Workplace Heterogeneity in Wage Growth

Diego Battiston*, Martin Friedrich** and Ines Helm****

very preliminary - do not circulate

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Abstract

We study differential wage growth across firms. To this end, we propose a statistical model that extends the workhorse model of wage determination by Abowd et al. (1999) to allow for firm-type-specific wage growth. We estimate the model using linked employer-employee data from Germany for the years 1996 to 2016. We show that wage growth differs across firms and that these differences can at least partially be explained by differential human capital accumulation. Workers keep the additional accumulated pay when switching firms. This has important considerations for our understanding of the sources of wage inequality. We show that the presence of firm-type specific wage growth biases the variance and sorting components of the AKM model. The dispersion of worker quality and sorting is less important in explaining wage inequality than previously thought.

Keywords: AKM, Wage Heterogeneity, Sources of Wage Inequality

JEL Classification: C23,J31,J62

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1 Introduction

Firms differ significantly in size, productivity, and the wages they pay. This has challenged the classical view of the labor market, prompting researchers to examine the role of firms in wage determination and wage inequality. The increased availability of rich administrative data, which allows to track the entire work history of individuals across firms has simplified this research. To date, the workhorse model to explain observed differences in earnings across workers and firms is the statistical model of wage determination first proposed by Abowd et al. (1999) (henceforth AKM), which assumes that earnings (wages) can be decomposed into an (unobserved) worker component, an (unobserved) firm component, and observed worker characteristics. This has led to a large literature studying the contribution of worker heterogeneity, firm heterogeneity, and worker-firm sorting to earnings dispersion (e.g. Card et al. (2013), Card et al. (2018), Song et al. (2019)).[1] More recently, a number of studies have provided extensions and relaxed some of the assumptions in the model: Engbom et al. (2023) have extended the standard AKM model to allow for time-varying firm pay policies, Lachowska et al. (2023) have analysed drift in the firm component of wages, Di Addario et al. (2023) allowed wages to depend on the identity of both the current and the last employer and Bonhomme et al. (2019), Bonhomme et al. (2023), and Kline et al. (2020) have studied limited mobility bias that arises when only few workers move across firms.

Another restriction of the standard AKM model is that it does not allow for dynamic returns that may be heterogeneous across firms. The model instead constrains earnings differences across firms to a constant premium the firm pays to the worker while employed there. As a consequence, wage growth is restricted to take place only through the accumulation of general experience and when the worker moves to a higher-paying firm.[2] Related micro-level evidence suggests, however, that firms are heterogeneous not only in levels but also in terms of wage growth, for example, due to differences in training provision (e.g. Parent (1999) or Booth and Bryan (2005)), hierarchical structures and promotion possibilities (e.g. Huitfeldt et al. (2023)), or due to differential learning from co-workers (e.g. Cornelissen et al. (2017), Jarosch et al. (2021) and Herkenhoff et al. (2018)). In the presence of such heterogeneous wage growth profiles, the AKM model and thus also decompositions of the sources of wage dispersion based on this model are likely misspecified.

In this paper, we relax the assumption of homogeneous wage growth across firms and

[1]The AKM model has also been used to study diverse topics like gender wage gaps (Card et al. (2016)), rent sharing (Card et al. (2018)), or knowledge spillovers across firms (Serafinelli (2019)).

[2]Implicitly, the model also assumes that wage hierarchies are homogenous across firms (Di Addario et al. (2023)).

study the existence and magnitude of firm-specific wage growth and its consequences for our understanding of the sources of wage inequality. We do so by extending the AKM model to allow for differential wage growth across firms similar to Arellano-Bover and Saltiel (2021).[3] We then show that in the presence of heterogeneous dynamic benefits to experience across firms, the standard AKM model missspecifies the wage variance components. The degree of this misspecification and which components are misspecified depends on the portability of the experience premiums.

Specifically, we allow for firm-specific wage growth by incorporating firm-type specific returns to experience into the AKM model defining firm types via a kmeans alogrithm grouping firms with similar wage growth distributions following Bonhomme et al. (2019). We term these firm-specific premiums in wage growth *experience premiums*. In our baseline model, we assume full portability of experience premiums, but in an extension we allow for past experience by firm type to be differentially valued depending on a worker's current firm type, thus allowing for experience premiums to be portable or firm-specific.

We then study the biases in the estimation of wage components and their implications for inequality decompositions, when heterogeneity in wage-growth profiles across firms is ignored and how they depend on the assumptions behind the portability of experience premiums. Simulating data under different assumptions, we then confirm that portability is a key factor for the size of the bias arising in the standard AKM model. In particular, the bias of the worker component of the wage variance increases with portability. Intuitively, if there is less portability, there is generally less impact of experience by firm type on wages and thus less misspecification. Instead, the bias of the firm component decreases with portability. The intuition is that with less portability returns to experience by firm-type act like firm-specific returns to tenure. Lastly, the sorting component is always biased and the degree of bias again depends on the portability, with larger bias if experience premiums are more portable. These simulations suggest that accounting for firm-type specific wage growth is likely important when analysing the sources of wage inequality, in particular, if transportability of experience premiums is high.

Drawing on more than four decades of administrative data from Germany that links information on workers with information on establishments allowing us to observe full employment histories of workers and their workplaces, we first document a large heterogeneity in wage-growth profiles across firms (even after accounting for differences in unobserved time-invariant firm and worker characteristics). We also show that workers coming from

[3] Arellano-Bover and Saltiel (2021) present evidence of differential on-the job learning across firms in Rio de Janeiro (Brazil) and Veneto (Italy).

firms with similar wage-growth profiles have similar wage growth prior to moving jobs, but wage growth after the move depends on the wage-growth profile of the destination firm. This suggests that wage growth differences between firms cannot be solely driven by workers with similar wage growth profiles sorting into the same firms.

We then estimate the extended AKM model. We first show that returns to experience differ considerably between firms and that these returns are largely portable across firms. Thus, these experience premiums are an important component of wages; in fact, they are of similar importance as static firm wage premiums. We also show indicative evidence that differential human capital accumulation can at least partially explain differences in wage growth profiles between firms, as firms providing larger wage-growth profiles also offer more training to their workers.

We then compare the findings from the extended dynamic AKM model to the benchmark model and confirm empirically that differences in experience premiums are loaded on the worker fixed effects, as expected given the high estimated portability of experience premiums across firms. In contrast, the estimated firm premiums in wage levels are largely similar across dynamic and static models. Similarly, we show that the dispersion of worker fixed effects across firm types is more similar in the dynamic model, which together with evidence that firms offering higher static wage premiums also offer larger experience premiums suggests that the static model overestimates the sorting of high-wage workers to high-wage firms.

In the last step, we then compare wage variance decompositions in the static and dynamic AKM model and show that the static model significantly overestimates the contribution of worker dispersion and of worker-firm sorting to wage inequality. In the dynamic AKM model the contribution of worker dispersion is up to 12 percentage points lower and the contribution of worker-firm sorting up to 10 percentage points lower.

Lastly, we examine the evolution of the different components of wage variance over time using the standard static AKM model and our extended version and show that experience premiums become less important over time.

Overall, we thus show that where a worker works matters for wage growth. Firm-type specific experience premiums are an important factor of wage determination, and accounting for these premiums changes our understanding of the sources of wage inequality.

2 Data

In this paper we use German social security records (Beschäftigtenhistorik, BEH) spanning more than four decades of labour market data, from 1975 to 2016, provided by the Institute of

Employment Research (IAB). The data include the population of workers and establishments covered by the social security system in Germany and contain detailed individual background information, such as the worker's wage, occupation, education, age, and sex, as well as information on the industry and region of an individual's workplace. In the data, we observe unique identifiers for individuals and the establishments they are working at and can thus follow workers across firms and over time.

We complement the BEH data with information from the IAB Establishment Panel (IAB-BP). The IAB-BP is an annual representative survey of currently around 16,000 firms available for the years 1993 to 2016. It contains detailed information not only on standard business characteristics, but also on on-the-job training provision. We use these additional measures to analyse the relationship between firm-specific wage growth and the firm's provision of training.

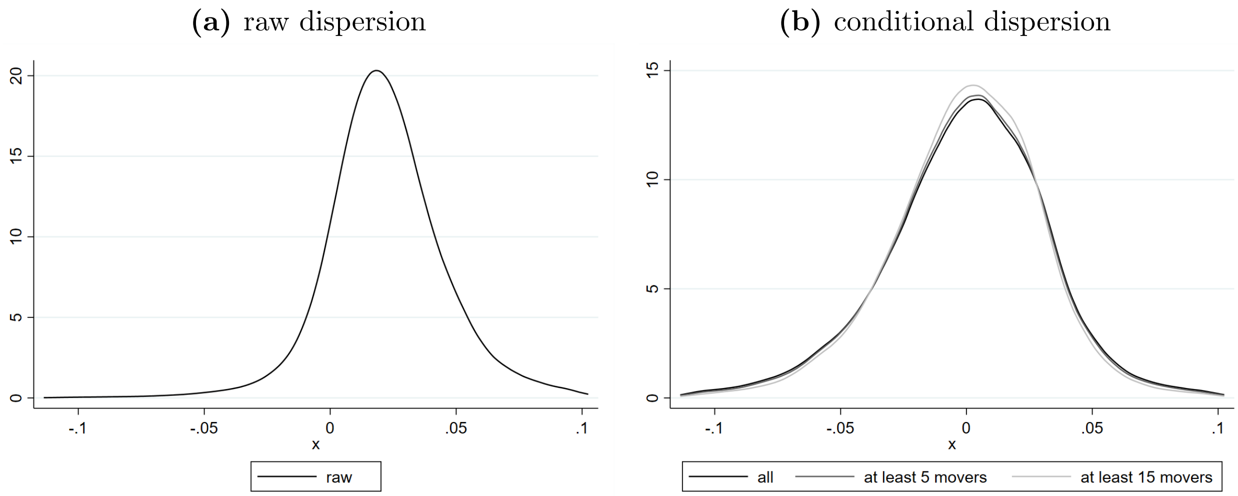
The long available time span of our data and the fact that we can follow workers across firms and over time is crucial for our analysis, as we need to observe workers' full employment histories to be able to calculate workers' entire history of accumulated experience at different firm types. We use the full observation period from 1975 to 2016 to calculate experience by firm types, but restrict the estimation period to 1996 to 2015. We also limit our analysis to individuals aged 18 to 39 years. These two restrictions imply that we observe full employment histories for all workers, as individuals who are 39 at the beginning of our estimation period in 1996, are 18 years old in 1975. Additionally, due to the overlap of our sample period with German reunification and the absence of data for East German workers prior to reunification, our analysis focuses on individuals whose initial employment observation occurred in West Germany.

