Workplace Heterogeneity in Wage Growth

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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, indicating that acquired human capital is largely general. 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 considerably in size, productivity, and in the wages they pay. This has challenged the classical view of the labour market and has prompted researchers to study the role of firms in wage determination and for wage inequality. Increased access to rich administrative data that allows to track the entire work history of individuals across firms over long periods of time 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). The model 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 the dispersion of earnings (e.g. Card et al. (2013), Card et al. (2018), Song et al. (2019)). A first generation of studies has typically found that firms play an important role in wage determination, but also concluded that the sorting between firms and workers is not a significant source of wage dispersion (see Card et al. (2018)).[1] This finding has been challenged by a number of recent studies that focus on the so-called limited mobility bias that arises in the AKM model when only few workers move across firms, indicating that bias correction increases the contribution of sorting and reduces the contribution of firms to wage dispersion (Bonhomme et al. (2019), Bonhomme et al. (2023) Kline et al. (2020)). The AKM model has also been used to study diverse topics like wage gender gaps (Card et al. (2016)), rent sharing (Card et al. (2018)), or knowledge spillovers across firms (Serafinelli (2019)).

A limitation of the standard AKM model is that it does not allow for dynamic returns that may be heterogeneous across firms. The model thus 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]

Existing decompositions of the sources of wage dispersion based on the AKM model are based on these assumptions. Related microlevel 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

[1] The more recent literature stipulates however also that increased wage dispersion between firms and increased assortative matching are important drivers of increases in wage dispersion (Card et al. (2013), Song et al. (2019)).

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

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)). Consequently, firms differ in their wage-growth profiles. The existence of such heterogeneous wage-growth profiles implies that existing models of wage determination used to analyse the sources of rising wage inequality have been misspecified, necessitating a reassessment of the sources of rising wage inequality.

In this paper, we study the existence and magnitude of differential wage growth across firms 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. We then show that in the presence of dynamic benefits to experience that are heterogeneous across firms, the standard AKM model missspecifies the wage variance components. This misspecification 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. In our baseline model, we assume full portability of these 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 portability of firm type-specific experience. 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 missspecification. 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 returns 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 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 compared to firm premiums in wage levels. 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 high level-wage-premium firms offer larger returns to experience 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 returns to experience are an important factor of wage determination, and accounting for these returns changes our understanding of the sources of wage inequality.

2 Previous Findings and Related Studies

A study that closely relates to our paper is Arellano-Bover and Satiel (2023) who empirically estimate heterogenous returns to experience accumulated at different types of firms for Rio de Janeiro (Brazil) and Veneto (Italy). Although their emphasis is on establishing on-the-job learning as the main driver of these differences, our study focusses on understanding and quantifying the extent to which the sources of wage inequality can be misestimated when ignoring heterogeneity in firm-specific dynamic components of wage growth and independently of any source. Our approach also extends the idea of portability in a more general way, allowing for a richer set of interactions between past and current employment. Therefore, the way in which ignored dynamic components are loaded into worker, firm and sorting components can be substantially different.

Our paper relates to a number of studies estimating the importance of difference across firms in explaining wage inequality (Abowd et al., 1999; Card et al., 2013, 2018; Sorkin, 2018; Song et al. 2019; Bonhomme et al., 2019; Lachowska et al., 2023). Most of this literature has focused on static differences between firms and the importance of worker-firm matching components, but the role of heterogeneity and the dynamic behaviour of wages within firms has received much less attention. A notable example is Abowd et al. (1999, 2006) who allows returns to tenure to vary across firms, however, this rely on the strong assumption that the value of past experience is homogeneous across firms. More recently, Engbom et al. (2023) have extended the standard AKM model to allow for idiosyncratic firm-year components, but they are not persistent components of individuals' wages. Gregory (2021) uses a macro model to quantify differences in life-cycle earnings due to differences across firms in human capital provision; however, their study ignores the employment trajectory of workers by focussing on stayers within firms.

In the literature, studies such as Abowd et al. (1999) and Card et al. (2013) have found that the worker component accounts for approximately 60% of the variance in wages, the firm component for around 20%, and the sorting component is typically low, close to zero in some cases. However, recent critiques, including work by Andrews(2012), Card et al. (2013) and Bonhomme et al. (2019), have highlighted the limitations of the AKM model, particularly its potential to underestimate the impact of worker-firm sorting due to limited mobility across firms, often referred to as "mobility bias". Unlike these recent studies which primarily address mobility bias, our research focus on a different limitation of existing studies based on the AKM. We refine the AKM model by incorporating previously ignored dynamic components that can lead to an over- or underestimation of the static components' importance, including sorting. By integrating these overlooked factors, our work aims to provide a more nuanced understanding of wage inequality, drawing attention to the need for a reevaluation of the contributions of worker heterogeneity, firm effects, and worker-firm sorting to wage dispersion.

The relation between current wages and the identity of past and current employers has been recently studied by Di Addario et al. (2023), who estimate the relative importance of the immediately previous employer on the current employment wage. Their findings suggest a negligible effect for past employment over current wages; however, their setting is suitable to detect the immediate effect of job transitions on wage levels and does not capture the importance of wage growth or the full employment trajectory.

3 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). Details about the data are described in Bender et al., (2000). 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. We observe a range of 25 to 30 million individuals per year of the data.

We complement the BEH data with information from three different surveys: the IAB Establishment Panel (IAB-BP), the Linked Personnel Panel (LPP), and the German Management and Organisational Practices survey (GMOP). The IAB Establishment Panel 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, such as sales, value added or investments but also on on-the-job training provision. Instead, LPP and GMOP surveys include information on human resources and management practices, such as, for example, whether firms provide performance interviews or development plans to their employees. We use these additional firm-level measures in Part A to analyse the relationship between firm-specific wage growth and the firm's provision of training.

While our dataset spans from 1975 to 2016, we need to calculate the accumulated experience at different types of firms. Since this information is not reported retrospectively, we need to calculate it from the panel structure. Therefore, we use the period 1996-2015 for estimating the extended AKM model, while the earlier period 1975-1996 serves to broaden the temporal scope within which we can trace each worker's employment history during the estimation period. We also limit our analysis to individuals aged 18 to 39 years in each year-sample. This age restriction means that, at the start of our estimation period in 1996, we are able to follow the employment trajectory of the oldest cohort (those aged 39) back to when they were 18 years old. Additionally, due to the overlap of our sample period with the country's reunification, our analysis exclusively includes individuals whose initial observation occurred in West Germany.

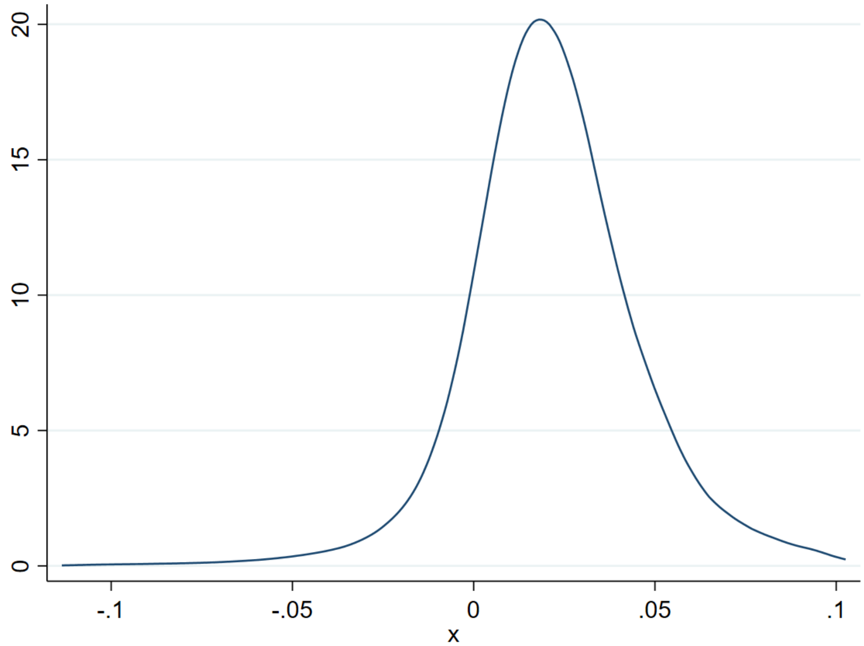
4 Descriptive Evidence on Wage Growth Heterogeneity

In this section we document the extent of heterogeneity in wage-growth across firms in the raw data and after controlling for a number of compositional confounders. We also study the dynamic of wages for individuals moving across firms associated with different wage-growth profiles.

4.1 Dispersion in Firm-specific Returns to Tenure

In Figure 1, we plot the distribution of firm-specific tenure coefficient from a regression of the form $lnw_{ijt} = \alpha + \gamma_j tenure_{i(j)} + \epsilon_{ijt}$ where lnw_{ijt} is the logarithm of wages for individual i working at firm j in year t. Returns to tenure are allowed to vary across firms (i.e. individual tenure is interacted with a firm fixed effect). The figure shows a large observed dispersion in wage growth. Results indicate that there is an additional 2.7% yearly wage growth when moving from a firm in the 25th percentile to a firm in the 75th percentile.

An obvious concern when interpreting Figure 1 is that the sorting of workers with different characteristics across firms and the different composition of the workforce within firms can confound with the variation in tenure. In order to get a measure of the slope of tenure within firms clean from these compositional issues, we estimate it using a two-step procedure. We



This figure displays the distribution of estimated firm-specific returns to tenure from equation $lnw_{ijt} = \alpha + \gamma_j tenure_{i(j)} + \epsilon_{ijt}$.

Figure 1: Distribution of Firm-specific Returns to Tenure

first estimate Equation (1), an almost saturated version of the mincerian equation:

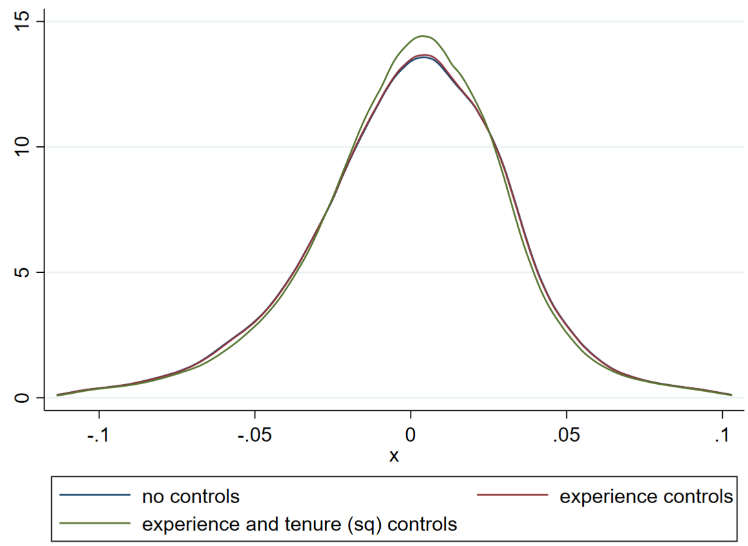
$$lnw_{ijt} = \alpha_i + \psi_j + \gamma_{ij} tenure_{i(j)} + \beta X_{ijt} + \delta_t + \epsilon_{ijt} \quad (1)$$

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

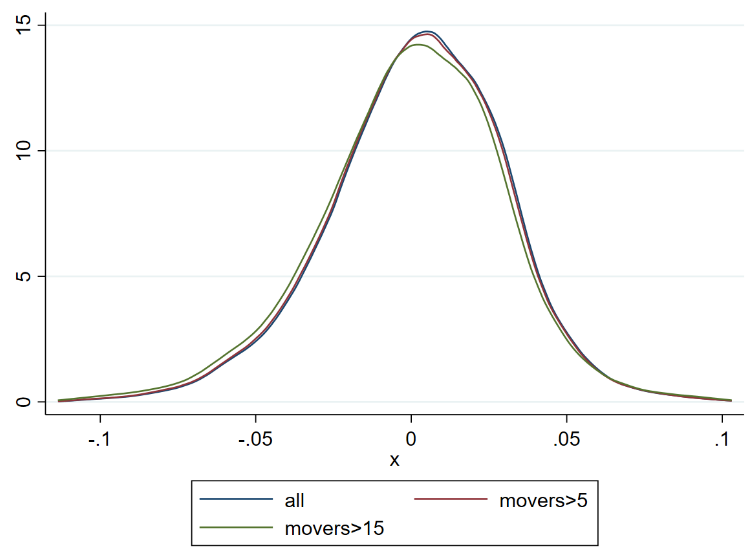
α_i, ψ_j and δ_t account for individual, firm, and year fixed effects. We account for observable time-varying characteristics of the worker X_{ijt} that can confound with tenure (such as age or general experience). The tenure coefficient is now allowed to vary across individuals within each firm. This means that it estimates the average wage growth for every individual-firm pair after netting out individual and firm intercepts and changes in wages explained by secular changes across all firms or driven by general experience accumulation. We then estimate Equation (2) to decompose the individual-firm specific slope into individual and firm components. Intuitively, suppose that an individual is a "fast learner" and systematically receives regular wage increases at any firm where she works. Then, we want to consider this as an attribute of the worker and not an intrinsic characteristic of the firms where she worked.

In Figure 2, we present the estimated distribution of firm-specific wage growth effects, denoted as $\tilde{\psi}_j$, across different firms obtained from Equations (1) and (2). This distribution reflects variations in wage growth that are attributed to the unique characteristics of each firm, net of selection of workers that experience differential wage increases regardless of the firm they work for. In Panel (a), we include various control variables in Equation (1). Additionally to the baseline fixed effects and age controls, we include controls for general experience and quadratic tenure effects. It's crucial to mention that our analysis for estimating 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. One potential issue with $\tilde{\psi}_j$ estimates is that they might be derived from a limited number of observations for many firm-worker pairings, potentially introducing significant noise into the results. To address this concern, Panel (b) offers supporting evidence that the variation in firm-specific tenure effects remains similar even when focusing only on firms observed to have more than 5 or more than 15 movers. The findings from both panels confirms that there is significant variability in wage growth patterns across firms even for a given individual, indicating that such patterns are not solely a result of individual worker characteristics or the sorting between firms and workers.

