City-size and assortative matching in the Mexican formal labor market

Jorge Pérez Pérez[*]   Jorge Meléndez[†]   José G. Nuño-Ledesma[‡]

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Abstract

We investigate the benefits of larger labor markets in facilitating better matching between workers and firms in a middle-income country. Relying on a a matched employer-employee dataset comprising the near universe of formal workers in Mexico, we estimate models of log-wages with additive worker and workplace fixed effects. The correlation of these effects within a geographical area serves as a proxy for sorting. The impact of city size on matching is modest in Mexico. Doubling city size enhances assortative matching by just half what would be expected from previous estimates for Germany. The reduced city-size effect is primarily associated with differences in the proportion of employment in the service industry and the preponderance of small firms between Mexico and Germany, while not strongly linked to the relative prevalence of informality and union coverage.

Keywords: Assortative matching; City size; Agglomeration; Mexico; Wage determination

JEL Codes: J21, J24, J31, O15, R23

1   Introduction

"City-size wage gaps" are earnings differentials explained by salary premia that larger cities enjoy over smaller ones. These between-city wage gaps contribute more to within-country wage inequality than earnings differentials among workers in the same metropolis (Baum-Snow and Pavan, 2012; Card et al., 2013; Combes and Gobillon, 2015; Gould, 2007). City-size wage gaps are the product of a combination of several agglomeration externalities. Foremost among these effects is the easier worker-workplace matching process that occurs in larger cities (D'Costa and Overman, 2014; Dauth et al., 2022; Duranton and Puga, 2004). Intuitively, the better matching process fuels a virtuous cycle wherein better matches enhance productivity, which raises salaries, attracting better candidates to the city.

The majority of the literature on worker-workplace matching in cities examines developed economies. There is a paucity of research on the matching dynamics in developing economies where the labor market is afflicted with structural problems such as persistent underemployment and high levels of informality that may act as obstacles to the pairing process. We set out to bridge this gap. We describe matching externalities in the Mexican labor market, an economy with marked differences between regions and cities and where a substantial proportion of workers are active in the informal sector (Pérez Pérez and Nuño-Ledesma, 2022). This analysis is important because previous work finds that workers and establishments contribute to wage dispersion in developing economies in different proportions than in developed economies. In particular, workplace-level wage determinants are more important in explaining wage differentials (Bassier, 2023; Diallo et al., 2022; Frías et al., 2022; Pérez Pérez and Nuño-Ledesma, 2022). Thus, we expect the matching process to show different dynamics in developing countries.

We find that the association between city size and the degree of positive assortative matching in formal labor markets is weaker in Mexico relative to other countries. Doubling city size increases the correlation coefficient between worker and workplace fixed effects in Mexican cities by 1.4 to 4.5 p.p. depending on the specification.[1] This figure contrasts with the one found for Germany in Dauth et al. (2022), of 6.1 to 7.9 p.p. When we turn to the reasons behind this difference, we find that the size of the informal labor market is negatively correlated with the strength of

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

assortative matching in the formal labor market. We also find that unions have a negligible effect on the relationship between city size and matching. Nevertheless, our estimates suggest that neither of these variables can account for the diminished strength of matching externalities in Mexico. Instead, we argue that the industry composition in Mexico and the preponderance of small firms reduce matching externalities.

We use matched employer-employee data from social security records comprising the near-universe of formal workers in Mexico from 2004 to 2018. These data have recently been used, among other ends, to survey recent dynamics in Mexico's income inequality, to investigate the relationship between increased international trade and wage premia in Mexico, and to decompose total Mexican wage dispersion into worker and workplace components (Puggioni et al., 2022; Frías et al., 2022; Pérez Pérez and Nuño-Ledesma, 2022).

To measure assortative matching, we follow standard labor and urban economics methodology. We estimate models of log-wages with additive worker and workplace fixed effects using the approach first popularized by Abowd et al. (1999) and then widely embraced by ample empirical literature (Card et al., 2013, 2018; Dauth et al., 2022). We show the validity of our models' specifications through several validation exercises. Leveraging these econometric estimates, we then perform a variance decomposition to separate the total variance of wages into components attributable to the variance of workplace- and workplace-level fixed effects, along with their covariance, which we use as our primary object of investigation and which we interpret as a metric for assortative matching.

We measure the covariance of worker and workplace fixed effects at the metropolitan area and local labor market level. To provide context to our estimations, we contrast them against equivalent metrics obtained from research studying labor markets in Germany. We estimate the average covariance between worker and workplace fixed effects in Mexico at the city level hovers at 0.21, compared to 0.16 in Germany (Dauth et al., 2022). To examine whether Mexico experiences the city-size wage gaps phenomenon documented in other labor markets, we correlate the variance and covariance of our employer and employee fixed effect estimates to their corresponding city size. We find a positive association between city size and assortative matching. At the metropolitan area level, the slope of the relationship between log city size and the correlation coefficient between workplace and worker fixed effect estimates is 0.014. This slope is substantially lower than the

slope of 0.069 estimated by Dauth et al. (2022). At the local labor market level, this slope is 0.031, closer but still smaller than that for Germany. Estimates controlling for additional fixed effects show smaller and non-statistically significant slopes, implying that agglomeration forces due to better matching in labor markets are weaker in Mexico.

We then turn to the possible mechanisms behind the dampened agglomeration forces in Mexican labor markets. Compared to developed-country labor markets, Mexico's labor markets have a large share of labor informality and lower power of unions. We find a robust negative correlation between the degree of positive assortative matching and the share of informal labor in a city. However, controlling for informality does not change the slope of the matching vs. city size coefficient. We do not find an effect of unionization rates on matching strength. Together, these exercises suggest that neither of these differences is responsible for the reduced advantages of city size for labor markets.

We contribute to three strands of literature. First, we provide an additional example to the set of studies documenting the presence of city-size wage gaps not only in developed countries as discussed by Baum-Snow and Pavan (2012); Gould (2007); D'Costa and Overman (2014), and De la Roca, Jorge and Puga, Diego (2016), but also in developing economies (Chauvin et al., 2017; Combes et al., 2020; De la Roca et al., 2023; Duranton, 2016). Our estimates for Mexico, a middle-income country with high labor informality, validate these previous estimates. Second, we contribute to the literature on matching in labor markets and agglomeration forces (Andersson et al., 2007; Baum-Snow and Pavan, 2012; Behrens et al., 2014; Dauth et al., 2022), by showing that agglomeration forces are somewhat weaker in Mexico and that labor informality reduces positive assortative matching in formal labor markets. In doing so, we also contribute to the literature on informal labor markets Ulyssea (2018) and their relationship with formal ones (Levy Algazi, 2018; Ulyssea, 2010). Lastly, we contribute to the small but growing set of studies, such as Frías et al. (2022) and Pérez Pérez and Nuño-Ledesma (2022), that adapt multi-dimensional fixed effects models to the Mexican case.

