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

Dogan Gülümser†

November 6, 2024

JOB MARKET PAPER

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Abstract

This paper examines how firms' uncertainty about match productivity in newly created roles affects hiring decisions, entry wages, and workers' labor market outcomes. Using Swedish matched employer-employee data, I analyze 1.6 million new matches and show that firms raise hiring standards by selecting more experienced workers and poaching workers from other firms for the new roles. Workers taking on new roles earn 3% higher entry wages conditional on time-varying and time-invariant worker and firm characteristics. Tenure in new roles is longer on average, leading to an eight percent earnings premium within a given employment relationship. Event study estimates support a causal interpretation of the new job wage premium. This paper sheds light on a previously undocumented source of employer hiring uncertainty - firms' previous experience in hiring for a particular occupation - which contributes to the wage dispersion among similar workers.

Keywords:

JEL Codes: J31, J23, J63

*I would like to thank Lena Hensvik and Peter Fredriksson for their invaluable guidance and support. I would also like to thank Alan Manning, Rafael Lalive, Giulia Vattuone, Oskar Skans, Antoine Bertheau, Georg Graetz, Christoph Hedtrich, Arizo Karimi, Espen Moen, Guillaume Névo, Sebastien Willis, and participants to seminars and conferences at UCLS Spring and Annual Meetings, AMSE Conference in Applied Econometrics (Marseille), Nordic Workshop on Register Data and Economic Modelling (Aarhus), Barcelona Labor Economics Meeting (AEET), EALE (Bergen 2024), LSE Labour Workshop, SUDSWEC (SU 2024), 8th Swedish Conference in Economics (Lund) for helpful comments.

†Department of Economics and UCLS, Uppsala University, Sweden. dogan.gulumser@nek.uu.se.

1 Introduction

A large literature suggests that employer uncertainty about worker skills at the hiring stage is an important determinant of employee selection, starting wages and subsequent wage growth. This literature has, to a large extent, focused on the role of worker experience as a source of employer learning (Farber and Gibbons 1996; Altonji and Pierret 2001; Lange 2007; Fredriksson et al. 2018). As workers accumulate experience, more information about their productivity becomes available to employers. However, very little attention has been paid to the role of firms' hiring experience for entry wage inequality. That is, what happens to match outcomes when firms enter a segment of the labor market for the first time?

This paper addresses this gap by examining how employer uncertainty about the productivity of newly created roles affects sorting and wage formation. New roles arise when firms employ a worker in an occupation for the first time. Thus, the key distinction between hiring a worker for a new versus an old job is the firm's prior employment experience in an occupation at the time of hiring. The main goal of this paper is to explore how employer uncertainty in new jobs influences employee selection, wage determination, and workers' post-hiring outcomes. This study is the first to provide evidence on the role of employer experience within an occupation as a driver of wage differentials.

To frame the empirical analysis, I propose a simple model to illustrate the relationship between job age and entry wages. I extend the stochastic job matching model due to Jovanovic (1979) and Pissarides (2000) by distinguishing the types of jobs firms create. The key assumption is that new jobs entail greater heterogeneity in match productivity than old jobs due to higher uncertainty. I show that firms increase their hiring standards and reservation productivity, which leads to higher entry wages for new jobs compared to old ones.

I use Swedish matched employer-employee data from 1996 to 2013 and focus on 1.6 million new matches. New jobs arise when firms expand along a new occupation. Old jobs, on the other hand, can entail expansion as well as replacement hires. The main empirical challenge is that new job expansions can be correlated with increases in firm productivity. Potential differences in outcomes between new and old jobs might thus arise due to the firm expansion or the lack of employment experience in an occupation.

To deal with this empirical challenge, I assign each new hire into one of three groups: (i) new jobs, (ii) expansion hires into old jobs, and (iii) replacement hires to old jobs. I then compare new jobs and expanding old jobs to net out the effect of expansion. By doing so, I plausibly identify the effect of greater hiring uncertainty.

The theoretical model predicts that firms increase their hiring standards for occupations in which they have limited experience. I provide empirical evidence consistent with this prediction. I show that firms hire workers with 2 years more labor market experience for new roles compared to old roles. Moreover, firms screen on current labor market status by poaching workers from other firms, and reducing hiring of long-term unemployed workers to new jobs. For example, the probability of poaching the worker from another firm is 2 percentage points higher for new jobs compared to old jobs within firms.

Another key prediction from the theoretical model is that firms raise reservation productivity for new jobs, which leads to higher entry wages. Again, the empirical findings are consistent with this prediction. Workers entering new jobs have 3-3.5% higher entry wages than workers entering old jobs, conditional on time-varying firm effects, and time-varying occupation-by-location effects. The entry wage premium is observed across all skill groups and increases with occupational distance, with an additional 0.8% wage premium when the new job is more dissimilar to the existing occupations within firms.

I further investigate wage responses among new and old job entrants using an event study design. I compare workers making a job-to-job transition to expanding jobs within the same occupation and local labor market, while controlling for experience and education. I find that workers starting a new job receive entry wages that are, on average, 3% higher than those entering an old job. Wage differentials between the two groups evolve in the same way before the move. Moreover, the new job wage premium persists over time. Consistent with the fact the pre-trends are the same for the group entering a new job and an old job, I show that my findings are robust to controlling for unobserved worker skills.[1]

How large is the new job wage premium? My findings indicate that new job wage premium is as large as the wage gains associated with job-to-job mobility in my data (3.5-4%), which is widely acknowledged as a primary driver of wage growth over the life cycle (Topel and Ward 1992; Jinkins and Morin 2018). Furthermore, the differential wage gain from starting a new job is approximately two-thirds of the total wage growth a worker would typically experience within the same occupation over a five-year period, after adjusting for age and education effects (around 4.5%).

Firms' higher willingness to screen for new roles would imply that entrants in new roles

[1]To examine whether unobservable worker skills explain the new job wage premium, I estimate a two-way fixed effects model following Abowd et al. (1999) (AKM) using pre-dated data (1985-95) to obtain worker skill measures. The unobserved worker skills (AKM worker fixed effects) cannot explain the new job wage premium.

should be better matched compared to entrants in old jobs. To investigate match quality differences, I compare post-hiring outcomes for workers entering positions created in new vs. old jobs within firms. I show that workers who enter new jobs within firms have 12% lower 1st-year separation probability and 4% higher probability of staying after three years. Conditional on staying for at least three years, wage growth does not differ by firms' experience with a job, which implies that uncertainty is resolved at the meeting phase, and there is no differential productivity revelation within the match. Higher entry wages and longer match duration result in 8 percent higher within-job earnings (around €4000) for workers entering new jobs compared to entrants to old jobs within the same firm. I conclude that demand-side information frictions have a substantial impact on workers' labor market outcomes.

I perform a range of robustness checks and heterogeneity analysis to validate my findings. I show that my results are robust to different definitions of jobs, e.g., when I define occupations at the more detailed level (4-digit instead of 3-digit). I further assess whether differential firm characteristics play any role in the observed effects. I show that the new job wage premium is present across all firm age, size and firm employment growth categories.[2]

I examine whether the data are consistent with alternative theories. I refute compensating differentials and monopsony as explanations for new job wage premium. First, the longer tenure associated with new jobs suggests that compensation for higher risk or unobserved job-specific disamenities is unlikely.[3] However, job size at entry varies across new and old jobs. New jobs are of smaller size during the initial year of employment, around 80% of jobs employ a single worker in the first year. One would presume that workers seek compensation or job security (i.e., longer tenure) if they are expected to work alone. I further show that new job wage premium does not vary by job size at entry, suggesting that wage differential is not attributable to monetary compensation for working alone. Second, time-varying firm effects hold hiring rate of firm at a given time constant, which makes it unlikely that monopsonistic competition can explain the wage premium for new hires.[4] I conclude that neither of the alternative theories can explain new job wage premium.[5]

[2] I also examine main wage results using different samplings of workers and firms, e.g., when focusing on firms that have been established after 1996, or more experienced workers. I obtain very similar results.

[3] Alternatively, firms could try mitigating the risk of high turnover in small sized jobs by offering higher wages. Again, this would not lead to systematic differences in match duration.

[4] Yet, I relax time-varying firm controls to test for monopsony by exploring whether the new job wage premium varies along the employment growth gradient. I show that new job wage premium is not driven by high employment growth firms.

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

This paper contributes to several strands of literature. My main contribution is to the literature on the role of employer uncertainty on firm- and worker labor market outcomes (Farber and Gibbons 1996; Altonji and Pierret 2001; Lange 2007; Fredriksson et al. 2018; Oyer and Schaefer 2011). My paper is the first to consider firms' occupation experience as another, previously unexplored, source of information frictions. As such, I document that hiring behavior changes when firms hire for a new job.

The previous literature has extensively documented that recruitment activities involve costs and uncertainty due to frictions in the labor market (Manning 2011; Oyer and Schaefer 2011; Le Barbanchon et al. 2023b), and are influenced by active labor market policies.[6] Several papers provide empirical evidence of replacement costs due to exogenous worker separations (e.g., Jäger and Heining 2022; Ginja et al. 2023). Survey evidence show that hiring costs and obstacles arise due to skill shortages and screening costs (Barron et al. 1985; Barron and Bishop 1985; Bertheau et al. 2023), and create incentives for firms to fill positions internally when they can (Bertheau 2021; Chan et al. 2023). In my setting, for instance, this way of handling uncertainty is impossible for firms that hire to new roles - in particular when these are further away in the occupational space. To this literature, I bring the idea that hiring frictions are not uniform within firms. There is heterogeneity in hiring frictions within the firm at a given time based on the firms' relative experience in employing workers in a given occupation. This intra-firm heterogeneity in hiring frictions is often ignored, but I show that they have significant implications for firms' employee selection and workers outcomes.

I also contribute to the vast literature documenting wage inequality among similarly skilled workers. Previous literature has shown that various job and firm characteristics play crucial roles in variation in wages (Kline 2024). These include inter-industry wage differentials (Krueger and Summers 1988; Thaler 1989), firm age wage differentials (Brown and Medoff 2003; Babina et al. 2019; Schmieder 2023), and inter-firm wage differentials (Abowd et al. 1999; Card et al. 2013; Card 2022). Recent studies underscore the role of information frictions in driving wage dispersion. Jäger et al. (2024) show that workers' limited knowledge of alternative job opportunities exacerbates wage dispersion by reducing workers' ability to leverage outside options. Similarly, Cullen et al. (2022) show that employers' limited knowledge on prevailing market wage causes wage dispersion. When firms use salary benchmark tools, they compress

[6] Active labor market policies influence these hiring decisions by altering the external labor market conditions that firms face. Butschek and Sauermann (2022) show that making employment protection legislation less strict causes employers to be less selective in hiring. Butschek (2022) show that employers increased their hiring threshold after the introduction of minimum wage in Germany.

new hires wages towards the median of the wage distribution. Building on this theme, my paper identifies a new source of information friction leading to wage dispersion: firms' previous employment experience in an occupation.

Third, I contribute to the literature on the importance of the jobs/matches in workers' careers. Previous literature has documented that various firm attributes matter in workers' careers. For instance, Arellano-Bover (2024) shows that employer size in first job substantially increases lifetime earnings. Also, job-level mismatch (Fredriksson et al. 2018) and occupation-level mismatch (Guvenen et al. 2020) are shown to be crucial for worker-level outcomes in the labor market. I contribute to this literature by showing that job age at entry matters for workers' careers.[7] Babina et al. (2019) and Schmieder (2023) find that newly established firms pay a large wage premium; I argue that conditional on firm age, job age also matters for workers' job-level outcomes and lead to substantial differences in earnings.

The rest of the paper is outlined as follows. Section 2 outlines a simple framework illustrating the relationship between job age and entry wages. Section 3 provides information on data, analysis sample, and the construction of main variables. I outline the empirical strategy in section 4. I provide the main results in section 5. I discuss alternative interpretation of results in section 6. Finally, section 7 concludes.

2 Theoretical Framework

Here, I provide a simple theoretical model to illustrate the relationship between job age and entry wages. I make a simple extension to a model with stochastic match productivity by introducing inspection costs and two types of jobs: new and old (Jovanovic 1979; Pissarides 2000, ch. 6).

I assume that workers and firms are ex-ante identical and search randomly. Upon meeting, the match-specific productivity (y), which is drawn from the distribution function $G(y)$, is revealed. Search is sequential, and job matches are rejected through the optimal choice of reservation productivity, so not all meetings result in match formation. Thus, there is ex-post match-specific heterogeneity even though workers and firms are ex-ante identical.

Firms can expand by creating a position in an occupation they did not previously have (new

[7]Given that I define a *job* at the within-firm level, my concept of job age differs from that in Autor and Dorn (2009), where job age pertains to the age composition of occupations, as well as from the approach in Autor et al. (2024), which considers job age in the context of new roles emerging across the entire economy over time

job, N), or in an occupation they already have (old job, O).[8] The key difference between new and the old jobs is the firms' previous experience in employing workers in a given occupation. Firms enter a different segment of the labor market when they introduce a new occupation. Thus, I assume that match productivity in new jobs is characterized by more heterogeneity. The translation of this key assumption to the model is wider productivity distribution for new jobs $H(y, \sigma)$ than an old job $G(y)$, where σ is the relative dispersion parameter. In other words, the productivity distribution of new jobs is a mean-preserving spread of the distribution of old jobs. [9]

In this context, relative dispersion in productivity distribution in new jobs (σ) can stem from various factors. On the one hand, firms are not as able to gauge the quality or credentials of candidates in the occupation they hire for the first time.[10] On the other hand, the workers also lack information about how productive this new job will be in this particular firm. Workers might be knowledgeable about how to perform the set of tasks in their own occupation, but uncertainty extends beyond their individual skill set to the broader dynamics of the job within the firm. As a result, workers face challenges in accurately assessing the potential productivity of new jobs. These points collectively contribute to the larger dispersion of the match-specific productivity in a new job.

2.1 Job Matchings in New and Old Jobs

The output of each job match j is distinct and depends on a parameter y. I assume that labor is the only input and the output of each match is y_j efficiency units of labor. Firms and workers follow a reservation rule which determines the job creation decision, i.e., whether to match or not.

Following from workers and firms being ex-ante identical, I assume that reservation productivity $y_{R(j)}$ is common to all job-worker pairs within job types $j \in N, O$ - new and old. A worker-firm contact becomes a match if it is above a certain reservation productivity y_R.

[8] Note that when the terms *new* and *old* are used in reference to jobs, it pertains to the firm and not to the market.

[9] I assume that during the hiring process the match productivity distributions are constant. Relative dispersion, thus, is unrelated to how many draws firms take for new jobs. Once firms reject a particular draw, they can draw from the same distribution again. As long as they haven't consummated a new job, they can keep on drawing from the same distribution. A job becomes old once a worker has been hired to new occupation.

[10] Also, employers use current employees' referrals to reduce uncertainty when hiring new workers (see, for instance, Dustmann et al. 2016; Hensvik and Skans 2016). However, when firms hire for new jobs, they have no possibility to obtain occupation-specific private information through these referrals, as no worker is currently employed in the newly created role. This absence of insider knowledge adds another layer of uncertainty to the hiring process, particularly when the new occupation is dissimilar to the existing occupations.

The rate of job contacts is given by $m = m(u,v)$ and labor market tightness is given by $\theta = v/u$. The rate of job matching is $[1-G(y_R)]m$. Vacancy filling rate is given by: $q(\theta) = [1-G(y_R)]m(u,v)/v = [1-G(y_R)]q(\theta)$. Workers move to new jobs at rate $q^w = [1-G(y_R)]m(u,v)/u = [1-G(y_R)]\theta q(\theta)$.

Remember that match productivity distribution is more dispersed in new jobs, $H(y,\sigma)$ for new, and $G(y)$ for old jobs. A marginal increase in spread (σ) increases reservation productivity:[11]

$$\frac{\partial y_R(\sigma)}{\partial \sigma} = \left[\int_0^{y_R(\sigma)} H_\sigma(x,0)\mathrm{d}x\right] \geq 0 \tag{1}$$

Intuitively, this occurs mainly because the mean-preserving spread increases the prospect of finding a more productive match. A mean-preserving spread improves productivity draws above the mean while diminishing those below it. Since search is sequential, firms and workers can turn down job offers below a certain threshold, i.e., matches whose productivities below the reservation cutoff, y_R. Consequently, the higher productivity of jobs above the mean yields greater benefits compared to the lower productivity of jobs below the mean.

The reservation productivity y_R is such that all $y \geq y_R$ are accepted. Since all job contacts with productivities $y \geq y_{R(j)}$ are accepted, the fraction of acceptable job contacts for a job j is:

$$\int_{y_{R(j)}}^1 dG(y) = 1 - G(y_{R(j)}) \tag{2}$$

for a job j and for a given productivity distribution $G()$. Since the reservation productivity is higher in new jobs, the rate of acceptable worker-firm meetings will be lower: $[1-H(y_{R(N)})] < [1-G(y_{R(O)})]$. In other words, there will be fewer acceptable contacts in new jobs if distribution is more dispersed.

2.2 Value Functions and Wage Determination

Firms: Assume that productivity of a job is given by y_j. The value of the job (J_j) is shown by:

$$rJ_j = y_j - w(y_j) - sJ_j \tag{3}$$

[11] See appendix 8.1 for proof.

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

$$rV_j = -c - I_j(\sigma) + q(J_j - V_j) \tag{4}$$

where c is some fixed cost of holding the vacancy open and $I_j(\sigma)$ is the cost of inspection. I assume that inspection cost is an increasing function of relative productivity dispersion:$\frac{\partial I_j(\sigma)}{\partial \sigma} > 0$. Hence, new jobs incur higher inspection costs. In equilibrium, $V_j = 0$, the job creation condition is given by:

$$\frac{y_j - w(y_j)}{r+s} = \frac{c + I_j(\sigma)}{q(\theta)} \tag{5}$$

Equation (5) shows the equilibrium relationship between the expected net benefit of creating a job and the associated costs. An increase in reservation productivity in new jobs is counterbalanced by a corresponding rise in inspection costs, reflecting a trade-off between the benefits of better opportunities and the costs associated with screening them. Left-hand side represents the present value of the expected net gain from a job. The term on the right-hand side captures the costs of maintaining a vacancy, including the fixed cost c and the inspection cost $I_j(\sigma)$. The denominator $q(\theta)$ represents the job-finding rate as a function of labor market tightness θ. New jobs are associated with higher reservation productivity and higher inspection costs.

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

Workers: Workers follow a reservation wage rule to decide which jobs to match and which jobs to reject. A worker randomly faces a new or an old job. I assume there is no on-the-job search.[12] A worker would accept a job if the value of employment exceeds value of unemployment. Thus, a worker would a accept a wage offer w_j if it satisfies $W_j \geq U$.