3 Wage Growth Heterogeneity: Motivating Evidence

This section provides descriptive evidence on heterogeneities in wage growth profiles across firms. We first document substantial variation in average returns to tenure across firms and then study wage growth dynamics for individuals moving across firms with different wage growth profiles.

3.1 Dispersion in Firm-specific Returns to Tenure

We first provide descriptive evidence of differential wage growth across firms by plotting the unconditional distribution of average within-firm (log-)wage growth net of year effects in Figure 1.[4] There is substantial observed dispersion in average wage growth across firms. Average yearly wage growth of the firm at the 75th percentile is 2.7 percent higher than at the 25th percentile and moving from the 10th to the 90th percentile firm implies a 5.5 percent difference in yearly wage growth.



This figure displays the distribution of estimated firm-specific returns to tenure $\tilde{\psi}_j$ estimated using equations (1) and (2) as described in the text.

Figure 1: Firm-specific Returns to Tenure

An obvious concern when interpreting Figure 1a is that the heterogeneity in wage growth across firms does not reflect firm-specific returns to tenure but instead the sorting of workers with high wage growth into the same firms and thus reflects individual- and not firm-specific heterogeneity in wage growth. To get a measure of firm-specific returns to tenure net of individual heterogeneity we thus employ a two-step procedure estimating

$$lnw_{ijt} = \alpha_{ij} + \gamma_{ij} tenure_{i(j)t} + \beta X_{ijt} + \delta_t + \epsilon_{ijt} \quad (1)$$

$$\hat{\gamma}_{ij} = \tilde{\alpha}_i + \tilde{\psi}_j + r_{ij}. \quad (2)$$

In the first step, we estimate a saturated Mincerian equation by regressing log wages on

[4] These stem from a regression of the form $lnw_{ijt} = \alpha_t + \gamma_j tenure_{i(j)t} + \epsilon_{ijt}$ where lnw_{ijt} is the logarithm of wages for individual i working at firm j in year t and $tenure_{i(j)t}$ measures years of tenure of individual i in firm j.

worker-firm specific fixed effects (α_{ij}), tenure ($tenure_{i(j)t}$) allowing for worker-firm specific returns to tenure (γ_{ij}), a quadratic in experience (X_{ijt}) and year fixed effect (δ_t) (equation (1)). We thus estimate worker-firm specific returns to tenure netting out worker-firm specific level differences in wages and accounting for wage growth differences that stem from general experience. In a second step, we regress the estimated worker-firm specific returns to tenure ($\hat{\gamma}_{ij}$) on worker and firm fixed effects ($\tilde{\alpha}_i$ and $\tilde{\psi}_j$) to net out the individual component of worker-firm-specific wage growth (equation (2)).[5] One concern with this regression is that we may now face limited mobility bias in the second stage estimation which may mechanically increase the variance of the firm-specific component of wage growth, $\tilde{\psi}_j$. We thus repeat the estimation restricting the set of firms to firms with at least 5 and at least 15 movers, respectively. The results are shown in Figure 1b. There is still considerable variation in firm-specific wage growth after netting out individual components even if we restrict the sample to firms with at least 15 movers. In fact, the dispersion tends to be even larger than in Figure 1a (the 25th to 75th percentile difference is now 3.8 percent), indicating a negative correlation between average individual and firm wage growth.

Overall, the findings from both exercises indicate that there is significant variability in wage growth patterns across firms that is not solely a result of individual characteristics or the sorting between firms and workers. In the next section, we will show further evidence supporting the notion that firms offer different wage growth profiles by comparing the wage growth of workers changing jobs across firms offering different wage growth profiles.

3.2 Event Study on the Wage Growth of Job Changers

If the variation in wage growth across firms is mainly due to sorting, individuals who change firms will tend to not experience systematic changes in wage growth. If, on the other hand, firms offer heterogeneous wage growth paths, then individuals who join a firm where other workers have high wage growth will on average experience increased wage growth, while those who join a firm where others have little wage growth will experience a reduction in wage growth. We thus divide firms into quartiles of wage growth to study the wage growth dynamics of workers who move across different firm types. This exercise provides complementary evidence on the heterogeneity in wage growth while uncovering potential selection patterns due to non-exogenous job-to-job transitions.

In panel (a) of Figure 3 we plot event studies by quartile of origin of the job mover.

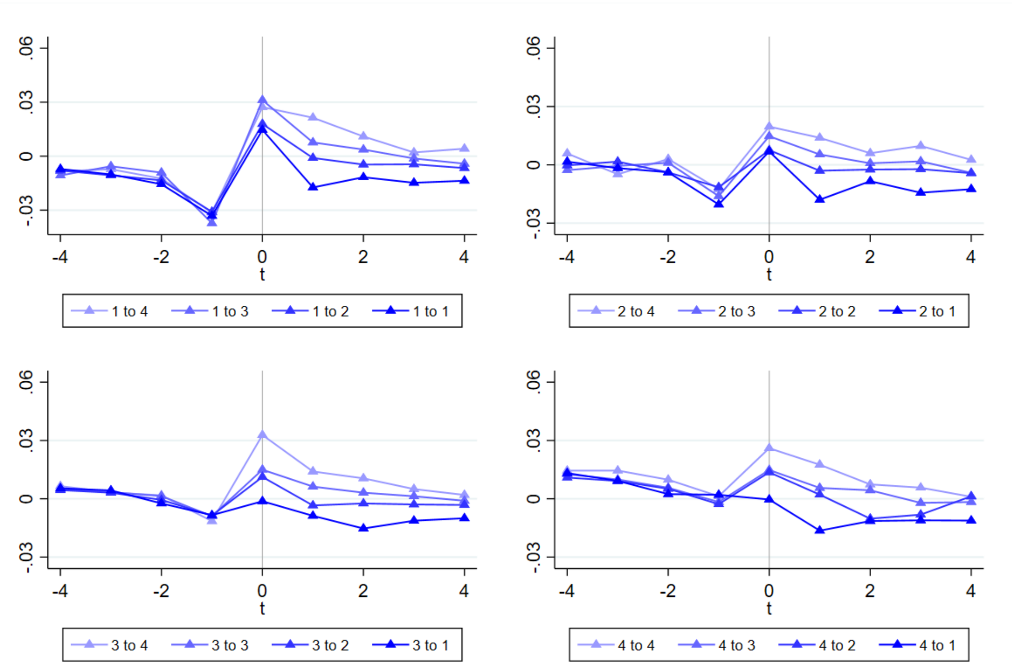
[5] Note that our sample in equation (1) isn't limited to individuals who have changed firms, even though our subsequent analysis in equation (2) requires that each firm has at least two such movers.

Interestingly, there is no dynamic selection by destination firm: Workers who move from firms within the same wage growth quartile to destination firms with different wage growth profiles have similar wage growth prior to the move. Workers moving to higher quartile firms have, however, larger wage growth after the move, as is expected if firms offer different wage growth profiles. In panel (b) of Figure 3, we instead show event studies separating job switchers according to the destination quartile. Results are symmetric to panel (a). Wage growth at destination firms is largely homogeneous independently of the quartile of the pre-transition firm while wage growth before transition largely reflects the ordering of wage growth quartiles, again suggesting that firms differ in the wage growth profiles they offer.[6]

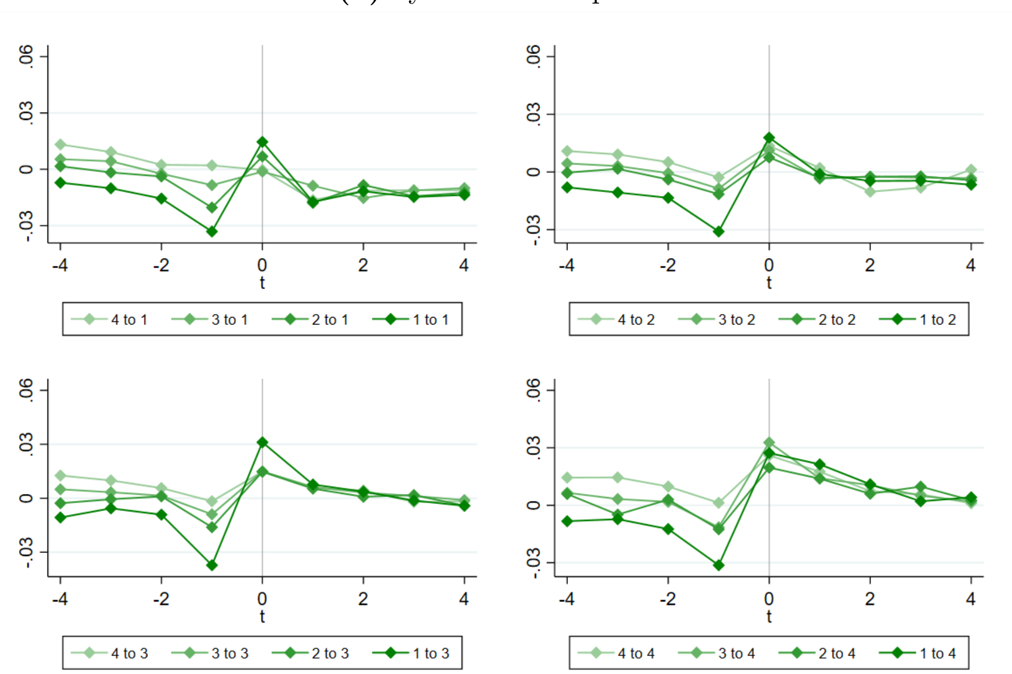
Overall, these findings suggest that there is substantial heterogeneity in average wage growth across firms and that this heterogeneity is not primarily driven by worker selection, but instead stems from different firms offering different wage growth profiles to their workers indicating that wage growth depends on the firm an individual is working at.