The rest of the paper proceeds as follows. Section 2 details the data and the Mexican context. Section 3 details our AKM model estimation. Section 4 estimates the relationship between assortative matching and city and local-labor-market-level covariates and estimates the relationship between matching, city size, and informality in Mexico. Section 6 concludes.

2 Data

Our data consists of social security records from the Mexican Social Security Institute (IMSS by its acronym in Spanish). The Institute is the Mexican government's main social security, pension, and public health administrator. Salaried workers in the private sector are required to register with IMSS by law. By the government's estimation, 83% of all formal workers are affiliated with IMSS (Pérez Pérez and Nuño-Ledesma, 2022). The records at our disposal report monthly observations from November 2004 to December 2018. This last month of the data contained information for about 20.1 million workers.[2] Notwithstanding its wide coverage, our data have some limitations. A different agency manages records for public employees, so they do not appear in our data. Daily earnings above 25 "units of measurement and update" (approximately 140 USD) are censored. Naturally, information from informal workers (persons working in the shadow economy) is absent from IMSS data. Informality is widespread in Mexico; according to the country's National Survey of Occupation and Employment (ENOE by its acronym in Spanish), 55% of all workers operate in the informal economy Banco de México (2023).

Our dependent variable of interest is the natural logarithm of real daily taxable income.[3] Taxable income may include remunerations made to the worker other than wage. The dataset also includes information on gender, age, and registration date to IMSS. The dataset does not include information on education or hours worked. Our primary sample of interest is prime-age men (25-54 years old) who have likely concluded their education. Thus, their estimated worker effect should include wage variance attributable to education. Regarding employer information, the data includes workplace and economic sector identifiers.

We complement IMSS data with city-level characteristics from Mexican censuses and intercensal surveys for 2005, 2010, and 2020. We construct city-level labor informality rates using data from Mexico's labor survey, ENOE. Regarding local-labor-market-level characteristics, we rely on the definition of local labor markets (and the associated dataset) used by Aldeco et al. (2023), which divides Mexico into 777 local labor markets.[4]

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[2] See online appendix A for details on variable construction and descriptive statistics.

[3] As Dauth et al. (2022) note, using nominal or real wages only changes the scale of the firms' fixed effects.

[4] Aldeco et al. (2023) calculate commuting zones using the methodology in Fowler and Jensen (2020). B in the Appendix provides detail about the commuting zone construction.

3 Model and Estimation

We follow the methodology used by Abowd et al. (1999), Card et al. (2013), Card et al. (2018). We estimate econometric models (frequently referred to as "AKM models") where log wages are a function of additive worker and workplace effects:

$$\ln(wage_{it}) = \alpha_i + \psi_{J(i,t)} + X'_{it}\beta + r_{it}. \tag{1}$$

Here, $wage_{it}$ is the real wage of worker i at time t. The vector of fixed effects α_i captures the influence of all time-invariant worker characteristics. Similarly, the vector of fixed effects $\psi_{J(i,t)}$ collects time-invariant factors at the workplace level for workplace J where worker i was employed at time t. The vector X_{it} includes control variables, which in our estimations include functions of age and time-interval trends. We estimate equation (1) by OLS with a preconditioned iterative gradient method (Card et al., 2013).[5] We generate estimates of the model for three discrete time segments: 2004-2008, 2009-2013, and 2014-2018. In AKM models, worker mobility identifies firm and worker effects. As pointed out by Abowd et al. (1999), these effects can be disentangled by worker mobility –generated when workers change employers– that creates a network of directly or indirectly connected workplaces. We restrict estimation to the largest "connected set" of workplaces in each time interval across which workers change jobs at least once (Abowd et al., 1999).[6]

Table 1 shows summary statistics of our estimations. The AKM models explain about 90% of the variance of log wages each period. The variance of worker effects decreased over time, while the variance of worker effects and the covariance between worker and workplace effects increased over time. The correlation coefficient between worker and workplace effects is between 0.21 and 0.25, much lower than that found for Germany by Dauth et al. (2022) of 0.64 in 2008-2014.

We follow Card et al. (2013) and use our estimated model to decompose the variance of wages into the shares attributed to each component:

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[5]We provide validation exercises for the linearity in equation (1) and the uncorrelatedness of the error term r_{it} and the fixed effects and covariates in online appendix section C. Specifically, we follow Card et al. (2013) and show that firms are exchangeable: for a worker, moving from firm A to firm B has approximately the same effect on wages as moving from firm B to firm A. Pérez Pérez and Nuño-Ledesma (2022) also provide evidence of the validity of AKM models in this sample.

[6]Online appendix table A.1 shows that descriptive statistics are similar in the full and connected set samples.

Table 1: AKM Model Estimation Results

	Interval 1 2004-2008	Interval 2 2009-2013	Interval 3 2014-2018
Worker and workplace parameters			
Number of worker effects	5,576,345	6,920,461	8,941,908
Number of workplace effects	523,701	554,593	695,749
Summary of parameter estimates			
St. dev. of worker effects	0.504	0.486	0.472
St. dev. of workplace effects	0.444	0.479	0.487
Correlation worker/workplace effects	0.212	0.231	0.259
Goodness of fit			
St. dev. of log wages	0.772	0.792	0.793
RMSE	0.238	0.237	0.233
R squared	0.909	0.913	0.916
Adj. R squared	0.905	0.910	0.913
Variance Shares			
Worker effects	0.426	0.376	0.354
Workplace effects	0.330	0.366	0.377
2 Cov(worker effects, workplace effects)	0.159	0.172	0.189

Source: Authors' calculations using IMSS data. Results from estimating equation (1) via OLS with a pre-conditioned gradient method following Card et al. (2013). Estimations are restricted to prime-aged men (ages 25-54) in the largest connected set per time interval. All the estimations include the following controls: age, age squared, age cube, and a monthly time trend. RMSE is the root mean squared error.

$$\text{Var}(\ln \text{wage}_{it}) = \underbrace{\text{Var}(\alpha_i)}_{\text{workers}} + \underbrace{\text{Var}(\psi_{\mathbf{J}(i,t)})}_{\text{workplaces}} + \text{Var}(x'_{it}\beta) + \text{Var}(r_{it})$$

$$+ 2\underbrace{\text{Cov}(\alpha_i, \psi_{\mathbf{J}(i,t)})}_{\text{sorting}} + 2\,\text{Cov}(\psi_{\mathbf{J}(i,t)}, x'_{it}\beta) + 2\,\text{Cov}(\alpha_i, x'_{it}\beta). \tag{2}$$

The last rows of Table 1 show the results of this decomposition. Worker effects explained about 42% of wage variance in 2004-2008, and their contribution to total variance has decreased over time. In contrast, the contribution of workplace effects and sorting has been increasing over time. Sorting explains 15 % of wage variance in 2004-2008, whereas it explains about 19% of wage variance in 2014-2018. This pattern suggests that assortative matching is increasingly important in determining wage variance in Mexico over time.[7]