The net worth of unemployed worker is given by:

$$rU = z + q^w \left(W_j - U\right) \tag{6}$$

where q_i is the job transition rate. The value of employment to the worker is job-specific and

[12] I show empirically that main entry wage results are present for workers entering from unemployment and employment.

given by:

$$rW_j = w_j + s\left(U - W_j\right) \tag{7}$$

The value of employment increases with w_j.

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

$$w_j = argmax(W_j - U)^{\beta}(J_j - V_j)^{1-\beta} \tag{8}$$

The first-order condition satisfies:

$$(W_j - U) = \beta(J_j + W_j - V_j - U) \tag{9}$$

Substituting the value of employment (eq. 7), value of job (eq. 3), and value of unemployment (eq. 6) into equation 9, and taking into account in equilibrium $V_j = 0$, we get to the wage equation:

$$w_j = \beta(y_j + \theta(c + I_j(\sigma))) + (1-\beta)z \tag{10}$$

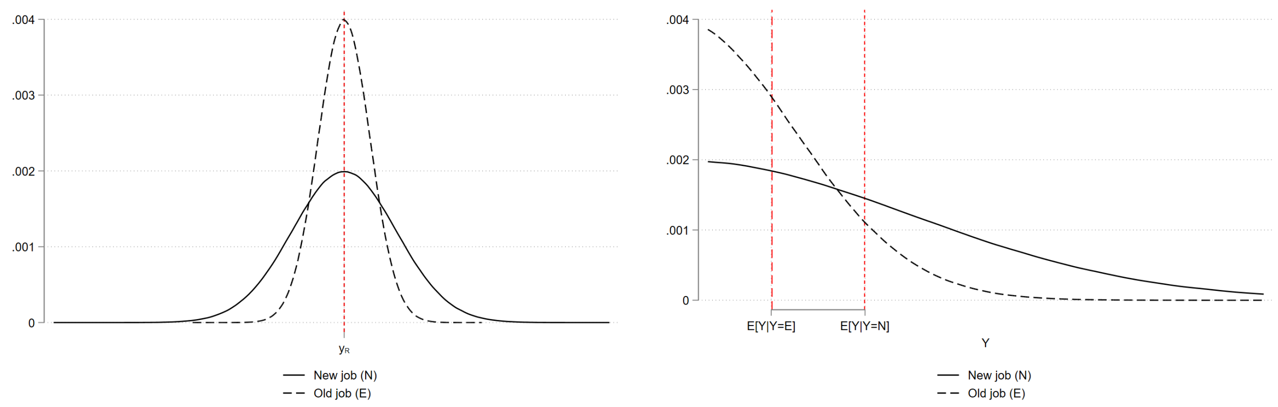
The wage rate is a function of reservation productivity (y_j), vacancy posting and inspection costs $(c, I_j(\sigma))$, market tightness (θ), and workers' outside options (z). Most importantly, I am interested in wage differentials in new vs old jobs. Remember that the two dimensions along which new and old jobs differ are the reservation productivity, $y_{R(j)}$, and inspection costs, $I_j(\sigma)$. I assume outside options, bargaining power, and vacancy costs c are identical across jobs.[13] Notice that the labor market tightness (θ) does not play a role in wage differences.

New jobs have higher reservation productivity, following from equation 1, $(y_{R(N)} > y_{R(O)})$. More dispersed productivity distribution leads to higher reservation productivity, thus resulting in higher wages. Moreover, higher inspection cost also positively affect wages. The intuition is that keeping a vacancy unfilled incurs costs for firms. Therefore, the wage gain is higher for the worker who fills a vacancy that is expensive to keep open (ibid.).

This simple matching process shows that higher heterogeneity in the match productivity

[13] Empirically, I will compare workers who are in the same occupation, industry, and location in order to hold outside options constant across new and old job takers.

Figure 1: EX-ANTE AND EX-POST MATCH PRODUCTIVITY DISTRIBUTIONS



(a) EX-ANTE PRODUCTIVITY DISTRIBUTION **(b)** EX-POST PRODUCTIVITY DISTRIBUTION

Notes: This figure illustrates 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) shows the ex-post match productivities conditional on forming the match. Workers and firms do not form a match if the expected math productivity is below a certain threshold, so expected match productivity in new jobs will be higher.

distribution for new jobs yields higher expected productivity, higher entry wages, and higher inspection costs (by assumption).

Figure 1 depicts a simple visualization of ex-ante and ex-post match productivity distributions and associated expected productivities. Panel A shows the ex-ante expected productivity distributions for two jobs. The vertical red line shows the expected productivity associated with each position, which is assumed to be the same for the two jobs. Ex-post, however, there will be productivity and wage differentials.

2.3 Empirical Implications

Wage premium: The model predicts that new jobs have higher entry wages than old jobs due to higher reservation productivity. Thus, conditional on market tightness, and observable worker characteristics there is a new job entry wage premium: $w_N > w_O$

Tenure and turnover: While the model does not generate predictions on tenure (or turnover), I empirically evaluate turnover patterns across jobs. Intuitively, if firms become more picky due to higher uncertainty in new jobs, the matches in new jobs are of higher match quality with lower turnover and longer match duration.

Wage growth: The model has the simplifying assumption regarding the productivity of the match being revealed upon meeting. I will compare wage growth across new and old jobs. If wage growth does not differ across jobs, then the data are consistent with the simplifying assumption on instant revelation of uncertainty.

Earnings within match: The model predicts that there is new job wage premium. If new and old job entrants' tenure or wage growth trajectories do not differ new jobs should be associated with substantial earnings premium within match for new jobs.

Hiring standards: I cannot directly observe hiring standards since the pool of applicants is unknown. But I empirically examine the characteristics of the new hires across new and old jobs within firm. If firms are using observable characteristics (e.g., experience, labor market status) as a way of reducing uncertainty/inspection costs, new job entrants should be more experienced and less likely to be coming from unemployment. Firms become more selective by not considering job contacts below a reservation productivity value. If the applicant pool is identical across new and old jobs, firms selecting more experienced workers would imply that they consider a smaller share of applicants as suitable, thus, increasing hiring standards.

3 Data

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

3.1 Data sources and sample construction

Demographic Information: The demographic information (year of birth, 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. The level of education is constructed from a discrete variable (SUN2000niva) indicating the highest completed education level attained by the individuals.

Wages and Occupations: The data on wages and occupations are from Statistics Sweden's Wage Structure Statistics (WSS henceforth). Sampled firms must report wages and occupations (SSYK-96, corresponding to ISCO-88) for each worker who was employed in September. The data cover the entire public sector workforce and approximately 50 percent of the private sector. The sampling procedure of private sector firms is based on firm size, with larger firms having a higher probability of being included.[14] The wage measure reflects the employee's earnings during the sampling month, expressed in full-time monthly equivalent wages. All wage components, including piece rate and performance pay, except overtime pay, are included in the wage measure.

Employment Registers and Earnings: I use linked employer-employee register data where one can track employees and employers over time. These data are collected from tax registers, cover the universe of workers and firms, and can be matched to WSS data. Each employment spell is observed with the first and last months of employment relationship. I rely on employment registers to define new hires, tenure, separations, experience, and earnings (monthly, employer-specific, and annual).[15] I define a *new hire* as a worker who started working at a firm for the first time. Temporary layoffs and callbacks are not identified as new hires, so individuals who return to their previous employer are excluded from the new hires sample.

Multiple job holdings are prevalent, so I do not restrict workers to being single job holders. If there are multiple jobs within a year, I keep the employment that is observed in WSS. I rely on WSS data to identify new and old jobs at the firm level since tax registers do not include occupational information. Due to the sampling of the WSS data, not every firm is observed each year. To identify firms' expansions in new and old jobs, I restricted the sample to firms sampled in at least two consecutive years in WSS. The broadest condition is that the worker must be newly hired in a given year t.[16]

I utilize tax registers to identify new hires, covering the universe of job spells. These data do not contain occupation information. Since a job is a combination of firm and occupation, I complement this data with the WSS to acquire workers' occupations. As I explain in detail below, I exploit the variation in the number of workers within a job cell in order to differentiate jobs from each other. However, due to the firm-based sampling methodology of the WSS data, some firms may randomly exit the sampling frame from one year to the next. Consequently, I apply a set of criteria to categorize workers into different types of hires.

The first criterion is the worker must be observed within a firm for the first time.[17] Second,

[14] Sampling of private sector firms in (Wage structure statistics, WSS) is stratified by firm size with the sampling probabilities 3, 12, 41, 70, and 100 percent for the firm size intervals 1–9, 10– 49, 50–199, 200– 499, and 500–, respectively.

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

[16] Since I rely on employment registers when defining hires, the sampling nature of WSS data is not of concern. Thus, we can identify new hires in WSS even though it is a given firm's first sampling year. The requirement for two consecutive years is due to information on occupations.

[17] To focus on the information regarding the position and not the worker, I disregard promotions since the

I impose the restriction that a firm must be sampled for at least two consecutive years. This restriction allows me to calculate the changes in the job size. The rationale for this restriction follows from the sampling nature of the WSS data, as one needs at least two consecutive years of sampling of a given firm.[18] Consequently, this restriction results in the exclusion of new hires in the first sampling year of the firm and new job creations that originate from the firm births as, by definition, all hires are in newly created occupations within a firm. As a result, each firm included in the WSS must have been sampled for a minimum of two years, and sampling should be consecutive. I provide two robustness checks in the analysis to make sure the sampling of firms is not an issue. First, I consider firms that have been sampled in all years between 1996-2013. Second, I restrict the sample to firms that have been established after 1996. The results are robust to both restrictions and discussed in section 5.2. Third, I exclude firms operating in the temporary employment industry or other recruitment agencies. The next section describes the grouping of hires.

3.2 Distinguishing the types of jobs in the data

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

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

where j, o, and t represent firm, occupation (3-digit), and year, respectively.[19] The variable L_{jot} represents job size. The grouping of new hires is based on the change in job size from one year to the next. Below, I examine the construction of each group in detail.

The first group, new job (N), emerges when a firm hires to an occupation for the first time,

worker's productivity is not unknown to the firm.

[18] Note that the sampling is at the firm level and not at the worker level. So, if a firm is sampled in a given year, all workers employed in that firm are included.

[19] Appendix table A2 shows an example of breakdown of occupations. I carry out the same analysis using 4-digit occupations as well as a robustness.

given that it has not employed anyone in that occupation in the past m years.[20] This group is defined as *new jobs* created within a firm, indicating the jobs in which the firm's previous employment experience is zero. Following this logic, all new hires into existing occupations within a firm fall into the *old jobs* group, in which the firm has at least 2 years of prior experience in employing workers. Moreover, it is possible to categorize old jobs into two groups based on changes in job size. If the employment in an old job increases from one year to another, $L_{jot} - L_{jot-1} > 0$, all new hires are classified as expansion hires into an existing occupation (E). If, on the contrary, the number of workers employed in an old job decreases, $L_{jot} - L_{jot-1} \leq 0$, then the new hires are classified as replacements, (R). [21] Assume two workers are hired into the same *old job* in a given year; they are either expansion-hires in an existing occupation (E) or replacements (R). There is, however, variation between expanding into an existing occupation and being a replacement across occupations within a firm. If the firm grew in an existing occupation from $t-1$ to t, all new hires to this particular occupation at time t are categorized as expansions into an existing occupation. Conversely, newly hired workers are considered replacements in and old job if the firm downsizes between $t-1$ and t in a particular occupation. Thus, new hires into the same job cell are classified as either expansion hires in existing occupations or replacements, not a combination. In summary, new job (N) is the job experiencing employment growth from a base of zero, (E) is the job that experiences growth from a base of non-zero, and (R) is turnover without employment growth.

Notably, distinguishing hires in this way has the advantage of identifying different types of frictions that may potentially lead to differences in wage and other outcomes. First, contrasting expansion hires in a preexisting role (E) to replacements (R) shows the effect of expanding a particular job, conditional on having previous experience in both occupations. Second, comparing new jobs (N) to expanding old jobs (E) allows one to identify information frictions regarding the firm' missing employment experience in a particular occupation. In the next section, I will analyze sample statistics on workers taking on new vs old jobs, and firms creating new vs old jobs. Firm-level observations are weighted by the weights provided in the original Wage Structure Statistics data (lon).

[20] m ranges from 1 to 17, corresponding to the first (1996) and last (2013) year of the data, denoting all previous years in which the firm was observed.

[21] Note that by this definition, an old job has no individual-level variation between an expansion hire (E) and a replacement (R) due to the lack of data indicating who is replacing whom.

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)	9.99	9.90	9.88	9.90
1st-year separation	0.086	0.11	0.13	0.11
Age	39.3	33.8	32.1	33.4
Female	0.43	0.44	0.47	0.45
Experience at entry	15.3	12.3	11.5	12.1
Tenure (months)	60.4	55.2	48.7	53.4
Education				
Compulsory or less	0.16	0.14	0.13	0.14
High school	0.52	0.53	0.53	0.53
College	0.32	0.33	0.34	0.33
Occupations				
Professionals	0.15	0.15	0.13	0.15
Technicians and associate professionals	0.20	0.17	0.18	0.17
Clerks	0.20	0.11	0.13	0.12
Service workers and shop sales workers	0.066	0.20	0.24	0.21
Skilled agricultural and fishery workers	0.015	0.0046	0.0068	0.0053
Craft and related trades workers	0.13	0.083	0.080	0.083
Plant machine operators and assemblers	0.13	0.14	0.13	0.13
Elementary occupations	0.11	0.14	0.12	0.13
# distinct jobs (firm x occupation)	10757	43503	23019	37411.9
Observations	19861	1172438	459395	1651694
Panel B. Firms				
Firm age	12.1	13.6	14.3	12.4
Firm size	37.0	62.2	74.9	40.6
Firm growth rate (DHS)	0.28	0.23	-0.030	0.30
Value added pc (Thousand SEK)	569.8	568.1	562.5	573.7
# 3-digit occupations	5.04	5.25	5.70	5.39
# New hires	7.80	8.21	8.45	8.43
Observations	8642	47291	40900	8473

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 old expanding job, in old replacing jobs, and all hires, respectively. Panel B shows the mean statistics at the firm-year level. Columns 1-4 in Panel B represent firm characteristics among firms that hire into new jobs, old expanding jobs, old replacing jobs, and firms that hire both to new and old jobs, respectively.

3.3 Descriptive statistics

Workers and firms: Table 1 shows descriptive statistics of the individual- and firm-level variables used in the main analysis. The columns represent different groups of hires based on whether they are entrants to a new or an old job (expansion or replacements). Column 4 shows all hires. The first panel shows the characteristics of newly hired workers, while the second represents hiring firms. First, workers who enter into a new job differ along several dimensions from workers entering old jobs. New job takers are older, more experienced, and slightly less likely to be college graduates, but more likely to work in a high-skill occupation. Second, occupational distribution at the first digit is balanced across jobs, other than clerical occupations being more represented in new jobs. Occupational distribution describes that the jobs are not equally distributed, with more clerical positions and fewer sales workers in new jobs.[22] Workers in new jobs are less likely to leave within the first year of the match, and the expected tenure upon hiring is longer. I will control for time- and location-specific occupation characteristics to allow for comparisons across new and old jobs within each occupation-location at a given time, ensuring that these differences are consistently accounted for in the analysis.

It is also worth noting that new hires in new jobs are represented to a much lesser extent compared to other expansions (E) and replacements (R).[23] Job size in new jobs is small compared to old jobs. However, the share of new jobs (employment-weighted) constitute around %14 of all jobs (10,757/77,279).

Firms that introduce new vs old jobs differ along age and size dimensions. New jobs are more likely to be found in smaller and younger firms. However, they do not differ in productivity (value-added per capita). These firms also have a slightly higher employment growth rate measured by the DHS index (Davis et al. 1996).[24] However, this is mainly driven by the fact that they were initially small. Total number of hires is slightly lower in firms that introduce new jobs. To ensure these differences do not confound my results, I will control for time-varying firm characteristics in the analysis (firm-by-year fixed effects), to make sure that such characteristics are accounted for throughout within the regression framework.

3.3.1 Most Common Occupations in New and Old Jobs

Table 2 presents the distribution of the most common occupations among new hires across three categories: new jobs, expanding old jobs, and replacing old jobs. Distribution of occupations shows that the skill level of occupations in new and old jobs are very similar. In new jobs, office clerks and store clerks hold the largest shares, at 4.8% and 4.2% respectively, indicating

[22] I exclude managers from the main analysis sample because managerial roles centers on leadership skills and follows less occupation-dependent pathways. However, I also provide robustness checks when these roles are also included.

[23] This is due to in WSS data large firms are over-sampled, while we expect new job introduction in small and young firms.

[24] DHS index is defined as $2\frac{L_t - L_{t-1}}{L_t + L_{t+1}}$, with L_t being the employment in year t.

Table 2: MOST COMMON OCCUPATIONS IN NEW AND OLD JOBS

New Jobs		Old Jobs (Expanding)		Old Jobs (Replacing)	
Occupations	**Share(%)**	**Occupations**	**Share(%)**	**Occupations**	**Share(%)**
Office clerks	4.8	Salespersons	8.8	Salespersons	13.3
Store clerks	4.2	Personal care w.	7.5	Personal care w.	7.1
Client info clerks	3.9	Finance and sales	5.5	Finance and sales	7.1
Finance and sales assoc.	3.9	Engineering sci. techs	4.6	Engineering sci. techs	4
Numerical clerks	3.6	Computing professionals	4.4	Motor-vehicle drivers	3.8
Admin. associates	3.3	Motor-vehicle drivers	3.9	Helpers in restaurants	3.7
Helpers and cleaners	3.3	Architects, engineers	3.5	Helpers and cleaners	3.6

Notes: This table shows the share of most common occupations among new hires for new jobs, old expanding jobs, and old replacing jobs.

a larger share of administrative roles. For expanding and replacing old jobs, salespersons, personal care workers, and finance and sales associates dominate, highlighting the growth in customer-facing and care-giving positions.

4 Empirical Strategy

I present the main estimating equation used in this study. Throughout the analysis, I examine labor market outcomes for newly hired workers entering old and new jobs. The main estimating equations take the following form:

$$y_{ijot} = \beta \text{New Job}_{jot} + \lambda_{jt} + \lambda_{o\ell t} + X'_{it}\delta + \epsilon_{ijt} \tag{11}$$

where New Job_{jot} is the main variable of interest indicating the job types new hires enter, and the main coefficient of interest is β. New Job_{jot} is a categorical variable that varies at the *job* level. It identifies three groups of jobs as explained in section 3.2. The estimates of β give differential labor market outcomes y_{ijot} associated with a new job vs. an old job in a firm, which I explain below in detail.

I investigate the differential outcomes of new jobs compared to old ones across three dimensions: firms' selectiveness in hiring, the new job wage premium, and workers' subsequent labor market outcomes. To understand the differential hiring behavior of firms across jobs, y_{ijot} comprises variables such as the probability of being a job-to-job mover or long-term unemployed, and labor market experience at entry. y_{ijot} is ln(entry wage) when analyzing the differential entry wage across jobs. For post-hiring outcomes, it takes first-year separation indicator, the probability of retaining a job for at least three years, wage growth, and earnings associated with the match.

