Local Labor Markets and Market Power*

Tristany Armangué-Jubert
UAB and BSE

Sebastian Espinoza-Rojas
UCL

Nicolás Herrera La Rotta
UCSB

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PRELIMINARY - PLEASE DO NOT CIRCULATE

Abstract

Labor markets in large metropolitan areas are segmented. The literature has referred to these micro-markets as "Local Labor Markets" and has typically used location and industry, or occupation, to delineate them. This is problematic for two reasons: 1) delineations rely on arbitrary administrative boundaries for regions, industries, and occupations, and 2) this implicitly assumes that the structure of the larger market does not change. In this paper, we use the metro expansion in Santiago de Chile to show that transport infrastructure can change what constitutes a local labor market and thus have knock-on effects on labor market power and aggregate outcomes. We build a simple theoretical framework that delivers testable predictions to guide our analysis. We find empirical evidence that after a relevant reduction of commuting costs, workers from previously small markets have higher probabilities of changing local labor market and enjoy higher wages. Lastly, we find that in labor markets affected by the reduction of commuting costs, mean markdowns fall around 10 percentage points.

JEL Classification: J61, J64, R23, R38.

*Armangué-Jubert: IDEA, Universitat Autonoma de Barcelona, Cerdanyola del Valles, 08193, Spain, tristany.armangue@barcelonagse.eu, Espinoza-Rojas: Department of Economics, University College London, 30 Gordon St, London, WC1H 0AN, UK sebastian.espinoza@ucl.ac.uk, Herrera: Department of Economics, University of California Santa Barbara, CA 93106, United States jherreralarotta@ucsb.edu. Espinoza-Rojas gratefully acknowledges financial support from the Stone Centre at UCL. All errors are ours.

1 Introduction

In large metropolitan areas, labor markets are segmented. Workers have access to a subset of jobs, which is determined by a myriad of factors including location, skills, industry, or occupation, among others. The literature has referred to these segmented markets as "Local Labor Markets" and has typically used location and industry, or occupation, to delineate them. This is problematic for two reasons: 1) delineations rely on arbitrary administrative boundaries for regions, industries, and occupations, and 2) this implicitly assumes that the structure of the larger market does not change. What constitutes a local labor market has important implications for labor market outcomes in a metropolitan area.

This paper studies how spatial frictions and commuting costs in a large metropolitan area endogenously lead to "local labor markets", challenging the assumption that urban agglomeration inherently reduces employer market power. In particular, we examine how a significant change in the commuting time matrix across locations leads to a change in the delineations of local labor markets. In other words, we ask whether changes in transport infrastructure can change the structure of the labor market in a large metropolis. To that end, we use a significant expansion of the metro system in Santiago de Chile that started in 2006 and continues to this day as a natural experiment. Using administrative panel data covering 20 percent of all workers, we document that workers that lived in locations that received the introduction of a new metro line and worked at smaller and less competitive labor markets became more likely to switch to employers outside of their previous local labor market and were paid higher wages. Similarly, we find the previously small local labor markets that were exposed to new metro lines saw a reduction in average wage markdowns of around 10 percentage points.

We begin by building a simple model of local labor markets to guide our empirical strategy. The model features two segregated labor markets and two corresponding types of workers. Workers face a utility cost of providing labor to the market that is different to their type. One of the markets is perfectly competitive, meaning that firms act as wage takers and workers are paid their marginal product, and the other features a single monopsonist that sets wages strategically interiorizing the labor supply functions of workers of both types and the wage set in the competitive market. The model yields

three theoretical predictions that guide our empirical analysis. First, reducing the cost of providing labor across markets leads to higher wages in the monopsonistic market. Second, reducing the cost of providing labor across markets leads to a lower markdown in the monopsonistic market. Third, reducing the cost of providing labor across markets leads to a higher probability of workers with the monopsonistic market type providing labor in the competitive market.

