“AGGLOMERATION ECONOMIES AND ASSORTATIVE MATCHING IN THE CHILEAN LABOR MARKET: AN EMPIRICAL STUDY”

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Agglomeration Economies and Assortative Matching in the Chilean Labor Market: An Empirical Study

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Abstract

This study analyzes the Chilean Unemployment Insurance dataset, a longitudinal sample of over one million Chilean workers' monthly job records, finding a positive correlation between city size and wages. After controlling for worker and firm heterogeneity, the data suggest that doubling city size it's associated with an average increase in wages of 1.6%. Using the 1952 city populations as an instrument to solve endogeneity issues, this population-elasticity estimate remains robust. Given the significant variation in the data, salaries can be decomposed by estimating worker and firm fixed effects, allowing for a matching measure in the analysis of spatial wage disparities. Findings reveal that the co-location of high-productivity workers and firms in cities accounts for 42.9% of city-level wage variance. Further, larger cities promote a higher degree of assortative matching due to the broader range of available firms.

Keywords: agglomeration economies, assortative matching, geographical wage disparities.

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1 Introduction

The micro-foundations of agglomeration economies identify three mechanisms through which agglomeration influences productivity. These mechanisms correspond to matching, sharing, and learning effects, which allow us to distinguish the agglomeration economies by the mechanism driving them (Duranton & Puga, 2004).

The gains from the use of common infrastructure, sharing a wider variety of inputs, risks, and urban specialization are included within the sharing mechanism. Matching between workers and firms in bigger cities has an effect on productivity because bigger cities allow workers and firms to improve the quality of matches, have higher chances of matching since the labor pool is bigger and reduce hold-up problems between agents. Lastly, learning is faster and of better quality in bigger cities by bringing together a large number of people (Duranton & Puga, 2004) and facilitating the diffusion of ideas and knowledge (Marshall, 1890).

It has been in the attention of researchers to determine whether the wage differentials are purely explained by compositional differences of high-productivity workers working in bigger cities or a real productivity advantage caused by the concentration of people in cities (Glaeser & Maré, 2001). When controlling for observable skills characteristics of workers, previous literature has found that spatial differences on the skill composition of workers and firms have explained up to half of the wage disparities between cities (Combes et al., 2008). In many countries, spatial wage disparities have been a policy concern, which has led to an increase in research on this topic, usually in wealthy countries that have left a lack of research in developing countries (Glaeser and Henderson, 2017; Chauvin et al., 2020).

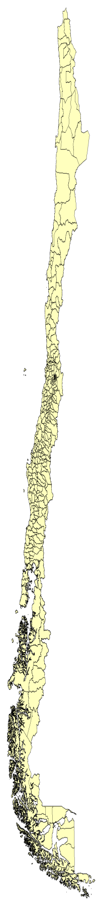
The validity of the already existing urban economics literature in developing countries relies on the similarities between urbanization in rich and poor countries which have enormous political and social differences (Chauvin et al., 2020). It is the aim of this paper to contribute to this branch of literature.

In order to find a common definition of cities and make this study comparable among the literature, the functional areas defined by the Ministry of Housing & Urbanism (MINVU) with support from other state institutions (Ministerio de Vivienda y Urbanismo et al., 2021) are followed to define the cities in Chile. The purpose of this is to use standardized frameworks of urban planning and to represent the real morphology of cities that surpass administrative and territorial limitations.

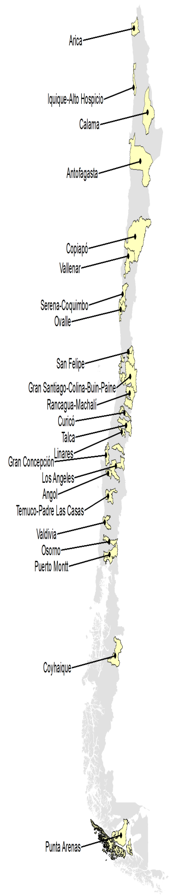
According to the Organization for Economic Cooperation and Development (OECD), in 2015, Chile had only 26 functional areas where 75.7% of the urban population lived, which was only surpassed by South Korea, Turkey, Japan, Luxemburg, United Kingdom, and the Netherlands (OECD, 2022) The latest definitions of functional areas published by the MINVU reveal that there are 29 functional areas in Chile as shown in Figure 1. It was estimated that, in 2022, almost 88.7% of the whole population of Chile lived in urban areas and very few cities concentrate almost all of the workforce. For example, from the data used in this paper, in 2018, 60.8% of the workers from the private sector worked at some firm located in Gran Santiago (the biggest city), followed by Gran Valparaíso with a 6.4%.

Using formal sector employees, Figure 2, depicts the relationship between mean monthly wages and city size. Panel (a) shows that the mean monthly earnings for someone living in Santiago are about $869 USD[1] and the monthly salary is higher, the bigger the city. The cities of Copiapó, Antofagasta, Calama, and Iquique are an exceptional case and are expected to have higher than predicted mean wages, given that they are cities with a high percentage of their workers working in the mining industry, which is composed of high-paying firms and high productivity workers. In panel (b) the plots predicted mean salaries after controlling for mining rates making the relationship between salaries and city size clearer.

[1] 1 USD equals 805,3 CLP

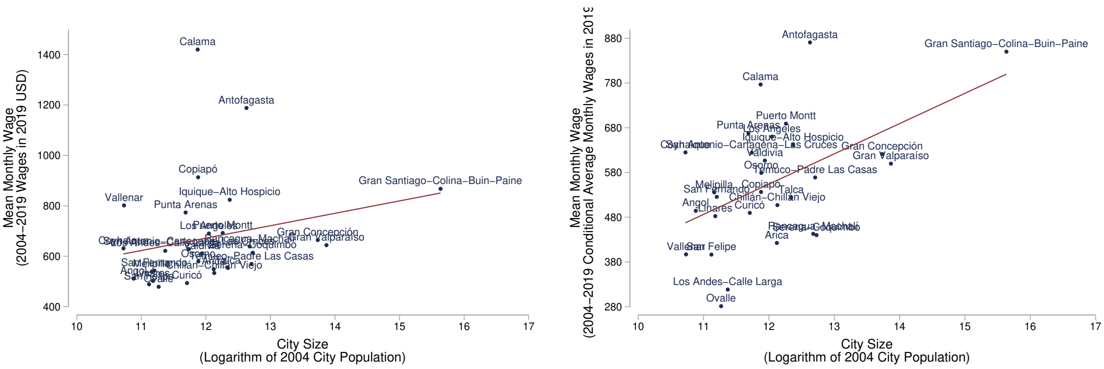


(a) 346 municipalities of Chile.



(b) 29 functional areas conformed by 134 municipalities.

Figure 1: Panel (a) shows the whole set of municipalities and panel (b) shows the subset of municipalities that conforms the 29 functional urban areas defined by the National Institute of Statistics.



(a) No controls

(b) Controlling for Mining Rate

Figure 2: City-average monthly salaries

The relationship between earnings and city size, accounting for worker heterogeneity, is estimated, and a statistically significant relationship between these two variables is found. The estimations are made following Combes and Gobillon (2015) two-step estimation strategy to make the recent literature in urban economics comparable to this research. The advantage of following this two-step estimation is discussed in section 4.2.

After controlling for workers' observable characteristics such as education, age, tenure, economic activity, and workers fixed effects, wage disparities between cities remain large. By focusing on the matching mechanism mentioned before, it can be understood how wages are affected by the differences in the proposed measures of matching between firms and workers.

In this paper, administrative data from the unemployment insurance database is used covering 1,471,015 private sector workers from 2004 to 2019, which allows for the use of different estimation techniques to empirically investigate the determinants of wage dispersion in Chile, specifically on the matching mechanism mentioned earlier.

Given that bigger cities may have higher wages because of compositional differences in firm's and workers' characteristics, wages are conditioned on their characteristics, in order to remove the proportion of the wage disparities that are explained by observable characteristics and not by enhancements in productivity arising from working in higher populated areas.

To inspect the evolution of wage differences between cities over time, and which observable job and worker characteristics explain at least part of them, Figure 3 shows the evolution of the cross-sectional variation for city-level average wages and a new measure of wages defined as city-level residual wages. Residual wages are constructed by predicting wages at the worker level and then taking the difference between actual and predicted wages for every observation[2]. Lastly, city-level residual wages refer to the mean residual wages of cities.

