Workers, Workplaces, Sorting, and Wage Dispersion in Mexico

Jorge Pérez Pérez* José G. Nuño-Ledesma†

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Abstract

Between 2004 and 2018, the spread of wages in Mexico's private labor sector remained stable. Nonetheless, the underlying factors behind salary dispersion underwent significant shifts nationally and regionally. To uncover these changes, we analyze a matched employer-employee dataset comprising the near-universe of Mexico's formal workforce. We estimate log wage models with worker and workplace fixed effects capturing over 90% of wage variation. We then decompose national and regional earnings dispersions into worker, workplace and assortative matching components. At the national level, we find that sorting increased its importance over time, from explaining 16% of total wage variance to 19% by the end of the period. Worker- and workplace-specific factors contributed between 35% to 42% and 33% to 38% to the total spread of remunerations, respectively. However, while worker-level factors were the main contributors to salary variability in the 2004-2008 period, workplace factors became the more important force in the 2014-2018 time segment. The influence of workplace factors on wage dispersion correlates negatively with regional economic development: it is lowest in the North, Mexico's most-developed region, and largest in the South, the country's least-prosperous region.

Keywords: assortative matching, Mexico, regional development, wage dispersion, workplace wage premia

JEL Codes: J21, J31, R23, O15, O54

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*Banco de México. Corresponding author. Email: jorgepp@banxico.org.mx.

†University of Guelph. Email: jnuno@uoguelph.ca.

1 Introduction

In most countries, wage dispersion has increased over the last decades, widening salary discrepancies within and between cities, regions, and industries. These earnings gaps have attracted the attention of researchers, policymakers, and the public at large (Katz et al. 1999; Acemoglu and Autor 2011). Consequently, some countries have implemented measures to attenuate the adverse effects of growing salary disparities between communities (Kline and Moretti 2014). At the same time, research investigating reasons behind the expansion of wage divergences is growing. In particular, there has been recent interest in using two-way fixed effects models *à la* Abowd, Kramarz, and Margolis (henceforth AKM; Abowd et al. 1999) to decompose wage variance into components associated with worker-level characteristics, average workplace-level wage premia, and assortative matching (Card et al. 2023; Dauth et al. 2022; De la Roca and Puga 2017).[1] While there is a substantial literature examining wage differences across regions and urban wage premia (D'Costa and Overman 2014, for example), less attention has been devoted to wage differences within regions. We describe recent trends of wage dispersion in Mexican regions.

Recent work documents that establishments and workers contributions to total earnings variance are different between developed and developing countries. In particular, average workplace premia play a more influential role in developing economies (Alvarez et al. 2018; Gerard et al. 2021; OECD 2021; Frías et al. 2022; Bassier 2023; Diallo et al. 2022). Within this context, we set to find out whether similar development-specific trends may exist within Mexico. We estimate AKM models to estimate how the contributions to wage variance attributable to worker- and workplace-level factors, as well as their covariance evolved between 2004 and 2018. We then use these estimates to perform variance decomposition exercises at national and regional levels for 2004-2008, 2009-2013, and 2014-2018.

We use an administrative dataset with matched employer-employee observations covering more than 80% of formal workers in Mexico between 2004 and 2018. The data allow us to use panel data methods to achieve our goals. The estimated AKM models offer a good approximation of the determinants of wages, explaining over 90% of the variation in wages in all regions. Our analysis unearths interesting dynamics. We begin by noting that wage dispersion in Mexico and its regions

[1] Throughout the document, we use the terms "firm" and "workplace;" "worker" and "person," and "sorting" and "assortative matching" interchangeably.

remained relatively constant in this period, which is surprising in an international context marked by rising wage discrepancies. In contrast with this stability, we show that the contributions to total wage spread attributable to worker-level factors, average workplace wage premia, and their covariance exhibited significant changes. In 2004-2008, worker-level factors contributed the most to wage variance. By 2014-2018, workplace-level wage premia had become the main force propelling wage dispersion in Mexico and its regions. In concordance with previous work, we find that average workplace-level factors explain a larger share of earnings variance compared to developed countries. Although comparable to other developing economies, the ability of workplaces to set wages in Mexico is substantially stronger compared to other OECD members (OECD 2021).

There are notable differences in economic performance between the relatively thriving North, the moderately successful Center and Center-North regions, and the substantially less affluent South. This regional heterogeneity makes Mexico a good setting to examine differences in wage variance determinants across regions. Some examples of heterogeneity between regions include: different industry specialization, varying importance of informality in local markets, and differences in the evolution of the formal employment share (Alcaraz et al. 2015; Chávez-Martín del Campo and García Loredo 2015; Rangel González and Llamosas-Rosas 2021; Juárez-Torres et al. 2022). In addition, labor markets in the Northern, Central-Northern, and Central regions exhibit a high degree of integration between them and move in concert with national employment trends. In contrast, markets in the South do not share the same underlying economic cycles, and shocks stemming from this area tend not to propagate to the rest of the country (Delajara 2011; Delajara 2013).[2]

We uncover a negative relationship between regional economic progress and the importance of workplace factors in determining wage dispersion in the private formal labor market. Compared to the rest of the country, establishment-level wage premia play a more prominent role in forming wage variance in the South, the country's least developed region. In the relatively prosperous

[2]We use the regional classification defined by the Mexican Central Bank. The regions cluster states according to geographical proximity and economic similarity in indicators such as employment, the prevalence of the agricultural, manufacturing, and tourism sectors, and level of retail sales, among others (Banco de México 2011). The regions contain the following Mexican states: the *North* includes Baja California, Chihuahua, Coahuila, Nuevo León, Sonora, and Tamaulipas; the *Center-North* gathers Baja California Sur, Aguascalientes, Colima, Durango, Jalisco, Michoacán, Nayarit, San Luis Potosí, Sinaloa and Zacatecas; the *Center* contains by Mexico City, Estado de México, Guanajuato, Hidalgo, Morelos, Puebla, Querétaro and Tlaxcala; the *South* includes Campeche, Chiapas, Guerrero, Oaxaca, Quintana Roo, Tabasco, Veracruz, and Yucatán.

North, workplace-level factors' contribution to earnings dispersion is the lowest. These findings provide further evidence supporting an inverse relationship between economic prosperity and the importance of workplace factors in shaping earnings variance. Lastly, we also encounter evidence indicating that, over time, assortative matching explains an increasing proportion of the salary variance. To our knowledge, we provide the first decomposition of wage variance into workplace and worker factors in Mexican regions and offer the first empirical study documenting a negative relationship between within-country economic development and the relative importance of workplace-level factors in forming wage dispersion.

The rest of the paper proceeds as follows. In the next section, we survey the relevant literature. Section 3 describes the dataset we use. In part 4, we offer some facts about wage inequality for formal workers in Mexico using our dataset. We follow in section 5 by outlining the methodology behind our worker and workplace fixed effects models. Section 6 shows our results about the contribution of workers, workplaces, and assortative matching on wage variance in Mexico and discusses regional differences. Last, section 7 concludes.

2 Relevant Literature

Much of the existing literature explains the sustained rise in local wage disparities through productivity gaps between high- and low-skilled workers (e.g., Katz and Murphy 1992; Juhn et al. 1993; Goldin and Katz 2010). However, there is a workplace component to wage inequality because some pay higher wages than others to equally skilled employees (Krueger and Summers 1988; Van Reenen 1996; Card et al. 2013). This workplace-level contributor to compensation variation can be due to assortative matching; a phenomenon that may emerge in markets with worker and workplace heterogeneity, wherein the most skill-intensive (and productive) workplaces hire highly skilled workers. When worker and workplace quality are complements in production, productivity and remunerations may increase with assortative matching. This pairing process can aggravate geographical disparities because, for example, the regions with a prevalence of already unproductive plants may see their pool of highly productive candidates drained. There is evidence that sorting is an important force in determining the wage distribution in several countries (Card et al. 2013; Card et al. 2018; Torres et al. 2018; Dauth et al. 2022). We complement this literature.

Our work speaks to examinations of wage inequality in Latin America. (Esquivel et al. 2010; Lustig et al. 2013; Campos-Vazquez and Lustig 2017; Puggioni et al. 2022). Esquivel et al. (2010) and Lustig et al. (2013) find that income inequality decreased in the period from the mid-1990s to the mid- 2000s, mainly due to a reduction in the wage differential between more educated and less educated workers. In a related vein, Messina and Silva (2019) track an inverse U-shaped evolution of wage inequality in Latin America between 1995 and 2015. They note the important contribution to this pattern of falling wage dispersion across workplaces in some Latin American countries, including Brazil and Ecuador. This finding aligns with our conclusion regarding the importance of workplace factors in explaining wage variance in Mexico.

Closely related to our work, Puggioni et al. (2022) use non-parametric methods and the same dataset we rely on to provide a detailed description of the distribution of log-earnings of formal workers in Mexico, with particular attention to its skewness and kurtosis; offer a panoramic view of the recent dynamics of wage variability, and describe the effect of transitions from and to the formal sector on the earnings of workers. We complement their efforts by taking a different approach when studying wage variance. Instead of describing the wage distribution's higher moments, we decompose its variance into components that can be ascribed to the fixed characteristics of workers and their workplaces.

A related strand of research studies how worker composition and segregation within workplaces affects wage inequality (Lopes de Melo 2018; Song et al. 2018). An important insight from these works is that workers' earnings may vary non-monotonically with respect to the workplace type. Segregation within workplaces would result in non-linearities in the log-wage equation. The main implication for our research is that the effects retrieved from our log-linear earnings model may not admit a structural interpretation, a point already implied by Abowd et al. (1999).

We contribute to the literature on wage disparities and assortative matching in three ways. First, we complement efforts to document wage disparities within countries (Combes et al. 2008; Rice et al. 2006; Boeri et al. 2021; Gerard et al. 2021; Dauth et al. 2022). Second, we expand our understanding of the sources of wage disparities in developing countries. Third, we supplement previous work examining wage variance trends in Latin American countries culturally and economically similar to Mexico (Alvarez et al. 2018; Gerard et al. 2021). These investigations tend to report country-wide patterns resulting from wage-setting policies and non-market non-skill-based sorting, such as discrimination. To our knowledge, we provide the first study detailing the interplay between wage disparities, sorting, and worker- and workplace-specific factors in Mexico.

We also contribute to a growing literature using administrative data to study labor markets in developing countries. AKM models require detailed information on job and wage histories. This demanding data requirement is one of the reasons why the literature estimates AKM models primarily for countries with rich and reliable administrative data, which tend to be highly developed (e.g., Abowd et al. 1999; Gruetter and Lalive 2009; Card et al. 2013; Dauth et al. 2022). The closest paper to ours within the strand of work using governmental data to study developing labor markets is Frías et al. (2022), which applies the same framework we use to a similar dataset but to different ends. They investigate the relationship between increased international trade and wage premia in Mexico. In contrast, we are interested in scrutinizing internal sources of variability in remunerations (as opposed to external factors such as out-of-country demand) and documenting their effect on overall salary inequality.

3 Data

We use social security records from *Instituto Mexicano del Seguro Social* (IMSS), a Mexican governmental organization that assists public health, pension management, and social security. All salaried workers employed in the private sector must register with IMSS by law. According to estimates using the National Survey of Occupation and Employment (ENOE), 83% of the formal workforce in 2022 was registered in IMSS. Self-employed persons can register with IMSS; if so, they can access some parts of the social security system. By default, self-employed workers register with the equivalent of one legal minimum salary. Records from self-employed workers represent around 0.1% of the complete IMSS database. If a worker reports more than one employment in the same workplace, we keep the job with the highest reported wage. Only 2.5% of workers reported having jobs in more than one workplace in December 2018.

The IMSS social security information is published monthly. We use records for the period between November 2004 and December 2018.[3] The number of workers in the database was 12.8

[3]We end our analysis in 2018 because the period from 2019 to 2022 involves substantial changes in Mexico's labor market because of the onset of the COVID-19 pandemic and significant increases in the minimum wage. Nevertheless, we provide some descriptive statistics including the period from 2019 to 2022 in Appendix Figures B.1 and B.2.

million in November 2004 and 20.1 million by December 2018. Our wage variable of interest is the daily taxable income.[4] We also use information on the period of employment, gender, and birth year. Wages over 25 UMAs ("units of measure and update") are top-coded.[5]

Our data lacks key variables that would enhance the accuracy of our analysis. For example, IMSS does not report schooling, education, or on-the-job training information. Similarly, our dataset does not have information on the exact number of hours worked by a given employee; consequently, we cannot classify workers as employed either full or part-time. IMSS does not collect information regarding workers in the informal economy. Informal employment is high in Mexico, representing around 55% of total employment in 2018 (INEGI 2018). Therefore, the dataset we use excludes a substantial number of workers.[6]

IMSS uses the *registro patronal* (employer registry number) as a workplace identifier. The *registro* corresponds to an employer but not a physical location. For example, workers operating in a single plant can work for more than one employer as identified by their *registro patronal*.[7] Strictly speaking, we do not report plant effects as estimated by previous research leveraging the AKM methodology. In our study, the "workplace" contributor to wage variability is the "*registro patronal* component" of wage variance.

Descriptive statistics. Table 1 presents some IMSS wage data characteristics for selected years. For any given year, our sample includes 73 to 113 million wage observations for men 25-54 years old and 39 to 69 million female wage observations for the same age range. Column (4) of the Table shows that, compared to 2005, the average real daily wage for prime-age men fell by 0.7% from 2009 to 2014, then rose by 1.5% by 2018. These changes were accompanied by a modest increase in the spread of earned wages between 2005 to 2018, as shown in column (5). Women's average real wages increased steadily, from about 326 pesos in 2005 to about 345 pesos a day in 2018. The standard deviation of women's salaries also has modest growth over time.

[4]This variable includes various forms of compensation other than salary (e.g., paid vacations and bonuses) while excluding additional non-taxable payments.

[5]For 2018, this limit was 2,015 MXN daily, about 102 USD.

[6]Information on workers in the public sector is not included in the IMSS database because a separate institution manages their social security.

[7]The identifiers of the *registro patronal* we use are anonymized. We cannot precisely identify individual workers or workplaces within the dataset. The Mexican Central Bank's EconLab (our data supplier) constructs the masked identifiers before providing the dataset. Using the anonymized identifiers instead of the original *registros* is inconsequential to our econometric analysis and results.

Throughout the rest of the document, we aim to document the roles that average workplace-level remuneration premia, worker-specific traits, and the sorting of workers and workplaces according to their productivity play in determining these trends in wage variance.

Table 1: Descriptive Statistics: Prime-age Workers, National Level

				Real wage		
	(1)	(2)	(3)	(4)	(5)	(6)
	Observations	Workers	Firms	Mean	Std. dev	Percent censored
Workers:						
Panel A. Men						
2005	73,855,547	7,859,299	736,700	394.575	406.256	2.336
2009	80,069,659	8,537,478	730,716	394.594	403.065	2.359
2014	98,566,773	10,164,871	756,699	391.698	407.856	2.300
2018	113,516,335	11,631,939	847,644	397.765	410.689	2.626
Panel B. Women						
2005	39,579,722	4,135,996	538,141	326.635	330.534	0.933
2009	46,347,336	4,831,194	580,715	332.782	336.956	1.044
2014	57,801,647	5,887,757	620,835	339.536	351.473	1.158
2018	69,681,317	7,168,224	701,385	345.607	355.114	1.455
Workplaces:						
Panel C. Small (one to five workers)						
2005	12,382,829	1,630,742	666,940	162.421	153.811	-
2009	12,383,348	1,604,428	649,718	165.101	162.509	-
2014	12,546,682	1,642,327	637,418	163.765	176.774	-
2018	14,184,631	1,857,317	714,223	167.514	188.636	-
Panel D. Medium (6 to 50 workers)						
2005	29,724,426	3,716,913	194,960	264.179	281.003	-
2009	32,710,175	4,038,355	210,079	266.053	283.905	-
2014	37,605,930	4,687,221	239,738	260.780	289.614	-
2018	42,133,610	5,345,985	268,394	263.412	298.941	-
Panel E. Large (more than 50 workers)						
2005	71,328,014	7,539,567	28,027	453.819	421.866	-
2009	81,323,472	8,585,684	32,749	448.240	416.739	-
2014	106,215,808	11,033,376	41,130	439.039	419.706	-
2018	126,879,411	13,332,484	47,674	441.733	418.222	-

Source: Authors' calculations using IMSS data. Observations correspond to the sum of all the monthly observations in a year. Real wages using prices of July 2018. Percent censored is the percentage of observations with wages exactly equal to the upper wage limit of 25 minimum wages or UMAs.

Panels C, D, and E of Table 1 show the number of firms in our dataset by number of workers. Although most workplaces in our sample employ less than six individuals, the bulk of employment is concentrated in larger firms. Small firms pay wages that are about half of the average wage in the sample.