My empirical analysis uses two sets of fixed effects. First, I incorporate occupation-by-local labor market-by-year fixed effects ($\lambda_{o\ell t}$) to account for time-varying shifts in demand for specific skills. Second, I apply firm-by-year fixed effects to control for unobserved, time-invariant firm characteristics and firm-level demand conditions. This approach allows for a comparison of workers entering the same firm but in different roles. Additionally, X'_{it} is a vector of individual characteristics, including gender, experience, education, and age fixed effects. Using firm-year fixed effects enables me to examine firms' selectiveness, wages, and workers' subsequent labor market outcomes by comparing the outcomes of workers entering the same firm. My preferred specification, thus, holds workers' outside options at the aggregate level constant.

When examining the new job wage premium, I additionally estimate another version of equation 11. This second version replaces firm-by-time fixed effects by industry-by-year (3-digit) fixed effects. In this *across-firm* comparison, I flexibly control for firm age and log firm size to address young-firm and large-firms wage premiums, as previously shown to be important determinants in workers' wages and other labor market outcomes.[25] Comparison is thus among workers entering firms operating in the same market, subject to similar product demand, isolating time-varying industry-specific conditions.

5 Main Results

This section presents the main results. In the first subsection, I investigate how firms' selectiveness differs when hiring for new and old jobs. In the second subsection, I examine entry wage differentials across job types. The third subsection examines workers sorting into positions based on unobservable characteristics. Lastly, in the fourth subsection, I document subsequent labor market outcomes based on the initial position that workers enter.

5.1 Firms' employee selection

It is important to understand firms' employee selection for new and old jobs due to its importance for worker reallocation across jobs. In this section, I explore how firms' employee

[25] Previous literature documented that the relationship between wages and the firm's age is positive, Which turns negative after addressing the selection of workers and firms. Or, conditional on worker characteristics, young firms pay more (See, for instance, Brown and Medoff 2003; Burton et al. 2018; Babina et al. 2019; Schmieder 2023)

Table 3: FIRMS' DIFFERENTIAL EMPLOYEE SELECTION

Dependent variable:	$\mathbb{1}$(J2J Mover)	$\mathbb{1}$(Long-term Unemployed)	Experience at entry
	(1)	(2)	(3)
Omitted category: Old job (Expanding)			
New job	0.019***	-0.0064**	2.07***
	(0.0046)	(0.0031)	(0.16)
Old job (Replacing)	-0.0055***	0.0044***	0.029
	(0.0016)	(0.0010)	(0.065)
Observations	1574148	1574148	1574148
Adjusted R^2	0.273	0.135	0.456
Mean dependent variable	.72	.11	15.11
Occupation (3-digit) x LLM x Year FE	✓	✓	✓
Firm x Year FE	✓	✓	✓

Notes: 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 1996 to 2013. 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.

selection differs across new and old jobs based on observable worker characteristics. The main rationale behind examining firms' hiring behavior across jobs is that hiring is a decision under uncertainty where workers' productivity is not directly observable. When firms create new roles, they would not want to add another layer of uncertainty to the hiring process. So, the main hypothesis is that firms would become more selective when hiring workers for newly created roles within firms.

Behrenz 2001 and Eriksson and Rooth 2014 provide survey evidence on employer recruitment behavior from field experiments in Sweden. They find that employers screen mostly based on previous experience and contemporaneous labor market status, finding that employers attach a negative value to long-term unemployment spells. To understand firms' employee selection, I focus on workers' current labor market status, the probability of being long-term unemployed (unemployed longer than one year), and labor market experience at entry. All these characteristics at entry carry important indications about worker productivity and are directly observable by employers.

Table 3 presents the main results on firms' selectiveness. I evaluate firms' selectiveness for new and old positions by investigating the differences in workers' labor market status at entry. Column (1) shows the results from regressing the job-to-job mobility indicator on the "New Job" categorical variable.[26] The estimates suggest that the probability that firms hire workers from other firms for new jobs is approximately 2-2.5 percentage points higher than entrants into old positions.[27] Column (2) shows that the probability of being long-term unemployed is 1.2 (0.8) percentage points less likely for workers entering newly created roles compared to replacements (expansions in old jobs). Overall, the results suggest that firms are more likely to poach workers from other firms when introducing new roles and are less likely to hire long-term unemployed people for new positions. These results provide suggestive evidence of firms' differential selectiveness across job types based on current labor market status, as they may associate unemployment spells with skill depreciation.[28] Notice also that differential selection criteria apply to old jobs based on whether they are expanding or stagnating/shrinking. Note that the comparison is among workers entering the same firm, so I hold firm-level skill composition via firm-by-year fixed effects constant at entry. Also, demand for specific occupations may differ across labor markets due to varying labor market tightness (occupation x municipality). These concerns are also addressed by occupation x local labor market x year fixed effects.

Hiring workers for newly created jobs within firms entails higher uncertainty for firms. However, new roles within firms may imply increased responsibilities, such as establishing new teams or departments. While such explicit job-specific requirements are unobservable due to the inherent limitations of register data, potential worker-level outcomes include new hires' labor market experience or occupational tenure. The sampling framework of WSS data, from which occupational information is derived, introduces random attrition among workers, posing significant limitations in accurately measuring workers' occupational tenure. Nevertheless, labor market experience is observable for each worker, allowing the examination of the assumption that firms tend to select relatively more experienced candidates for newly created positions.[29] Column 3 displays the results from estimating labor market experience on

[26] It's worth noting that I use the month gap between employment spells as a proxy for non-employment duration, as I lack access to data on unemployment spells. Based on this duration, I construct a job-to-job mobility indicator, denoting instances where the duration between consecutive jobs is no more than two months. By this definition, %72 of new entrants are job-to-job movers in my data.

[27] This is supportive empirical evidence to Elsby et al. 2022; as in their model, expanding firms poach employed workers, and job-to-job movers enter expanding positions. While they seek replacements, they also match with unemployed workers.

[28] Edin and Gustavsson 2008 and Cohen et al. 2023 provide evidence from Sweden and Germany regarding the significance of non-employment spells on skill depreciation.

[29] Behrenz 2001 shows that 60% of employers consider labor market experience the most crucial selection crite-

job types and shows that new job entrants have, on average, two years more labor market experience than those entering pre-existing positions. This finding suggests that firms tend to favor experienced workers for new jobs, consistent with possible job-specific prerequisites for new roles within firms.

5.2 New job wage premium

Next, I investigate the new job wage premium. Table 4 presents the main estimating results from two different versions of Equation 11: the comparison of entrants across firms in Panel A and within firms in Panel B. Column (1) shows the β estimates from Equation 11. The results in the first panel show entry wage differentials among workers entering different firms, conditional on industry-by-year, occupation-by-local labor market-year fixed effects, and individual-level covariates such as education, age, experience, and gender. Panel A column (1) suggests that new jobs have 3.1 (2.9 + 0.25) percent higher entry wages than replacing old jobs and 2.9 percent higher than expanding old jobs. The estimate on "Old job (Replacing)" shows differences in entry wages between expanding and replacing old jobs. The findings suggest that firms do not encounter frictions due to expanding a particular job, conditional on having prior experience in employing workers in both occupations.

Remember from the previous section that firms select workers on observables for new jobs, i.e., job-to-job movers and more experienced workers. These findings may raise the question whether the new job wage premium is present only for workers coming from another job. Workers who were previously unemployed are expected to have a lower level of outside options, which negatively affects their wages.[30] Column (2) shows the entry wage differences conditional on previous labor market status. The results suggest that being a job-to-job mover is important but cannot explain the new job wage premium.[31] It is important to note that job movers obtain around 4.4% higher entry wages compared to workers entering from unemployment.

Further, as already descriptively documented in section 3.3, firms that introduce new jobs differ from firms hiring old jobs along several dimensions: they are younger, grow faster, and are smaller.[32] Thus, in columns (3) and (4), I further control for symmetric employment growth

rion.

[30]The Burdett and Mortensen 1998 model would predict that new jobs pay more because they are filled by job-to-job movers, who have, on average, higher level of outside options.

[31]Note that J2J mover indicator can be a bad control since firms select workers based on this variable. Table A5 replicates the same table among job-to-job movers only, and shows very similar results.

[32]See figures A1 for firm size distributions, and A2 for firm growth distributions.

Table 4: New job wage premium

Dependent var: ln(Entry Wage) **Panel A. Across-firms**	(1)	(2)	(3)	(4)	(5)
Omitted category: Old job (Expanding)					
New job	0.029***	0.028***	0.027***	0.029***	0.023**
	(0.0050)	(0.0049)	(0.0049)	(0.0049)	(0.0075)
Old job (Replacing)	-0.0025	-0.0018	-0.000080	0.0012	-0.00031
	(0.0018)	(0.0018)	(0.0018)	(0.0017)	(0.0024)
log(Firm size)	0.00013	0.00018	0.00020	0.0010	0.00039
	(0.0014)	(0.0014)	(0.0014)	(0.0013)	(0.0016)
J2J mover		0.043***	0.042***	0.042***	0.033***
		(0.0026)	(0.0026)	(0.0027)	(0.0043)
Firm growth rate (DHS index)			0.0073*	0.0052	0.0073
			(0.0034)	(0.0032)	(0.0045)
log(value added per capita)				0.031***	0.015***
				(0.0041)	(0.0040)
Observations	1651691	1651691	1651691	1425755	1425755
Adjusted R^2	0.733	0.736	0.736	0.751	0.845
Fixed effects					
Occupation (3-digit) x LLM x Year FE	✓	✓	✓	✓	✓
Industry (3-digit) x Year	✓	✓	✓	✓	✓
Worker FE					✓
Panel B. Within-firm	(1)	(2)	(3)	(4)	(5)
Omitted category: Old job (Expanding)					
New job	0.030***	0.030***	0.039***	0.034***	0.023*
	(0.0038)	(0.0038)	(0.0051)	(0.0074)	(0.0091)
Old job (Replacing)	-0.0012	-0.0010	0.00011	0.0017	-0.0022
	(0.0021)	(0.0021)	(0.0024)	(0.0033)	(0.0019)
J2J mover		0.036***	0.033***	0.032***	0.032***
		(0.0012)	(0.0012)	(0.0012)	(0.0024)
Observations	1651691	1651691	1651691	1651691	1651691
Adjusted R^2	0.766	0.768	0.787	0.794	0.848
Fixed effects					
Occupation (3-digit) x LLM x Year FE	✓	✓	✓	✓	✓
Firm x Year FE	✓	✓			
Firm x Year x Occ(1-digit) FE			✓		
Firm x Year x Occ(2-digit) FE				✓	
Firm FE					✓
Worker FE					✓

Notes: Dependent variable is log entry wages. Each column represents a separate regression. All regressions flexibly control for age, gender, labor market experience, and education. Standard errors clustered at 3-digit industry level for regressions in panel A, and at firm level for regressions in panel B. There are fewer observations in panel A column 4 than in columns 1-3 because the value added is only available for non-financial corporations in Sweden (in real SEK for the base year 2006). Main results exclude managerial positions. I provide the results including these positions in Appendix Table A4 rate and log of value added per capita. The firm growth rate implies that firms that grow by 10 percent pay about 0.08 percent higher wages for new hires. The estimate of log(value added per capita) suggests that a one percent increase in value added per capita is associated with approximately a 0.031 percent increase in entry wages, holding other factors constant.[33] The sample size reduces a little as the information on value added is present only for non-financial firms. Notice that conditional on time-varying firm-level characteristics; the entry-wage premium is reduced to around 2.1 percent. The last column adds worker fixed effects to the regression to address endogenous sorting concerns to new jobs and obtain similar entry-wage responses, which I will discuss below in detail.

It is important to highlight certain aspects of across-firms specification. First, this specification cannot account for certain firm-level idiosyncrasies, such as demand conditions and differential firm-level wage-setting practices. Secondly, although the specifications in Panel A aim to control for factors likely to affect the premium paid for new jobs, as indicated in section 3.3 and descriptively shown in Table 1, new jobs tend to be concentrated in younger and smaller firms, highlighting some distinctive characteristics of firms. These aspects are the primary rationale for conducting within-firm analysis, where firm-level characteristics and overall demand conditions are held constant at the time of entry for newly recruited workers.[34]

Next, panel B shows within-firm wage differentials by controlling for firm-by-year fixed effects. The estimates in columns (1) and (2) suggest that the new job entry wage premium is around 3 percent. Thus, it is evident that the wage premium for new jobs exists even when we compare entrants into the same firm. This specification implies comparing workers recruited to the same firm. Notice, however, that within-firm comparison is identified by firms that hire to both old and new jobs. Thus, I produce same results by restricting analysis to firms that hire for new and old jobs in a given year (see appendix Table A3).

However, it is important to note that this specification implies comparison across different occupations within a given firm. Therefore, variations in the entry wages of different positions may arise from comparing very different occupations within a firm, even though the skill-specific labor demand at a particular labor market is held fixed through occupation-local labor market-year fixed effects. To further compare workers entering similar occupations within a firm, in columns (3) and (4), I compare workers who enter the same 1-digit and 2-digit occupations within the firm but solely differ in the 3-digit, respectively. The results demonstrate that

[33] Value added is defined as the total revenues minus intermediate consumption of goods and services.

[34] Expanding positions may be found in firms that experience higher demand in the product market, inducing mechanically higher entry wages for workers rather than due to the nature of hiring or positions.

the wage premium associated with the positions created in new occupations can be attributed to the newness of the jobs, rather than comparison across dissimilar occupations within firms. This set of results helps us better understand employers' screening processes for prospective employees across different positions.

The advantages of firm-level analysis in our understanding of mechanisms are manifold: First, the identification ensures that the firm-specific demand shocks are accounted for, and one can discern how employers differentially screen candidates for different roles. If the firm has a high demand for a given period, then both the entrants to expanding new jobs and to expanding old have exposure to that high demand, but we still see a larger response for expansions along a new occupation. Notice that new entrants to old jobs within the firm do not differ in entry wages based on whether the job is expanding or replacing. Thus, whether a firm is expanding or replacing an old job category does not play a role in entry wages.

The average new job wage premium is likely to obscure heterogeneity across skill levels, experience groups, occupational distance, as well as across different segments of the labor market. Previous studies documented that employers' search efforts depend on job skill requirements and document substantial heterogeneity in screening costs across occupations (Barron and Bishop 1985; Barron et al. 1997; Van Ours and Ridder 1992).[35]

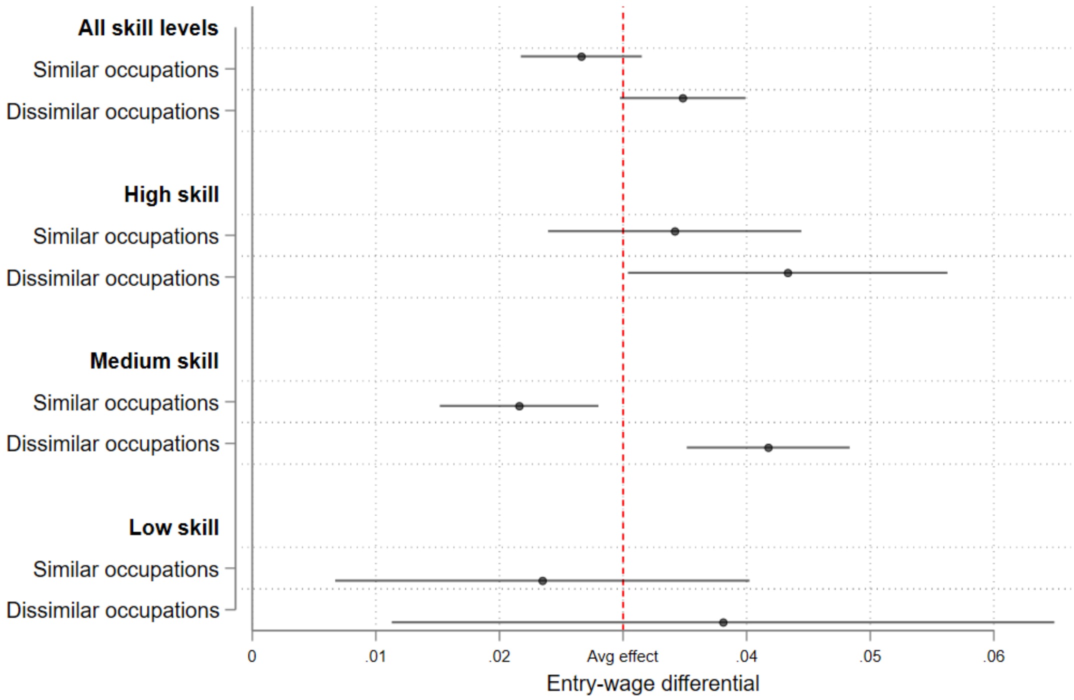
5.2.1 New Job Wage Premium by Occupational Similarity

I provide further evidence that my findings are driven by firms' lack of hiring experience in newly created roles by breaking down New Job_{jot} into two distinct subsets. Some new occupations along which firms expand are likely to differ significantly from the existing occupations within the firm. Specifically, I expect that if the new occupation is similar to any of the preexisting occupation categories within the firm, the new job wage premium should be lower. This is because jobs within the same broad occupational categories are likely to require comparable skills and responsibilities, enhancing firms' ability to leverage existing knowledge and experience in the hiring process. Conversely, if the results were primarily driven by general shifts in demand for a worker's skills, we would expect both similar and dissimilar new jobs to have same entry wage premium.

To test this hypothesis, I distinguish between new jobs in similar and dissimilar occupations, defined by the broad occupational category of the new job (determined by the first digit

[35]Van Ours and Ridder 1993 shows that jobs that require higher education take double the time to fill (20 weeks) compared to primary education (10 weeks).

Figure 2: New Job Wage Premium by skill and occupational distance



Notes: The figure shows the coefficients on New Job_{jot} indicator from separately estimated regressions for each skill level, keeping expanding and replacing old job entrants in the control group. Similar occupations are defined as those sharing the same first digit, indicating that the new job falls within the same broad occupational category as any of the existing occupation within firm. Occupations not meeting this criterion are classified as dissimilar. The vertical dashed red line shows the average estimate from Panel B. column 2 in Table 4. The regressions include same set of controls as in Equation 11. High, medium, and low-skilled occupations are ISCO occupational groups 2 to 3, 4 to 8, and 9 respectively.

of the occupation code). I then estimate the following regression:

$$\ln(\text{entry wage})_{ijot} = \beta_1 \text{New Job}^{Similar}_{jot} + \beta_2 \text{New Job}^{Dissimilar}_{jot} + \lambda_{jt} + \lambda_{o\ell t} + X'_{it}\delta + \epsilon_{ijt} \quad (12)$$

where New $\text{Job}^{Similar}_{jot}$ and New $\text{Job}^{Dissimilar}_{jot}$ are indicators for new jobs that fall within similar and dissimilar occupations to preexisting occupations in the firm, respectively. I construct similar and dissimilar occupations using two alternative methods. In the first method, similar occupations are those that share the same first digit as existing occupations within the firm, while dissimilar occupations differ at the first digit. For the second measure of occupational distance, I use observed transitions between occupations, following Belot et al. 2019; Le Barbanchon et al. 2023a.[36]

Figure 2 shows the estimates of β_1 and β_2 from estimating (12) using pooled and separate

[36]Using Swedish administrative data from 1996 to 2013, I track workers over time to construct occupational transitions both within and between firms. I then calculate the share of transitions between occupations, retaining the two most common transitions as "similar" occupations and classifying the remainder as dissimilar.

regressions. While the new job wage premium exists across all skill groups, they vary by occupational similarity. Consistent with my predictions, the wage premium is higher for new jobs that are more dissimilar to existing occupations within the firm.[37] Appendix Figure A3 replicate Figure 2 using this second measure and gives very similar results.