(a) with controls



(b) more movers



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 2: Firm-specific Returns to Tenure Conditional on Individual and Firms Controls

4.2 Event Study on the Wage Growth of Job Changers

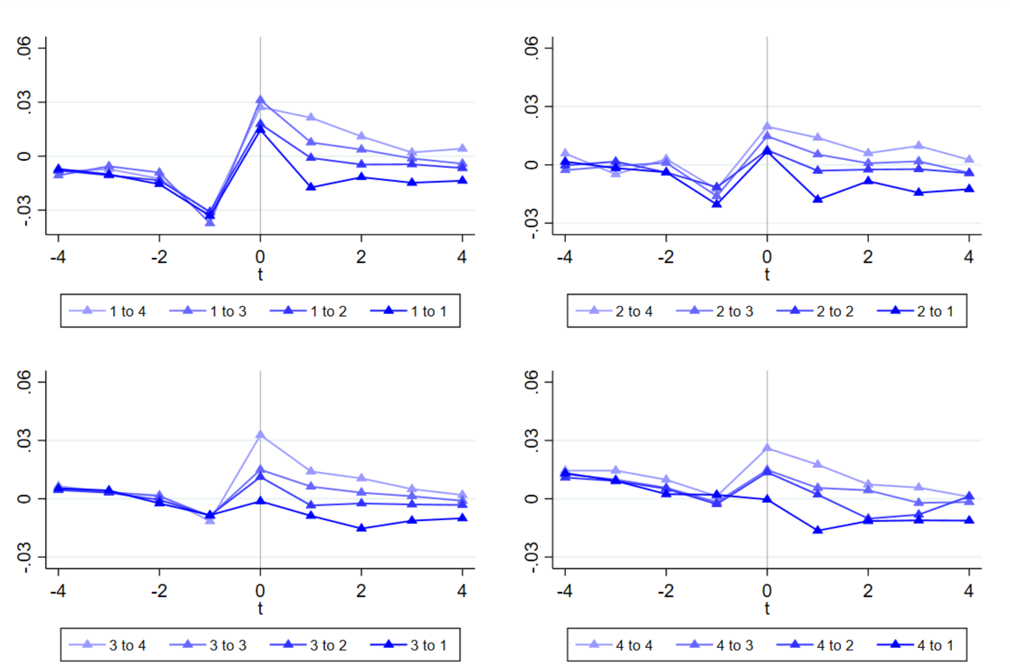
If we divide firms into quartiles of wage-growth, we can study the dynamic of wages for workers who move across quartiles. This exercise provides complementary evidence about the heterogeneity in wage growth while uncovering potential selection patterns due to non-exogenous job-to-job transitions.[3]

In panel (a) of Figure 3 we plot the event study by quartile of origin of the job mover. Interestingly, there is no dynamic selection by destination firm. This can be seen by the strong overlapping patterns of movers from the same quartile independently of the destination firm. Although trends are stable for most years before the job transition (notice that wage growth is net of secular changes), the figure reveals that the period immediately before the job transition is associated to a more negative wage change. This can reflect some transition cost but also some endogenous decision to transition to a different firm. For instance, workers with a negative wage shock are more likely to leave the firm the next period. The discrete jump at $t =$ shows that there is an association between the levels and the changes of firms quartiles. In this sense, the difference between the last wage at the old firm and the first wage at the new firm correlates positively with the (wage-growth) quartile of the destination firm. Importantly, after workers transition to the new firm, wage growth remains higher if the worker is at a higher quartile destination firm. This is important as it reveals that workers that are broadly similar in their past wage-growth start to receive wage increases that depend on the destination firm. This suggests that wage-growth is not driven entirely by workers characteristics.

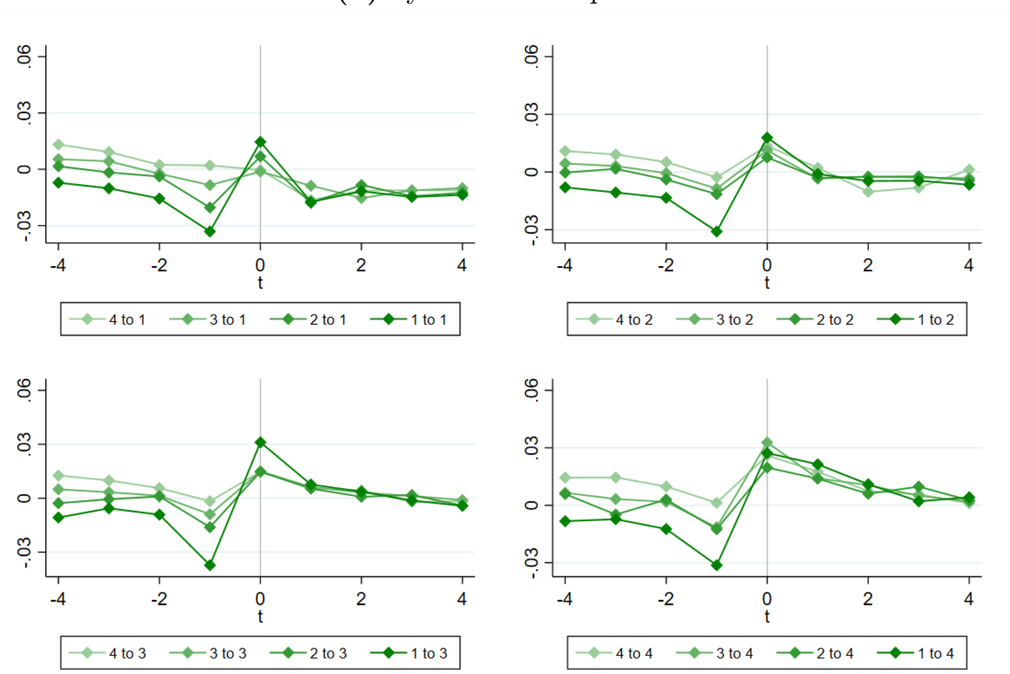
Panel (b) of Figure 3 we show the results of the event study by the destination quartile of job movers. Results are symmetric to Panel (a) if we switch the direction of the change. Wage growth at destination firm is largely homogeneous independently of the quartile of the pre-transition firm while wage growth before transition largely reflect the firm quartile.

[3]In the following sections we adopt a more comprehensive methodology to classify firms according to their wage-growth profiles that accounts not only the typical wage-growth inside the firm but also other moments of the distribution. In order to keep the approach more transparent and to ease interpretation we perform the event study by splitting firms on quartiles of the average wage-growth distribution where wage growth is net out from year fixed effects and the interaction between education and age dummies. Although previous AKM studies have conducted related event studies by grouping firms on the average wage (see e.g. Card et al., 2016) in order to validate the assumptions behind the model, it is not obvious that the same conclusions can be extended to mobility across firms with different wage-growth levels.

(a) by origin quartile



(b) by destination quartile



This figure displays the annual percentage change of wage 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 $\Delta log(w_{itj})$ on year fixed effects and dummies for the interaction between education and categories. The horizontal axe corresponds to the year relative to the job transition.

Figure 3: Event Study for Wage Growth of Job Changers

Although the event study is useful to illustrate that heterogeneity on wage growth substantially depends on firm characteristics and that there is no strong selection patterns, the short run time horizon does not allow to capture the full dynamic due to experience accumulated at different types of firms. For instance, workers transition from 3rd quartile to 4th quartile may have accumulated more experience in firms from lower quartiles while those transitioning from 2nd quartile 2 to 4th quartile may have acumulated more experience at higher quartiles. Quantifying the full extent to which past experience at different firms can affect future wages, requires a more suitable / less descriptive approach. Allowing for this type of longer-run effects of past experience is the object of our study in the following sections.

5 Estimating the Sources of Wage Inequality in the Presence of Wage-Growth Heterogeneity

5.1 The Canonical Static AKM Model

The workhorse tool for studying the sources of wage inequality in labour markets has been the empirical model proposed by Abowd, Kramarz, and Margolis (1999). The canonical model can be described by the following empirical equation:

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

The AKM model assumes that the worker component α_i capture skills or other factors rewarded equally across employers. Similarly, wages are allowed to vary due a number of time-varying characteristics such as age or experience (but rewarded equally among all firms) or according to year-specific effects. These factors are embedded in the set of variables X_{it}. Wages include a firm (or establishment) component ψ_j where index j can be described more precisely as $j = J(i,t)$ to indicate that it corresponds to the firm where the individual i is employed in year t. The firm component is a proportional premium paid by firm j to all workers independently of the year or characteristics of the worker. Following Card et al. (2013), this component is interpreted in a broad sense as it could capture rent-sharing, efficiency wages, or strategic wage posting behavior (as in Burdett and Mortensen (1998) or Moscarini and Postel-Vinay (2012)). Finally, any firm-worker specific matching components of wages (such as those implied by Mortensen and Pissarides (1994)) are included in the residual term as well as worker-year shocks. Importantly, it is assumed that these residual factors, are idiosyncratic and exogenous. This assumption is crucial for identification of α_i and ψ_j. Estimation of these components follow from the variation created by workers switching between firms (within a given connected set of firms).

Card et. al (2013) discuss and summarize the necessary assumptions for identifying the worker and firm component and show that a sufficient condition is strict exogenous worker mobility. 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). On the other hand mobility patterns such as workers moving based on a better firm-worker specific matching value violate this assumption. Similarly, the exogenous mobility assumption is violated if workers experiencing negative/positive shocks tend to move afterwards to some type of firms with higher probability. Card et. al (2013) provide some indirect empirical tests that suggest that the exogenous mobility is a plausibly assumption in the context of the German labour market. For instance, one of the implications of workers moving systematically due to a better firm-worker matching unobserved component is a lack of symmetry in the wage increase when workers move from low to high pay firms compared to the reduction in wage when workers move from high to low pay firms. Intuitively, only workers with a large positive matched component will move from high to low pay firms (e.g. when the worker is particularly well suited for the low pay firm). This will tend to overestimate the firm component of low pay firms. Card et. al (2013) show that most of the transitions across firms in different quartiles of the wage distribution display a strong symmetry.

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:

$$\begin{aligned} var\left(\ln w_{ijt}\right) = {} & var\left(\hat{\alpha}_i\right) + var\left(\hat{\psi}_j\right) + var\left(X_{it}'\hat{\beta}\right) + var(\hat{r}_{it}) \\ & + 2cov\left(\hat{\alpha}_i, \hat{\psi}_j\right) + 2cov\left(\hat{\alpha}_i, X_{it}'\hat{\beta}\right) + 2cov\left(\hat{\psi}_j, X_{it}'\hat{\beta}\right) \end{aligned} \tag{4}$$

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. (2012)) and hence assortative matching of high wage workers into high wage firms may be upward biased (see e.g. Lentz et al (2018) or Bonhomme et al (2018)). This has implications for the measurement of wage inequality since too much dispersion of wages is assigned to $cov\left(\hat{\alpha}_i, \hat{\psi}_j\right)$. Corrected estimation methods (e.g. Andrews et al. (2012), Bonhomme et al., (2021)) has shown a lower degree of assortative matching compared to the earlier wage variance decompositions.

5.2 Augmented Dynamic AKM Model

In the presence of workplace heterogeneity in wage growth due to factors as differential learning or different portability of acquired human capital, the static AKM may be incorrectly specified and consequently the sources of wage dispersion incorrectly estimated. Our hypothesis is that the place where the worker acquired experience matters for future earnings. Assuming that firms can be classified into different groups or types $g = 1, ..., G$, we can extend Equation (3) to account for heterogeneous firm-type returns to past experience:

$$ln(w_{it}) = \alpha_i + \psi_j + X_{it}^{\prime}\beta + \sum_g \left(\theta_{1g} Exp_{git} + \theta_{2g}(Exp_{git} * Exp_{it})\right) + r_{it} \quad (5)$$

The variable Exp_{git} accounts for the experience of worker accumulated in firms type g up until year t. We include the interaction term between type-specific experience and total experience $\theta_{2g}(Exp_{git} * Exp_{it})$ to allow for depreciation after a worker leaves a firm type g.

Notice that Equation (5) implicitly assumes that experience accumulated at a firm type g is fully portable when moving to a different type of firm. This is evident from the observation that the returns to Exp_{git} are independent of the worker's current firm at time t. To better capture a scenario where experience gained at one type of firm is not completely transferable—and where the extent of this transferability may vary depending on the type of destination firm—we expand the empirical model as follows:

$$
\begin{aligned}
\ln(w_{it}) = {} & \alpha_i + \psi_j + X_{it}'\beta \\
& + \sum_{\tilde{g}} \sum_{g} \left(\theta_{1g\tilde{g}} Exp_{\tilde{g}it} + \theta_{2g\tilde{g}}(Exp_{\tilde{g}it} \times Exp_{it})\right) \mathbb{1}[FType_{it} = g] \\
& + r_{it}
\end{aligned} \tag{6}
$$

Now the term $\theta_{1g\tilde{g}} Exp_{\tilde{g}it} + \theta_{2g\tilde{g}}(Exp_{\tilde{g}it} \times Exp_{it})$ 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. This implies that the assumption of full portability of past experience is retained only for switches within the same type of firms.

5.3 Bias Due to Ignoring Dynamic Components

We now derive and interpret the bias in the estimation of Equation (3) when the true model include dynamic components such as in (5) and (6). 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 (5):

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

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 De la 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:

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

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 $\hat{\psi}$ [4]. On the other hand, 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:

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

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:

[4] 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

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

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. [5]

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 $cov(\Gamma_{gj}, \alpha_i) > 0$.