The standard deviation of wages increased from 0.2 to 0.27 between 2004 and 2015 then remained stagnant until the end of the sample period. Although observable characteristics of the workers reduce a substantial amount of the level of wage dispersion between cities, revealing that compositional differences of workers' and jobs' characteristics explain part of the cross-sectional variation of wages at the city level. When controlling for the industry of each worker in the wage regression, the level of wage inequality is reduced by half, which is consistent with the existence of high-paying industries, such as the mining industry, concentrated in a few cities. Even when the level of wage inequality between cities is reduced by conditioning on workers, job, and industry characteristics, the city-level wage disparities still remain large.

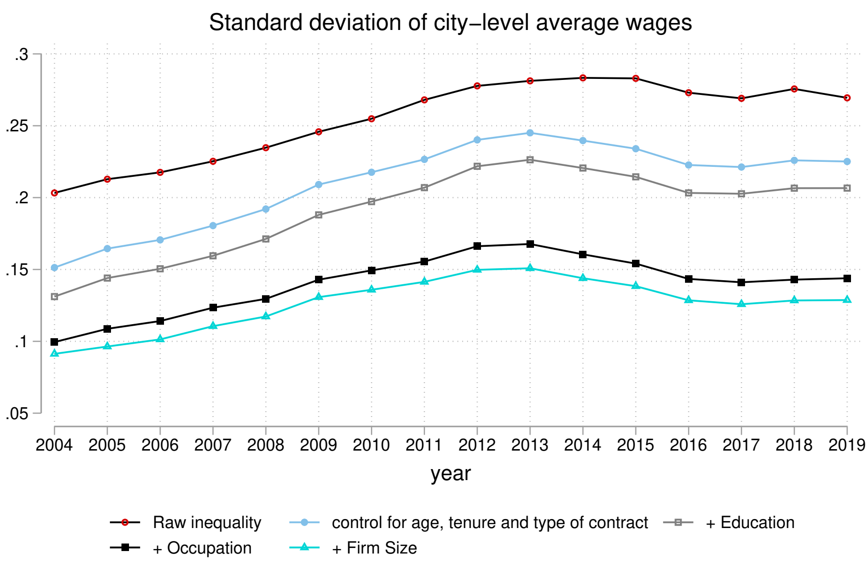


Figure 3: The figure shows the cross-sectional standard deviation of city-average wages and residual wages

When turning into the Assortative Matching section of the paper, the estimation of worker and firm fixed effects followed the AKM specification from Abowd et al. (1999) which decomposes salaries into observable worker characteristics, individual heterogeneity, firm heterogeneity and residual variation. These estimated fixed effects are used to calculate the covariance between the mean quality of workers (represented by worker fixed effects) and the mean quality of firms, as demonstrated by (Dauth et al., 2022). It is found that there is a pattern of co-location between higher-paying firms and higher-productivity

[2]This is done for four different specifications. For example, the first specification controls for age, tenure, and type of contract, then a residual is calculated for every observation, which corresponds to the component of wages that is not explained by the covariates included.

workers in bigger cities. Then, a measure of within-city assortative matching is created for every city and a statistically significant relationship between the degree of assortative matching and city size is found. This finding implies that, on average, more productive workers are more likely to be matched with more productive firms in bigger cities.

This paper primarily contributes to the estimation of the static productivity effect of agglomeration economies utilizing a unique and rich administrative dataset, which, interestingly, has not been previously used for this purpose in Chile. This research aims to assess the congruence between recent findings in the urban economics field and the phenomena of urban wage premiums observed in developing countries, specifically through the lens of the matching mechanism. We believe these insights will provide valuable contributions to our understanding of wage disparities in urban areas of Chile.

The remainder of this paper is organized as follows: In section 2, the data and the definition of the functional areas that will be referred to as cities are presented. In section 3, a simplified model of heterogeneous agents that describes some of the mechanisms by which agglomeration economies can emerge is described. In section 4, the empirical strategy for estimating static agglomeration effects and results is presented. Section 5 introduces the matching of workers and firms as one of the mechanisms of how agglomeration has an effect on productivity, and the method used to measure assortative matching empirically. Section 6 presents the importance of the co-location of firms and workers in explaining wage disparities and the relationship between the degree of assortative matching and city size. Section 7 shows the results of the estimated effect of enhancing the quality of matches within cities on aggregate earnings. Section 8 concludes.

2 Data

The main data set used comes from the Unemployment Insurance (UI) program, a social security instrument created in 2002, which became mandatory for people that began a working relationship in the private sector after October of 2002, but not for people that had a job contract previous to that date. The Unemployment Insurance Dataset is a worker-level panel that covers 20% of all affiliated workers of the unemployment insurance and is representative of the totality of the workers that have UI. It should be noted that the workers who are in the UI are dependent workers over 18 years old that are covered by labor laws, while workers subject to (a) internship programs, (b) people younger than 18 years old, (c) domestic service workers, (d) retired workers, (e) independent workers and (f) public sector workers, are not part of the UI.

The UI dataset follows the job history of private sector workers linking them to their respective employer at the time of the job recording. It contains information about monthly earnings, education, age, tenure, gender, type of contract, and firm characteristics such as firm size and type of industry. The goal is for the results to be representative of the private sector workers of the Chilean Labor Market. Estimations made by Gómez-Lobo and Micco (2023) show that by February 2017, the contributors to the UI were 87% of potential contributors and for which 11% accounted for informality employment and only 2% were workers that could but did not enter the UI which suggests that the results obtained using the UI dataset are a good approximation of the formal private sector workers. The population data for every city was retrieved from the National Institute of Statistics.

2.1 Sample Restrictions

The sample used for all estimations includes workers aged between 18 and 65 years old. Workers with monthly wages below 115 USD are excluded from the sample to filter out any jobs that could be considered marginal. Finally, workers' education is categorized by the highest degree of education completed, such as (a) Primary Education (b) Secondary Education, and (c) Tertiary education.

2.2 Definition of cities

Urbanization as an ongoing process across different countries has made it more difficult to clearly categorize geographical areas as urban since medium size cities and the interconnection between cities and rural life start to create new areas that reveal characteristics that are both urban and suburban (OECD, 2012). To solve this issue, the OECD in 2012 published a re-definition of what a functional urban area is and applied its methodology to 28 OECD countries. Abandoning previous definitions based on administrative boundaries and using a new approach that characterizes urban areas as functional economic units conformed by urban cores and hinterlands whose labor markets are connected and deeply integrated to the cores, allows to have a common unit enabling cross-country comparisons (OECD, 2012).

In this , it is used the recently published definition of functional areas by the Ministry of Housing and Urbanism (Ministerio de Vivienda y Urbanismo et al., 2021), which follows the bases of the OECD (2012) and defines 29 urban functional areas in Chile, which are referred to as cities.

2.3 Descriptive Statistics

Descriptive statistics at the worker level are shown in Table 1. From 2004 to 2019 there are 99,789,578 monthly observations for a total of 1,471,015 workers whose average age is 37.47 years. 64,5% of them are male and 66.2% work with an indefinite contract. Tenure is calculated as the number of months that a worker stays continuously in the same firm and the average tenure per worker corresponds to 27.01 months. Regarding the level of education of workers, 66% of them have completed secondary education.

TABLE 1: Descriptive statistics, Chile, individual-level monthly data from January 2004 to June 2019.

Variable	Mean	Std. Dev	Min	Max
2004-2019				
Wage	669,277	610,967.7	100006	1.03e+08
Age	37.47	11.25	18	65
Tenure	27.01	30.68	1	186
Primary education	0.22	0.41	0	1
Secondary Education	0.66	0.47	0	1
Tertiary Education	0.11	0.31	0	1
Indefinite Contract	0.66	0.47	0	1
Female	0.35	0.47	0	1

Note: This table presents descriptive statistics for Chilean individual-level monthly data from January 2004 to June 2019. Wage is measured in Chilean Pesos (CLP) and adjusted for inflation until June 2019. The variable "Indefinite Contract" represents whether the employment contract is indefinite (1) or not (0). Female is a binary variable indicating gender, where 1 denotes female and 0 denotes male.

