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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. To uncover these changes, we analyze an employer-employee dataset comprising the near-universe of Mexico's formal employment. We estimate log wage models and decompose earnings dispersions into worker, workplace and sorting components. At the national level, we find that sorting increased its importance over time. While worker-level factors were the main contributors to salary variability in the 2004-2008 period, workplace factors became as important as worker-level factors in the 2014-2018 time segment. The influence of workplace factors on wage dispersion correlates negatively with per capita GDP at the regional level.
Keywords: Assortative matching, regional development, wage dispersion, workplace wage premia
JEL Classification: J21, J31, R23, O15, O54

Resumen: Entre 2004 y 2018, la dispersión de los salarios en el sector privado formal de México se mantuvo estable. No obstante, los factores subyacentes detrás de la dispersión salarial experimentaron cambios significativos. Para analizar estos cambios, se estudia una base de datos empleador-empleado que comprende casi la totalidad del empleo formal en México. Se estiman modelos para el logaritmo de los salarios y se descompone la dispersión salarial en componentes de trabajador, lugar de trabajo y emparejamiento selectivo entre trabajadores y empresas. A nivel nacional, se encuentra que el emparejamiento selectivo incrementó su importancia en el tiempo. Mientras que el componente de trabajador fue el principal contribuyente a la variabilidad salarial en el periodo 2004-2008, el componente de lugar de trabajo se volvió tan importante como el componente de trabajador en 2014-2018. La influencia del componente de lugar de trabajo en la dispersión salarial está correlacionada negativamente con el PIB per cápita a nivel regional.
Palabras Clave: Emparejamiento selectivo, desarrollo regional, dispersión salarial, primas salariales de lugar de trabajo

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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 the dispersion of formal wages in Mexico and its regions 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

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

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 as important as worker-level factors in determining wage dispersion in Mexico and its regions. In concordance with previous work for developing countries, 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 contribution of the workplace-level component to overall wage variance in Mexico is substantially stronger compared to other OECD members (OECD 2021).[2]

There are notable differences in economic performance between regions in Mexico. The average GDP per capita from 2005 to 2021 (in 2013 prices) was 14,280 USD in the North, 10,980 USD in the Center, 9,467 USD in the Center-North, and 9,429 USD in the 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).[3]

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 region with the lowest GDP per capita. In the North, which has the highest per-capita GDP, the workplace-level factors'

[2]A difficulty for cross country-comparisons of wage variance and its determinants is the fact that employer-employee datasets, such as the one we study here, often have some degree of top-coding for high wages. In our data, about 2.5% of observations have top-coded wages. We provide additional details about top-coding in our dataset in Section 2. Our results only apply for the variance of wages after top-coding.

[3]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.

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.[4] The number of workers in the database was 12.8 million in November 2004 and 20.1 million by December 2018. Our wage variable of interest is the daily taxable income.[5] 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.[6]

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,

[4]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.

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

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

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.[7]

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*.[8] 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 of workers ages 25 to 54 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.[9] Column (4) of the Table shows that, compared to 2005, the average daily wage (in real terms) for prime-age men fell by 0.1% from 2005 to 2014, but rose by 1.7% from 2005 to 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. 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.

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.

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

[8]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.

[9]There is a lot of entry and exit to the formal labor market as measured by the IMSS dataset. For example, in every month from 2017 to 2019, hires account for between 7 and 8% of formal jobs, and separations account for a similar fraction of jobs (Banco de México 2020).

Table 1: Descriptive Statistics: Workers ages 25-54, National Level

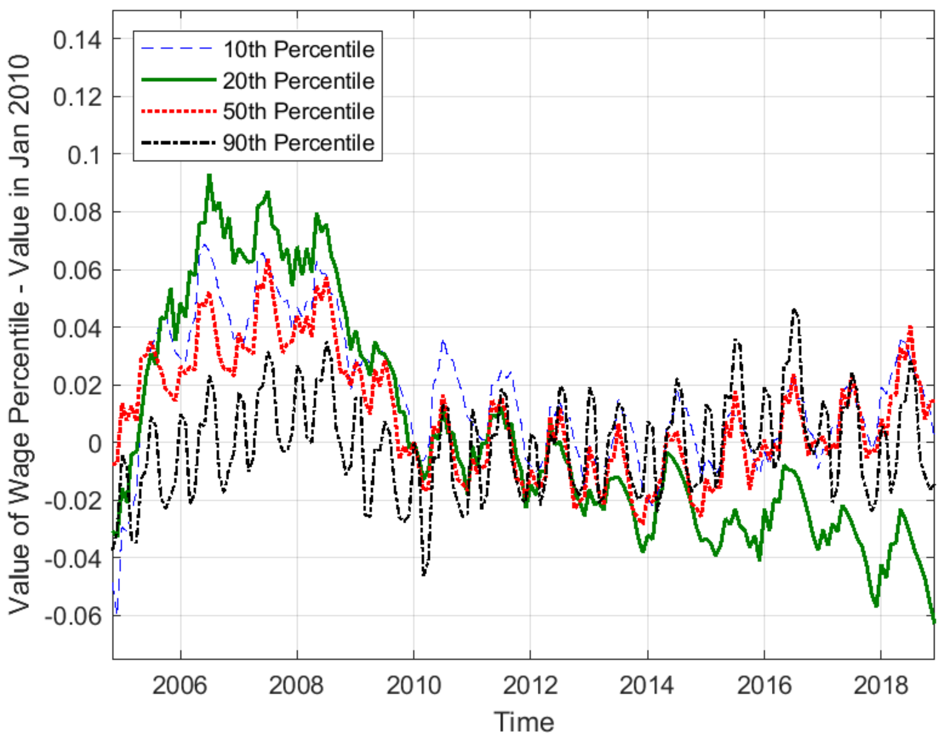
				Real wage		
	(1)	(2)	(3)	(4)	(5)	(6)
	Obs.	Workers	Workplaces	Mean	Std. dev	Pct. censored
Workers:						
Panel A. Men						
2005	73,847,545	7,864,702	581,276	394.589	406.167	2.675
2009	80,065,916	8,534,181	559,974	394.602	402.992	2.690
2014	96,354,574	10,098,159	562,463	394.200	409.212	2.649
2018	110,844,774	11,560,529	627,001	401.186	412.367	2.058
Panel B. Women						
2005	39,570,500	4,136,995	308,426	326.686	330.536	1.099
2009	46,339,329	4,781,718	332,276	332.815	336.948	1.216
2014	56,843,723	5,858,578	351,099	340.743	352.479	1.361
2018	68,544,441	7,135,265	397,088	347.333	356.220	1.108
Workplaces:						
Panel C. Small(one to five workers)						
2005	12,845,600	1,490,607	666,825	162.381	153.546	-
2009	12,865,756	1,471,655	649,483	165.006	162.093	-
2014	13,010,582	1,484,398	636,534	163.973	176.711	-
2018	14,683,120	1,645,216	712,901	167.764	188.512	-
Panel D. Medium(6 to 50)						
2005	29,862,016	3,327,105	194,857	264.153	280.885	-
2009	32,934,436	3,631,814	210,010	266.019	283.807	-
2014	37,517,185	4,119,739	236,561	262.288	290.817	-
2018	41,925,153	4,583,963	264,380	265.280	300.490	-
Panel E. Large(more than 50 workers)						
2005	70,710,429	7,183,985	28,020	453.858	421.800	-
2009	80,605,053	8,212,430	32,757	448.266	416.686	-
2014	102,670,530	10,352,600	40,467	441.980	421.072	-
2018	122,780,942	12,466,615	46,808	445.444	419.656	-

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.

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.[10]

Figure 1: Trends in Percentiles of Log Real 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 real wages of men 25-54 years old, relative to the values of these percentiles in January of 2010.

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,

[10]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.

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 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 formal sector 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. [11]

[11] 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

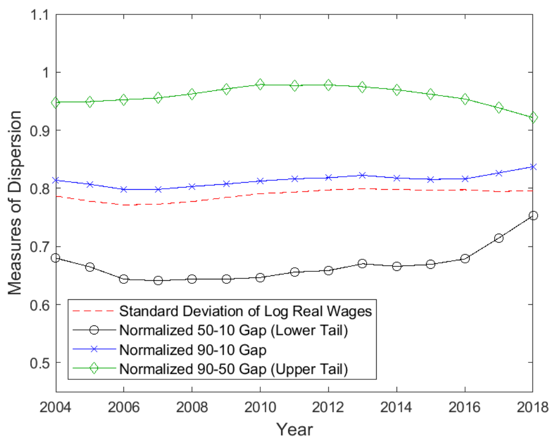
Source: Authors' calculations using IMSS data. Normalized percentile gaps are differences in percentiles divided by the corresponding differences in percentiles of a standard normal variable. For example, the 90th-10th gap is divided by $\Phi^{-1}(0.9) - \Phi^{-1}(0.1)$, where $\Phi(\cdot)$ stands for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

Figure 3: Mexico and its Geographical Regions

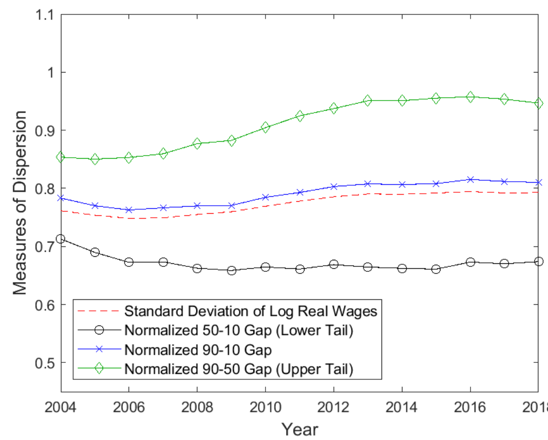
Source: Author's illustration using information from Banco de México (2011).