Using our model predictions as a guide, we use a monthly panel covering 20 percent of the working population in the Greater Santiago de Chile metropolitan area to study the effects of a large expansion of the metro system that has spanned the last two decades. The data provides detailed information about workers' home and work location, as well as firm identifiers. Following Nimczik (2023), we use the network implied by firm-to-firm transitions between the years 2000 and 2005 to identify groups of firms as belonging to different local labor markets. We then use data from 2006 to 2021 to evaluate the effects of the expansion of the metro on different local labor markets, depending on their size.

Our paper is related to three strands of the literature. First, we speak to the literature that studies spatial labor market frictions in urban environments. Moretti (2011) studies the effects of productivity shocks on local labor markets and their propagation to other markets through changes in employment, wages and housing costs. Manning and Petrongolo (2017) build a spatial search model to assess how "local" labor markets in the UK are. In their model, workers are characterized by their location and face a cost of distance when searching for jobs, which makes two otherwise equal jobs at different distances have a different valuation by workers. The main finding is that labor markets in the UK are "relatively local" - the estimated utility of being offered a job decays exponentially at a rate of 0.25 per kilometer - but that local policies do not have large effects due to knock-on equilibrium effects. Similarly, Marinescu and Rathelot (2018) use data from the US and estimate that job-seekers are 35 percent less likely to take a job that is 10 miles away from their place of residence, compared to an equal job in the location where they live. Our paper contributes to this literature by showing how transportation infrastructure can fundamentally alter the nature of local labor markets, challenging the implicit assumption in previous literature that market boundaries are fixed.

Secondly, we build on the literature that studies the interplay between transport infrastructure and labor markets. Gibbons et al. (2019) use firm-level data from the UK with high geographical resolution to study the effects of new road infrastructure on employment and productivity. New roads are found to lead to higher employment in treated areas, an inflow of firms, and higher labor productivity. Heblich et al. (2020) use historical data spanning between 1801 and 1921 to show that the introduction of steam trains fundamentally changed the structure of Greater London, leading to an agglomeration of jobs and longer commutes by distance. An implication of their finding is that a change in the transport infrastructure lead to a dramatic change in labor market structure, as we show for Santiago de Chile. Allen and Arkolakis (2022) build a quantitative general equilibrium spatial model with a detailed transportation network to evaluate the welfare gains from improving different links in the network, and find highly variable returns to improvements in the transport infrastructure. Our findings, which show that gains from reduced transportation utility costs are dependent on the previous labor market structure, speak to their finding of the importance of well-targeted infrastructure investment, albeit for slightly different reasons. To evaluate the effects of the introduction of large Bus Rapid Transit system in Bogotá, Tsivanidis (2022) develops a quantitative urban model with different worker types and transport modes. Welfare gains are found to be somewhat mitigated by equilibrium migration responses. We add to this literature by drawing a direct link between transport infrastructure and labor market competition, and by showing that better public transport reduces monopsony power in previously uncompetitive markets.

Finally, this paper is related to a growing body of work that studies the sources of labor market power. Amodio et al. (2024) employ a framework with non-atomistic firms and informal self-employment, where strategic interaction in wage setting and a large informal self-employment sector lead to wage markdowns, to study labor market power in Peru. In a seminal paper, Berger et al. (2022) build general equilibrium model characterized by oligopsony and firm differentiation. In their model, labor market power arises from upward sloping labor supply curves and strategic interaction in hiring decisions. We contribute to this literature by documenting a direct link between transportation costs, effective concentration of the labor market - through accessibility -, and labor market power.

The rest of the paper is structured as follows. Section 2 discusses the institutional background and the data used in our analysis. Section 3 presents the empirical framework, including the definition and measurement of labor markets, our empirical strategy, and the main results. Section 4 introduces the structural model, which formalizes the mechanisms underlying our empirical findings. Section 5 describes the calibration of the model parameters. Section 6 presents the counterfactual analyses, evaluating the implications of alternative labor market structures. Finally, Section 7 concludes with a discussion of the main findings and their broader implications.

