(1)	(2)	(3)	(4)	(5)
Omitted category: Expanding old jobs					
New job	0.046***	0.031***	0.030***	0.038***	0.029***
	(0.0043)	(0.0038)	(0.0037)	(0.0041)	(0.0061)
Old job (Replacing)	0.0014	0.0012	0.0014	0.00042	-0.0019*
	(0.0024)	(0.0020)	(0.0020)	(0.0025)	(0.00093)
J2J mover			0.033***		
			(0.0011)		
Observations	1765512	1765512	1765512	1765512	1765512
Adjusted R^2	0.734	0.783	0.784	0.791	0.805
Occupation x LLM x Year FE	✓	✓	✓	✓	✓
Firm x Year FE	✓	✓	✓		
Worker controls		✓	✓	✓	✓
Firm x Year x Skill FE				✓	
Firm FE					✓
Worker FE					✓

Notes: $^{*}p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. This table reports baseline estimates of the new job wage premium. The dependent variable is log entry wages. The coefficient on "New job" gives the difference in entry wages between workers hired into newly created jobs and those hired into expanding old jobs (the omitted category); "Old job (Replacing)" gives the analogous difference for replacement hires. Each column is a separate regression. Worker controls are age, gender, labor market experience, and education; LLM denotes local labor market. Panel A reports across-firm specifications with occupation × LLM × year and industry x year fixed effects. Panel B reports within-firm specifications: column 3 additionally controls for a job-to-job mover indicator; column 4 saturates with firm x year x skill fixed effects; column 5 is a two-way fixed-effects (AKM-style) specification with firm and worker fixed effects. Standard errors are clustered at the 2-digit industry level in Panel A and at the firm level in Panel B. The number of observations in Panel A columns 4–5 is smaller than in columns 1–3 because value added per worker is only available for non-financial corporations in Sweden (in real SEK, base year 2006).

Firm-by-year fixed effects absorb wage determinants common to all hires at the firm in a given year. They do not, however, absorb shocks that affect different parts of the firm differently. As emphasized in the pass-through literature (Card et al., 2018; Kline et al., 2019; Maibom and Vejlin, 2021), firms may adjust wages differently across worker groups in response to common shocks. Column (4) therefore introduces firm-by-year-by-skill fixed effects, which absorb skill-specific wage shocks within firms. Identification then comes from comparing new and old jobs within the same firm-year and skill group.[27] The new job wage premium remains positive and statistically significant under these stricter controls, indicating that the baseline result is not driven by broad skill-specific wage adjustments within firms.[28]

Worker fixed effects To assess whether the new job wage premium reflects time-invariant unobserved worker productivity, I estimate a complementary specification that adds worker fixed effects. This specification absorbs persistent differences across workers, while controlling for firm fixed effects, occupation-by-year fixed effects, and the same observable worker characteristics as in the baseline:

$$\ln(\text{entry wage})_{ijot} = \gamma \, \text{New Job}_{jot} + \alpha_i + \lambda_{j(i,t)} + \lambda_{ot} + X_{it}'\delta + \epsilon_{ijot}, \tag{14}$$

where α_i denotes worker fixed effects, $\lambda_{j(i,t)}$ denotes firm fixed effects, λ_{ot} occupation-by-year fixed effects, and X_{it} worker controls. This specification is not identical to the baseline firm-by-year design: firm fixed effects replace firm-by-year fixed effects so that worker fixed effects can be included while preserving identifying variation.

Table 2 column (5) 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 new job wage premium remains identical to the baseline, suggesting that the premium is not driven by time-invariant unobserved differences in worker ability.

at entry.

[27]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.

[28]Appendix Figure B4 further tightens the comparison by augmenting the within-firm baseline with firm-by-year-by-occupation fixed effects at the 1- and 2-digit ISCO levels. Under these specifications, identification comes from comparisons of new and old jobs across narrow 3-digit occupations within the same broad occupational family and firm-year. The estimated premium remains stable, suggesting that the result is not driven by shocks common to broad occupational functions within the firm.

5.1.1 Job age-wage profile

The model outlined in section 2 predicts that the new job wage premium should decline as firms accumulate employment experience in an occupation. I test this prediction by estimating how the entry wage premium varies with job age. Job age is defined as the number of years since a firm–occupation pair is first observed in the data. New jobs have age zero, while older firm–occupation pairs are grouped into age categories.

Figure 2 shows that new jobs carry a 4.5 percent wage premium relative to jobs that have existed within the firm for 13 years or more. The premium declines sharply after the first year and becomes statistically indistinguishable from zero after six to eight years.[29]

These patterns are consistent with the interpretation that firms learn about hiring in an occupation as they accumulate employment experience. In the language of the model, the effective uncertainty associated with new jobs declines with job age, and the wage premium fades after six to eight years.

5.1.2 Heterogeneity by occupation groups

In this section, I examine whether the new job wage premium is concentrated in particular parts of the occupational structure. One concern is that new jobs may be associated with ex ante higher productivity, for example, because firms create new roles when adopting new technologies or expanding into high-value functions. If so, the new job indicator may partly capture high-skill or technology-complementary roles rather than limited firm experience in the occupation. More generally, the average premium may mask substantial heterogeneity across skill groups.[30] To assess these possibilities, I estimate Equation (12) separately by broad one-digit ISCO occupation group.

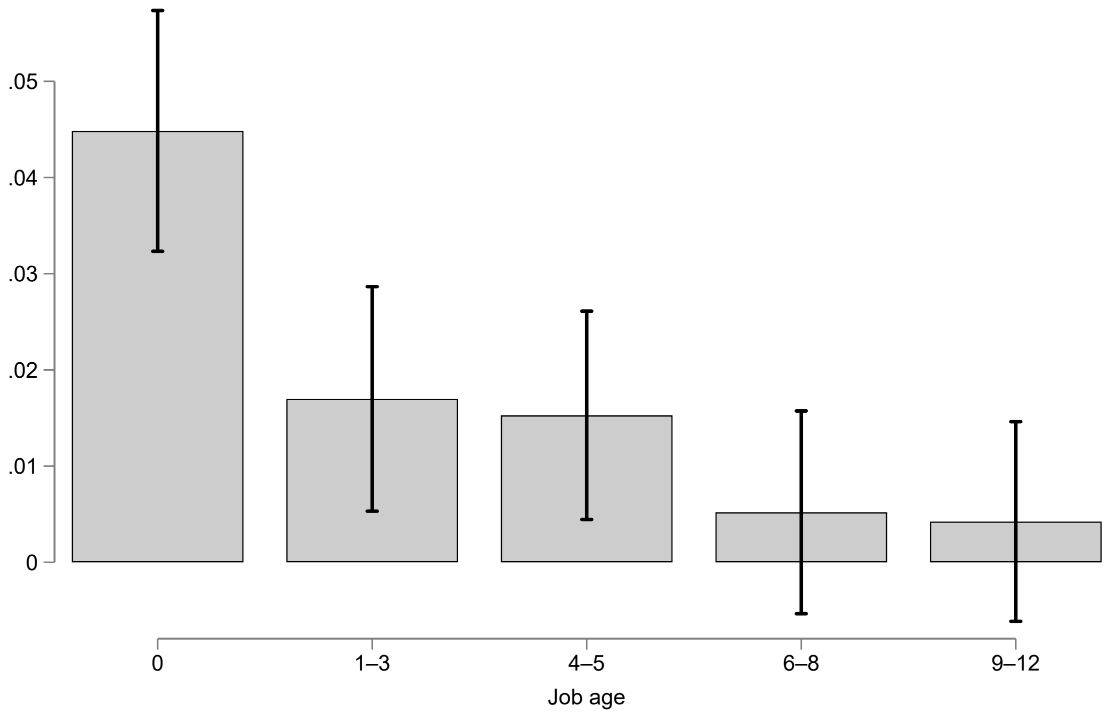
Figure 3 shows that the new job wage premium is present across broad occupation groups. Point estimates are around 4–5 percent for managers, professionals, and technicians, and about 3 percent for clerks. The premium is particularly large in sales, at roughly 7 percent, and remains sizable for machine operators, at around 4 percent. The exception is elementary occupations, where the estimate is small and imprecise.

These patterns suggest that the premium is not confined to high-skill occupations. This

[29] 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 aggregate occupation-specific wage floors, while the firm-by-year fixed effects absorb firm-level changes in agreement affiliation. If the premium reflected a permanent shift in bargaining regime, it should persist for subsequent hires into the occupation. The gradual decline documented here is instead consistent with a transitory friction that resolves with experience.

[30] 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).