[6]Note that the figures also reveal an Ashenfelter dip prior to the move, which is larger for individuals moving from lower wage-growth firms. This may reflect temporary shocks that induce moving which vary by firm type. There is however little indication that this implies a different selection of workers moving given the similarity of post-move outcomes.

(a) by origin quartile



(b) by destination quartile



This figure displays the annual percentage change in wages of individuals moving between firms located at different quartiles of the wage-growth distribution. Wage growth is calculated as a residual of a regression of log wages on year fixed effects and dummies for the interaction between education and age categories. The horizontal axe corresponds to the year relative to job transition.

Figure 2: Event Study for Wage Growth of Job Changers

4 Empirical Framework

4.1 AKM Model and Wage Growth Heterogeneity

Canonical Static AKM Model The workhorse model for studying the sources of wage inequality is the statistical model of wage determination first proposed by Abowd et al. (1999) which assumes that wages can be decomposed into a worker component, a firm component and observed worker characteristics. Specifically, (log-) wages of worker i in firm j at time t are modelled as

$$ln(w_{ijt}) \quad = \quad \alpha_i + \psi_j + X_{it}^{'}\beta + r_{ijt}, \tag{3}$$

where α_i captures time-invariant worker-specific effects such as skills or other factors rewarded equally across employers, ψ_j are constant firm-specific pay premiums independent of worker type and X_{it} captures time-varying characteristics such as age or experience (but rewarded equally among all firms) and year-specific effects. Finally, any firm-worker specific matching components of wages (such as those implied by Mortensen and Pissarides (1994)) are included in the residual term. Importantly, it is assumed that these residual factors, are idiosyncratic and exogenous. This assumption is crucial for the identification of α_i and ψ_j. Card et al. (2013) discuss and summarize the necessary assumptions for identifying the worker and firm components and show that a sufficient condition is strict exogeneity of worker mobility.[7]

Augmented Dynamic AKM Model The static AKM Model restricts wage growth to occur only when individuals move to higher-paying firms (or through general experience) and does not allow for workplace heterogeneity in wage growth. The evidence provided in Section 3 suggests however, that these are potentially important. We thus extend the baseline static AKM model to allow for differential wage growth across firms by allowing the returns to experience to differ depending on the firm they have been acquired in and thus by allowing firms to offer experience premiums. To reduce the dimensionality of the problem, we group firms into types g=1,...G. We explain the grouping in more detail in Section 4.4 below. We thus extend equation (3) to account for heterogeneous firm-type specific returns to past experience:

[7]Note that this assumption does not rule out systematic mobility of workers in a way that is correlated with α_i or ψ_j (e.g. workers are allowed to move more frequently from low to high pay firms than in the opposite direction, or static characteristics of the firm are allowed to be more attractive for workers).

$$ln(w_{ijt}) = \alpha_i + \psi_j + X_{it}^{'}\beta + \sum_g (\theta_{1g} Exp_{git} + \theta_{2g}(Exp_{git} * Exp_{it})) + r_{it} \tag{4}$$

The variable Exp_{git} measures the experience worker i accumulated in firm type g up until year t. The interaction term $(Exp_{git} * Exp_{it})$ allows for concave wage experience profiles to depend on total experience (Exp_{it}), that is we allow the value of additional experience to decay for workers with more experience.

Equation (4) implicitly assumes that experience premiums accumulated at firm type g are fully portable when moving to a different firm type, as the returns to experience by firm type are independent of the worker's current firm. However, experience accumulated at firm type g may not be fully transferable and the transferability may depend on the worker's current firm type. We thus extend the dynamic model to allow for experience premiums to only be partially transferable:

$$\begin{aligned}
\ln(w_{ijt}) = {} & \alpha_i + \psi_j + X_{it}'\beta \\
& + \sum_g (\theta_{1g} Exp_{git} + \theta_{2g}(Exp_{git} * Exp_{it})) \\
& + \sum_{\tilde{g}} \sum_{g \neq 1} \left(\tilde{\theta}_{1g\tilde{g}} Exp_{\tilde{g}it} + \tilde{\theta}_{2g\tilde{g}}(Exp_{\tilde{g}it} \times Exp_{it})\right) \mathbb{1}[FType_{it} = g] \\
& + r_{it}.
\end{aligned} \tag{5}$$

Now the term $\tilde{\theta}_{1g\tilde{g}} Exp_{\tilde{g}it} + \tilde{\theta}_{2g\tilde{g}}(Exp_{\tilde{g}it} \times Exp_{it})$ allows for returns to experience accumulated in firm type $\tilde{g}$ to differ depending on the type of firm where the worker is currently employed and measures the difference of returns relative to the returns of a worker currently working in the lowest firm type ($g = 1$). If there is full portability, $\theta_{1g\tilde{g}}$ and $\theta_{2g\tilde{g}}$ will be 0 for all $(g, \tilde{g})$ and we are back to the original model. If instead, all returns are firm-type specific, only experience at the current firm type g matters and hence all cross-group components are 0. Note that we continue to assume full portability for switches within the same type of firms.

4.2 Wage Variance Decompositions

Assuming equation (3) is the accurate model and meets all identification conditions, wage dispersion can be broken down into various sources as per the following variance decomposition:

$$
\begin{aligned}
var\left(\ln w_{ijt}\right) = {} & var\left(\hat{\alpha}_i\right) + var\left(\hat{\psi}_j\right) + var\left(X'_{it}\hat{\beta}\right) + var(\hat{r}_{it}) \\
& + 2cov\left(\hat{\alpha}_i, \hat{\psi}_j\right) + 2cov\left(\hat{\alpha}_i, X'_{it}\hat{\beta}\right) + 2cov\left(\hat{\psi}_j, X'_{it}\hat{\beta}\right)
\end{aligned}
\tag{6}
$$

The terms $var\left(\hat{\alpha}_i\right)$, $var\left(\hat{\psi}_j\right)$ and $cov\left(\hat{\alpha}_i, \hat{\psi}_j\right)$ have received large attention as they capture the degree of wage heterogeneity due to dispersion in worker-specific components, firm-specific components and systematic sorting of workers across firms, respectively.

A recent body of literature has focused on some finite sample issues related to the estimation of equations (3) and (4). A problem arising from the high dimensionality of (3) is that the variance of firm fixed effects is likely to be upward biased because of limited mobility bias (Maré and Hyslop (2006); Andrews et al. (2008)) and hence the degree of assortative matching of high wage workers into high wage firms may be underestimated (see e.g. Lentz et al (2018) or Bonhomme et al. (2019)). This has implications for the measurement of wage inequality since too little dispersion of wages is assigned to $cov\left(\hat{\alpha}_i, \hat{\psi}_j\right)$. Studies using estimation methods that correct for limited mobility bias (e.g. Andrews et al. (2012), Bonhomme et al. (2023)) reveal that $var\left(\hat{\psi}_j\right)$ accounts for a lower share and $cov\left(\hat{\alpha}_i, \hat{\psi}_j\right)$ accounts for a higher share of the total variance in log wages than was previously thought.

4.3 Bias Due to Ignoring Dynamic Components

Note: this section is still very preliminary!

We now derive and interpret the bias in the estimation of equation (3) when the true model include dynamic components such as in equations (4) and (5). For simplicity, we ignore the role of X_{it} and we start by analysing extreme cases where acquired experience is fully portable or only relevant within the type of firm where it was accumulated.

Full Portability of Type-specific Experience: If experience accumulated at past type of firms is heterogeneous but does not change when moving across types, there is a bias component loaded mostly on the individual fixed effect. To see this, consider the further simplified example with no interaction between type-specific and total experience, define $\omega_{it} = ln(w_{it})$, normalize $E(Exp_{git}) = 0$. Under these assumptions, consider the firm-demeaned version of equation (4):

$$\omega_{it} - \bar{\omega}_j = \alpha_i(\iota_{it} - \bar{\iota}_j) + \sum_g \theta_g(Exp_{git} - E\bar{x}p_{gj}) + (r_{it} - \bar{r}_j) \tag{7}$$

Where ι_{it} is a individual-period indicator variable and bars above the variables indicate averages within type across time and individuals. If the second term of equation (7) is omitted in the estimation, we can derive the asymptotic probability limit for $\hat{\alpha}_i$ as follows:

$$\begin{aligned} plim(\hat{\alpha}_i) &= \frac{cov(\iota_{it} - \bar{\iota}_j, \omega_{it} - \bar{\omega}_j)}{var(\iota_{it} - \bar{\iota}_j)} \\ &= \frac{cov(\iota_{it} - \bar{\iota}_j, \alpha_i(\iota_{it} - \bar{\iota}_j) + \sum_g \theta_g(Exp_{git} - E\bar{x}p_{gj}) + (r_{it} - \bar{r}_j))}{var(\iota_{it} - \bar{\iota}_j)} \end{aligned}$$

Assuming strict exogeneity in the idiosyncratic component, $cov(\iota_{it} - \bar{\iota}_j, r_{it} - \bar{r}_j) = 0$, the expression simplifies to:

$$plim(\hat{\alpha}_i) = \alpha_i + \sum_g \theta_g \frac{cov(\iota_{it} - \bar{\iota}_j, Exp_{git} - E\bar{x}p_{gj})}{var(\iota_{it} - \bar{\iota}_j)}$$

Notice that the term $cov(\iota_{it} - \bar{\iota}_j, Exp_{git} - E\bar{x}p_{gj})/var(\iota_{it} - \bar{\iota}_j)$ is the population regression coefficient between individual type-specific experience (demeaned from mean experience at firm level) and individual fixed effects. Therefore, it corresponds to $E(Exp_{git}|i = i) = E\bar{x}p_{gi}$ and we can write:

$$plim(\hat{\alpha}_i) = \alpha_i + \sum_g \theta_g E\bar{x}p_{gi} \tag{8}$$

Equation (8) indicates that under full portability the excluded heterogeneous returns to type-specific experience are loaded into the individual component of wages.