4   Assortative Matching and City Size

We analyze how the strength of positive assortative matching varies with city size across Mexican cities. Our measure of matching intensity is the correlation coefficient between estimated worker and workplace fixed effects. We conduct our analysis at two geographical aggregations: metropolitan areas (INEGI, 2018) and commuting zones as defined by Aldeco et al. (2023). Metropolitan areas only include the largest cities in the country, while commuting zones are a more refined category, including population centers in addition to the largest cities. We also calculate these correlation coefficients at the metropolitan area-industry and commuting zone-industry levels, to delimit the analysis to specific labor markets further.[8]

We then regress the estimated correlation coefficients on the logarithm of the population as a measure of city size.[9] For these analyses, we pool the correlation coefficients in a single model

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[7]A pervasive issue in these decompositions is the bias in the plug-in OLS estimates of the variance components of equation (2). Kline et al. (2020) show that even if OLS estimates of the fixed effects are unbiased, estimates of their variance may be biased, usually attenuating estimates of the covariance between worker and workplace fixed effects. Bonhomme et al. (2019) show that the bias in these variance components worsens when there is limited mobility of workers across workplaces. To address these issues, in Appendix section D, we repeat the decomposition using alternative estimators for the variance components of equation 2. The results of these decomposition exercises with limited mobility bias corrections are similar to the baseline results.

[8]We use a three-digit NAICS industry classification. Our data includes 22 industries. For the estimates at the commuting zone by industry level, we exclude cells with fewer than 50 workers or fewer than five firms.

[9]In Appendix Table E.1, we show that we obtain similar results using log-employment as a proxy variable of labor market size.

and include binary variables indicating the period accounted for in the regression.[10]

We show the results in Table 2. Panel A, column 1 shows that the correlation between city size and assortative matching for Mexico's metropolitan areas is positive and statistically significant but much smaller than that found in Dauth et al. (2022) for Germany. Doubling city size increases the correlation coefficient between worker and workplace fixed effects by 1.6 p.p. This correlation is weak even for the country's largest urbanized areas, indicating weak agglomeration externalities.

Columns 2, 3, and 4 of panel A show estimates of the city-size-matching correlation for different labor market aggregations.[11] Although the associations we encounter are still relatively small, they are significantly stronger than the estimated for metropolitan areas. Doubling the size of a local-labor-market-industry cell increases assortative matching by 3.1 p.p., which is still half of the association found by Dauth et al. (2022). Figure 2 shows the estimated relationship and compares it to the analog figure in Dauth et al. (2022).

In the remaining panels in Table 2, we show estimates from alternative specifications, which we conducted to gauge the robustness of our findings. Panel B demeans the estimated workplace fixed effects by industry. By doing this, the estimated correlations between city size and matching control for different industry compositions across cities. Using these "residual" fixed effects, the association between city size and matching is weaker than in previous panels. This pattern of results indicates that part of the effect seen in the estimates with unadjusted fixed effects was due to industries with better labor market matching located in larger cities.

Panel C instruments current population with population in 1990 to avoid reverse causality between labor market matching and population growth. The IV estimates are larger, although they fall inside the confidence interval of the OLS estimates.

Panel D calculates the dependent variable –correlations between worker and workplace fixed effects by geographical area– using fixed effects estimated using the limited mobility bias correction proposed by Bonhomme et al. (2019).[12] With this correction, the estimated correlations

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[10]Appendix table E.2 shows that we obtain similar results if we estimate these regressions for each time interval separately. Interestingly, our estimates of the association between city size and matching are usually higher for the 2014-2018 time interval.

[11]For the commuting zone by industry estimates, we restrict to cells with more than five firms and more than 50 workers, following Dauth et al. (2022).
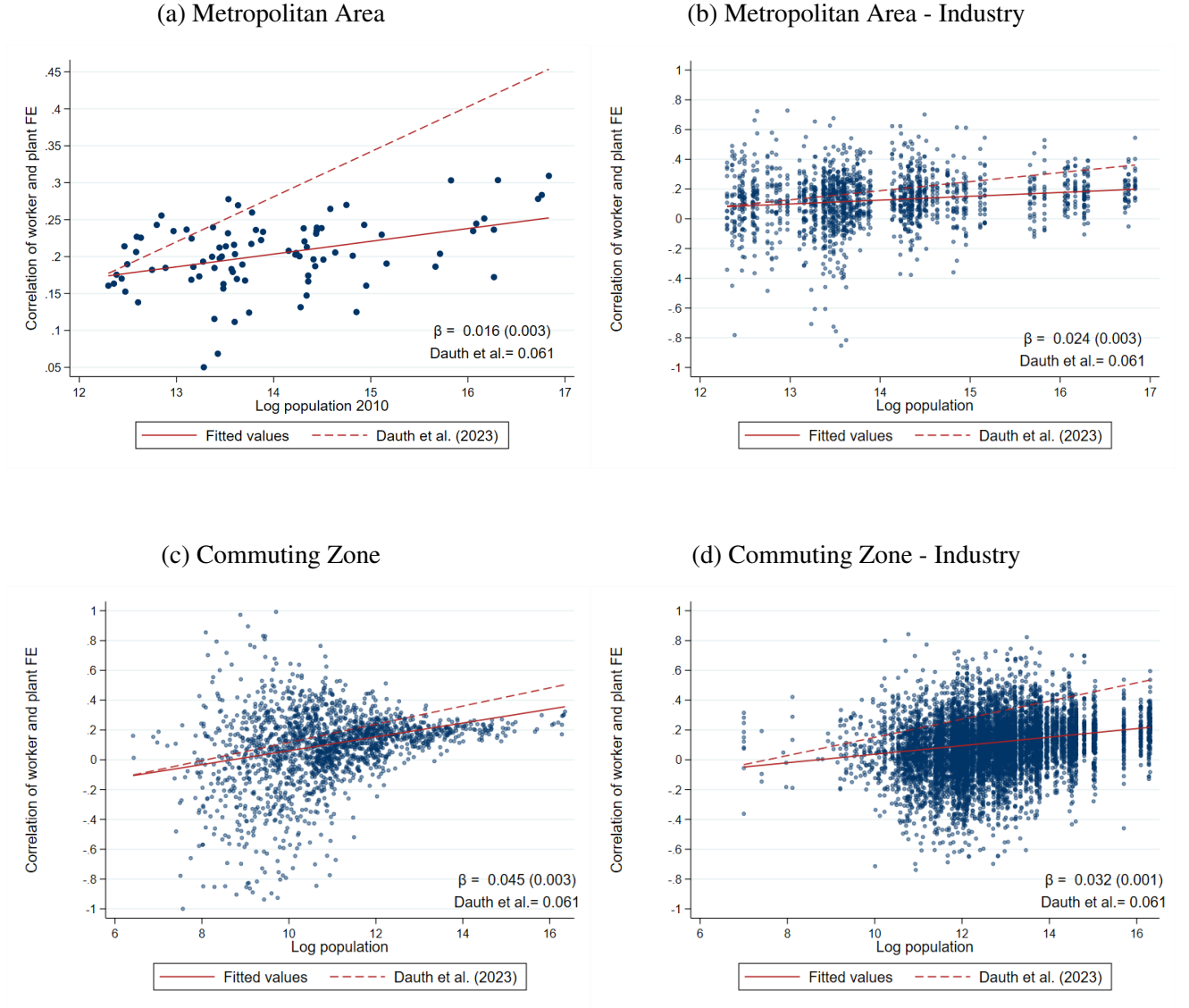
[12]For these estimates, we cluster firms into five clusters using 20 percentiles of the within-firm distribution of wages as clustering variables. Then, we re-estimate the AKM model with this reduced workplace effect number of parameters and recalculate the correlations between worker and workplace effects.