Table 2 shows descriptive statistics regarding the job observations for the 2004-2019 period and each sub-sample. There are 490,485 firms in the whole sample differing in size, industry, and location. When the sample is divided into observations from the years 2004 to 2009 and 2010 to 2019 separately, the total amount of observations per period is 27,826,277 and 71,963,301 respectively. The biggest sample period has on average 53.2 monthly observations per worker. The number of unique person-firm pairs from the first and second sub-sample corresponds to 2,720,063 and 3,223,758 respectively, which implies an average of 2.38 jobs per worker in the last sub-sample.

TABLE 2: Descriptive statistics

Variable	Amount of:
(1) 2004-2009	
Observations	27,826,277
Workers	927,152
Avg obs per worker	30.012
Unique person-firm observations	2,720,063
Average jobs per worker	2.933
(2) 2010-2019	
Observations	71,963,301
Workers	1,353,319
Avg obs per worker	53.175
Unique person-firm observations	3,223,758
Average jobs per worker	2.382
(3) 2004-2019	
Observations	99,789,578
Workers	1,471,015
Avg obs per worker	67.837
Unique person-firm observations	7,553,979
Average jobs per worker	5,135

Lastly, descriptive statistics at the city-level are shown in Table 3. One key finding is that the population of cities is highly skewed, the top 10% of cities are at least 3.5 times larger than cities from the bottom 75%. In panel (b) wage disparities also emerge as the top 10% of cities have more than 31% higher mean wages than the cities from the bottom 75%. Variations in the percentages of workers within different education categories across cities suggest an uneven distribution of workers' education between them.

TABLE 3: Descriptive statistics, Chile, city-level aggregated monthly data from January 2004 to June 2019.

Variable	Mean	Std. Dev.	Min	Max	P25	P50	P75	P90
2004-2009								
Wage	414230	109410	312975	793575	340484	388177	439251	545110
Age	3.53	.02	3.48	3.56	3.52	3.53	3.54	3.56
Primary education	.35	.07	.21	.50	.29	.36	.40	.44
Secondary School	.55	.06	.43	.71	.51	.54	.60	.63
Tertiary Education	.09	.02	.05	.16	.07	.09	.10	.12
Tenure	7.72	.42	6.90	8.48	7.41	7.60	8.04	8.33
Indefinite Contract	.51	.07	.37	.63	.46	.52	.57	.60
Population	462438	1181324	51590	6473980	113112	169175	281746	964763
2010-2019								
Wage	615336	205407	424619	1343064	490933	563593	638902	842807
Age	3.61	.01	3.57	3.64	3.60	3.61	3.62	3.63
Primary education	.26	.07	.14	.42	.21	.25	.31	.34
Secondary School	.63	.06	.51	.77	.60	.63	.69	.71
Tertiary Education	.10	.02	.05	.18	.08	.09	.11	.12
Tenure	15.79	1.35	13.41	19.50	14.79	15.61	16.29	17.44
Indefinite Contract	.63	.06	.49	.75	.59	.61	.68	.71
Population	507552	1291420	54773	7083313	123919	179643	314716	1016338

3 Agglomeration Economies

Following Combes and Gobillon (2015) it is assumed a setting with individual heterogeneity among workers and firms. The output of a representative firm located in city c at date t which uses labor $L_{c,t}$ and capital for production $K_{c,t}$ is denoted by $Y_{c,t}$. The profits for a firm located in c in time t correspond to:

$$\pi_{c,t} = p_{c,t}Y_{c,t} - w_{c,t}L_{c,t} - r_{c,t}K_{c,t} \tag{1}$$

Here, $p_{c,t}$ represents the price of the output that firms produce, $w_{c,t}$ denotes the cost of labor and $r_{c,t}$ corresponds to the cost of capital. The production function is assumed to be a Cobb-Douglas:

$$Y_{c,t} = \frac{A_{c,t}}{a^a(1-a)^{1-a}}(s_{c,t}L_{c,t}^a K^{1-a}) \tag{2}$$

$A_{c,t}$ denotes the total factor productivity, $s_{c,t}$ corresponds to the local skill of workers, and $0 < a < 1$. The wage equation is obtained from the first order conditions as follows:

$$w_{c,t} = \left(p_{c,t} \frac{A_{c,t}}{r_{c,t}^{(1-a)}} \right)^{\frac{1}{a}} s_{c,t} = B_{c,t} s_{c,t} \tag{3}$$

Here, $B_{c,t}$ represents the composite local labor productivity and allows to represent almost all agglomeration economies considered in the literature (Combes & Gobillon, 2015). The presence of public goods that benefits all the population within a city by making composite labor productivity higher in bigger cities is believed to be responsible for the higher local TFP $A_{c,t}$ through the sharing of indivisible goods, production facilities and marketplaces.

Secondly, the spatial concentration of workers induces local knowledge spillovers, making firms more productive, also by making $A_{c,t}$ larger in bigger cities. Even though market forces could make the cost of capital $r_{c,t}$ or the price of goods $p_{c,t}$ higher or lower in bigger cities, due to the lack of availability of public data, dispersion forces are not going to be identified and net agglomeration economies is going to be measured by the elasticity of population estimated. This elasticity is driven by local or market agglomeration effects that dominate dispersion effects.

Given the availability of the employer-employee linked data from the UI data set, equation (3) can be expressed at the worker-level by assuming that the local efficient labor $s_{c,t} L_{c,t}$ is described as:

$$s_{c,t} = \sum_{i \in \{c,t\}} s_{i,t} l_{i,t} \tag{4}$$

Where $l_{i,t}$ is the sum of the hours worked by individual i at time t and $s_{i,t}$ it's the individual labor efficiency of worker i at date t. Now profit maximization yields a new wage equation at the individual level corresponding to equation (5).

$$w_{i,t} = B_{c,t} s_{i,t} \tag{5}$$

4 Estimation Approach of Static Agglomeration Effects

In this section, the static agglomeration effects are estimated following Combes and Gobillon (2015). This procedure corresponds to a two-step estimation specification of the population elasticity with respect to wages. The local composite productivity effect from equation (5), $B_{c,t}$ is specified as a function of local characteristics and unobserved local effects in equation (6):

$$B_{c,t} = Z_{c,t}\gamma + \eta_{c,t} \tag{6}$$

The individual effective units of labor $s_{i,t}$, from equation (5) assumed to be a function of individual time-varying characteristics and an individual time invariant component ϕ_i.

$$s_{i,t} = exp(X_{i,t}\beta + \phi_i + e_{i,t}) \tag{7}$$

By replacing equation (6) and (7) in equation (5) and applying logarithm, the following log wage equation is obtained:

$$w_{i,c,t} = \phi_i + \eta_{c,t} + X_{i,t}\beta + Z_{c,t}\gamma + \delta_t + \epsilon_{i,c,t} \tag{8}$$

where $w_{i,c,t}$ is the log wage for worker i working in city c at time t, ϕ_i is a worker fixed effect, $\eta_{c,t}$ is a city random error at time t, δ_t is a month-year indicator and $X_{i,t}$ is a vector of time-varying worker and firm characteristics, $Z_{c,t}$ is the log population of city c at time t, and $\epsilon_{i,c,t}$ is an individual error term.

One issue arising from the specification described in equation (8) is the correct estimation of standard errors given the intra-class correlation of the disturbances that belong to the same group.

Given that equation (8) incorporates the presence of two disturbances η_c and $\epsilon_{i,t}$ making observations within a city c correlated. The mobility of workers across different labor markets makes observations from different cities correlated. This implies that there is no way of grouping to be able to cluster standard errors. A discussion related to this topic is provided by Moulton (1990).

Not accounting for intra-class correlation can lead to under-estimated standard errors and finding statistical relationships when in reality they are spurious. The reason why the second step estimation is pursued in this is to make it comparable with previous literature as in (Roca & Puga, 2017) and to make the assumption of independently distributed individual disturbances more credible.