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

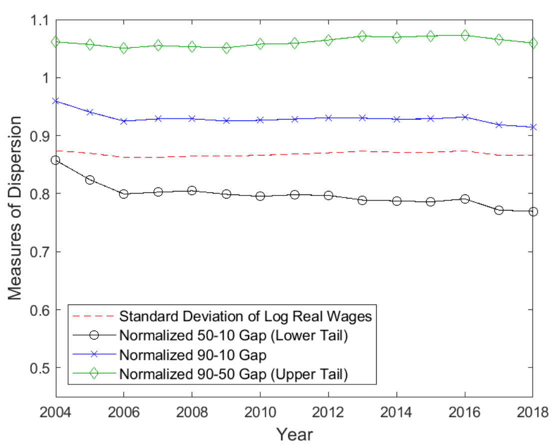
(a) North



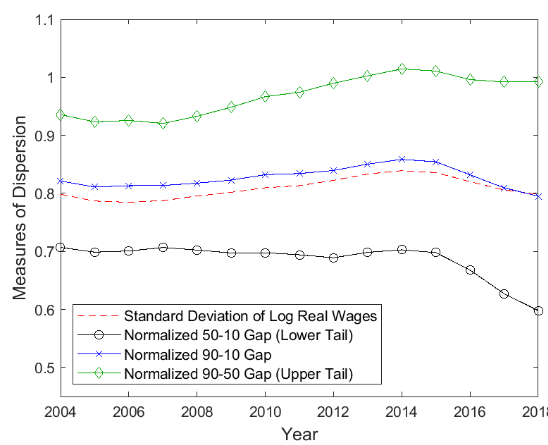
(b) Center-North



(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.[12] 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.[13]

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: 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

[12] 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.

[13] 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.

of log wages. In each interval, our database has between 324 and 519 million worker-year observations corresponding to eleven to sixteen million individuals. The standard deviation of salaries rose from 0.81 in the 2004-2008 interval to 0.83 in 2014-2018. Average real wages decreased from the first to last interval.

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 96% of all worker-year observations and 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.[14]

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

[14]The fixed effects α_i and $\psi_{\mathbf{J(it)}}$ are only separately identified for workers that move across firms. We follow Card et al. (2013) to also estimate the fixed effects α_i for workers who do not change firms, but who have coworkers that do so, such that the firm effect for their firm is identified. For these workers, we calculate α_i by subtracting the firm effect $\psi_{\mathbf{J(it)}}$ and the effect of covariates $X_{it}'\beta$ from their wage, and then average these remainders over time.

Table 2: Descriptive Statistics for Prime-Age Men - 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.	Workers	Mean	Std. dev.	All obs.	Workers	Mean	Std. dev.
Nov 2004-2008	324,468,447	11,835,313	5.627	0.813	311,941,032	11,363,073	5.657	0.808
Ratio: largest connected/all					96.14	96.01	100.53	99.39
2009-2013	431,227,399	13,526,466	5.600	0.826	417,008,147	13,083,589	5.625	0.823
Ratio: largest connected/all					96.70	96.73	100.45	99.65
2014-2018	518,128,252	15,920,775	5.609	0.831	505,015,793	15,512,438	5.628	0.829
Ratio: largest connected/all					97.47	97.44	100.35	99.71
Change from first to last interval			-0.018	0.018			-0.029	0.021

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.

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 11.3 to 15.5 million worker effects and 850 thousand to 1 million 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 the determination of wage variance 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 2014-2018, 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

Table 3: AKM Model Estimation Results. Prime-Age Men

	Interval 1 2004-2008	Interval 2 2009-2013	Interval 3 2014-2018
Worker and workplace parameters			
Number of worker effects	11,363,073	13,083,589	15,512,438
Number of workplace effects	858,480	892,929	1,009,320
Summary of parameter estimates			
St. dev. of worker effects	0.539	0.520	0.503
St. dev. of workplace effects	0.463	0.493	0.503
Correlation worker/workplace effects	0.208	0.226	0.262
Correlation worker effects/Xb	-0.079	-0.034	-0.067
Correlation workplace effects/Xb	-0.002	0.008	0.003
Goodness of fit			
St. dev. of log wages	0.808	0.823	0.829
RMSE	0.195	0.198	0.200
R Squared	0.942	0.942	0.942
Adj. R Squared	0.939	0.940	0.940

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.

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 44% 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 4.1 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 3.4 p.p.[15]

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.

[15] 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 close to 99% of the total log-wage variance across periods.

Table 4: Wage Variance Decomposition for Prime-Age Men, 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	0.653	0.678	0.687	0.033
Variance of worker effects	0.290	0.270	0.253	-0.037
Variance of workplace effects	0.214	0.243	0.253	0.039
Variance of covariates (Xb)	0.019	0.012	0.015	-0.003
Variance of residual	0.038	0.039	0.040	0.002
2Cov(worker effects, workplace effects)	0.104	0.116	0.133	0.029
2Cov(worker effects, covariates)	-0.012	-0.004	-0.008	0.003
2Cov(workplace effects,covariates)	-0.000	0.001	0.000	0.001
Variance shares				
Variance of worker effects	0.444	0.398	0.369	-0.075
Variance of workplace effects	0.328	0.359	0.369	0.041
Variance of covariates (Xb)	0.029	0.018	0.023	-0.007
Variance of residual	0.058	0.058	0.058	-0.000
2Cov(worker effects, workplace effects)	0.159	0.171	0.193	0.034
2Cov(worker effects, covariates)	-0.018	-0.006	-0.012	0.006
2Cov(workplace effects, covariates)	-0.000	0.001	0.001	0.001
Counterfactuals for variance of log wages				
1. No rise in correl. of worker/workplace effects		0.668	0.659	
2. No rise in var. of firm effects		0.649	0.647	
3. Both 1 and 2		0.639	0.620	

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.

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 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 contribution of the workplace component in the determination of wage differentials increased while the share of workers in labor unions decreased.[16] On the other hand, the contribution of sorting (as measured by the covariance between the two effects) as a percentage of the overall wage variance is roughly comparable to the same contribution estimated for other countries.[17]

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.[18]

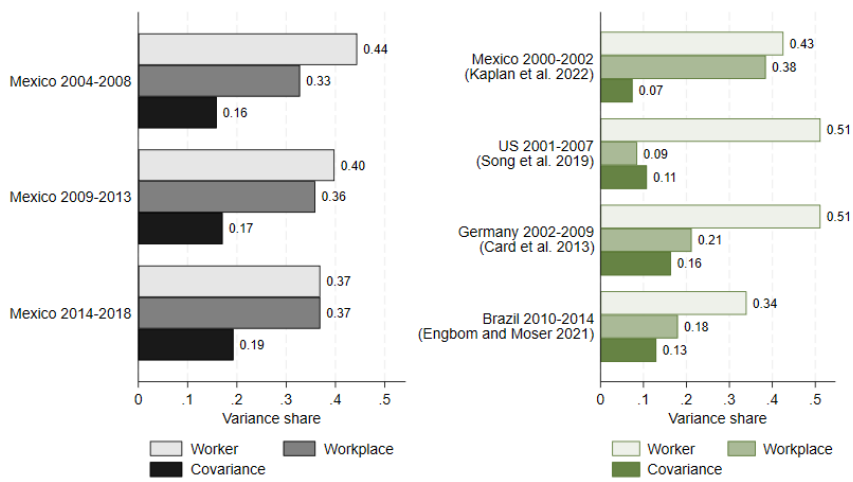
Table 5 shows average wages, average worker fixed effects, and average workplace effects for the country and each sub-national region. Workers in the North and Center regions of the country tend to have larger fixed effects, while these tend to be lower in the South.

[16] 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).

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

[18] 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 for Prime-Age Men



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.

Workplaces in the North and Center have higher workplace premia. The variance of wages is larger in the center, as well as the variance of worker effects. In contrast, the variance of worker effects for the south region is the smaller across regions. The north has the smallest variance of workplace wage premia.

Table 5: Average Worker and Workplace Fixed Effects by Region. Prime-Age Men

	Log Wage		Worker effect		Workplace effect	
	Average	Variance	Average	Variance	Average	Variance
National						
2004-2008	5.66	0.65	2.78	0.29	2.78	0.21
2009-2013	5.62	0.68	2.76	0.27	2.78	0.24
2014-2018	5.63	0.69	2.74	0.24	2.77	0.25
North						
2004-2008	5.67	0.59	2.77	0.30	2.80	0.17
2009-2013	5.64	0.63	2.76	0.28	2.80	0.20
2014-2018	5.67	0.63	2.76	0.27	2.79	0.21
Center-North						
2004-2008	5.57	0.56	2.73	0.25	2.74	0.21
2009-2013	5.54	0.60	2.72	0.24	2.75	0.23
2014-2018	5.55	0.62	2.70	0.22	2.73	0.25
Center						
2004-2008	5.75	0.74	2.83	0.31	2.81	0.23
2009-2013	5.70	0.75	2.81	0.29	2.81	0.26
2014-2018	5.68	0.75	2.78	0.27	2.78	0.27
South						
2004-2008	5.50	0.62	2.71	0.24	2.69	0.24
2009-2013	5.51	0.66	2.71	0.22	2.72	0.29
2014-2018	5.50	0.67	2.67	0.21	2.71	0.31

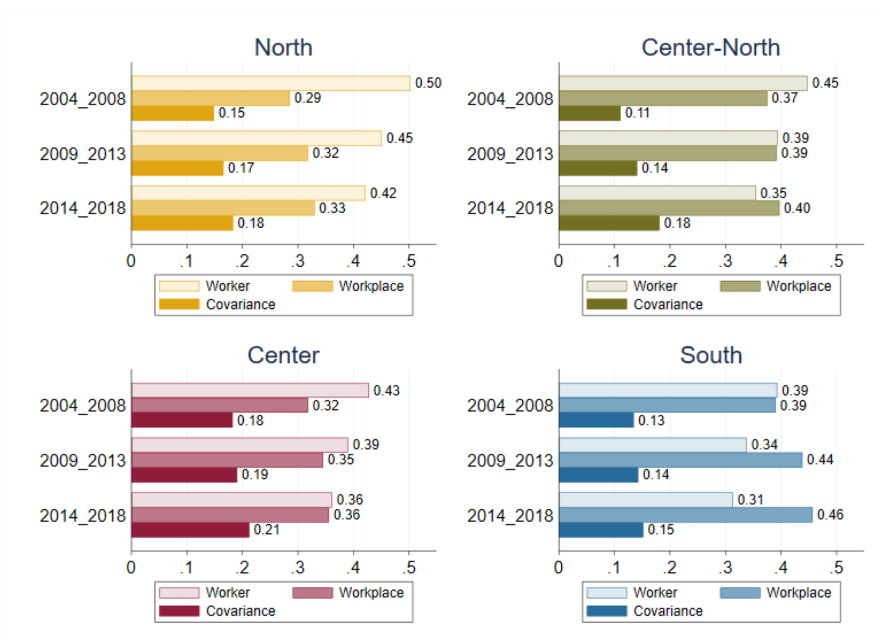
Source: Authors' calculations using IMSS data.Log wages, worker fixed effects and workplace fixed effects for each region, using the estimates of the AKM model from equation (1).