Table 2: City Size and Assortative Matching in Mexico's Formal Labor Markets

Dependent variable: Correlation of worker and workplace FE				
	(1)	(2)	(3)	(4)
	Metro	Metro-Industry	CZ	CZ-Industry
A: Baseline model				
Log Population	0.0157***	0.0244***	0.0452***	0.0314***
	(0.003)	(0.003)	(0.003)	(0.001)
R^2	0.340	0.032	0.081	0.059
B: Correlation of worker and residual workplace FE				
Log Population	0.0137***	0.0017***	-0.0576	0.0021***
	(0.003)	(0.000)	(0.059)	(0.000)
R^2	0.339	0.032	0.002	0.058
C: Log population instrumented with log population in 1990				
Log Population	0.0183***	0.0228***	0.0472***	0.0317***
	(0.003)	(0.003)	(0.003)	(0.001)
R^2	0.336	0.032	0.080	0.059
First-stage F	2,601.43	49,040.4	66,566.9	149,502
N for Panels A-C	90	1,648	1,795	7,972
D: Corrected for limited mobility bias				
Log population	0.0117***	0.00428	0.0244***	0.0290***
	(0.004)	(0.003)	(0.002)	(0.001)
R^2	0.113	0.002	0.0436	0.0601
N	90	1,647	1,777	5,225
E: Dropping the 10% largest and 10% smallest areas				
Log Population	0.0203***	0.0267***	0.0233***	0.0357***
	(0.004)	(0.004)	(0.003)	(0.001)
R^2	0.488	0.048	0.085	0.051
N	54	986	588	6,639

Source: Author's calculations using IMSS and census data. The columns show the results of regressions of the correlation coefficient between worker and workplace effects from AKM model estimates and log population at different geographical aggregation levels. All the regressions pool data from the three intervals: 2004-2008, 2009-2013, and 2014-2018, and include dummies by interval. Metro stands for metropolitan area. CZ stands for commuting zone. For column 4, we restrict to cells with more than five firms and more than 50 workers. Panel A shows baseline estimates. Panel B shows estimates with workplace fixed effects demeaned by industry. Panel C instruments log population in the three intervals with log population in 1990. First-stage F is the first stage F-statistic. Panel D shows estimates using the Bonhomme et al. (2019) correction, where workplaces are clustered into five clusters according to within-workplace wage distributions before estimating the AKM model. Panel E shows estimates excluding the 10% largest and smallest areas by population. Robust standard errors in parentheses. *: p<0.1, **: p<0.05, ***: p<0.01.

Figure 1: City Size and Assortative Matching in Mexico's Formal Labor Markets

(a) Metropolitan Area

(b) Metropolitan Area - Industry

β = 0.016 (0.003)
Dauth et al.= 0.061

β = 0.024 (0.003)
Dauth et al.= 0.061

(c) Commuting Zone

(d) Commuting Zone - Industry

β = 0.045 (0.003)
Dauth et al.= 0.061

β = 0.032 (0.001)
Dauth et al.= 0.061

Source: Author's calculations using IMSS data. Each panel shows a scatterplot for the relationship between log population and the correlation between estimated worker and workplace effects from AKM models at different geographical aggregation levels. For comparison, each panel also displays a dashed line with the implied relationship if the coefficient for the relationship were the same as that estimated by Dauth et al. (2022). For panel d, we restrict to cells with more than five firms and more than 50 workers. We classify industries according to a 3-digit NAICS classification. The bottom-right values display the slope of a linear regression corresponding to the displayed relationship. The regressions include dummies for each time interval.

are smaller, suggesting that limited mobility is not dampening our estimates of the strength of matching externalities.

Last, panel E removes the largest and smallest cities from the sample. The results are similar in this restricted sample, implying the small association we find is not due to the smallest cities or Mexico City's influence.

Overall, the city-size advantage for matching in the labor market is weaker in Mexico compared to the results of Dauth et al. (2022). We now explore possible explanations for this difference.

5   Why are Matching Agglomeration Externalities Weak in Mexico?

There are many differences between labor markets in developed and less advanced economies ,which may debilitate labor market matching and its agglomeration externalities. We concentrate on two of the main differences between the labor markets of Mexico and Germany, which has been the object of previous analyses similar in spirit to ours.

First, labor market informality is high in Mexico. According to Mexico's ENOE, 55% of employed workers labor in the informal economy as of 2022. Informal workers may not pay income taxes, lack labor stability, and do not have access to social security through their employers. The presence of a large informal labor market may depress assortative matching processes and city-size wage advantages for multiple reasons. From the labor supply side, informal labor markets may attract workers who would otherwise join the formal sector and match with a firm there. Although informal workers are less productive in general (Levy Algazi, 2018), if they were to join low-productivity formal firms instead of informal firms, this would enhance assortative matching compared to a scenario where low-productivity informal firms are either hiring productive workers or not hiring.[13]

From the labor demand side, informality may dampen formal firms' productivity because of

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[13]It is also possible that informality strengthens matching in the formal sector because of its role as a stepping stone in the labor market. Many workers in Mexico enter the labor force through the informal market and only obtain formal jobs later in life. If these workers are better informed about their abilities at this stage, they may search for firms where they are a better match. However, since our results point towards reduced matching externalities in Mexico, this stepping-stone role must no be the primary mechanism through for informality affecting formal labor market matching.

competition. It may also encourage formal firms to have some informal workers, who may be less productive but charge lower wages and may be poor matches for the firm.

Another substantial difference between Mexico's and Germany's labor markets is the limited power of unions in Mexico. In 2018, the collective bargaining coverage (percentage of employees with a legal right to bargain) in Mexico and Germany was 10% and 54%, correspondingly (OECD, 2023). Card et al. (2013) argue that the declining power of unions in Germany increased the importance of assortative matching in determining wage inequality. However, if this were the case for Mexico, we would expect that Mexico's labor markets would have stronger assortative matching.