2 Model

To guide our empirical strategy, we build a simple model of local labor markets. Consider a city with a measure 1 of workers and two segmented local labor markets, A and B. Market A is large and competitive, whereas market B is a single firm monopsony. Workers are of one of two types A or B that determine their cost of providing labor to other markets, and decide where to work given their type. For simplicity, we normalize the cost of providing labor to the market equal to the workers' type to 0 and assume that costs are symmetric. Let μ_A and μ_B denote the mass of workers of type A and B, respectively, such that $\mu_A + \mu_B = 1$. In a world with perfect homogeneity of firms and workers, these markets could be interpreted purely as locations, and the worker types as places of residence. To be more general, we refer to local labor markets and types instead. Workers derive utility from their wages and from the costs of providing their labor to their local labor market of choice. Finally, we assume firms are homogenous and operate a production technology with labor as its only input to produce an homogenous good with price normalized to one.

2.1 The Problem of the Workers

Workers decide where to work conditional on their type. The utility for worker i, of type l, that works in market m is given by

$$U_{i(l),m} = w_m - \theta_{lm} - \epsilon_{im},$$

where w_m is the wage in market m, θ_{lm} is the average cost of providing their labor to a firm in market m, given their type l, and ϵ_{im} is the idiosyncratic cost for worker i to provide their labor in market m. In this two-market economy with normalized costs within markets and symmetric costs across:

$$\theta_{mn} = 0 \text{ if } m = n \text{ and } \theta_{mn} = \theta \text{ if } m \neq n.$$

The idiosyncratic cost is assumed to follow a Type-I Extreme Value distribution. Given this assumption, the probability that worker i, of type A, chooses to work in local labor market B is given by the following logit probability (McFadden, 1977):

$$P_{i(A),B} = \text{Prob}\left[\arg\max_{m\in\{A,B\}} \left\{U_{i(A),m}\right\} = B\right] = \frac{\exp\left(w_B - \theta\right)}{\exp\left(w_B - \theta\right) + \exp\left(w_A\right)} \tag{1}$$

It follows from equation 1 that given wages and costs θ, the labor supply to market A is the sum of the mass of workers of each type that choose to work in market A, i.e.

$$L_A^S = \mu_A \left(\frac{\exp\left(w_A\right)}{\exp\left(w_A\right) + \exp\left(w_B - \theta\right)}\right) + \mu_B \left(\frac{\exp\left(w_A - \theta\right)}{\exp\left(w_A - \theta\right) + \exp\left(w_B\right)}\right) \tag{2}$$

and

$$L_B^S = \mu_A \left(\frac{\exp\left(w_B - \theta\right)}{\exp\left(w_A\right) + \exp\left(w_B - \theta\right)}\right) + \mu_B \left(\frac{\exp\left(w_B\right)}{\exp\left(w_A - \theta\right) + \exp\left(w_B\right)}\right) \tag{3}$$

2.2 The Problem of the Firms

Firms in market $m \in \{A, B\}$ produce a homogenous output good that is traded in a perfectly competitive market, using a production function of the form

$$Y = L^\alpha, \quad \alpha \in (0, 1)$$

The marginal product of labor is then given by

$$MPL_m = \frac{\partial Y}{\partial L} = \alpha L^{\alpha-1} \tag{4}$$

2.2.1 Market A: Perfect Competition

Market A is perfectly competitive. The problem of the representative firm in market A is then to choose labor taking the wage as given

$$\max_{L_A} \; L^{\alpha} - w_A L_A$$

The first order condition for profit maximization pins down the equilibrium wage $w_A = MPL_A = \alpha L_A^{\alpha-1}$. Solving for labor demand in market A then yields

$$L_A^D(w_A) = \left(\frac{\alpha}{w_A}\right)^{\frac{1}{1-\alpha}} \tag{5}$$

Finally, since the market is perfectly competitive and wages are equal to labor's marginal product, the markdown in market A is 1:

$$MD_A = \frac{MPL_A}{w_A} = 1$$

2.2.2 Market B: Monopsony

The monopsonist in market B chooses wages to maximize profit interiorizing the labor supply function that it faces.