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 11% and 21% of the wage variance. A large workplace component in wage variance is also present in all four Mexican geographical regions.

The average GDP per capita from 2005 to 2021 (in 2013 prices) was 14,280 USD in the North, 10,980 USD in the Center, 9,467 USD in the Center-North, and 9,429 USD in the South. The contribution of workplace-specific effects to overall wage variance is negatively related to this level of regional per-capita GDP. 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.[19]

Figure 6: Estimated Worker and Workplace Contributions to Variance of Log Real Wages by Region. Prime-Age Men



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). Note that these shares do not add to 1 since we are omitting some terms from the decomposition in equation (2).

[19] 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. All the regions follow these national trends.

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 3.7% of workers are in the top decile of worker-specific wage premia and work in top-decile establishments, in the South, this number is 1.33%. 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.

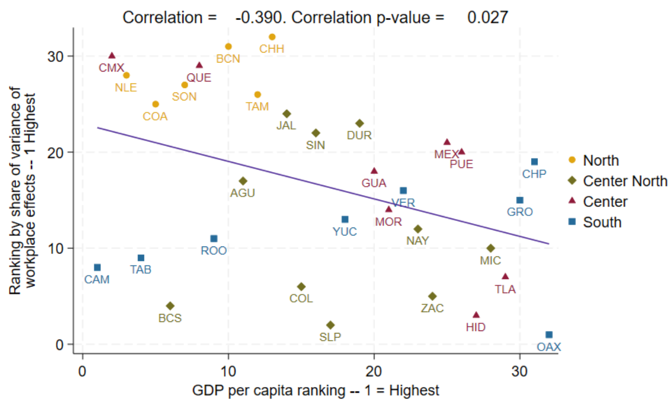
There are many potential mechanisms that could explain these regional differences in the contributions of the different components to overall wage inequality. While accounting for all of them is difficult, we now highlight a few of them:

- **Labor market power.** Firms may have more discretion to set wages below the marginal productivity of labor in places where they have market power, such that they face a low labor supply elasticity (Berger et al. 2022). In less competitive labor markets, and to the extent that the labor supply elasticities faced by firms varies across them, 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 similar-productivity 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.

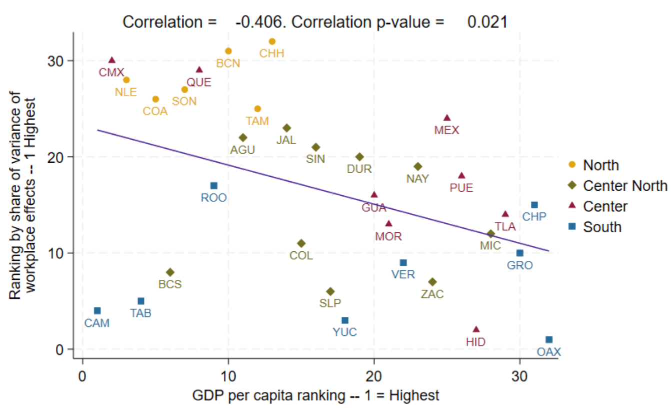
  In the appendix, Table B.14 shows average HHIs by region for each interval in our sample. Labor market concentration correlates with measures of labor market power (Azar et al. 2022). We calculate indices for both number of employees and payrolls (Berger et al. 2022). In general, private formal labor markets in Mexico show a rela-

Figure 7: Correlation between Rankings of GDP per Capita and Variance Share of Workplace Effects. Prime-Age Men.

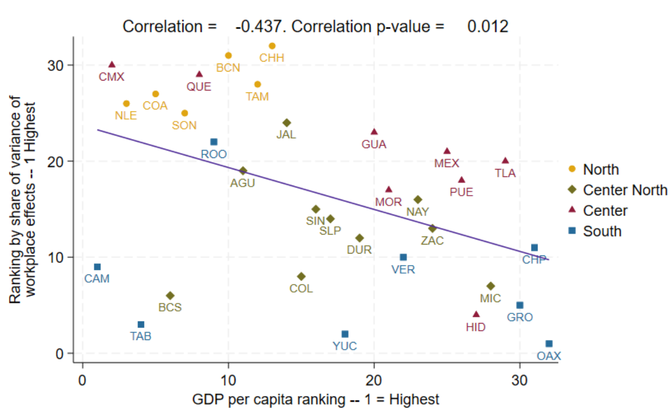
(a) 2004-2008



(b) 2009-2013



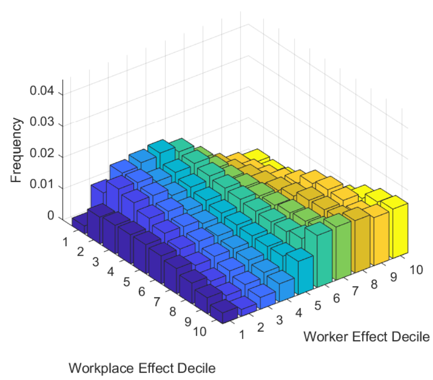
(c) 2014-2018



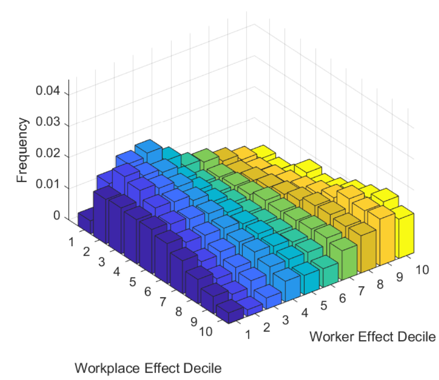
Source: Authors' calculations using IMSS data. We obtain GDP per capita rankings by averaging real GDP over the analysis period and dividing over population from the 2010 census. The numbers on the header of each graph are Pearson correlation values between the rankings –i.e. rank correlations, and their associated p-value.

Figure 8: Regional Differences in Assortative Matching 2014-2018. Prime-Age Men

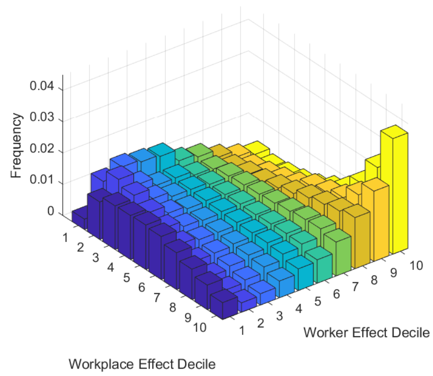
(a) North



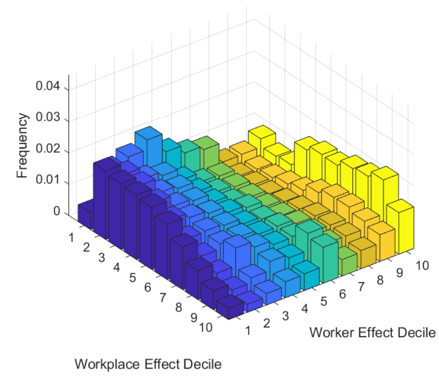
(b) Center-North



(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.

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

- **Industrial composition.** Mexican regions differ in their patterns of industrial specialization. The North has the largest share of manufacturing sector workers (40.6%), while the Center has the largest share of services workers (48.7%), and the South has the majority of oil and tourism workers (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 –that has the largest share of services workers– 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).

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 equal workplace effects as the most significant component of wage variance in 2014-2018. Nevertheless, the variance of wages for women would also be about 9.6% 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 attributed to assortative matching slightly increases. 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.[20]

Variance decomposition across sectors. Table B.12 in the Appendix shows a decomposition of the wage variance across sectors.[21] 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

[20]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 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.

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

into four quartiles of the firm wage distribution.[22] 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 third and fourth quartiles of the firm wage distribution, and that the firms in the highest quartile 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 for private formal-sector employees 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 equaling the importance of 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 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 per capita GDP, 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

[22] 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.