Figure 2: 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 level.

makes it unlikely that the average new job wage premium is driven solely by skill upgrading or by the creation of high-productivity roles. Instead, the presence of a premium across both white-collar and blue-collar occupations is consistent with a more general mechanism: wages differ when firms hire into occupations in which they have limited prior employment experience.

5.1.3 How large is the new job wage premium?

So far, I have documented a robust new job wage premium. I assess its magnitude in two ways. First, I benchmark it against the wage gain associated with job-to-job mobility. Second, I interpret it in terms of workers' positions in the within-occupation residual wage distribution.

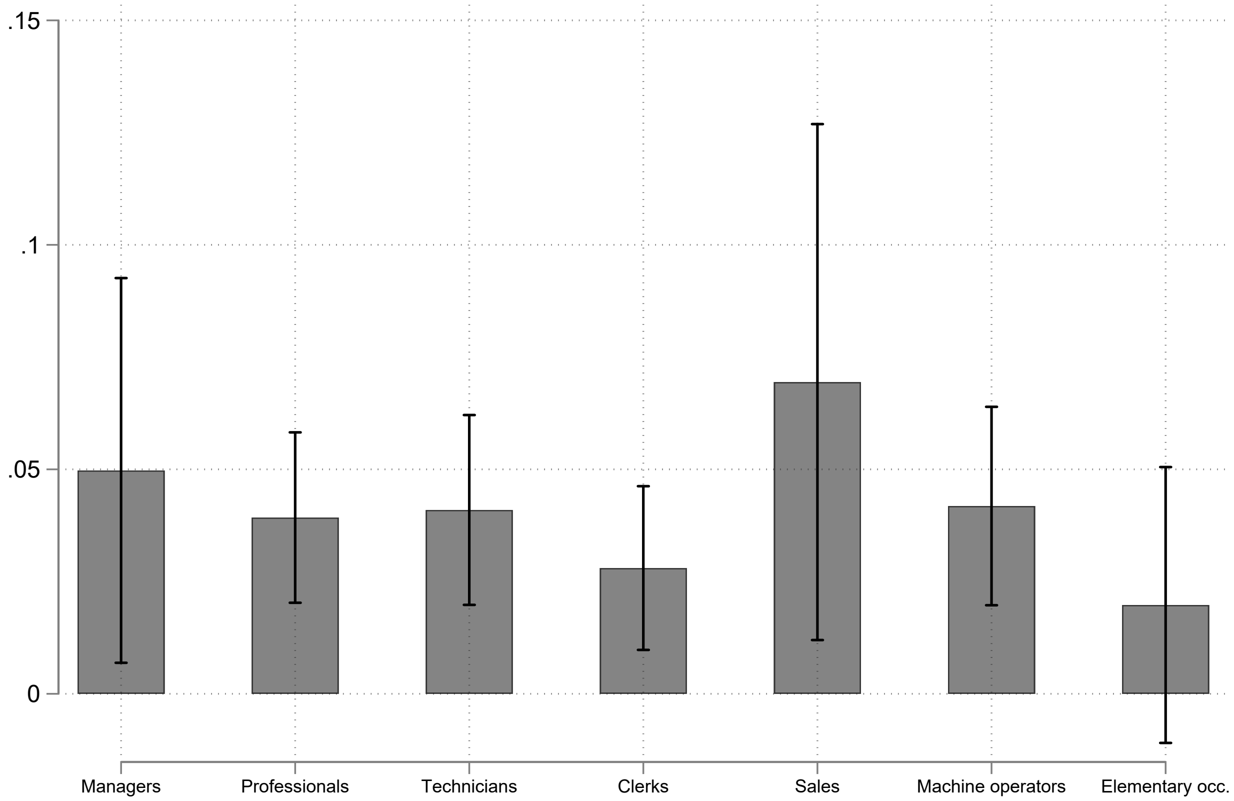
Returns to job-to-job mobility. Previous research identifies job-to-job mobility as a key driver of wage growth over the life cycle (Topel and Ward, 1992; Adda and Dustmann, 2023). In my sample, job-to-job movers earn entry wages that are 3.3 percent higher than workers entering from non-employment, conditional on worker characteristics and experience at entry. Panel B, column (3) of Table 2 shows that the new job wage premium is of similar magnitude. Importantly, the two premia are estimated in the same specification, so the new job wage premium is measured net of the job-to-job mover effect. This comparison is informative because the two premia capture distinct margins of wage growth: the job-to-job premium reflects on-the-job search and upward movement along the job ladder, whereas the new job wage premium reflects entry into a newly created job within a firm. Their similar magnitudes suggest that transitions into new jobs are a quantitatively important, and previously overlooked, source of wage growth.

Position in the wage distribution. To interpret the size of the new job wage premium in distributional terms, I map it into the residual wage distribution of new hires. I first estimate Equation 12 separately for each one-digit occupation group and obtain an occupation-specific new job wage premium (see Figure 3). I then relate these estimates to the corresponding residual wage distributions.[31] For each occupation, I compute the percentile that a median worker would reach in the residual wage distribution when entering a new job.

Figure 4 plots, for each broad occupation group, the 10th–90th percentile range and the interquartile range, marks the median, and overlays γ_s together with its corresponding percentile label. This visualization shows both the degree of within-occupation wage dispersion and the size of the estimated premium. For each occupation, the triangle marker and its percentile label indicate the percentile to which a median worker's position in the within-occupation residual wage distribution would shift when entering a new job.

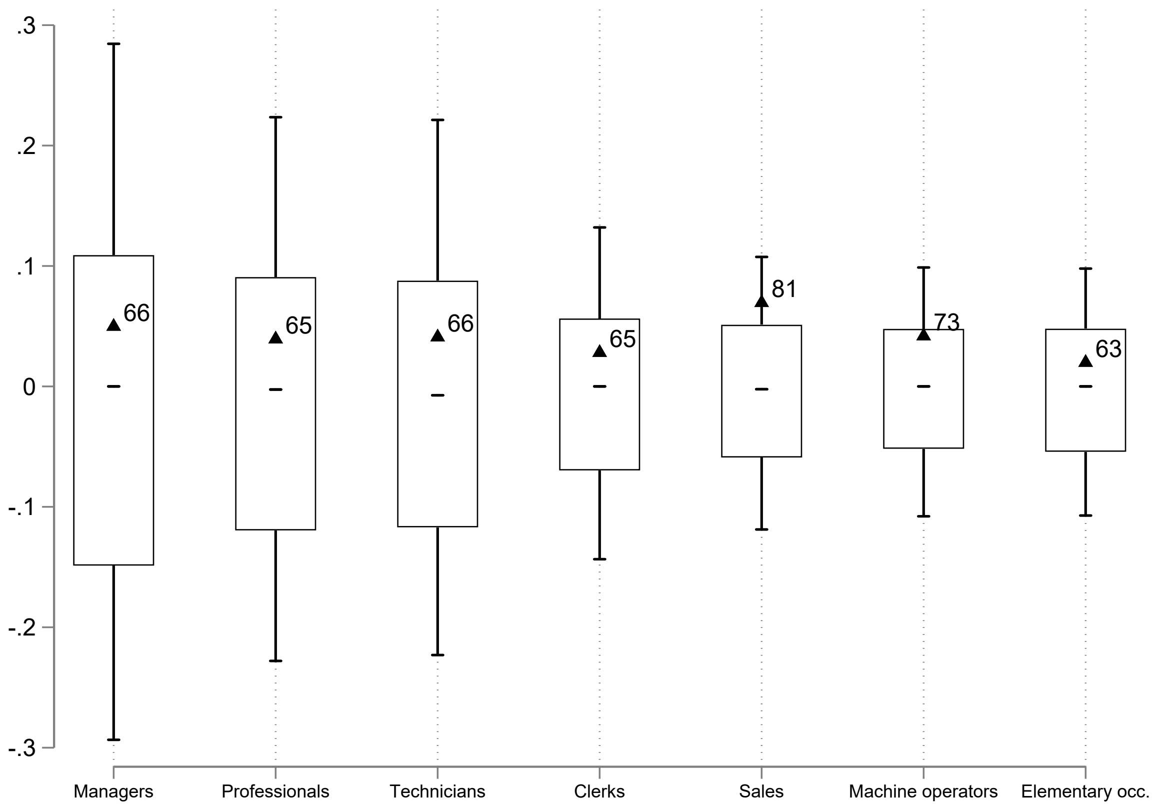
[31] I residualize wages on age, experience, gender, education, occupation-by-year, and firm-by-year effects.

Figure 3: 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 (12) 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 craft and related trades (ISCO 7).