$$\begin{aligned} &\max_{w_B} \; L_B^{\alpha} - w_B L_B \\ &\text{subject to } L_B = \mu_A \left(\frac{\exp\left(w_B - \theta\right)}{\exp\left(w_A\right) + \exp\left(w_B - \theta\right)}\right) + \mu_B \left(\frac{\exp\left(w_B\right)}{\exp\left(w_A - \theta\right) + \exp\left(w_B\right)}\right) \end{aligned}$$

The first order condition is given by

$$\alpha L_B^{\alpha-1} \frac{\partial L_B}{\partial w_B} - L_B - w_B \frac{\partial L_B}{\partial w_B} = 0 \tag{6}$$

where

$$\frac{\partial L_B}{\partial w_B} = \mu_A \frac{\exp\left(w_B + w_A + \theta\right)}{\left[\exp(w_B) + \exp(w_A + \theta)\right]^2} + \mu_B \frac{\exp(w_B + w_A + \theta)}{\left[\exp(w_B + \theta) + \exp(w_A)\right]^2} \tag{7}$$

2.3 Equilibrium

An equilibrium is a labor supply to each market and a wage in each market such that labor supply equals labor demand in each market and the sum of the labor supply to both markets is equal to the total mass of workers, i.e.

$$\begin{aligned} L_A^S(w_A, w_B, \theta) &= L_A^D(w_A) \\ L_B^S(w_A, w_B, \theta) &= L_B^D(w_A, w_B, \theta) \\ L_A^S + L_B^S &= 1 \end{aligned}$$

Equations 2 and 5 show the equilibrium relationship between wages in the competitive market A and the monopsonistic market B and consitute the first equilibrium condition:

$$\left(\frac{\alpha}{w_A}\right)^{\frac{1}{1-\alpha}} = \mu_A \left(\frac{\exp(w_A)}{\exp(w_A) + \exp(w_B - \theta)}\right) + \mu_B \left(\frac{\exp(w_A - \theta)}{\exp(w_A - \theta) + \exp(w_B)}\right) \quad (8)$$

Equation 6, together with the equilibrium condition that $L_B = 1 - \left(\frac{w_A}{\alpha}\right)^{\frac{1}{\alpha-1}}$, leads to

$$\alpha \left[1 - \left(\frac{w_A}{\alpha}\right)^{\frac{1}{\alpha-1}}\right]^{\alpha-1} \frac{\partial L_B}{\partial w_B} = 1 - \left(\frac{w_A}{\alpha}\right)^{\frac{1}{\alpha-1}} + w_B \frac{\partial L_B}{\partial w_B}$$

which together with equation 7 constitutes the second equilibrium condition. The two equilibrium conditions pin down wages in each market, given a set of parameters. The resulting equilibrium wages, and equations 2 and 3 pin down the equilibrium labor supply to each market.

2.4 Discussion

What are the equilibrium effects of lowering the cost θ of providing labor to the market different to a worker's type? As θ decreases, it becomes less costly for workers to provide labor in the other local labor market. The monopsonist in market B has to adjust wages upwards to compensate workers of type B that might otherwise go to market A. This intuition is formalized by our first proposition.

Proposition 1 *Lower costs of providing labor to markets not equal to a worker's type*

(lower θ) lead to higher wages in market B (w_B).

Proof 1 *See Appendix A1.*

Through the change in wages, the markdown in market B also changes. In particular, with lower cost θ and the associated increase in wages in market B, the markdown in market B falls. This is formalized by our second proposition.