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

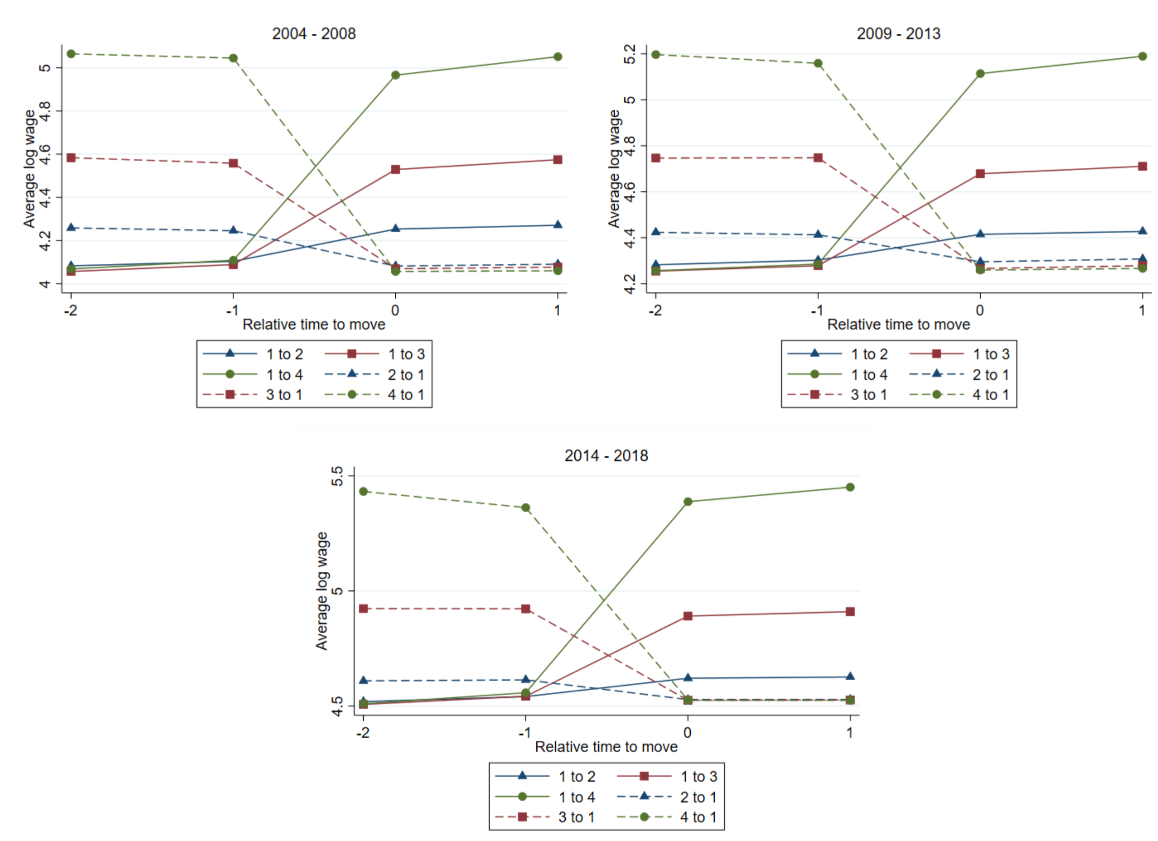
A Exchangeability

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.

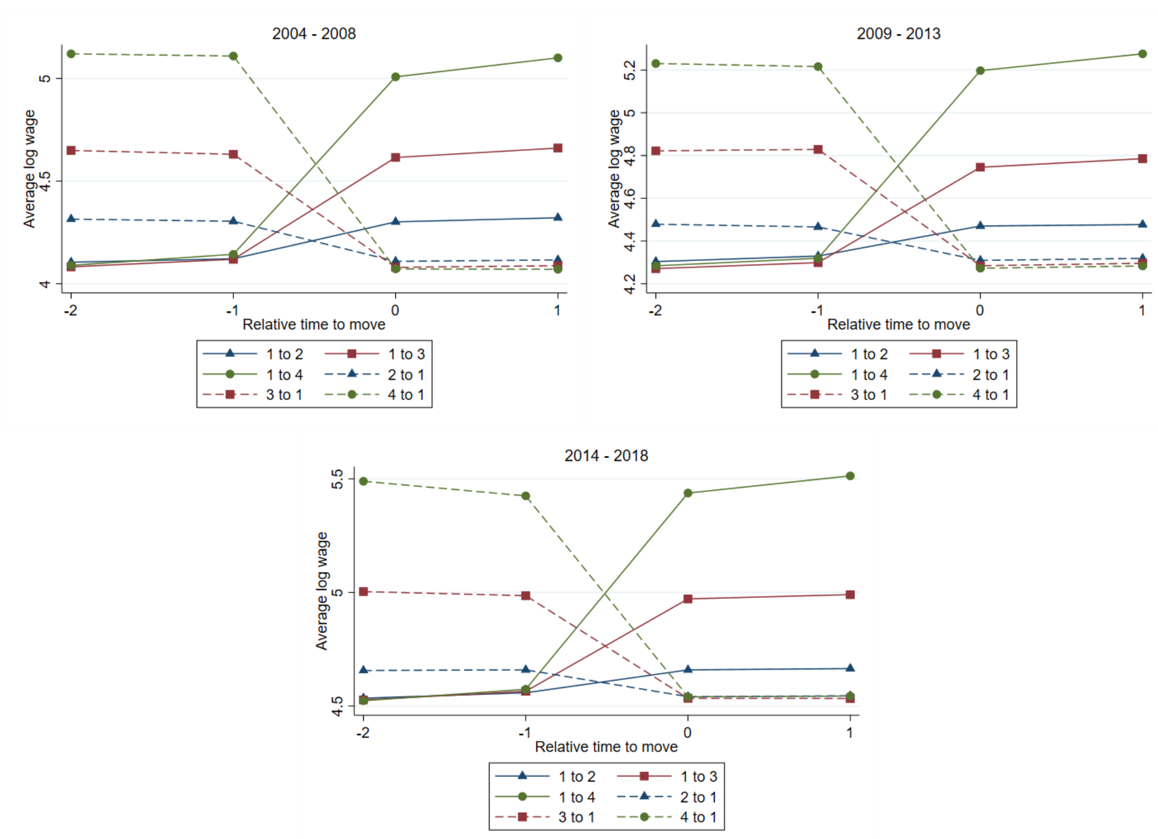
An additional challenge to the uncorrelatedness of the residual term in equation (1) and the right-hand-side variables is selective migration. If, for example, the South region experiences a downturn (leading to low values of the residual term for individuals in the region) that induces migration into 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 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

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



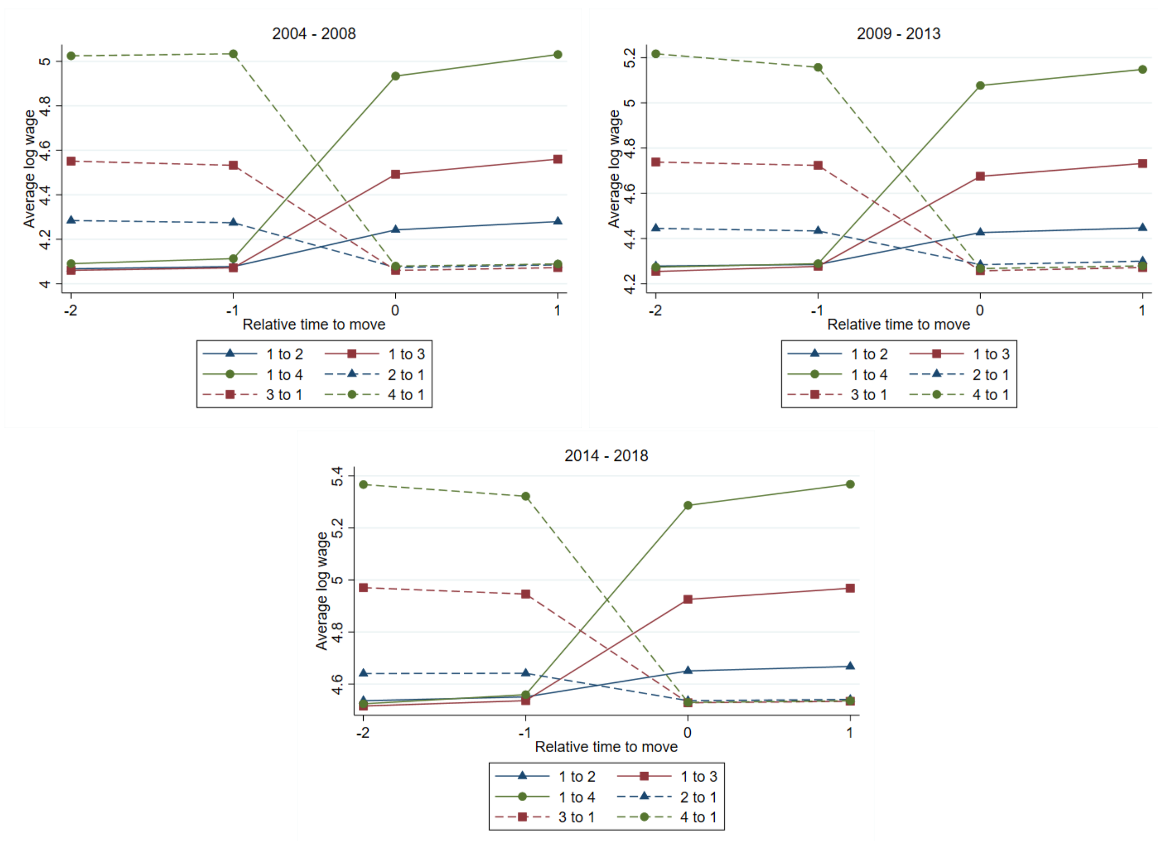
Source: Authors' calculations using IMSS data. The graph shows average worker wages for workers who move between an origin workplace to destination workplace, from two months before the move to one month after the move. The lines group workers according to the quartiles of average co-worker wages in 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.