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. 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 percentiles—from the 50th to the 65th percentile—equivalent to an increase of about one to two deciles. Across occupations, the upward shift ranges from about 13 percentiles in elementary occupations to 31 percentiles in sales occupations. These magnitudes indicate that the new job wage premium is large enough to move a typical worker noticeably upward in the wage distribution among comparable new hires.

5.2 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 takes place 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 spent in the labor market at entry.[32]

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.[33] 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 the long-term unemployed. 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.[34]

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 into

[32]Evidence from surveys and field experiments 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 percent of employers view experience as a key selection criterion.

[33]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 percent of new entrants are job-to-job movers in my data.

[34]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.

Table 3: Firms' differential employee selection

Dependent variable:	$\mathbb{1}$(J2J Mover)	$\mathbb{1}$(Long-term Unemployed)	$\mathbb{1}$(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 nine 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.

old jobs.[35] Experience is an observable proxy for information about the worker: longer employment histories provide additional signals about past performance, which may be particularly valuable when the firm has limited occupation-specific information about what predicts success in the role.[36]

Figure 5 shows that these selection patterns also decline with job age. Entrants into newly created jobs are more likely to be job-to-job movers and experienced workers, and less likely to come from long-term unemployment. These differences are largest when the firm first enters the occupation and fade as the firm accumulates employment experience in that occupation. This pattern mirrors the job age-wage profile in Figure 2 and is consistent with the interpretation that firms apply higher hiring standards when they have limited prior experience in an occupation.

Furthermore, I find differential selection within old jobs: expanding old jobs exhibit different selection patterns from replacing old jobs, implying that hiring frictions related to expansion remain even conditional on prior occupational experience. However, these differences in entrant composition do not translate into wage differences between expanding and replacing old jobs.[37]

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 C4, 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 by 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 C5 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.

5.3 Worker sorting on unobservables

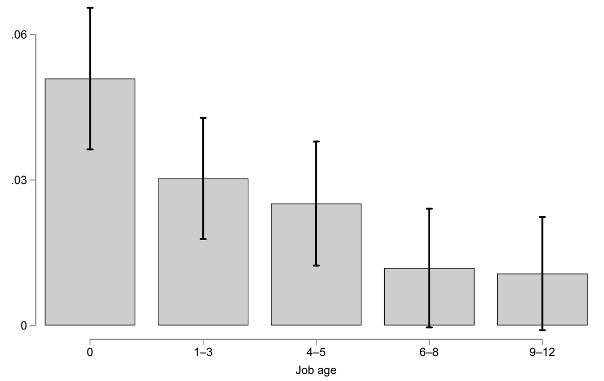
In Section 5.1, I show that the new job wage premium persists after including worker fixed effects (Table 2, column (5)). The identification of the new job wage premium in that speci-

[35] *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.

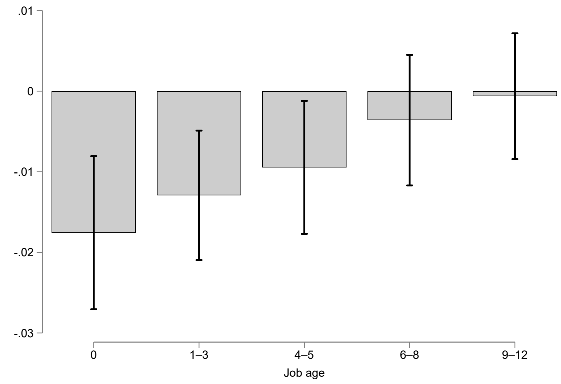
[36] New jobs within firms may also differ from old jobs because they can involve additional responsibilities, such as establishing new teams; I discuss this alternative channel in Section 6.2.

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

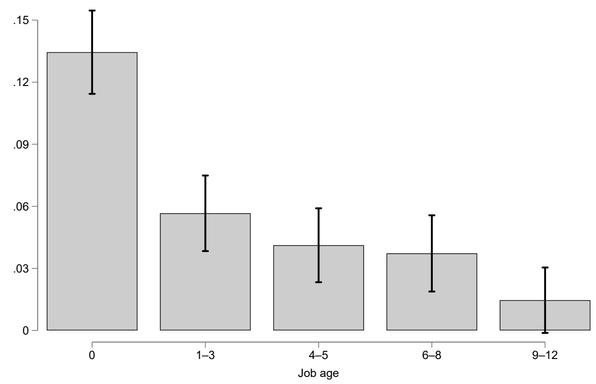
Figure 5: Job age profiles of entrant selection



(a) Job-to-job mover



(b) Long-term unemployed



(c) Experienced worker

Notes: This figure plots coefficients from regressions of entrant characteristics on job age categories. Job age is defined as the number of years since a given firm–occupation pair is first observed in the data, computed as the current year minus the first year that the firm–occupation pair appears. Job age is grouped into six bins: 0; 1–3; 4–5; 6–8; 9–12; and 13+. The omitted category is job age 13+. Panel (a) reports effects on the probability that the entrant is a job-to-job mover. Panel (b) reports effects on the probability that the entrant comes from long-term unemployment. Panel (c) reports effects on the probability that the entrant has more than ten years of labor-market experience. All regressions include the baseline controls and fixed effects from Equation (12). Whiskers denote 95% confidence intervals. Standard errors are clustered at the firm level.

fication 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) in explaining the new job wage premium.[38]

I measure workers' portable human capital using AKM person effects estimated in a pre-analysis period (1985-96).[39] 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:

$$\ln w_{it} = \theta_i + \psi_{j(i,t)} + X_{it}'\delta + \varepsilon_{it}, \tag{15}$$

where w_{it} is worker i's monthly earnings in year t at firm $j(i,t)$, and 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. X_{it}' includes year fixed effects together with education-group indicators interacted with quadratic and cubic polynomials in (age $-$ 40), omitting the linear term, so that the profile is flat at age 40.[40]

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

$$\hat{\theta}_i = \phi \,\text{New Job}_{jot} + \lambda_{jt} + \lambda_{ot} + X_{it}'\delta + \epsilon_{ijot}, \tag{16}$$

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 6 plots the estimated new job wage premium and the sorting parameter. The left panel ("Across-firms") shows entry wage differentials (γ) 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.

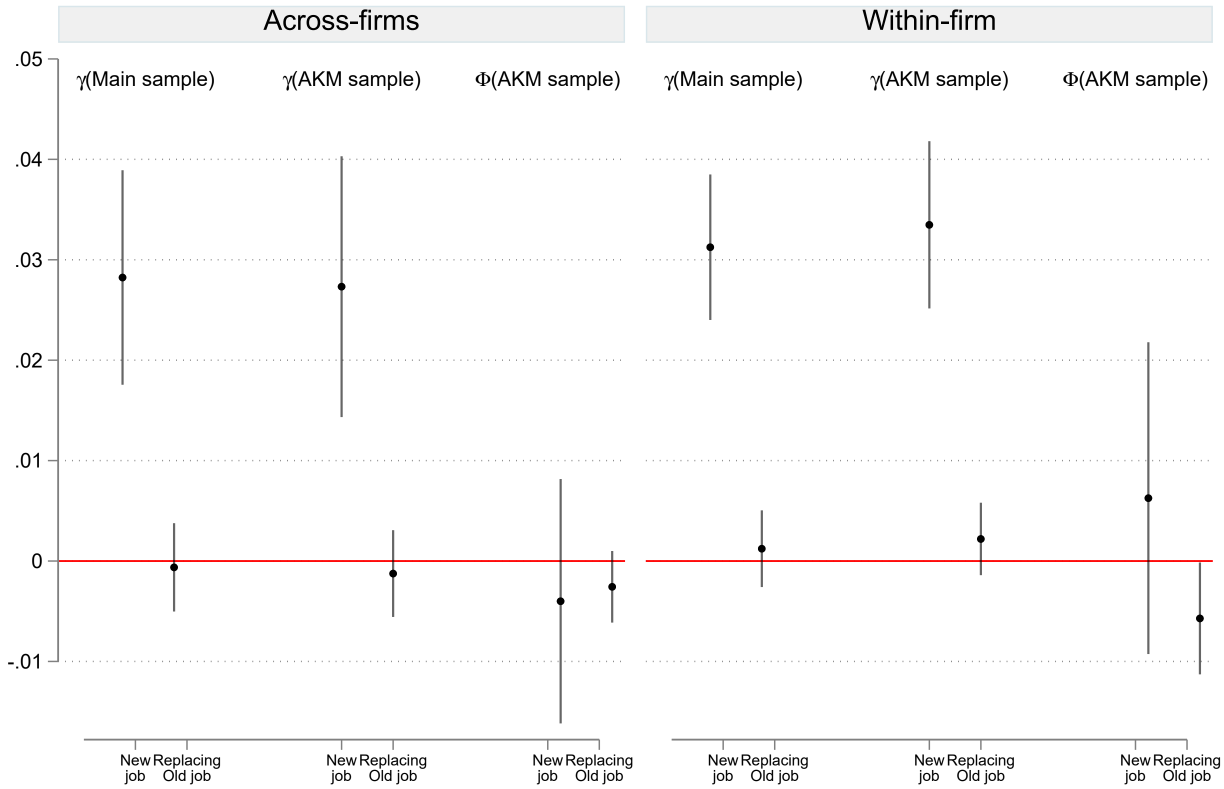
The figure shows that the sorting estimates are much smaller—about one-fifth of γ—and statistically indistinguishable from zero (Table C7). Together, these results imply that differences

[38]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.