Proposition 2 *Lower costs of providing labor to markets not equal to a worker's type (lower θ) lead to a lower wage markdown in market B.*

Proof 2 *See Appendix A2.*

Finally, through a reduction in the cost of providing labor to the other local labor market also affects the probability that workers of type B work in market A. Despite the fact that wages in market B increase and the markdown in market B decreases, which are second-order effects, lower costs lead to more workers of type B working in market A. This is formalized in our third and last proposition.

Proposition 3 *Lower costs of providing labor to markets not equal to a worker's type (lower θ) lead to a higher probability of working in market A for workers of type B.*

Proof 3 *See Appendix A3.*

The intuition is that despite lower θ also increasing the attractiveness of market B through higher wages, this effect is dominated by the direct effect through lower costs because the monopsonist in market B does not fully compensate for the reduction in cost due to its market power.

This simple model of local labor markets of different nature - more and less competitive - produces three testable predictions that guide our empirical analysis in the sections to follow: lower costs across markets lead to higher wages and lower markdowns in uncompetitive markets, and to higher probability of workers from uncompetitive markets to work in other markets.

3 Institutional Background and Data

3.1 Institutional Setting

Greater Santiago de Chile[1] is home to over 40% of the country's population, or around 8 million people. A significant share of Chile's economic activity is also located in Greater Santiago, yet, as in many other Latin American metropolises, the spatial distribution of labor opportunities and outcomes is highly unequal. High-wage jobs are concentrated in the eastern financial and business districts, whereas low-wage employment is spread across the periphery (Figure 1). Similarly, the price of housing per square meter in the wealthiest municipalities is more than twice that of the poorest. These spatial disparities interact with frictions, such as transportation costs, to determine the effective access of workers to different jobs.

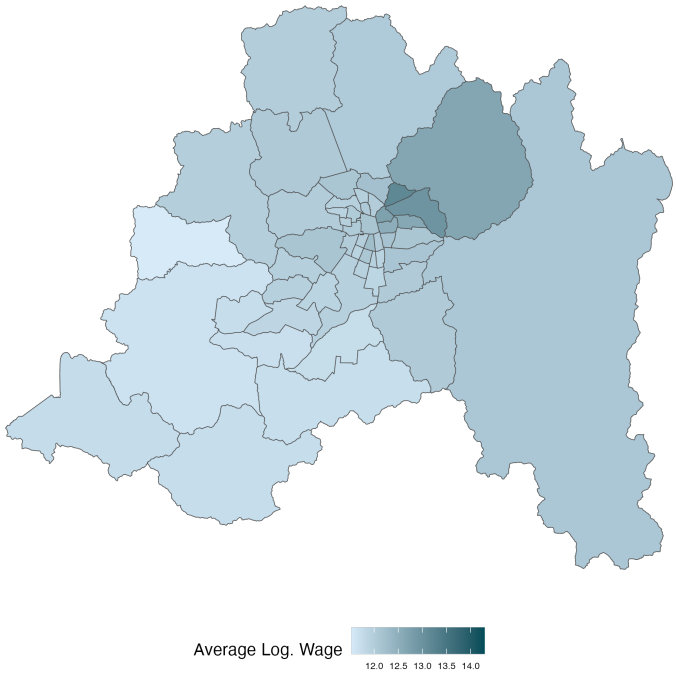
The most significant policy affecting Greater Santiago over the last two decades has arguably been the massive expansion of the Metro de Santiago system, and its integration with the suburban train network. Previously, workers from the periphery that wanted access to business centers in inner Santiago and to the eastern financial and business districts had to rely on the extensive but inefficient bus network, which was majorly constrained by heavy congestion. The major expansion of the metro system between 2005 and 2023 dramatically reduced transit times between previously disconnected areas and the rest of Greater Santiago. Figure 2 graphically shows the evolution of the metro network between 2000 and 2020.