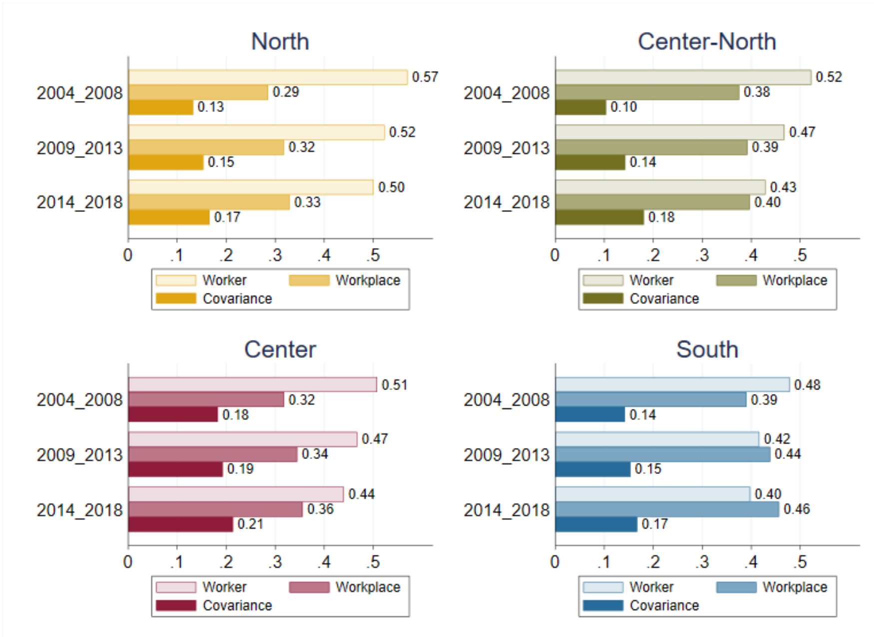
a slightly larger share of variance attributed to worker effects and smaller variance shares due to sorting. Figure A.4 shows that our results in terms of the regional variation in variance shares are also robust to allowing for differential time effects across regions. The results here are similar to 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	0.653	0.678	0.687
Variance of worker effects	0.340	0.321	0.307
Variance of workplace effects	0.213	0.244	0.255
Variance of region-time FE (rt)	0.003	0.003	0.006
Variance of covariates (Xb)	0.023	0.022	0.027
Variance of residual	0.038	0.039	0.040
2 Cov(worker effects, workplace effects)	0.098	0.117	0.131
2 Cov(worker effects, covariates)	-0.065	-0.062	-0.071
2 Cov(workerplace effects, covariates)	0.003	0.002	0.003
2 Cov(worker effects, rt)	-0.000	-0.005	-0.006
2 Cov(workplace effects, rt)	-0.001	-0.004	-0.005
2 Cov(covariates, rt)	-0.000	-0.000	-0.000
Variance shares			
Variance of worker effects	0.520	0.473	0.447
Variance of workplace effects	0.327	0.361	0.372
Variance of region-time FE (rt)	0.005	0.005	0.009
Variance of covariates (Xb)	0.036	0.032	0.039
Variance of residual	0.058	0.058	0.058
2 Cov(worker effects, workplace effects)	0.150	0.172	0.191
2 Cov(worker effects, covariates)	-0.099	-0.091	-0.104
2 Cov(workplace effects, covariates)	0.005	0.003	0.004
2 Cov(worker effects, rt)	-0.000	-0.008	-0.008
2 Cov(workplace effects, rt)	-0.002	-0.005	-0.008
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	0.596	0.627	0.631	0.035
Variance of worker effects	0.299	0.283	0.266	-0.033
Variance of workplace effects	0.170	0.199	0.208	0.038
Variance of covariates (Xb)	0.019	0.012	0.015	-0.004
Variance of residual	0.037	0.036	0.039	0.002
2Cov(worker effects, workplace effects)	0.089	0.104	0.116	0.027
2Cov(worker effects, covariates)	-0.015	-0.005	-0.010	0.005
2Cov(workplace effects,covariates)	-0.004	-0.002	-0.003	0.001
Variance shares				
Variance of worker effects	0.503	0.451	0.422	-0.081
Variance of workplace effects	0.285	0.318	0.330	0.045
Variance of covariates (Xb)	0.032	0.020	0.024	-0.008
Variance of residual	0.062	0.058	0.061	-0.001
2Cov(worker effects, workplace effects)	0.149	0.166	0.183	0.034
2Cov(worker effects, covariates)	-0.025	-0.009	-0.016	0.009
2Cov(workplace effects, covariates)	-0.007	-0.004	-0.005	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	0.559	0.600	0.624	0.065
Variance of worker effects	0.251	0.237	0.221	-0.030
Variance of workplace effects	0.210	0.235	0.248	0.038
Variance of covariates (Xb)	0.019	0.013	0.015	-0.004
Variance of residual	0.036	0.037	0.037	0.001
2Cov(worker effects, workplace effects)	0.062	0.085	0.113	0.051
2Cov(worker effects, covariates)	-0.017	-0.007	-0.012	0.005
2Cov(workplace effects,covariates)	-0.001	0.001	0.001	0.002
Variance shares				
Variance of worker effects	0.448	0.394	0.355	-0.093
Variance of workplace effects	0.375	0.392	0.397	0.022
Variance of covariates (Xb)	0.034	0.021	0.025	-0.009
Variance of residual	0.065	0.062	0.060	-0.005
2Cov(worker effects, workplace effects)	0.111	0.141	0.181	0.070
2Cov(worker effects, covariates)	-0.030	-0.012	-0.019	0.011
2Cov(workplace effects, covariates)	-0.002	0.002	0.001	0.003

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	0.737	0.748	0.752	0.015
Variance of worker effects	0.315	0.292	0.272	-0.043
Variance of workplace effects	0.235	0.258	0.268	0.033
Variance of covariates (Xb)	0.019	0.012	0.016	-0.003
Variance of residual	0.039	0.042	0.042	0.003
2Cov(worker effects, workplace effects)	0.134	0.142	0.160	0.026
2Cov(worker effects, covariates)	-0.007	-0.001	-0.006	0.001
2Cov(workplace effects,covariates)	0.002	0.002	0.001	-0.001
Variance shares				
Variance of worker effects	0.427	0.390	0.361	-0.066
Variance of workplace effects	0.318	0.345	0.356	0.038
Variance of covariates (Xb)	0.025	0.017	0.021	-0.004
Variance of residual	0.053	0.056	0.056	0.003
2Cov(worker effects, workplace effects)	0.182	0.190	0.212	0.030
2Cov(worker effects, covariates)	-0.009	-0.002	-0.008	0.001
2Cov(workplace effects, covariates)	0.002	0.002	0.002	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	0.618	0.664	0.671	0.053
Variance of worker effects	0.243	0.225	0.210	-0.033
Variance of workplace effects	0.241	0.291	0.306	0.065
Variance of covariates (Xb)	0.019	0.013	0.016	-0.003
Variance of residual	0.040	0.041	0.040	0.000
2Cov(worker effects, workplace effects)	0.083	0.095	0.102	0.019
2Cov(worker effects, covariates)	-0.012	-0.004	-0.007	0.005
2Cov(workplace effects,covariates)	0.003	0.004	0.004	0.001
Variance shares				
Variance of worker effects	0.393	0.338	0.313	-0.080
Variance of workplace effects	0.390	0.438	0.457	0.067
Variance of covariates (Xb)	0.031	0.019	0.023	-0.008
Variance of residual	0.065	0.062	0.060	-0.005
2Cov(worker effects, workplace effects)	0.135	0.143	0.152	0.017
2Cov(worker effects, covariates)	-0.020	-0.007	-0.010	0.010
2Cov(workplace effects, covariates)	0.005	0.006	0.006	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

	Interval1 2004-2008	Interval2 2009-2013	Interval3 2014-2018
Panel A: Women			
Worker and workplace parameters			
Number of worker effects	6,239,485	7,681,099	9,649,303
Number of workplace effects	518,753	608,429	715,765
Summary of parameter estimates			
St. dev. of worker effects	0.560	0.541	0.529
St. dev. of workplace effects	0.415	0.446	0.450
Correlation worker/workplace effects	0.162	0.190	0.216
Correlation worker effects/Xb	-0.185	-0.139	-0.197
Correlation workplace effects/Xb	0.005	0.008	0.007
Goodness of fit			
St. dev. of log wages	0.764	0.783	0.781
R Squared	0.949	0.947	0.946
Adj. R Squared	0.947	0.945	0.944
Panel B: Men			
Worker and workplace parameters			
Number of worker effects	11,363,073	13,083,589	15,512,438
Number of workplace effects	858,480	892,929	1,009,320
Summary of parameter estimates			
St. dev. of worker effects	0.539	0.520	0.503
St. dev. of workplace effects	0.463	0.493	0.503
Correlation worker/workplace effects	0.208	0.226	0.262
Correlation worker effects/Xb	-0.079	-0.034	-0.067
Correlation workplace effects/Xb	-0.002	0.008	0.003
Goodness of fit			
St. dev. of log wages	0.808	0.823	0.829
R Squared	0.942	0.942	0.942
Adj. R Squared	0.939	0.940	0.940
Panel C: All			
Worker and workplace parameters			
Number of worker effects	17,918,191	20,960,076	25,417,209
Number of workplace effects	1,010,420	1,057,854	1,189,035
Summary of parameter estimates			
St. dev. of worker effects	0.545	0.526	0.511
St. dev. of workplace effects	0.444	0.475	0.483
Correlation worker/workplace effects	0.212	0.229	0.257
Correlation worker effects/Xb	-0.114	-0.071	-0.113
Correlation workplace effects/Xb	-0.002	0.005	0.001
Goodness of fit			
St. dev. of log wages	0.797	0.811	0.813
R Squared	0.944	0.943	0.943
Adj. R Squared	0.941	0.941	0.941

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	0.584	0.614	0.610	0.026
Variance of worker effects	0.314	0.293	0.279	-0.035
Variance of workplace effects	0.173	0.199	0.203	0.030
Variance of covariates (Xb)	0.021	0.014	0.022	0.001
Variance of residual	0.030	0.033	0.033	0.003
2 Cov(worker effects, workplace effects)	0.075	0.092	0.103	0.027
2 Cov(worker effects, covariates)	-0.030	-0.018	-0.031	-0.001
2 Cov(workplace effects, covariates)	0.001	0.001	0.001	0.000
Variance shares				
Variance of worker effects	0.538	0.477	0.458	-0.081
Variance of workplace effects	0.296	0.325	0.333	0.036
Variance of covariates (Xb)	0.037	0.022	0.036	0.000
Variance of residual	0.051	0.053	0.054	0.003
2 Cov(worker effects, workplace effects)	0.129	0.150	0.168	0.040
2 Cov(worker effects, covariates)	-0.052	-0.029	-0.051	0.001
2 Cov(workplace effects, covariates)	0.001	0.001	0.001	-0.000
Counterfactuals for variance of log wages				
1. No rise in correl. of worker/workplace effects		0.599	0.586	
2. No rise in var. of workplace effects		0.581	0.571	
3. Both 1 and 2		0.573	0.555	

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.