The new job wage premium is consistent across occupations, regardless of skill level. The existence of new job wage premium across all skill groups, and increasing effect by dissimilarity provide evidence that the wage premium is driven by firms' lack of employment experience in occupations.[38]

5.2.2 Worker Fixed Effects

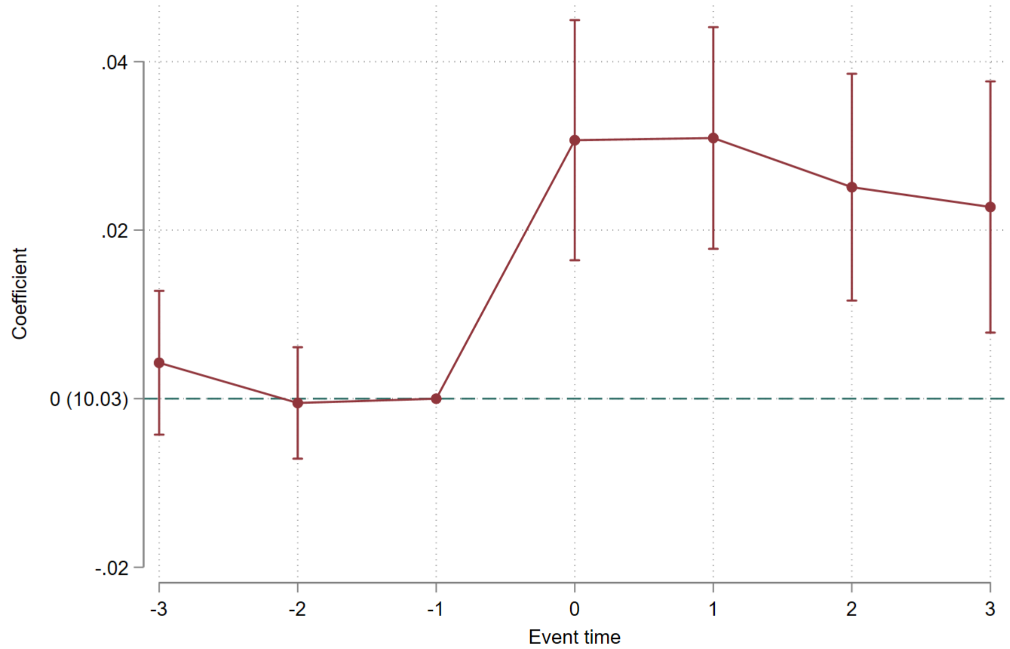
While the empirical evidence presented in the previous section suggests that new jobs are associated with higher entry wages, it is worth investigating whether the premium is due to the unobserved productivity of the workers or unobserved complementarities between workers and firms. One thing that occupation-time fixed effects and other worker-level covariates cannot capture is that workers in particular occupations can be selected on unobservables. Thus, the workers' skill bundles can also differ across occupations. For these reasons, I introduce worker and firm fixed effects holding other sets of fixed effects the same as in equation 11 to control for selection and unobserved heterogeneity.

The results in Table 4 column (5) provide the results with worker fixed effects. Panel A controls for industry-by-year fixed effects instead of firm fixed effects, whereas panel B includes firm fixed effects, thus showing results from estimating an augmented version of AKM. Regressions with worker fixed effects account for all time-invariant characteristics of the individual, thereby factoring in the direct impact of an individual's time-invariant unobserved skills. However, the model identification relies on multiple hires for a given worker, and for the β estimates to be identified, workers must have been hired in different types of jobs (new vs old jobs) in different firms. Since I focus on new hires, this results in the reduction of the sample size. The entry wage premiums are similar, suggesting workers who have entered new jobs have had the same wage differences conditional on observed and unobserved (time-invariant) characteristics. Overall, I present evidence that a firm's experience with a particular occupation (proxied by job age) is an additional source of within-firm wage dispersion.

[37] Appendix Table A10 shows that the new job wage premium is significantly higher when the new job occupation is dissimilar.

[38] Appendix Figure A7 shows the new job wage premium separately for each occupation group at the 1st-digit.

Figure 3: EVENT STUDY ESTIMATES



Notes: The figure shows the event study estimates of the β_m parameters in Equation (13), together with the 95% confidence intervals. Standard errors are clustered at the worker level. The treated group consists of workers entering new jobs. Control group consists of workers who are entering an old job in the same occupation and location. The regressions flexibly control for age and education.

5.3 Event Study Estimates

In order to provide causal interpretation to my estimates, I further carry out event-study analysis. The event-study approach allows one to observe how wages evolve over time in relation to the entering a new job, with the observation of wage dynamics both before and after entering the new job. If the estimates on pre-treatment period are significantly different from zero, it suggests a causal impact of the new job on wages, assuming the underlying parallel trends assumption is satisfied. To understand whether new job wage premium corresponds to a causal effect, I estimate the following equation:

$$ln\, w_{it} = \sum_{m=-3, m\neq -1}^{3} \beta_m \text{New Job}_{jo,t-m} + \alpha_i + q'_{it}\psi + \lambda_{o\ell t} + \varepsilon_{it}, \tag{13}$$

where the term $(\sum_{m=-3}^{4} \beta_m \text{New Job}_{jo,t-m})$ captures the effect of transitioning to a new job, where (m) indicates different time periods relative to the event (i.e., entering a new job). Equation (13) represents an event-study regression model, commonly used to examine the dynamic effects of a specific event (in this case, starting a new job) on an outcome variable which represents the log of wages for individual i at time t. The coefficients (β_m) measure how the log wage changes m periods before or after the job change. (α_i) accounts for time-invariant characteristics specific to each individual, controlling for unobserved heterogeneity that might influence wages. $q'_{it}\psi$ represents a set of control variables that vary over time, capturing other factors that might influence wages besides the job change such as age and education level. $\lambda_{o\ell t}$ controls for time-specific shocks that vary across regions and occupations, accounting for broader macroeconomic conditions or local labor market trends that might affect wages. Finally, ε_{it} is the idiosyncratic error term, capturing unexplained variation in wages.

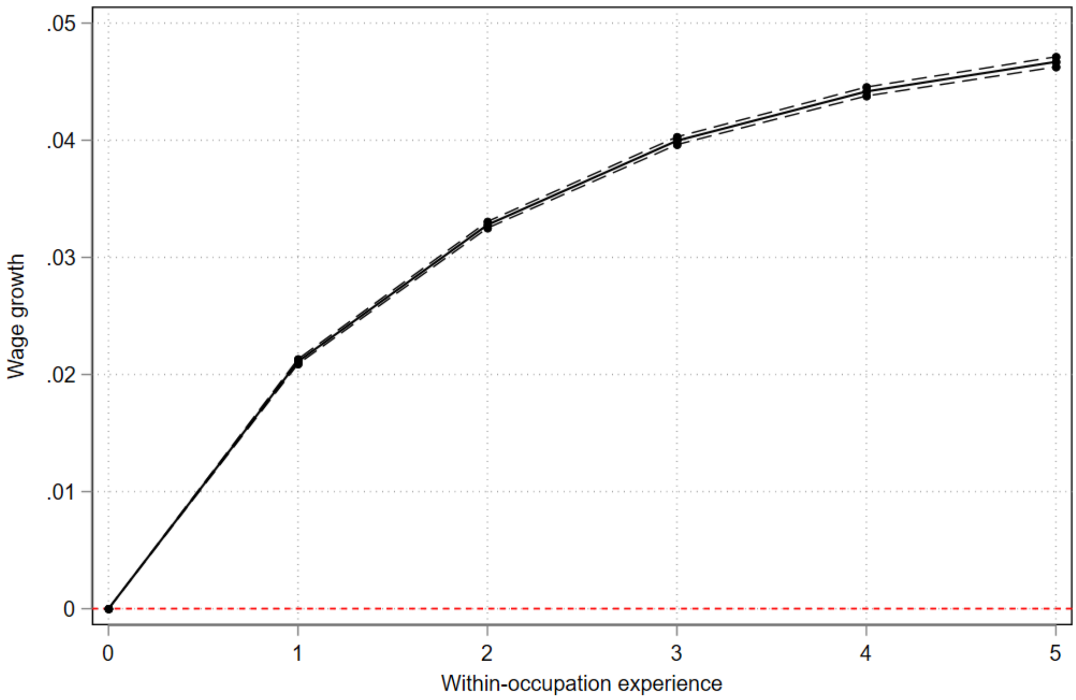
The event-study analysis shows that event study coefficients before the event are statistically indistinguishable from zero. At the time of the event, there is a significant positive impact on wages of approximately 3% (consistent with the main estimates in Table 4). This effect decreases slightly over the subsequent three years, stabilizing at around 2.3%, suggesting a slightly diminishing but persistent impact of the job change on wages. Further, the event study estimates are robust to different selection of samples and control group (see Appendix Figure ??).

5.3.1 Interpretation of magnitudes

The significance of new job wage premium can be understood through two key interpretations. First, these premiums can be contextualized within the broader literature on job mobility. Previous research has documented that between-firm job mobility is the primary source of wage growth over the life cycle (Topel and Ward 1992; Adda and Dustmann 2023). In my sample, job-to-job movers obtain entry wages 3 to 4 percent higher than those of workers coming from non-employment, conditional worker characteristics and newness of the job at entry. The estimates in panel B, column (3) of Table 4 suggest that the new job wage premium is as large as the wage premium of job-to-job movers. In other regressions, the new job wage premium is shown to be at least half of what an average job mover receives. This comparison highlights that new jobs offer a considerable wage premium.

Second, I relate my main estimates to within occupation wage growth. The main comparison group in across-firms specification is the workers who are employed in the same occupation, same local labor market, and same industry, one is entering a new job and the other is entering an old job. Figure 4 shows the average wage progression within occupation. An average worker experiences %3.5 real wage growth over 5 years, net of age and year effects. If a worker is lucky enough to enter a new job, the wage increase she receives is equivalent to the cumulative wage growth a worker would typically experience within-occupation over five

Figure 4: WITHIN-OCCUPATION WAGE PROGRESSION



Notes: The figure illustrates wage growth within a given occupation, with the starting wage in a worker's first year in the occupation normalized to zero. I regress wages on occupational tenure, conditional on occupation, age, year, and education fixed effects. $ln(w_{it}) = \gamma OccupationTenure_{(i,t)} + \lambda_o + \lambda_t + \lambda_{age} + \lambda_{edu} + \varepsilon_{it}$

years.

Robustness: A job is defined as the firm x year x occupation at the 3-digit level. However, it is possible to define jobs at i) firm x year x occupation at the 4-digit as a robustness check. The results in table A6 provide similar and significant estimates, suggesting that new job wage premiums are robust to various definitions of a job. Another robustness check is to focus on a subsample of firms - firms that were established after 1996, which is the first year we can observe occupations in the data. The reason for this robustness check is to make sure that a firm did not employ anyone in an occupation before 1996, but I cannot observe. The estimation results are shown in table A7.

5.4 Sorting into new jobs

I documented the entry wage differentials among different types of hires within- and across firms, holding factors affecting labor demand at the market- and the firm-level constant. The endogeneity problem, however, can arise from high-ability workers self-selecting into new positions created in a new occupation.[39] Thus, it is important to investigate whether the entry-wage premium reflects the sorting of high-ability individuals into newly created roles. Therefore, I examine possible indications of sorting on unobservable worker characteristics, i.e., high-skilled workers sorting into new positions. To this end, I estimate the AKM (Abowd et al. 1999) model to construct a measure of human capital. When I estimate the AKM model, I rely on data covering the universe of private sector employees from 1985-96, the only available years before the main estimating sample.[40] Specifically, I estimate the model of the log wage of worker i in year t with additive effects for workers and firms:

$$ln\, w_{it} = \theta_i + \psi_{j(i,t)} + X'_{it}\gamma + \varepsilon_{it} \tag{14}$$

where w_{it} is worker i's monthly earnings in year t at firm $j_{(i,t)}$. θ_i is the worker-specific effects, and X'_{it} denote year fixed effects and educational attainment dummies interacted with quadratic and cubic age polynomials (following model specifications in Card et al. 2013 and Eliason et al. 2023). Since I use pre-dated data to estimate the worker fixed effects, they are exogenous to the type of position that workers are hired into.[41] Then, I use the estimated (time-invariant) worker effects $\hat{\theta}_i$ as the measure of unobserved worker skills. To get a sense of sorting, I relate the estimated person effects $\hat{\theta}_i$ to the type of position, New Job$_{jot}$. So, I estimate:

$$\hat{\theta}_i = \phi \text{New Job}_{jot} + \lambda_{kt} + \lambda_{o\ell t} + X'_{it}\delta + \epsilon_{ijt} \tag{15}$$

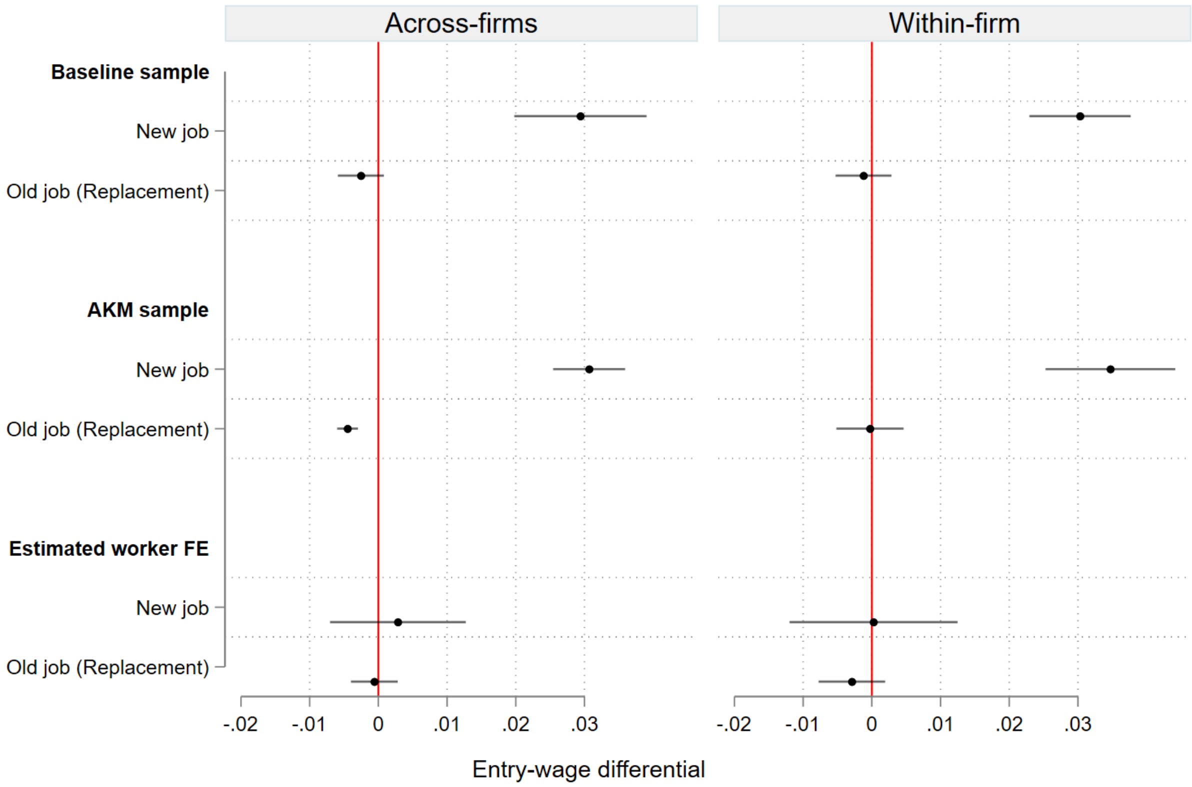
where the main parameter of interest is ϕ, which determines the degree of sorting to new jobs. Figure 5 plots the main results. Estimates shown in the first panel are from the main estimating sample as presented in Table 4 used for within-firm specifications. The second panel shows the estimates from the same specification but uses observations in the pre-dated data (the AKM sample). Reassuringly, the estimates are the same across different samples (see top two panels in Figure 5). It is worth noting that the workers in the AKM sample are older compared to the main sample, which makes comparison across workers entering new and old jobs even more comparable (see Table A1 for descriptive statistics of AKM sample). The last panel shows the estimates of ϕ, our focal estimates in the sorting analysis. One should expect lower estimates of ϕ compared to wage-premium, such that some estimated entry wage

[39] Theoretical motivation behind this is workers direct their search.

[40] Table A1 shows the summary statistics used in the AKM sample.

[41] The wage measure used in this regression is monthly earnings. Appendix table A8 shows the replicate of the analysis from AKM estimates using WSS. Since WSS data is a sample of firms, worker and firm fixed effects are identified through moves between sampled firms.

Figure 5: ESTIMATES OF NEW JOB WAGE PREMIUM AND SORTING PARAMETERS



Notes: The figure shows entry wage estimates from the baseline sample, and AKM sample, together with the estimates of ϕ from equation 15. The first chunk shows the β estimates from equation 11 comparing workers across- and within-firms. The second chunk shows the entry-wage premium estimates using a pre-dated AKM sample (1985-1996) across and within firms. The bottom panel of the figure shows the estimates of ϕ from equation 15, and uses only the pre-dated AKM sample. All regressions control for the same set of individual and firm-level covariates. Standard errors are clustered on the 3-digit industry for across-firm specification and on the firms for within-firm estimations.

differentials are due to higher unobserved skilled workers entering particular positions. The skill measure ($\hat{\theta}_i$) has the same scale as the wage, and the size of the selection responses can be compared to wage responses (Carlsson et al. 2016). The estimates presented in the last panel show that the differences in the estimated person effects are much lower (around one-tenth) than the main estimates β, and are not statistically significant (see the estimates presented in Table A9). Wage premiums associated with different types of positions cannot be explained by high-ability workers self-selecting into positions in newly created roles.