We test the relationship between informality, unionization, and matching in formal labor markets in columns 1 to 4 of Table 3. There, we regress assortative matching on city size as in section 4, but we also control for the labor market informality rate and the unionization rate. We do so for different geographical aggregations. At the metropolitan-area-industry level, we find that the informality rate has a negative effect on formal labor market assortative matching. A 10 % increase in the informality rate reduces the correlation between worker and firm effects in 2.7 p.p. In turn, increasing the unionization rate does not affect the correlation. Further, controlling for these variables does not change the estimated size of the city-size-matching relationship, even though they explain a significant share of the variance. At the commuting zone level, where we lack unionization information, we still find a negative relationship between informality and matching.

We follow a more agnostic approach in column 5 of Table 3. We take advantage of having repeated estimates for three different time intervals and estimate regressions with commuting-zone fixed effects (in addition to dummies for each interval). This way, we are comparing the evolution of assortative matching in commuting zones where the population grew faster to commuting zones where it grew slower instead of comparing commuting zones in the cross-section. This comparison renders the coefficients on both population and informality insignificant. This findingcontrasts sharply with the results of Dauth et al. (2022), which find that the relationship between city size and matching holds after controlling for additional fixed effects. The same pattern holds for columns 6 to 8 at the commuting-zone-industry level: controlling for additional fixed effects renders the relationship between city size and matching insignificant. These findings highlight that agglomeration externalities in Mexico's formal labor markets are weaker than what was found by Dauth

Table 3: City Size and Assortative Matching in Mexico's Formal Labor Markets: Additional Controls

Dependent Variable: Correlation of worker and workplace FE

|	(1) City-Industry	(2) City-Industry	(3) CZ	(4) CZ	(5) CZ	(7) CZ-Industry	(8) CZ-Industry	CZ-Industry
Log population	0.0244*** (0.003)	0.0227*** (0.003)	0.0452*** (0.004)	0.0277*** (0.004)	0.1300 (0.084)	0.0314*** (0.001)	-0.0428 (0.039)	-0.0414 (0.028)
Informality Rate		-0.2715*** (0.021)		-0.2610*** (0.033)	-0.0808 (0.224)			
Unionization Rate		-0.0595** (0.025)						
CZ FE					Yes		Yes	
CZ-Industry FE								Yes
N	1,648	1,647	1,795	1,795	1,735	7,972	7,972	7485
R^2	0.032	0.148	0.081	0.103	0.577	0.059	0.165	0.739

Source: Author's calculations using IMSS, ENOE, and census data. The columns show the results of regressions of the correlation coefficient between worker and workplace effects from AKM model estimates and log population at different geographical aggregation levels and with different specifications. Metro stands for metropolitan area. CZ stands for commuting zone. For columns 6 to 8, we restrict to cells with more than five firms and more than 50 workers. Robust standard errors in parentheses. *: $p<0.1$, **: $p<0.05$, ***: $p<0.01$.

et al. (2022).

Since Mexico's labor market features are not behind the weaker matching externalities, we now explore the role of other features of the Mexican economy that are not specific to the labor market but affect the economy as a whole: industry composition and firm size. Compared to Germany, where 71% of employment is in services (Bank, 2023), Mexico has a larger share of manufacturing employment and employment in other sectors. If matching externalities were stronger in the service industry, then part of the reason behind the weaker matching could be the lower share of service jobs. Figure 2, panels A and B show binned scatterplots displaying the relationship between city size and labor market matching at the commuting zone level for service and non-service sectors. The relationship between city size and matching in the services industries is much steeper.

We estimate regressions of population and matching by sector at the commuting-zone level and then obtain weighted averages of the slopes separating industries into services and others. For services, the weighted average slope is 0.046. In contrast, the average slope for non-service sectors is 0.015. These findings suggest that agglomeration forces are stronger in the services sectors.

Figure 2: City Size and Assortative Matching in Mexico's Formal Labor Markets: Industry and Firm Size Differences

(a) Services

(b) Non-Services

(c) Large Firms

(d) Small Firms
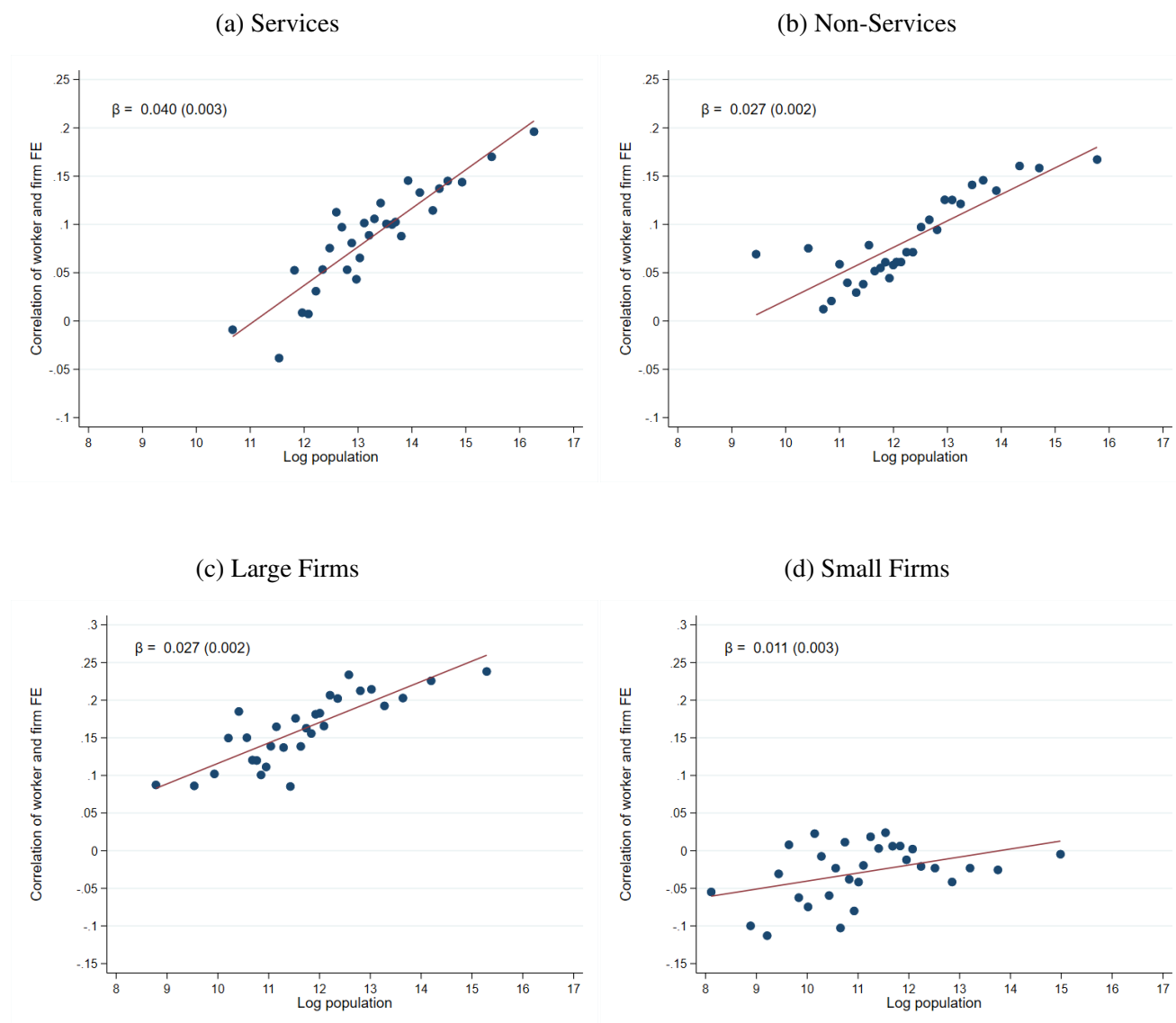
Source: Author's calculations using IMSS data. Each panel shows a binned scatterplot for the relationship between log population and the correlation between estimated worker and workplace effects from AKM models at the commuting zone-industry level. We restrict to cells with more than five firms and more than 50 workers. Panels a and b show the relationship for service and non-service industries, respectively. We classify industries according to a 3-digit NAICS classification. Panels c and d show the relationship separating large firms (more than 16 workers) and small firms (fewer than 16 workers). The top left values display the slope of a linear regression corresponding to the displayed relationship. The regression includes dummies for each time interval. Standard errors in parentheses.