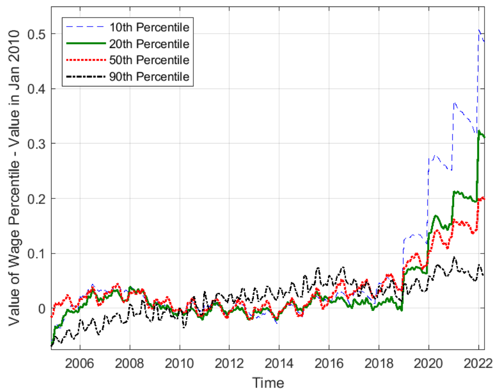
Table B.7: Wage Variance Decomposition, National Level. All Workers Ages 25-54

	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	0.635	0.658	0.661	0.026
Variance of worker effects	0.297	0.276	0.261	-0.036
Variance of workplace effects	0.197	0.225	0.233	0.035
Variance of covariates (Xb)	0.020	0.013	0.017	-0.002
Variance of residual	0.036	0.037	0.038	0.002
2 Cov(worker effects, workplace effects)	0.103	0.114	0.127	0.024
2 Cov(worker effects, covariates)	-0.017	-0.008	-0.015	0.002
2 Cov(workplace effects, covariates)	-0.000	0.001	0.000	0.000
Variance shares				
Variance of worker effects	0.468	0.420	0.395	-0.073
Variance of workplace effects	0.311	0.342	0.352	0.042
Variance of covariates (Xb)	0.031	0.019	0.026	-0.006
Variance of residual	0.056	0.057	0.057	0.001
2 Cov(worker effects, workplace effects)	0.162	0.174	0.192	0.030
2 Cov(worker effects, workplace)	-0.027	-0.013	-0.023	0.004
2 Cov(workplace effects, covariates)	-0.000	0.001	0.000	0.000
Counterfactuals for variance of log wages				
1. No rise in correl. of worker/workplace effects		0.650	0.638	
2. No rise in var. of workplace effects		0.622	0.615	
3. Both 1 and 2		0.622	0.603	

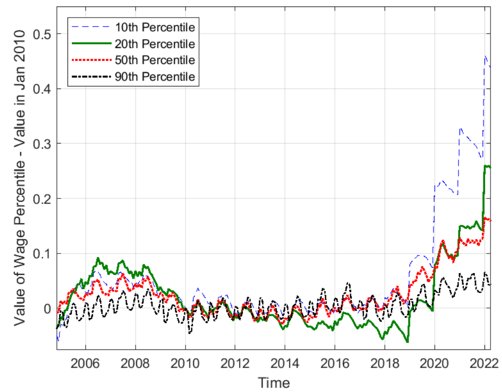
Source: Authors' calculations using IMSS data. Variance decomposition results from equation (2) using the estimated worker and workplace fixed effects from equation (1). The "Variance and covariance" rows show the values of the variance of log wages in the estimation sample of prime-age men and its components. 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.

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

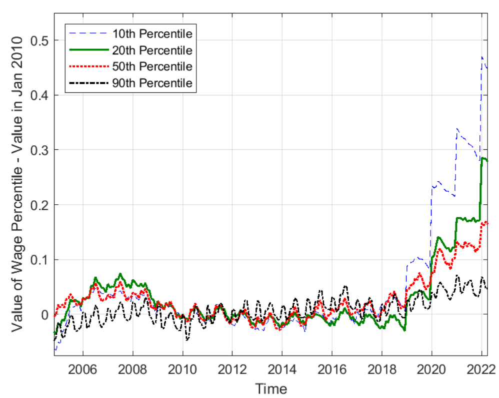
(a) Women



(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.

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	0.635	0.658	0.661
Variance of worker effects	0.334	0.315	0.300
Variance of workplace effects	0.198	0.225	0.233
2 Cov(worker effects, workplace effects)	0.100	0.114	0.125
Variance shares			
Variance of worker effects	0.526	0.478	0.454
Variance of workplace effects	0.311	0.342	0.352
2 Cov(worker effects, workplace effects)	0.158	0.173	0.189
Men			
Variance and covariance			
Total variance of log wages	0.653	0.678	0.687
Variance of worker effects	0.340	0.321	0.307
Variance of workplace effects	0.214	0.243	0.253
2 Cov(worker effects, workplace effects)	0.101	0.116	0.132
Variance shares			
Variance of worker effects	0.520	0.473	0.447
Variance of workplace effects	0.328	0.358	0.369
2 Cov(worker effects, workplace effects)	0.154	0.171	0.192
Women			
Variance and covariance			
Total variance of log wages	0.584	0.614	0.610
Variance of worker effects	0.325	0.309	0.292
Variance of workplace effects	0.173	0.199	0.203
2 Cov(worker effects, workplace effects)	0.076	0.092	0.103
Variance shares			
Variance of worker effects	0.557	0.504	0.479
Variance of workplace effects	0.296	0.325	0.333
2 Cov(worker effects, workplace effects)	0.130	0.150	0.169

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	0.653	0.678	0.687
Variance of worker effects	0.290	0.270	0.253
Variance of workplace effects	0.214	0.243	0.253
2 Cov(worker effects, workplace effects)	0.104	0.116	0.133
Variance shares			
Variance of worker effects	0.444	0.398	0.369
Variance of workplace effects	0.328	0.359	0.369
2 Cov(worker effects, workplace effects)	0.159	0.171	0.193
Normalization to 40 years			
Variance and covariance			
Total variance of log wages	0.653	0.678	0.686
Variance of worker effects	0.290	0.270	0.253
Variance of workplace effects	0.214	0.243	0.253
2 Cov(worker effects, workplace effects)	0.104	0.116	0.133
Variance shares			
Variance of worker effects	0.444	0.398	0.369
Variance of workplace effects	0.328	0.359	0.369
2 Cov(worker effects, workplace effects)	0.159	0.171	0.193
Normalization to 50 years			
Variance and covariance			
Total variance of log wages	0.653	0.678	0.687
Variance of worker effects	0.290	0.270	0.253
Variance of workplace effects	0.214	0.243	0.253
2 Cov(worker effects, workplace effects)	0.104	0.116	0.133
Variance shares			
Variance of worker effects	0.444	0.398	0.369
Variance of workplace effects	0.328	0.359	0.369
2 Cov(worker effects, workplace effects)	0.159	0.171	0.193

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			
Variance of log wages	0.653	0.678	0.687
Variance of worker effects	0.290	0.270	0.253
Variance of workplace effects	0.214	0.243	0.253
2Cov(worker effects, workplace effects)	0.104	0.116	0.133
Connected set using 3 months per year			
Variance of log wages	0.650	0.675	0.682
Variance of worker effects	0.286	0.266	0.249
Variance of workplace effects	0.217	0.248	0.257
2Cov(worker effects, workplace effects)	0.098	0.112	0.128
Leave-one-out connected set			
Variance of log wages	0.644	0.667	0.674
Variance of worker effects	0.298	0.274	0.253
Variance of workplace effects	0.202	0.234	0.247
2Cov(worker effects, workplace effects)	0.108	0.120	0.135
KSS corrected in leave-one-out connected set			
Variance of log wages	0.644	0.667	0.674
Variance of worker effects	0.295	0.271	0.250
Variance of workplace effects	0.204	0.235	0.248
2Cov(worker effects, workplace effects)	0.104	0.118	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). 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 "Connected set using 3 months per year" Panel shows the estimates in the connected set using observations from January, May and September for each year. The "Leave-one-out Connected Set" panel shows estimates in the workplaces that remain in the connected set in every leave-one-out sample using the same three months per year. 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 "observation" leave-one-out estimator, leaving out worker-workplace observations one at a time. To approximate the components, we use the JLL algorithm. See Kline et al. (2020) for details.

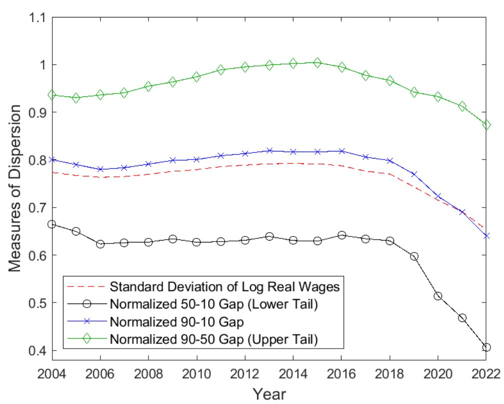
Table B.11: Variance Decomposition with Bonhomme et al.'s (2019) Correction for Limited Mobility Bias

	Interval 1 2004-2008	Interval 2 2009-2013	Interval 3 2014-2018
No clusters			
Variance and covariance			
Total variance of log wages	0.653	0.678	0.687
Variance of worker effects	0.290	0.270	0.253
Variance of workplace effects	0.214	0.243	0.253
2Cov(worker effects, workplace effects)	0.104	0.116	0.133
Variance shares			
Variance of worker effects	0.444	0.398	0.369
Variance of workplace effects	0.328	0.359	0.369
2Cov(worker effects, workplace effects)	0.159	0.171	0.193
5 clusters			
Variance and covariance			
Total variance of log wages	0.654	0.679	0.687
Variance of worker effects	0.284	0.265	0.252
Variance of workplace effects	0.162	0.190	0.200
2Cov(worker effects, workplace effects)	0.156	0.167	0.179
Variance shares			
Variance of worker effects	0.434	0.390	0.366
Variance of workplace effects	0.247	0.280	0.291
2Cov(worker effects, workplace effects)	0.238	0.246	0.261
10 clusters			
Variance and covariance			
Total variance of log wages	0.654	0.679	0.687
Variance of worker effects	0.273	0.254	0.238
Variance of workplace effects	0.171	0.199	0.215
2Cov(worker effects, workplace effects)	0.158	0.169	0.179
Variance shares			
Variance of worker effects	0.418	0.375	0.346
Variance of workplace effects	0.261	0.294	0.312
2Cov(worker effects, workplace effects)	0.242	0.249	0.261
15 clusters			
Variance and covariance			
Total variance of log wages	0.654	0.679	0.687
Variance of worker effects	0.262	0.242	0.229
Variance of workplace effects	0.185	0.214	0.225
2Cov(worker effects, workplace effects)	0.156	0.168	0.179
Variance shares			
Variance of worker effects	0.401	0.356	0.333
Variance of workplace effects	0.283	0.315	0.327
2Cov(worker effects, workplace effects)	0.239	0.247	0.260

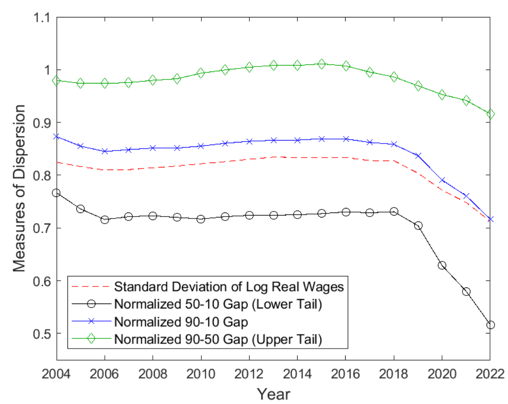
Source: Authors' calculations using IMSS data. We use 20 percentiles of the within workplace log wage distribution to cluster workplaces in 5, 10 and 15 groups to estimate the AKM model. The first panel shows the original estimates for variance of worker and establishment effects and the covariance between 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).