However, this approach has two caveats. First, by the nature of the estimated worker effects, the left-hand side of the equation 15 does not vary within an individual, while the right-hand side covariates change within an individual across time. Second, worker fixed effects estimated from AKM may not capture unobserved worker productivity or whether new positions are selected on unobserved productivity. For these reasons, in the next section, I address sorting issues by investigating within-worker changes.

I have demonstrated that the estimated worker fixed effects do not vary across jobs, indicating that workers are not selected based on unobservable characteristics. Additionally, I presented further evidence that the wage premium linked to new jobs is not a result of systematic worker sorting into these positions. Having established persistent entry wage differentials across various specifications and addressed sorting concerns, I now turn to examining subsequent labor market outcomes for workers entering different jobs.

5.5 Differences in Post-Hiring Outcomes and Match Quality

In this section, I analyze differences in match quality between old and new jobs by examining post-hiring outcomes within-firm. I use match quality measures (along with entry wages) that are widely used in the literature (see, among others, Lalive 2007; Nekoei and Weber 2017). These include i) first-year separation rate, ii) the probability of staying in the job for at least three years, iii) on-the-job wage growth, iv) standard deviation of wages within spell, v) and total earnings within the job.[42]

The uncertainty at the hiring stage may affect other characteristics of the match beyond wages. In Section 5.1, I provided evidence that firms tend to hire more experienced workers when filling newly created roles. If they select workers based on observable characteristics to offset higher ex-ante uncertainty for the new jobs, it could create differences in match quality due to ex-post uncertainty.

To investigate differences in post-hiring outcomes across job types, I run regressions similar to equation 11, where y_{ijot} takes one of the above-mentioned match quality measures. I compare workers entering the same firm in the same year. Other covariates and fixed effects are the same as in the main specification. The 1st-year separation probability takes a value of one if the maximum job duration is 1 year. Job earnings refer to the total income gained from a given employment relationship. Wage growth is the three-year difference in log wages for individuals who have stayed in the same firm.[43]

Table 5 represents the results for subsequent labor market outcomes of entrants. The first column shows the probability of separating from the job within the first year is 1.1 pp lower. Column (2) shows that staying in the firm after 3 years is 1.7 pp higher. The 3-year wage

[42]Other match quality measures extensively used in the literature are based on workers' subjective assessments such as job satisfaction, which are usually not present in register data Belot et al. (2024).

[43]The sample is reduced to around one-quarter of the original size because the wage data are collected via sampling and wage growth within the job is observed for workers who stay in the same job for three years.

Table 5: POST-HIRING OUTCOMES

Dependent variable:	$\mathbb{1}$(1st-year separation)	$\mathbb{1}$(Stay in t+3)	3-year wage growth	sd(wage)	Within-job earnings$_{ij}$
	(1)	(2)	(3)	(4)	(5)
Omitted category: Old job (Expanding)					
New job	-0.011***	0.017***	-0.0013	-0.0030	0.079***
	(0.0035)	(0.0066)	(0.0013)	(0.0021)	(0.023)
Old job (Replacing)	0.00033	-0.00046	0.00031	-0.00041	-0.0015
	(0.0013)	(0.0022)	(0.00049)	(0.00077)	(0.0075)
Observations	1651691	1651691	452952	452952	1651691
Adjusted R^2	0.230	0.273	0.295	0.332	0.439
Mean dependent variable	.11	.47	.04	.09	13.07
Occupation (3-digit) x LLM x Year FE	✓	✓	✓	✓	✓
Firm x Year FE	✓	✓	✓	✓	✓

Notes: This table presents post-hiring outcomes for 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 firm. Note that Columns (3) and (4) have fewer observations, as they focus specifically on employees who stayed for at least three years. All regressions include the same set of individual-level covariates, and standard errors are clustered at the firm level.

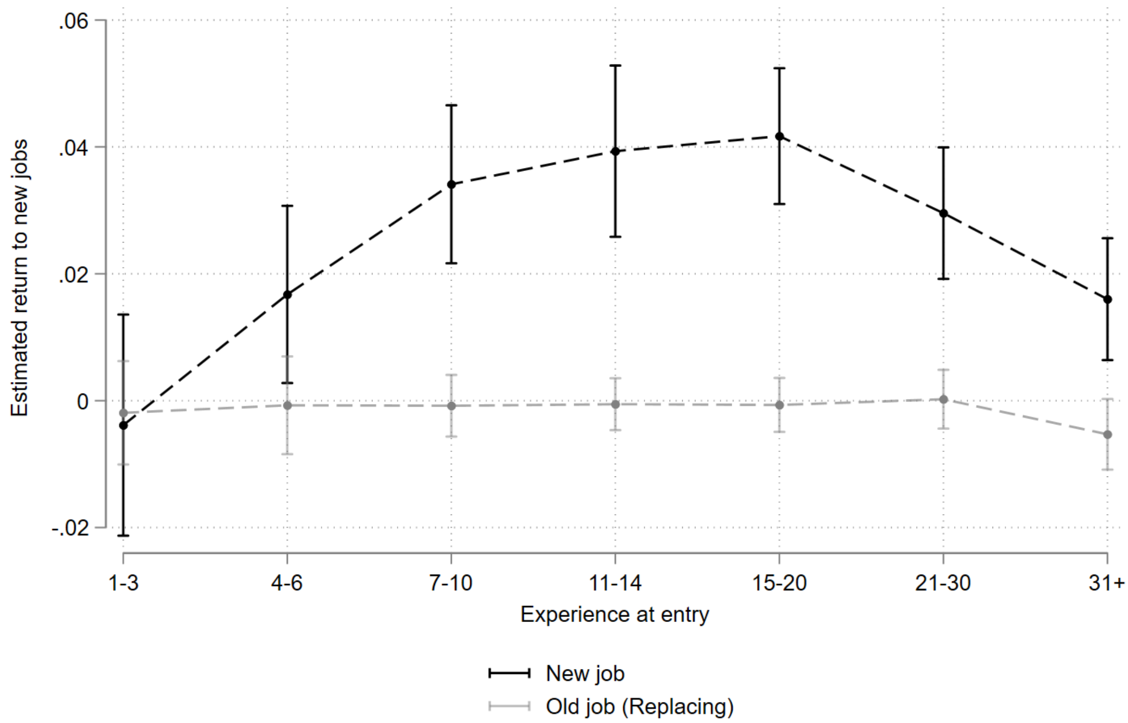
growth does not show a discernible pattern across jobs, suggesting no clear evidence of the convergence or divergence of wages. Thus, the initial premium at entry spills over the job spell. The last column shows that entrants in new jobs earn, on average, %8 percent more within the job match. This difference translates into an average of 40 000 SEK (around $4000) more earnings within the job. Remember that within-job earnings are a product of hours worked, match duration, and hourly wages. Since the average wage growth does not differ across jobs, the initial premium and longer tenure translate into substantial earnings differences.

These findings align with the assumption that differential firm selectivity results in significant differences in match quality. Through the lens of the theoretical framework described in section 2, longer match duration shows that the remaining uncertainty after pre-hire screening seems lower for new jobs than for old ones. Overall, I provide evidence that the match quality is higher in new jobs.

5.6 Heterogeneity in New Job Wage Premium

I further assess how entry-wage differentials vary across workers' experience levels. Figure 6 shows the entry wage differentials across experience gradient. The black line plots the *new*

Figure 6: ENTRY WAGE PREMIUM BY EXPERIENCE



Notes: The figure shows the estimated coefficients on an interaction terms between New Job_{jot} and years of labor market experience at entry. The reference group comprises workers entering old replacing jobs. The dashed black line represents the new job wage premium compared to old job replacements, while the dashed gray line illustrates the estimated difference in entry wages between expanding old jobs and replacing old jobs. The regression includes same set of controls as in Equation 11, excluding experience fixed effects.

job (differential between new roles and replacements), while the gray line represents the *old jobs (expansion)*, contrasting expansions along existing roles and replacements. First, the wage premium is present for workers with at least four years of experience at entry. The highest wage differential at entry is among the workers with seven to twenty years of labor market experience, which can go up to 4%. There is, however, no heterogeneity by experience in the entry wages among expansion hires in existing positions to replacements.

5.6.1 Firm-level heterogeneity

I also examine whether new job wage premium differs across firm age, firm size, and industries. Since new jobs tend to be found in smaller and younger firms (see Table 1), it is important to investigate whether the effects are concentrated among firms with particular characteristics. Firm size often correlates with resources, market power, and organizational practices, while firm age may reflect stability, reputation, and accumulated human capital, all of which can significantly affect wage structures, and in turn new job wage premium. Appendix figures A4 and A5 show that estimates are comparable across firm age and firm size dimensions. Firms, regardless of age or size, are paying similar wage premiums for new jobs. Further, A6 shows that the effect is present across all industries and of a comparable size.

6 Alternative theories and interpretations of results

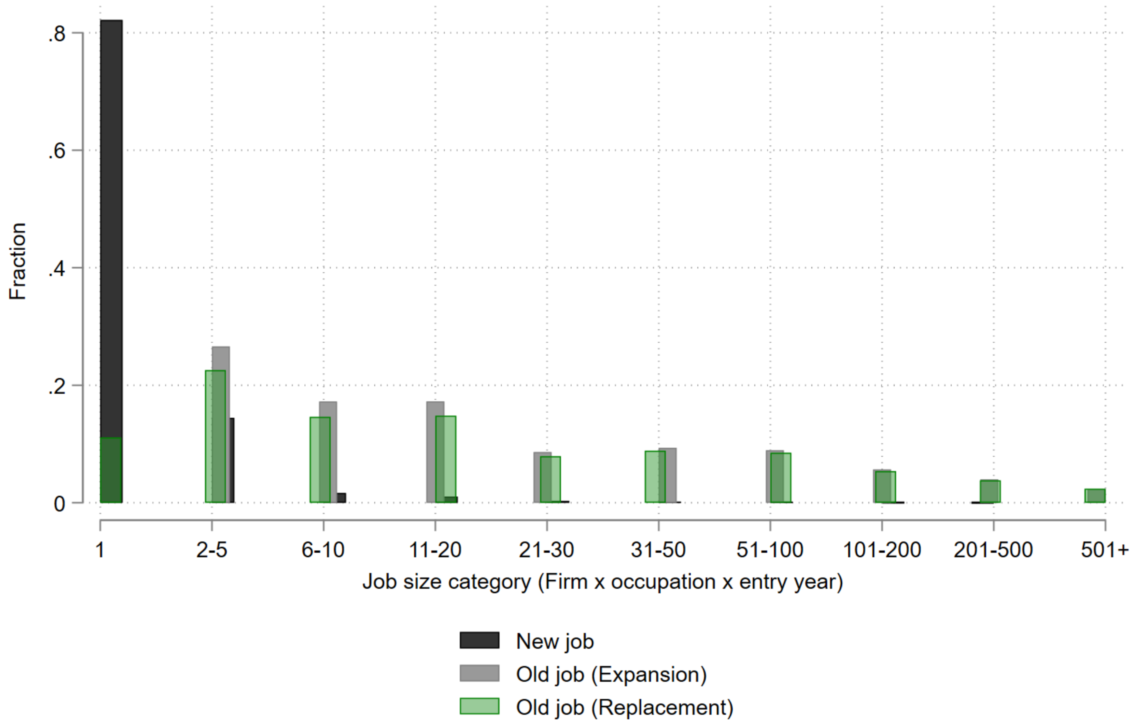
In this section I discuss alternative models that can generate higher entry wage prediction for new jobs. Potential candidates are compensating wage differentials and monopsonistic competition. Compensating wage differentials arises as a natural explanation for higher wages for new jobs if workers consider these jobs more risky and demand higher wages to be compensated for uncertainty. I will use turnover results to evaluate the possibility of being compensated for being in new jobs. Another potential candidate is monopsonistic competition, which can lead to higher wages for new jobs if new job wages increase with the hiring rate of firms. I evaluate these alternative theoretical mechanisms in the data.

6.1 Compensating wage differentials

Workers consider both monetary and non-monetary aspects of jobs when deciding whether to accept the job offer or not (Rosen 1986; Lavetti 2023). Workers entering new jobs might demand more compensation for some job characteristics that are peculiar to new jobs. If there are differences in amenities across new and old jobs, workers would demand compensation, leading to higher entry wages. First, using turnover results to evaluate this theory as a potential explanation will be informative. As shown in Table 5, the compensation differentials theory for potentially *riskier* jobs is inconsistent with workers' turnover as new job entrants have longer tenure. If workers were compensated for disamenities specific to new jobs, we would not expect them to stay longer in these jobs. However, workers in new jobs are more likely to work alone during their first year. Thus, examining whether the wage premium differs by job size at entry is a useful exercise.

When firms expand into new occupations, the job size in the first year tends to be smaller than that of old jobs. Figure 7 illustrates the distribution of job size (firm x occupation x entry year) for new and old jobs. Around %82 of new job categories contain a single worker within firms. We observe a monotonically decreasing job size among old jobs. If we assume that workers would demand extra compensation for working alone, we should see a decreas-

Figure 7: THE DISTRIBUTION OF JOB SIZE AT ENTRY



Notes: The figure shows job size distribution among new hires (workers with tenure=0). Expanding old jobs employ at least 2 workers, by definition. New jobs and replacing old jobs can employ one worker.

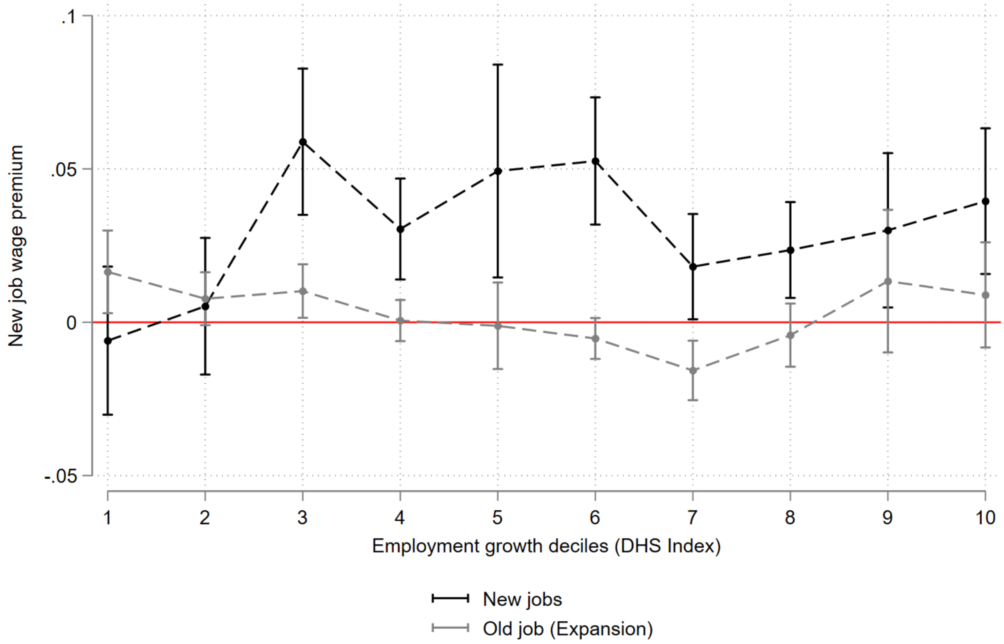
ing wage premium along job size.[44] Thus, I test the assumption of compensation for being alone on the job by investigating the entry wage differential by job size. If workers are indeed compensated for being alone (or few) in their jobs, then one would expect the entry wage to decrease with job size. Table A11 presents the interaction of the main effects with job size at entry. The compensation for being alone does not drive the wage premium results. Thus, I rule out compensating wage differentials as a potential mechanism behind wage differences.

6.2 Monopsony

In monopsonistically competitive labor markets, firms face an upward-sloping labor supply curve (Manning 2003). One implication of this is wages and the hiring rate of the firm should be positively correlated. Schmieder (2023) demonstrates that higher entry wages at new firms are fully explained by the new firms' higher employment growth, which he attributes to monopsonistic competition in labor markets. I have already shown (in Table 4, panel A, column 3), that firm growth rate is positively related to entry wages, suggesting affirmative ev-

[44]Workers, in reality, should be aware that they will be alone in the first year to be compensated.

Figure 8: Wage premium across firm growth deciles



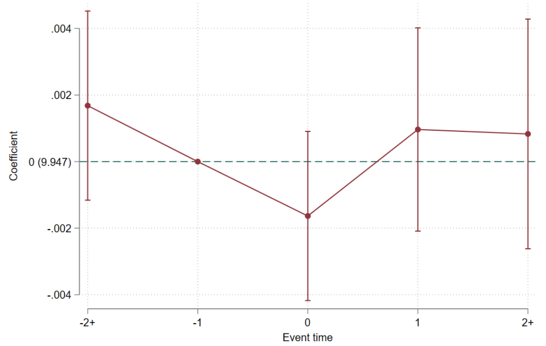
Notes: The figure shows the estimated coefficients on interaction terms between New Job$_{jot}$ and firm' employment growth deciles in Equation 11. The reference group comprises workers entering expanding old jobs. The dashed black line represents the new job wage premium compared to expanding old jobs, while the dashed gray line illustrates the estimated difference in entry wages between expanding old jobs and replacing old jobs. The regression includes same set of controls as in Equation 11, replacing firm-by-time fixed effects by industry-by-time fixed effects.

idence for monopsony power in the labor markets. However, In panel B of the same table, I have shown that workers entering new jobs are paid more compared to workers entering old jobs in the same firm and year. This comparison is maintained by including firm-by-year fixed effects in the regression, which holds firms' hiring rate constant at a given time. This suggests that monopsony cannot be the sole explanatory theory for the new job wage premium.

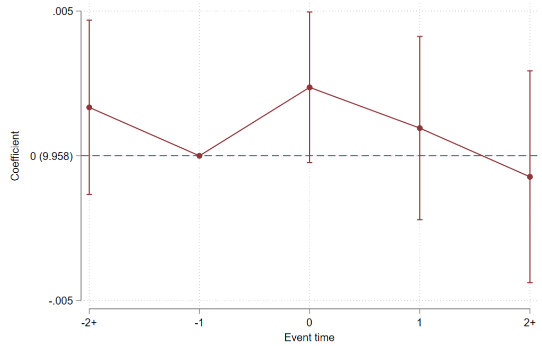
Here I provide two additional tests for the monopsony channel following Schmieder (2023) and Kroft et al. (2020). First, I investigate the relationship between firm growth rate and new job wage premium. To understand whether monopsony plays any role in the new job wage premium, I investigate how the premium differs across firms along the firm growth deciles. If the new job wage premium is found to be increasing with the firm growth rate, then monopsony would be plausible explanation for why new jobs are paid more. Second, I examine whether the firm that hire workers to new job pay, on average, higher wages for all of its workers compared to other expanding firms.