Allowing for Heterogeneity in Portability of Type-specific Experience: In the most general case given by Equation (6), all components determining wages and wage dispersion will be biased in a magnitude that will depend on the degree and heterogeneity of portability. Also, our proposed AKM extension maintain the assumption of full portability of experience within the same type of firms, so biases also arise when this assumption is violated. In order to understand better the potential biases arising under different underlying assumptions we perform a number of simulations that confirm our findings for the cases of full/non portability and provides intuition for more general cases.

Simulations We construct a panel of workers and firms which are grouped into learning types $G = 0, 1$. The simulation draw idiosyncratic static individual fixed effects α_i that varies across individual types from a normal distribution. Firms are randomly allocated to types. Worker i is matched to firm j and allowed to move to another firm k based on

[5] 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.

the period transition probabilities P_ijk which depends 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 - which is in turn correlated with the firm fixed effect), and a network parameter that affects the probability of transitioning across firms of the same type. Using the (steady state) transition probabilities we simulate a panel of 130,000 workers, 1,000 firms and 20 years.

We then simulate the fixed effects of each firm which are correlated (positively) with the learning type and we allow for assortative matching between ψ_j and α_i. Thus, we define psi_j as the sum of three components. First, a fully idiosyncratic component $\zeta_j \sim N(0, 0.4)$. Second, a component correlated with the average α_i in the firm across all the observed years. Finally, a component correlated with the firm type g

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

Where $z \sim N(1.2g - 0.6, 0.6)$ generates correlation between the firm fixed effect and the learning type.

The returns to experience accumulated at each firm type are given by β_0 and β_1. We start by assuming that a portion η of the experience accumulated at a firm is retained when a worker switches firms. We also assume no further depreciation of this retained experience stock if the worker subsequently moves to another firm. For simplicity we assume linear returns to experience of any type. We define the wage equation in the following way:

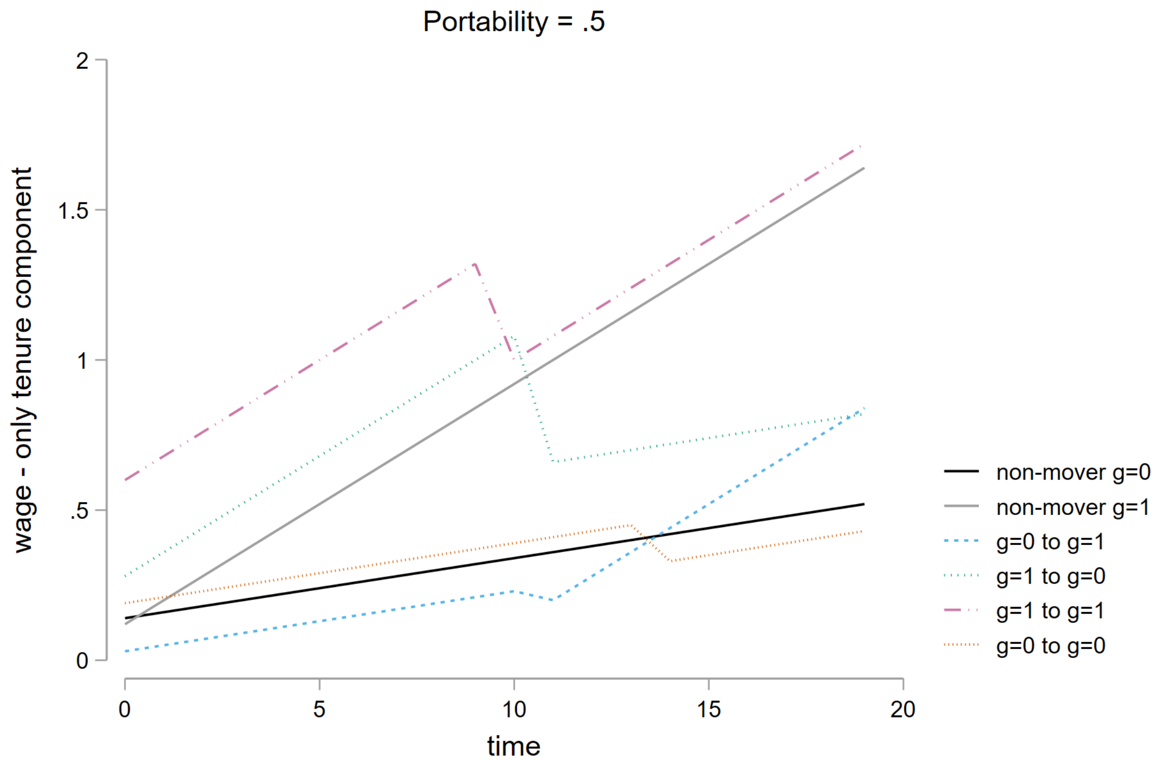
$$ln(w_{ijt}) = \alpha_i + \psi_j + (1-\eta)\beta_{g(j)}Tenure_{ij} + \eta\left(\beta_0 Exp^0_{it} + \beta_1 Exp^1_{it}\right) + r_{ijt}$$

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
$sd(g)$	0.5
$sd(r)$	0.8
$corr(g(j), \psi_j)$	0.58
$corr(g(j), \alpha_i)$	0.56

Table 1: Parameters used in Simulations

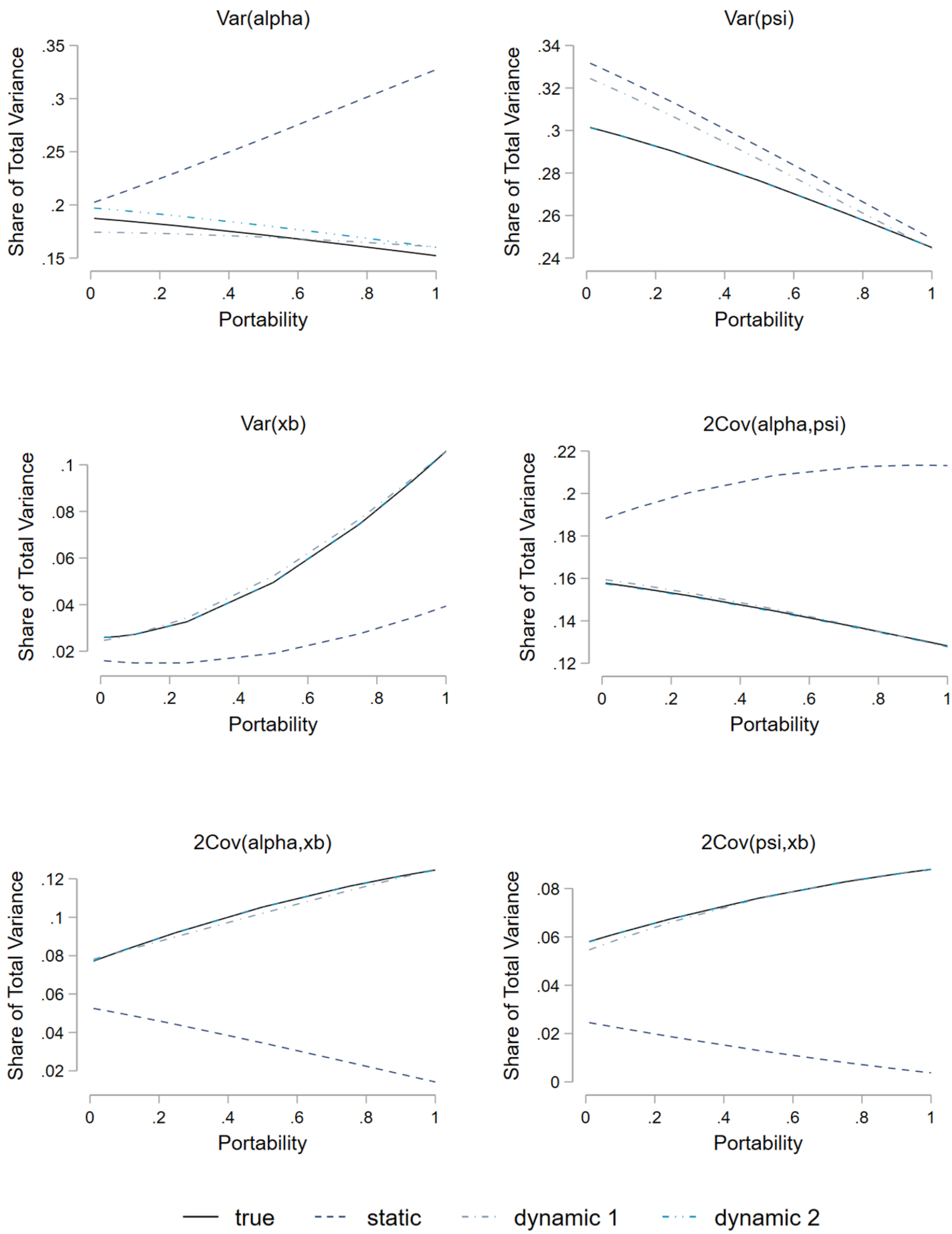
In order to illustrate the type of wage dynamics generated by of our simulations, in Figure 4 we provide examples of wage profiles from the simulated data. In the figure we set the portability parameter $\eta = 0.5$. The figure depicts the negative discontinuous drop in wage due to the non-full portability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

We estimate the static and dynamic versions of the wage equation for different values of portability η. Notice that the equation that we use to simulate wages allows for some accumulated experience to be lost even when the worker transition to a firm within the same type (which is likely a more realistic assumption). On the other hand, our augmented AKM specification assumes full portability of experience across firms of the same type. In order to capture the potential bias due to this misspecification of the augmented AKM model, we estimate two dynamic versions of the wage equation. First, the model we propose for our empirical analysis as described by Equation 6. Second, the same specification that generates the data. For each one of the models (static, dynamic 1 and dynamic 2) we estimate the wage decomposition from Equation (4) and compare it with the true components used in the simulated data.



This figure displays the estimated wage decomposition using different empirical specifications. Each panel corresponds to a different component of wage.

Figure 5: Bias in Variance Components from Simulations

Figure 5 displays the components of wage dispersion for the different specifications. The analysis reveals clear patterns associated with the portability of experience between firms. The static model demonstrates an increasing bias in the worker component as portability rises. This is because, with lower portability, the effect of experience accumulated in specific firm types on wages is diminished, leading to less model misspecification. When workers carry less of their past experience to new firms, the static model's inability to account for this dynamic results in a greater deviation from accurately reflecting wage determinants based on worker-specific effects.

For the firm component within the static model, the bias decreases with an increase in portability. This occurs because lower experience portability makes the returns to experience resemble firm-specific returns to tenure more closely. As portability enhances, the model becomes more capable of distinguishing between general tenure effects and those returns uniquely attributable to experience within specific firm types, thus reducing bias. The static model also inaccurately estimates sorting components, with a notable bias towards overstating worker-firm sorting. In contrast, the dynamic first empirical specification shows that the firm component is primarily where misspecification occurs, especially under conditions of low portability. This misspecification diminishes as portability increases and becomes small under full portability. This finding suggests that the assumption of full portability within types do not create significant biases if violated. Reassuringly, simulations are in line with the predicted biases analysed above for the extreme cases of full and non portability.

5.4 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 and Satiel (2022). The classification follows from the k-means minimization problem, formulated as follows:

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

where $\hat{G}_j(\Delta w)$ denotes the empirical cumulative distribution function (cdf) of wage growth, $ln\tilde{w}_{ijt}$, for firm j. In this equation, 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 calculated 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. This method provides a detailed view of the patterns of wage growth across 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 within the firm.

	1996-2000			2001-2005			2006-2010			2011-2015		
Group:	**1**	**2**	**3**	**1**	**2**	**3**	**1**	**2**	**3**	**1**	**2**	**3**
Firm Characteristics												
Average (ln) Wage (5y)	3.75	4.24	4.58	3.72	4.25	4.62	3.68	4.21	4.64	3.76	4.25	4.68
Average (ln) Wage Growth (5y)	0.01	1.01	2.01	3.01	4.01	5.01	6.01	7.01	8.01	9.01	10.01	11.01
Establishmt Premium (Static)	-0.10	0.15	0.28	-0.41	-0.12	0.01	0.09	0.36	0.52	-0.36	-0.14	0.02
Establishmt Premium (Dynamic)	-0.09	0.16	0.28	-0.41	-0.13	-0.01	0.11	0.38	0.53	-0.35	-0.14	0.02
Establishment Size	171	352	2157	128	268	2042	154	246	1814	159	278	2084
Worker Characteristics												
Age 18 to 25	0.15	0.10	0.08	0.17	0.10	0.07	0.17	0.09	0.07	0.13	0.09	0.07
Age 26 to 50	0.70	0.72	0.74	0.68	0.72	0.75	0.66	0.70	0.73	0.63	0.65	0.67
Age 51 to 65	0.15	0.18	0.19	0.15	0.18	0.18	0.18	0.21	0.21	0.24	0.26	0.27
Low Skilled	0.18	0.15	0.12	0.20	0.14	0.09	0.19	0.12	0.08	0.20	0.11	0.06
Medium Skilled	0.76	0.77	0.74	0.74	0.77	0.72	0.75	0.76	0.71	0.74	0.74	0.69
High Skilled	0.06	0.08	0.15	0.06	0.10	0.18	0.06	0.12	0.21	0.07	0.15	0.25
Share	0.09	0.62	0.28	0.12	0.58	0.30	0.16	0.54	0.30	0.16	0.56	0.27
N	1,450,917			1,299,081			1,248,191			1,269,846		

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 Figures 6 and 7 for the $K = 5$ for each one of the 4 data periods. The figures show that firms with higher returns to experience as defined by K, also provide more training. The findings suggests that the partition into types capture a meaningful aspect of wage growth that can be potentially associated to portable skills such as those acquired trough training. Naturally, omitted variables could explain the correlation between training provision and wage growth, however it is reassuring that the correlation becomes even stronger when training at individual level is considered (Figure 7).