4 Stylized Facts About the Distribution of Wages in Mexico

Before outlining the methodology we employ to decompose the total dispersion of formal earnings in Mexico, we describe overall trends in the wage distribution. Figure 1 exhibits deviations of percentiles of real daily log-wages from values of the same percentiles in 2010 for males between the ages of 25 and 54 (prime age). From 2006 to 2010, wages fell in real terms in all the percentiles shown, albeit for the 90th percentile the decrease was small. From 2010 to 2018, there were further real wage losses at the bottom of the distribution in the 20th percentile, with wage compression in the left tail. The 10th percentile does not decrease as much because of the presence of the minimum wage.[8]

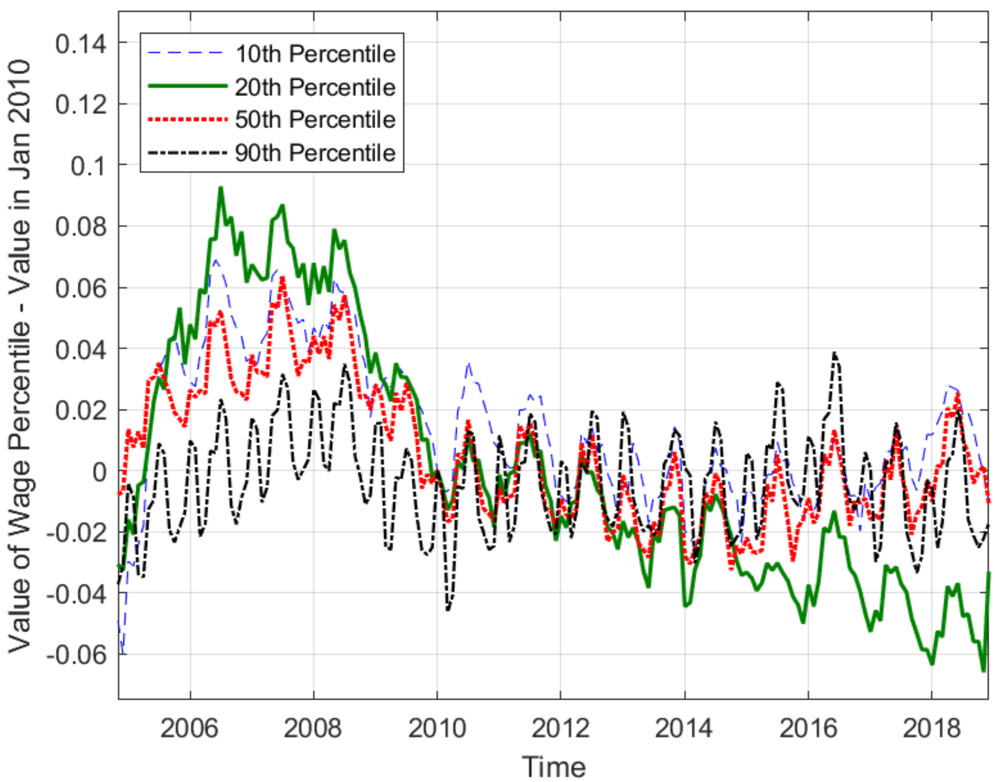
Figure 2 shows the spread of real daily wages for prime-aged men. We display the standard deviation of log wages and the normalized gaps between chosen percentiles. These normalized gaps provide an adjusted measure of wage disparity, scaling the raw gaps by the equivalent gaps in a standard normal distribution. If the log wages were distributed normally, all lines on the graph would overlap. This is because, under the assumption of normality, the standardized percentile gaps would coincide with the standard deviation of the distribution. To put it another way, lines representing the disparity in earnings between the 10th and 90th or the 50th and 90th percentiles would coincide with the line showcasing the standard deviation.

Figure 2 suggests a departure from a normal wage distribution. Notably, the normalized 90-50 gap is positioned well above the line representing the standard deviation, indicating a more pronounced wage disparity between the median and the 90th percentile than would be expected under a normal distribution. This observation is a testament to high wage dispersion in the upper half of the wage distribution for prime-aged men.

Notwithstanding the sustained fall of real wages across most earning percentiles documented

[8] Figure B.1, panel (b) in the Appendix shows that these patterns changed from 2019 to 2022 due to minimum wage changes and the onset of the COVID-19 health emergency. This latest period shows wage compression attributed particularly to increases in the lower wage percentiles. In the decade before 2019, annual increments in the minimum wage hovered around 4%. Between 2019 and 2022, the average yearly increment was 18%. These relatively sharper increments in minimum wage can lead to less dispersion in the worker-level wage determinants for the lower tail of the wage distribution.

Figure 1: Trends in Percentiles of Log Wages for Prime-age Men



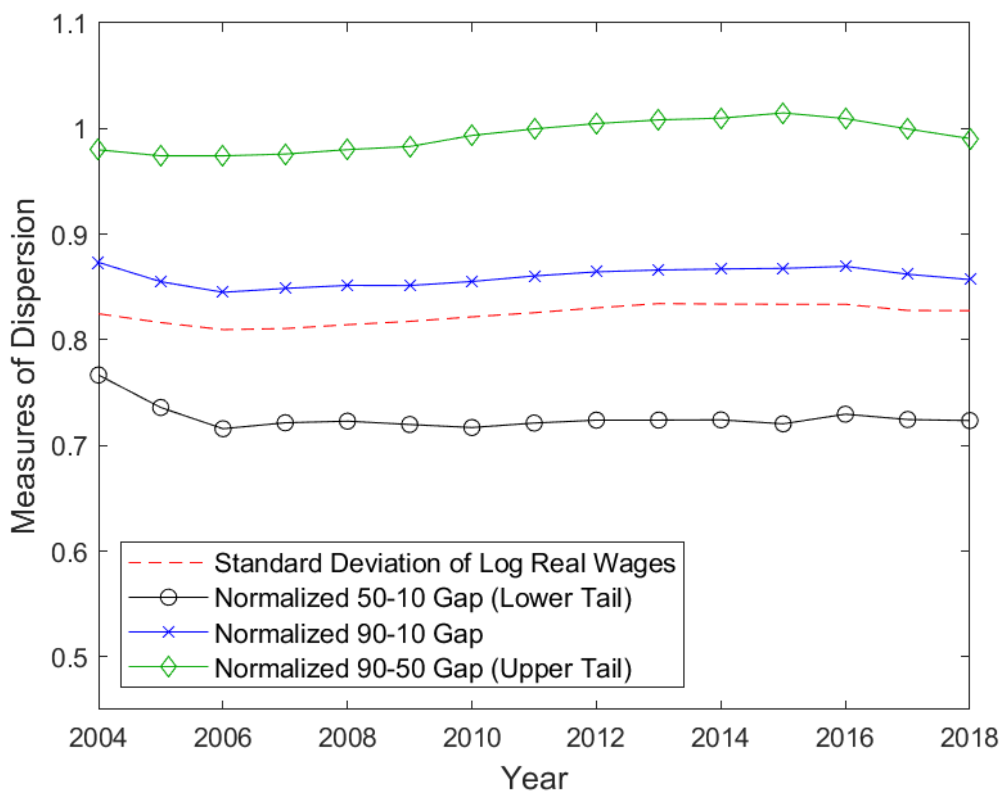
Source: Authors' calculations using IMSS data. The lines depict the values of the 10th, 20th, 50th and 90th percentile of the wages of men 25-54 years old, relative to the values of these percentiles in January of 2010.

in Figure 1 and small changes in lower- and upper-tail wage dispersion, Figure 2 visually demonstrates that, perhaps surprisingly, overall earnings dispersion in Mexico remained relatively immobile, even though differences in levels between the normalized gaps of the lower and upper tails remained significant. Thus, the first notable stylized fact regarding Mexico's recent wage dynamics is a remarkably stable earnings dispersion. As we discuss next, this feature reappears in the different subnational regions.

Figures 3 and 4 show Mexico and its geographical regions, and the regional equivalents to Figure 2. Although the overall trends are similar in the country's sub-regions, wage dispersion as measured by the standard deviation is higher in the Center and South. This standard deviation is steady for all regions in the sample periods, except for the South. There, it decreases from 2014 to 2018. Lower-tail inequality decreased in the South in the same period. Together, Figures 2 and 4 show that wage distributions at the national and regional levels have remained remarkably stable. This stylized fact contrasts with findings in other contexts, where similar metrics of wage inequality exhibit consistently increasing trends. [9]

[9]For example, graphs in Card et al. (2013) equivalent to our Figures 2 and 4 show an increasing growth rate of wage dispersion among full-time male workers in West Germany between 1985 and 2009, with an acceleration in the rate of growth starting in 1996.

Figure 2: Upper-Tail, Lower-Tail and Overall Wage Inequality Trends for Prime-Age Men, National Level



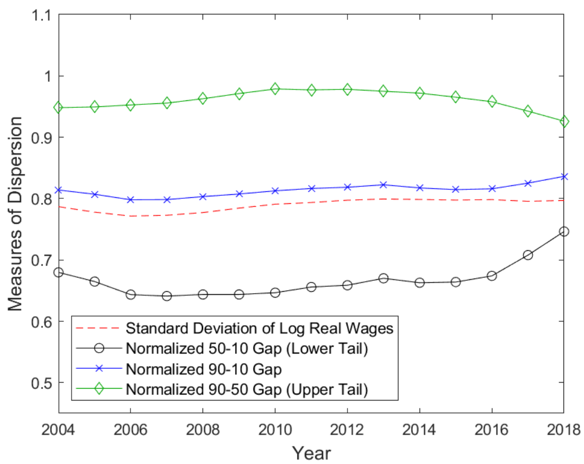
Source: Authors' calculations using IMSS data. Normalized percentile gaps are differences in percentiles divided by the corresponding differences in percentiles of a standard normal variable. For example, the 90th-10th gap is divided by $\Phi^{-1}(0.9) - \Phi^{-1}(0.1)$, where $\Phi(\cdot)$ stands for the standard normal distribution function.

Figure 3: Mexico and its Geographical Regions

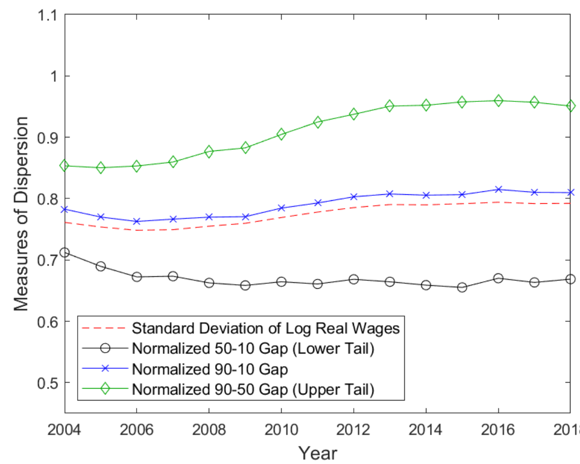
Source: Author's illustration using information from Banco de México (2011).

Figure 4: Upper-Tail, Lower-Tail and Overall Wage Inequality Trends for Prime-Age Men, Regional Level

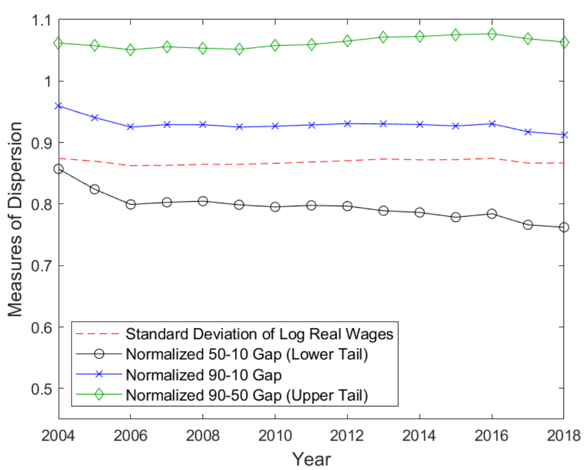
(a) North



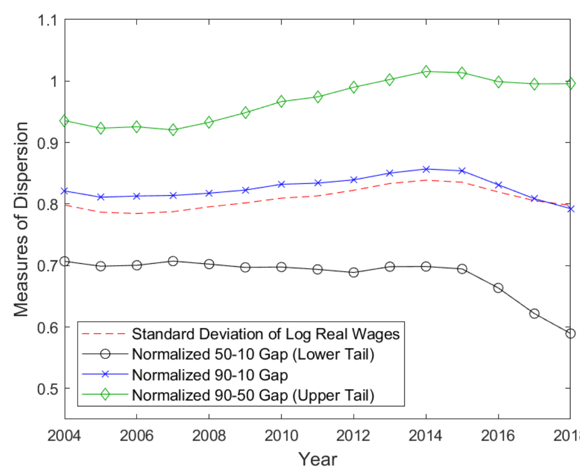
(b) Center-North



(c) Center



(d) South



Source: Authors' calculations using IMSS data. Normalized percentile gaps are differences in percentiles divided by the corresponding differences in percentiles of standard normal variable. For example, the 90th-10th gap is divided by $\Phi^{-1}(0.9) - \Phi^{-1}(0.1)$, where $\Phi(\cdot)$ stands for the standard normal distribution function.

5 Methodology

To isolate the assortativeness, worker-, and workplace-specific components of the evolution of wage variability in the Mexican private formal labor market, we follow Card et al. (2013). We begin by adopting the widely embraced econometric approach proposed by Abowd et al. (1999), where log wages follow a linear specification:

$$\ln(\text{wage}_{it}) = \alpha_i + \psi_{\mathbf{J}(it)} + X_{it}'\beta + r_{it}. \tag{1}$$

Here, wage_{it} is the real wage of worker i at time t. The worker fixed effects α_i are constant within any given time interval and capture worker-specific skills, abilities, and other characteristics that receive equivalent compensation across firms. Similarly, the workplace effects $\psi_{\mathbf{J}(it)}$ capture a similar wage premium or discount that accrues to all workers employed in the same workplace J (Card et al. 2013). The vector X_{it}' contains observable characteristics, including a time trend, age squared, and age cube in our specification.[10] We estimate equation (1) by OLS. The identification assumption is that the error term r_{it} is not correlated with the covariates or the worker and workplace dummies. We address this assumption's implications when we talk about job exchangeability in Appendix A.[11]

We define positive (negative) assortative matching as the positive (negative) correlation between worker and workplace fixed effects as measured by the covariance $Cov(\alpha_i, \psi_{\mathbf{J}(it)})$; where, by definition, the magnitudes of the worker and workplace effects increase according to their productivity. Assuming complementarity in production between workplaces and workers, the covariance between these two effects will be positive if high-quality workplaces tend to hire highly productive workers, and their remuneration is larger than that of low-productivity workers employed in the same place.

To ease the comparison of our estimates to previous studies, the analysis in this section discusses estimations for men aged 25 to 54 (prime-age). We split our sample into three periods:

[10] We normalize all the age terms to percentage deviations from 30 years old. For our baseline specification, we do not include time effects since they would be highly collinear with the linear age effect (Dauth et al. 2022). We estimate models with time effects in section 6.3.

[11] Our use of real instead of nominal earnings is inconsequential to our main results. Given that log-real wages are the sum of the logarithm of nominal wages plus the logarithm of the price deflator, this latter term *de facto* functions as a constant added to the fixed effects of all workplaces. Therefore, using real wages does not affect the estimation of the variance of worker and workplace effects and their covariance.

2004-2008, 2009-2013, and 2014-2018. For each one of the four time periods, columns (1) to (4) of Table 2 show the number of worker-year observations for prime-age males that had more than one job, the number of individuals, and the average and standard deviation of log wages. In each interval, our database has between 158 and 297 million worker-year observations corresponding to five to nine million individuals. The standard deviation of salaries rose from 0.77 in the 2004-2008 interval to 0.79 in 2014-2018. Average real wages have decreased throughout the sample.

Worker and workplace fixed effects can only be identified leveraging worker mobility within a "connected set" of workplaces. This set consists of workplaces linked by workers who have switched jobs at least once between them, as described by Abowd et al. (1999). Columns (5) to (8) of Table 2 show the corresponding descriptive statistics for the largest connected set of prime-age male workers. The largest connected set contains at least 94% of all worker-year observations and 97% of all individuals in a given interval. Average wages in the connected set are slightly higher than in the overall sample, while standard deviations are marginally smaller. The large size of the connected set relative to the entire sample, the comparable mean salaries, standard deviations, and the similar trends of the average wage and salary dispersion imply that we lose little by directing our attention to said connected group.

Variance decomposition. Following Card et al. (2013), under the assumption that the error term and the covariates in equation (1) are uncorrelated, the variance of log wages in a given period can be decomposed as:

$$\begin{aligned}\mathrm{Var}(\ln \mathrm{wage}_{it}) = &\underbrace{\mathrm{Var}(\alpha_i)}_{\text{workers}} + \underbrace{\mathrm{Var}(\psi_{\mathbf{J}(it)})}_{\text{workplaces}} + \mathrm{Var}(X_{it}'\beta) + \mathrm{Var}(r_{it}) \\ &+ 2\underbrace{\mathrm{Cov}(\alpha_i, \psi_{\mathbf{J}(it)})}_{\text{sorting}} + 2\,\mathrm{Cov}(\psi_{\mathbf{J}(it)}, X_{it}'\beta) + 2\,\mathrm{Cov}(\alpha_i, X_{it}'\beta).\end{aligned} \tag{2}$$

The first term corresponds to the variance of log wages explained by time-invariant worker characteristics, while the second term corresponds to the contribution of workplace differences to wage inequality. The sorting term measures the contribution of assortative matching to wage variance.