The fact that most of the bias is loaded into $\hat{\alpha}_i$ does not imply that $\hat{\psi}_j$ is unbiased, however, the bias tend to be small and close to zero under some symmetry conditions. To illustrate this point, let's examine a simplified example involving two types $g = L, H$, similar to the approach Roca and Puga (2017) use to highlight the bias associated with the city size premium. Working in a firm type H is associated to a static (log) premium of ψ relative to working in a firm type L with normalized premium equal to zero. Individuals can be heterogeneous, but since Equation (3) exploits variation within individuals, we can ignore the worker component. Individuals are observed for n periods and switch to a firm of a different type in period $m < n$. Wage does not increases with experience in a firm type L but every period worked in a firm type H has an additional premium θ (e.g., after m periods, the worker's experience at H is valued θm). The accumulated experience at H can be portable in a share $0 \leq \rho \leq 1$. Individuals and firms are otherwise similar. The OLS estimator of the static firm fixed effect (in this case, represented by ψ) can be written as the difference in average (log) wage within the individual before and after switching firms. For workers switching from L to H, $\hat{\psi}^{LH} = \psi + \frac{1+n-m}{2}\theta$. For workers switching from H to L, $\hat{\psi}^{HL} = \psi + (\frac{1+m}{2} - \rho m)\theta$. Under full portability ($\rho = 1$), the later can be written as $\hat{\psi}^{HL} = \psi + (\frac{1-m}{2})\theta$. Denote the share of workers switching from L to H as $0 \leq \gamma \leq 1$ and assume for simplicity that $m = n/2$. The mean estimated bias is $(\gamma\hat{\psi}^{LH} + (1-\gamma)\hat{\psi}^{HL}) - \psi = \theta(\frac{1-m}{2} - \gamma m)$. The bias is equal to zero if $\gamma = \frac{m-1}{2m}$ which approximates $1/2$ when m is large. This result illustrates that when the flows of workers across types of firms is balanced, the bias loaded into the firm static component tends to be small.

To see the relevance of these results, we can decompose the variance of wages using the estimable $\tilde{\alpha}_i \approx \alpha_i + \sum_g \theta_g \bar{Exp}_{gi}$. In this analysis, ignore the role of X_{it}, we use ψ_j directly from the population model based on the fact that the bias is likely to be small:

$$
\begin{aligned}
var\left(\ln w_{ijt}\right) = {} & var\left(\alpha_i + \sum_g \theta_g \bar{Exp}_{gi}\right) + var\left(\psi_j\right) + var(r_{it}) \\
& + 2cov\left(\alpha_i + \sum_g \theta_g \bar{Exp}_{gi}, \psi_j\right) \\
= {} & \underbrace{var\left(\alpha_i\right) + var\left(\sum_g \theta_g \bar{Exp}_{gi}\right)}_{var(\tilde{\alpha}_i)} + var\left(\psi_j\right) + var(r_{it}) \\
& + \underbrace{2cov\left(\alpha_i, \psi_j\right) + 2cov\left(\sum_g \theta_g \bar{Exp}_{gi}, \psi_j\right)}_{2cov(\tilde{\alpha}_i, \psi_j)}
\end{aligned} \tag{9}
$$

Equation (9) indicates that under full portability, the true variance of wages attributable to the time-invariant worker component, $var(\alpha_i)$, is significantly overestimated by $var(\tilde{\alpha}_i)$. Similarly, the sorting component contributing to wage dispersion is also overestimated when $cov\left(\sum_g \theta_g \bar{Exp}_{gi}, \psi_j\right) > 0$. This condition typically arises when workers, over time, are more likely to gain experience at firms offering higher wages, leading to an overestimation of the sorting effect. Conversely, underestimating this effect would suggest the opposite trend, where workers accumulate less experience at such firms.

Type-specific Experience Not Portable Across Types: It is possible to show that this second extreme case leads to firm fixed effect being biased as they will account for the heterogeneity in omitted type-specific experience. In the simple example with two types of firms, setting the portability parameter ρ to zero, does not change $\hat{\psi}^{LH}$ but now $\hat{\psi}^{HL} = \psi + (\frac{1+m}{2})\theta$. The bias of the estimated firm fixed effect for type H for any share γ of movers from L to H and $m = n/2$ is given by $(\gamma\hat{\psi}^{LH} + (1-\gamma)\hat{\psi}^{HL}) - \psi = \theta(1 + n(2 - 3\gamma))/2$. This bias is relatively large for any value of γ, for instance, when flows from/to type H firm are balanced ($\gamma = 1/2$), the bias is $\theta(2+n)/4$ which is also increasing with the number of periods the worker is observed. Intuitively, flows of workers moving from H to L experience a sharp decrease in wage due to the lost experience which is confounded with the static premium of H. For workers moving from L to H, the increase in wage is built over time but the average wage is systematically higher at H and thus captured by $\hat{\psi}$ [8]. On the other hand,

[8] Also, notice that in this example, the longer the worker is observed the more experience workers accumulate at H-type firms, increasing in turn the size of the omitted term

the bias loaded into the individual component will tend to be low. In this example, different individuals with same experience in the firm moving out from the same firm will experience a similar drop in wages due to lost type-specific experience , thus this common jump will be net out from the individual static component. The fact that experience across individuals is not homogeneous within the same firm (type) can introduce some bias but it is likely small and attenuated if the baseline model controls for individual tenure.

In order to calculate the bias in the estimation of the firm component, we can write the true (demeaned at individual level to eliminate worker component) as:

$$\omega_{it} - \bar{\omega}_{ig} = \alpha_i(\iota_{it} - \bar{\iota}_{ig}) + \sum_g \theta_g(Exp_{git} - \bar{Exp}_{ig})\iota_{gt} + (r_{it} - \bar{r}_{ig}) \quad (10)$$

Where ι_{gt} is an indicator for the firm where the individual is employed in period t being type g. The probability limit of $\hat{\psi}_j$ can be calculated now as:

$$\begin{aligned} plim(\hat{\psi}_j) &= \psi_j + \frac{cov(\iota_{it} - \bar{\iota}_{ig}, \sum_g \theta_g(Exp_{git} - \bar{Exp}_{ig})\iota_{gt})}{var(\iota_{it} - \bar{\iota}_{ig})} \\ &= \psi_j + \theta_g \frac{cov(\iota_{it} - \bar{\iota}_{ig}, Exp_{git} - \bar{Exp}_{ig})}{var(\iota_{it} - \bar{\iota}_{ig})} \\ &= \psi_j + \theta_g \frac{cov(\iota_{it} - \bar{\iota}_{ig}, (Exp_{git} - \bar{Exp}_{ig})\iota_{gt})}{var(\iota_{it} - \bar{\iota}_{ig})} \\ &= \psi_j + \theta_g \Gamma_{gj} \end{aligned}$$

Where $\Gamma_g j$ is the population coefficient of a regression between demeaned type-specific experience (for the type of firm j) on firm fixed effects. Intuitively, $\hat{\psi}_j$ will be overestimated (underestimated) for high-wage (low-wage) firms if workers tend to spend more time in high-wage firms. On the other hand, the bias on the individual component tend to be smaller as firm demeaning tend to absorb most of the differences in type-specific premium. [9]

Taking into account that $var(\psi_j + \theta_g \Gamma_{gj}) > var(\psi_j)$ in the most likely case that workers tend to spend more time at high-pay firms, the firm component of wage dispersion will be overestimated and the sorting component will be overestimated if $cov(\Gamma_{gj}, \alpha_i) > 0$.

[9] It is easy to show that $plim(\hat{\alpha}_i) - \alpha_i = \theta_g \frac{cov(\iota_{it} - \bar{\iota}_j, (Exp_{git} - \bar{Exp}_{gj})\iota_{gt})}{var(\iota_{it} - \bar{\iota}_j)}$. Therefore, if type-specific experience is homogeneous within firms (i.e. $Exp_{git} \approx \bar{Exp}_{gj}$), the bias will be small.

Portability of Type-specific Experience: General Case In the most general case given by equation (5), the components determining wages and wage dispersion will be biased with the magnitude of the bias depending on the degree of portability. To better understand the potential biases arising under different degrees of portability, we perform simulations that confirm our findings for the cases of full/non portability and provide intuition for the general case.

Simulations We construct a panel of firms and workers with two types of firms $G = \{0, 1\}$ and assume that wages are determined by the following equation:

$$ln(w_{ijt}) = \alpha_i + \psi_j + (1-\eta)\beta_{g(j)}Tenure_{ijt} + \eta\left(\beta_0 Exp^0_{it} + \beta_1 Exp^1_{it}\right) + r_{ijt},$$

where α_i and ψ_j are defined as in Section 4.1, $Tenure_{ijt}$ measures tenure of worker i in firm j and time t, and Exp^0_{it} and Exp^1_{it} measure the experience in type 0 and type 1 firms, respectively. The term η measures the degree of portability of experience across firm types. If $\eta = 1$, experience is fully portable across firm types, if $\eta = 0$, instead all acquired knowledge is firm-specific. The returns to experience accumulated at each firm type are given by β_0 and β_1 and we assume steeper experience profiles if experience is acquired in type 1 firms ($\beta_1 > \beta_0$). For simplicity, we assume no further depreciation of the retained experience stock if the worker subsequently moves to another firm and that returns to experience are linear. Note that this model, is more flexible as our empirical model in equation (5), as we do not assume full portability within firm types.

Static individual fixed effects α_i are drawn from a normal distribution. Firms are randomly allocated to types 0 and 1, with half of firms allocated to each category. The static firm fixed effects ψ_j are simulated as the sum of three components: a fully idiosyncratic component $\zeta_j \sim N(0, 0.4)$; a component correlated with the average α_i in the firm thus allowing for sorting based on levels; and a component correlated with firm type g:

$$\psi_j = \zeta_j + 0.2\frac{E(\alpha_i|j)}{sd(\alpha)} + 0.4\frac{E(z|j)}{sd(z)}$$

.