Figure 6: Training Provision by Firm Type (K=5)

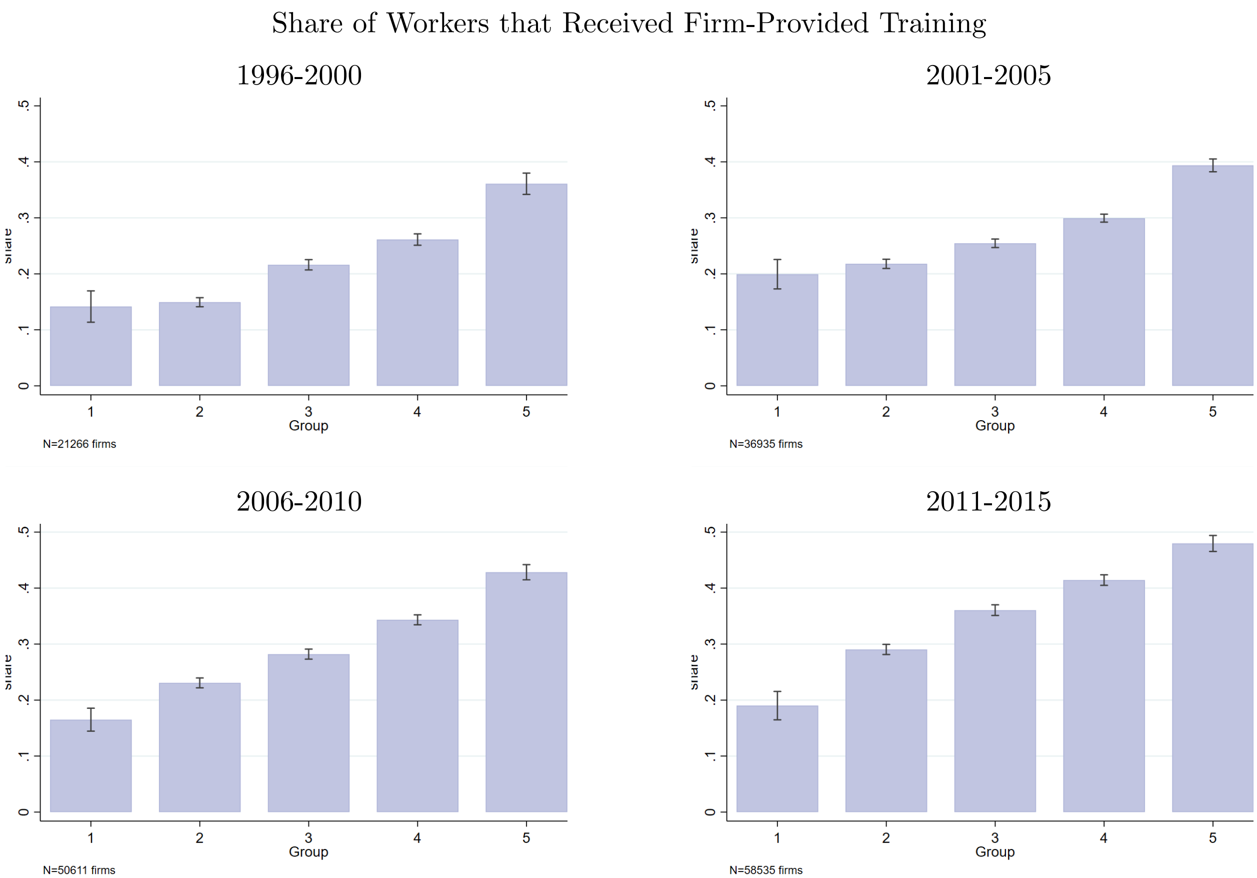


Figure 7: Training Provision by Firm Type of the Worker (K=5)

6 Main Results

6.1 Returns to Experience in the Augmented Dynamic Model

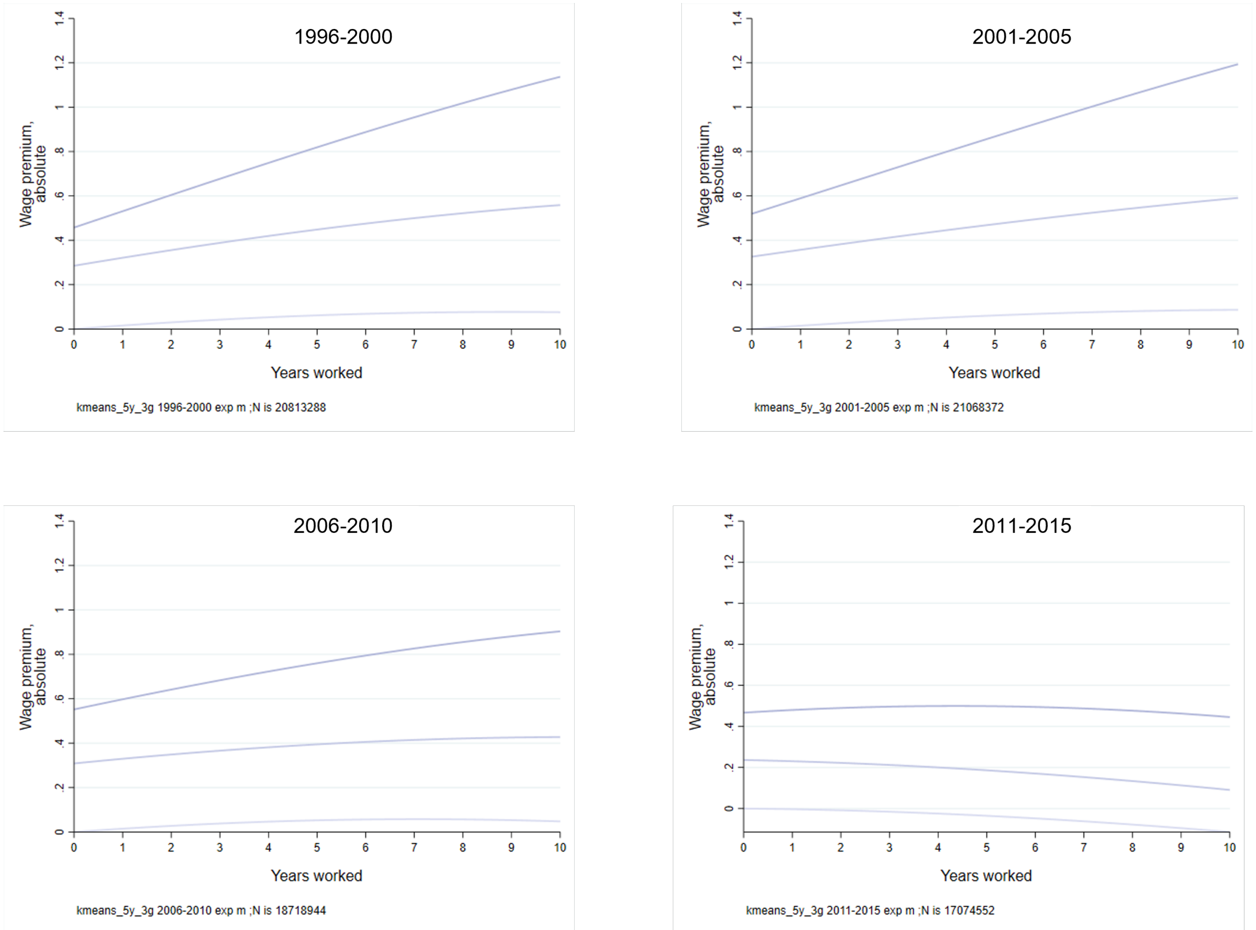
In Table 3 we present main regressions for the static model, the dynamic model with non differential returns to past experience by type of current employer and finally the full extended model where returns to type of experience also depend on the currently employer. In all cases, regressions control for total experience and its square, tenure at the current firm and its square and fixed effects for person, establishment and year. We report the estimates for the 4 sample periods separately and grouping firms in 3 types.[6] Estimates indicate that where workers accumulate experience matters but there is also heterogeneity in how different type of firms reward past experience at a given type of experience. For instance, experience accumulated at the highest wage growth type (i.e. G=3) is relatively less rewarded at the

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

second type of firm (G=2), indicating some degree of non-portability.

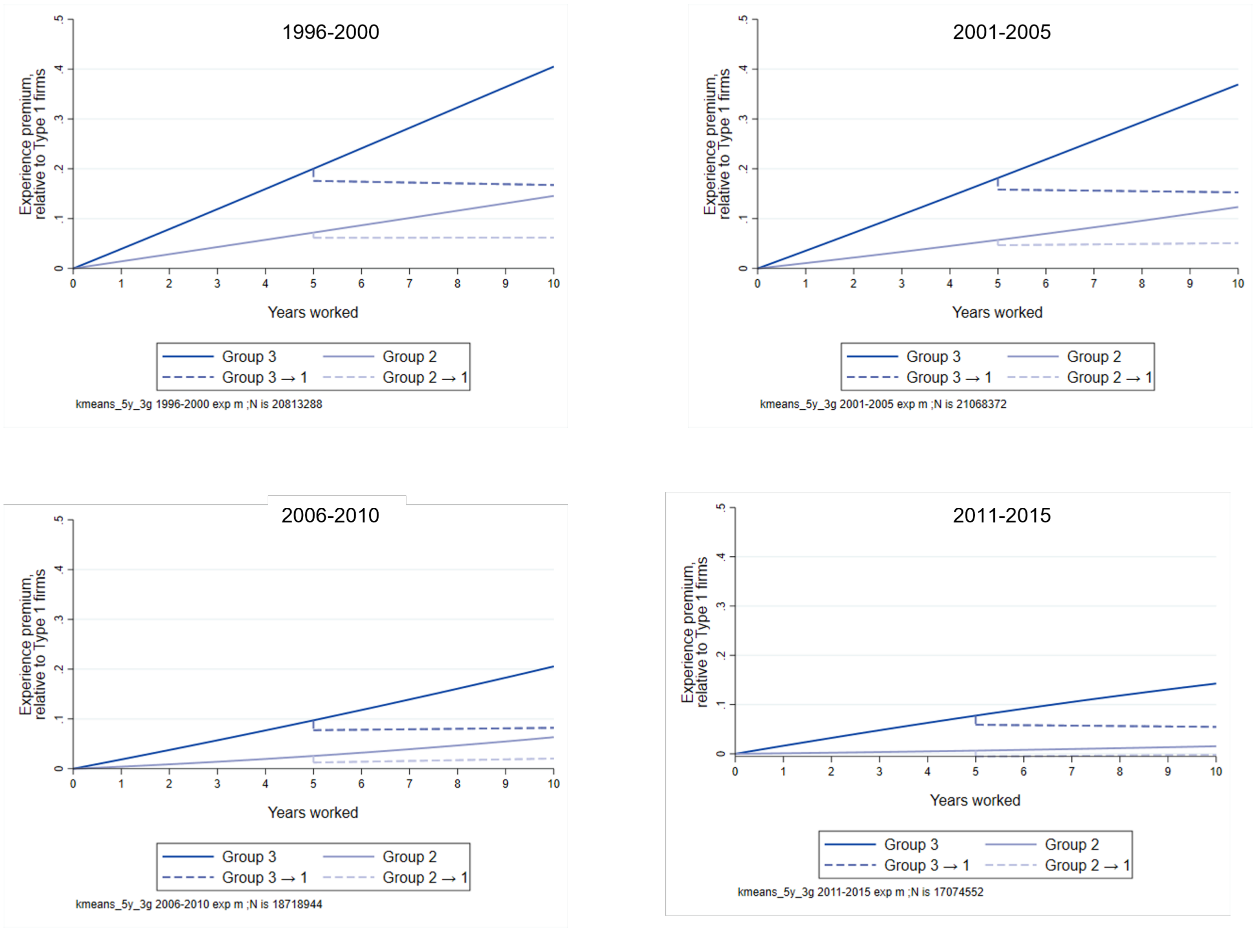
Results from Table 3 are hard to interpret numerically given the large number of interaction terms. For this reason, we also illustrate the earning profiles graphically in Figures 8 and 9 for the dynamic model and three firm types. In Figure 8 we report the wage profile of workers that do not change firms for the case when firms are grouped into three wage-growth groups. Consistently with our descriptive analysis, returns to experience vary considerably across firm types. The graph also shows that high (level) wage premium firms offer higher returns to experience on average. Appendix Figure A1 report similar results for the case of 10 wage-growth groups.

In Figure 9, 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). We also we overlap in dashed lines the profile of workers that switch to the lowest group. Although there is some sharp discontinuous fall in the experience premium for these job changers, these jumps are not too large, indicating that a substantial portion of acquired experience is portable (i.e. stays with the worker even if the worker leaves the firm). Since the profiles measure wage differences relative to the omitted group, the negative vertical jump at the switching time (assumed 5 years after the worker started working) indicates some small depreciation of the value of accumulated stock of experience due to changing firm and the flat profile afterwards indicates that the additional experience accumulated at the firm of the lowest type (G=1) is rewarded according to the lower return experienced by those workers at G=1 firms. It is important to highlight that the graph does not show how wage's level evolves as the worker switch across firms, but only how the relative premium changes across experience. In Appendix figure A2, we translate premium changes into the wage's level behaviour for workers of firms in groups 2 and 3 switching to a firm in group 1.



This figure illustrates the wage profiles estimated using the dynamic AKM model (Equation 6) for three different types of firms. Firm groups estimated using the k-means algorithm described in the text. Each sub-graph corresponds to a separate regression for a different sample period.