Figure 8 shows the new job wage premium estimates along employment growth deciles. New jobs are paid more even in shrinking firms, and there does not exist and increasing rela-

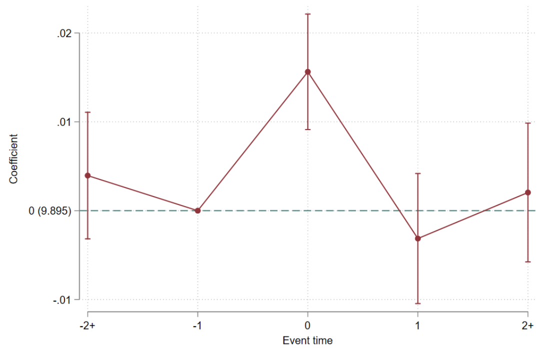
Figure 9: FIRM-LEVEL EVENT STUDY ESTIMATES - WAGE PER WORKER



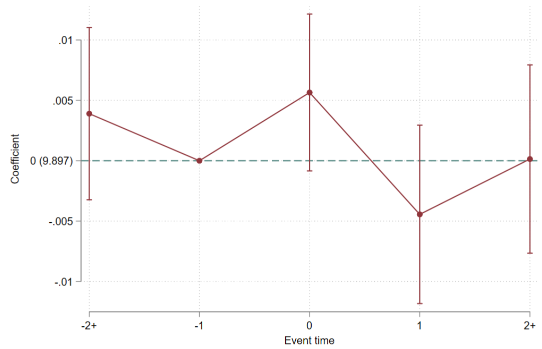
(a) ALL WORKERS



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

tionship between firm growth rate and wage premium estimates. I thus reject the possibility of monopsony being an explanation for new job wage premium.

For the second point, I conduct firm-level event study analysis to examine the evolution of average wages in firms that introduce new jobs in comparison to other expanding firms. I estimate the following event study regressions:

$$ln\, w_{jt} = \sum_{\tau=-2}^{3} \gamma_\tau \mathbb{1}(\text{New Job}_{j,t-\tau}) + \alpha_j + \lambda_{kt} + \varepsilon_{jt}, \tag{16}$$

where the term $\sum_{\tau=-2}^{3} \gamma_\tau \mathbb{1}(\text{New Job}_{j,t-\tau})$ captures the effect of introducing a new job within the firm, where (τ) indicates different time periods relative to the event. $\mathbb{1}(\text{New Job}_{j,t-\tau})$ represents an indicator function which takes 1 if the firm introduces a new job in year t. Equation

(16) represents an event-study regression model, commonly used to examine the dynamic effects of a specific event (in this case, introducing a new job) on an outcome variable which represents the log of average wages per worker at firm j at time t. The coefficients (γ_τ) measure how the log average wage changes τ periods before or after. (α_j) accounts for time-invariant characteristics specific to each firm. λ_{kt} controls for time-specific shocks that vary across industries. Finally, ε_{jt} is the idiosyncratic error term, capturing unexplained variation in wages.

Figure 9 Panel (a) and (b) show the event study estimates where the outcome is the average wages per worker of all and incumbent workers, respectively. Firms that introduce new jobs do not statistically differ in average pay from other firms. Panel (c) and (d) of the same figure shows the evolution of average wages firms pay to newly hired workers including and excluding new jobs, respectively. Panel (c) shows that firms that create new jobs pay new hires on average 1.4% higher wages. This finding is unsurprising since new hires include new job entrants as well. A more direct test for monopsony is to examine whether they pay other new hires more compared to other firms. Reassuringly, firms do not differ in new hires pay if we exclude new jobs. Another benefit of event study estimates is the examine wages in pre- and post-periods of new job creation, compared to other firms that expand along an old job. These estimates further show that firms that introduce new jobs do not systematically differ from other firms.

7 Conclusion

Previous research has documented that workers experience diverse labor market outcomes influenced by firm and individual job match characteristics. However, precise mechanisms that drive these differences were somewhat limited. In particular, no prior research has explored how information frictions on the demand side lead to differential wages and worker outcomes. In this paper, I provided first evidence on the impact of firms' lack of employment experience in a particular occupation on firms' employee selection, wages, and worker outcomes. My results show that hiring frictions lead to distinct labor market outcomes among observably similar workers, highlighting the critical role of hiring uncertainty and screening processes in shaping workers' labor market outcomes.

I interpret my findings within the stochastic job matching framework, where more heterogeneity in productivity distribution increases reservation productivity, leading to higher wages. I further scrutinized my results using alternative theories, confirming the robustness of my overall conclusions.

The findings of this study highlight several key insights. I demonstrate that job age affects firms' hiring decisions which have implications for worker reallocation and match quality. Firms select workers based on their observable characteristics (job movers and more experienced) to reduce the inherent uncertainties associated with new jobs. Match quality is higher in new jobs and workers entering new jobs are subject to better labor market outcomes which are not attributable to unobserved differences among workers. Workers who are employed in the same occupation, industry, and local labor market are paid differently across firms because of different employment experiences in firms. The paper contributes to our understanding of one the mechanisms that leads to wage dispersion by emphasizing the importance of demand-side information frictions in understanding labor market inequalities.

Finally, unraveling one mechanism driving wage differentials, this study provides crucial insights for policymakers seeking to address hiring frictions and wage inequality. A better understanding of the sources of labor market frictions and potential consequences on workers and firms may help policymakers design more effective active labor market policies. For instance, flexible employment contracts offer workers and firms the opportunity to assess the quality of the match on the job and help mitigate the adverse consequences associated with lower flexibility and mobility. Reducing frictions in the hiring process is crucial, and labor market institutions play a vital role in addressing such frictions to achieve this goal. This paper hopefully provides a contribution to the advancement of our knowledge.

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8 Appendix

8.1 Theory appendix

This part mainly follows from Mortensen 1986.

Definition: The productivity distribution of new jobs is given by H, and a mean-preserving spread of productivity distribution of old jobs G. They are both defined on the positive values of y, and have the same mean if and only if

$$\int_0^y H(x)\mathrm{d}x \geq \int_0^y G(x)\mathrm{d}x, \text{ for all } y > 0.$$

Assume $H(y, \sigma)$ is a mean-preserving spreads of G where σ is a parameter of relative dispersion

$$\lim_{\sigma \to 0} \int_0^y \{[H(x,\sigma) - G(x)]/\sigma\}\mathrm{d}x = \int_0^y H_\sigma(x,0)\mathrm{d}x \geq 0, \text{ for all } y,$$

Let $y_R(\sigma)$ denote the reservation productivity associated with more spread distribution $H(y, \sigma)$.

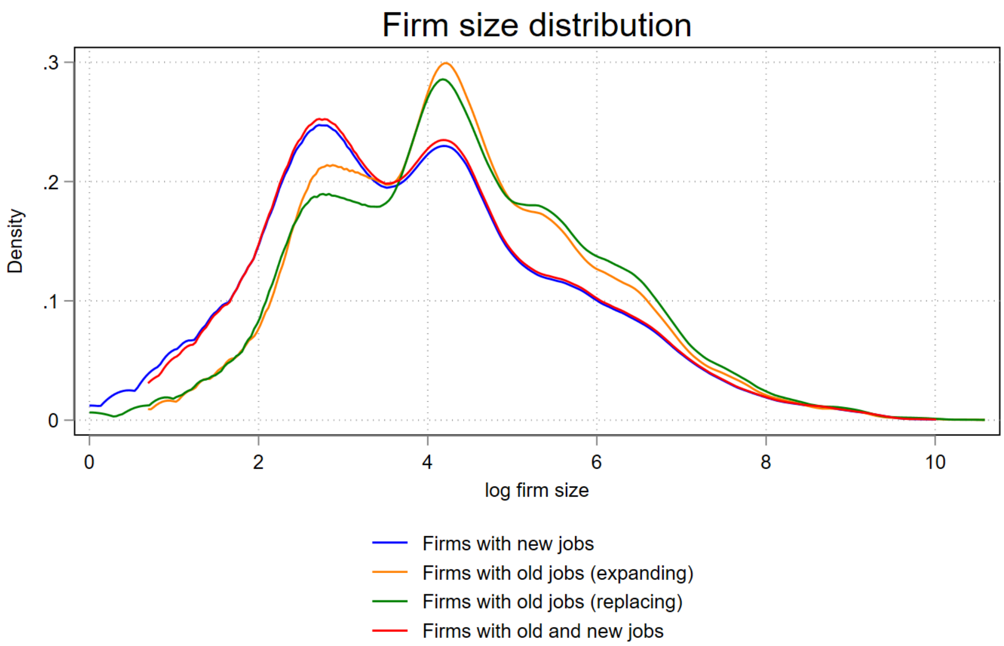
$$y_R(\sigma) = E[y] + \lambda \int_0^{y_R(\sigma)} H(x,\sigma)\mathrm{d}x$$

Consequently, a marginal increase in spread also increases reservation productivity.

$$\frac{\partial y_R(\sigma)}{\partial \sigma} = \left[\lambda \int_0^{y_r(\sigma)} H_\sigma(x,0)\mathrm{d}x\right] \geq 0$$

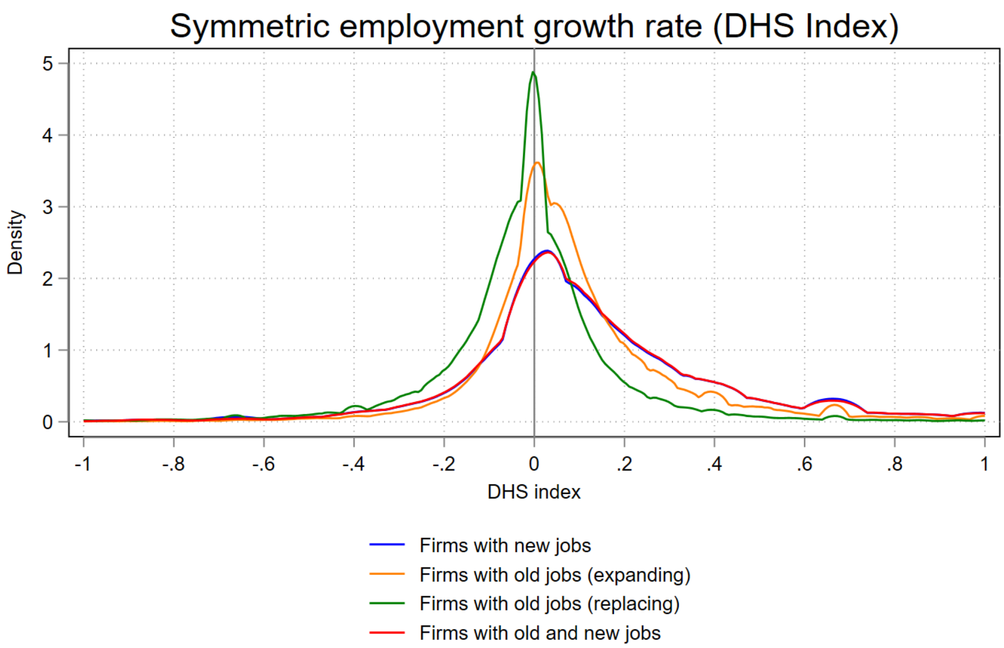
Appendix: Figures

Figure A1: Firm size distribution by types of hires



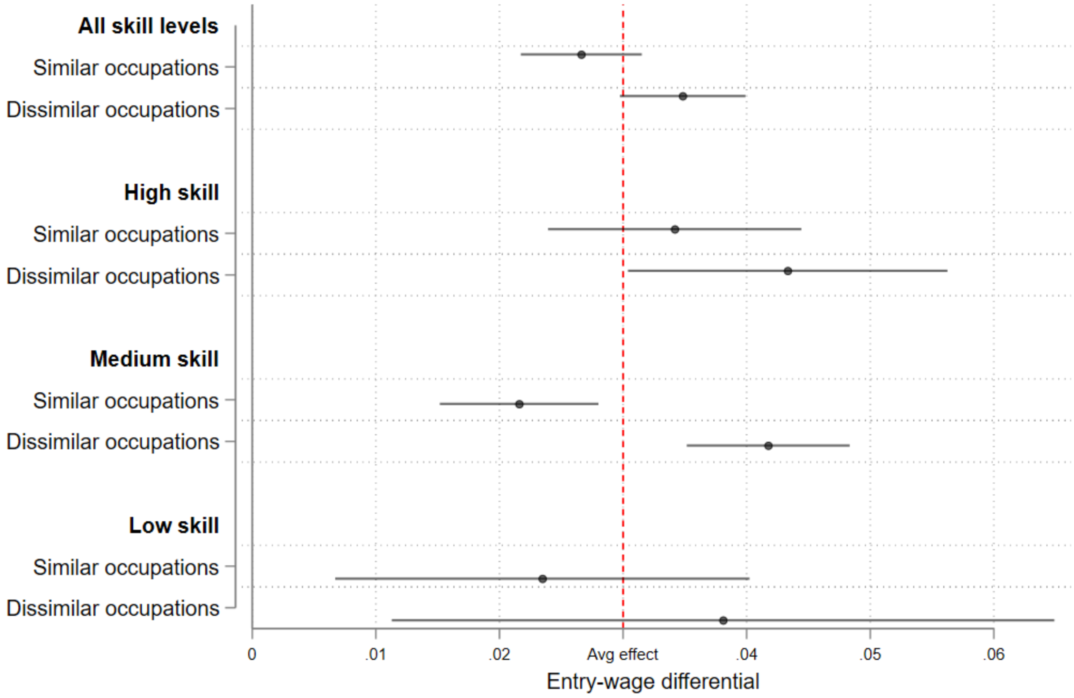
Notes: This figure shows firm size distribution of firms that introduce new jobs (blue), expanding old jobs (yellow), replacing old jobs (green), and firms that introduce both new and old job (red) in a given year.

Figure A2: Firm growth rate distribution by types of hires



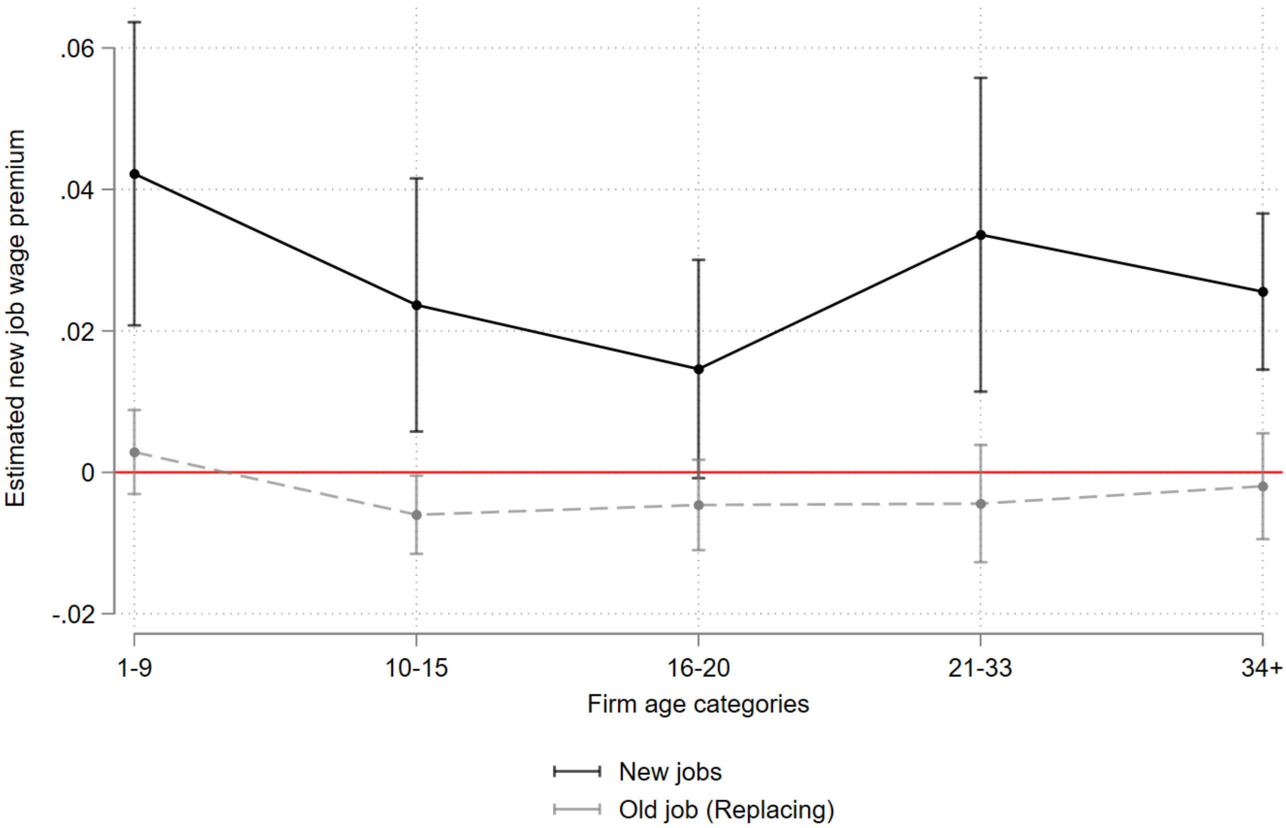
Notes: This figure shows firm size distribution of firms that introduce new jobs (blue), expanding old jobs (yellow), replacing old jobs (green), and firms that introduce both new and old job (red) in a given year.