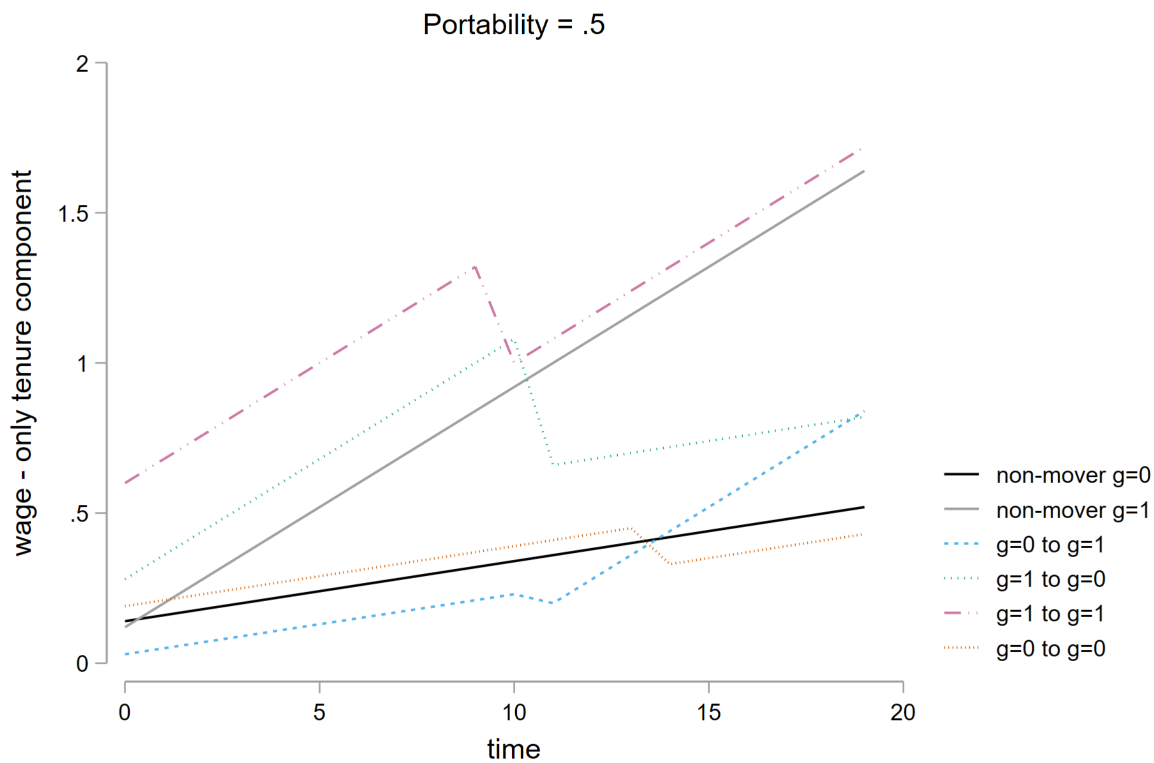
In particular, we assume $z \sim N(1.2g - 0.6, 0.6)$ generating a positive correlation between the firm fixed effect and firm type g.

Worker i is matched to firm j and allowed to move to another firm k based on period transition probabilities P_{ijk} which depend on a mobility parameter (the higher this parameter, the more likely the worker leaves the firm each period), a sorting parameter (which increases assortative matching between α_i and the type of the firm), and a network parameter that affects the probability of transitioning across firms of the same type. These transition probabilities pin down both $Tenure_{ijt}$ and Exp^g_{it}. Using the (steady state) transition probabilities we simulate a panel of 130,000 workers, 1,000 firms and 20 years. Table 1 summarises the parameters used in the simulation.

(β_0, β_1)	(0.02, 0.08)
(N Firms, N Workers)	(1K, 130K)
Sorting Prob	0.5
Network Effect	0.2
Mobility Prob	0.5
Mobility-Sort Slope	-0.05
$sd(\alpha)$	1
$sd(\psi)$	1
$sd(r)$	0.8
$corr(g(j), \psi_j)$	0.58
$corr(g(j), \alpha_i)$	0.56

Table 1: Simulation Parameters

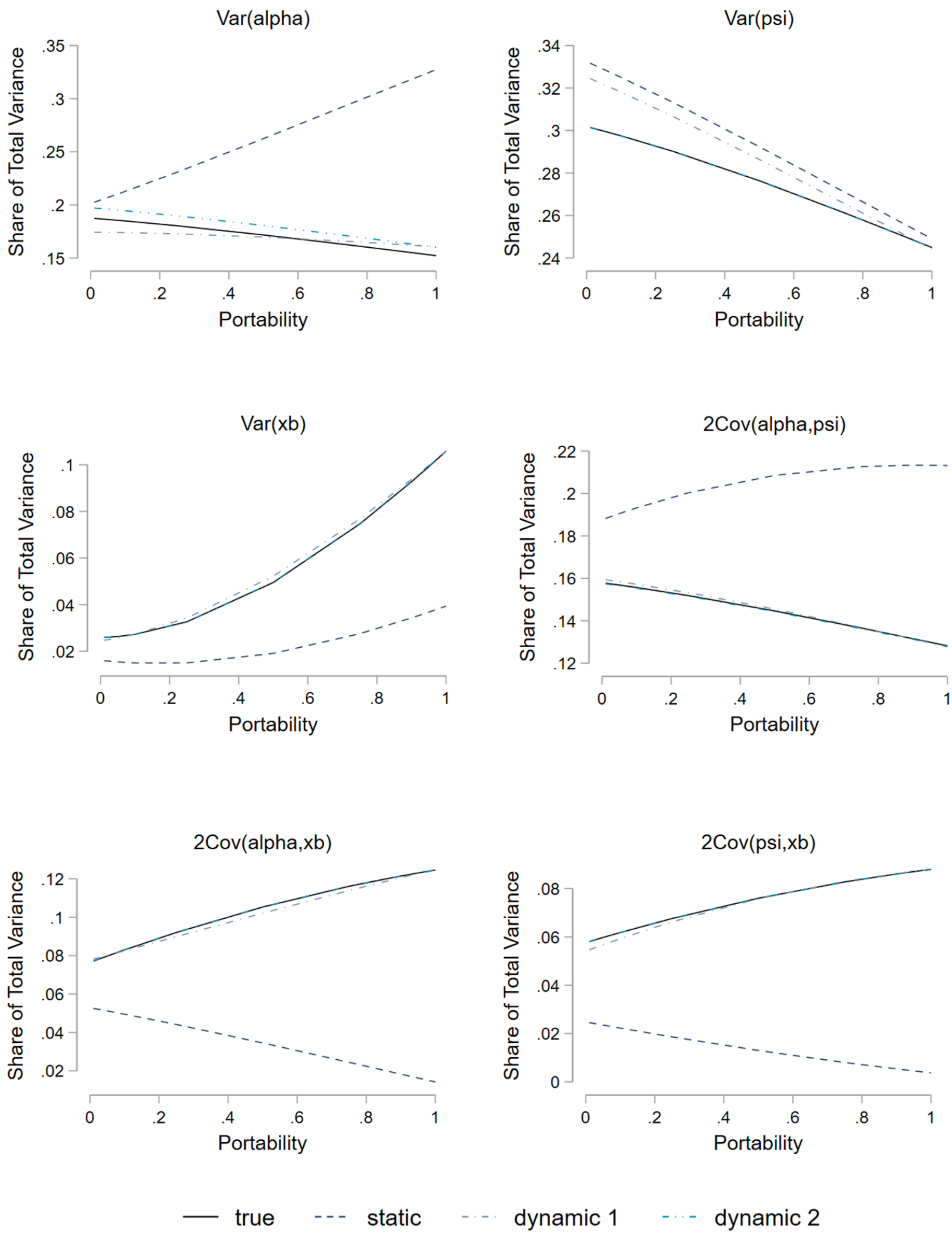
In order to illustrate the type of wage dynamics generated by our simulations, in Figure 4 we provide examples of wage profiles from the simulated data. In the figure we set the portability parameter $\eta = 0.5$. The figure depicts the negative discontinuous drop in wages due to the non-full portability of experience.



This figure displays wage profiles for different job transitions with workers accumulating experience at a firm type 0 or 1 and then moving to a different type. We also include non-movers at each type of firm. The portability parameter is set to $\eta = 0.5$.

Figure 3: Examples of Simulated Wage Profiles

We then estimate the static and dynamic versions of the wage equation described in Section 4.1 flexibly varying η between 0 and 1 in steps of 0.05. Notice that the equation we use to simulate wages allows for accumulated experience to be partially lost even when the worker transitions to a firm within the same type, while our augmented dynamic AKM specification assumes full portability of experience across firms of the same type. In order to evaluate the potential bias due to this misspecification, we estimate two dynamic versions of the wage equation. First, the model we propose for our empirical analysis as described by equation (5) (*dynamic* 1), and second, the specification that generates the data (*dynamic* 2). For each of the models, we then decompose the wage variance as in equation (6) and compare it to the true components of the simulated data.



This figure displays estimated wage variance decomposition using the simulated data for the static and dynamic models of wage determination described in Section 4.1 and 4.4. Each panel corresponds to a different component of the wage variance.

Figure 4: Bias in Variance Components from Simulations

Figure 4 displays the components of the wage variance for the different specifications. In the presence of dynamic returns to experience by firm type all components of the wage variance are estimated with bias in the static model. The degree of this bias depends on the portability of firm-type specific experience across firms. In particular, the bias in the worker component, $Var(\alpha_i)$, increases if portability rises. This is because if portability is high, workers keep the additional returns when switching firms and thus they are loaded on the worker-fixed effects, α_i, as shown in Section 4.3. Instead, with low portability, more of the returns are firm-specific and thus lost when switching firms, leading to less misspecification.

The bias of the firm component of the wage variance, $Var(\psi_j)$, instead decreases with increased portability. This occurs because lower portability makes the returns to experience resemble firm-specific returns to tenure and thus they are loaded on the firm fixed effect ψ_j if omitting firm-specific returns to tenure from the model. The static model also inaccurately estimates the sorting components and in particular the covariance between worker and firm fixed effects ($Cov(\alpha_i, \psi_j)$). It is upward biased thus overstating worker-firm sorting in our specification as we assumed a positive relationship between firm fixed effects and the high wage-growth firm type, but would be downward biased if instead assuming a negative relationship.

In contrast, our preferred dynamic empirical specification *dynamic* 1 provides largely unbiased estimates of the wage variance components. The only larger misspecification occurs in the firm component of the wage variance ($Var(\psi_j)$) when portability is low. This misspecification diminishes as portability increases. This finding suggests that the assumption of full portability within types is a valid approximation of the true model if portability is high.