[39]Appendix Table C2 presents summary statistics for the sample of workers and firms included in the AKM estimation over 1985-96. Approximately two-thirds 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 1985-96.

[40]The wage measure used in this regression is monthly earnings. Appendix Table C6 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.

Figure 6: 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 16. The left panel reports γ estimates across firms; the right panel reports γ estimates within firms. In each panel, the first two sets of points correspond to γ estimated on the main sample and on the pre-dated AKM sample, respectively. The third set of points show ϕ from Equation 16, 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.

in estimated person effects are negligible relative to the new job wage premium. Thus, I find no evidence that entrants into newly created roles are positively selected on unobserved productivity. The premium cannot be attributed to high-ability workers sorting into new jobs.

5.4 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 into 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.[41]

I estimate variants of Equation 12 that replace the dependent variable with measures of match quality, comparing workers who enter the same firm in the same year. I consider five outcomes that capture distinct dimensions of match quality: separation and retention, measured by $\mathbb{1}$(1st-year separation) and $\mathbb{1}$(Stay in $t+3$); and the returns to the match, measured by cumulative within-job earnings, three-year wage growth, and the standard deviation of wages among stayers.[42] All specifications include the same covariates and fixed effects as in the baseline.

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 (3.4 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 4,000 EUR). These patterns are consistent with the selection mechanism in the model: if firms apply higher reservation productivity thresholds in new jobs, accepted matches should be positively selected and may exhibit higher subsequent match quality.

[41] 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).

[42] Within-job earnings are total earnings accumulated over the employment relationship. Wage growth is the three-year change in log wages conditional on remaining in the same firm; this restriction reduces the sample to roughly one-quarter of the original size because wage data are sampled annually.

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
	(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.

5.5 Heterogeneity by occupational similarity

The theoretical model in Section 2 predicts a new job wage premium that arises because pre-hire uncertainty about match productivity leads firms to apply higher 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 that is dissimilar to the occupations in which the firm already employs workers, because the firm can draw less on prior experience. In contrast, if the premium primarily reflects, for instance, differences in marginal productivity across jobs or broad shifts in demand for particular worker skills, one would expect similar and dissimilar new jobs to exhibit comparable premia and similar worker composition.

To distinguish between these channels, I exploit variation in how similar a newly introduced occupation is to the firm's existing occupations, using occupational similarity based on the skill content of occupations. I measure similarity using 35 skills from the O*NET database 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).[43]

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):

$$\text{AngSep}_{oo'} = \frac{\sum_{k=1}^{K} s_{ok} \times s_{o'k}}{\left[\left(\sum_{k=1}^{K} s_{ok}^2\right) \times \left(\sum_{k=1}^{K} s_{o'k}^2\right)\right]^{1/2}}, \tag{17}$$

and define occupational distance as $\text{Dis}_{oo'} = 1 - \text{AngSep}_{oo'}$. Because O*NET level scores are non-negative, the measure is bounded between zero and one: it equals zero for occupations with identical skill profiles and one for occupations with orthogonal skill profiles.[44] For each new job in occupation d, I compute the angular distance from d to the firm's closest existing occupation. 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 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 stronger selection: they are 4 pp

[43]Appendix Table C9 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.

[44]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.

Table 5: New job wage premium and employee selection by skill similarity

	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 12.

more likely to be filled by job-to-job movers (compared to 1.3 pp for similar), 11 pp more likely to hire experienced workers (compared to 7.3 for similar), and 1 pp 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).[45] These patterns are consistent with the interpretation that when the skill content of the new occupation is more distant from the firm's existing workforce, both the wage premium and hiring selectivity increase.[46]

Taken together, these results show that the new job wage premium is systematically larger when the newly introduced occupation is less similar to the firm's existing occupational structure. The same pattern appears in hiring margins: dissimilar new jobs are filled more selectively, particularly through greater reliance on job-to-job hires and experienced workers. These findings are difficult to reconcile with an interpretation based solely on broad shifts in skill demand or higher marginal productivity of newly created roles. Instead, they are more consistent with the view that firms face greater match-specific uncertainty when introducing roles that are further from their existing stock of knowledge, and that this uncertainty shapes both wages and worker selection.

5.6 Robustness checks

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 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) misclassifications 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 Figure B4 (*4-digit occupations*) reports estimates under the 4-digit definition and shows results very similar to the baseline, indicating that the estimated new job

[45] Appendix Table C11 reports estimates using a continuous measure of skill novelty. Moving from the 25th to the 75th percentile of skill novelty is associated with approximately 1.4 percent higher entry wages.

[46] As a complementary measure, I define occupational similarity based on observed worker transitions between occupations, following Belot et al. (2019) and Le Barbanchon et al. (2023a). For each new job in destination occupation d, I compute the transition share from any occupation the firm already employs. New jobs with low inflow shares from the firm's existing occupations are classified as dissimilar. Appendix Table C10 shows that the point estimates follow the same directional pattern as in the main O*NET-based analysis: the entry wage premium is larger for dissimilar new jobs, and dissimilar new jobs also exhibit stronger selection on job-to-job status and experience. However, for this alternative transition-based measure, the differences between similar and dissimilar new jobs are not statistically significant at conventional levels.

wage premium is not driven by the occupational aggregation choice.[47]

A second robustness check addresses a concern that firms with short panel coverage may contribute noisily to the estimates, or that entry and exit selection may confound the definition of new jobs. Appendix Figure B4, *7+ consecutive years*, addresses this by restricting the sample to firms observed in the data for at least seven consecutive years. The estimated premium remains close to the baseline, indicating that the result is not driven by short-lived firms or firm-level entry and exit dynamics.

Finally, as noted in Section 5.1, Appendix Figure B4 shows that the premium remains similar when absorbing firm-by-year shocks at the 1- and 2-digit occupation levels. The estimated premium is very similar to the baseline.

Firm-level heterogeneity Younger and smaller firms are more likely to create new jobs (Table 1). I therefore examine whether the premium varies by firm age, firm size, and industry. Appendix Figure B5 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 premium is not concentrated in a narrow set of firms.

6 Alternative theories and interpretations of results

The evidence so far is most consistent with an information frictions interpretation: the premium is larger in occupations that are more novel to the firm and declines with occupation-specific employment history. However, these patterns do not by themselves rule out other mechanisms. In this section, I consider four alternative explanations for 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 role content, promotion dynamics, and team-building responsibilities: early hires may receive higher wages because they are expected to establish routines, build teams, or face different promotion prospects. The third is monopsonistic competition: if wages increase with firms' hiring rates, the premium may reflect firm growth rather than occupation-specific uncertainty. The fourth is task reallocation within firms: introducing a new occupation may alter the content of existing occupations and thereby affect the within-firm comparison.

[47] A related measurement concern is that the WSS records wages in September-October, so the wage measure may not coincide exactly with the wage at the actual start date. This would be problematic if hires into new and old jobs occurred at systematically different times of the year. In unreported results, the estimated premium is unchanged when I control for the hiring-month. This suggests that the new job wage premium is not driven by differences in the timing of hiring relative to the September wage observation.

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.