Figure A3: HETEROGENEITY BY WORKERS' SKILLS AND OCCUPATIONAL DISTANCE (TRANSITION-BASED)



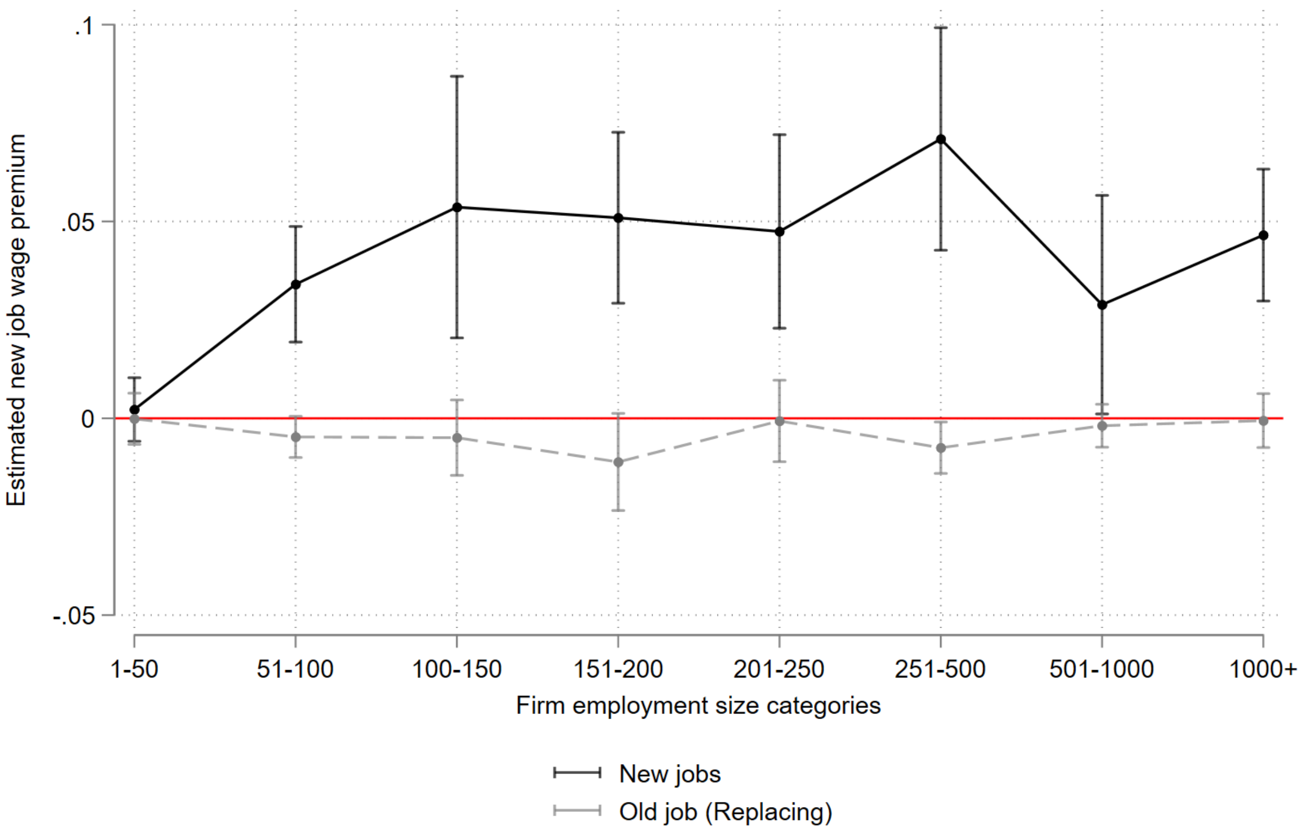
Notes: The figure shows the coefficients on New Job$_{jot}$ indicator from separately estimated regressions for each skill level, keeping expanding and replacing old job entrants in the control group. Similar occupations are defined as those sharing the same first digit, indicating that the new job falls within the same broad occupational category as any of the existing occupation within firm. Occupations not meeting this criterion are classified as dissimilar. The vertical dashed red line shows the average estimate from Panel B. column 2 in Table 4. The regressions include same set of controls as in Equation 11. High, medium, and low-skilled occupations are ISCO occupational groups 2 to 3, 4 to 8, and 9 respectively.

Figure A4: New Job Wage Premium: Heterogeneity by Firm Age



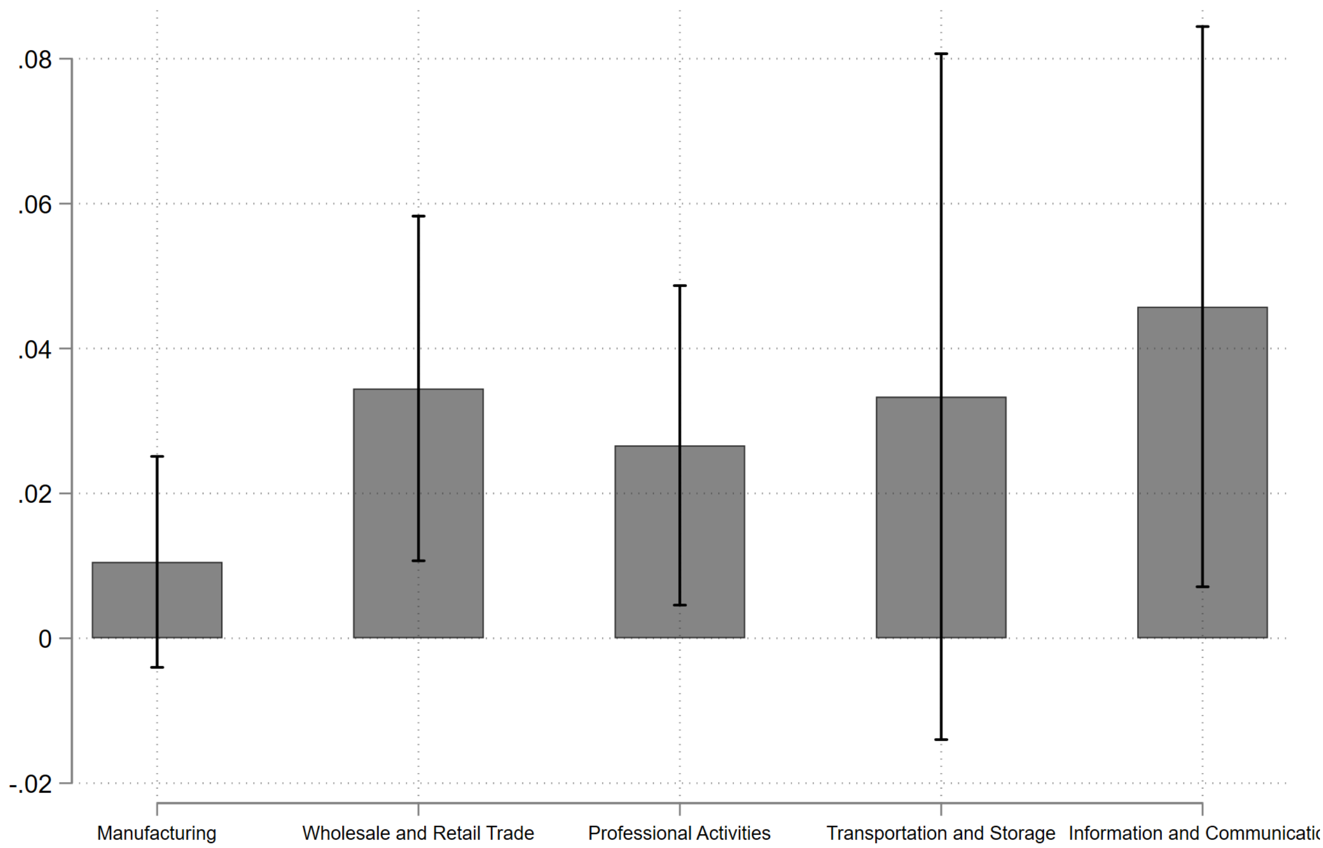
Notes: This figure shows how new job entry wage premium differs across firm age categories. Firm age is defined as the total number of years a firm has employed at least one worker since 1985, the earliest year in the matched employer-employee data. Firms that existed before 1985 are categorized in the firm age group 34+. I estimate equation (11) within each firm size categories. The dependent variable is entry wages. Each regression controls for occupation-by-local labor market-by-year fixed effects, firm-by-time fixed effects, age fixed effects, experience, nine education field fixed effects, and gender. Whiskers show 95% confidence intervals. Standard errors are clustered by firm level.

Figure A5: NEW JOB WAGE PREMIUM: HETEROGENEITY BY FIRM SIZE



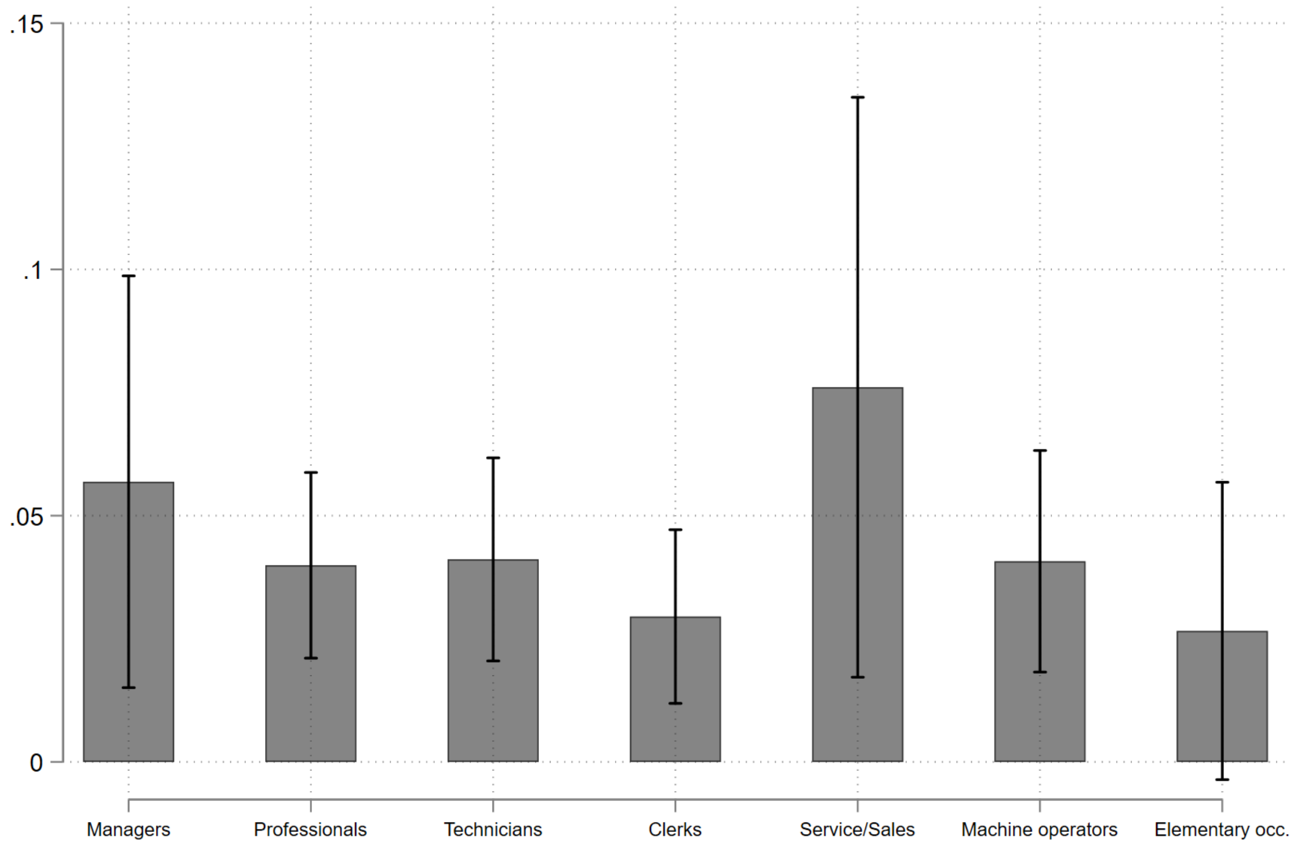
Notes: This figure shows how new job entry wage premium differs across firm size categories. Firm size is total number of employed in sampling month (September). I estimate equation (11) within each firm size categories. The dependent variable is entry wages. Each regression controls for occupation-by-local labor market-by-year fixed effects, firm-by-time fixed effects, age fixed effects, experience, nine education field fixed effects, and gender. Whiskers show 95% confidence intervals. Standard errors are clustered by firm level.

Figure A6: New Job Wage Premium: Heterogeneity by Industry



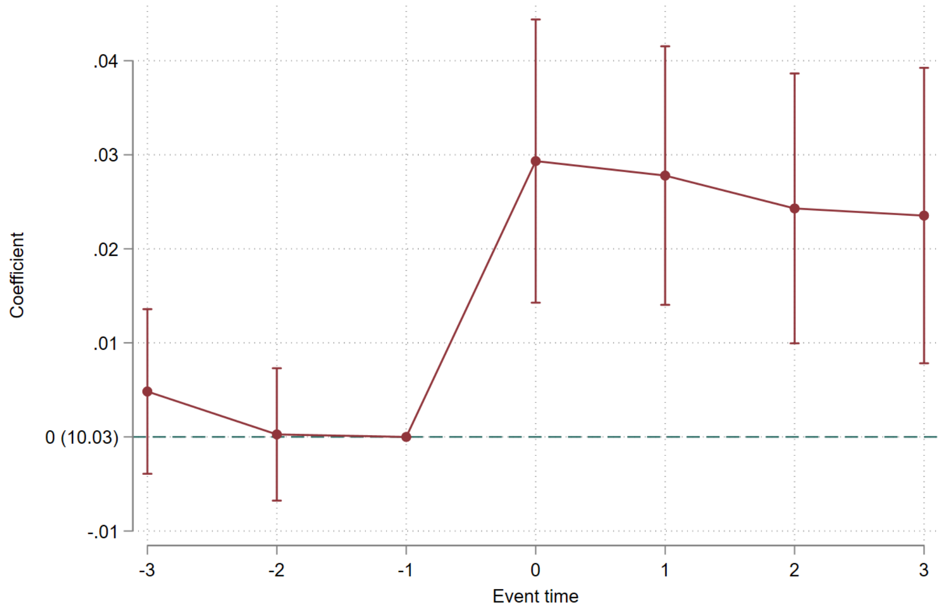
Notes: This figure shows how new job entry wage premium differs across industry groups. I group workers according to broad industry classification Standard for Swedish industry classification (SNI) codes, which are based on NACE. I estimate equation (11) within each seventeen 1-digit industry. The dependent variable is entry wages. Each regression controls for occupation-by-local labor market-by-year fixed effects, firm-by-time fixed effects, age fixed effects, experience, nine education field fixed effects, and gender. Whiskers indicate 95% confidence intervals. Standard errors are clustered by firm. I report five largest industry groups (that cover around %70 of total employment in my data) ranked by total employment.

Figure A7: New Job Wage Premium: Heterogeneity by Occupation

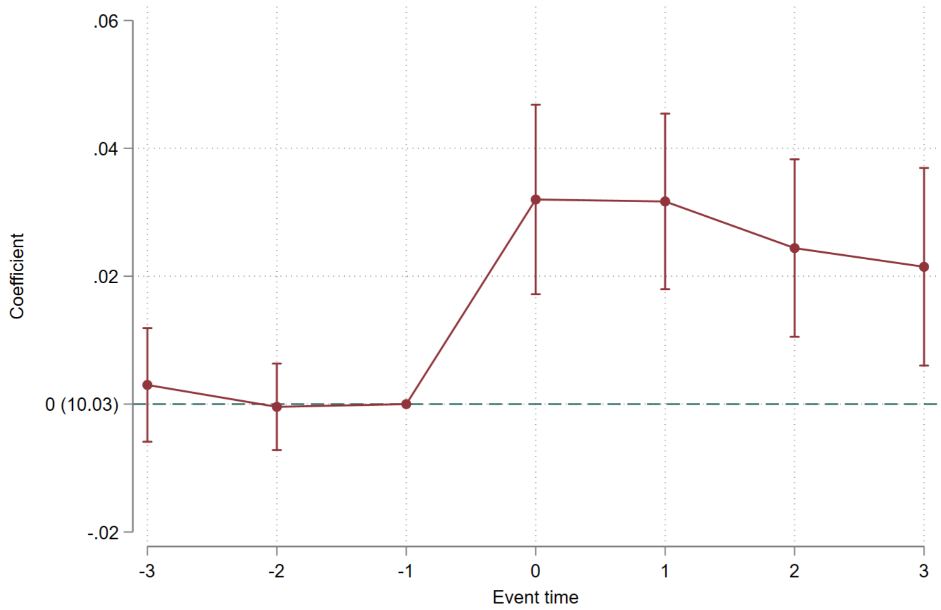


Notes: This figure shows how new job entry wage premium differs across occupation groups. I group workers according to broad ISCO (International Standard Classification of Occupations) codes. I then estimate equation (11) within each occupation. Each regression controls for occupation-by-local labor market-by-year fixed effects, firm-by-time fixed effects, age fixed effects, experience, nine education field fixed effects, and gender. Whiskers indicate 95% confidence intervals. Standard errors are clustered by firm. I do not have sufficient data on workers in the military (ISCO 10), in agricultural occupations (ISCO 6), and in craftsmen (ISCO 7).

Figure A8: WORKER-LEVEL EVENT STUDY ESTIMATES



(a) INCLUDING ENTRANTS TO OLD REPLACING JOBS IN THE CONTROL GROUP



(b) JOB-TO-JOB MOVERS ONLY

Notes: The figure shows the event study estimates of the β_m parameters in Equation (13), together with the 95% confidence intervals. Standard errors are clustered at the worker level. The treated group consists of workers entering new jobs. In Panel (a) the control group consists of workers who are entering both expanding and replacing old job. In Panel (b) the sample consists of workers entering new and old job from employment, without intervening non-employment period. In both panels the control group consists of workers who are entering both expanding and replacing old job. The event study regressions further control for age and education.

Appendix: Tables

Table A1: AKM SAMPLE STATISTICS

Panel A. Workers	AKM sample (1985-1996)			
	New job (N)	Old job (E)	Old job (R)	All
ln(entry wage)	10.0	10.0	10.00	10.0
1st-year separation	0.067	0.077	0.099	0.082
Age	44.2	42.4	41.6	42.2
Female	0.42	0.41	0.45	0.42
Experience at entry	18.1	17.9	18.0	17.9
Tenure (months)	65.6	65.4	58.4	63.7
Education				
Compulsory or less	0.18	0.15	0.12	0.14
High school	0.54	0.53	0.54	0.53
College	0.29	0.32	0.34	0.32
Occupations				
Professionals	0.16	0.18	0.17	0.18
Technicians and associate professionals	0.21	0.22	0.24	0.23
Clerks	0.19	0.10	0.11	0.11
Service workers and shop sales workers	0.055	0.13	0.16	0.14
Skilled agricultural and fishery workers	0.015	0.0052	0.0085	0.0062
Craft and related trades workers	0.14	0.11	0.11	0.11
Plant machine operators and assemblers	0.14	0.14	0.13	0.14
Elementary occupations	0.088	0.11	0.077	0.10
# distinct jobs (firm x occupation)	10757	43503	23019	37880.0
Observations	13566	543333	180823	737722

Panel B. Firms	New job (N)	Old job (E)	Old job (R)	New and Old (E,R)
Firm age	12.4	13.6	14.4	12.5
Firm size	45.5	80.8	101.0	48.6
Firm growth rate (DHS)	0.29	0.23	-0.011	0.31
Value added pc (Thousand SEK)	573080.6	590304.9	588719.6	576075.0
# 3-digit occupations	5.53	6.02	6.70	5.81
# New hires	9.52	10.5	11.3	10.1
Observations	7813	41315	35360	7706

Notes: The table shows descriptive statistics of workers who have been present in the AKM estimation using pre-period (1985-1996). Panel A shows mean statistics at the worker-year level of new hires used in the analysis data, who were present in the AKM estimation sample. Columns 1-4 in Panel A represent new hires in a new job, in an old expanding job, in old replacing jobs, and all hires, respectively. Panel B shows the mean statistics at the firm-year level. Columns 1-4 in Panel B represent firm characteristics among firms that hire into new jobs, old expanding jobs, old replacing jobs, and firms that hire both to new and old jobs, respectively..