Still, these do not explain the shortfall in these slopes compared to Dauth et al. (2022).

Another endemic feature of Mexico's economy is a firm-size distribution overtly concentrated on small firms compared to developed countries and countries with similar development levels (Levy Algazi, 2018). Previous evidence shows that agglomeration effects are more substantial for larger firms and that agglomeration positively affects firm size (Li et al., 2012). Eeckhout and Kircher (2018) show that in a labor market matching model, firm size and worker quality sorting are positively correlate under some complementarity conditions.

Figure 2, panels c and d, shows the relationship between city size and assortative matching at the commuting zone level, separating the sample into large firms (more than 16 workers) and small firms (fewer than 16 workers), following the firm size classification of Levy Algazi (2018). The differences between these relationships for small and large firms are striking. For small firms, the correlation between log population and assortative matching is negative for a large share of commuting zones, and the increase in this correlation as the population grows is moderate: doubling the population only leads to a 1.1 p.p. increase in the correlation coefficient between worker and workplace fixed effects. For large firms, the picture is quite different. Assortative matching is positive throughout commuting zones, and the slope of the relationship between population and matching is 0.027. These findings validate the hypothesis that labor market matching externalities are at play mainly for large firms.

The evidence in Figure 2 suggests that industrial composition and firm size account for the stronger matching externalities found in Dauth et al. (2022) compared to those for Mexico.

6   Concluding Remarks

Using administrative Mexican social security records, we provide a descriptive analysis of the underlying mechanisms of wage variation and worker-firm sorting patterns in the country. We show that city size is positively correlated with the intensity of positive assortative matching. However, the correlation is weaker than estimations previously reported by similar exercises conducted in Germany. The results persist even when we consider limited worker mobility, different industry compositions across cities, and a potential reverse causality between labor market matching and population growth. Our findings suggest that agglomeration externalities, which often amplify

positive assortative matching in larger cities, are a frail force in Mexico's labor market. The softer association between city size and matching points to differences in the underlying labor market structures and economic conditions unique to economies with large informal sectors, a small share of workers in service industries, and weak collective bargaining coverage.

Declaration of Generative AI and AI-assisted technologies in the writing process

Statement: During the preparation of this work the authors used ChatGPT 3.5 and ChatGPT 4.0 in order to check spelling, improve clarity and format BibTeX entries. After using this tool/service, the author(s) reviewed and edited the content as needed and take(s) full responsibility for the content of the publication.

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Online Appendix - Not for Publication

A   Data and Descriptive Statistics

We use IMSS data previously analyzed in Pérez Pérez and Nuño-Ledesma (2022). IMSS refers to the Instituto Mexicano del Seguro Social, a Mexican government organization that handles public health, pension management, and social security. Private sector employees are required by law to register with IMSS. According to Mexico's labor survey, about 83% of the formal workforce in 2022 were registered with IMSS. Self-employed individuals have the option to register with IMSS, granting them access to certain aspects of the social security system. Typically, self-employed workers register with the equivalent of one legal minimum salary. Self-employed records make up approximately 0.1% of the overall IMSS database. In cases where a worker reports multiple jobs, we retain the job with the highest reported wage. Only 2.5% of workers reported having more than one job in December 2018.

The IMSS social security information is available on a monthly basis. We analyze records spanning from November 2004 to December 2018. Our analysis concludes in 2018 due to significant changes in Mexico's labor market resulting from the COVID-19 pandemic and substantial increases in the minimum wage during the period from 2019 to 2022. The database initially consists of 12.8 million workers in November 2004 and grows to 20.1 million workers by December 2018. Our main variable of interest is the daily taxable income, which encompasses various forms of compensation, excluding additional non-taxable payments such as paid vacations and bonuses. Wages exceeding 25 UMAs (units of measure and update) are capped. In 2018, this cap stood at 2,015 MXN daily, approximately 102 USD.

IMSS identifies workplaces through an employer registry number, known as "registro patronal." The registry number pertains to an employer rather than a physical location. This means that workers who operate in the same plant can have multiple employers, each identified by their registro patronal. For the purposes of our analysis, we utilize anonymized identifiers for the registro patronal, which prevents the precise identification of individual workers or firms within the dataset. The dataset we received from the Mexican Central Bank's EconLab already contains these masked identifiers, and this anonymization process does not affect our econometric analysis or its results. Our study does not explicitly report plant effects as estimated in previous research that

utilizes the AKM methodology.

Table A.1, reproduced from Pérez Pérez and Nuño-Ledesma (2022), displays a summary of the IMSS data. We divide our data into three time intervals: 2004-2008, 2009-2013, and 2014-2018. Within each year, our sample includes a substantial number of wage observations, ranging from 73 to 113 million for men aged 25-54. In column (2) of the table, we observe a 0.7% decrease in the average real daily wage for prime-age men between 2009 and 2014 when compared to 2005. However, this decline is followed by a 1.5% increase by 2018. Column (3) illustrates a widening gap in earned wages between 2005 and 2018.

Table A.1: Descriptive Statistics: Prime-age Men, National Level

	Real wage			
	(1)	(2)	(3)	(4)
	Observations	Mean	Std. dev	Percent censored
2005	73,855,547	394.575	406.256	2.336
2009	80,069,659	394.594	403.065	2.359
2014	98,566,773	391.698	407.856	2.300
2018	113,516,335	397.765	410.689	2.626

Source: Authors' calculations using IMSS data. Observations correspond to the sum of all the monthly observations in a year. Real wages are daily taxable income registered in IMSS, expressed in real terms using prices from July 2018. Percent censored is the percentage of observations with wages exactly equal to the upper wage limit of 25 minimum wages or units of measure and update per year.