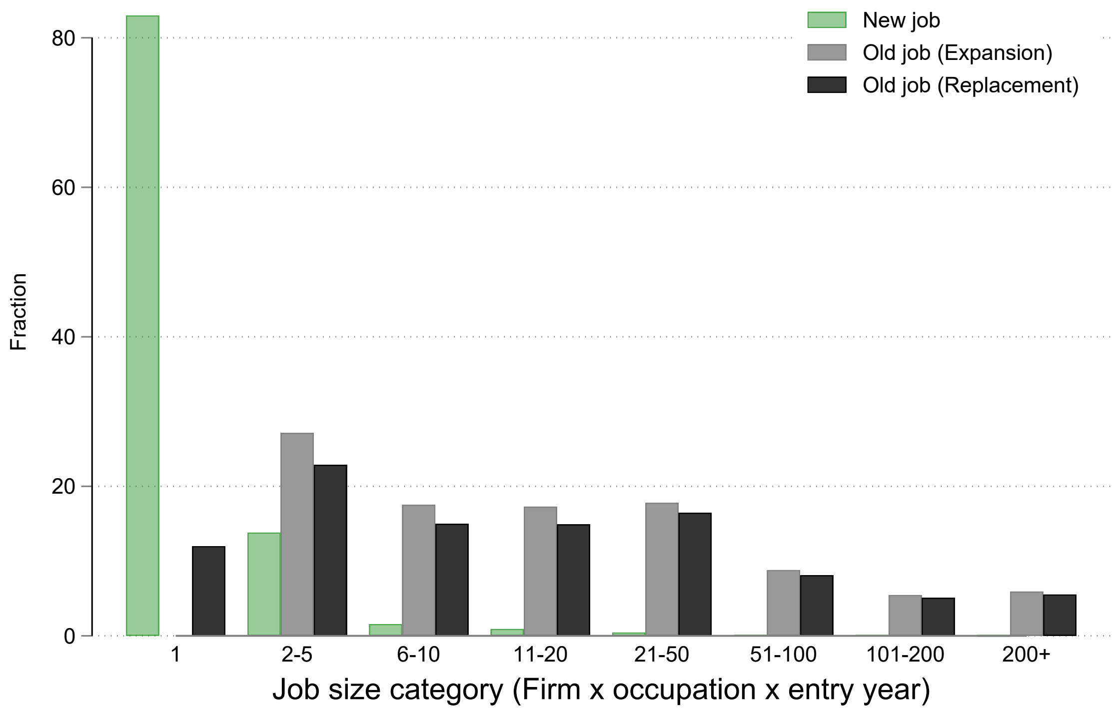
Table 4 shows that entrants into new jobs have longer tenure than comparable entrants into old jobs. This difference persists even after conditioning on entry wages (Appendix Table C8). If the premium merely compensates workers for job-specific disamenities, turnover should not be systematically lower among new job entrants, especially conditional on wages. These turnover results are difficult to reconcile with the theory of compensating differentials.

A salient feature of new jobs is, however, the low number of workers during the first year of employment. Figure 7 shows that new jobs are more likely to employ a single worker. Approximately 80 percent of new jobs consist of a single worker in their first year. Working in small teams may be an undesirable job feature due to, e.g., weaker peer support (Hensvik and Rosenqvist, 2019; Azmat et al., 2025). 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 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 team size. Column (2) shows 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 a gradient suggests that uniqueness is unlikely to be the primary driver of the new job wage premium.

Column (3) in Table 6 further 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) shows the 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 new jobs appear less demanding in terms of overtime work.

Figure 7: 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.

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.

These results make it difficult to interpret the premium as compensation for worse non-wage job attributes. A different possibility, however, is not that new jobs are less attractive, but that the first hire into a new occupation performs a substantively different role within the firm. I turn to that interpretation next.

6.2 Role content, team-building, and promotion dynamics

An 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 from* 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 responsibilities, 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, 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.

Second, the occupational similarity results in Table 5 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. 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.

New jobs within firms may offer different promotion prospects or entail team-building responsibilities. I examine two proxies for the team-building and promotion channels. 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

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.

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. I next turn to a conceptually different mechanism that operates at the firm level rather than the job level.

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.[48] In line with his main finding, Table 2, Panel A, columns (2) and (3) show 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 is unlikely to fully account for the new job wage premium on its own.

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. If new job creation reflects solely an increase in 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:

$$\ln w_{jt} = \alpha_j + \lambda_t + \sum_{\tau=-3}^{3} \gamma_\tau \, \mathbb{1}[K_{jt} = \tau] + \varepsilon_{jt}, \tag{18}$$

where $K_{jt} = t - E_j$ is event time, E_j is the first year in which firm j introduces a new job, α_j are firm fixed effects, λ_t are year fixed effects, and ε_{jt} is the error term. The control group consists of firms that only expand along old jobs during the sample period and are never-treated. I estimate the parameters $\{\gamma_\tau\}$ using the imputation estimator of Borusyak et al. (2024).[49] The

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

[49]Treatment in this design is staggered (firms introduce new jobs in different years). Conventional two-way fixed-effects OLS estimators of dynamic event-study specifications can place negative weights on long-run treat-

implicit reference is the pre-treatment period more than three years before the event together with never-treated firm-years. Standard errors are clustered at the firm level.

Figure 8 shows that firms introducing new jobs do not pay higher wages compared to firms that expand in old jobs. Panels (a) and (b) show no differences in levels in the wages paid to all workers or to incumbents. By contrast, Panels (c) and (d) show that firms creating new jobs pay higher wages to newly hired workers, but not to entrants into old jobs once new job hires are excluded. The estimated 2 percent increase in average wages for all new hires in Panel (c) is therefore consistent with the new job wage premium documented in Table 2, since this group includes both entrants into new jobs and entrants into old jobs.[50]

If monopsonistic competition drives the premium, firms introducing new jobs should also pay higher wages to other newly hired workers in old jobs. Panel (d) shows no such difference: firms that introduce new jobs offer comparable wages to new hires into old jobs. Moreover, the event-study estimates show no differential wage trends before or after the event relative to firms that expand only along existing occupations. Taken together, the evidence does not support an explanation based on monopsonistic competition operating through firm-level hiring intensity or firm-wide pay differences.

6.4 Task reallocation within firms

While the event-study evidence argues against monopsony, introducing a new occupation could still affect the internal organization of work within the firm. I therefore discuss whether task reallocation across jobs can account for the premium.

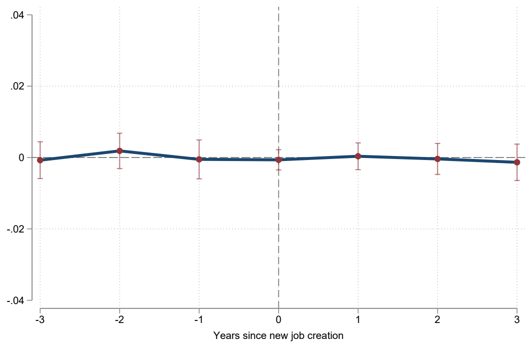
The within-firm design compares newly created roles to existing roles within the same firm-year. However, introducing a new occupation may reallocate tasks across jobs, thereby altering the composition of the comparison group.

Two pieces of evidence suggest that such reallocation is limited. First, the firm-level event studies in Figure 8 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

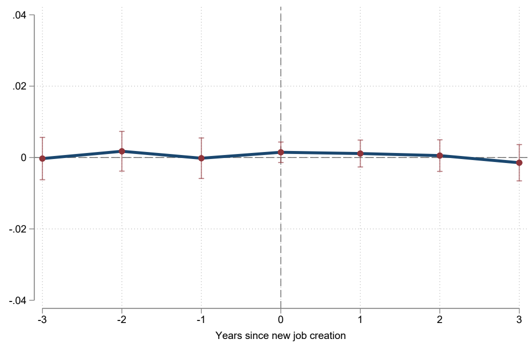
ment effects and contaminate pre-trend tests with post-treatment heterogeneity. The imputation estimator of Borusyak et al. (2024) avoids both problems.

[50] At first glance, the 2 percent average effect may appear large: with 18 percent of new hires going into new jobs (Table 1, Panel B), a 3.1 percent per-hire premium would mechanically imply a firm-wide effect of only 0.56 percent. The event-study specification, however, weights firm-years equally. Small firms, in which a single new job hire can constitute the majority of that year's hiring, therefore receive disproportionate weight, raising the new job share well above the aggregate figure and bringing the implied average effect in line with the estimated 2 percent.