Table A2: An example of Occupation categories

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

Note: The table shows a major group of occupations categorized under code 31, following the structure of ISCO-88: https://ilostat.ilo.org/methods/concepts-and-definitions/classification-occupation/

Table A3: NEW JOB WAGE PREMIUM: RESTRICTING SAMPLE TO FIRMS THAT INTRODUCE OLD AND NEW JOBS

Dependent var: ln(Entry Wage) **Panel A. Across-firms**	(1)	(2)	(3)	(4)
Omitted category: Old job (Expanding)				
New job	0.040***	0.039***	0.039***	0.045***
	(0.0058)	(0.0057)	(0.0057)	(0.0060)
Old job (Replacing)	0.0023	0.0031	0.0085*	0.0085*
	(0.0040)	(0.0039)	(0.0037)	(0.0040)
log(Firm size)	-0.00075	-0.00077	-0.00081	-0.0010
	(0.0020)	(0.0020)	(0.0019)	(0.0020)
J2J mover		0.045***	0.045***	0.043***
		(0.0029)	(0.0029)	(0.0029)
Firm growth rate (DHS index)			0.037***	0.029**
			(0.0089)	(0.010)
log(value added per capita)				0.013*
				(0.0063)
Observations	325866	325866	325866	285120
Adjusted R^2	0.778	0.780	0.781	0.792
Fixed effects				
Occupation (3-digit) x LLM x Year FE	✓	✓	✓	✓
Industry (3-digit) x Year	✓	✓	✓	✓
Panel B. Within-firm	(1)	(2)	(3)	(4)
Omitted category: Old job (Expanding)				
New job	0.040***	0.038***	0.049***	0.040***
	(0.0059)	(0.0058)	(0.0080)	(0.012)
Old job (Replacing)	0.0041	0.0044	0.012	0.015
	(0.0042)	(0.0042)	(0.0062)	(0.0092)
J2J mover		0.043***	0.040***	0.039***
		(0.0026)	(0.0026)	(0.0026)
Observations	325681	325681	321780	319191
Adjusted R^2	0.788	0.789	0.802	0.807
Fixed effects				
Occupation (3-digit) x LLM x Year FE	✓	✓	✓	✓
Firm x Year FE	✓	✓		
Firm x Year x Occ(1-digit) FE			✓	
Firm x Year x Occ(2-digit) FE				✓

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: The table shows new job wage premium estimates for firms that hire for both new and old jobs, i.e., identifying firms in within-firm analysis. Panel A. (Panel B.) shows results across-firms (within-firm). The introduction of worker fixed effects to the regressions taxes heavily on the data because the identification relies on multiple observations within workers over time, and entering identifying firms. So they are not included. Standard errors clustered on 3-digit industry (Firm) for Panel A. (Panel B.).

Table A4: New Job Wage Premium: Including Managers

Dependent var: ln(Entry Wage) **Panel A. Across-firms**	(1)	(2)	(3)	(4)	(5)
Omitted category: Old job (Expanding)					
New job	0.028***	0.027***	0.026***	0.028***	0.020**
	(0.0050)	(0.0049)	(0.0049)	(0.0045)	(0.0071)
Old job (Replacing)	-0.00065	0.000078	0.0015	0.0030	-0.00010
	(0.0019)	(0.0019)	(0.0019)	(0.0017)	(0.0021)
log(Firm size)	0.00049	0.00054	0.00055	0.0014	0.00038
	(0.0014)	(0.0014)	(0.0014)	(0.0013)	(0.0015)
J2J mover		0.042***	0.042***	0.042***	0.034***
		(0.0025)	(0.0025)	(0.0027)	(0.0042)
Firm growth rate (DHS index)			0.0061	0.0040	0.0066
			(0.0034)	(0.0031)	(0.0042)
log(value added per capita)				0.032***	0.014***
				(0.0038)	(0.0039)
Observations	1717056	1717056	1717056	1483431	1483431
Adjusted R^2	0.755	0.757	0.757	0.772	0.863
Fixed effects					
Occupation (3-digit) x LLM x Year FE	✓	✓	✓	✓	✓
Industry (3-digit) x Year	✓	✓	✓	✓	✓
Worker FE					✓

Panel B. Within-firm	(1)	(2)	(3)	(4)	(5)
Omitted category: Old job (Expanding)					
New job	0.032***	0.031***	0.042***	0.041***	0.020*
	(0.0038)	(0.0038)	(0.0050)	(0.0072)	(0.0086)
Old job (Replacing)	0.0013	0.0015	0.0018	0.0043	-0.0019
	(0.0020)	(0.0020)	(0.0022)	(0.0031)	(0.0018)
J2J mover		0.036***	0.033***	0.032***	0.033***
		(0.0012)	(0.0012)	(0.0012)	(0.0023)
Observations	1717056	1717056	1717056	1717056	1717056
Adjusted R^2	0.784	0.786	0.810	0.816	0.864
Fixed effects					
Occupation (3-digit) x LLM x Year FE	✓	✓	✓	✓	✓
Firm x Year FE	✓	✓			
Firm x Year x Occ(1-digit) FE			✓		
Firm x Year x Occ(2-digit) FE				✓	
Firm FE					✓
Worker FE					✓

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: The table shows new job wage premium estimates including managerial positions. Panel A. (Panel B.) shows results across-firms (within-firm). The introduction of worker fixed effects to the regressions taxes heavily on the data because the identification relies on multiple observations within workers over time, and entering identifying firms. So they are not included. Standard errors clustered on 3-digit industry (Firm) for Panel A. (Panel B.).

Table A5: NEW JOB WAGE PREMIUM: RESTRICTING SAMPLE TO JOB-TO-JOB MOVERS

Dependent var: ln(Entry Wage) **Panel A. Across-firms**	(1)	(2)	(3)	(4)
Omitted category: Old job (Expanding)				
New job	0.031***	0.030***	0.031***	0.024**
	(0.0051)	(0.0050)	(0.0048)	(0.0085)
Old job (Replacing)	-0.0023	-0.00059	0.00090	-0.0015
	(0.0018)	(0.0019)	(0.0017)	(0.0031)
log(Firm size)	-0.00056	-0.00054	0.00037	0.00014
	(0.0015)	(0.0015)	(0.0013)	(0.0017)
Firm growth rate (DHS index)		0.0073	0.0053	0.0072
		(0.0038)	(0.0037)	(0.0055)
log(value added per capita)			0.030***	0.013**
			(0.0042)	(0.0043)
Observations	1185148	1185148	1014558	1014558
Adjusted R^2	0.727	0.727	0.743	0.856
Fixed effects				
Occupation (3-digit) x LLM x Year FE	✓	✓	✓	✓
Industry (3-digit) x Year	✓	✓	✓	✓
Worker FE				✓
Panel B. Within-firm	(1)	(2)	(3)	(4)
Omitted category: Old job (Expanding)				
New job	0.032***	0.040***	0.034***	0.026*
	(0.0041)	(0.0061)	(0.0090)	(0.012)
Old job (Replacing)	-0.0013	0.00022	0.0024	-0.0029
	(0.0023)	(0.0027)	(0.0038)	(0.0024)
Observations	1185148	1185148	1185148	1185148
Adjusted R^2	0.758	0.775	0.782	0.855
Fixed effects				
Occupation (3-digit) x LLM x Year FE	✓	✓	✓	✓
Firm x Year FE	✓			
Firm x Year x Occ(1-digit) FE		✓		
Firm x Year x Occ(2-digit) FE			✓	
Firm FE				✓
Worker FE				✓

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: The table shows new job wage premium estimates for workers who are entering from employment, i.e., job-to-job movers. Job-to-job movers are workers with less than 2 months of intervening non-employment spell between two jobs. Panel A. (Panel B.) shows results across-firms (within-firm). Standard errors clustered on 3-digit industry (Firm) for Panel A. (Panel B.).

Table A6: NEW JOB WAGE PREMIUM: NEW JOB DEFINED AT 4TH-DIGIT OCCUPATION (INSTEAD OF 3-DIGIT)

Dependent var: ln(Entry Wage) **Panel A. Across-firms**	(1)	(2)	(3)	(4)	(5)
Omitted category: Old job (Expanding)					
New job	0.034***	0.033***	0.032***	0.034***	0.019**
	(0.0045)	(0.0045)	(0.0045)	(0.0042)	(0.0059)
Old job (replacing)	-0.0027	-0.0020	-0.00063	0.00032	-0.0014
	(0.0017)	(0.0017)	(0.0018)	(0.0017)	(0.0021)
log(Firm size)	0.0012	0.0013	0.0013	0.0016	0.00045
	(0.0014)	(0.0013)	(0.0013)	(0.0013)	(0.0016)
J2J mover		0.041***	0.041***	0.040***	0.033***
		(0.0026)	(0.0026)	(0.0028)	(0.0042)
Firm growth rate (DHS index)			0.0060	0.0043	0.0072
			(0.0038)	(0.0034)	(0.0043)
log(value added per capita)				0.029***	0.015***
				(0.0043)	(0.0040)
Observations	1651691	1651691	1651691	1425755	1425755
Adjusted R^2	0.748	0.750	0.750	0.763	0.849
Fixed effects					
Occupation (4-digit) x LLM x Year FE	✓	✓	✓	✓	✓
Industry (3-digit) x Year	✓	✓	✓	✓	✓
Worker FE					✓
Panel B. Within-firm	(1)	(2)	(3)	(4)	(5)
Omitted category: Old job (Expanding)					
New job	0.035***	0.034***	0.035***	0.032***	0.016*
	(0.0030)	(0.0030)	(0.0044)	(0.0059)	(0.0078)
Old job (replacing)	-0.0013	-0.0011	-0.0021	-0.0032	-0.0026
	(0.0018)	(0.0018)	(0.0022)	(0.0025)	(0.0018)
J2J mover		0.035***	0.032***	0.031***	0.032***
		(0.0012)	(0.0012)	(0.0012)	(0.0022)
Observations	1651691	1651691	1651691	1651691	1651691
Adjusted R^2	0.779	0.781	0.796	0.802	0.853
Fixed effects					
Occupation (4-digit) x LLM x Year FE	✓	✓	✓	✓	✓
Firm x Year FE	✓	✓			
Firm x Year x Occ(1-digit) FE			✓		
Firm x Year x Occ(2-digit) FE				✓	
Firm FE					✓
Worker FE					✓

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: The table shows new job wage premium estimates for an alternative definition of a *job*, using 4-digit occupations instead of 3-digit. Panel A. (Panel B.) shows results across-firms (within-firm). Standard errors clustered on 3-digit industry (Firm) for Panel A. (Panel B.).

Table A7: New job wage premium: Firms established after 1996

Dependent var: ln(Entry Wage) **Panel A. Across-firms**	(1)	(2)	(3)	(4)
Omitted category: Old job (Expanding)				
New job	0.046*	0.045*	0.043*	0.040*
	(0.019)	(0.019)	(0.020)	(0.020)
Old job (Replacing)	-0.0017	-0.0011	0.0013	-0.00069
	(0.0047)	(0.0045)	(0.0037)	(0.0042)
log(Firm size)	-0.0028	-0.0028	-0.0023	-0.0015
	(0.0045)	(0.0046)	(0.0045)	(0.0068)
J2J mover		0.032***	0.032***	0.034***
		(0.0052)	(0.0053)	(0.0054)
Firm growth rate (DHS index)			0.023	0.0024
			(0.025)	(0.034)
log(value added per capita)				0.033
				(0.026)
Observations	76027	76027	76027	62863
Adjusted R^2	0.805	0.806	0.806	0.811
Fixed effects				
Occupation (3-digit) x LLM x Year FE	✓	✓	✓	✓
Industry (3-digit) x Year	✓	✓	✓	✓
Panel B. Within-firm	(1)	(2)	(3)	(4)
Omitted category: Old job (Expanding)				
New job	0.051*	0.051*	0.068	0.010
	(0.021)	(0.021)	(0.039)	(0.051)
Old job (Replacing)	0.0015	0.0017	0.0022	-0.016
	(0.0049)	(0.0049)	(0.010)	(0.014)
J2J mover		0.031***	0.029***	0.029***
		(0.0043)	(0.0043)	(0.0043)
Observations	75399	75399	74340	73745
Adjusted R^2	0.811	0.813	0.819	0.822
Fixed effects				
Occupation (3-digit) x LLM x Year FE	✓	✓	✓	✓
Firm x Year FE	✓	✓		
Firm x Year x Occ(1-digit) FE			✓	
Firm x Year x Occ(2-digit) FE				✓

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: The table shows new job wage premium estimates for firms that have been established after 1996, the first year I can observe occupations in the data. Panel A. (Panel B.) shows results across-firms (within-firm). The introduction of worker fixed effects to the regressions taxes heavily on the data because the identification relies on multiple observations within workers over time. So they are not included. Standard errors clustered on 3-digit industry (Firm) for Panel A. (Panel B.).

Table A8: Sorting - AKM (Using wages as outcome from WSS sample)

	Across Firms			Within Firm		
	(1)	(2)	(3)	(4)	(5)	(6)
	ln(Entry Wage$_{ijt}$)	ln(Entry Wage$_{ijt}$)	$\hat{\theta}_i$	ln(Entry Wage$_{ijt}$)	ln(Entry Wage$_{ijt}$)	$\hat{\theta}_i$
Omitted category: Old job (Expanding)						
New job	0.029***	0.034***	0.0036	0.030***	0.031***	-0.0023
	(0.0049)	(0.0047)	(0.0060)	(0.0038)	(0.0074)	(0.0052)
Old job (Replacing)	-0.0025	-0.0066***	-0.0034	-0.0012	-0.0070*	-0.0048*
	(0.0017)	(0.0015)	(0.0021)	(0.0021)	(0.0040)	(0.0026)
Observations	1589344	264009	264009	1574148	250376	250376
Adjusted R^2	0.735	0.742	0.461	0.769	0.775	0.481
Occupation (3-digit) x LLM x Year FE	✓	✓	✓	✓	✓	✓
Industry x Year	✓	✓	✓			
Firm x Year FE				✓	✓	✓

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: The table shows entry wage estimates for different samples (main and AKM sample), together with results from estimating equation 15. Columns 1 and 4 show the original entry-wage premium estimates from estimating equation 11. Columns 2 and 5 show the entry-wage premium estimates using a pre-dated AKM sample (1985-1996), across and within firms, respectively. Columns 3 and 6 show the estimates of ϕ from equation 15, and are using only the AKM sample. All regressions control for the same set of individual and firm-level covariates. Standard errors clustered on 3-digit industry (Firm) for columns 1-2-3 (4-5-6).

Table A9: Sorting - AKM (Using earnings as outcome from tax registers)

	Across Firms			Within Firm		
	(1)	(2)	(3)	(4)	(5)	(6)
	ln(Entry Wage$_{ijt}$)	ln(Entry Wage$_{ijt}$)	$\hat{\theta}_i$	ln(Entry Wage$_{ijt}$)	ln(Entry Wage$_{ijt}$)	$\hat{\theta}_i$
Omitted category: Old job (Expanding)						
New job	0.029***	0.031***	0.0024	0.030***	0.035***	0.00025
	(0.0049)	(0.0027)	(0.0050)	(0.0038)	(0.0048)	(0.0062)
Old job (Replacing)	-0.0025	-0.0045***	-0.00058	-0.0012	-0.00027	-0.0029
	(0.0017)	(0.00077)	(0.0017)	(0.0021)	(0.0025)	(0.0025)
Observations	1589344	680374	680374	1574148	662850	662850
Adjusted R^2	0.735	0.733	0.181	0.769	0.767	0.192
Occupation (3-digit) x LLM x Year FE	✓	✓	✓	✓	✓	✓
Industry x Year	✓	✓	✓			
Firm x Year FE				✓	✓	✓

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: The table shows new job wage premium estimates for different samples (main and AKM sample), together with results from estimating equation 15 using log earnings as the outcome in the AKM. Columns 1 and 4 show the original entry-wage premium estimates from estimating equation 11. Columns 2 and 5 show the entry-wage premium estimates using a pre-dated AKM sample (1985-1996), across and within firms, respectively. Columns 3 and 6 show the estimates of ϕ from equation 15, and are using only the AKM sample. All regressions control for the same set of individual and firm-level covariates. Standard errors clustered on 3-digit industry (Firm) for columns 1-2-3 (4-5-6).

Table A10: Entry Wage Premium by Occupational Distance

Dependent variable: log(entry wage)	All skills pooled regression	High skill	Mid skill	Low skill
	(1)	(2)	(3)	(4)
Omitted category: Old jobs (Expanding and Replacing)				
New Job	0.027***	0.034***	0.022***	0.023***
	(0.0025)	(0.0052)	(0.0033)	(0.0086)
$\mathbb{1}$[Dissimilar]	0.0082**	0.0091	0.020***	0.015
	(0.0035)	(0.0082)	(0.0044)	(0.014)
Observations	1651689	524630	910698	216361
Adjusted R^2	0.767	0.627	0.692	0.755
Occupation (3-digit) x LLM x Year FE	✓	✓	✓	✓
Firm x Year FE	✓	✓	✓	✓

Notes: The table presents the coefficients of β and γ for the New Job_{jot} and $\mathbb{1}[\text{Dissimilar}]_{jot}$ indicators, obtained by estimating the following equation: $\log(\text{entry wage})_{ijot} = \beta \text{New Job}_{jot} + \gamma \mathbb{1}[\text{Dissimilar}]_{jot} + \lambda_{jt} + \lambda_{o\ell t} + X'_{it}\delta + \epsilon_{ijt}$. The results are shown from pooled regressions (column 1) and separately estimated regressions by skill level (columns 2–4), with expanding and replacement entrants grouped under the control category. Here, the $\mathbb{1}[\text{Dissimilar}]_{jot}$ takes value one if new job is in a dissimilar occupation which are occupations where the new job does not share the same first-digit code as any of the existing occupation within the firm. $\mathbb{1}[\text{Dissimilar}]_{jot}$, thus, captures the difference between dissimilar and similar new jobs in entry wage premium. New jobs that fall within the same first-digit occupation code are classified as similar. The regressions include the same control variables as in Equation 11. High-, medium-, and low-skilled occupations correspond to ISCO occupational groups 2–3, 4–8, and 9, respectively.

Table A11: Heterogeneity by job size

Dependent variable: log(Entry Wage)	Within firm	Across firms
	(1)	(2)
Omitted category: Old job (Expanding and Replacing)		
New Job	0.031***	0.031***
	(0.0036)	(0.0040)
New job $\times$ Job size$_{jot}$	-0.00022	0.00012
	(0.00015)	(0.00017)
Observations	1651691	1651691
Adjusted R^2	0.767	0.733
Occupation (3-digit) x LLM x Year FE	✓	✓
Firm x Year FE	✓	
Industry x Year FE		✓

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: The table shows how new job wage premium estimates change by the job size at entry (total employment in firm x occupation x year). Omitted category consists of both old jobs - expanding and replacing. The regressions flexibly control for age, experience, educational attainment, and gender. First column makes within-firm across jobs comparison, and the second column makes across firms across jobs comparison. Standard errors clustered on firm (3-digit industry) for column (1) (column (2).