Abowd et al. (1999) show that AKM estimates identify fixed effects for workers and workplaces within a "connected set" of workplaces where there is a shared pool of workers who switch jobs at least once. Our estimates use the largest connected set within each time interval. A workplace is part of the connected set if at least one of its workers has worked or will work in a different workplace during the given time interval. Direct connections between every pair of workplaces are not necessary for a connected set to exist.

Table A.2, reproduced from Pérez Pérez and Nuño-Ledesma (2022), shows the number of worker-month observations for prime-age men that had more than one job, the number of individuals, and the average and standard deviation of log wages. In each interval, our database consists of 158 to 297 million worker-month observations representing 5 to 9 million individuals. The standard deviation of salaries slightly increased from 0.77 in the 2004-2008 interval to 0.79 in

the 2014-2018 interval. Average real wages exhibited a consistent upward trend throughout the sample. Columns (5) to (8) of Table A.2 display the corresponding descriptive statistics for the largest connected set of prime-age male workers. This largest connected set encompasses at least 94% of all worker-year observations and 97% of all individuals within a given interval. Average wages within the connected set are slightly higher compared to the overall sample, while standard deviations are marginally smaller. Given the substantial size of the connected set relative to the entire sample, the similar mean salaries, standard deviations, and comparable trends in average wages and salary dispersion, our focus on this connected group does not involve a significant loss of detail.

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

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

Source: Authors' calculations using IMSS microdata. Statistics for men 25 to 54 years old who had more than one job, 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.

We complement the IMSS data with city-level and commuting-zone level covariates. To calculate informality and unionization rates, we use the Occupation and Employment Survey of the National Institute of Statistics and Geography (INEGI). The informality rate is the percentage of workers who do not have social security benefits over the total number of workers. The unionization rate is the percentage of workers who state they belong to a union over the total number of formal workers. We calculate quarterly rates from 2004 to 2018 for the 43 biggest Mexican cities and then averages at city levels for estimation periods (2004-2008, 2009- 2013, 2014-2018). We also calculate the informality rate at the commuting-zone level, using the 2005, 2015, and 2020 Population and Housing Censuses to calculate informality at this geographic level.

B Details about Commuting Zone Construction

We use commuting zones for Mexico calculated by Aldeco et al. (2023). We provide a summary of their methodology to build commuting zones here. Using residence-workplace data from the Mexican census of 2010, Aldeco et al. (2023) group municipalities according to their similarity in commuting patterns, using the same methodology as Fowler and Jensen (2020) for the US. First, they calculate a commuting dissimilarity index for each pair of municipalities i, j:

$$D_{ij} = 1 - \frac{f_{ij} + f_{ji}}{\min\left(\sum_l f_{il}, \sum_l f_{lj}\right)} \quad \text{(B.1)}$$

This index grows larger as the share of workers that commute between municipalities i and j becomes smaller. After building the index, they cluster the municipalities based on this index using a hierarchical clustering algorithm.

C Exchangeability

We reproduce the evidence of exchangeability shown in Pérez Pérez and Nuño-Ledesma (2022) in this section. According to Card et al. (2013), if the residual term in equation (1) is uncorrelated with the variables on the right-hand side, workers who move from workplace A to workplace B should, on average, experience a wage change opposite in sign to workers moving in the opposite direction. To explore this in our dataset, we follow Card et al. (2013) and present an event study in Figure C.1, adapted from Pérez Pérez and Nuño-Ledesma (2022). The plot illustrates the aver-

age wages of workers who changed jobs during each time interval of our analysis period. These workers may transition from "low-wage" to "high-wage" workplaces or vice versa. We categorize workplaces based on the quartile of the average wage of their co-workers in the initial job and the corresponding quartile in the final job. We then calculate average wages before and after the job switch for each category. Our analysis excludes observations from establishments with only one worker and focuses on "direct" moves, meaning moves without an unemployment spell between jobs.

The Figure reveals that different mobility groups, classified by the average wage of co-workers, have distinct average wage levels before and after a job move. Prior to the move, average wages in the quartile of origin exhibit a monotonic variation with respect to the destination quartile. For instance, workers moving from quartile 4 (highest average co-worker wage) to quartile 1 (lowest mean co-worker wage) have higher average wages before the job switch compared to those moving from quartile 3 to 1, and so on. Additionally, the absolute change in average wages when transitioning from one quartile to another is equivalent in magnitude to the variation associated with the opposite change. This symmetry aligns with an additive wage model that incorporates worker and workplace fixed effects, similar to the one we estimate.

Figure C.1: Exchangeability: Average Log Wage Around Movement by Quartile of Average co-workers' Wages in the Origin and Destination Workplace
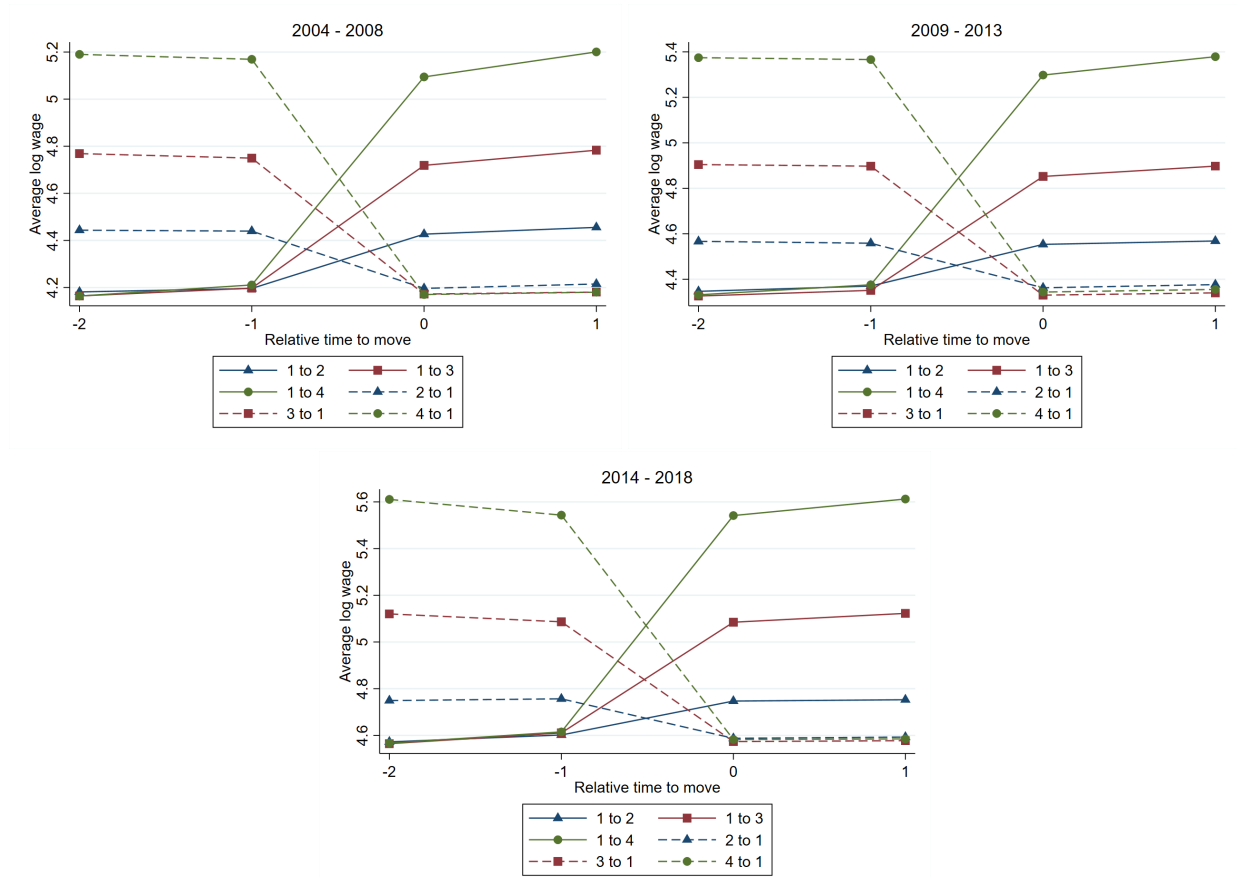
Source: Authors' calculations using IMSS data. The graph shows average worker wages for workers who move between an origin workplace to destination workplace, from two months before the move to one month after the move. The lines group workers according to the quartiles of average co-worker wages in 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.