The opening of Line 4 (2005) connected large residential areas in the southeastern periphery (La Florida, Puente Alto), where a significant share of Santiago's lower-income workers live, with job-dense areas in the east (Providencia, Las Condes). Similarly, the extension of Line 5 (2011) improved access for western municipalities such as Maipú and Pudahuel, integrating them more directly with Santiago's central business districts. The second major phase of the expansion began in the 2010s, with the opening of Line 6 (2017), Line 3 (2019), and the modernization and expansion of the Nos-Estación Central suburban rail line (2017–2023). These projects marked a shift in strategy, not just extending existing corridors but improving direct connectivity within the metropolitan region and integrating suburban areas into Santiago's transit system.

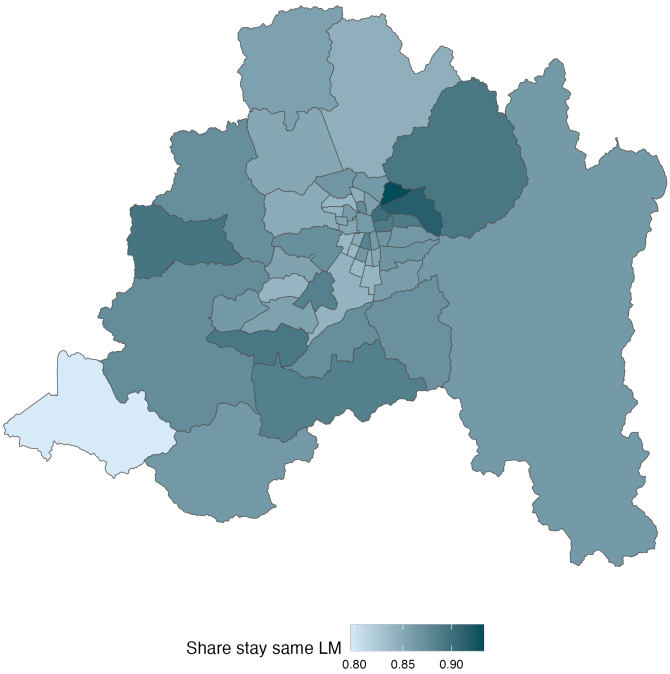
[1] Oficially: Región Metropolitana de Santiago.

Figure 1: Geographical Distribution of Main Outcomes (2003-2005)