Instead of equation (8), the following specification is estimated by OLS:

$$w_{i,t} = \phi_i + X_{i,t}\beta + \theta_{c(i,t)} + \epsilon_{i,t} \tag{9}$$

In a second step, the estimated city fixed effects θ_c are used to calculate the population elasticity as follows:

$$\theta_c = log(pop_c)\gamma + \eta_c \tag{10}$$

Equation (9) controls for worker observed and unobserved skills by including individual fixed-effects to capture time-invariant characteristics of each worker. This provides a more precise estimate of γ and enables comparison of the estimations that do not account for it to assess the proportion of the elasticity that was due to skill compositions and not a real productivity effect of agglomeration. Until now we are assuming that local characteristics, such as population, are not correlated to any unobserved local shocks that may increase earnings and population at the same time. This potential source of bias is going to be addressed in section 4.2.

4.1 Results

Table 4 presents the estimation results of the two-step estimation procedure. In column (1), the 29 city fixed effects are estimated without considering workers' unobserved skills. In column (2), the city fixed effects are regressed against the log population of cities in 2004, where an elasticity of 0.0284 is found. This elasticity is almost twice as large as the one found in column (4), which controls for workers' skill heterogeneity, where the elasticity is 0.0161. It is observed that city size is not a strong predictor of wages, with only 6% of the variance being explained by city size, as seen in column (4).

TABLE 4:
Two-step estimation of static urban wage premium

	(1) Log Earnings	(2) City Premium	(3) Log Earnings	(4) City Premium
Log Population		0.0284*		0.0161*
		(0.0145)		(0.0081)
log(age)	6.280***		-1.983***	
	(0.0275)		(0.1120)	
log(age)^2	-0.847***		0.786***	
	(0.0039)		(0.0223)	
log(tenure)	0.128***		0.0716***	
	(0.0006)		(0.0001)	
Type of Contract	-0.202***		-0.0891***	
	(0.0007)		(0.0004)	
Individual FE	No	No	Yes	No
City Indicator	Yes	No	Yes	No
Economic Activity FE	Yes	No	Yes	No
Time FE	Yes	No	Yes	No
Firm Size	Yes	No	Yes	No
Observations	99789578	29	99735393	29
R2	0.398	0.045	0.771	0.060
Std. Errors	Clustered at Worker level	Robust	Clustered at Worker Level	Robust

Notes: (1) Time invariant estimation of city fixed effects. (2) There are 29 cities, log population refers to the logarithm of the 2004 urban population. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors in parenthesis.

The relationship between city premium and city size is shown in Figure 4. It is observed that a worker living in Santiago immediately earns on average 8% more than a worker living in the smallest city. An even greater premium is found in very specialized cities, such as Calama and Antofagasta, after controlling for industry, firm, and worker characteristics, which is explained by the high mining sector wages.

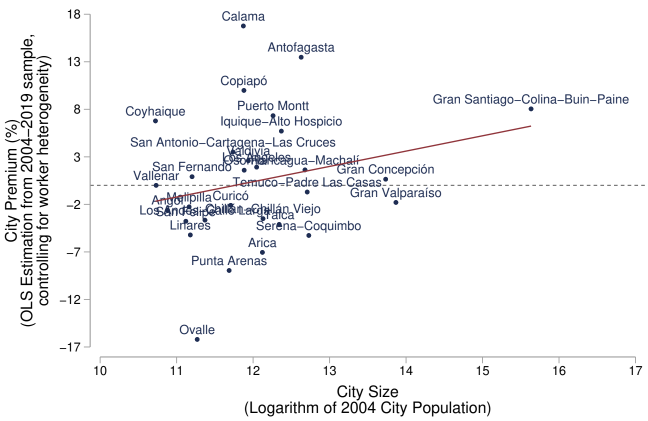


Figure 4: City premium and city size. OLS estimation of city premium controlling for worker heterogeneity, age, tenure, type of contract, industry, firm size and time fixed effects.

4.2 Robustness Check

Table 5 explores the sensitivity of the previous elasticity to the smallest cities in the sample. Column (2) drops cities below 50,000 inhabitants, finding a higher elasticity of 0.0215. Additionally, a dummy for cities with more than 10% of their workers in the mining industry is included to account for particularly specialized cities with higher wages. The elasticity drops to 0.019%. Excluding all mining cities and cities below the threshold of 50,000 population results in an elasticity of 0.029 statistically significant at 1% level.

The static agglomeration effects were estimated using a two-stage approach, as in (Combes & Gobillon, 2015), (Glaeser & Maré, 2001), and (Roca & Puga, 2017), to reduce biases from individual characteristics and address estimation issues with standard errors. Table 6 presents the single-step regression of city size and earnings. In column (1), the elasticity without controlling for individual unobserved skills is found to be 4%, which is reduced by half when including workers' fixed effects, as seen in column (2), which is very similar to the elasticity found in the two-step regression.

To address the problem of reverse causality, where city characteristics can improve earnings and attract workers, thus increasing city size and higher wages can attract workers, also increasing city size (Roca & Puga, 2017), historical population is used as an instrument for current city size, following previous literature (Ciccone and Hall, 1996; Combes et al., 2008). The sample period is separated to investigate if there has been an evolution in the population elasticity over time. Results in Table 7 show that OLS estimates for two sub-periods have an elasticity of 0.0176 and 0.0218, respectively. In column (2), 2SLS estimates using 1952 log population as an instrument for current population in each city are presented, yielding practically the same estimates of 0.0194 and 0.0191 for the first and last periods, respectively.

In Table 8, time-variant city fixed effects are identified using our data set, which has sufficient variation per year in the sample. The time-variant elasticities estimated for the periods (2004-2009) and (2010-2019) are 0.0176 and 0.0218, respectively. In column (2), the 2SLS estimation results are shown and the elasticities are similar to those obtained in the time-invariant fixed effects regression.

TABLE 5:
Two-step estimation of static urban wage premium

	(1) Log Earnings	(2) City Premium	(3) City Premium	(4) City Premium
Log Population		0.0215**	0.0190**	0.0229***
		(0.0079)	(0.0077)	(0.0065)
log(age)	-1.983***			
	(0.1120)			
$\log(age)^2$	0.7860***			
	(0.0223)			
log(tenure)	0.0716***			
	(0.0001)			
Type of Contract	-0.0891***			
	(0.0004)			
Individual FE	Yes	No	No	No
City Indicator	Yes	No	No	No
Occupation FE	Yes	No	No	No
Time FE	Yes	No	No	No
Firm Size	Yes	No	No	No
Mining City	No	No	Yes	No
Observations	99735393	27	27	22
R2	0.771	0.097	0.377	0.228
Std. Errors	Clustered at Worker level	Robust	Robust	Robust

[a] Notes: Results from column (1) excludes cities below 50000 habitants. (2) Excludes the same observations as (1) and includes a dummy to control for cities with more than 10% of their workers working at a mining related job. (3) excludes mining cities. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Corresponding standard errors in parenthesis.

TABLE 6:
One-step estimation of static urban wage premiums

	(1) Log Earnings	(2) Log Earnings
Log Population	0.0392***	0.0198***
	(0.0003)	(0.0002)
log(age)	7.381***	-2.7801***
	(0.0296)	(0.1127)
$\log(age)^2$	-1.009***	0.9170***
	(0.0042)	(0.0224)
log(tenure)	0.1250***	0.1660***
	(0.0006)	(0.0003)
$\log(tenure)^2$	-0.0057***	-0.0214***
	(0.0002)	(0.0001)
Type of Contract	-0.2460***	-0.0767***
	(0.0008)	(0.0004)
Worker FE	No	Yes
Firm FE	No	No
Occupation FE	Yes	Yes
Time FE	Yes	Yes
Firm Size	Yes	Yes
Observations	99789578	99735393
R2	0.326	0.772
Clustered Std. Errors	Worker	Worker

Notes: Log Population included alongside all other covariates. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors clustered by worker are shown in parentheses.

TABLE 7:
Correlation between Time-Invariant City Fixed Effect & City Size

	OLS	2SLS
Panel A: City fixed effect (2004-2009)		
Log Population	0.0189**	0.0194*
	(0.0080)	(0.0101)
Observations	29	29
R2	0.296	0.296
Panel B: City fixed effect (2010-2019)		
Log Population	0.0225**	0.0191**
	(0.0085)	(0.0097)
Observations	29	29
R2	0.319	0.317

Notes: (2SLS) Logarithm of 1952 city population was used as instrument for log population. Robust standard errors in parenthesis. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

TABLE 8:
Correlation between Time-Variant City Fixed Effect & City Size.