Figure 8: Estimated Experience Premium for K=3 groups. Dynamic Model



This figure illustrates the wage experience premium of workers in firms type-2 and type-3, relative to the omitted category (type-1) based on the Estimates of Equation 6. Groups are estimated using the k-means algorithm described in the text. The figure also displays the evolution of the premium for workers switching to a firm type-1 5 years after working in the corresponding firm. Each sub-graph corresponds to a separate regression for a different sample period.

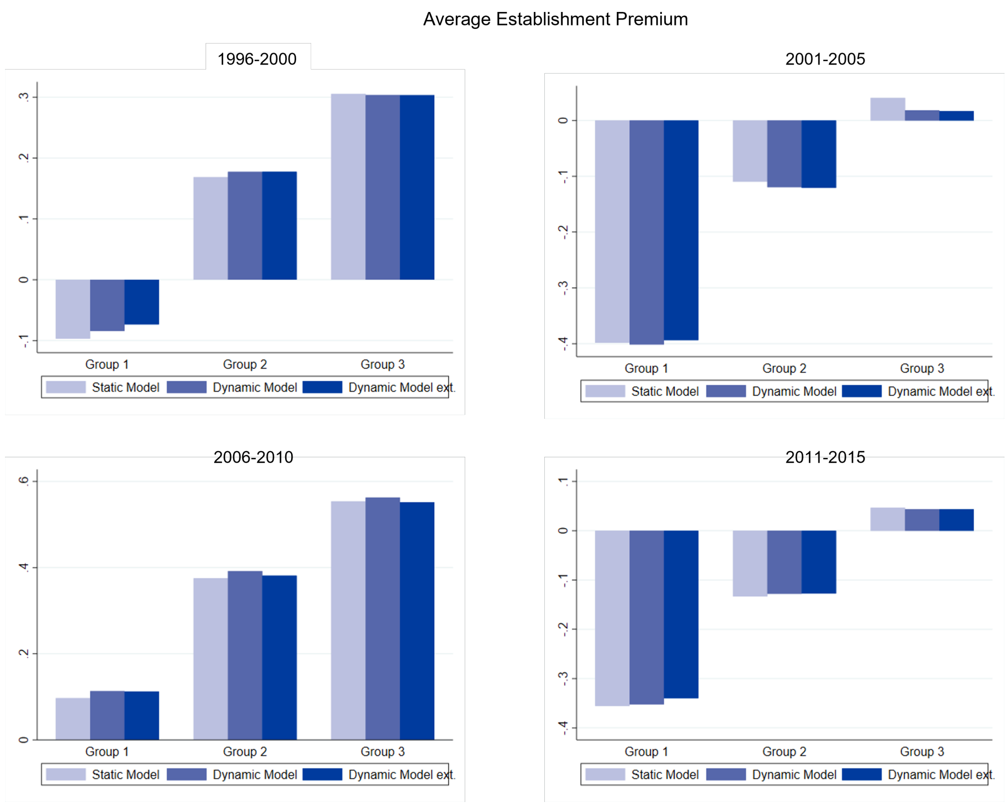
Figure 9: Experience Premium Relative to Non-switchers at Type-1 Firms

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
		1996-2000			2001-2005			2006-2010			2011-2015	
Exp	0.0451***	0.0280***	0.0289***	0.0427***	0.0219***	0.0230***	0.0301***	0.0184***	0.0192***	0.0080***	-0.0058***	-0.0050***
	(0.00030)	(0.00040)	(0.00040)	(0.00040)	(0.00050)	(0.00050)	(0.00050)	(0.00060)	(0.00060)	(0.00050)	(0.00060)	(0.00060)
Exp Sq	-0.0012***	-0.0013***	-0.0013***	-0.0009***	-0.0008***	-0.0008***	-0.0010***	-0.0010***	-0.0010***	-0.0011***	-0.0009***	-0.0009***
	(0.00000)	(0.00001)	(0.00001)	(0.00000)	(0.00001)	(0.00001)	(0.00000)	(0.00001)	(0.00001)	(0.00000)	(0.00001)	(0.00001)
Firm Tenure	0.0020***	0.0024***	0.0023***	0.0031***	0.0031***	0.0029***	0.0025***	0.0027***	0.0027***	0.0009***	0.0007***	0.0006***
	(0.00005)	(0.00005)	(0.00005)	(0.00005)	(0.00005)	(0.00005)	(0.00006)	(0.00006)	(0.00006)	(0.00006)	(0.00006)	(0.00006)
Firm Tenure Squared	-7.33e-5***	-0.0001***	-0.0001***	-0.0001***	-0.0001***	-0.0001***	-0.0001***	-0.0002***	-0.0002***	-4.93e-5***	-4.96e-5***	-4.69e-5***
	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)
Exp at G3		0.0556***	0.0488***		0.0509***	0.0444***		0.0343***	0.0291***		0.0143***	0.0093***
		(0.00030)	(0.00050)		(0.00040)	(0.00060)		(0.00050)	(0.00060)		(0.00050)	(0.00060)
Exp at G3 × Exp		-0.0014***	-0.0012***		-0.0011***	-0.0009***		-0.0011***	-0.0009***		-0.0013***	-0.0011***
		(0.00000)	(0.00003)		(0.00000)	(0.00002)		(0.00000)	(0.00002)		(0.00000)	(0.00002)
Exp at G2		0.0309***	0.0282***		0.0262***	0.0241***		0.0199***	0.0167***		-0.0011*	-0.0042***
		(0.00030)	(0.00040)		(0.00040)	(0.00040)		(0.00050)	(0.00050)		(0.00050)	(0.00050)
Exp at G2 × Exp		-0.0010***	-0.0009***		-0.0006***	-0.0006***		-0.0009***	-0.0008***		-0.0009***	-0.0008***
		(0.00000)	(0.00001)		(0.00000)	(0.00001)		(0.00000)	(0.00001)		(0.00000)	(0.00001)
Exp at G1		0.0195***	0.0180***		0.0167***	0.0158***		0.0168***	0.0158***		-0.0014*	-0.0017**
		(0.00050)	(0.00050)		(0.00050)	(0.00060)		(0.00060)	(0.00060)		(0.00060)	(0.00060)
Exp at G1 × Exp		-0.0012***	-0.0010***		-0.0008***	-0.0007***		-0.0012***	-0.0011***		-0.0010***	-0.0010***
		(0.00002)	(0.00002)		(0.00002)	(0.00002)		(0.00001)	(0.00002)		(0.00001)	(0.00001)
Exp at G3 × Working at G3			0.0067***			0.0064***			0.0051***			0.0050***
			(0.00040)			(0.00040)			(0.00040)			(0.00040)
Exp at G3 × Exp × Working at G3			-0.0003***			-0.0002***			-0.0002***			-0.0002***
			(0.00003)			(0.00002)			(0.00002)			(0.00002)
Exp at G2 × Working at G3			0.0050***			0.0026***			0.0048***			0.0035***
			(0.00020)			(0.00020)			(0.00020)			(0.00020)
Exp at G2 × Exp × Working at G3			-0.0002***			-5.32e-5***			-0.0002***			-0.0001***
			(0.00001)			(0.00001)			(0.00001)			(0.00001)
Exp at G1 × Working at G3			0.0105***			0.0086***			0.0116***			0.0113***
			(0.00070)			(0.00070)			(0.00050)			(0.00040)
Exp at G1 × Exp × Working at G3			-0.0009***			-0.0006***			-0.0008***			-0.0006***
			(0.00005)			(0.00004)			(0.00003)			(0.00003)
Exp at G3 × Working at G2			0.0032***			0.0036***			0.0039***			0.0035***
			(0.00040)			(0.00040)			(0.00040)			(0.00040)
Exp at G3 × Exp × Working at G2			-0.0002***			-0.0002***			-0.0001***			-0.0001***
			(0.00003)			(0.00002)			(0.00002)			(0.00002)
Exp at G2 × Working at G2			0.0024***			0.0025***			0.0030***			0.0032***
			(0.00020)			(0.00020)			(0.00020)			(0.00020)
Exp at G2 × Exp × Working at G2			-7.8e-5***			-7.54e-5***			-9.72e-5***			-0.0001***
			(0.00001)			(0.00001)			(0.00001)			(0.00001)
Exp at G1 × Exp × Working at G2			-0.0001***			-9.32e-5***			-7.4e-5***			0.0000104
			(0.00001)			(0.00001)			(0.00001)			(0.00001)
Observations	20,813,287	20,813,287	20,813,287	21,068,373	21,068,373	21,068,373	18,718,945	18,718,945	18,718,945	17,074,551	17,074,551	17,074,551
R2	0.9235	0.9243	0.9244	0.9406	0.9412	0.9412	0.9483	0.9485	0.9485	0.9468	0.9470	0.9470
Within R2	0.02751	0.03826	0.03868	0.0187	0.02773	0.02805	0.02345	0.0275	0.02778	0.02627	0.02896	0.02918

Table 3: Estimated Static and Dynamic Models

6.2 Model Comparison

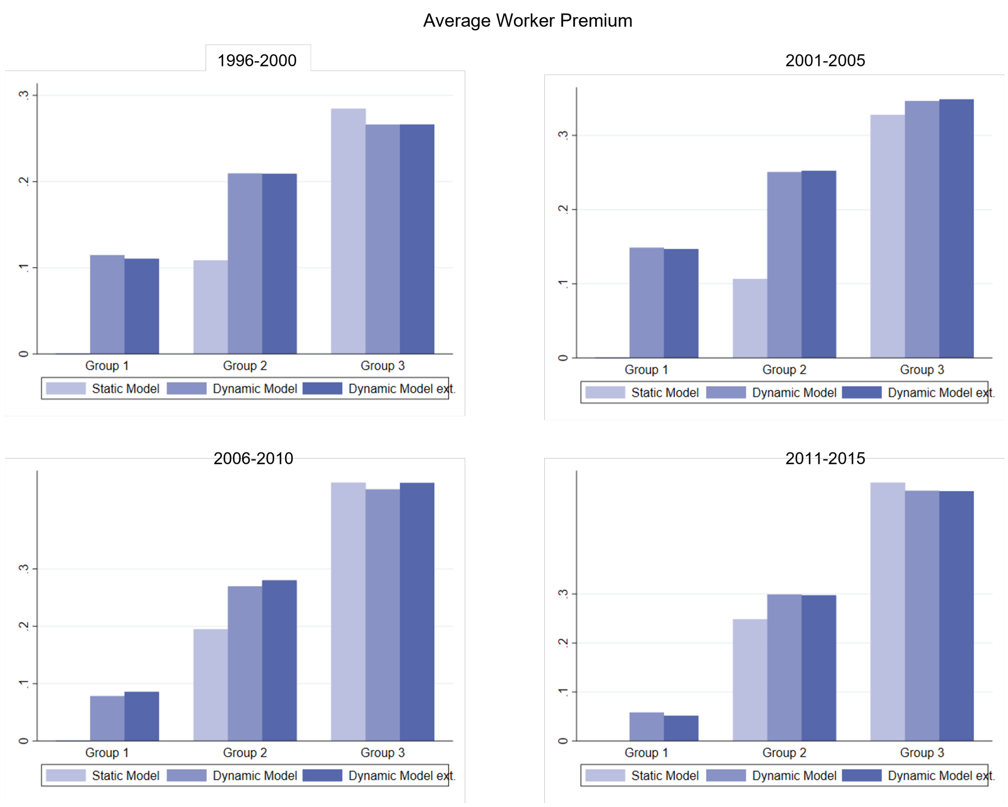
Average Estimated Premiums According to the dynamic model estimates displayed in Table 3 and Figure 9, there is a substantial part of the type-specific experience that remains portable once the worker switches to a firm in a different group. Our derivations and discussion in previous section imply that establishment static premium should not be largely affected once we account for the dynamic omitted components. On the other hand, we expect larger bias in the estimation of the worker component. In Figure 10 we show the average estimated establishment premium across firm groups (for K=3) in the static model, the baseline dynamic model (Equation 5) and the extended dynamic version (Equation 6). Consistent with the high portability of experience, results confirm that there is little bias in the firm static component.



This figure reports the average establishment fixed effect for each firm group (with K=3) for the static AKM model, the baseline dynamic specification (Equation 5) and the extended dynamic specification (Equation 6). Firms are classified into groups based on the k-means algorithm discussed in the text. Each sub-graph corresponds to a separate regression for a different sample period.

Figure 10: Average Establishment Premium - Static vs. Dynamic Models

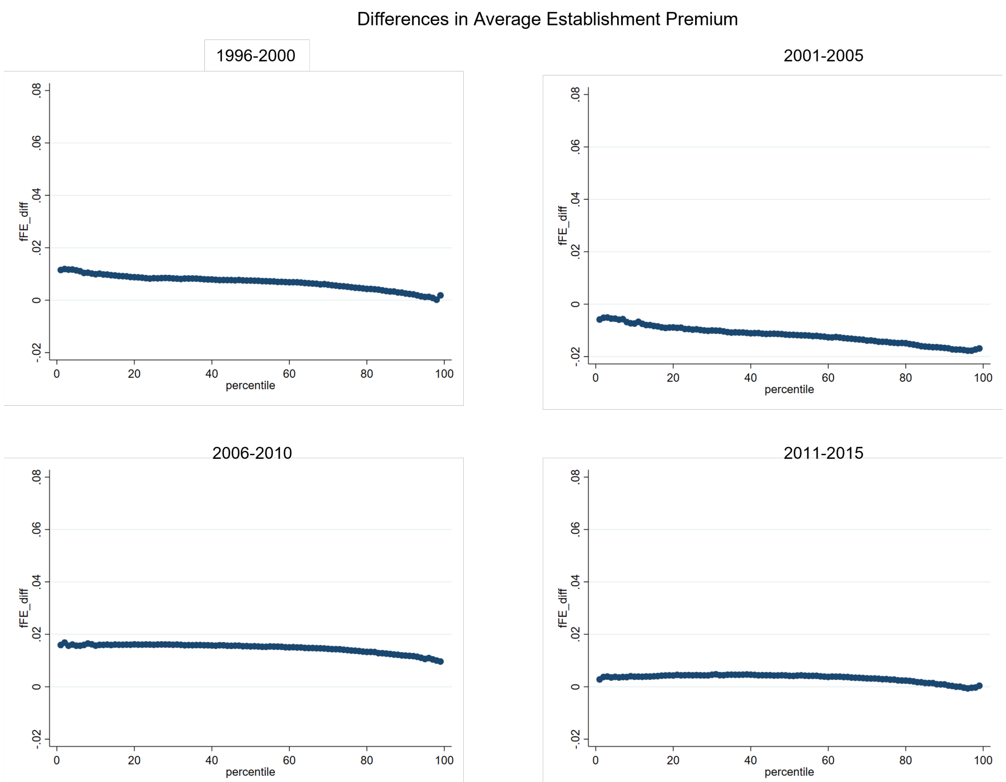
In contrast, Figure 11 shows that the average worker premiums across firm types differ substantially between the static and the dynamic model(s). This is particularly salient for the lowest wage-growth group (G=1) and to some extent for the intermediate group (G=2), while differences across models are much less pronounced for the high wage-growth group (G=3). The static model assigns larger differences in worker premium across learning groups by underestimating the worker component in the lower wage growth groups. Intuitively, the lack of wage growth identified separately by the dynamic model is assigned to a lower worker average component in the static model. Figures A3 and A4 in the Appendix show similar patterns when 5 or 10 firm groups are considered.