We estimate the model in equation (1) by OLS with a pre-conditioned iterative gradient method. To compute the decomposition in equation (2), we replace the parameters with their OLS estimates

Table 2: Descriptive Statistics - Overall Sample and Workers in the Largest Connected Set

	All sample				Individuals in largest connected set			
			Log wage				Log wage	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Interval	All obs.	Individuals	Mean	Std. dev.	All obs.	Individuals	Mean	Std. dev.
Nov 2004-2008	158,543,931	5,721,179	5.525	0.772	150,458,370	5,576,345	5.556	0.772
Ratio: largest connected/all					94.91	97.51	100.61	100.01
2009-2013	226,528,652	7,072,043	5.487	0.791	216,360,702	6,920,461	5.515	0.792
Ratio: largest connected/all					95.51	97.91	100.51	100.11
2014-2018	297,395,413	9,069,558	5.488	0.793	288,394,833	8,941,908	5.507	0.793
Ratio: largest connected/all					97.01	98.61	100.31	100.01
Change from first to last interval			-0.0371	0.0211			-0.0491	0.0211

Source: Authors' calculations using IMSS microdata. Statistics for men 25 to 54 years old who changed jobs during each period, i.e. were employed in more than one workplace. Log wage is the log of daily taxable income registered in IMSS, expressed in real terms using prices from July 2018. "Ratio: largest connected/all" is the ratio of the corresponding statistic in the largest connected set to its counterpart in the full sample.

and calculate the sample analogs of each variance and covariance term.

Andrews et al. (2012), Kline et al. (2020), and Bonhomme et al. (2023) show that there may be substantial bias in estimates of variance shares in AKM models like the one we estimate. These biases arise in settings with low worker mobility across workplaces, such that the estimate of the variance components in equation (2) has a large small-sample bias. We show that our findings are robust to adjustments for limited mobility bias in section 6.3.

6 Decomposition of the Variance of Formal Workers' Wages in Mexico: 2004-2018

In this section, we show estimates of the AKM model in (1) for the entire Mexican private formal labor market. We first show a summary of the estimated model and argue that it explains a large share of the variance of wages of formal workers. Then, we highlight the increasing role of assortative matching in explaining the variance of wages in Mexico. Last, we compare our estimates to those from other countries.

Table 3 summarizes the estimated models for each time interval: 2004-2008, 2009-2013, and 2014-2018. Our models include 5.5 to 8.9 million worker effects and 520 to 690 thousand workplace effects each period. We report the standard deviations of the estimated workplace and worker effects and their correlation. We also report the models' root mean squared error (RMSE) and their adjusted R^2. The estimated models have high explanatory power, with high adjusted R^2 values in each interval.

The results in Table 3 show several patterns of interest. First, consider how the variance of worker and workplace effects follow opposing trends: the standard deviation of worker effects decreases over time while that of workplace effects increases. These patterns suggest that workplace-specific effects were increasingly important in propelling wage variance trends in Mexico.

Additionally, the correlation between worker and workplace effects grows over time, which hints at an increasing influence of positive assortative matching on the dispersion of wages. Figure B.6 in the Appendix offers visual evidence of this trend. We plot the joint distributions of the estimated worker and workplace effects (grouped by deciles) for 2004-2008, 2009-2013, and 2014-

Table 3: AKM Model Estimation Results

	Interval1 2004-2008	Interval2 2009-2013	Interval3 2014-2018
Worker and workplace parameters			
Number of worker effects	5,576,345	6,920,461	8,941,908
Number of workplace effects	523,701	554,593	695,749
Summary of parameter estimates			
St. dev. of worker effects	0.504	0.486	0.472
St. dev. of workplace effects	0.444	0.479	0.487
Correlation worker/workplace effects	0.212	0.231	0.259
Correlation worker effects/Xb	-0.123	-0.074	-0.104
Correlation workplace effects/Xb	-0.051	-0.045	-0.048
Goodness of fit			
St. dev. of log wages	0.772	0.792	0.793
RMSE	0.238	0.237	0.233
R Squared	0.909	0.913	0.916
Adj. R Squared	0.905	0.910	0.913

Source: Authors' calculations using IMSS data. Results from estimation of equation (1) via OLS. Observations correspond to the largest connected set per time interval. "Xb" stands for covariates and includes the following controls: age, age squared, age cube, and a monthly time trend.

2018, classifying the fixed effects by deciles. Comparing the panels in Figure B.6's clarifies the secular tendency for higher-wage workers to sort to workplaces with more significant wage premia.

We suspect that the democratization of the internet and the more common use of online job platforms may be drivers of the increased sorting. Starting in 2013, Mexico experienced a dramatic expansion in high-speed internet access. Between 2013 and 2020, the coverage of broadband telecommunications expanded by 227.2%, growing from 23 to 77 lines per 100 persons: the starkest increase in coverage among OECD members (IFT 2021). Similarly, the use of job-matching platforms has expanded significantly. The proportion of job-seekers that report preferring to look for a position online grew from 71% in 2014 to 95% in 2018 (AIMX 2014; AIMX 2018). Along with the increased use of online job-search platforms by workers, during the same period, there has been a parallel expansion in the number of websites offering job-searching services (AIMX 2018).

6.1 Decomposing Wage Variance

We now present estimates of contributions made by these two components to total wage variance. To quantify the individual contributions of worker effects, workplace effects, and sorting, we conduct a variance decomposition analysis based on equation (2) in each period considered.

As we noted when commenting on the results from Table 3, the dispersion of worker and workplace effects trend in opposite directions. At the same time, the correlation between these factors increases over time. Table 4 shows how these opposing trends contributed to the increase in the variance of wages in Mexico's private formal labor market from 2004 to 2018. Worker effects went from accounting for a 42% share of prime-age male workers' wage variance in 2004-2008 to less than 36% of their variance in 2014-2018. This decrease happened as the variance of wages increased by about 5%. In contrast, workplace effects account for a 4.7 percentage points (p.p.) higher share of variance in the last period compared to the initial period. Simultaneously, the variance share from the covariance of worker and workplace effects increased by 3 p.p.[12]

The last rows of Table 4 show a counterfactual calculation following Card et al. (2013). For these counterfactuals, we keep the correlation of worker and workplace effects and the variance of workplace effects at their 2004-2008 levels and calculate the implied variance of wages for 2009-2013 and 2014-2018. These are scenarios where matching technologies do not improve over time, and the wage-setting power of workplaces remains constant. Without the increase in the importance of workplace effects and assortative matching in determining wages, the variance of wages would be 10% smaller in 2014-2018.

Card et al. (2013) argue that in the absence of an increase in the importance of workplaces and assortative matching, Germany's wage variance would have been about 25% lower in 2002-2009. We find that the rise in the importance of these factors in Mexico has been smaller. Nevertheless, the importance of workplaces for the variance of wages in Mexico is substantial. Average workplace wage premia are more consequential to the evolution of worker-workplace sorting in Mexico, unlike most national labor markets analyzed with the AKM methodology. The high share of variance attributed to workplace premia is consistent with previous work utilizing worker-workplace

[12] A deeper regional analysis revealed that wage variance, whether from worker characteristics, workplace factors, or their sorting, is largely a within-region phenomenon. As shown in Table B.13 in the appendix, within-region variance consistently contributed 99% to total log-wage variance across periods.

Table 4: Wage Variance Decomposition, National Level

	Interval 1 2004-2008	Interval 2 2009-2013	Interval 3 2014-2018	Change from int. 1 to 3
Variance and covariance				
Total variance of log wages	0.596	0.627	0.628	0.032
Variance of worker effects	0.254	0.236	0.222	-0.032
Variance of workplace effects	0.197	0.230	0.237	0.040
Variance of covariates (Xb)	0.019	0.013	0.016	-0.004
Variance of residual	0.055	0.054	0.053	-0.002
2 Cov(worker effects, workplace effects)	0.095	0.108	0.119	0.024
2 Cov(worker effects, covariates)	-0.017	-0.008	-0.012	0.005
2 Cov(workplace effects, covariates)	-0.006	-0.005	-0.006	0.000
Variance shares				
Variance of worker effects	0.426	0.376	0.354	-0.073
Variance of workplace effects	0.330	0.366	0.377	0.047
Variance of covariates (Xb)	0.032	0.020	0.025	-0.006
Variance of residual	0.091	0.087	0.084	-0.008
2 Cov(worker effects, workplace effects)	0.159	0.172	0.189	0.030
2 Cov(worker effects, covariates)	-0.029	-0.013	-0.019	0.009
2 Cov(workplace effects, covariates)	-0.011	-0.008	-0.009	0.001
Counterfactuals for variance of log wages				
1. No rise in correl. of worker/firm effects	0.596	0.618	0.608	
2. No rise in var. of workplace effects	0.596	0.587	0.578	
3. Both 1 and 2	0.596	0.585	0.568	

Source: Authors' calculations using IMSS data. Variance decomposition results from equation (2) using the estimated worker and workplace fixed effects from equation (1). The "Variance and covariance" rows show the values of the variance of log wages in the estimation sample of prime-age men and its components. The "Variance shares" rows show the share of the overall variance in log wages in the sample attributed to each one of its components. The first three columns correspond to time intervals, and the last columns is the change from 2004-2008 to 2014-2018. The "Counterfactuals for variance of log wages" rows show the variance of wages assuming that the correlation of worker/workplace effects and the variance of workplace effects had remained constant at 2004-2008 values.

longitudinal data from Mexico before 2002 (Frías et al. 2022), and with research pointing out an increase in inequality across as opposed to within workplaces (Song et al. 2018). Figure 5 illustrates this difference. The left panel displays our estimates for the contributing shares of worker and workplace effects to total wage variance in Mexico for the considered intervals. The right panel presents equivalent estimations from previous work studying Mexico (Frías et al. 2022), the United States (Song et al. 2018), Germany (Card et al. 2013), and Brazil (Engbom and Moser 2022). In the Mexican economy, worker and workplace effects contribute equally to trends in wage inequality. Intriguingly, the command that workplaces have to determine wage differentials increased while the share of workers in labor unions decreased.[13] On the other hand, the contribution of sorting (as measured by the covariance between the two effects) is roughly comparable to the shares estimated for other countries.[14]

6.2 Regional Differences

We now examine how wage differences across workers, workplaces, and assortative matching –as estimated from our AKM model– contribute to wage variance in Mexican regions. We apply the decomposition of equation (2) to the variance of wages in our estimated model sample, dividing the sample into regions.[15]

Table 5 shows average wages, average worker fixed effects, and average workplace effects for the country and each sub-national region. Workers in the North and Center regions of the country tend to have larger fixed effects, while these tend to be lower in the South. Workplaces in the North have higher workplace premia.

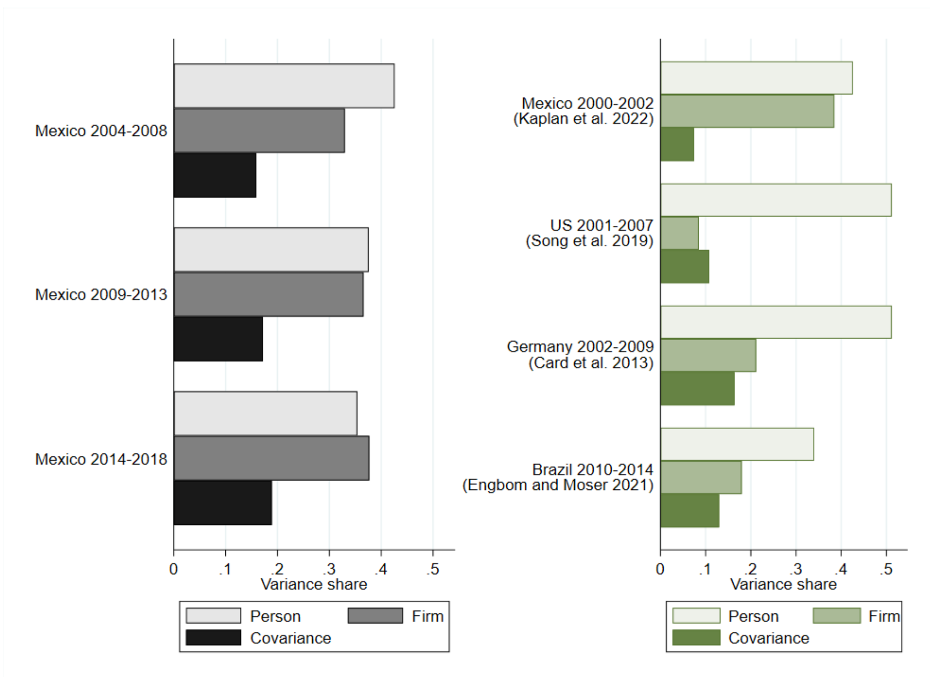
Figure 6 shows how the worker- and workplace-level determinants and their correlation contributed to wage spread in the four sub-national regions. In all four, assortative matching explains between 13% and 21% of the wage variance. The strong ability of workplaces to influence wage disparities is also present in all four Mexican geographical regions.

[13] In particular, according to Mexico's Ministry of Labor, the proportion of salaried workers that belong to a union diminished from 17% to 12% between 2005 and 2018 (STPS 2022).

[14] The share of variance attributed to workplace effects in Mexico is also more extensive than that of other OECD countries: see OECD (2021).

[15] Strictly speaking, since we do not re-estimate the model per region, equation (2) may not hold exactly by region because the OLS residual may correlate with covariates in each regional sub-sample. Nevertheless, the share of variance attributed to this correlation is negligible.

Figure 5: Comparing Estimated Worker and Workplace Contributions to Wage Variance



Source: Authors' calculations from IMSS data, and reported values from Frías et al. (2022), Song et al. (2018), Card et al. (2013). and Engbom and Moser (2022). The left panel shows variance shares attributed to worker effects, workplace effects and their covariance in each time period from Table 4. The right panel shows equivalent variance shares for different countries from different studies.

Table 5: Average Worker and Workplace Fixed Effects by Region

	Average log wage	Average worker effect	Average workplace effect
National			
2004-2008	5.56	2.67	2.46
2009-2013	5.51	2.63	2.42
2014-2018	5.51	2.63	2.37
North			
2004-2008	5.56	2.65	2.50
2009-2013	5.51	2.63	2.45
2014-2018	5.54	2.62	2.39
Center-North			
2004-2008	5.49	2.64	2.48
2009-2013	5.44	2.62	2.43
2014-2018	5.43	2.60	2.36
Center			
2004-2008	5.64	2.72	2.45
2009-2013	5.59	2.69	2.43
2014-2018	5.57	2.66	2.39
South			
2004-2008	5.41	2.63	2.45
2009-2013	5.41	2.64	2.36
2014-2018	5.37	2.59	2.33

Source: Authors' calculations using IMSS data. Average log wages, worker fixed effects and workplace fixed effects for each region, using the estimates of the AKM model from equation (1).

The contribution of workplace-specific effects to overall wage variance correlates negatively with the level of regional development. Workplace fixed effects are relatively more important in determining wage variance in the South, followed by the Center-North, Center, and last by the northern region. The contribution of worker effects follows precisely the opposite pattern. These motifs resemble local levels of general economic development: historically, Northern and Southern Mexico have been the country's most and least economically mature regions (Alix-Garcia and Sellars 2020).

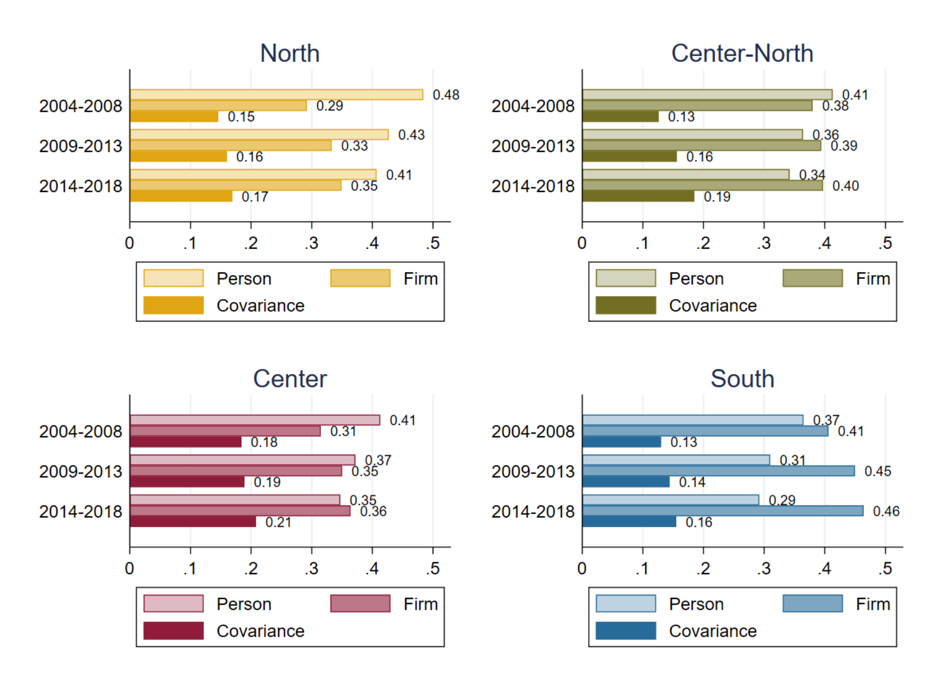
Our findings do not suggest that the consistent decline in the importance of worker-level factors determining wages implies a backward trend or a "rollback" of the development achieved by the Mexican economy in recent decades. Instead, the patterns we uncover in the regions reveal a diverse rate of economic progress in different parts of Mexico.[16]

Figure 7 shows variance decompositions by state, ranking the states by average per-capita GDP. States with lower GDP per capita tend to have a larger share of wage variances attributed to wage differences between workplaces. The rank correlation between per-capita GDP and the workplace variance share is negative and increases in absolute value in 2014-2018 relative to 2004-2008. States with high specialization –such as Campeche and Tabasco which are oil producers– display large variance shares attributed to worker factors. Nevertheless, other states in the south such as Chiapas and Oaxaca also display large workplace-related variance components.