D   Variance Decomposition with Limited Mobility Bias Corrections

In this section we show that the results of variance decompositions are similar in the baseline estimates and in estimates with limited mobility bias corrections. Table D.1 show variance decompositions with different corrections.

Columns 1 to 3 show the baseline estimates. Columns 4 to 6 show estimates from a model

clustering firms into groups following Bonhomme et al. (2019). We calculate twenty percentiles of the within-firm distribution of wages. Then, we cluster firms into five clusters using the percentile values as variables to cluster. Last, we reestimate the AKM model using firm cluster indicators instead of firm indicators, and recalculate the variance decomposition. The results show slightly higher variance shares attributed to assortative matching.

Columns 7 to 9 show results of the variance decomposition using a leave-one-out variance components estimators from Kline et al. (2020). In this case, the variance shares are similar to those from the baseline estimates.

Table D.1: Variance Decompositions with Different Corrections for Limited Mobility Bias

	Baseline			Bonhomme et al. (2019)			Kline et al. (2020)		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Interval 1	Interval 2	Interval 3	Interval 1	Interval 2	Interval 3	Interval 1	Interval 2	Interval 3
	2004-2008	2009-2013	2014-2018	2004-2008	2009-2013	2014-2018	2004-2008	2009-2013	2014-2018
Variance and covariance									
Total variance of log wages	0.60	0.63	0.63	0.60	0.63	0.63	0.60	0.63	0.63
Variance of person effects	0.25	0.24	0.22	0.23	0.22	0.21	0.25	0.23	0.22
Variance of firm effects	0.20	0.23	0.24	0.16	0.19	0.20	0.19	0.23	0.23
2 Cov(person effects, firm effects)	0.09	0.11	0.12	0.14	0.15	0.16	0.10	0.11	0.12
Variance shares									
Variance of person effects	0.43	0.38	0.36	0.39	0.34	0.33	0.42	0.37	0.35
Variance of firm effects	0.33	0.37	0.38	0.27	0.30	0.31	0.32	0.36	0.37
2 Cov(person effects, firm effects)	0.16	0.17	0.19	0.24	0.25	0.26	0.17	0.17	0.19
Remainder	0.08	0.08	0.07	0.10	0.11	0.10	0.09	0.10	0.09

Source: Authors' calculations using IMSS data. The columns display the results of variance decompositions following equation (2) of the main text. Columns (1) to (3) display the baseline estimates using unadjustes estimated worker and workplace fixed effects. Columns (4) to (6) display estimates using the Bonhomme et al. (2019) correction, where workplaces are clustered into five clusters according to within-workplace wage distributions before estimating the AKM model. Columns (7) to (9) show estimates using the Kline et al. (2020) correction, where the variance components are calculated using leave-one-out estimators.

E Additional Estimates

Table E.1: Estimates with Log Employment as Independent Variable

	(1) Metro	(2) Metro-Industry	(3) CZ	(4) CZ-Industry
Dependent variable: Correlation of worker and plant FE				
Log employment	0.0151 ***	0.0200***	0.0332***	0.0302***
	(0.003)	(0.003)	(0.002)	(0.001)
R^2	0.33	0.05	0.12	0.06
N	90	1,648	1,795	7,972

Source: Author's calculations using IMSS and census data. The columns show results of regressions of the correlation coefficient between worker and workplace effects from AKM model estimates and log employment, at different geographical aggregation levels. All the regressions pool data from the three intervals: 2004-2008, 2009-2013, and 2014-2018, and include dummies by interval. Metro stands for metropolitan area. CZ stands for commuting zone. For column 4, we restrict to cells with more than 50 workers and more than 5 firms. Robust standard errors in parentheses. *: p<0.1, **: p<0.05, ***: p<0.01.

Table E.2: City Size and Assortative Matching in Mexico's Formal Labor Markets: Estimates by Interval

	Dependent variable: Correlation of worker and workplace FE			
	(1)	(2)	(3)	(4)
	Metro	Metro-Industry	CZ	CZ-Industry
A: 2004-2008				
Log Population	0.0121	0.0202***	0.0388***	0.0351***
	(0.0072)	(0.0070)	(0.0064)	(0.0026)
N	30	543	572	2,417
R^2	0.091	0.015	0.056	0.059
B: 2009-2013				
Log Population	0.0170**	0.0207***	0.0496***	0.0322***
	(0.0063)	(0.0068)	(0.0069)	(0.0025)
N	30	544	600	2,653
R^2	0.206	0.017	0.083	0.053
C: 2014-2018				
Log Population	0.0182***	0.0328***	0.0465***	0.0281***
	(0.0058)	(0.0068)	(0.0058)	(0.0022)
N	30	561	623	2,902
R^2	0.263	0.040	0.097	0.047

Source: Author's calculations using IMSS and census data. The columns show results of regressions of the correlation coefficient between worker and workplace effects from AKM model estimates and log employment, at different geographical aggregation levels. Each panel corresponds to a different time interval. Metro stands for metropolitan area. CZ stands for commuting zone. For column 4, we restrict to cells with more than 50 workers and more than 5 firms. Robust standard errors in parentheses. *: $p<0.1$, **: $p<0.05$, ***: $p<0.01$.

Appendix References

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