4.4 Grouping Firm Types

In the previous analysis, we have assumed that firms can be grouped into types but we have not provided a working definition of types. In order to assign J firms into K types, we use a K-Means algorithm similar to Bonhomme et al. (2019) and Arellano-Bover and Saltiel (2021). The classification follows from the k-means minimization problem, formulated as follows:

$$\min_{k(1),\dots,k(J),F_1,\dots,F_K} \sum_j n_j \int \left(\hat{G}_j(\Delta w) - F_{k(j)}(\Delta w)\right)^2 d\mu(\Delta w), \tag{11}$$

where $\hat{G}_j(\Delta w)$ denotes the empirical cumulative distribution function of net wage growth for firm j, n_j represents the number of workers in firm j, and $k(1), \ldots, k(J)$ denotes the partition of firms into K classes. The functions F_1 to F_K are the cumulative distribution functions of wage growth for the identified classes, with μ as a measure, either discrete or continuous, supported on a finite grid.

We group firms into $K = 3$, 5, or 10 clusters to examine the impact of different levels of granularity on our analysis of wage growth dynamics. The growth in log wages, $\Delta ln\tilde{w}_{ijt}$ is net of year fixed effects and individual characteristics, (specifically, we residualise it from the interaction between education, age group, and gender fixed effects). The empirical distribution function of wage growth is determined based on deciles calculated from five-year moving averages of wages within firms.

Our model estimates a single partition of firms for the entire observation period, but firms are permitted to change class over time, reflecting that wage growth profiles can change over time. Table 2 shows characteristics of firms when classified into three types. Notably, the order of types correlates not only with average wage growth (as expected) but also with the average wage level in the firm, with the firm fixed effects (both from the static and the dynamic specifications), with the size of the firm and with the average skill level in the firm.

	Group 1	Group 2	Group 3
	(1)	(2)	(3)
Firm Characteristics			
Average (ln-)Wage (5y)	3.75	4.24	4.58
Average (ln-)Wage Growth (5y)	0.01	0.013	0.022
Establishment Premium (Static)	-0.10	0.15	0.28
Establishment Premium (Dynamic)	-0.09	0.16	0.28
Establishment Size	171	352	2,157
Worker Characteristics			
Aged 18 to 25	0.15	0.10	0.08
Aged 26 to 50	0.70	0.72	0.74
Aged 51 to 65	0.15	0.18	0.19
Low Skilled	0.18	0.15	0.12
Medium Skilled	0.76	0.77	0.74
High Skilled	0.06	0.08	0.15
Share	0.09	0.62	0.28
N	137,440	900,550	412,927

Table 2: Characteristics of firms by type

We also validate the grouping of firms by correlating the partition with matched survey data on whether the firm provides training to workers. These results are shown in Figure 5 for the $K = 5$. The figure shows that firms providing higher experience premiums, also provide more training and allow more workers to be trained. This suggests that in line with Arellano-Bover and Saltiel (2021) one component of differential wage growth across firms is differential learning. There may however also be other reasons for differential wage growth, which we plan to explore in more detail in the future.

(a) Share of Firms providing Training **(b)** Share of workers receiving training

Figure 5: Training Provision by Firm Type (K=5)

5 Main Results

5.1 Wage Profiles and Experience Premiums

In Table 3 we present the main regressions for the static model, the dynamic model assuming full portability of returns to experience by firm type, and the full extended model where returns to experience by firm type are allowed to depend on the current employer. In all specifications, regressions control for a quadratic in tenure at the current firm and person, firm, and year fixed effects. We report the estimates for firms divided into three firm types.[10] Column (1) presents the estimates of the static model. Returns to experience profiles are concave and returns to experience are sizeable on average with 33.1 log points after 10 years. This suggests that experience in the labor market increases wages by close to 40 percent within 10 years of entering the labor market. Columns (2) and (3) indicate however that returns to experience depend on the type of firm a worker works in, with returns varying between 7.5 log points for low wage-growth firms (g=1) and 42.6 log points for high wage-growth firms (g=3) after 10 years. Workers who are consistently employed in type 3 firms over a period of 10 years thus gain a close to 40 percent experience premium over workers consistently employed in type 1 firms. A comparison of the dynamic model assuming full portability and the fully flexible dynamic model in column (3) further shows that returns to experience by firm type are largely portable, as the coefficients on the baseline experience

[10] We also estimate the models for 5 and 10 types, available upon request.

by firm type variables change only little.

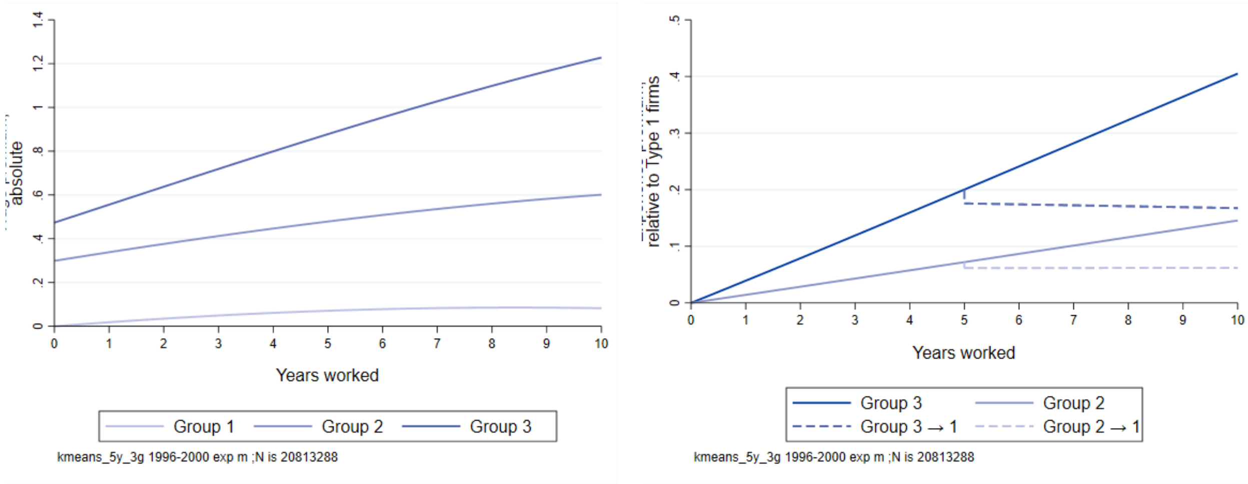
To further illustrate these findings, we plot the estimated wage profiles and returns to experience by firm type from the dynamic model in Figure 7. Panel (a) shows wage profiles with level firm premiums in type 1 firms normalized to zero for easier readability. The figure confirms that differences in wage growth by firm type are important for workers' wages. The figure also shows that firms offering higher experience premiums are firms who also provide high static firm premiums. In fact, after 10 years differences in wages caused by differential wage growth in type 1 compared to type 3 firms are of similar size as differences in static firm premiums. The positive correlation between experience premiums and static premiums will also play an important role when analyzing the biases in wage variance decompositions due to the omission of firm-type specific wage-growth in Section 4.3. Appendix Figure A1 reports similar results for the case of 10 wage-growth groups.

In panel (b) of Figure 7, we report the returns to experience for the two highest wage growth groups (g=2,3) relative to the lowest wage growth group (g=1). Note that the graph only shows how the relative experience premiums change with time in the labor market and not how total wage levels evolve. We also overlap in dashed lines the profile of workers that switch firms to the lowest group after 5 years. The figure confirms that returns to experience are largely portable across firm types. The negative vertical jump in the year of the job change shows only a small depreciation of the accumulated stock of experience and the flat profile afterward indicates that the additional experience accumulated at the firm of the lowest type (g=1) is rewarded according to the lower returns experienced at these firms. In Appendix Figure A2, we instead present full wage profiles and show that the loss in static firm premiums instead matters considerably when switching to the lowest firm type.

	Static (1)	Dynamic Fully Portable (2)	Dynamic Extended (3)
Exp	0.0451***		
	(0.0003)		
Exp Sq	-0.0012***		
	(2.56e-6)		
Exp at G3		0.0556***	0.0488***
		(0.0003)	(0.0005)
Exp at G3 × Exp		-0.0014***	-0.0012***
		(4.08e-6)	(2.66e-5)
Exp at G2		0.0309***	0.0282***
		(0.0003)	(0.0004)
Exp at G2 × Exp		-0.0010***	-0.0009***
		(3.1e-6)	(9.92e-6)
Exp at G1		0.0195***	0.0180***
		(0.0005)	(0.0005)
Exp at G1 × Exp		-0.0012***	-0.0010***
		(2.2e-5)	(2.37e-5)
Exp at G3 × Working at G3			0.0067***
			(0.0004)
Exp at G3 × Exp × Working at G3			-0.0003***
			(2.64e-5)
Exp at G2 × Working at G3			0.0050***
			(0.0002)
Exp at G2 × Exp × Working at G3			-0.0002***
			(1.03e-5)
Exp at G1 × Working at G3			0.0105***
			(0.0007)
Exp at G1 × Exp × Working at G3			-0.0009***
			(4.61e-5)
Exp at G3 × Working at G2			0.0032***
			(0.0004)
Exp at G3 × Exp × Working at G2			-0.0002***
			(2.67e-5)
Exp at G2 × Working at G2			0.0024***
			(0.0002)
Exp at G2 × Exp × Working at G2			-7.8e-5***
			(9.46e-6)
Exp at G1 × Working at G2			
Exp at G1 × Exp × Working at G2			-0.0001***
			(1.24e-5)
Firm Tenure	0.0020***	0.0024***	0.0023***
	(5.2e-5)	(5.2e-5)	(5.25e-5)
Firm Tenure Squared	-7.33e-5***	-0.0001***	-0.0001***
	(2.4e-6)	(2.42e-6)	(2.45e-6)
Observations	20,813,287	20,813,287	20,813,287