We now highlight differences in assortative matching across regions. In Figure 8, we show the 2014-2018 regional joint distributions of worker and workplace fixed effects. In these Figures the effect deciles are grouped with respect to national estimates. While in the Center, over 4.49% of workers are in the top decile of worker-specific wage premia and work in top-decile establishments, in the South, this number is 1.71%. It does not differ much from the fractions of workplaces across worker fixed effect deciles in the bottom establishments. The North and Center-North also display stronger assortative matching patterns than the South, but they are still less visible than those in the Center.

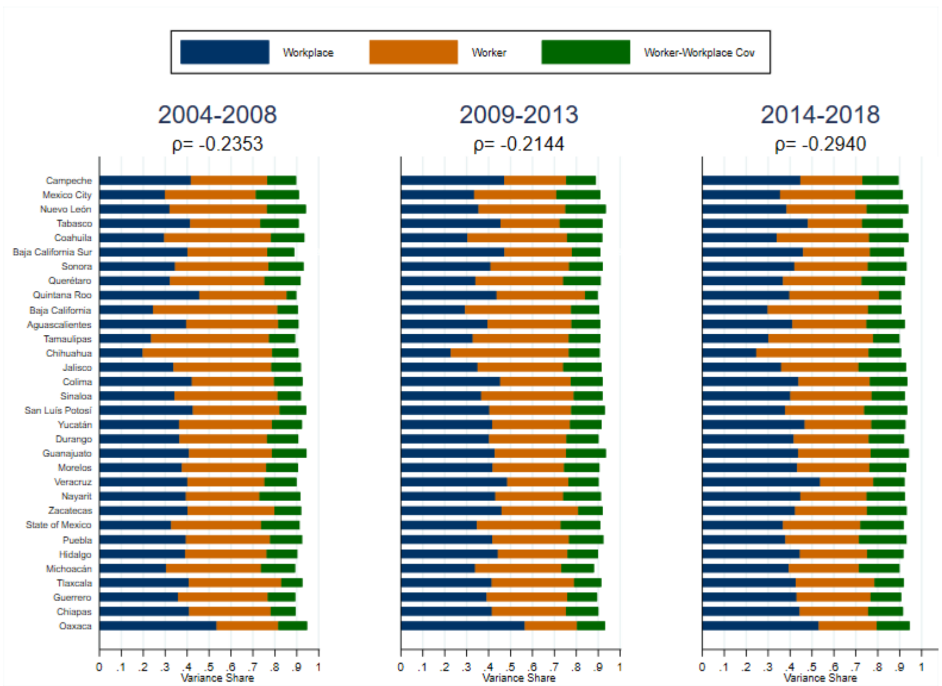
[16] In Appendix Tables B.1 to B.4, we present wage variance decomposition exercises for each of the Mexican regions. Recall that, as shown in Table 4, nationally, there is a minor rise in total wage variance, a drop in the contribution made by worker effects, and a rise in both workplace and sorting shares. Three regions (Center-North, Center, and South) follow these national trends. However, in the North, total wage variance first rises between 2004-2008 and 2009-2013, to then slightly drop in the subsequent time segment, yet the contributions to wage dispersion by the components under study align with the national patterns.

Figure 6: Estimated Worker and Workplace Contributions to Wage Variability by Region



Source: Authors' calculations using IMSS data. The Figure depicts the variance shares attributed to worker fixed effects, workplace fixed effects, and their covariance in the overall variance of wages in each region, using the estimates of the AKM model from equation (1) and the decomposition in equation (2).

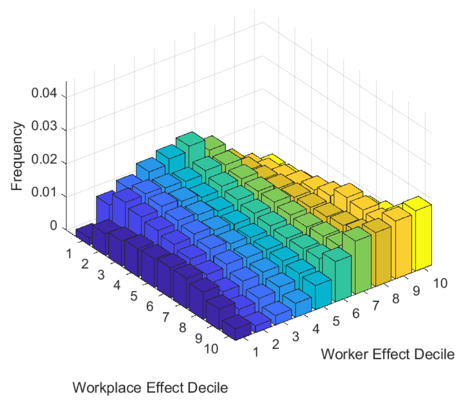
Figure 7: Estimated Worker and Workplace Contributions to Wage Variability by State, Ranking States by Per-Capita GDP



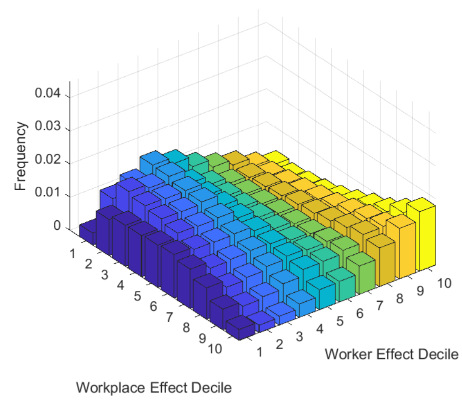
Source: Authors' calculations using IMSS data. The Figure depicts the variance shares attributed to worker fixed effects, workplace fixed effects, and their covariance in the overall variance of wages in each state, using the estimates of the AKM model from equation (1) and the decomposition in equation (2). States are ranked by their average per-capita GDP in each time interval. The numbers above each panel are rank correlations between per capita GDP and the workplace variance share.

Figure 8: Regional Differences in Assortative Matching 2014-2018

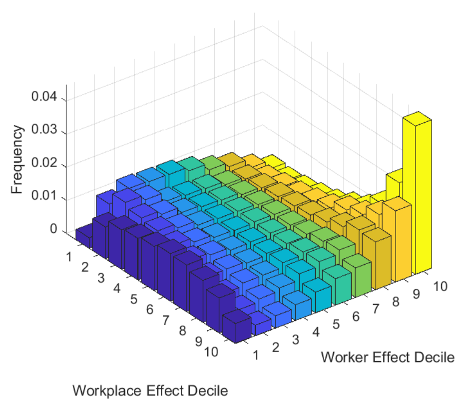
(a) North



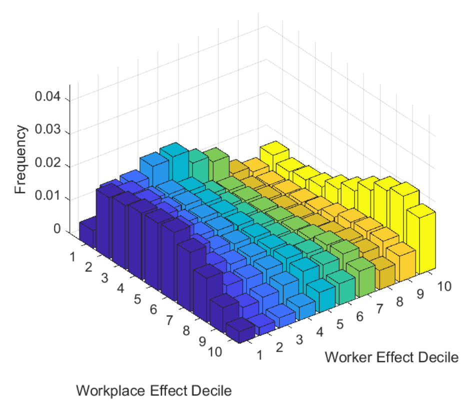
(b) Center-North



(c) Center



(d) South



Source: Authors' calculations using IMSS data. Panels depict the joint distribution of estimated worker and workplace effects from equation (1) by deciles of the national marginal worker and fixed effect distributions.

There are many potential mechanisms that could explain these regional differences in the contributions of the different components to overall wage inequality. While accounting for all of them is difficult, we now highlight a few of them:

- **Differences in educational attainment.** There are substantial regional disparities in educational attainment across regions. The South region lags relative to the rest of the country.[17] Lack of education and differences in education would lead to a lower variance of worker fixed effects (which include worker educational wage premia) and a larger wage-setting capacity by workplaces.

- **Labor market power.** Firms may have more discretion to set wages below the marginal productivity of labor in places where they face a low labor supply elasticity (Berger et al. 2022). In less competitive labor markets, and to the extent that labor supply elasticity varies across firms, we would expect more wage differences across firms. In contrast, in places where the labor market is more competitive, all firms face a perfectly elastic labor supply and pay the market wage for comparable workers. In such a setting, there would not be differences in wages across firms for workers with the same worker fixed effect. To see if there is evidence of higher labor market power in some regions, we calculate private formal labor market Herfindahl-Hirschman indexes (HHI) of labor market concentration at the commuting zone-sector level.

  In the appendix, Table B.14 shows average HHIs by region for each interval in our sample. Labor market concentration correlates with measures of labor market power (Azar et al. 2022). We calculate indices for both number of employees and payrolls (Berger et al. 2022). In general, private formal labor markets in Mexico show a relatively high degree of concentration relative to the US, where comparable HHIs range from 0.11 to 0.27. Moreover, these concentration indexes are higher for the south, where the contribution of firm effects to overall wage variance is highest. We note, however, that the parallel between labor market concentration and labor market power is not as straightforward in our setting because of informality in labor markets: the large share of informal employers in the south may moderate

[17] As an example, in 2016, 33.6 and 39.7% of the population ages 25 to 34 in Oaxaca and Chiapas (Southern region states), respectively, had not completed primary education. This high percentage contrasts with only 7.8% in Mexico City (Center) and 10.7% in Nuevo León (North) (INEE 2018).

the labor market power that formal firms are able to exert.

- **Industrial composition.** Mexican regions differ in their patterns of industrial specialization. Most of the manufacturing sector is located in the north (40.6%), most of the services sector locates in the center (48.7%), and the south has larger shares of oil and tourism (55.0%). These industrial composition differences may lead to differences in the importance of each wage component in determining wage dispersion. In a companion paper (Pérez Pérez et al. 2023), we show that assortative matching is stronger in the services sector at the (private formal) local labor market level. Therefore, we would expect a larger share of variance attributed to matching in the center region –where the services sector has the largest employment share– relative to other regions.

- **Firm size.** Appendix Figure B.7 shows the relationship between workplace size and the worker, workplace and sorting components of total wage variance for the 2014-2018 period. Across all four regions, there is a negative correlation between firm size and the share of variance attributed to workers and firms, and a positive correlation between assortative matching and firm size. Therefore, we would expect sorting to play a more influential role in regions with more large firms (e.g. the north and center), compared to regions with a low prevalence of large firms relative to smaller enterprises (like the south).

- **City size and informality.** Smaller cities with more informal labor in the south may have weaker assortative matching, leading to a lower share of variance attributed to covariance of worker and firm fixed effects (Dauth et al. 2022). Pérez Pérez et al. (2023) show that there is a city-size wage premium due to better assortative matching in large cities for Mexico, and that larger labor market informality leads to weaker assortative matching.

6.3 Additional Evidence and Robustness

We now summarize additional estimation exercises to probe the robustness of our results. We estimate AKM models for women and the sample of all workers aged 25-54, finding similar results to those for prime-age men. Our results are also robust to different specifications of the AKM model in equation (1) and to variance decompositions using corrections for limited mobility bias

(Andrews et al. 2012; Bonhomme et al. 2019; Kline et al. 2020). Across all these exercises, we still see a large share of variance attributed to workplaces in Mexico and an increasing importance of assortative matching in explaining wage inequality.

Comparing men, women, and all workers. The variance trends we document are slightly different for women. In Appendix Figure B.1, we show that wages have increased from 2010 to 2018 in the 10th, 50th, and 90th percentiles of women's wage distributions. Figure B.2 in the Appendix shows that overall formal wage inequality has decreased for women and men, with a sharper decrease in lower-tail inequality from 2018 to 2022 probably due to the increases in the minimum wage in the period.

Our AKM models are also adequate in explaining wages for women and the entire sample. In Appendix Table B.5, we show estimates of the AKM model for men, women, and all workers ages 25 to 54. The additive effects model explains a high share of the variance of log wages for women and the overall sample. All samples show an increasing variance of workplace effects over time and a decreasing variance of worker effects. The correlation of worker and establishment effects is slightly larger for men in all periods.

Our findings regarding the importance of workplaces also hold for women's wages. Appendix Tables B.6 and B.7 show the variance decomposition results in equation (2) for the women and all workers samples. For women, workplace effects and the correlation of workplace and worker effects explain an increasing share of variance over time, similar to our results for men in Table 4. Workplace effects explain a lower percentage of the variance of overall wages for women and do not overtake workplace effects as the most significant component of wage variance in 2014-2018. Nevertheless, the variance of wages for women would also be about 8% lower in 2014-2018 if the workplace and matching components had not increased their importance. The picture is similar in the sample with all workers ages 25-54.

Alternative model specifications. In Appendix Figure B.3, we calculate the shares of variance attributed to workers, workplaces, and assortative matching with different model specifications: excluding time trends, excluding top-coded observations, including time trends interacted with sector indicators, including controls for workplace size, and a quartic polynomial in age (Lemieux 2006). Across all specifications, we still find that workplaces account for a large share of variance and that assortative matching is becoming increasingly important.

Alternative specifications for age effects. Our baseline estimates include linear and quadratic terms in age and do not include time effects as they are collinear with age effects. In Appendix Table B.8, we show estimates using time effects and omitting the linear term on age. The results are similar to those from the baseline estimates. We also show estimates using different normalizations for the age terms in Appendix Table B.9, since Card et al. (2018) show that different normalizations may change the estimates. In our case, the different normalizations have little effect on the results.

Firm-by-year fixed effects. Snell et al. (2018) and Lachowska et al. (2023) generalize the AKM model by allowing the firm effects to vary by year. We estimate models allowing the firm effects to vary by year and show the results in Table B.15. With this specification, the share of variance attributed to person and firm effects increase, and the share of variance attributed to assortative matching slightly decreases. Nevertheless, the overall patterns are similar to those in Table 4.

Variance decomposition for additional periods. We repeat the estimation on the prime-age men sample for every 4-year window starting in December 2004 - December 2008 and ending in December 2014 - December 2018. We plot the variance shares attributed to worker effects, workplace effects, and their covariance in each period in Appendix Figure B.4. The trends confirm the patterns found in Table 4: the relevance of workplace effects and assortative matching in explaining the variance of wages is increasing over time, while worker effects are losing importance.

Limited mobility bias. We address limited-mobility-bias concerns by re-estimating the variance decomposition in Table 4 with two alternative estimators: a corrected leave-one-out variance estimator following Kline et al. (2020) and an estimator clustering workplaces in groups following Bonhomme et al. (2019). Appendix Tables B.10 and B.11 show the results. Our corrected estimates of the variance components of log wages using the Kline et al. (2020) correction are virtually equal to those of Table 4. In contrast, our estimates using the Bonhomme et al. (2019) correction show smaller wage variance associated with the workplace and worker effects and larger variance shares due to assortative matching. Nevertheless, the inverse correlation between development and the share of variance attributed to workplace effects holds even when using this estimator as shown in Appendix Figure B.5.[18]

[18] Our relatively unchanged estimates contrast with those of Frías et al. (2022) and Engbom and Moser (2022), who find that their estimates have meaningful changes once they implement their limited-mobility-bias corrections. There are two reasons why our estimates do not change as much: First, there is substantial worker mobility across firms in

Variance decomposition across sectors. Table B.12 in the Appendix shows a decomposition of the wage variance across sectors.[19] The main patterns remain essentially unchanged. The dispersion of mean log wages expands simultaneously as the estimated contribution of worker-specific characteristics declines. The role of assortative matching increases across all three time intervals considered.

High- and low-wage firms. In Table B.16 we re-estimate the AKM models dividing firms into four quartiles of the firm wage distribution.[20] Then, we apply the variance decomposition in equation (2) accounting for limited mobility bias. The Table suggests that the firm share of variance is higher for the second and third quartiles of the firm wage distribution, and that the firms in the highest and lowest quartiles are the main drivers of the increase over time in the importance of assortative matching.

7 Conclusion

We quantify the proportion of the observed wage variance in Mexico attributed to worker-specific characteristics, average workplace-level salary premia, and assortative matching. Our exercise unearths two findings. First, the relatively stable wage variance observed over the 2004-2018 period in Mexico veils changes in its composition: the influence of workplace-level wage determinants increased and went from being the second most important component of wage dispersion to the first, overtaking worker-level factors, which declined in importance during the period. Second, the relevance of workplace-level factors plays a larger role in the South and are relatively less important in the North, which points to a negative relationship between local economic development and the preponderance of workplace-level wage determinants.

To conduct our analysis, we use a matched worker-workplace database with the near universe of private-sector workers in Mexico. To decompose total wage variance, we leverage estimations from AKM-style models of log wages with two-way fixed effects. Assortative matching plays an

our dataset, as evidenced by the fact that our connected set is a large share of the entire sample. Second, our time intervals are wider than those in Frías et al. (2022), allowing for more worker mobility in each time interval.

[19] To perform our calculations, we rely on the sector classification in the IMSS data, which we map to a 3-digit NAICS classification.

[20] We re-estimate for each quartile of the firm wage distribution because the variance decomposition in equation (2) does not hold within firm wage groups. Note that the variance of log wages in the full sample is much larger than these within-group variances because it also includes the between-group variance.

increasingly important part in shaping wage dispersion in Mexico. In agreement with previous work looking at other developing countries, workplace-specific salary premia contribute significantly to wage inequality in the country. Interestingly, the proportion by which workplaces explain wage discrepancies is the largest (smallest) in the southern (northern) region. The workplace-specific contribution to wage dispersion moves along regional levels of economic prosperity, being the largest (smallest) in the South (North), historically the least (most) affluent Mexican geographical region. Future research could examine other determinants of the differences in the share of variance attributed to workers, workplaces, and matching across regions.

Interesting avenues of research remain open for researchers wishing to expand on our work. Notably, starting in 2019, there has been a flurry of economic reforms that could directly impact the ability of workplaces to set wages. Examples include the reform of the former North-American Free Trade Agreement; the Mexican labor reform, which modified collective agreement regulations and altered formal labor dispute procedures; and, starting in 2021, reforms to regulate labor outsourcing. Furthermore, the pandemic induced changes in the Mexican labor market that may have altered the determinants of wage dispersion.