This figure reports the average worker fixed effect for individuals working at each firm groups (with K=3) for the static AKM model, the baseline dynamic specification (Equation 5) and the extended dynamic specification (Equation 6). Firms are classified into groups based on the k-means algorithm discussed in the text. Each sub-graph corresponds to a separate regression for a different sample period.

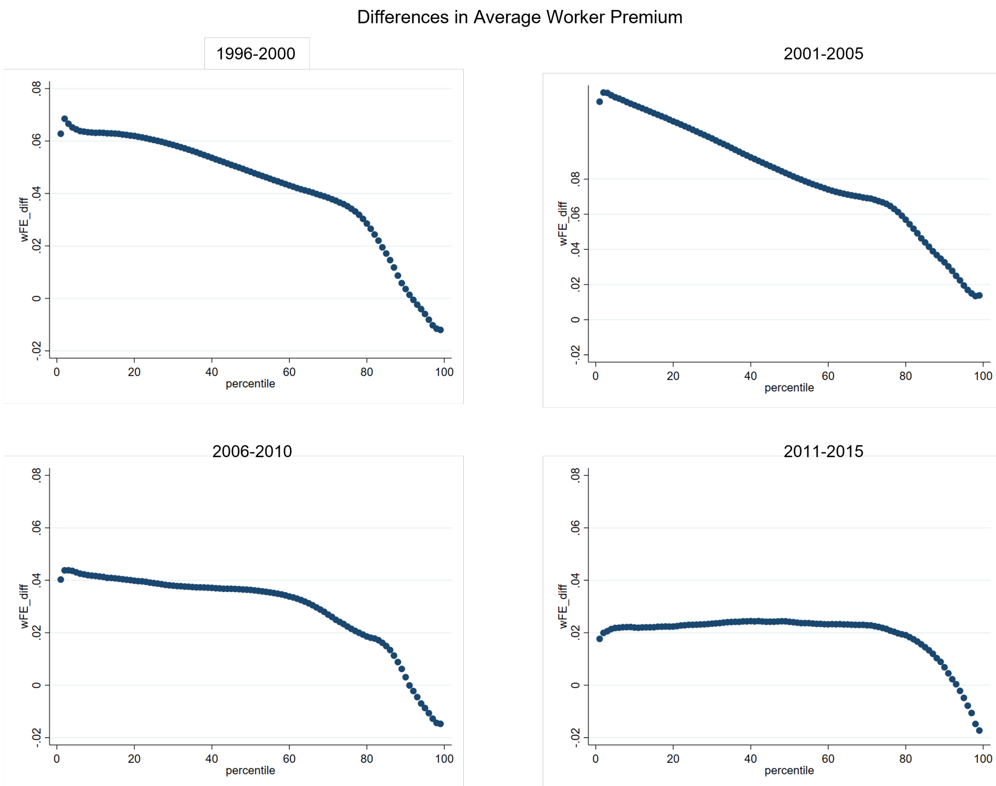
Figure 11: Average Worker Premium - Static vs. Dynamic Models

Differences in the Distribution of Estimated Premiums Although Figures 10 and 11 suggests that differences in the estimation of static premiums (specifically worker premium) are less prevalent for high wage firms/workers, we show more systematic evidence about this in Figures 12 and 13 where we plot the difference between the dynamic and static model premium estimation for each percentile of the distribution of estimated premiums (from the static model). A positive difference in a given percentile indicate that the average premium estimated by the dynamic model is higher than the average premium estimated by the static model at that percentile (of static model premium distribution). Figure 12 shows that differences in estimated establishment premium between models are small along the entire distribution (with differences being smaller for higher percentiles). On the other hand, worker premium show significant differences along the distribution, with differences shrinking only for the upper tail. The Figure reveals that the worker component is underestimated for almost all percentiles, thus the smaller average differences in group 3 observed in Figures 10 and 11 related to the fact that wage-growth and wage-levels, although correlated, do not perfectly overlap across firms. Figures A5 and A6 in the Appendix depict very similar pattern when 10 firm groups are used in the estimation of fixed effects.



This figure reports the differences between the average establishment fixed effect estimated by the static and dynamic AKM models at each percentile of the distribution of establishment fixed effects of the static model. Firms are classified into K=3 groups based on the k-means algorithm discussed in the text. Each sub-graph corresponds to a separate regression for a different sample period.

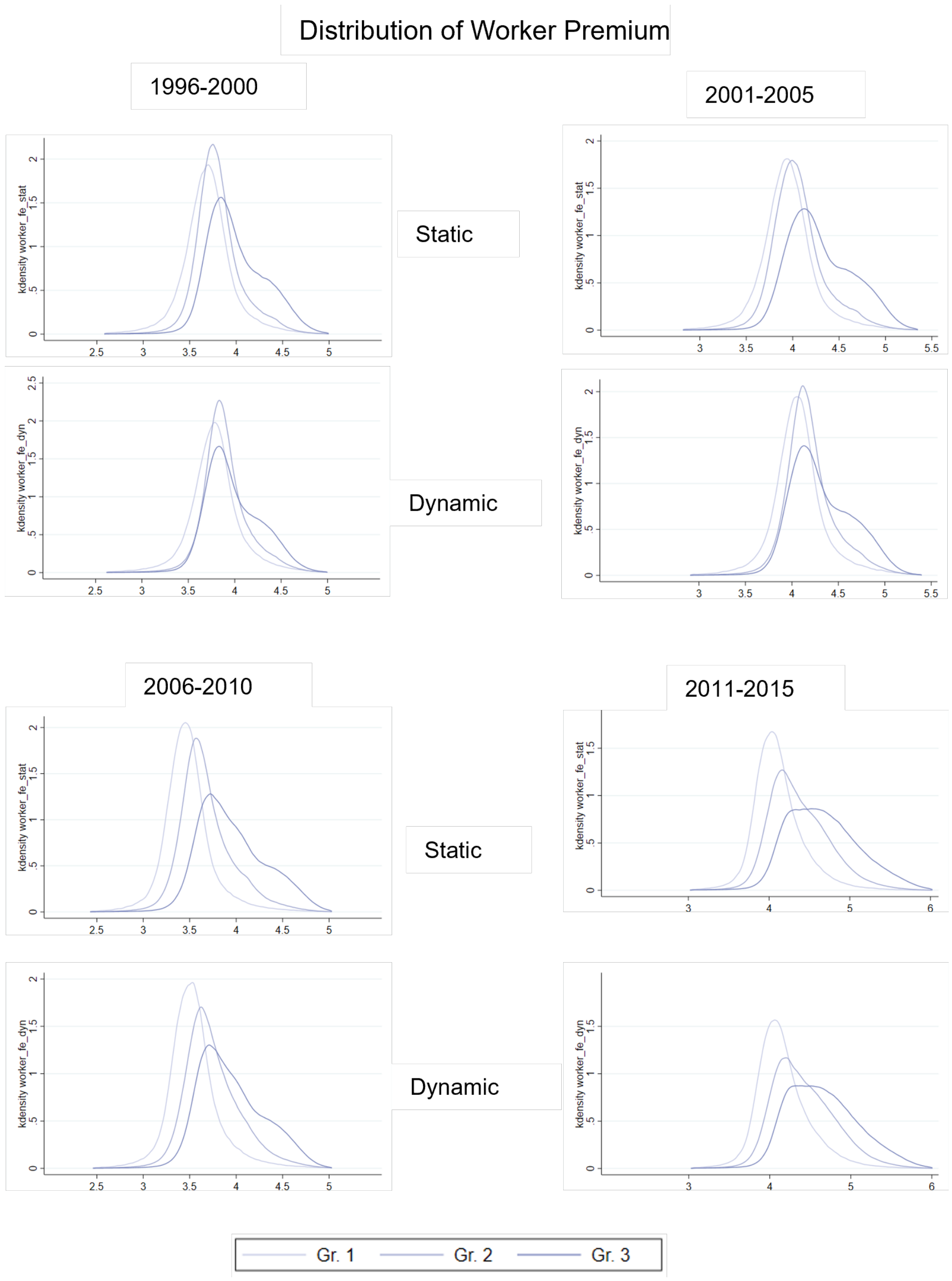
Figure 12: Differences in Estimated Establishment Premium - Static vs. Dynamic Models



This figure reports the differences between the average worker fixed effect estimated by the static and dynamic AKM models at each percentile of the distribution of worker fixed effects of the static model. Firms are classified into K=3 groups based on the k-means algorithm discussed in the text. Each sub-graph corresponds to a separate regression for a different sample period.

Figure 13: Differences in Estimated Worker Premium - Static vs. Dynamic Models

In Figure 14 we display the whole distribution of estimated worker premiums for each firm group (and K=3) for the static and the dynamic model. The Graph is also consistent with two patterns. First, the distribution of worker premiums across firm types more similar in dynamic model. Second, the static model seems to overestimate the sorting of high premium workers to high wage growth (and thus high level) firms.



This figure reports the kernel density of the distribution of worker fixed effects estimated by the static and dynamic AKM models. Firms are classified into K=3 groups based on the k-means algorithm discussed in the text. Each sub-graph corresponds to a separate regression for a different sample period.

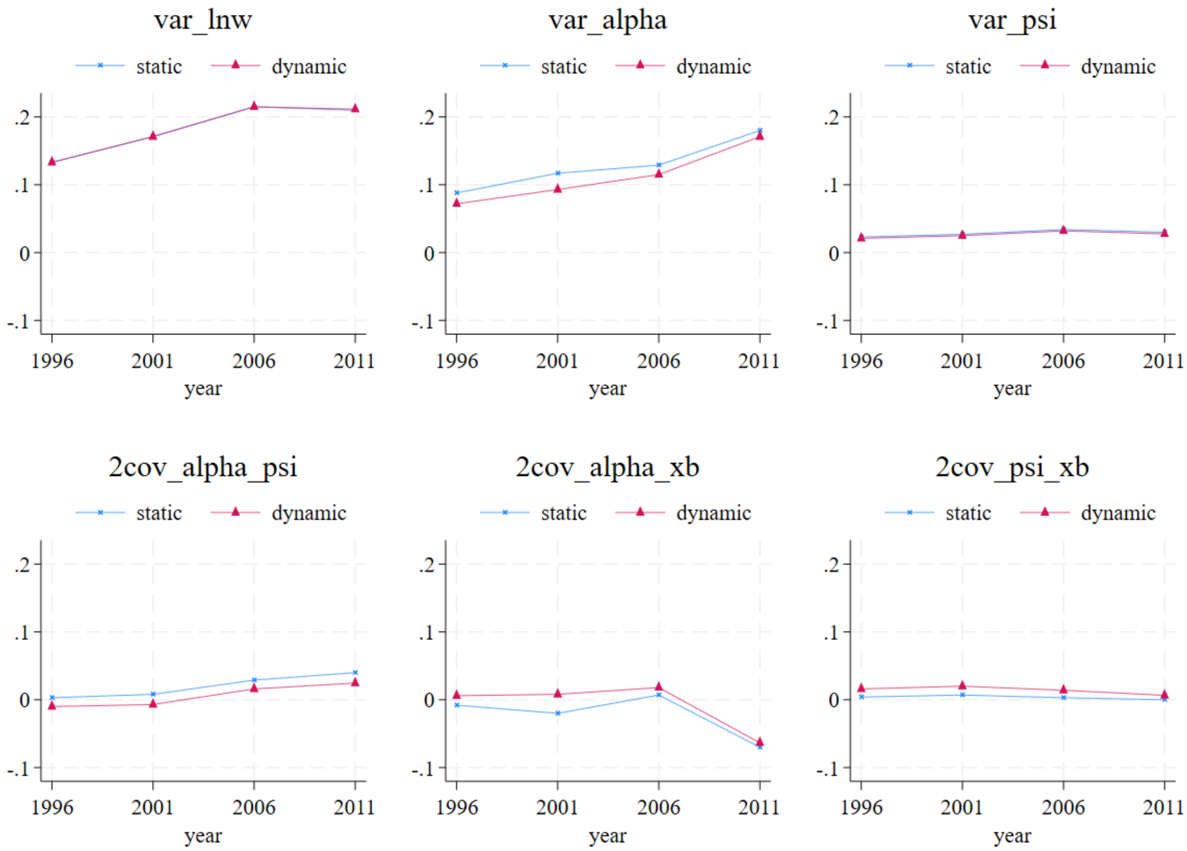
Figure 14: Distribution of Worker Premium - Static vs. Dynamic Models

6.3 Sources of Wage Heterogeneity

We finally use the different model estimates to calculate the importance of different sources of wage inequality. 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.