Table 3: Returns to Experience - Static and Dynamic Models

(a) absolute **(b)** relative & moving



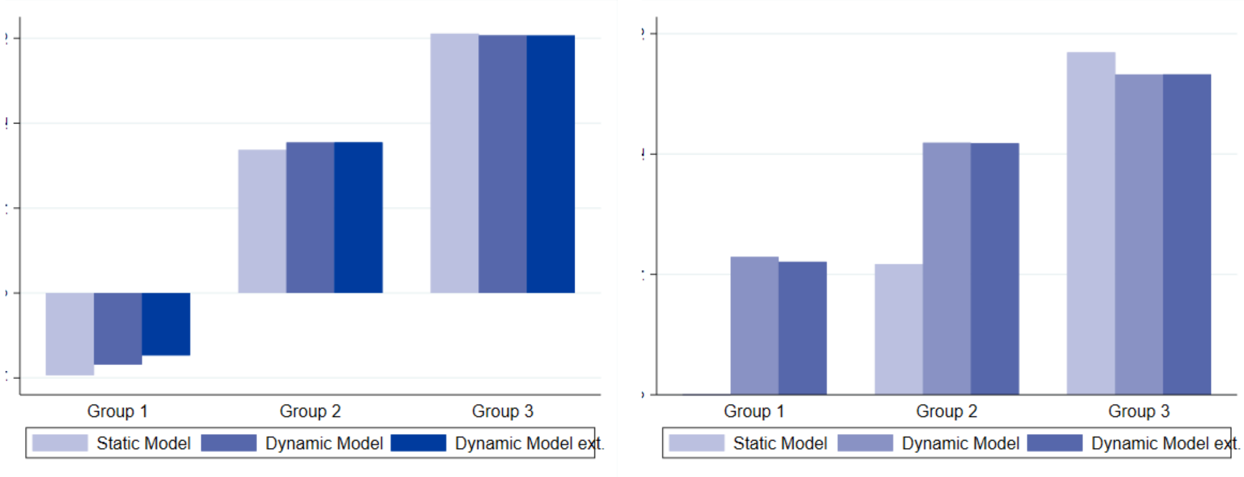
This figure illustrates the wage profiles estimated using the dynamic AKM model (equation (5)) with $K = 3$ for each of the three firm types. Firm types are determmined through a k-means algorithm as described in Section 4.4. In panel (a) static firm premiums are normalised such that the premium for type 1 firms is zero. Panel (b) presents experience premiums only. These are normalised such that they reflect premiums relative to type 1 firms. The figure also displays the evolution of the premium for workers switching to a firm type-1 5 years after working in the initial firm type.

Figure 6: Wage and Experience Premium Profiles - Dynamic Model

5.2 Model Comparisons

Average Estimated Premiums According to the dynamic model estimates displayed in Table 3 and Figure 7, most of the firm-type-specific experience premium is portable and thus remains with the worker once the worker switches to a firm in a different group. In Section 4.3, we have derived that in the case of high portability of experience premiums the bias in the static firm premium should be minor in the static model and hence static firm premiums should not change much across models, but the worker premium is considerably biased. In Figure 8 we show that this is indeed the case by comparing average estimated static firm and worker premiums across firm types between the static, the baseline dynamic, and the extended dynamic model. Panel (a) shows the average estimated establishment premiums across firm-types. Consistent with our derivations, there is little bias in the static firm component. Panel (b) shows average worker premiums by firm type. We normalize the static model's group 1 average premium to 0 for easier readability. Average worker premiums across firm types differ substantially between the static and dynamic model(s) as predicted in Section 4.3. In fact, average worker premiums in the static model are underestimated by close to 10 percent for workers in type 1 and 2 firms. Appendix Figure A3 shows similar patterns when 5 or 10 firm groups are considered.

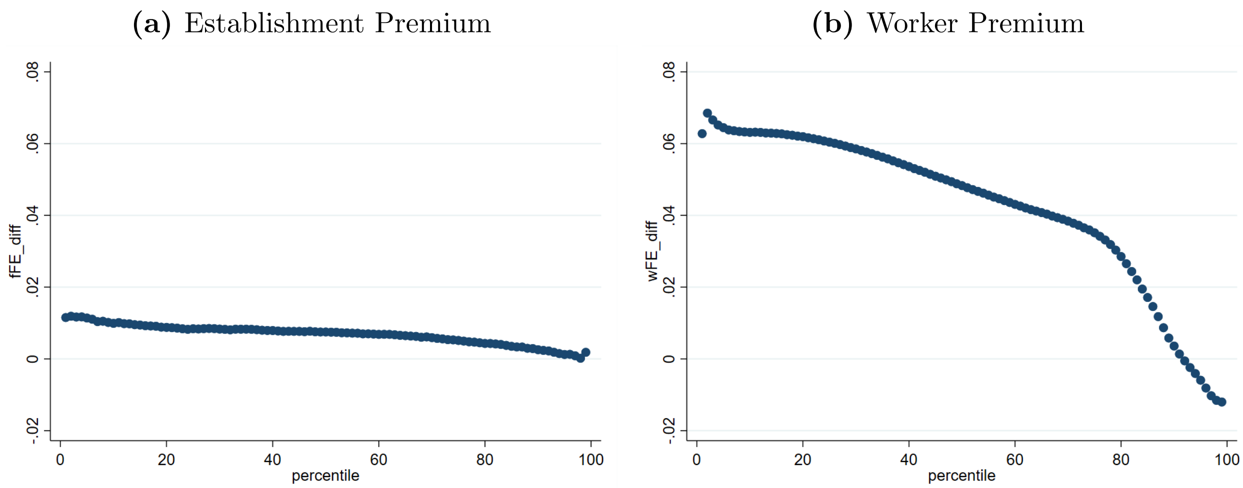
(a) Establishment Premium **(b)** Worker Premium



This figure reports the average establishment fixed effect (panel (a) and worker fixed effect (panel (b)) by firm type (with K=3) for the static AKM model, the baseline dynamic specification (equation (4)) and the extended dynamic specification (equation (5)). Firms are classified into groups based on the k-means algorithm discussed in Section 4.4.

Figure 7: Average Establishment and Worker Premiums - Static vs. Dynamic Models

Differences in the Distribution of Estimated Premiums In Figure 8 we instead plot the differences in estimated static worker and firm premiums between the static and dynamic model for each percentile of the distribution of estimated premiums (from the static model). A positive difference in a given percentile indicates that the average premium estimated by the dynamic model is higher than the average premium estimated by the static model at that percentile. Panel (a) shows that differences in estimated establishment premiums between models are small along the entire distribution (with differences being somewhat smaller for higher percentiles). Panel (b) on the other hand shows significant differences along the distribution of estimated worker premiums, with differences shrinking only for the upper tail.

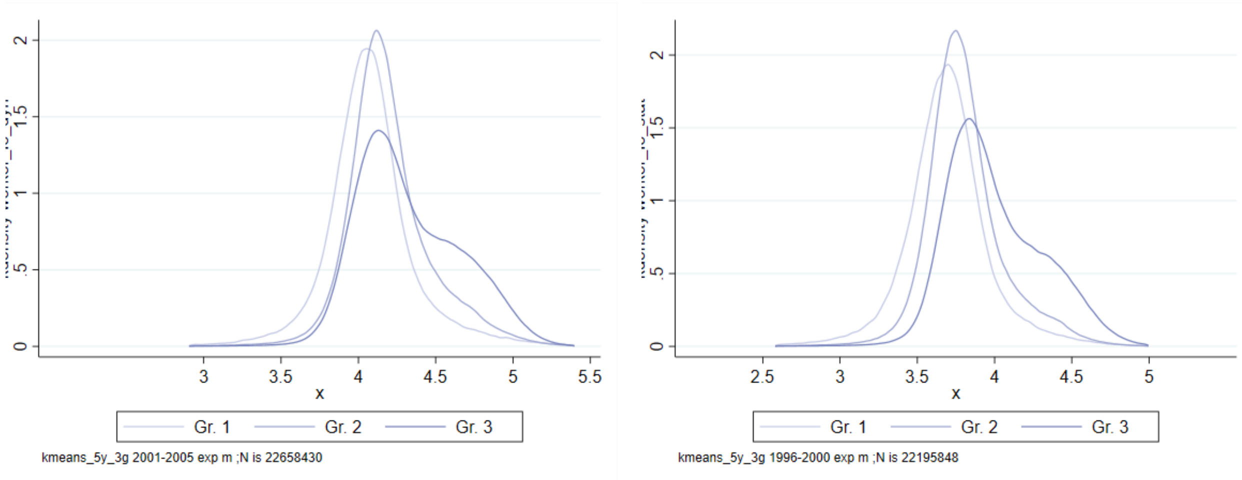


This figure reports the difference between the average establishment fixed effect estimated by the static and dynamic AKM model at each percentile of the distribution of establishment fixed effects of the static model in panel (a) and the difference between the average worker fixed effects at each percentile of the distribution in panel (b). Firms are classified into K=3 groups based on the k-means algorithm discussed in Section 4.4.

Figure 8: Differences in Estimated Premiums - Static vs. Dynamic Models

In Figure 9 we display the whole distribution of estimated worker premiums for each firm type (and K=3) for the static and the dynamic model. The graph is consistent with the earlier patterns. Further, the more similar distribution of worker premiums across firm types is more similar in the dynamic model, indicating that worker-firm sorting is overestimated in the static model.

(a) Static Model **(b)** Dynamic Model



This figure reports the kernel density of the distribution of worker fixed effects estimated by the static and dynamic AKM model, respectively. Firms are classified into K=3 groups based on the k-means algorithm discussed in the text.

Figure 9: Distribution of Worker Premiums across Firm Types

5.3 Sources of Wage Heterogeneity

We finally use the different model estimates to analyse which sources contribute to wage inequality by decomposing the wage variance into its components. This analysis is central to the contribution of this paper as it underscores the significance of dynamic factors, particularly the portability of experience premiums across firms, as key determinants of wage disparities, moving the discussion beyond traditional static views of wage formation.

Specifically, we decompose the total wage variance into the components indicated in equations (6) and (9). We use the leave-one-out connected set as in Kline et al. (2020) to address concerns of mobility bias in estimating wage components (Andrews, 2012).[11] Table 4 presents the decomposition for the static model, as well as for the dynamic model with $K = 3, 5, 10$ groups. Comparing the static model to the dynamic model, the results confirm that accounting for experience premiums by firm type is important when analysing the sources of wage inequality. The static model considerably overestimates the contribution of dispersion in worker quality and the static components of worker-firm sorting to wage inequality. In the dynamic AKM model, the contribution of dispersion in worker quality is up to 12 percentage points lower and the contribution of worker-firm sorting up to 10 percentage points lower. Instead, two other components are more important : the covariance

[11] Note that this is only a first step. We plan to estimate heteroskedastic fixed-effects (FE-HE) using the bias-corrected method from Kline et al. (2020) in the future.

between worker quality and $X\beta$ and the covariance between the static firm premium and $X\beta$. Note that $X\beta$ includes only the constant returns to experience component and firm tenure in the static model, but additionally includes experience premiums by firm type in the dynamic model. The positive $cov(\psi, X\beta)$ is driven by firms offering higher static firm premiums also offering higher experience premiums. The positive $cov(\alpha, X\beta)$ indicates that workers with higher worker quality are either more likely to accumulate experience in higher wage growth firms or more likely to stay longer in higher wage growth firms. Note that in contrast the direct contribution of the variance of $X\beta$ to wage dispersion only increases little (by 3 percentage points) once the decomposition allows for experience premiums by firm type. These differences are strongest in the model with 10 groups, which most flexibly allows for heterogeneity in experience premiums across firms.