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Online Appendix - Not for Publication

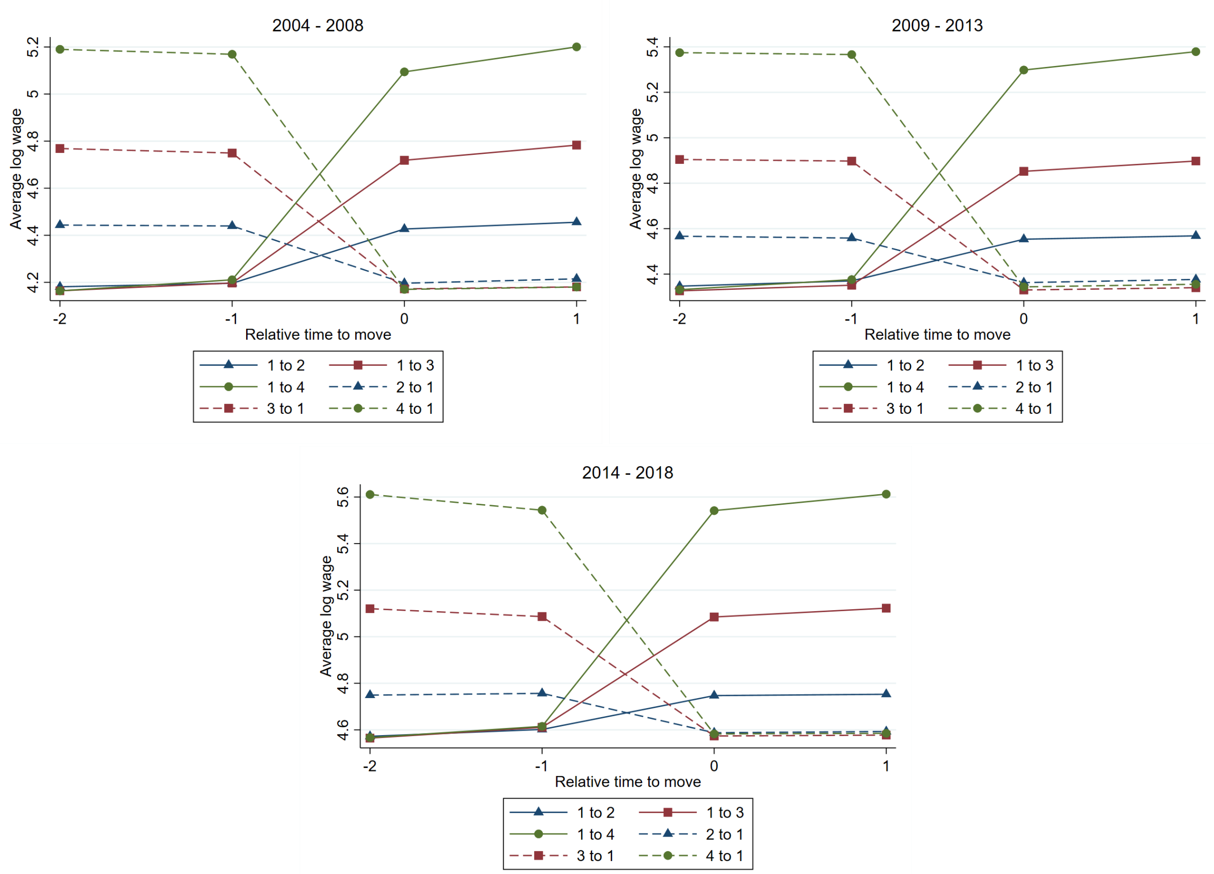
A Exchangeability

Card et al. (2013) show that if the residual term in equation (1) is uncorrelated with the right-hand-side variables, then, on average, a worker that moves from workplace A to workplace B should experience a wage change of the opposite sign to that experienced from a worker moving in the opposite direction. Following Card et al. (2013), Figure A.1 shows an event study to examine whether this holds in our dataset. The plot presents the average wages of workers who changed jobs for each time interval in our analysis period. Workers may move from "low-wage" to "high-wage" workplaces or *vice versa*. We classify workplaces based on the quartile of the average co-worker wage in their initial job and the corresponding quartile for their final job. We then compute average wages in the years before and after the job exchange for each cell. We exclude observations from establishments with only one worker. We keep only "direct" moves, that is, moves without an unemployment spell in the transition between jobs.

The Figure shows that different mobility groups classified by average co-worker wage have, on average, different wage levels before and after a move. For job-changers moving down the quartile classification, before a move, average wages in the quartile of origin vary monotonically with respect to the destination quartile. For example, average wages for workers moving from quartile four (the highest average co-worker salary) to quartile one (the lowest mean co-worker wage) are higher before the job switch than for those who go from quartile three to one, and so on. Additionally, the magnitude of the absolute change in average wages when moving from one quartile to another is equivalent to the variation associated with the opposite change. Such symmetry is consistent with an additive model for wages with worker and workplace fixed effects such as the one we estimate. We show that exchangeability also holds for women and the entire sample in Figures A.2 and A.3.

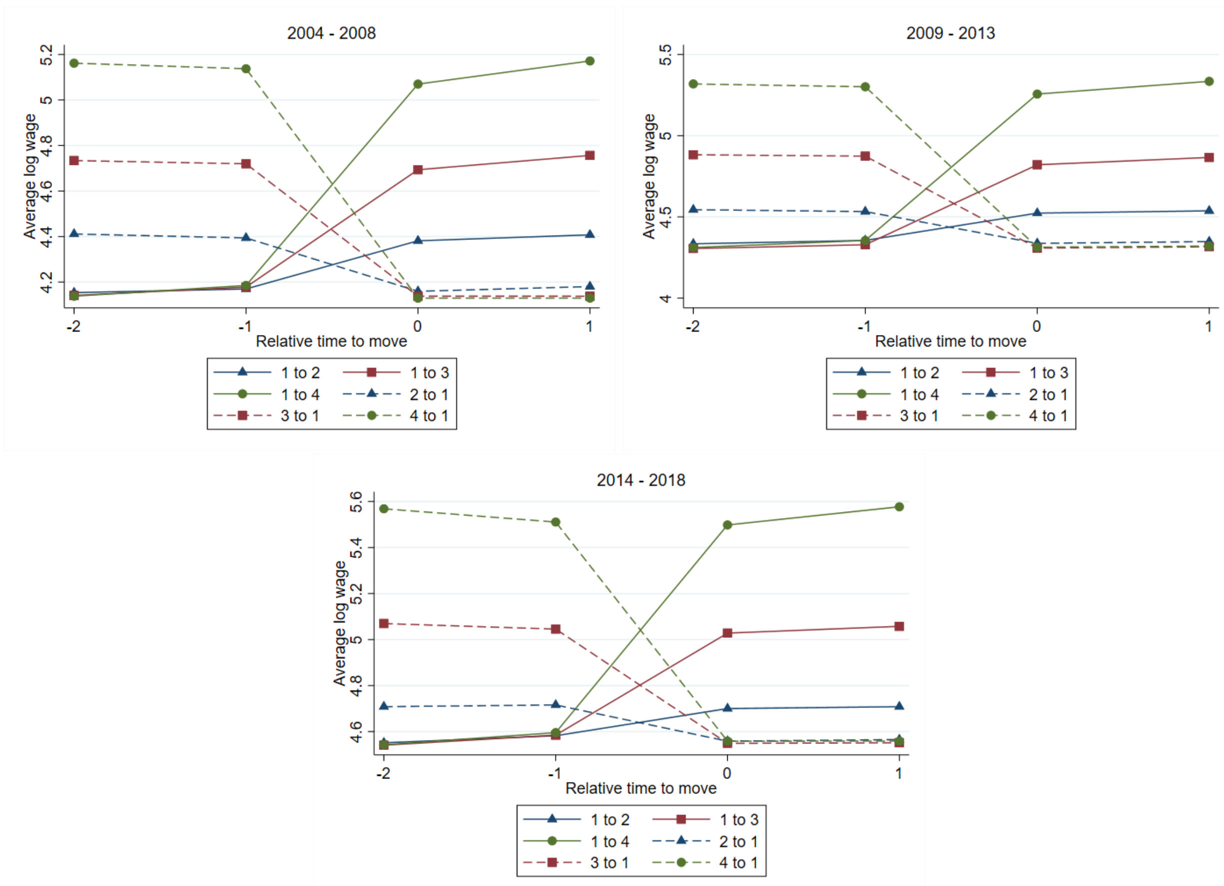
An additional challenge to the uncorrelatedness of the residual term in equation (1) and the right-hand-side variables is selective migration. If, for example, the South region experiences a downturn (leading to low values of the residual term for individuals in the region) that induces migration into other, higher-wage regions, then low realizations of the error term in the South would be associated with moves towards high-fixed-effect firms. To address this concern, we

Figure A.1: Exchangeability: Average Log Wage Around Movement by Quartile of Average Co-workers' Wages in the Origin and Destination Workplace. Prime-Age Men



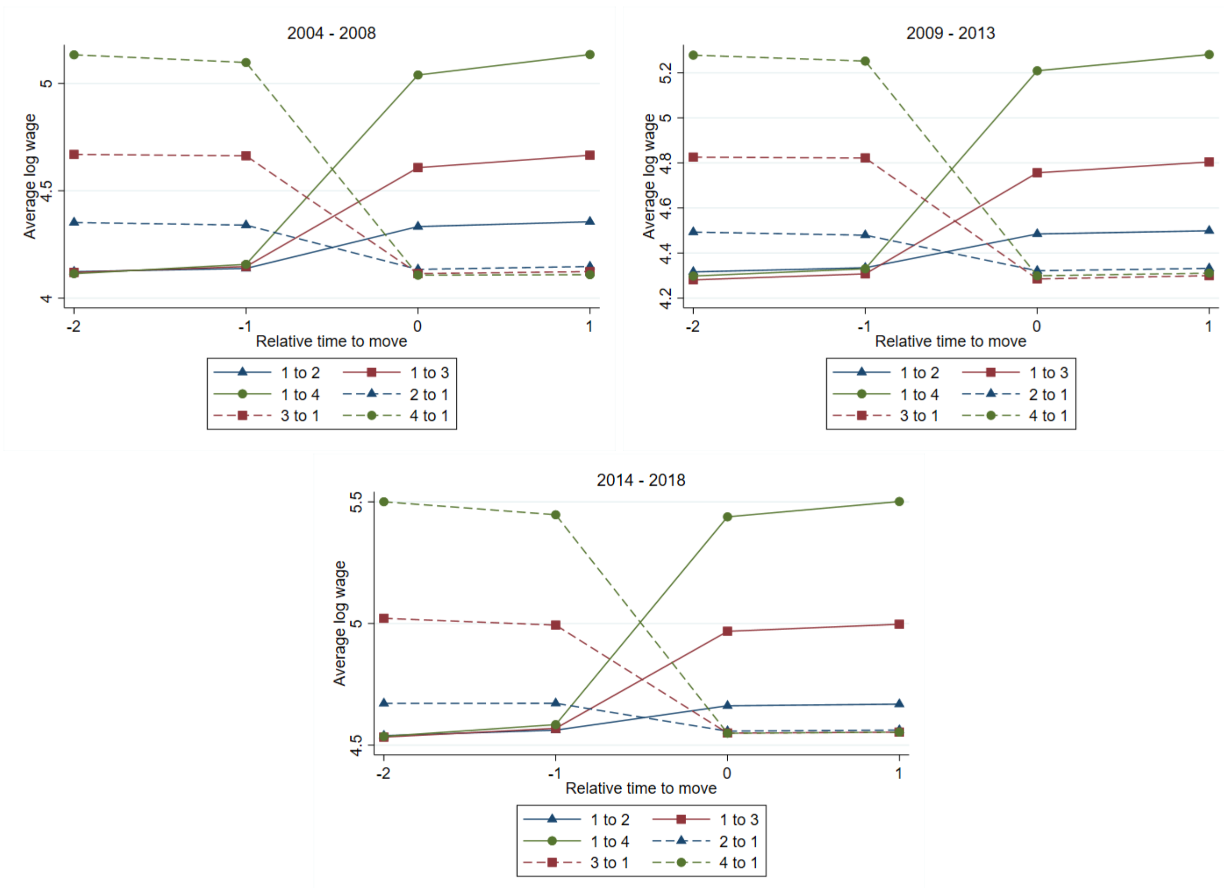
Source: Authors' calculations using IMSS data. The graph shows average worker wages for workers who move between an origin workplace to destination workplace, from two months before the move to one month after the move. The lines group workers according to the quartiles of average co-worker wages in the origin and destination workplaces. The panels correspond to different time intervals. We exclude observations from establishments with only one worker. We keep only "direct" moves without an unemployment spell in the transition between jobs.

Figure A.2: Exchangeability: Average Log Wage Around Movement by Quartile of Average Co-workers' Wages in the Origin and Destination Workplace. Women Ages 25-54



Source: Authors' calculations using IMSS data. The graph shows average worker wages for workers who move between an origin workplace to destination workplace, from two months before the move to one month after the move. The lines group workers according to the quartiles of average co-worker wages in the origin and destination workplaces. The panels correspond to different time intervals. We exclude observations from establishments with only one worker. We keep only "direct" moves without an unemployment spell in the transition between jobs.

Figure A.3: Exchangeability: Average Log Wage Around Movement by Quartile of Average Co-workers' Wages in the Origin and Destination Workplace. All Workers Ages 25-54



Source: Authors' calculations using IMSS data. The graph shows average worker wages for workers who move between an origin workplace to destination workplace, from two months before the move to one month after the move. The lines group workers according to the quartiles of average co-worker wages in the origin and destination workplaces. The panels correspond to different time intervals. We exclude observations from establishments with only one worker. We keep only "direct" moves without an unemployment spell in the transition between jobs.

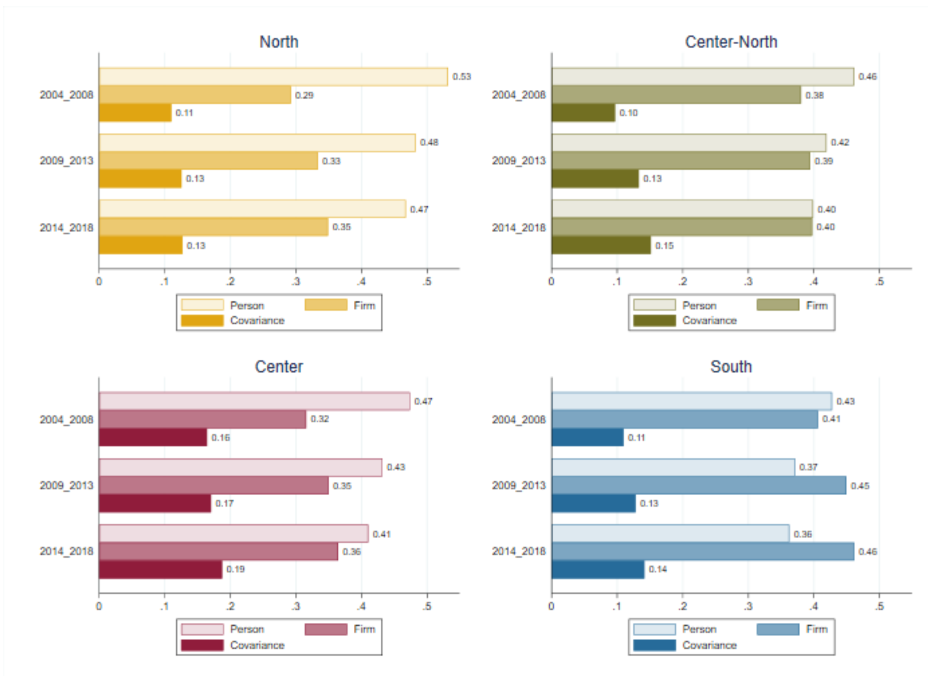
re-estimate the model allowing the time effects to vary by year and region. These time effects account for differential regional shocks that may induce migration. Table A.1 shows the results of this estimation. The results are similar to those in Table 4, albeit with a slightly larger share of variance attributed to worker effects and smaller variance shares due to sorting. Figure A.4 shows that our results in terms of the regional variation in variance shares are also robust to allowing for differential time effects across regions. The results here are similar to those from Figure 6 in the main text.

Table A.1: Wage Variance Decomposition With Fixed Effects by Region-Year

	Interval 1 2004-2008	Interval 2 2009-2013	Interval 3 2014-2018
Variance and covariance			
Total variance of log wages	0.596	0.627	0.628
Variance of person effects	0.287	0.272	0.262
Variance of firm effects	0.197	0.231	0.239
Variance of region-time FE (rt)	0.004	0.003	0.006
Variance of covariates (Xb)	0.020	0.019	0.024
Variance of residual	0.055	0.054	0.053
2 Cov(person effects, firm effects)	0.076	0.095	0.101
2 Cov(person effects, covariates)	-0.050	-0.049	-0.058
2 Cov(firm effects, covariates)	0.009	0.010	0.011
2 Cov(person effects, rt)	0.001	-0.006	-0.004
2 Cov(firm effects, rt)	-0.002	-0.003	-0.005
2 Cov(covariates, rt)	-0.000	-0.000	-0.000
Variance shares			
Variance of person effects	0.481	0.434	0.416
Variance of firm effects	0.330	0.368	0.381
Variance of region-time FE (rt)	0.007	0.005	0.009
Variance of covariates (Xb)	0.034	0.030	0.038
Variance of residual	0.091	0.087	0.084
2 Cov(person effects, firm effects)	0.127	0.152	0.161
2 Cov(person effects, covariates)	-0.084	-0.078	-0.092
2 Cov(firm effects, covariates)	0.016	0.016	0.018
2 Cov(person effects, rt)	0.001	-0.009	-0.007
2 Cov(firm effects, rt)	-0.003	-0.005	-0.007
2 Cov(covariates, rt)	-0.001	-0.000	-0.000

Source: Authors' calculations using IMSS data. Variance decomposition results from equation (2) using the estimated worker and workplace fixed effects from equation (1) including year by region fixed effects and excluding a linear term in age. The panel show variance decomposition for the samples of men 25-54. The "Variance and covariance" rows show the values of the variance of log wages in the estimation sample of prime-age men and its components. The "Variance shares" rows show the share of the overall variance in log wages in the sample attributed to each one of its components. The columns correspond to time intervals.