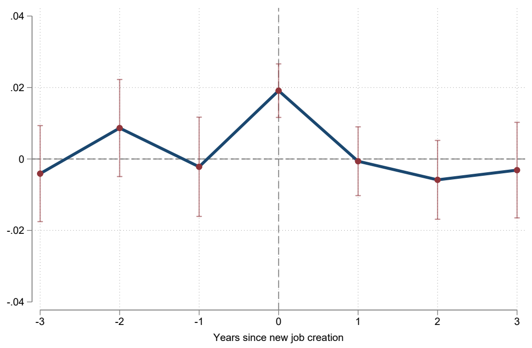
Figure 8: Firm-level event studies - wage per worker



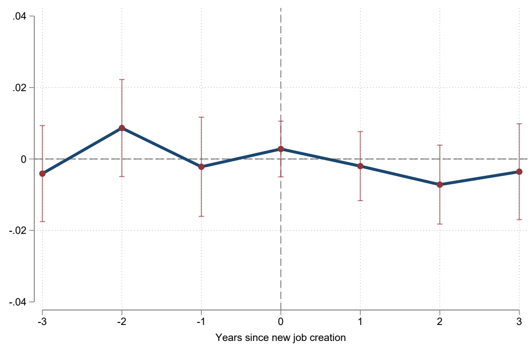
(a) All workers



(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 (18), 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) report event-study estimates for (a) all workers, (b) incumbents, (c) all new hires (into both new and old jobs), and (d) new hires excluding those entering new jobs.

reorganizing task assignments after introducing new roles, one might expect divergence in subsequent wage growth trajectories.

Taken together, these results provide little evidence that the introduction of a new occupation triggers substantial task reallocation affecting the wages of existing jobs. This makes it unlikely that changes in the composition of comparison jobs are the primary source of the estimated new job wage premium.

7 Conclusion

Previous research has documented that workers experience diverse labor market outcomes influenced by firm and individual job match characteristics. However, much less is known about how firm-side information frictions contribute to these differences. 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, and what this implies for match outcomes. I provide the first evidence on the impact of firms' employment experience in a particular occupation on employee selection, wages, and match outcomes. My findings underline that hiring frictions lead to diverse labor market outcomes among observably similar workers that are not explained by time-invariant worker heterogeneity, highlighting the role of information frictions in shaping workers' labor market outcomes.

I demonstrate that these information frictions affect firms' hiring decisions, which have implications for wage setting, worker reallocation and match quality. Firms select workers based on observables (prioritizing job-to-job movers and workers with longer labor market experience) to reduce the inherent uncertainty associated with new jobs. Match quality is higher in new jobs and workers entering new jobs receive higher entry wages and stay longer at the firm, gaps that are not attributable to time-invariant unobserved differences across workers. Workers employed in the same occupation and industry are paid differently across firms because firms differ in their occupation-specific employment histories. The paper contributes to our understanding of one of 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 structural change in the economy (Autor et al., 2024, 2026). 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. These mechanisms are likely to grow in importance as technological change accelerates.

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Online Appendix

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

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A. Theory appendix

B. Figure appendix

C. Tables appendix

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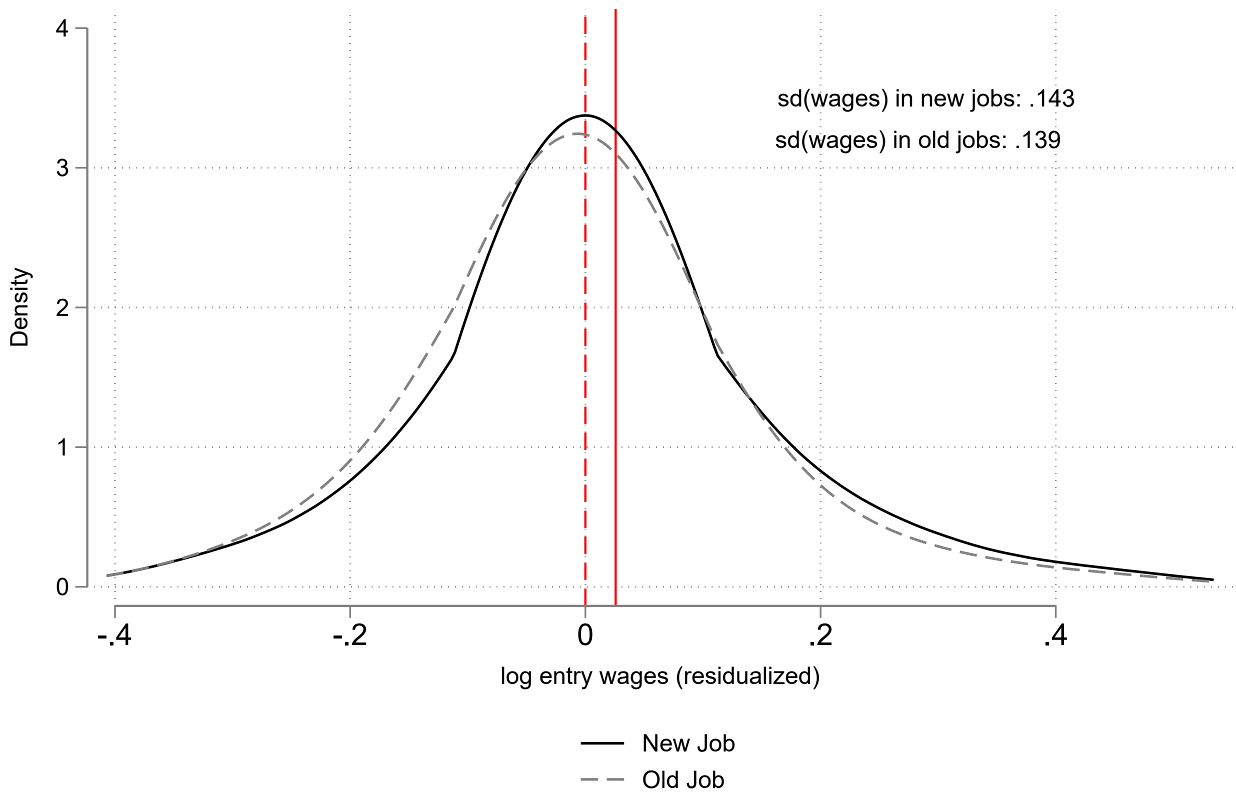
A Theory Appendix

A1 Empirical wage dispersion

The central assumption in the theoretical model is that new jobs are associated with greater dispersion in match productivity. Empirically, I observe only realized matches—worker–firm contacts in which productivity exceeds the reservation threshold ($y \geq y_{R,j}$) and a match is formed. Both residual wage dispersion and mean entry wages are higher in new jobs: the residualized standard deviation of log wages is 0.143 in new jobs compared to 0.139 in expanding old jobs. This pattern is consistent with the model's assumption of greater productivity dispersion in new jobs, though the gap is small (0.004 in absolute terms) and the mapping from latent productivity distributions to observed wage distributions depends on the standardized cutoff, which differs across job types.

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



Notes: Kernel density estimates of residualized log entry wages for workers in new jobs (solid) and expanding old jobs (dashed). Residuals from the main specification (Equation 12), winsorized at the 1st and 99th percentiles. Vertical lines indicate means.

A2 Wage equation derivation

The worker surplus is $W_j(y) - U = (w_j(y) - rU)/(r + s)$ and the firm's filled-job value is $J_j(y) = (y - w_j(y))/(r + s)$. Nash bargaining (7) gives

$$(1-\beta)\frac{w_j(y) - rU}{r+s} = \beta\,\frac{y - w_j(y)}{r+s}.$$

Expanding,

$$(1-\beta)\big(w_j(y) - rU\big) = \beta\big(y - w_j(y)\big),$$

and collecting terms yields

$$w_j(y) = (1-\beta)rU + \beta y, \qquad j \in \{O, N\}.$$

The wage is the standard Pissarides surplus-splitting wage, identical across job types under the assumed bargaining protocol. The hiring cost k does not appear because, under the Pissarides (2009) timing, it is sunk by the time bargaining occurs and is instead carried in the firm's vacancy Bellman (3) and job-creation condition (4).

A3 Reservation productivities

Given the common wage equation $w_j(y) = (1-\beta)rU + \beta y$, the filled-job value simplifies to

$$J_j(y) = \frac{y - w_j(y)}{r+s} = \frac{(1-\beta)(y - rU)}{r+s}.$$

Worker's acceptance margin. The worker accepts if $W_j(y) \geq U$, equivalently $w_j(y) \geq rU$, which reduces to $y \geq rU$. This holds for both types.

Firm's acceptance margin. The firm accepts if $J_j(y) - k_j \geq V_j$. Under free entry $V_j = 0$, this simplifies to $J_j(y) \geq k_j$. Substituting,

$$\frac{(1-\beta)(y - rU)}{r+s} \geq k_j \qquad \Longleftrightarrow \qquad y \geq rU + \frac{(r+s)k_j}{1-\beta}.$$

For old jobs ($k_O = 0$) this collapses to $y \geq rU$, coinciding with the worker's margin. For new jobs ($k_N = k > 0$), the firm's condition is strictly tighter and binds: $y_{R,N} = rU + (r+s)k/(1-\beta)$.