	Static		Dynamic - 3 Groups			Dynamic - 5 Groups			Dynamic - 10 Groups		
	abs.	rel.	abs.	rel.	diff.	abs.	rel.	diff.	abs.	rel.	diff.
Var(lnwage)	0.13	1.00	0.13	1.00	0.00	0.13	1.00	0.00	0.13	1.00	0.00
Var(alpha)	0.09	0.66	0.08	0.57	-0.09	0.07	0.55	-0.11	0.07	0.54	-0.12
Var(psi)	0.02	0.17	0.02	0.16	-0.01	0.02	0.16	-0.01	0.02	0.16	-0.01
Var(xb)	0.01	0.10	0.02	0.13	0.02	0.02	0.13	0.03	0.02	0.14	0.03
2 *Cov(alpha,psi)	0.00	0.02	-0.01	-0.06	-0.08	-0.01	-0.07	-0.09	-0.01	-0.08	-0.10
2 *Cov(alpha,xb)	-0.01	-0.06	0.00	0.02	0.08	0.00	0.03	0.10	0.01	0.05	0.11
2 *Cov(psi,xb)	0.00	0.03	0.01	0.11	0.08	0.02	0.12	0.09	0.02	0.12	0.09

Table 4: Sources of Wage Heterogeneity - Wage Variance Decomposition

6 Conclusion

In this paper, we augment the AKM model to account for firm-specific differences in wage growth across firms, providing new insights into the factors contributing to both wage determination and wage inequality. By analyzing comprehensive administrative employer-employee matched data from Germany, our research uncovers significant variability in wage growth across firms and a considerable impact of this variability on the sources wage dispersion. This enhancement of the AKM framework substantially improves our understanding of wage determination mechanisms and the structure of wage inequality.

more detail tbc

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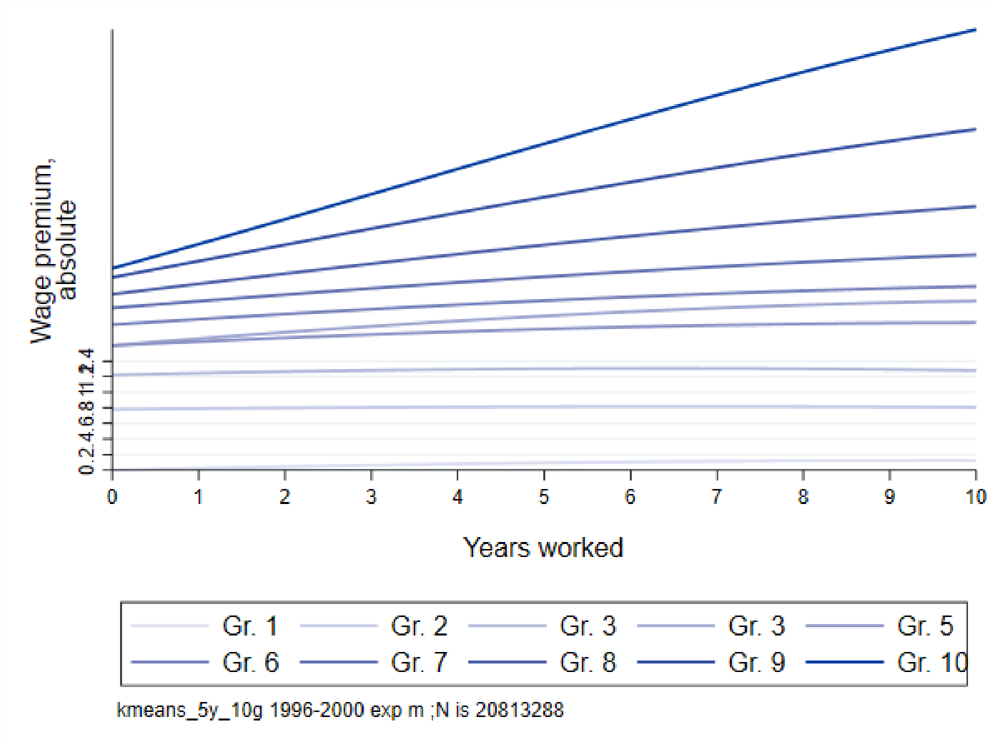
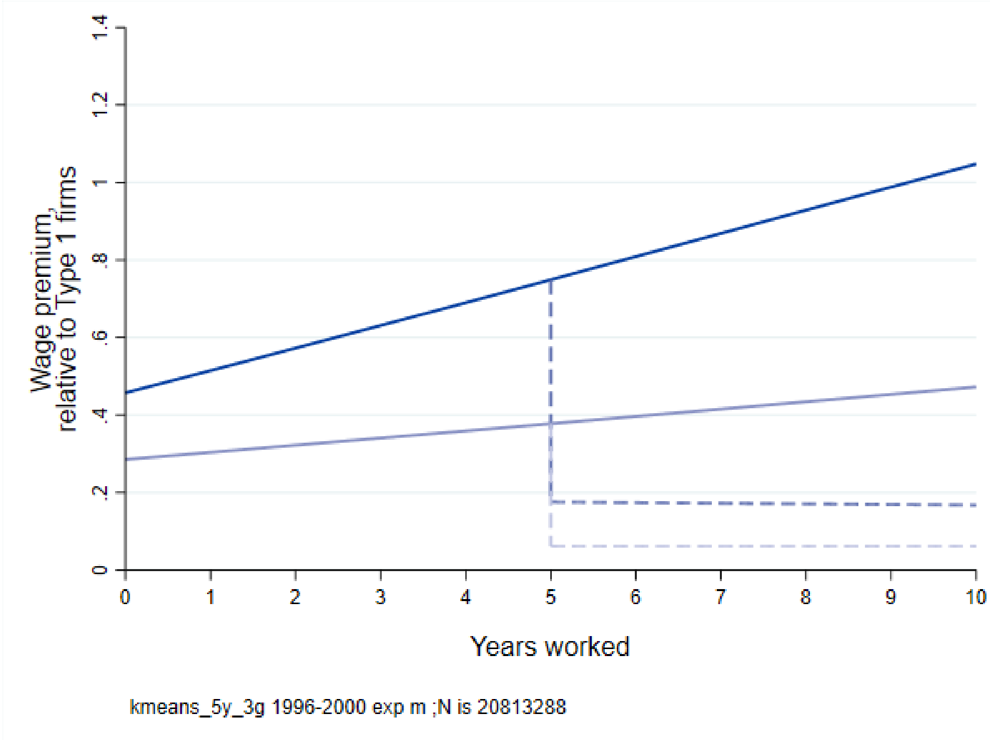
A Appendix Figures and Tables



This figure illustrates the wage profiles estimated using the dynamic AKM model (equation (5)) for ten different types of firms. Firm groups estimated using the k-means algorithm described in Section 4.4.

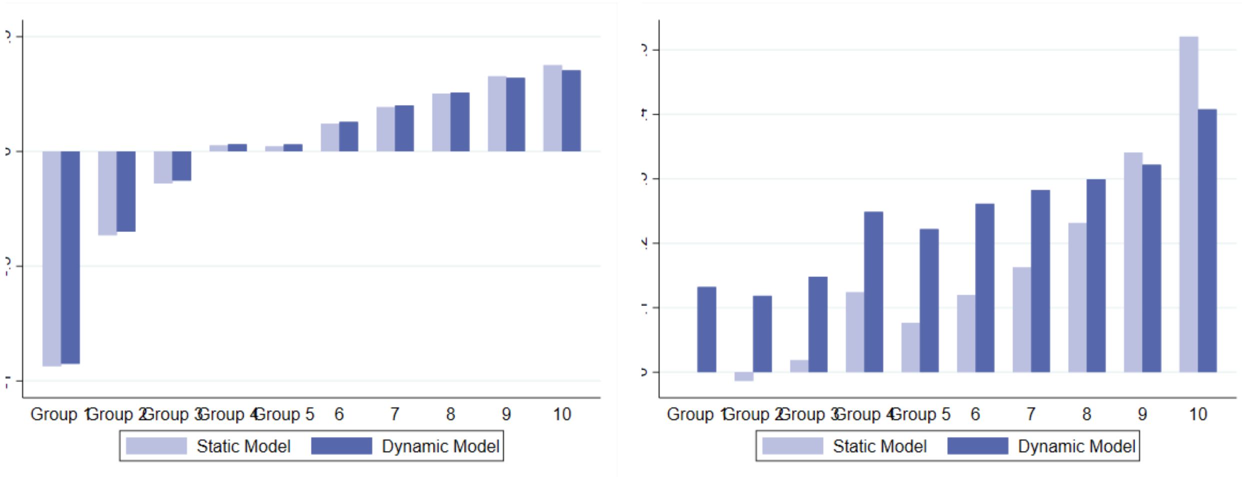
Figure A1: Estimated Experience Premium for K=3 groups. Dynamic Model



This figure illustrates wage profiles of workers in firms type-2 and type-3, relative to the omitted category (type-1) based on the Estimates of equation (5). Groups are estimated using the k-means algorithm described in Section 4.4. The figure also displays the evolution of wages for workers switching to a firm type-1, 5 years after working in the initial firm type.

Figure A2: Wage Profiles Relative to Non-switchers at Type-1 Firms

(a) Establishment Premium **(b)** Worker Premium



This figure reports the average establishment fixed effect (panel (a) and worker fixed effect (panel (b)) by firm type (with K=10) for the static AKM model, the baseline dynamic specification (equation (4)) and the extended dynamic specification (equation (5)). Firms are classified into groups based on the k-means algorithm discussed in Section 4.4.

Figure A3: Average Establishment and Worker Premiums - Static vs. Dynamic Model - K=10