Figure A.4: Estimated Worker and Workplace Contributions to Wage Variability by Region - Estimates with Fixed Effects by Region-Year



Source: Authors' calculations using IMSS data. The Figure depicts the variance shares attributed to worker fixed effects, workplace fixed effects, and their covariance in the overall variance of wages in each region, using the estimates of the AKM model from equation (1) and the decomposition in equation (2) including year-by-region fixed effects and excluding a linear term in age.

B Additional Tables and Figures

Table B.1: Wage Variance Decomposition, North Region. Men Ages 25-54

	Interval 1 2004-2008	Interval 2 2009-2013	Interval 3 2014-2018	Change from int. 1 to 3
Variance and covariance				
Total variance of log wages	0.538	0.570	0.567	0.029
Variance of worker effects	0.260	0.244	0.230	-0.030
Variance of workplace effects	0.157	0.190	0.198	0.041
Variance of covariates (Xb)	0.019	0.013	0.016	-0.003
Variance of residuales	0.051	0.050	0.050	-0.001
2 Cov(worker effects, workplace effects)	0.079	0.091	0.096	0.017
2 Cov(worker effects, covariates)	-0.020	-0.010	-0.015	0.005
2 Cov(workplace effects, covariates)	-0.009	-0.007	-0.008	0.001
Variance shares				
Variance of worker effects	0.484	0.427	0.407	-0.077
Variance of workplace effects	0.292	0.333	0.349	0.057
Variance of covariates	0.036	0.022	0.027	-0.009
Variance of residuals	0.095	0.088	0.089	-0.006
2 Cov(worker effects, workplace effects)	0.146	0.160	0.169	0.023
2 Cov(worker effects, covariates)	-0.038	-0.018	-0.027	0.011
2 Cov(workplace effects, covariates)	-0.017	-0.013	-0.015	0.002

Source: Authors' calculations using IMSS data. Variance decomposition results from equation (2) using the estimated worker and workplace fixed effects from equation (1). The "Variance and covariance" rows show the values of the variance of log wages in the estimation sample of prime-age men and its components. The "Variance shares" rows show the share of the overall variance in log wages in the sample attributed to each one of its components. The first three columns correspond to time intervals, and the last columns is the change from 2004-2008 to 2014-2018.

Table B.2: Wage Variance Decomposition, Center-North Region. Men Ages 25-54

	Interval 1 2004-2008	Interval 2 2009-2013	Interval 3 2014-2018	Change from int. 1 to 3
Variance and covariance				
Total variance of log wages	0.512	0.554	0.556	0.044
Variance of worker effects	0.211	0.202	0.190	-0.021
Variance of workplace effects	0.194	0.218	0.221	0.027
Variance of covariates (Xb)	0.019	0.013	0.016	-0.003
Variance of residuales	0.052	0.051	0.049	-0.003
2 Cov(worker effects, workplace effects)	0.064	0.086	0.103	0.039
2 Cov(worker effects, covariates)	-0.023	-0.011	-0.016	0.007
2 Cov(workplace effects, covariates)	-0.007	-0.005	-0.006	0.001
Variance shares				
Variance of worker effects	0.413	0.364	0.342	-0.071
Variance of workplace effects	0.380	0.394	0.397	0.017
Variance of covariates	0.038	0.023	0.028	-0.010
Variance of residuals	0.101	0.092	0.088	-0.013
2 Cov(worker effects, workplace effects)	0.126	0.156	0.185	0.059
2 Cov(worker effects, covariates)	-0.044	-0.020	-0.028	0.016
2 Cov(workplace effects, covariates)	-0.013	-0.009	-0.011	0.002

Source: Authors' calculations using IMSS data. Variance decomposition results from equation (2) using the estimated worker and workplace fixed effects from equation (1). The "Variance and covariance" rows show the values of the variance of log wages in the estimation sample of prime-age men and its components. The "Variance shares" rows show the share of the overall variance in log wages in the sample attributed to each one of its components. The first three columns correspond to time intervals, and the last columns is the change from 2004-2008 to 2014-2018.

Table B.3: Wage Variance Decomposition, Center Region. Men Ages 25-54

	Interval 1 2004-2008	Interval 2 2009-2013	Interval 3 2014-2018	Change from int. 1 to 3
Variance and covariance				
Total variance of log wages	0.682	0.694	0.702	0.020
Variance of worker effects	0.282	0.258	0.243	-0.039
Variance of workplace effects	0.215	0.243	0.256	0.041
Variance of covariates (Xb)	0.019	0.013	0.015	-0.004
Variance of residuals	0.058	0.058	0.056	-0.002
2 Cov(worker effects, workplace effects)	0.126	0.131	0.146	0.020
2 Cov(worker effects, covariates)	-0.012	-0.005	-0.009	0.003
2 Cov(workplace effects, covariates)	-0.005	-0.004	-0.005	0.000
Variance shares				
Variance of worker effects	0.413	0.372	0.347	-0.066
Variance of workplace effects	0.315	0.350	0.364	0.049
Variance of covariates	0.028	0.018	0.022	-0.006
Variance of residuals	0.085	0.084	0.079	-0.006
2 Cov(worker effects, workplace effects)	0.184	0.189	0.208	0.024
2 Cov(worker effects, covariates)	-0.018	-0.008	-0.013	0.005
2 Cov(workplace effects, covariates)	-0.007	-0.006	-0.007	0.000

Source: Authors' calculations using IMSS data. Variance decomposition results from equation (2) using the estimated worker and workplace fixed effects from equation (1). The "Variance and covariance" rows show the values of the variance of log wages in the estimation sample of prime-age men and its components. The "Variance shares" rows show the share of the overall variance in log wages in the sample attributed to each one of its components. The first three columns correspond to time intervals, and the last columns is the change from 2004-2008 to 2014-2018.

Table B.4: Wage Variance Decomposition, South Region. Men Ages 25-54

	Interval 1 2004-2008	Interval 2 2009-2013	Interval 3 2014-2018	Change from int. 1 to 3
Variance and covariance				
Total variance of log wages	0.565	0.622	0.607	0.042
Variance of worker effects	0.206	0.193	0.177	-0.029
Variance of workplace effects	0.229	0.280	0.281	0.052
Variance of covariates (Xb)	0.020	0.013	0.016	-0.004
Variance of residuales	0.058	0.058	0.054	-0.004
2 Cov(worker effects, workplace effects)	0.073	0.089	0.094	0.021
2 Cov(worker effects, covariates)	-0.017	-0.007	-0.010	0.007
2 Cov(workplace effects, covariates)	-0.005	-0.003	-0.004	0.001
Variance shares				
Variance of worker effects	0.365	0.310	0.292	-0.073
Variance of workplace effects	0.406	0.450	0.464	0.058
Variance of covariates	0.035	0.021	0.026	-0.009
Variance of residuals	0.102	0.093	0.089	-0.013
2 Cov(worker effects, workplace effects)	0.130	0.144	0.155	0.025
2 Cov(worker effects, covariates)	-0.031	-0.012	-0.016	0.015
2 Cov(workplace effects, covariates)	-0.008	-0.005	-0.007	0.001

Source: Authors' calculations using IMSS data. Variance decomposition results from equation (2) using the estimated worker and workplace fixed effects from equation (1). The "Variance and covariance" rows show the values of the variance of log wages in the estimation sample of prime-age men and its components. The "Variance shares" rows show the share of the overall variance in log wages in the sample attributed to each one of its components. The first three columns correspond to time intervals, and the last columns is the change from 2004-2008 to 2014-2018.

Table B.5: AKM Model Summary: Women, Men, and All Workers Age 25-54

	Interval 1 2004-2008	Interval 2 2009-2013	Interval 3 2014-2018
Panel A: Women			
Worker and workplace parameters			
Number of worker effects	2,600,846	3,463,498	4,824,406
Number of workplace effects	286,383	346,557	458,888
Summary of parameter estimates			
St. dev. of worker effects	0.544	0.520	0.507
St. dev. of workplace effects	0.395	0.427	0.429
Correlation worker/workplace effects	0.191	0.210	0.226
Correlation worker effects/Xb	-0.281	-0.221	-0.267
Correlation workplace effects/Xb	-0.070	-0.062	-0.057
Goodness of fit			
St. dev. of log wages	0.739	0.757	0.748
R Squared	0.920	0.921	0.920
Panel B: Men			
Worker and workplace parameters			
Number of worker effects	5,576,345	6,920,461	8,941,908
Number of workplace effects	523,701	554,593	695,749
Summary of parameter estimates			
St. dev. of worker effects	0.504	0.486	0.472
St. dev. of workplace effects	0.444	0.479	0.487
Correlation worker/workplace effects	0.212	0.231	0.259
Correlation worker effects/Xb	-0.123	-0.074	-0.104
Correlation workplace effects/Xb	-0.051	-0.045	-0.048
Goodness of fit			
St. dev. of log wages	0.772	0.792	0.793
R Squared	0.909	0.913	0.916
Panel C: All			
Worker and workplace parameters			
Number of worker effects	8,271,051	10,420,514	13,822,322
Number of workplace effects	627,949	672,769	830,982
Summary of parameter estimates			
St. dev. of worker effects	0.516	0.495	0.482
St. dev. of workplace effects	0.427	0.461	0.466
Correlation worker/workplace effects	0.215	0.232	0.254
Correlation worker effects/Xb	-0.169	-0.118	-0.158
Correlation workplace effects/Xb	-0.058	-0.052	-0.053
Goodness of fit			
St. dev. of log wages	0.764	0.781	0.778
R Squared	0.910	0.913	0.916

Source: Authors' calculations using IMSS data. Results from estimation of equation (1) via OLS. Observations correspond to largest connected set per time interval. "Xb" stands for covariates and includes the following controls age, age squared, age cube, and a monthly time trend.

Table B.6: Wage Variance Decomposition, National Level. Women Ages 25-54

	Interval 1 2004-2008	Interval 2 2009-2013	Interval 3 2014-2018	Change from int. 1 to 3
Variance and covariance				
Total variance of log wages	0.546	0.573	0.559	0.013
Variance of person effects	0.296	0.271	0.257	-0.039
Variance of firm effects	0.156	0.183	0.184	0.029
Variance of covariates (Xb)	0.021	0.014	0.022	0.001
Variance of residual	0.044	0.045	0.045	0.001
2 Cov(person effects, firm effects)	0.082	0.093	0.098	0.016
2 Cov(person effects, covariates)	-0.045	-0.027	-0.040	0.005
2 Cov(firm effects, covariates)	-0.008	-0.006	-0.007	0.001
Variance shares				
Variance of person effects	0.542	0.473	0.460	-0.082
Variance of firm effects	0.285	0.319	0.330	0.044
Variance of covariates (Xb)	0.039	0.024	0.039	0.001
Variance of residual	0.080	0.079	0.080	-0.000
2 Cov(person effects, firm effects)	0.150	0.163	0.176	0.025
2 Cov(person effects, covariates)	-0.082	-0.047	-0.072	0.011
2 Cov(firm effects, covariates)	-0.015	-0.011	-0.013	0.002
Counterfactuals for variance of log wages				
1. No rise in correl. of person/firm effects	0.546	0.563	0.545	
2. No rise in var. of firm effects	0.546	0.538	0.522	
3. Both 1 and 2	0.546	0.536	0.516	

Source: Authors' calculations using IMSS data. Variance decomposition results from equation (2) using the estimated worker and workplace fixed effects from equation (1). The "Variance and covariance" rows show the values of the variance of log wages in the estimation sample of prime-age men and its components. The "Variance shares" rows show the share of the overall variance in log wages in the sample attributed to each one of its components. The first three columns correspond to time intervals, and the last columns is the change from 2004-2008 to 2014-2018. The "Counterfactuals for variance of log wages" rows show the variance of wages assuming that the correlation of worker/workplaces effects and the variance of workplace effects had remained constant at 2004-2008 values.

Table B.7: Wage Variance Decomposition, National Level. All Workers Ages 25-54

	Interval 1 2004-2008	Interval 2 2009-2013	Interval 3 2014-2018	Change from int. 1 to 3
Variance and covariance				
Total variance of log wages	0.584	0.610	0.606	0.022
Variance of person effects	0.266	0.245	0.233	-0.033
Variance of firm effects	0.182	0.212	0.217	0.035
Variance of covariates (Xb)	0.019	0.013	0.017	-0.002
Variance of residual	0.053	0.053	0.051	-0.001
2 Cov(person effects, firm effects)	0.095	0.106	0.114	0.019
2 Cov(person effects, covariates)	-0.024	-0.013	-0.020	0.004
2 Cov(firm effects, covariates)	-0.007	-0.005	-0.006	0.000
Variance shares				
Variance of person effects	0.456	0.402	0.384	-0.071
Variance of firm effects	0.312	0.348	0.358	0.046
Variance of covariates (Xb)	0.033	0.021	0.028	-0.004
Variance of residual	0.090	0.087	0.084	-0.007
2 Cov(person effects, firm effects)	0.162	0.174	0.188	0.025
2 Cov(person effects, covariates)	-0.042	-0.022	-0.033	0.008
2 Cov(firm effects, covariates)	-0.012	-0.009	-0.011	0.002
Counterfactuals for variance of log wages				
1. No rise in correl. of person/firm effects	0.584	0.602	0.588	
2. No rise in var. of firm effects	0.584	0.572	0.561	
3. Both 1 and 2	0.584	0.572	0.553	

Source: Authors' calculations using IMSS data. Variance decomposition results from equation (2) using the estimated worker and workplace fixed effects from equation (1). The "Variance and covariance" rows show the values of the variance of log wages in the estimation sample of prime-age men and its components. The "Variance shares" rows show the share of the overall variance in log wages in the sample attributed to each one of its components. The first three columns correspond to time intervals, and the last columns is the change from 2004-2008 to 2014-2018. The "Counterfactuals for variance of log wages" rows show the variance of wages assuming that the correlation of worker/workplace effects and the variance of workplace effects had remained constant at 2004-2008 values.

Table B.8: Wage Variance Decomposition With Fixed Effects by Year

	Interval 1 2004-2008	Interval 2 2009-2013	Interval 3 2014-2018
All			
Variance and covariance			
Total variance of log wages	0.584	0.610	0.606
Variance of person effects	0.284	0.268	0.256
Variance of firm effects	0.182	0.212	0.217
2 Cov(person effects, firm effects)	0.079	0.091	0.097
Variance shares			
Variance of person effects	0.486	0.439	0.422
Variance of firm effects	0.312	0.347	0.359
2 Cov(person effects, firm effects)	0.136	0.150	0.160
Men			
Variance and covariance			
Total variance of log wages	0.596	0.627	0.628
Variance of person effects	0.287	0.272	0.261
Variance of firm effects	0.197	0.230	0.237
2 Cov(person effects, firm effects)	0.080	0.094	0.102
Variance shares			
Variance of person effects	0.481	0.433	0.416
Variance of firm effects	0.331	0.366	0.377
2 Cov(person effects, firm effects)	0.134	0.149	0.163
Women			
Variance and covariance			
Total variance of log wages	0.546	0.573	0.559
Variance of person effects	0.278	0.265	0.248
Variance of firm effects	0.156	0.183	0.185
2 Cov(person effects, firm effects)	0.067	0.079	0.082
Variance shares			
Variance of person effects	0.509	0.463	0.444
Variance of firm effects	0.285	0.319	0.330
2 Cov(person effects, firm effects)	0.122	0.137	0.146

Source: Authors' calculations using IMSS data. Variance decomposition results from equation (2) using the estimated worker and workplace fixed effects from equation (1) including year fixed effects and excluding a linear term in age. The panels show variance decompositions for the samples of all workers, men ages 25-54, and women ages 25-54. The "Variance and covariance" rows show the values of the variance of log wages in the estimation sample of prime-age men and its components. The "Variance shares" rows show the share of the overall variance in log wages in the sample attributed to each one of its components. The columns correspond to time intervals.

Table B.9: Wage Variance Decomposition With Normalization to Different Years. Men Ages 25-54

	Interval 1 2004-2008	Interval 2 2009-2013	Interval 3 2014-2018
Normalization to 30 years			
Variance and covariance			
Total variance of log wages	0.596	0.627	0.628
Variance of person effects	0.254	0.236	0.222
Variance of firm effects	0.197	0.230	0.237
2 Cov(person effects, firm effects)	0.095	0.108	0.119
Variance shares			
Variance of person effects	0.426	0.376	0.354
Variance of firm effects	0.330	0.366	0.377
2 Cov(person effects, firm effects)	0.159	0.172	0.189
Normalization to 40 years			
Variance and covariance			
Total variance of log wages	0.596	0.627	0.628
Variance of person effects	0.254	0.236	0.222
Variance of firm effects	0.197	0.230	0.237
2 Cov(person effects, firm effects)	0.095	0.108	0.119
Variance shares			
Variance of person effects	0.426	0.376	0.354
Variance of firm effects	0.330	0.366	0.377
2 Cov(person effects, firm effects)	0.159	0.172	0.189
Normalization to 50 years			
Variance and covariance			
Total variance of log wages	0.596	0.627	0.628
Variance of person effects	0.254	0.236	0.222
Variance of firm effects	0.197	0.230	0.237
2 Cov(person effects, firm effects)	0.095	0.108	0.119
Variance shares			
Variance of person effects	0.426	0.376	0.354
Variance of firm effects	0.330	0.366	0.377
2 Cov(person effects, firm effects)	0.159	0.172	0.189

Source: Authors' calculations using IMSS data. Variance decomposition results from equation (2) using the estimated worker and workplace fixed effects from equation (1) on the sample of men ages 25-54. The panels show results with alternative normalizations of the age variable: 30 years (baseline), 40 years, and 50 years. The "Variance and covariance" rows show the values of the variance of log wages in the estimation sample of prime-age men and its components. The "Variance shares" rows show the share of the overall variance in log wages in the sample attributed to each one of its components. The columns correspond to time intervals.