Surplus at the cutoff. At $y_{R,N}$, the firm's value of the filled job is

$$J_N(y_{R,N}) = \frac{(1-\beta)}{r+s} \cdot \frac{(r+s)k}{1-\beta} = k,$$

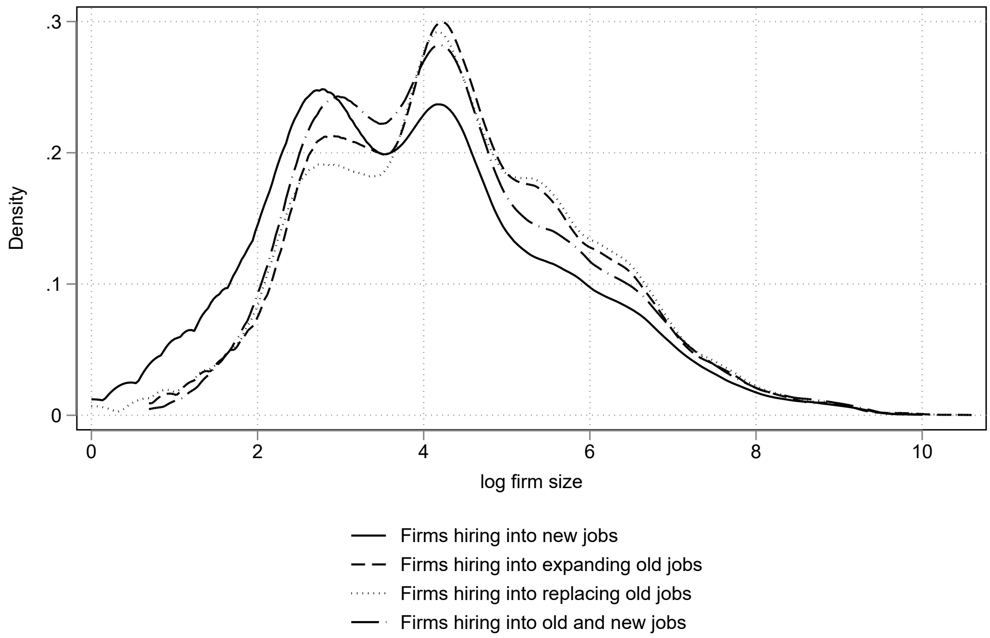
so the firm exactly recoups the hiring cost: $J_N(y_{R,N}) - k = 0$. The worker's surplus is

$$W_N(y_{R,N}) - U = \frac{w_N(y_{R,N}) - rU}{r+s} = \frac{\beta(y_{R,N} - rU)}{r+s} = \frac{\beta k}{1-\beta} > 0,$$

so the worker strictly prefers employment in a new job at the cutoff.

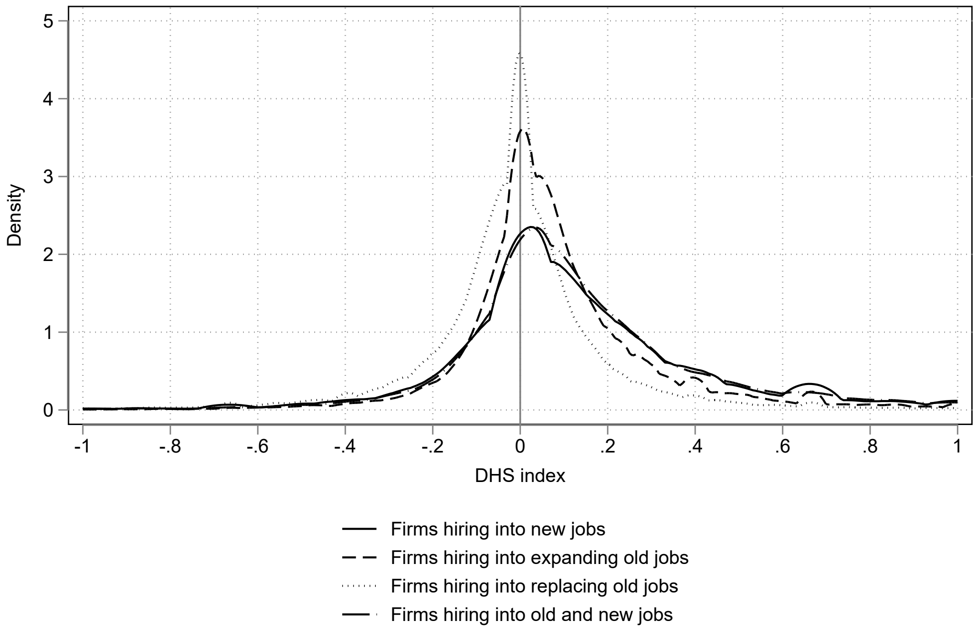
A4 Appendix Figures

Figure B1: Firm size distribution by types of hires



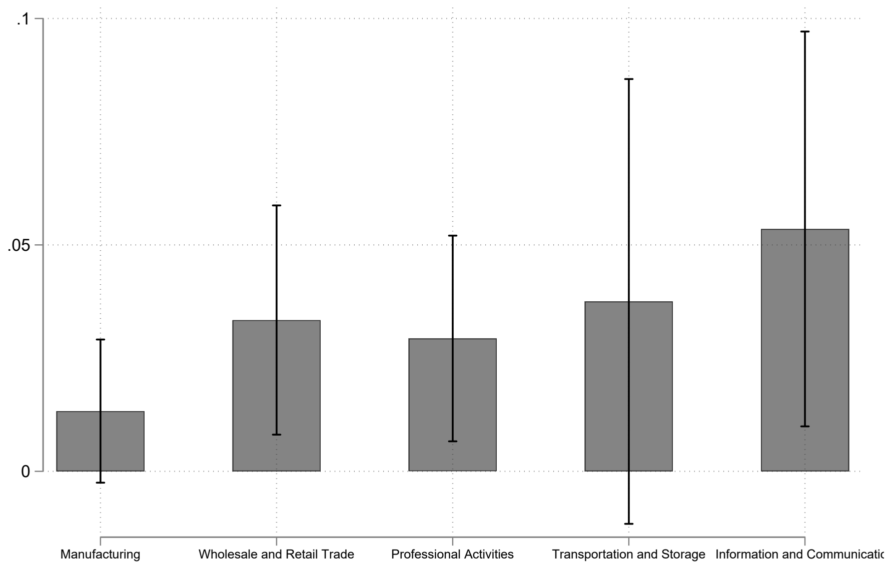
Notes: This figure plots kernel density estimates of log firm employment size in firm-years with different types of hiring. Firm size is measured as total employment in the sampling month (in logs). The solid line corresponds to firms hiring into new jobs, the dashed line to firms hiring into expanding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



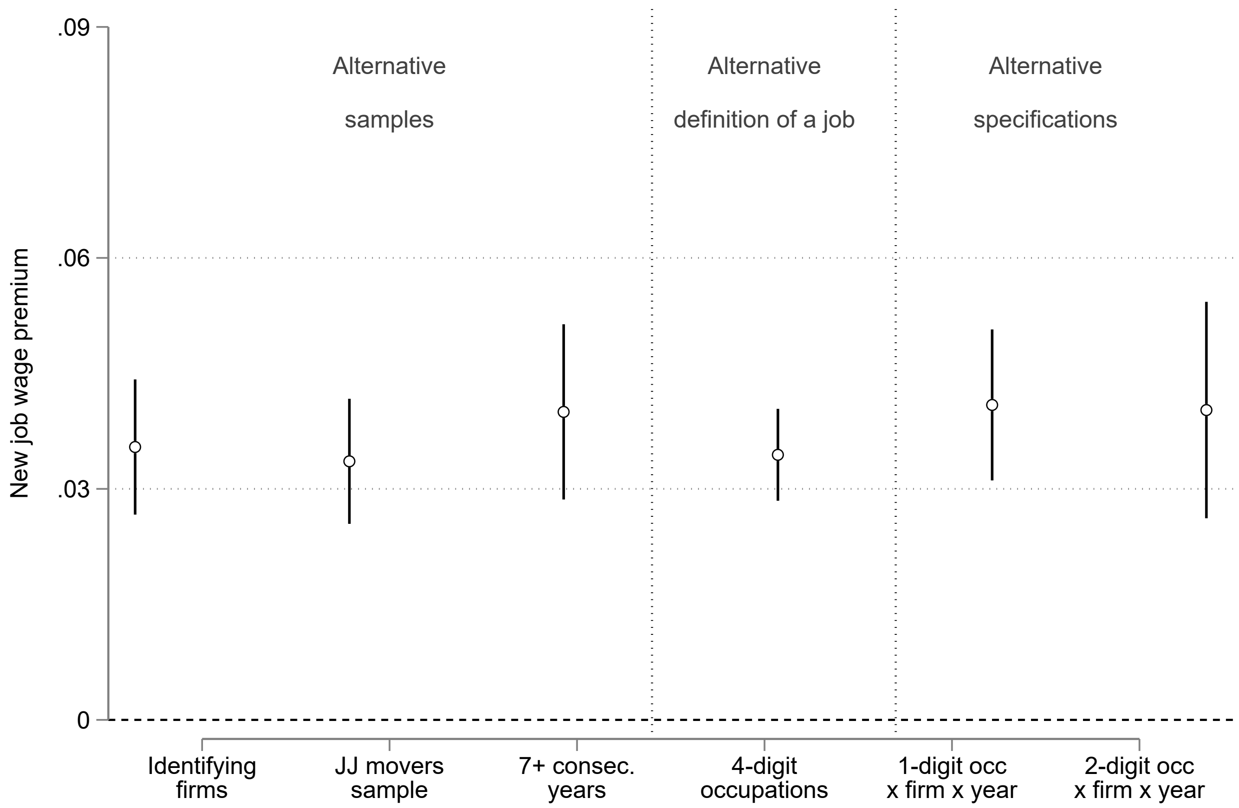
Notes: This figure plots kernel density estimates of firm employment growth rates (DHS index) in firm-years with different types of hiring. The solid line corresponds to firms hiring into new jobs, the dashed line to firms hiring into expanding old jobs, the dotted line to firms hiring into replacing 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 (12) 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.