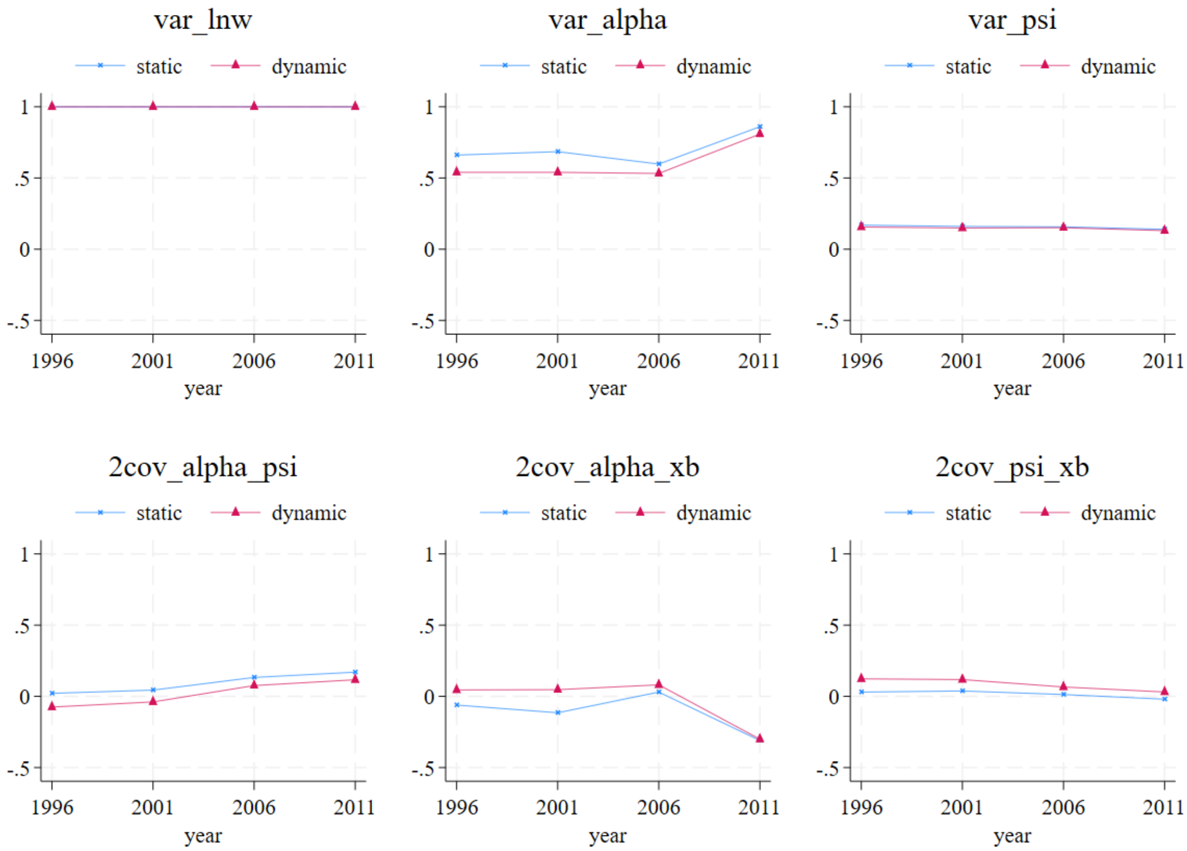
Specifically, we decompose the total wage variance into the components indicated in Equation 4, and for each one of the sub-periods in our data. In order to address the mobility bias in the estimation of wage components (Andrews, 2012) we use the heteroskedastic fixed-effects (FE-HE) bias-corrected method from Kline et al. (2020) which estimate the variance components on the leave-one-out connected set. Figure 14 presents a comparison of wage decomposition over time, contrasting the static against the dynamic model estimates. Figure 15 present the same results but components are normalized to measure the relative contribution to total wage inequality.

Results are consistent with some of the patterns discussed in previous subsections. Results indicate that the static model significantly overestimates the contribution of worker dispersion and worker-firm sorting to wage inequality. In the dynamic AKM model the contribution of worker dispersion is up to 12 percentage points lower for the first three periods (1996-2000; 2001-2005; 2006-2010) although the divergence across models is lower for the last periods. The contribution of worker-firm sorting is up to 10 percentage points lower in the dynamic model for all the periods.



This figure decompose the variance of wages into the different components from Equation 4 in the text using the static and dynamic AKM models. All models use the heteroskedastic fixed-effects bias-correction from Kline et al. (2020). Each year corresponds to a separate regression for a different sample period (which extends for four subsequent years).

Figure 15: Sources of Wage Heterogeneity - Absolute Contribution -



This figure decompose the variance of wages into the different components from Equation 4 in the text using the static and dynamic AKM models. The contribution of each component is normalized and the sum of all components is equal to one. All models use the heteroskedastic fixed-effects bias-correction from Kline et al. (2020). Each year corresponds to a separate regression for a different sample period (which extends to four subsequent years).

Figure 16: Sources of Wage Heterogeneity - Relative Contribution -

7 Conclusions

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

Our analysis exposes the shortcomings of previous studies based on the static AKM model in fully capturing the dynamics of wage progression within firms, highlighting the necessity for models that account more flexibly for how and where the experience of workers is accumulated. We show that the portability of accumulated experience across firms, coupled with the nuanced effects of worker mobility on firm-specific wage policies, are crucial determinants of wage trajectories. These findings challenge the traditional reliance on static models.

The decomposition of wage variance in this study reveals the pivotal role of dynamic factors, especially the portability of experience premiums, in shaping wage disparities. Comparing the outcomes of static and dynamic models, we identify a significant overestimation by static models of the importance of individual and (static) sorting components on wage inequality.

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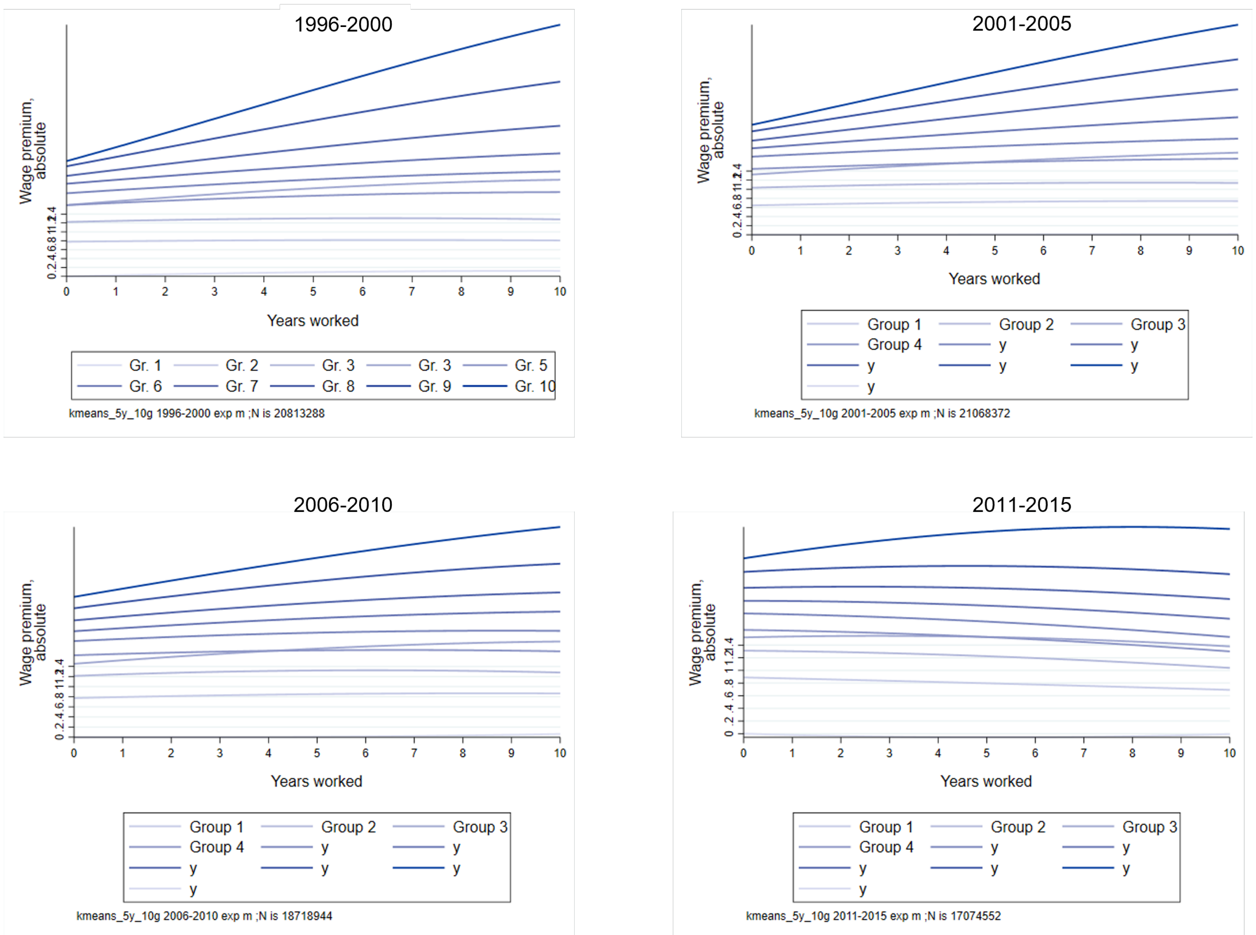
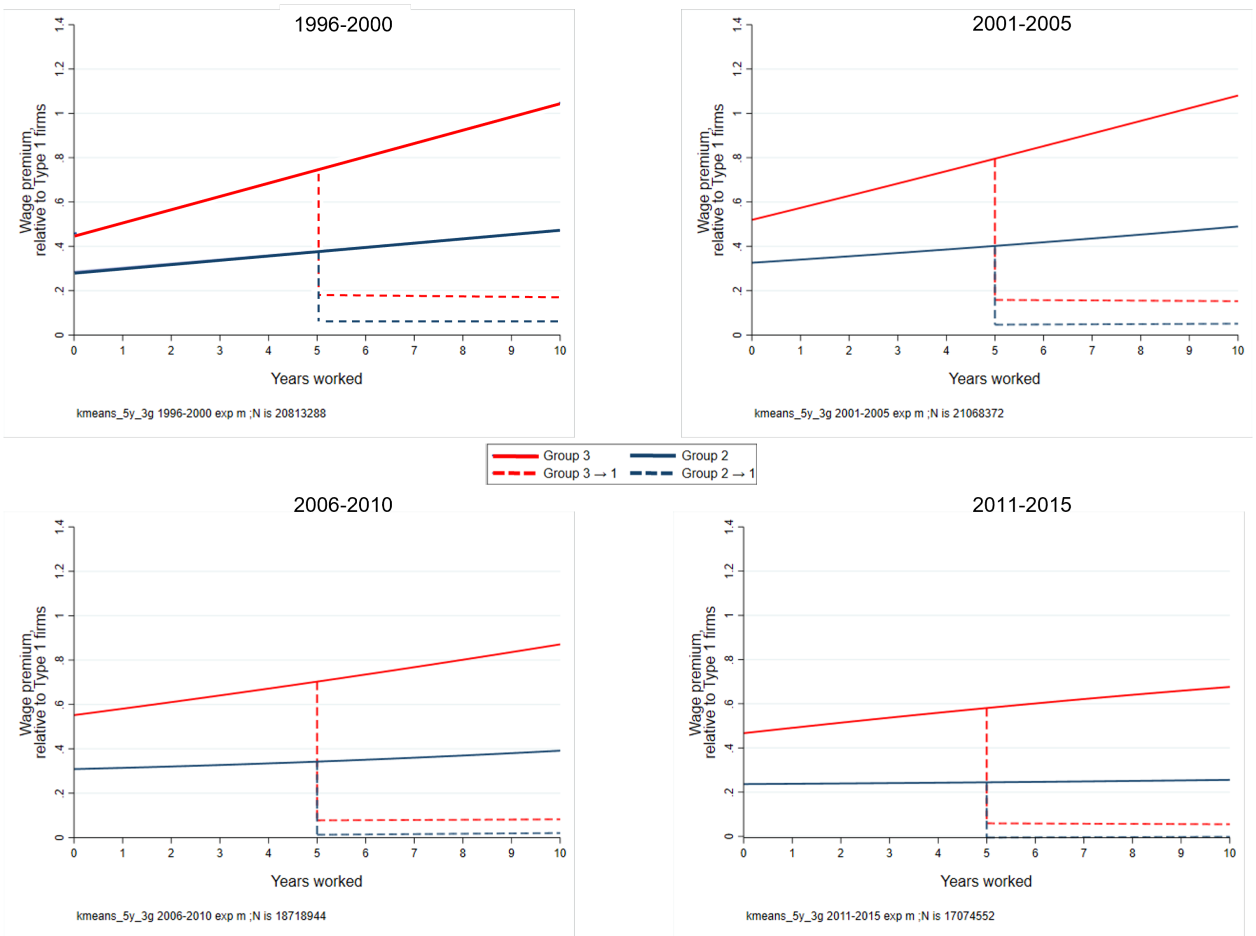
A Appendix Figures and Tables