Table B.10: Variance Decomposition with the Kline et al. (2020) Variance Estimator

	Interval 1 2004-2008	Interval 2 2009-2013	Interval 3 2014-2018
Connected set			
Total variance of log wages	0.596	0.627	0.628
Variance of worker effects	0.254	0.236	0.222
Variance of workplace effects	0.197	0.230	0.237
2 Cov(worker effects, workplace effects)	0.095	0.108	0.119
Leave-one-out connected set			
Total variance of log wages	0.596	0.627	0.628
Variance of worker effects	0.254	0.235	0.222
Variance of workplace effects	0.193	0.227	0.235
2 Cov(worker effects, workplace effects)	0.098	0.110	0.121
KSS corrected in leave-one-out connected set			
Total variance of log wages	0.596	0.627	0.628
Variance of worker effects	0.252	0.234	0.220
Variance of workplace effects	0.193	0.226	0.234
2 Cov(worker effects, workplace effects)	0.099	0.111	0.121

Source: Authors' calculations using IMSS data. Variance decomposition results from equation (2) using the estimated worker and workplace fixed effects from equation (1). The rows in each panel show the values of the variance of log wages in the estimation sample of prime-age men and its components. The "Connected Set" Panel shows the original estimates in the connected set from Table 4. The "Leave-one-out Connected Set" panel shows estimates in the workplaces that remain in the connected set in every leave-one-out sample. The "KSS Corrected in Leave-One-Out Connected Set" shows estimates of the variance components using the correction by Kline et al. (2020). We use the "match" leave-one-out estimator, leaving out worker-workplace matches one at a time. To approximate the components, we use 50 iterations of the JILA algorithm. See Kline et al. (2020) for details.

Table B.11: Variance Decomposition with Bonhomme et al.'s (2019) Correction for Limited Mobility Bias

	Interval 1 2004-2008	Interval 2 2009-2013	Interval 3 2014-2018
No clusters			
Variance and covariance			
Total variance of log wages	0.596	0.627	0.628
Variance of person effects	0.254	0.236	0.222
Variance of firm effects	0.197	0.230	0.237
2 Cov(person effects, firm effects)	0.095	0.108	0.119
Variance shares			
Variance of person effects	0.426	0.376	0.354
Variance of firm effects	0.330	0.366	0.377
2 Cov(person effects, firm effects)	0.159	0.172	0.189
5 clusters			
Variance and covariance			
Total variance of log wages	0.596	0.626	0.628
Variance of person effects	0.231	0.216	0.206
Variance of firm effects	0.159	0.188	0.197
2 Cov(person effects, firm effects)	0.144	0.154	0.161
Variance shares			
Variance of person effects	0.387	0.344	0.328
Variance of firm effects	0.266	0.301	0.313
2 Cov(person effects, firm effects)	0.241	0.247	0.256
10 clusters			
Variance and covariance			
Total variance of log wages	0.596	0.626	0.628
Variance of person effects	0.217	0.199	0.195
Variance of firm effects	0.171	0.204	0.209
2 Cov(person effects, firm effects)	0.147	0.158	0.162
Variance shares			
Variance of person effects	0.365	0.318	0.310
Variance of firm effects	0.287	0.327	0.333
2 Cov(person effects, firm effects)	0.246	0.252	0.258
15 clusters			
Variance and covariance			
Total variance of log wages	0.596	0.626	0.628
Variance of person effects	0.212	0.196	0.188
Variance of firm effects	0.178	0.208	0.219
2 Cov(person effects, firm effects)	0.147	0.158	0.161
Variance shares			
Variance of person effects	0.356	0.313	0.299
Variance of firm effects	0.299	0.333	0.348
2 Cov(person effects, firm effects)	0.246	0.252	0.257

Source: Authors' calculations using IMSS data. We use 20 percentiles of the within workplace log wage distribution to cluster workplaces in 5, 10 and 15 groups to estimate the AKM model. The first panel shows the original estimates for variance of worker and establishment effects and the covariance between the two effects and their respective variance shares. The other three panels show the analogue estimates using workplace clusters as in Bonhomme et al. (2019).

Table B.12: Wage Variance Decomposition Across Sectors

	(1) Interval 1 2004-2008	(2) Interval 2 2009-2013	(3) Interval 3 2014-2018	Change in variance (4)	Change in variance (5) Share
Std. dev. of mean log wages	0.359	0.374	0.377	0.0131	100.0
Std. dev. of mean worker effects	0.153	0.147	0.143	-0.0031	-23.7
Std. dev. of mean firm effects	0.255	0.270	0.275	0.0101	77.1
Correlation of mean worker effects and firm effects	0.562	0.608	0.633	0.0061	46.6

Source: Authors' calculations using IMSS data. "Std. dev. of mean log wages" is the standard deviation of average log wages across sectors. "Std. dev. of mean worker effects" is the standard deviation across sectors of the sector-averages of worker effects. "Std. dev. of mean workplace effects is the standard deviation across sectors of the sector-averages of workplace effects. "Correlation of mean worker effects and workplace effects" is the correlation of the sector-level average worker and workplace effects. The "Change in Variance" columns show the change in the variance components and the share of variance from 2004-2008 to 2014-2018.

Table B.13: Within and Between Region Variance Contribution to Total Variance

	Interval 1 2004-2008	Interval 2 2009-2013	Interval 3 2014-2018
Log of wages			
Total variance	0.596	0.627	0.628
Between region variance	0.006	0.004	0.005
Within region variance	0.590	0.622	0.623
Share of between region variance	0.01	0.01	0.01
Share of within region variance	0.99	0.99	0.99
Worker effects			
Total variance	0.254	0.236	0.222
Between region variance	0.001	0.001	0.001
Within region variance	0.252	0.234	0.221
Share of between region variance	0.01	0.00	0.01
Share of within region variance	0.99	0.99	0.99
Workplace effects			
Total variance	0.197	0.230	0.237
Between region variance	0.002	0.001	0.001
Within region variance	0.195	0.228	0.236
Share of between region variance	0.01	0.01	0.01
Share of within region variance	0.99	0.99	0.99
2 Cov(worker effects, workplace effects)			
Total covariance	0.095	0.108	0.119
Between region covariance	0.003	0.002	0.003
Within region covariance	0.093	0.106	0.117
Share of between region covariance	0.03	0.02	0.02
Share of within region covariance	0.98	0.98	0.98

Source: Authors' calculations using IMSS data. The first panel shows the contribution of the within and between region variance to the overall variance of log wages. The second and third panels are for worker and workplace effects respectively. The last panel shows the contributions of within- and between-region components to the overall worker-workplace covariance.

Table B.14: Herfindahl-Hirschman Index (HHI) by Region

	Interval 1 2004-2008	Interval 2 2009-2013	Interval 3 2014-2018
Employment-level HHI			
North	0.174	0.172	0.176
Center-North	0.172	0.170	0.169
Center	0.118	0.113	0.114
South	0.206	0.200	0.205
Payroll-level HHI			
North	0.214	0.209	0.213
Center-North	0.234	0.231	0.225
Center	0.152	0.140	0.138
South	0.270	0.266	0.271

Source: Authors' calculations using IMSS data. To calculate the Herfindahl-Hirschman Index (HHI) we assign each individual to a commuting zone and an industry. Afterwards, we calculate the total employment and payroll for each firm and each month. We then calculate employment- and payroll-level HHIs for each commuting zone and industry each month, and then average the results by month weighting by total employment/payroll in each industry to arrive at a commuting-zone level HHI. Then, we average across commuting zones weighing by employment or payroll to arrive at a regional HHI by month, and take the simple average across months to arrive at a regional HHI for each time interval.

Table B.15: Wage Variance Decomposition With Fixed Effects by Firm-Year

	Interval 1 2004-2008	Interval 2 2009-2013	Interval 3 2014-2018
All			
Variance and covariance			
Total variance of log wages	0.584	0.610	0.606
Variance of person effects	0.283	0.266	0.253
Variance of firm plus firm by year effects	0.189	0.219	0.227
2 Cov(person effects, firm plus firm by year effects)	0.075	0.087	0.091
Variance shares			
Variance of person effects	0.485	0.436	0.418
Variance of firm plus firm by year effects	0.324	0.359	0.374
2 Cov(person effects, firm plus firm by year effects)	0.128	0.142	0.150
Men			
Variance and covariance			
Total variance of log wages	0.596	0.627	0.628
Variance of person effects	0.286	0.270	0.257
Variance of firm plus firm by year effects	0.205	0.237	0.247
2 Cov(person effects, firm plus firm by year effects)	0.075	0.089	0.096
Variance shares			
Variance of person effects	0.479	0.430	0.409
Variance of firm plus firm by year effects	0.343	0.378	0.393
2 Cov(person effects, firm plus firm by year effects)	0.126	0.141	0.153
Women			
Variance and covariance			
Total variance of log wages	0.546	0.573	0.559
Variance of person effects	0.279	0.265	0.247
Variance of firm plus firm by year effects	0.163	0.190	0.195
2 Cov(person effects, firm plus firm by year effects)	0.061	0.074	0.075
Variance shares			
Variance of person effects	0.511	0.463	0.443
Variance of firm plus firm by year effects	0.299	0.332	0.350
2 Cov(person effects, firm plus firm by year effects)	0.112	0.128	0.133

Source: Authors' calculations using IMSS data. Variance decomposition results from equation (2) using the estimated worker and workplace fixed effects from equation (1) including firm by year fixed effects and excluding a linear term in age. The panels show variance decompositions for the samples of all workers, men ages 25-54, and women ages 25-54. The "Variance and covariance" rows show the values of the variance of log wages in the estimation sample of prime-age men and its components. The "Variance shares" rows show the share of the overall variance in log wages in the sample attributed to each one of its components. The columns correspond to time intervals.

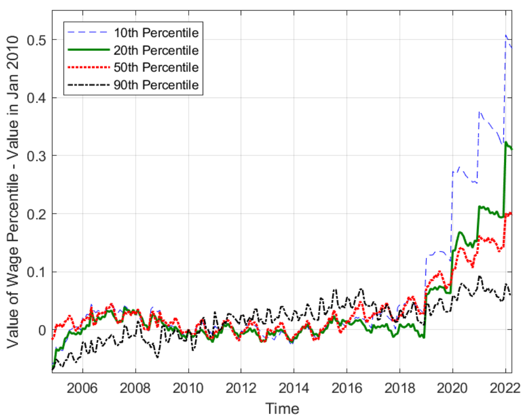
Table B.16: Wage Variance Decomposition by High- and Low-Wage Firms with Bonhomme et al.'s (2019) Correction for Limited Mobility Bias

	Interval 1 2004-2008	Interval 2 2009-2013	Interval 3 2014-2018
Below percentile 25			
Variance and covariance			
Total variance of log wages	0.013	0.008	0.004
Variance of person effects	0.025	0.011	0.066
Variance of firm effects	0.000	0.000	0.000
2 Cov(person effects, firm effects)	0.000	0.000	0.000
Variance shares			
Variance of person effects	1.934	1.376	16.589
Variance of firm effects	0.026	0.021	0.008
2 Cov(person effects, firm effects)	0.030	0.023	0.041
Between percentiles 25 and 50			
Variance and covariance			
Total variance of log wages	0.011	0.007	0.005
Variance of person effects	0.007	0.005	0.004
Variance of firm effects	0.001	0.001	0.000
2 Cov(person effects, firm effects)	0.000	0.000	0.000
Variance shares			
Variance of person effects	0.643	0.640	0.692
Variance of firm effects	0.116	0.114	0.086
2 Cov(person effects, firm effects)	0.031	0.024	0.019
Between percentiles 50 and 75			
Variance and covariance			
Total variance of log wages	0.013	0.015	0.016
Variance of person effects	0.008	0.008	0.009
Variance of firm effects	0.001	0.002	0.002
2 Cov(person effects, firm effects)	0.000	0.000	0.000
Variance shares			
Variance of person effects	0.622	0.573	0.540
Variance of firm effects	0.108	0.122	0.130
2 Cov(person effects, firm effects)	0.007	0.002	0.009
Above percentile 75			
Variance and covariance			
Total variance of log wages	0.343	0.360	0.373
Variance of person effects	0.237	0.236	0.240
Variance of firm effects	0.020	0.024	0.026
2 Cov(person effects, firm effects)	0.047	0.053	0.057
Variance shares			
Variance of person effects	0.692	0.657	0.644
Variance of firm effects	0.059	0.067	0.071
2 Cov(person effects, firm effects)	0.138	0.146	0.153

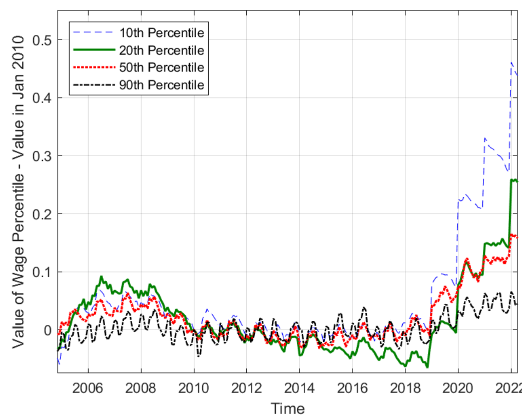
Source: Authors' calculations using IMSS data. We estimate a separate AKM model for each firm wage group. The percentile groups were obtained by calculating the average wage by firm in each interval. The percentiles used are the 25th , 50th and 75th percentiles. We use 20 percentiles of the within workplace log wage distribution to cluster workplaces in 5 groups to estimate the AKM model. Each panel shows the values of the variance of log wages in the estimation sample of prime-age men and its components. The "Variance shares" row show the share of the overall variance in log wages in the sample attributed to each one of its components. Columns correspond to time intervals.

Figure B.1: Trends in Percentiles of Log Wages for Men, Women, and all Workers Ages 25-54. 2004-2022

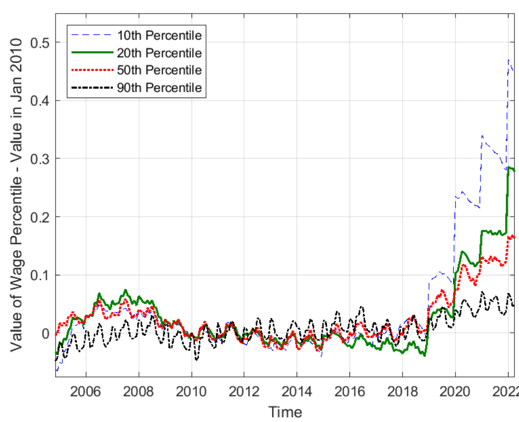
(a) Women



(b) Men



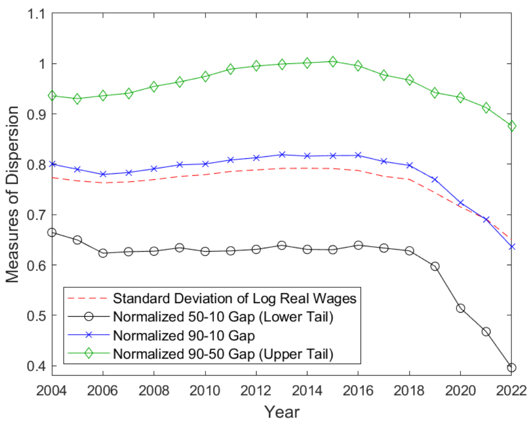
(c) All



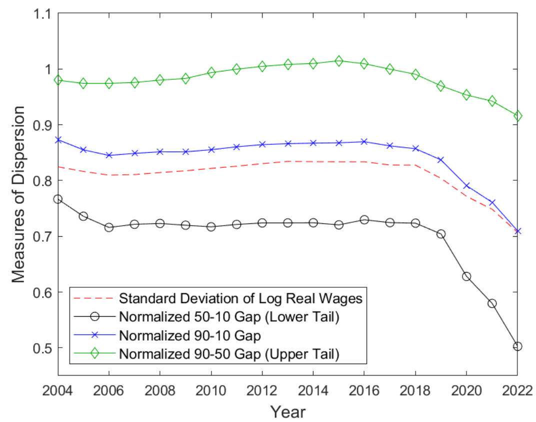
Source: Authors' calculations using IMSS data. The lines depict the values of the 10th, 20th, 50th and 90th percentile of the wages of workers 25-54 years old, relative to the values of these percentiles in January of 2010.