	OLS	2SLS
Panel A: City-year fixed effect(2004-2009)		
Log Population	0.0176*	0.0179*
	(0.0092)	(0.0097)
Time FE	Yes	Yes
Observations	174	174
R2	0.622	0.622
Panel B: City-year fixed effect (2010-2019)		
Log Population	0.0218**	0.0183*
	(0.0103)	(0.0097)
Time FE	Yes	Yes
Observations	290	290
R2	0.327	0.325

Notes: (2SLS) Logarithm of 1952 city population was used as instrument for log population. Standard errors clustered by city. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

5 Positive Assortative Matching

In the previous section, it was found that there are substantial wage differences after controlling for worker education and unobserved heterogeneity. In this section, it is analyzed if these disparities are explained by differences in the strength of assortative matching between workers and firms, specifically, through testing the hypothesis that in bigger cities the quality of each match is an increasing function of the number of agents in an economy (Duranton & Puga, 2004).

Following Abowd et al. (2004) it is expected that if the production function of the firms derived from the match is increasing both in worker productivity and firms productivity, such as the following Cobb-Douglas $Y_{ij} = q_i^{\alpha} q_j^{\beta}$, positive assorative matching will be optimal:

$$\frac{\partial Y_{ij}}{\partial q_i q_j} > 0 \tag{11}$$

Taking that the wage paid to the worker is proportional to the rent derived from the match, log wage equation results in the following equation:

$$log(wage_{ij}) = \gamma + \alpha log(q_i) + \beta log(q_j)$$

Even though this wage equation implies super-modularity in the production function, it does not imply log-supermodularity. Though there is no comparative advantage between workers and firms quality, positive assortative matching should hold.

5.1 Estimation Strategy

The estimation strategy presented in Abowd et al. (1999) refered as "AKM" is used to decompose workers' log earnings into unobserved worker and firm heterogeneity. The log wage for worker i at firm j at time t is specified as:

$$w_{i,t} = \alpha_i + \phi_{j(i,t)} + X_{i,t}\beta + \epsilon_{i,t} \tag{12}$$

The log wages of workers are determined by unobservable worker characteristics α_i, a firm component ϕ_j, and through time-varying observable characteristics $X_{i,t}$ which include month-year fixed effects.

Turning model (12) into matrix notation, log wages are written as:

$$W = X\beta + D\alpha + F\phi + \epsilon \tag{13}$$

To correctly identify worker and firm fixed effects, a group of firms and workers connected by worker mobility is needed for D and F to be full rank (Abowd & Creecy, 2002), for this purpose, the Stata module from Correia (2016) *"reghdfe"* was used to determine the connected sets of firms and workers and the estimation of the worker and firm fixed effects. Table 9 describes the number of observations, unique workers, and firms per different sample periods separated by the largest connected set and the whole sample. From 2010 to 2019 98.3% of the observations belong to the largest connected set similar to 97.2% of the observations within the largest connected from the period 2004 to 2009, given the high percentage of workers within the largest connected set, it should be enough to separately identify both fixed effects.

TABLE 9:
Descriptive statistics of fixed effects

	Number of Observations	Groups	# Observations per group Min	Avg	Max	Workers Min	Avg	Max
Panel A.1: Whole Sample (2010-2019)								
Worker	71,963,301	1,353,319	1	53.18	720	-	-	-
Firm		386,516	1	186.18	397,233	-	-	-
Panel A.2: Largest Connected Set (2010-2019)								
Worker	70,709,273	1,274,125	2	55.49	720	-	-	-
Firm		335,406	2	210.81	396,945	1	15.91	40,465
Panel B.1: Whole Sample (2004-2009)								
Worker	27,826,277	1,353,319	1	53.18	720	-	-	-
Firm		386,516	1	186.18	397,233	-	-	-
Panel B.2: Largest Connected Set (2004-2009)								
Worker	26,980,347	1,274,125	2	55.49	720	-	-	-
Firm		335,406	2	210.81	396,945	1	15.91	40,465

For the structural interpretation of the estimated fixed effects from Abowd et al. (1999) to hold as workers' unobserved skill premia and firms premia, there has to be no correlation between the log earnings residual and the workers' decision to enter the labor market, also, the firm assignment to workers has to be uncorrelated to the error term. This exogenous mobility assumption is characterized by:

$$E[\epsilon|X] = 0 \tag{14}$$

$$Pr[D, F|X, \epsilon] = Pr[D, F|X] \tag{15}$$

If (14) and (15) are satisfied, the orthogonality conditions necessary for the identification of α and ϕ are met[3]. Following Card et al. (2013), Abowd et al. (2019) and Dauth et al. (2022), in order to empirically check if (14) and (15) hold, workers moving from low/high to high/low premium firms must experience a symmetric increase/decrease in their wages. Figure 5 illustrates the average wage of workers who moved between jobs and for which their job history is complete 24 months previous and after the job change by the quartile of firm premia. The results found suggest that the additive form of the AKM model fits the data given the symmetry of the wage variations for the opposite directions of job movers from firms from different quartiles.

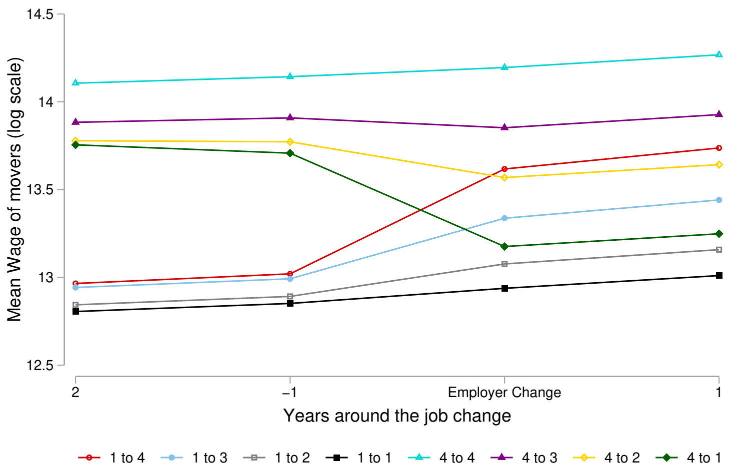


Figure 5: Mean log wages for workers who change jobs by quartile of estimated firm premia

In order to ensure the comparability of the fixed effects estimated across space, enough mobility of workers between different cities is needed. In Figure 6, the mobility of workers across firms from different cities is illustrated using a matrix of 29 by 29 cities. The color of each square represents the number of workers that moved from or to the corresponding city.

The first pattern worth noticing is that cities which have straight black squares on their entire row means they are connected by at least 500 workers to all other cities. Secondly, most city mobility ocurrs between nearby cities depicted by the black squares concentrated around the diagonal. These results suggests that there is enough mobility to ensure comparability of the fixed effect across space.

[3]A detailed discussion about the identification and estimation problems can be seen in Abowd and Creecy (2002).

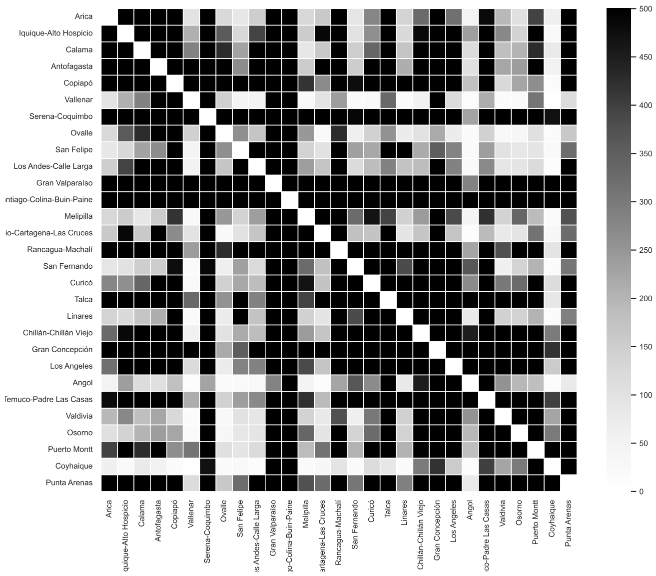


Figure 6: Between-city mobility of workers, each square represents the amount of workers that move between cities. Cities are sorted from north to south. Most mobility occurs between cities that are relatively not far from each other.