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

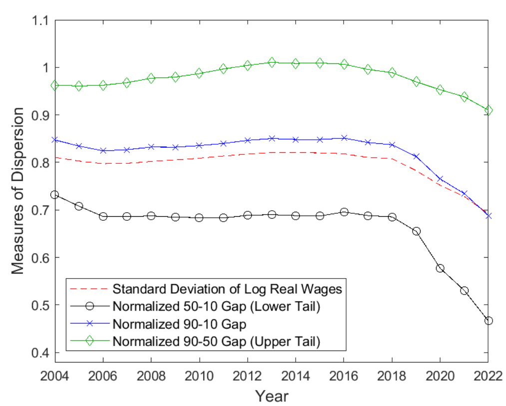
(a) Women



(b) Men

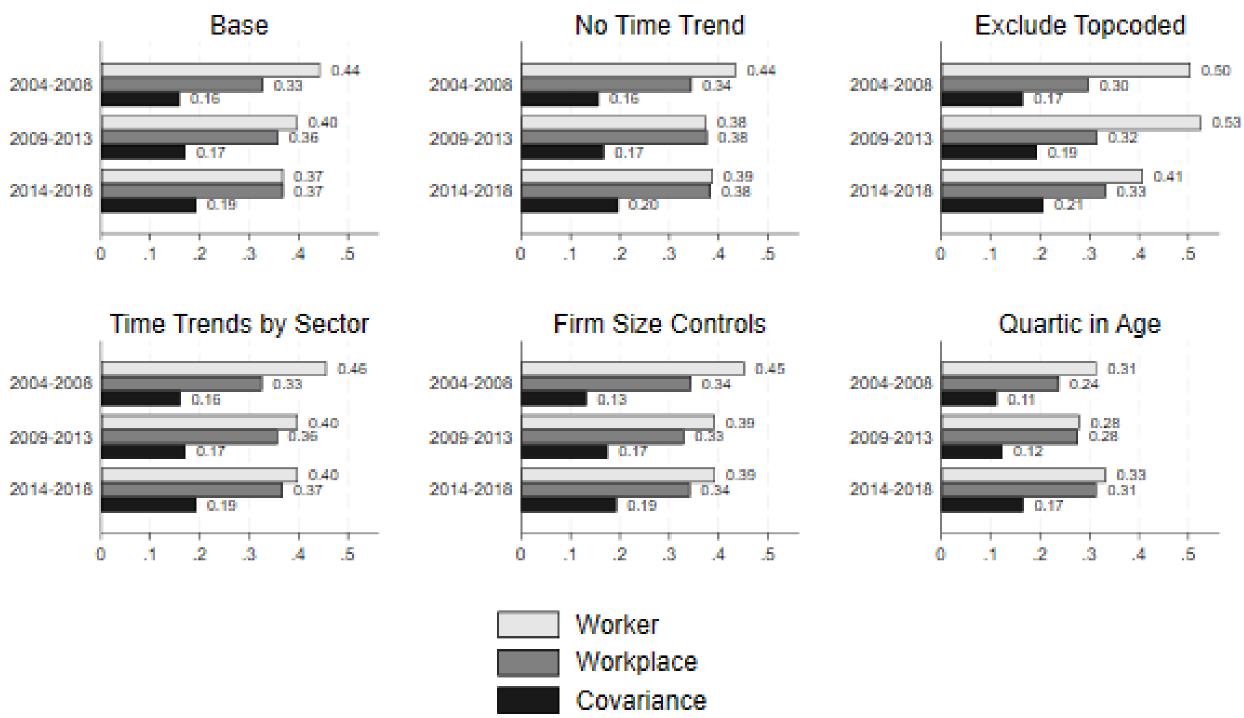


(c) All



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



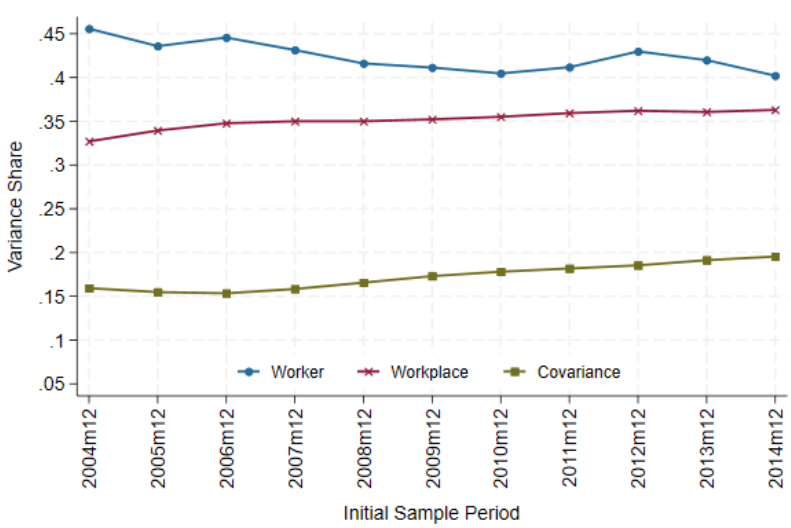
Source: Authors' calculations using IMSS data. The panels depict variance shares from variance decomposition results using equation (2). Each panel corresponds to a different model specification. Panel "Base" corresponds to the baseline estimates in Table 4, where the control set includes age, age squared, 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.

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	0.406	0.415	0.419	0.0101	100.0
Std. dev. of mean worker effects	0.170	0.160	0.154	-0.0051	-50.5
Std. dev. of mean workplace effects	0.274	0.289	0.296	0.0131	129.7
Correlation of mean worker effects and workplace effects	0.650	0.677	0.701	0.0021	20.8

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.

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.

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	0.653	0.678	0.687
Between region variance	0.007	0.004	0.005
Within region variance	0.645	0.672	0.681
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	0.290	0.270	0.253
Between region variance	0.002	0.001	0.001
Within region variance	0.288	0.269	0.252
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	0.214	0.243	0.253
Between region variance	0.002	0.001	0.001
Within region variance	0.212	0.242	0.252
Share of between region variance	0.01	0.00	0.00
Share of within region variance	0.99	0.99	1.00
2 Cov(worker effects, workplace effects)			
Total covariance	0.104	0.116	0.133
Between region covariance	0.004	0.003	0.003
Within region covariance	0.100	0.113	0.130
Share of between region covariance	0.04	0.02	0.02
Share of within region covariance	0.96	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
HHI with Employment			
North	0.210	0.205	0.202
Center-North	0.226	0.220	0.208
Center	0.151	0.138	0.135
South	0.277	0.269	0.262
HHI with Payroll			
North	0.277	0.270	0.263
Center-North	0.312	0.308	0.296
Center	0.206	0.182	0.173
South	0.379	0.369	0.365

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	0.628	0.657	0.659
Variance of worker effects	0.305	0.289	0.267
Variance of workplace plus workplace by year effects	0.175	0.205	0.218
2 Cov(worker effects, workplace plus workplace by year effects)	0.115	0.129	0.136
Variance shares			
Variance of worker effects	0.486	0.440	0.405
Variance of workplace plus workplace by year effects	0.280	0.313	0.331
2 Cov(worker effects, workplace plus workplace by year effects)	0.183	0.196	0.207
Men			
Variance and covariance			
Total variance of log wages	0.642	0.673	0.678
Variance of worker effects	0.286	0.270	0.247
Variance of workplace plus workplace by year effects	0.200	0.235	0.246
2 Cov(worker effects, workplace plus workplace by year effects)	0.113	0.126	0.138
Variance shares			
Variance of worker effects	0.445	0.401	0.365
Variance of workplace plus workplace by year effects	0.312	0.349	0.363
2 Cov(worker effects, workplace plus workplace by year effects)	0.176	0.187	0.204
Women			
Variance and covariance			
Total variance of log wages	0.659	0.677	0.665
Variance of worker effects	0.336	0.311	0.289
Variance of workplace plus workplace by year effects	0.173	0.200	0.205
2 Cov(worker effects, workplace plus workplace by year effects)	0.114	0.127	0.135
Variance shares			
Variance of worker effects	0.509	0.459	0.435
Variance of workplace plus workplace by year effects	0.262	0.296	0.309
2 Cov(worker effects, workplace plus workplace by year effects)	0.173	0.188	0.204

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.