Figure B.2: Upper-Tail, Lower-Tail and Overall Wage Inequality Trends for Prime-Age Men, Women and all Workers, National Level, 2004-2022

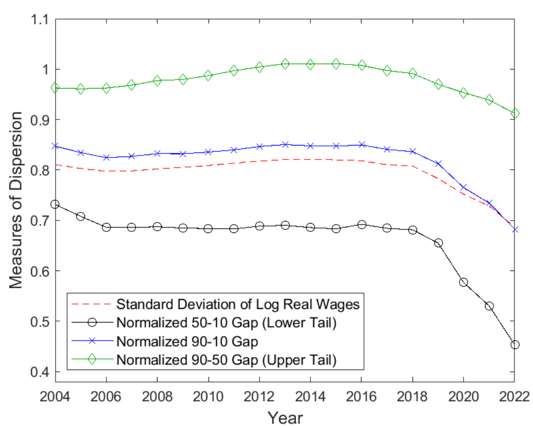
(a) Women



(b) Men

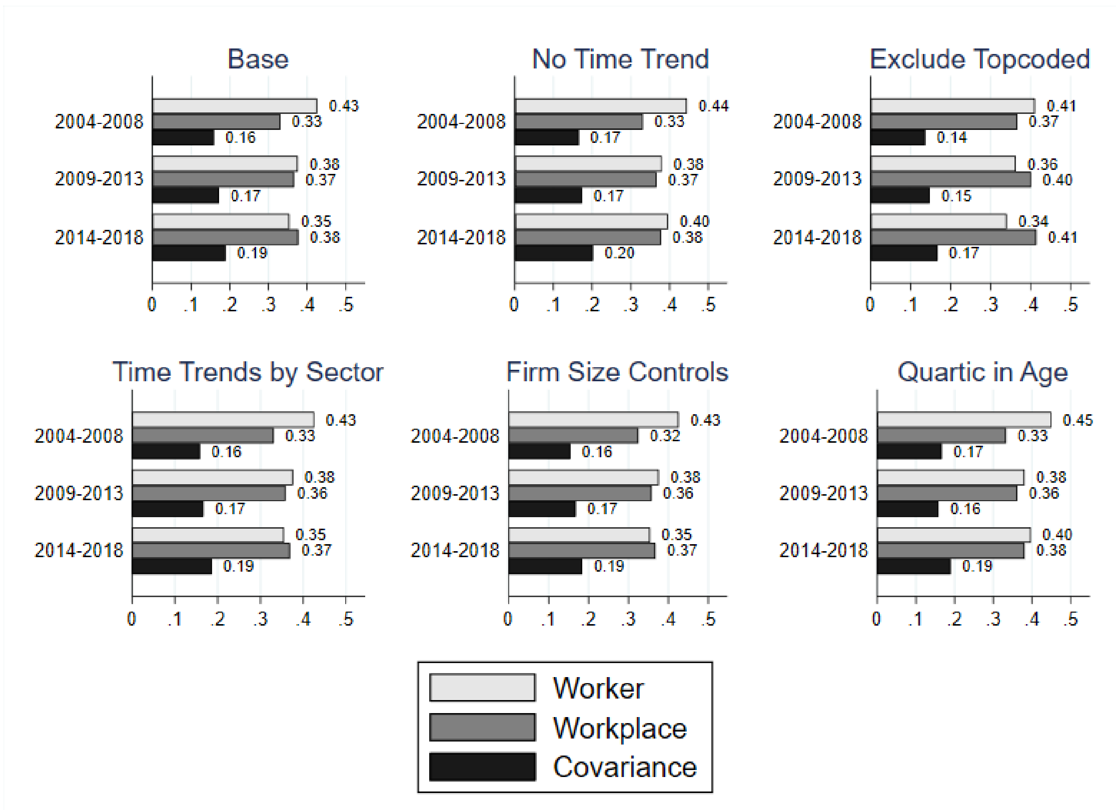


(c) All



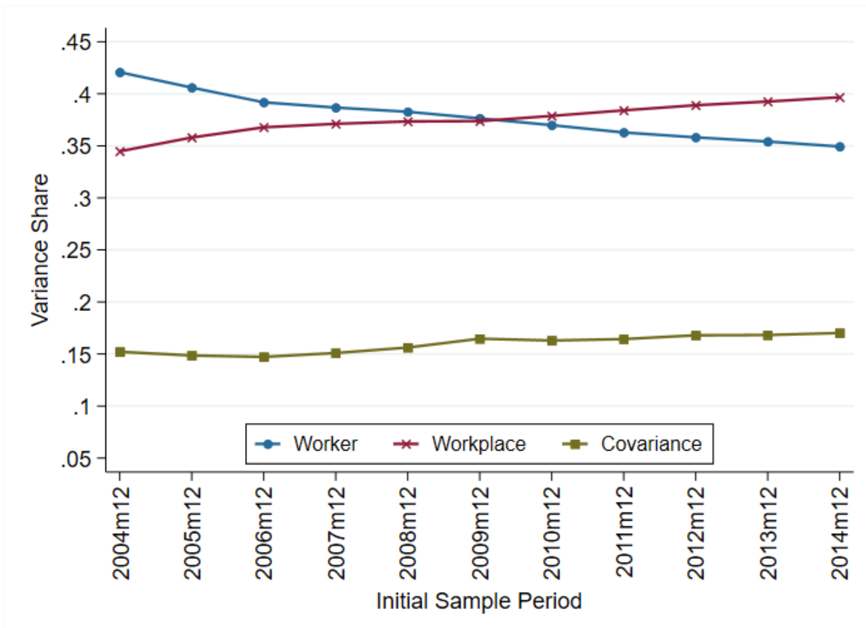
Source: Authors' calculations using IMSS data. Normalized percentile gaps are differences in percentiles divided by the corresponding differences in percentiles of standard normal variable. For example, the 90th-10th gap is divided by $\Phi^{-1}(0.9) - \Phi^{-1}(0.1)$, where $\Phi(\cdot)$ stands for the standard normal distribution function.

Figure B.3: Variance Shares Comparison Across Model Specifications



Source: Authors' calculations using IMSS data. The panels depict variance shares from variance decomposition results using equation (2). Each panel corresponds to a different model specification. Panel "Base" corresponds to the baseline estimates in Table 4, where the control set includes age, age squared, age cube and a time trend. Panel "No Time Trend" excludes the linear time trend from the control set. Panel "Exclude Topcoded" excludes top-coded observations. Panel "Time Trends by Sector" includes interactions of sector indicators ("actividad" in IMSS data) and a linear time trend. Panel "Firm Size Controls" includes a control for workplace size. Panel "Quartic in Age" includes age to the fourth power as a control. The rows in each panel correspond to time intervals.

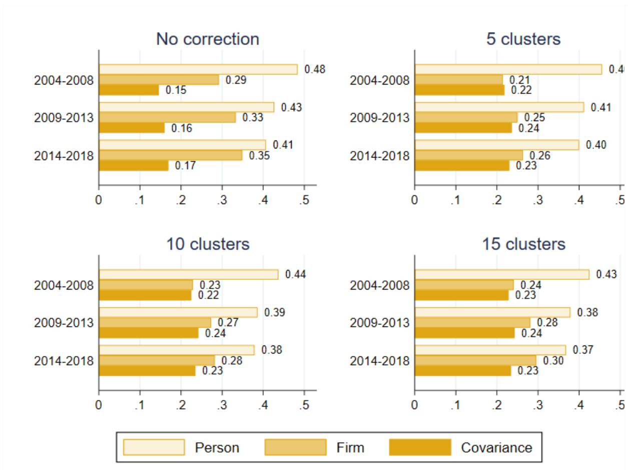
Figure B.4: Variance Decomposition for Additional 4-year Windows



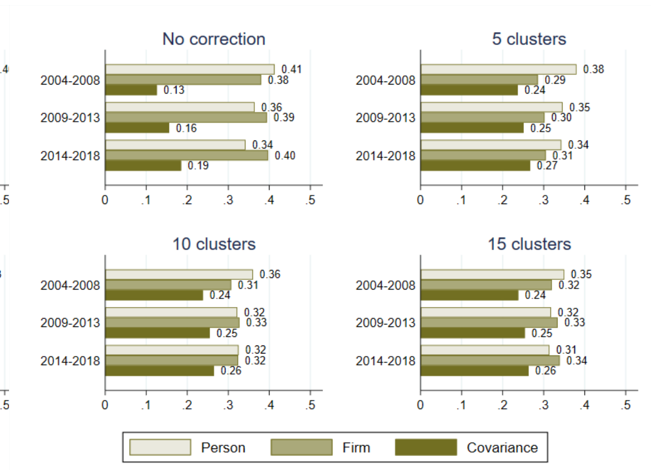
Source: Authors' calculations using IMSS data. The lines depict variance shares from variance decomposition results using equation (2). Each time point corresponds to an estimation using a 4-year period starting in the given month.

Figure B.5: Estimated Worker and Workplace Contributions to Wage Variability by Region with Bonhomme et al.'s (2019) Correction for Limited Mobility Bias

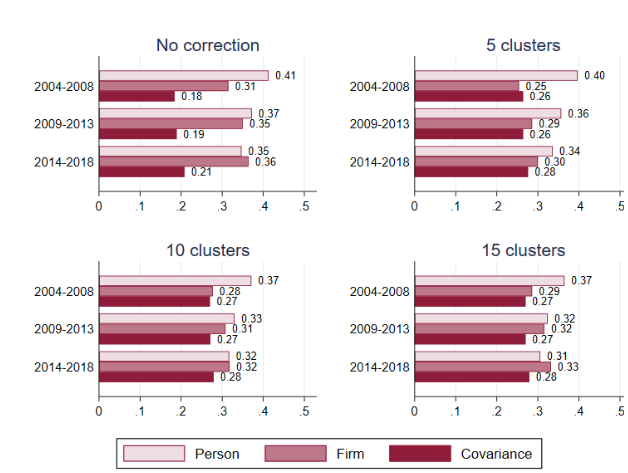
(a) North



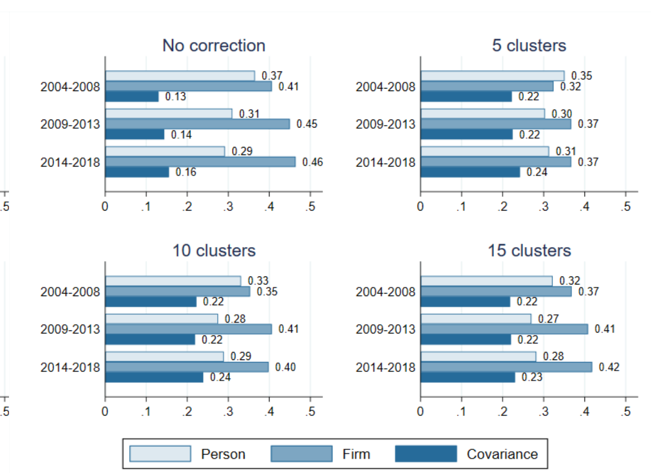
(b) Center-North



(c) Center



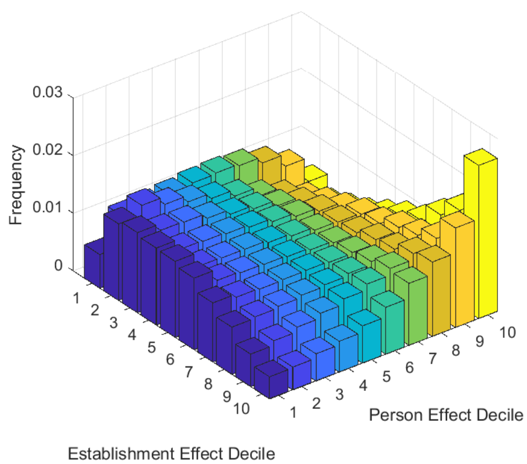
(d) South



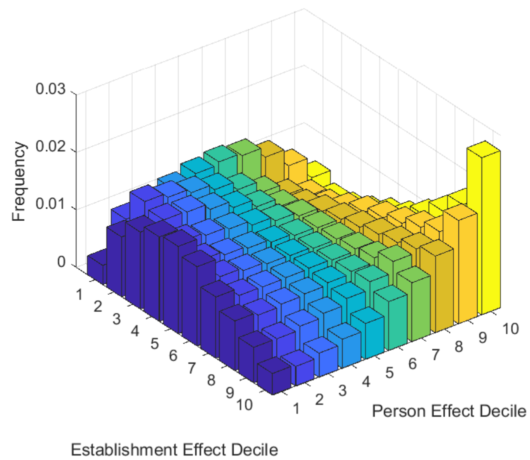
Source: Authors' calculations using IMSS data. The Figure depicts the variance shares attributed to worker fixed effects, workplace fixed effects, and their covariance in the overall variance of wages in each region, using the estimates of the AKM model from equation (1) and the decomposition in equation (2) Panel (a) shows the estimates without correcting for limited mobility bias. Panels (b) to (d) show the estimates correcting for limited mobility bias by grouping workplaces into 5, 10, and 15 clusters, as in Bonhomme et al. (2019).

Figure B.6: Changes in Assortative Matching: Joint Densities of Workplace and Worker Effects. National Level

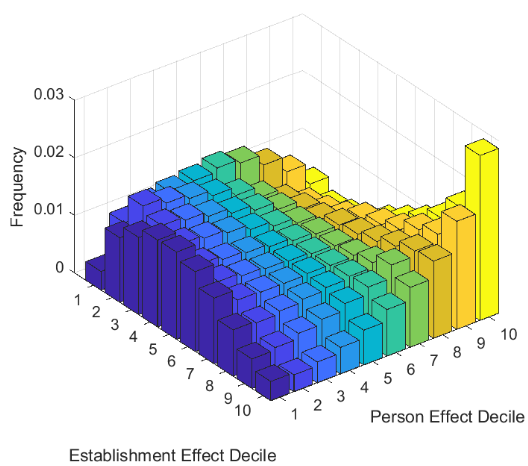
(a) 2004-2008



(b) 2009-2013

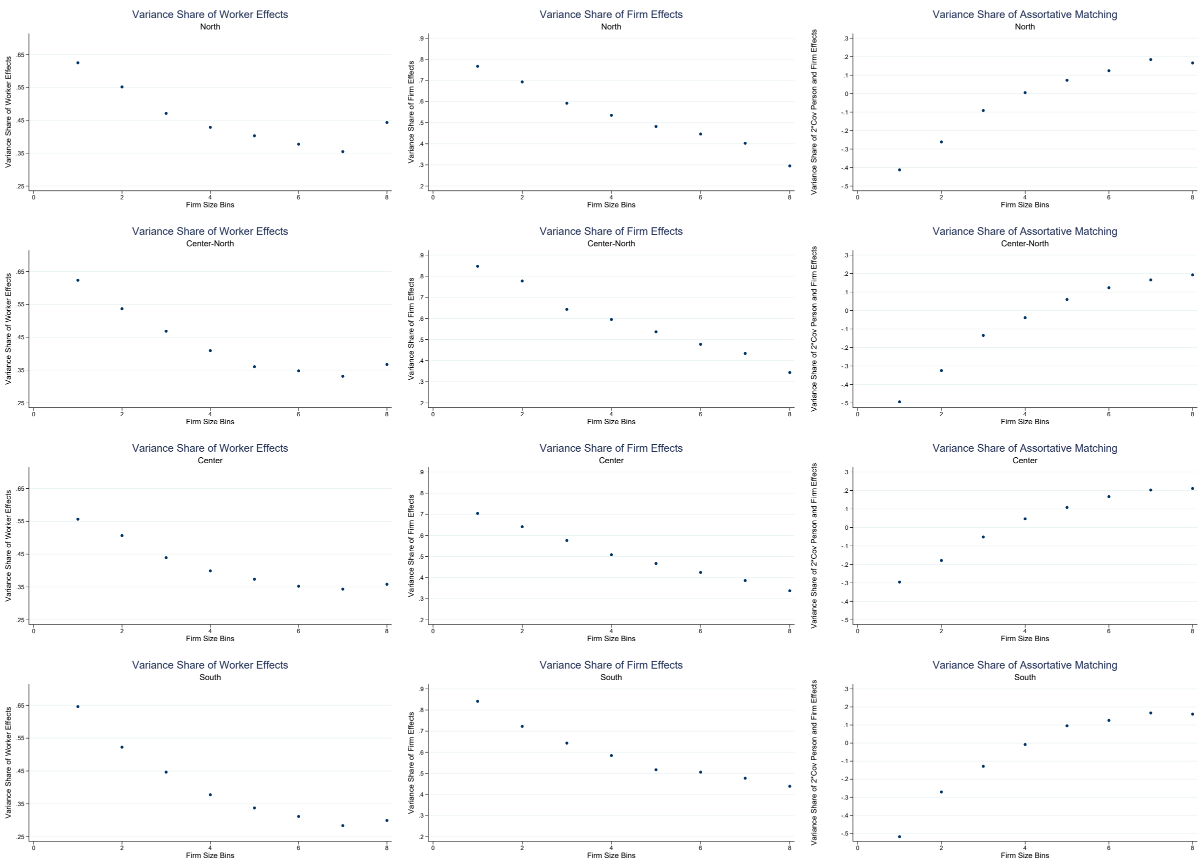


(c) 2014-2018



Source: Authors' calculations using IMSS data. Panels depict the joint distribution of estimated worker and workplace effects from equation (1) by deciles of the marginal worker and fixed effect distributions.

Figure B.7: Variance Share Components and Workplace Size in 2014-2018



Source: Authors' calculations using IMSS data. The panels show scatter plots depicting the relationship between the share of variance attributed to worker effects, firm effects, and assortative matching (covariance between worker and workplace effects) and the size of workplaces (firms) for 2014-2018. Workplaces are grouped in "firm size bins" from smaller to larger. These bins were obtained by calculating for each firm the mean number of employees. The first bin includes firms with size one. The following bins contain firm sizes greater than one. The firm size bins were obtained at the national level to be comparable between regions.