5.2 Measure of Assortative Matching

The degree of assortative matching is measured as the correlation between worker and firm fixed effects. Because of the positive assortative matching, a positive correlation is expected. For the largest connected set, the country-level correlation between worker and firm fixed effects is 0.0976.

To determine geographical wage differences through assortative matching between workers and firms, the covariance can be decomposed into two components, (16.1) the location pattern of firms' and workers' quality across cities and (16.2) the within-city pairing of workers and firms by their quality.

$$Cov(\alpha_i, \phi_j) = \underbrace{Cov\Big(E_c[\alpha_i], E_c(\phi_j]\Big)}_{(16.1)} + \underbrace{E\Big[Cov_c(\alpha_i, \phi_j)\Big]}_{(16.2)} \tag{16}$$

Both (16.1) and (16.2) use the expectation E_c and covariance Cov_c at the city c level. As Dauth et al. (2022) the first component (16.1) is going to be referred to as the *co-location* of workers and firms and (16.2) as the *average within city assortative matching*.

When $Cov(E_c[\alpha_i], E_c(\phi_j]) > 0$ on average high productivity workers locate where there are also high-productivity firms. In the urban economics literature, agglomeration economies explain this phenomenon through the expected quality of matches being an increasing function of the number of workers in a city, higher expected chances of matching in bigger cities, and aggregate increasing returns to scale in the aggregate production function of firms (Duranton & Puga, 2004).

Turning into the within-city positive assortative matching $E[Cov_c(\alpha_i, \phi_j)] > 0$ (Shimer, 2005) assignment model offers a consistent setup where high productivity workers are more likely to be employed in high productivity jobs.

Even though a positive correlation between worker and firm fixed effects is to be expected, previous literature has shown that in France and in the United States the estimated correlation was negative and close to zero respectively, suggesting that these results are a reflection of a limited mobility bias (Abowd et al., 2004). Andrews et al. (2012) shows using German data that limited mobility bias can have a large effect on the correlation if the number of worker movements per firms is small, making the estimated correlation negative.

6 Results

6.1 Co-Location between workers and firms

In order to analyze the sorting of workers and firms quality between cities, the average city level of worker and firm fixed effects was regressed against city size. Figure 7 (a) shows the relationship between worker quality and city size for the sample period from 2004 to 2009. No evidence was found supporting the sorting of higher quality of workers into bigger cities, the resulting elasticity is not statistically significant. Figure 7 (b) shows the results for the sample period from 2010-2019 and still no evidence of workers sorting into bigger cities was found.

Figure 8 plots the average firm fixed effects and city size. In panel (a) the result for the first period shows that a doubling of city size is associated with 2.5% higher city-average firm fixed effects, panel (b) shows this relationship for the last sample period. The estimated elasticity increases to 0.03. Both are statistically significant at 5% and 10% levels respectively.

Co-location emerges if both higher productivity worker and firms locate themselves together in cities. Figure 9 plots the mean worker FE against firm FE and depicts a strong relationship between them for the first period with a slope of 0.365 which almost doubles for the last sample period to 0.618, shown in panel (b). Table 10 depicts the results from the estimation of population elasticity and firm fixed effect, and the correlation between worker and firm fixed effects. In panel (B) it is shown that 57% of the city-level worker fixed effects variation is explained by the mean firm fixed effects in cities.

The results indicate that there is no sorting of workers in larger cities but high-paying firms do locate themselves in bigger ones and this relationship has increased over time.

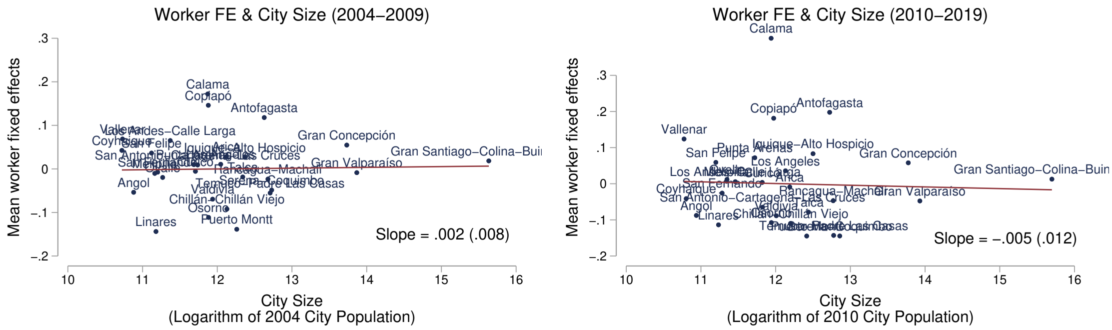


Figure 7: Worker effects & city size, there is no statistical significance between these two variables.

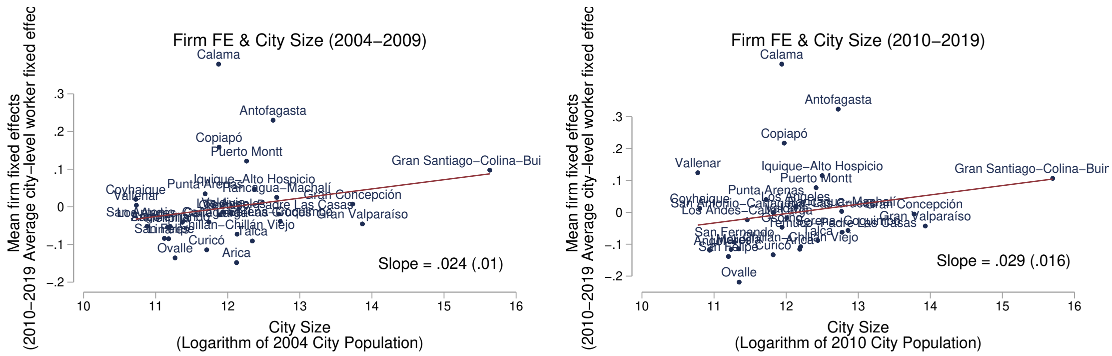


Figure 8: Firm effects & city size

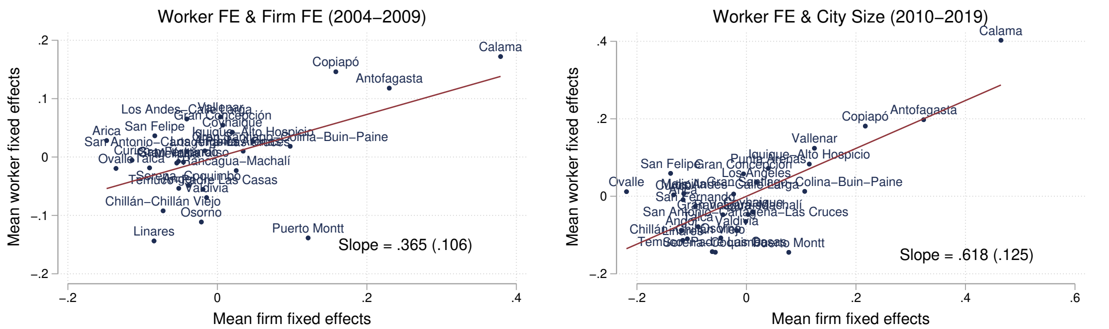


Figure 9: Co-location of worker & firm effects

TABLE 10:
Location & Co-Location of worker & firms.

	(1) 2004-2009	(2) 2010-2019
(A) Dependent Variable: Firm fixed effect		
Log Population	0.0245**	0.0293*
	(0.0098)	(0.0155)
Observations	29	29
R2	0.0523	0.0438
(B) Dependent Variable: Worker fixed effect		
Firm FE	0.365***	0.618***
	(0.1063)	(0.1249)
Observations	29	29
R2	0.294	0.566

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Robust standard errors in parentheses.