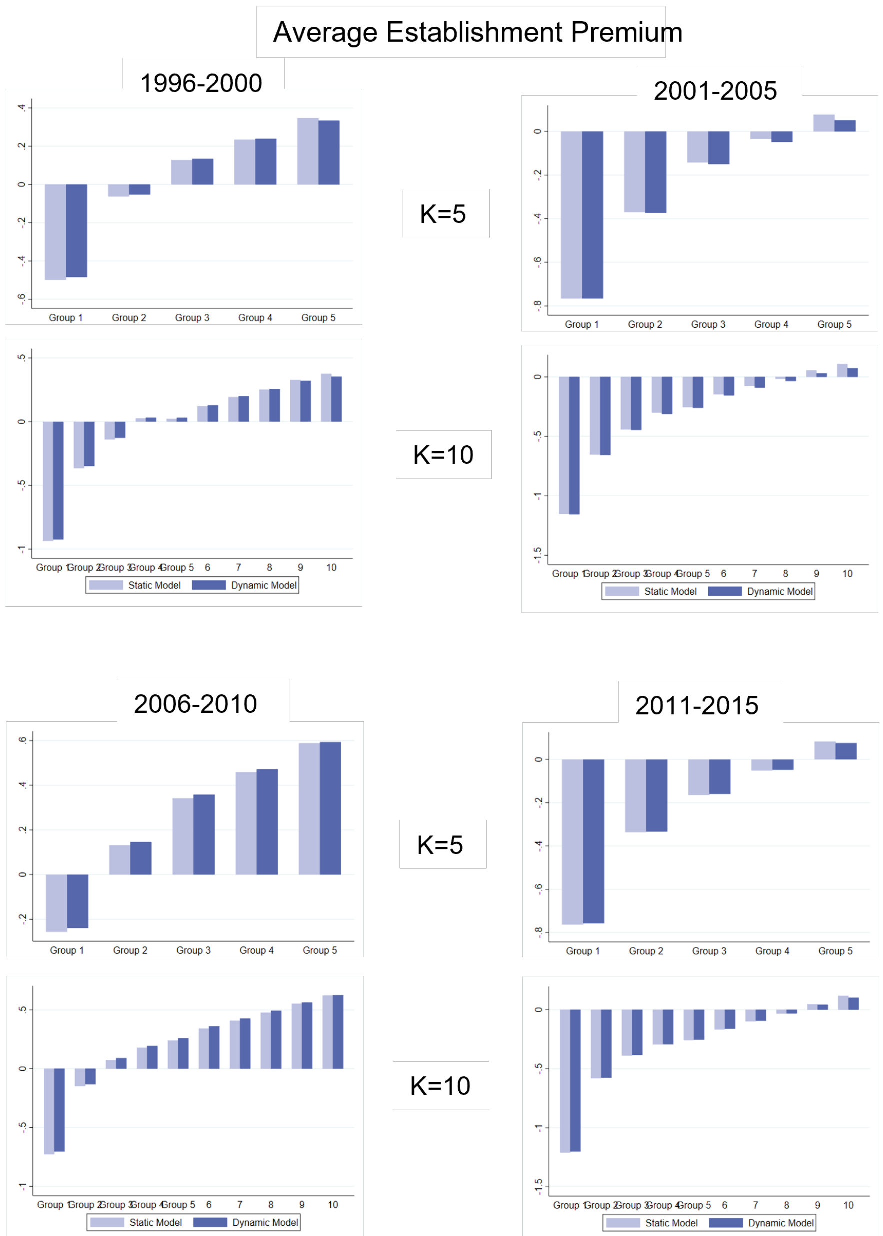
This figure illustrates the wage profiles estimated using the dynamic AKM model (Equation 6) for ten different types of firms. Firm groups estimated using the k-means algorithm described in the text. Each sub-graph corresponds to a separate regression for a different sample period.

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



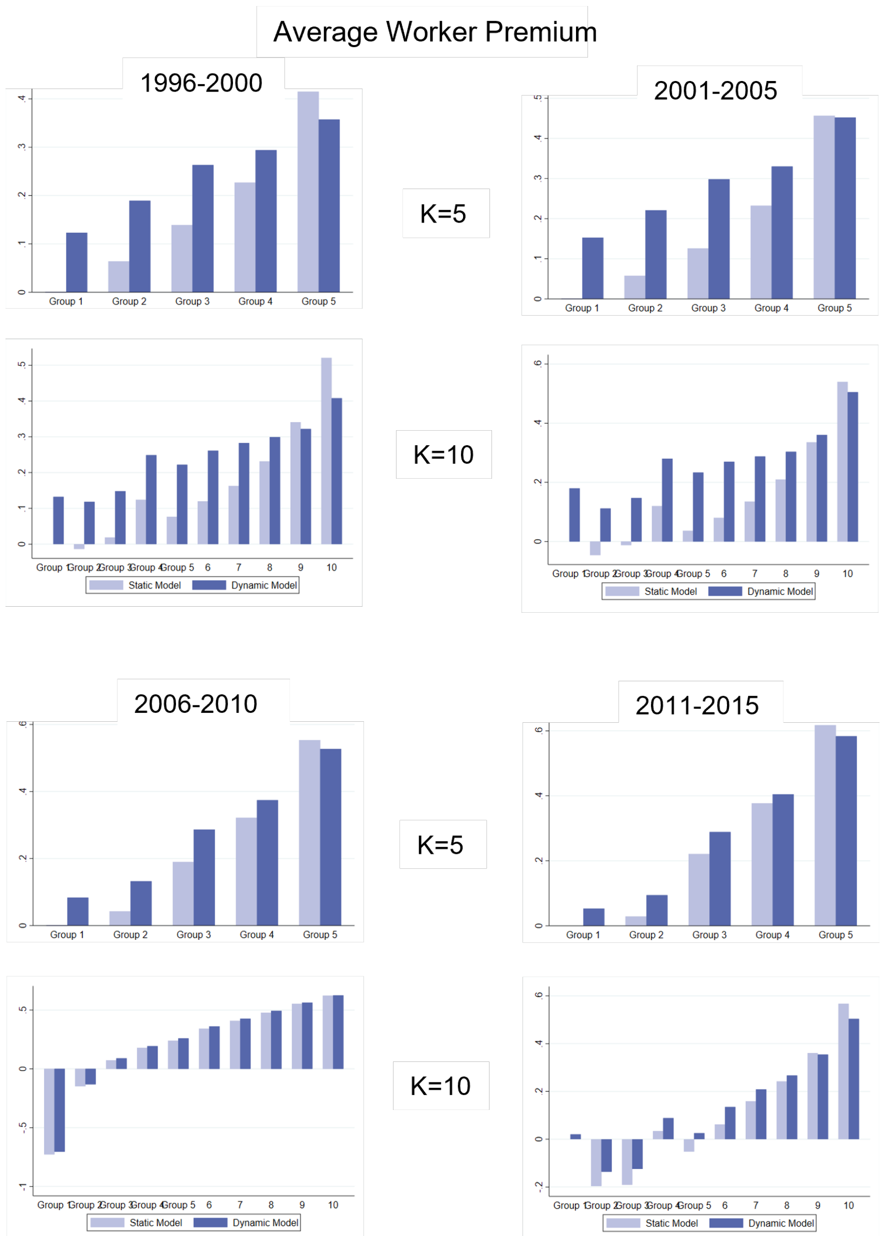
This figure illustrates the wage levels of workers in firms type-2 and type-3, relative to the omitted category (type-1) based on the Estimates of Equation 6. Groups are estimated using the k-means algorithm described in the text. The figure also displays the evolution ofwages for workers switching to a firm type-1, 5 years after working in the corresponding firm. Each sub-graph corresponds to a separate regression for a different sample period.

Figure A2: Experience Premium Relative to Non-switchers at Type-1 Firms - Levels



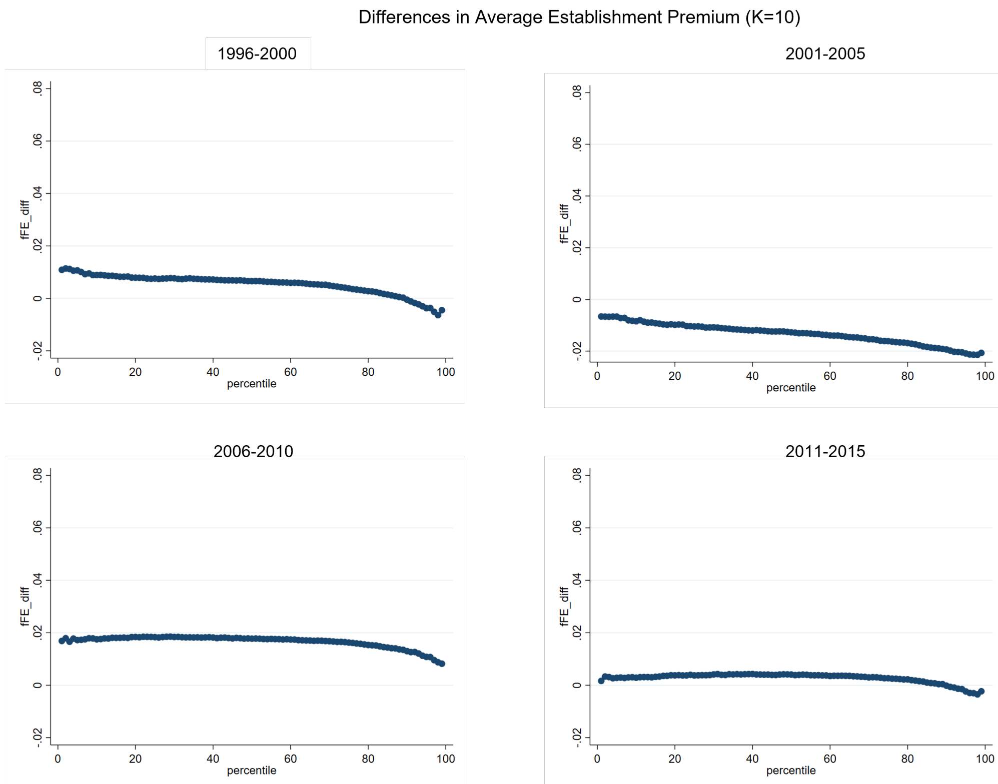
This figure reports the average establishment fixed effect for each firm group (with K=5 and K=10) for the static AKM model and the baseline dynamic specification (Equation 5). Firms are classified into groups based on the k-means algorithm discussed in the text. Each sub-graph corresponds to a separate regression for a different sample period.

Figure A3: Average Establishment Premium - Static vs. Dynamic Models - K = 5,10



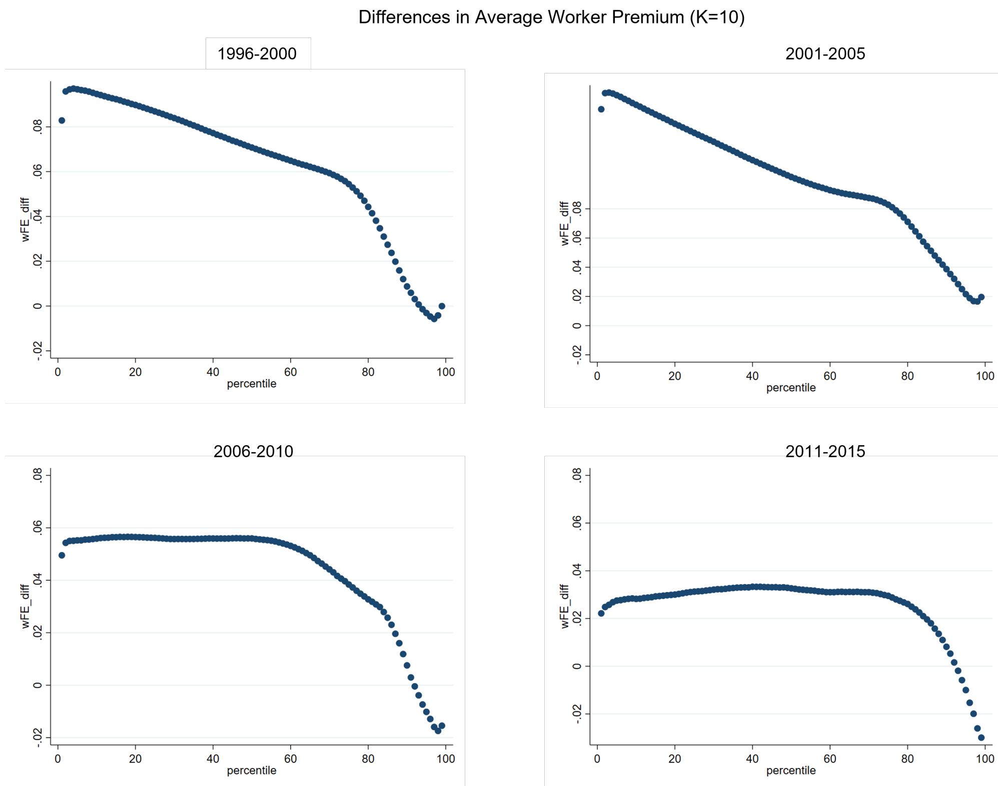
This figure reports the average worker fixed effect for individuals working at each firm groups (with K=5 and K=10) for the static AKM model and the baseline dynamic specification (Equation 5). Firms are classified into groups based on the k-means algorithm discussed in the text. Each sub-graph corresponds to a separate regression for a different sample period.

Figure A4: Average Worker Premium - Static vs. Dynamic Models - K = 5,10



This figure reports the differences between the average establishment fixed effect estimated by the static and dynamic AKM models at each percentile of the distribution of establishment fixed effects of the static model. Firms are classified into K=10 groups based on the k-means algorithm discussed in the text. Each sub-graph corresponds to a separate regression for a different sample period.

Figure A5: Differences in Estimated Establishment Premium - Static vs. Dynamic Models - K=10



This figure reports the differences between the average worker fixed effect estimated by the static and dynamic AKM models at each percentile of the distribution of worker fixed effects of the static model. Firms are classified into K=10 groups based on the k-means algorithm discussed in the text. Each sub-graph corresponds to a separate regression for a different sample period.

Figure A6: Differences in Estimated Worker Premium - Static vs. Dynamic Models - K=10