Figure B4: New job wage premium - Robustness



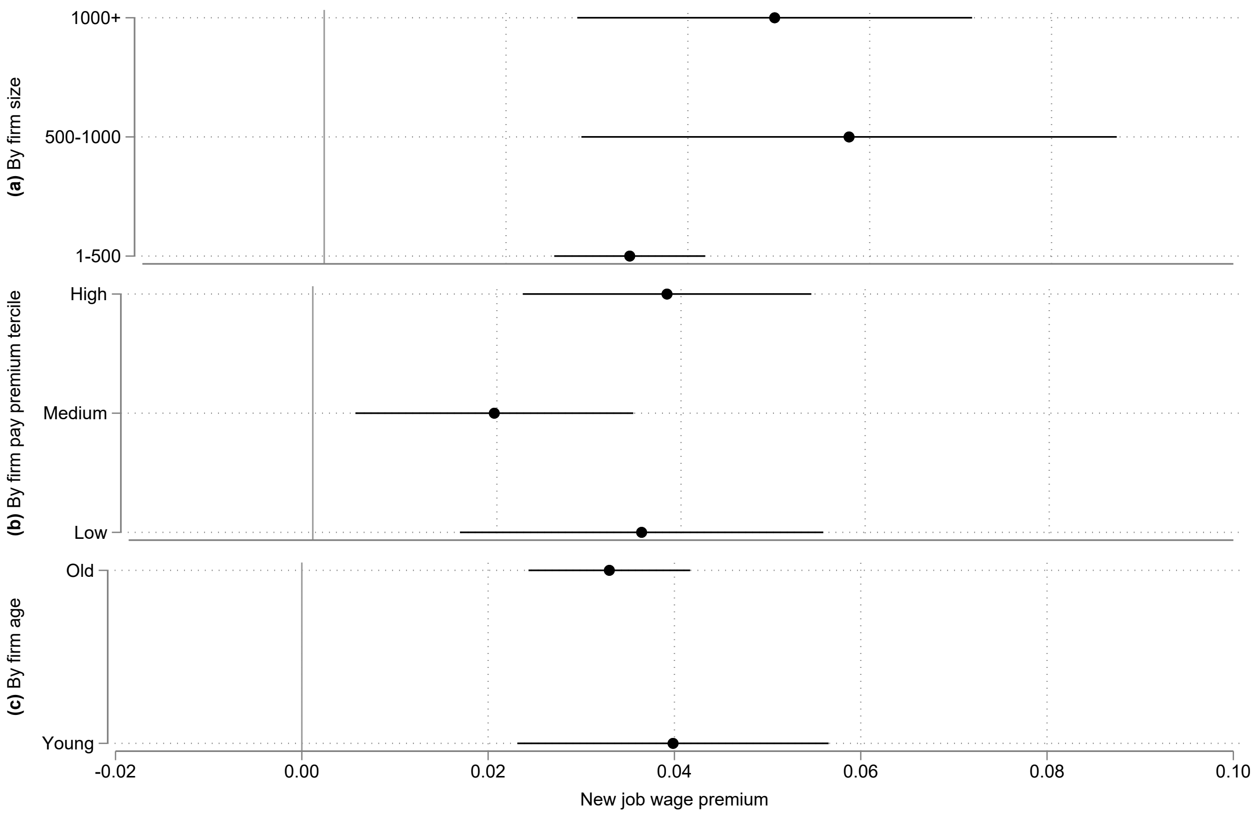
Notes: This figure plots the new job wage premium across alternative samples, job definitions, and specifications, all relative to the within-firm baseline. Each marker reports the coefficient on New Job from a regression of log entry wages on indicators for new jobs and replacing old jobs, with expanding old jobs as the omitted category. Whiskers show 95% confidence intervals; standard errors are clustered at the firm level. The x-axis is organized into three groups:

i) Sample restrictions. *Identifying firms* restricts the sample to firms that hire into both new and old jobs, and that therefore contribute to within-firm identification. *JJ movers* restricts the sample to job-to-job movers, defined as entrants with fewer than two months of intervening non-employment at the time of entry. *7+ consecutive years* restricts the sample to firms observed for at least seven consecutive years, so that occupations classified as new are unlikely to be pre-existing occupations that the data simply do not cover for short-panel firms.

ii) Job definition. 4-digit occupations redefines a job at the firm $\times$ 4-digit occupation level, rather than the baseline firm $\times$ 3-digit occupation level.

iii) Specifications. *1-digit occ $\times$ firm $\times$ year FE* and *2-digit occ $\times$ firm $\times$ year* FEs augment the within-firm baseline with fixed effects at the firm-by-year-by-occupation level (1- and 2-digit aggregation, respectively), so that identification comes from comparisons across narrow occupations within the same broad occupational family inside a firm-year.

Figure B5: New job wage premium heterogeneity by firm size, firm age, and firm wage premia



Notes: This figure plots new job wage premium from Equation 12, estimated separately by firm size, firm wage premium, and firm age categories. The omitted group consists of workers entering expanding old jobs. 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 size is measured as total employment. Firm wage premia are estimated firm fixed effects from an AKM decomposition. Firms are then divided into terciles based on their estimated fixed effect. 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".

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)	9137	27388	44168	
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: 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 C5: 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 7-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 C6: Sorting - AKM (Using wages as outcome from WSS sample)

	Across Firms			Within Firm		
	(1)	(2)	(3)	(4)	(5)	(6)
	ln(Entry Wage_{ijot})	ln(Entry Wage_{ijot})	$\hat{\theta}$	ln(Entry Wage_{ijot})	ln(Entry Wage_{ijot})	$\hat{\theta}$
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 16. Columns 1 and 4 report baseline estimates of the entry wage premium from Equation 12 in the main sample (across firms and within firms, respectively). Columns 2 and 5 re-estimate Equation 12 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 16 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 and 3 and at the firm level in Columns 4–6; Column 2 reports heteroskedasticity-robust standard errors because the AKM-restricted sample yields too few effective clusters at the 2-digit industry level.

Table C7: Sorting - AKM (Using earnings as outcome)

	Across Firms			Within Firm		
	(1)	(2)	(3)	(4)	(5)	(6)
	ln(Entry Wage$_{ijot}$)	ln(Entry Wage$_{ijot}$)	$\hat{\theta}_i$	ln(Entry Wage$_{ijot}$)	ln(Entry Wage$_{ijot}$)	$\hat{\theta}_i$
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 16. Columns 1 and 4 report baseline estimates of the entry wage premium from Equation 12 in the main sample (across firms and within firms, respectively). Columns 2 and 5 re-estimate Equation 12 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 16 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 and 3 and at the firm level in Columns 4-6; Column 2 reports heteroskedasticity-robust standard errors because the AKM-restricted sample yields too few effective clusters at the 2-digit industry level.

Table C8: Turnover results conditional on entry wages

Dependent variable:	$\mathbb{1}$ (1st-year separation)	$\mathbb{1}$ (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 C9: 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 C10: 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 12.

Table C11: New job wage premium and employee selection by continuous skill novelty

	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 12.