6.2 Decomposition of log wages

Given the structure for log wages in (12). The variance of expected log wages at the city level is given by:

$$\begin{aligned} var(E_c[ln(w_{it})]) = var(E_c[\alpha_i]) + var(E_c[\psi_{j(i,t)}]) + \\ var(E_c[X'_{it}\beta]) + 2cov(E_c[\alpha_i], E_c[\psi_{j(i,t)}]) + \\ 2cov(E_c[\alpha_i], E_c[X'_{it}\beta]) + 2cov(E_c[\psi_{j(i,t)}], E_c[X'_{it}\beta]) \end{aligned} \quad (17)$$

This allows to determine the importance of each wage component in explaining geographical wage differences across cities. In Table 11, columns (1) and (3) show the calculated variance and covariance for each one of the variables used in the AKM specification for the sample period 2004-2009 and 2010-2019 respectively. Columns (2) and (4) show the percentage contribution of each component relative to the overall variance of mean log wages for the sample period 2004-2009 and 2010-2019. The geographical differences that are of interest come from worker and firms, depicted by $Var(E_c[\alpha_i])$ and $Var(E_c[\phi_j])$. Lastly, the co-Location of firms and workers represented by $Cov(E_c[\alpha_i], E_c[\phi_j])$.

Table 11 shows the results from the variance decomposition of city-level average wages. In column (2), a key finding is that 31.4% of the city-level variation of wages is explained by the variation in worker unobserved skills, with a small increase for the last sample period as shown in column (4). The second highest source of variation in our specification comes from differences in co-location patterns with a 26.5% contribution of the overall variance for the first sample period, increasing to 42.9% in the period from 2010 to 2019 and thus becoming the most important source of variation of log wages.

These results suggest that almost half of the variations in average wages at the city-level are explained by high-paying firms located with high-skilled workers.

TABLE 11:
Decomposition of across-city variation in average wages

	(1) 2004-2009	(2) %	(3) 2010-2019	(4) %
Var mean log wages	0.0366	100	0.0601	100
Var mean worker effects	0.0057	15.6	0.0140	23.3
Var mean firm effects	0.0115	31.4	0.0202	33.6
Var mean Xb	0.0048	13.0	0.0054	9.0
2Cov(Worker,Firm)	0.0097	26.5	0.0258	42.9
2Cov(Worker,Xb)	-0.0024	-6.4	-0.0055	-9.2
2Cov(Firm,Xb)	0.0073	19.8	0.0056	9.4

Notes: Variance decomposition of city-average wages. Xb includes, type of contract dummy, the interaction between age and education dummies and time effects.

6.3 Within City Assortative Matching

In this section the relationship between within-city assortative matching and city size is analyzed. Given the AKM estimation of worker and firm fixed effects, the city-year correlation between worker and firm fixed effects is used as a measure of the degree of assortative matching for the city c at time t.

Table 12 shows the estimated population elasticity with respect to the degree of assortative matching. In panel (a) all cities are included. For the first period, doubling city size is associated with a 2.93% increase in the strength of assortative matching. A 33% decrease in the estimated population elasticity is seen in the second period. Given that the smallest cities have a lower turnover of workers between firms, the population elasticity is estimated using only 75% and 66% of the largest cities and the results are similar as in panel (a). This suggests that limited mobility bias is not affecting significantly the results. Bigger cities are associated with a higher degree of within-assortative matching, but the strength of this relationship has decreased over time.

TABLE 12:
Correlation between time-variant assortative matching & city size

	(2004-2009)	(2010-2019)
Dependent variable: $Corr_{c,t}(\psi_j, \alpha_i)$		
Panel A: All cities		
Log population	0.0293***	0.0195***
	(0.009)	(0.007)
Observations	174	290
R2	0.289	0.166
Panel B: Dropped 20% smallest cities		
Log population	0.0296***	0.0201***
	(0.004)	(0.002)
Observations	138	230
R2	0.287	0.166
Panel C: Dropped 33% smallest cities		
Log population	0.0231***	0.0154***
	(0.005)	(0.003)
Observations	114	190
R2	0.233	0.112

[a] Notes: All specifications include a dummy that takes the value 1 for cities with more than 10% of their workforce with a mining related occupation. (1) Uses all of the cities (2) Removes the cities below the 20% of the population distribution. (3) Removes the cities below the 33% of the population distribution. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Bootstrap cluster standard errors in parentheses.

Table 13 shows that the elasticity results calculating a unique correlation per city over the whole period (2010-2019) do not change much compared to those of Table 12. This supports that limited mobility bias seems to not be driving our results. Finally, using the population of 1952 as an instrument for city size, the population elasticity is estimated again using 2SLS and remains similar to previous estimates.

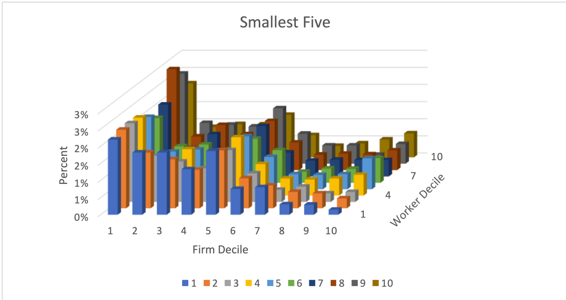
TABLE 13:
Correlation between time-invariant assortative matching & city size

	(1)	(2)	(3)
Dependent variable: $Corr_c(\psi_j, \alpha_i)$			
Panel A: OLS			
Log population	0.0248***	0.0293***	0.0247***
	(0.007)	(0.007)	(0.007)
Observations	29	23	19
R2	0.475	0.554	0.658
Panel B: 2SLS			
Log population	0.0234***	0.0283***	0.0220**
	(0.009)	(0.008)	(0.009)
Observations	29	23	19
R2	0.474	0.554	0.655

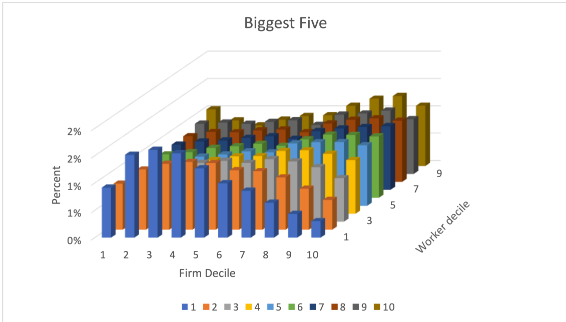
[a] Notes: All specifications include a dummy that takes the value 1 for cities with more than 10% of their workforce working at a mining industry related job. (1) all of the cities included (2) 20% of smallest cities were excluded. (3) 33% of the smallest cities were excluded. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Robust standard errors in parentheses.

Differences in the degree of correlation between different cities have been established, now it remains to investigate what drives these differences. Figure 10 shows the percentage of workers from a given decile that are paired with a firm from a certain decile for the five smallest and biggest cities. In panel (a) it can be seen that for any decile, workers are concentrated in firms from the lower deciles of the firm fixed effect distribution. Workers from the right tail of the distribution are matched with low paying firms. Panel (b) shows that the biggest five cities have a more even density of workers across the different deciles of firms. Particularly, in contrast with panel (a), the five biggest cities show that within a given worker decile, it is more likely that workers are matched with a job around the same decile as their own worker decile.

In order to see differences in the distribution of firm and worker types across different cities, Figure 11 plots the distribution of worker and firm fixed effects. In panel (a) the distribution of worker fixed effects for the five smallest and biggest cities is similar, which supports the argument of little sorting in workers' unobserved ability across different cities, but the same is not found for firm fixed effects. In panel (b) it can be seen that firm fixed effects in the biggest cities have higher variance. This means that in bigger cities there are both higher and lower-paying firms than the highest and lowest-paying firms in the five smallest cities.



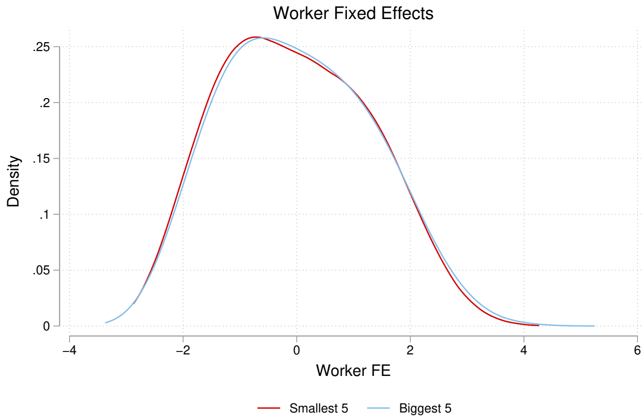
(a) Joint density of the five smallest cities.