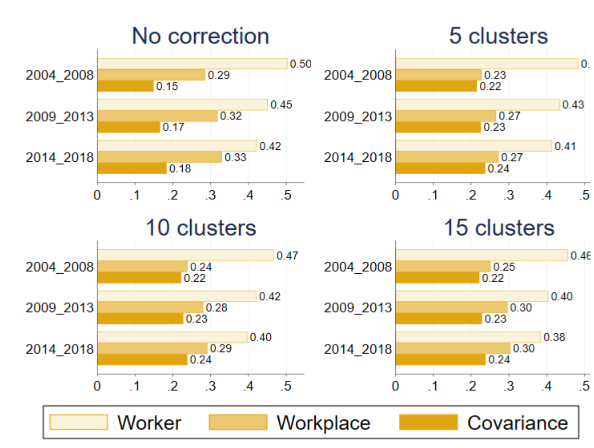
Table B.16: Wage Variance Decomposition by High- and Low-Wage Firms with Bonhomme et al.'s (2019) Correction for Limited Mobility Bias

	Interval 1 2004-2008	Interval 2 2009-2013	Interval 3 2014-2018
Below percentile 25			
Variance and covariance			
Total variance of log wages	0.034	0.026	0.014
Variance of worker effects	0.047	0.027	0.080
Variance of workplace effects	0.002	0.001	0.000
2Cov(worker effects, workplace effects)	-0.004	-0.002	-0.001
Variance shares			
Variance of worker effects	1.384	1.027	5.651
Variance of workplace effects	0.074	0.045	0.034
2Cov(worker effects, workplace effects)	-0.124	-0.070	-0.064
Between percentiles 25 and 50			
Variance and covariance			
Total variance of log wages	0.083	0.066	0.050
Variance of worker effects	0.067	0.053	0.046
Variance of workplace effects	0.006	0.004	0.002
2Cov(worker effects, workplace effects)	-0.003	-0.002	-0.001
Variance shares			
Variance of worker effects	0.804	0.800	0.934
Variance of workplace effects	0.073	0.062	0.036
2Cov(worker effects, workplace effects)	-0.037	-0.024	-0.015
Between percentiles 50 and 75			
Variance and covariance			
Total variance of log wages	0.157	0.140	0.126
Variance of worker effects	0.126	0.113	0.099
Variance of workplace effects	0.013	0.011	0.008
2Cov(worker effects, workplace effects)	-0.005	-0.004	-0.002
Variance shares			
Variance of worker effects	0.804	0.809	0.785
Variance of workplace effects	0.080	0.077	0.066
2Cov(worker effects, workplace effects)	-0.033	-0.028	-0.018
Above percentile 75			
Variance and covariance			
Total variance of log wages	0.516	0.532	0.532
Variance of worker effects	0.346	0.333	0.318
Variance of workplace effects	0.034	0.046	0.053
2Cov(worker effects, workplace effects)	0.072	0.087	0.095
Variance shares			
Variance of worker effects	0.670	0.625	0.598
Variance of workplace effects	0.065	0.087	0.100
2Cov(worker effects, workplace effects)	0.140	0.163	0.179

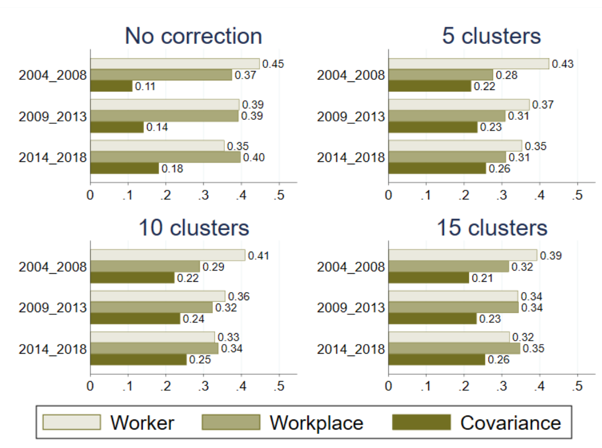
Source: Authors' calculations using IMSS data. We estimate a separate AKM model for each firm wage group. The percentile groups were obtained by calculating the average wage by firm in each interval. The percentiles used are the 25th , 50th and 75th percentiles. We use 20 percentiles of the within workplace 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.5: Estimated Worker and Workplace Contributions to Wage Variability by Region with Bonhomme et al.'s (2019) Correction for Limited Mobility Bias

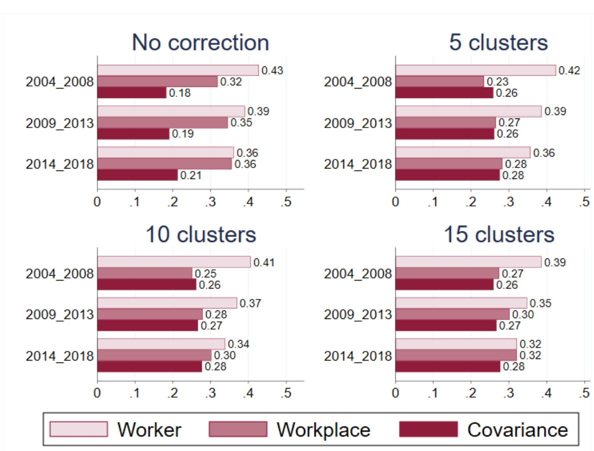
(a) North



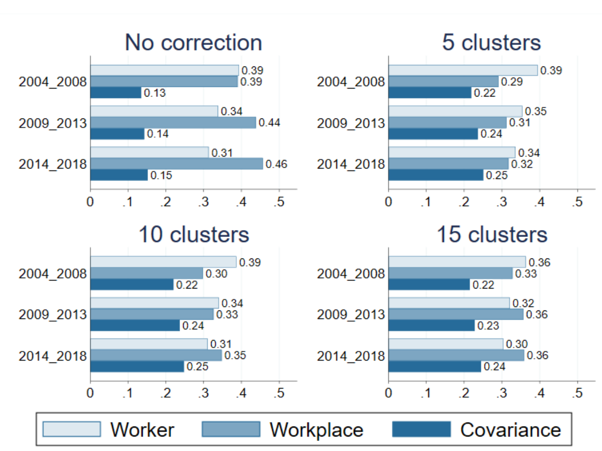
(b) Center-North



(c) Center



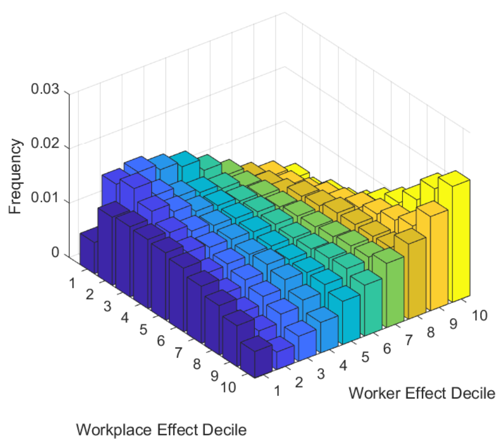
(d) South



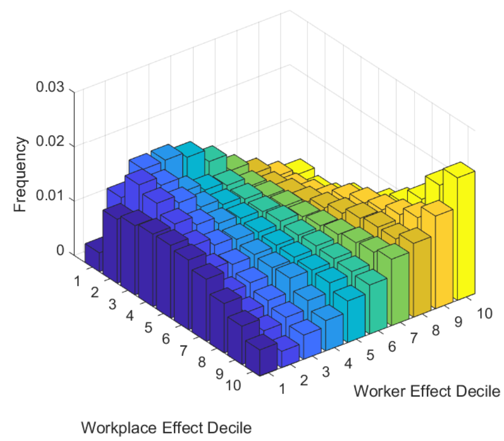
Source: Authors' calculations using IMSS data. The Figure depicts the variance shares attributed to worker fixed effects, workplace fixed effects, and their covariance in the overall variance of wages in each region, using the estimates of the AKM model from equation (1) and the decomposition in equation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

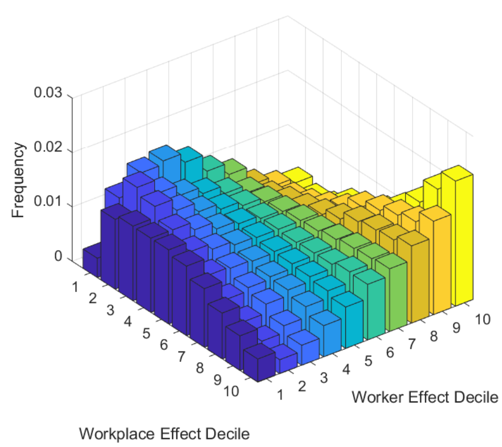
(a) 2004-2008



(b) 2009-2013

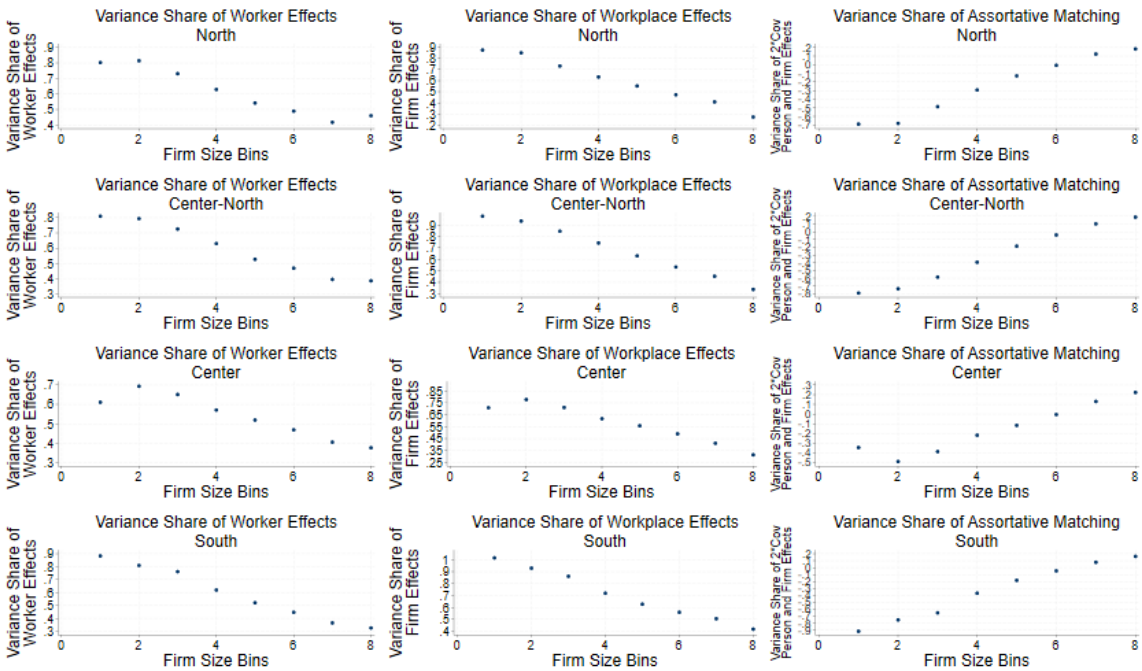


(c) 2014-2018



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.