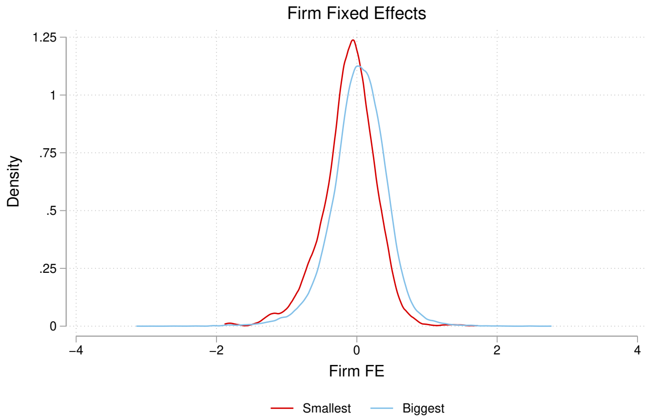
(b) Joint density of the five biggest cities

Figure 10: Joint density calculated from workers at June 2018. Firm and worker decile are based on firm and worker fixed effects estimated from AKM decomposition of log wages. Each bar represents the percentage of workers at a given decile working at a firm from an specified decile.

Figure 12 depicts the density of firms from each percentile of the firm fixed effect distribution for the five smallest and biggest firms. Workers with higher unobserved skills in smaller cities are restrained by a smaller pool of higher-productivity firms, increasing the likelihood that a high-productivity worker ends up working in a low-productivity firm making the degree of assortative matching lower in smaller cities.



(a) Density of worker fixed effects.



(b) Density of firm fixed effects.

Figure 11: Density of worker and firm fixed effects from the five smallest and biggest cities in Chile.

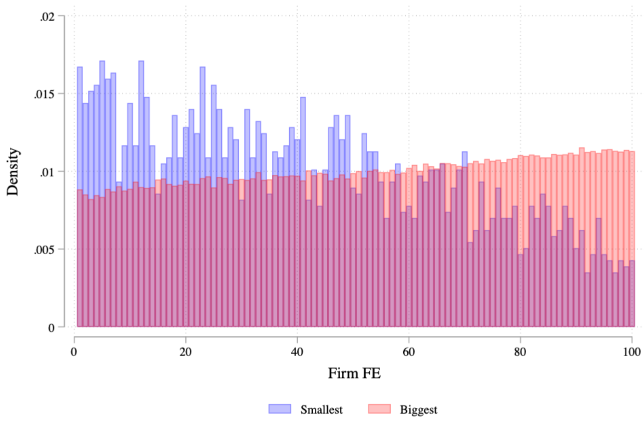


Figure 12: Density of firm fixed effects per percentile by five smallest and biggest cities in Chile.

7 Evaluating the effect of within-city assortative matching on aggregate earnings.

This section explores the potential impact of an increase in the within-assortative matching of cities on aggregate earnings. Aggregate earnings are defined as $\sum_c W_c N_c$, where W_c corresponds to the average monthly wage of each city and N_c the number of workers. Based on equation (12), the average fitted values for log wages at the city-level are specified as:

$$E_c(\hat{w_{it}}) = E_c(\alpha_i) + E_c(\phi_j) + E_c(X'_{it}\beta)$$

One of the limitations of the UI data is the lack of mobility of firms among cities. This is supported by the similarity between the relationship of the average firm fixed effects at the city level and population with respect to city fixed effects. In this section, average firm fixed effects at the city level will be used as a measure of the city's static premium.

Assuming that the city's premia are composed of purely matching, sharing, and learning mechanisms, and congestion forces. The following regression is estimated through OLS:

$$E_c(\phi_j) = log(pop)\gamma + Cov_c(\alpha_i, \phi_j)\beta + \eta_c \tag{18}$$

To measure the effect of an enhancement of within-city assortative matching on aggregate earnings, three scenarios are simulated. First, a scenario where all cities have the strength of assortative matching from the city with the highest within-city assortative matching. Secondly, a scenario where there is no within-city assortative matching, represented by $Cov_c(\alpha_i, \phi_j) = 0$. Lastly, a scenario where all cities have the strength of assortative matching from the city with the lowest degree of within-city assortative matching.

Table 14, shows the results from every simulated scenario. The first row represents the observed monthly average wages using only observations from June 2018[4]. Increasing the degree of within-assortative matching of every city to the level of Calama[5], leads to a 20.6% increase of national average wages and an increase of 944MM USD in aggregate earnings.

When there is no assortative matching within cities, the results a decrease of national average wages of 4.5% and a loss of 219MM USD. Lastly, simulating that all cities have the strength of within-city assortative matching from the city with the smallest degree

[4]Given that workers move through different cities, using the whole sample period means that the $Cov_c(\alpha_i, \phi_j)$ would be calculated using in some cases a same worker for two or more cities. The analysis is restricted for observations from June 2018.

[5]Calama has the highest covariance between worker and firm fixed effects.

would represent a decrease of national average wages of about 12.8% and a loss of 604 MM USD in aggregate earnings.

The benefits from improving the quality of matches within cities makes it relevant for future research to quantify the effects urban infrastructure improvements on matching and its effects on aggregate earnings.

This estimations have to be taken carefully given the limitation of the data. Further research is required to evaluate more precisely the effect of improving the quality of matches in cities on aggregate earnings.

TABLE 14:
Counterfactual results

	Monthly average wage (USD)	%Δ	$\sum_c (\Delta W_c) N_c$ (MM USD)
Observed	742		
Cov_c assumed for all cities			
(1) $max(Cov_c)$	895	20.6	944
(2) $Cov_c(\alpha_i, \phi_j) = 0$	709	-4.5	-219
(3) $min(Cov_c)$	647	-12.8	-604

Notes: Observed monthly average wage corresponds to the weighted average fitted values at the city level derived from the AKM estimation. %Δ represents the deviation of simulated national weighted average of monthly wages respect to observed average wages. (1) Correspond to the scenario where $Cov_c(\alpha_i, \phi_j) = max(Cov_c)$ for all cities. (2) Correspond to the scenario where $Cov_c(\alpha_i, \phi_j) = 0$ for all cities. (3) Correspond to the scenario where $Cov_c(\alpha_i, \phi_j) = min(Cov_c)$ for all cities.

8 Conclusion

Using individual data from the Chilean unemployment insurance scheme it was analyzed wage disparities between different cities. Even when controlling for job and worker characteristics this differences have persisted over the years.

The first results suggests that, as in previous literature in urban economics, workers earn higher nominal wages in bigger cities even after controlling for job and firm observed and unobserved characteristics, which supports the hypothesis of a wage premium where workers and firms have higher productivity due to matching, sharing, and learning mechanisms. In the particular case of Chile, there are some outliers, attributed to a few cities in the north that have a significant amount of mining firms paying higher than expected average wages.

The second set of results measure between and within-city assortative matching in the Chilean labor market. Using the AKM model, firm and worker fixed effects are estimated and only observations pertaining to the largest connected set are used to avoid limited mobility bias influencing the results. First, with the methods used, there is no evidence supporting the sorting of higher unobserved ability workers into bigger cities. However, the city-average as well as the variance of firm fixed effects is higher in bigger cities.

When looking at the different components explaining the wage disparities between different cities, the correlation between the city-level expectation of firm and worker fixed effects explains 43% of the city-average wages, this suggests that the co-location of workers and firms explains a great portion of the city-average wage differences. The second and third most important components are the variance of firm and worker fixed effects explaining 34% and 24% respectively.

Given that higher productivity workers and firms co-locate in bigger cities, it is also relevant to analyze if, within cities, these workers and firms are matched according to their productivity. The results from analyzing within-city assortative matching depict a positive and statistically significant relationship between the degree of assortative matching and city size. When looking at the availability of different types of firms in small and big cities, it is found that smaller cities have lower availability of high-paying firms forcing workers from higher deciles of the worker fixed effect distribution to be matched with low-paying firms.

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