(a) Average Logarithm of Wage

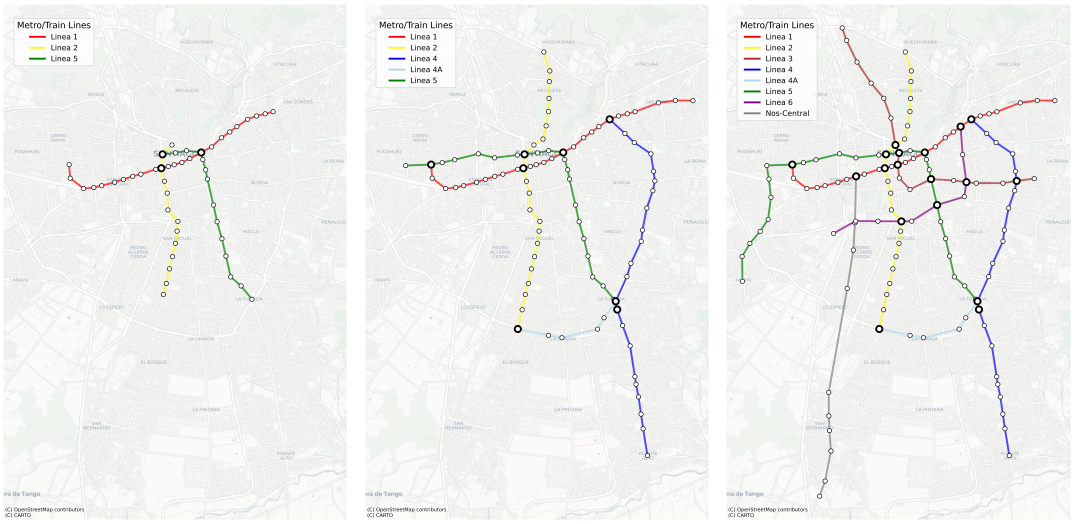


(b) Share of workers staying in the same labor market



NOTES: Figure A shows the average logarithm of wage for resident workers during the period 2003-2005. Figure B shows the share of resident workers who did not transition between labor markets during the period 2003-2005.

Figure 2: Metro Network Expansion



(a) Metro Network in 2000 (b) Metro Network in 2010 (c) Metro Network in 2020

NOTES: This figure shows a map of the metro and suburban rail system in Greater Santiago at three points in time: 2000, 2010, and 2020.

Line 6 connected Cerrillos and Los Leones, significantly reducing travel times for workers commuting from the southwestern periphery to the high-income eastern districts. A one-way journey between the two municipalities before the opening of Line 6 took 47 minutes, the same journey now takes 20 minutes[2]. Line 3 (2019) connected communities in the northwest with the east of Greater Santiago, via the center, integrating previously underserved areas such as Quilicura and Conchali into the metro network. Finally, Tren Nos-Estación Central (2017–2023) transformed suburban rail services, cutting travel times from Nos and San Bernardo, a working-class area with high rates of informality, to Santiago's central business district from over one and a half hours to just 25 minutes.

3.2 Data

Our analysis relies on multiple administrative datasets that provide detailed information on workers, firms, public transit infrastructure, and the housing market in Santiago. These data allow us to examine how labor wages, worker mobility, and labor market power evolved in response to the expansion of the metro and suburban train

[2]See https://www.metro.cl/noticias/detalle/1767

networks.

The primary dataset is a random sample that covers 20 percent of Chile's formal private-sector workers at a monthly frequency. The data are sampled from the administrative records kept by the Unemployment Insurance system. As our focus is on Greater Santiago, we have approximately 85 thousand monthly observations. The sample is drawn to be representative of the population in 2022, and workers' history is followed backwards and forwards from that point in time. Importantly, the data includes both residential and workplace locations, which allows us to map local labor markets and assign treatment depending on the municipality of residence and/or work. Similarly, the data includes both personal and firm identifiers, which allows us to estimate markdowns from separation elasticities as in Bassier et al. (2022).

To measure the impact of the metro expansion, we combine the individual panel data with georeferenced data on metro and train stations that includes their exact location and opening date. This allows us to define treatment areas - places gaining new metro or train lines - and control areas - places with no access yet to metro and train.

3.3 Descriptive Statistics

For the remainder of the paper, we classify local labor markets as either small or large based on deciles of the distribution of the number of firms. Markets in deciles 1 to 8 are small, and markets in deciles 9 to 10 are large.[3]. Workers in treated municipalities, residents in places that gained new metro or train lines, are comparable to those in control municipalities, residents in places that have not yet gained access to the network. Before the construction of the metro lines, the average log wage of workers in treated municipalities is slightly higher than in control municipalities (12.10 vs. 11.96, as shown in Table 1. The share of workers who remain in the same local labor market is similar across both groups (86% for both types).

[3]Alternative delineations of the groups, or using geographical span rather than number of firms, do not alter the results meaningfully.

Table 1: Summary Statistics by Municipality Type and Market Size

		Control Municipalities				Treatment Municipalities			
Market Size	Variable	Mean	Std. Dev.	Min	Max	Mean	Std. Dev.	Min	Max
Small	Log. Wage	11.90	0.85	7.26	15.19	12.11	0.83	7.26	14.49
	Work Same LLM	0.86	0.35	0.00	1.00	0.85	0.36	0.00	1.00
	Share College	0.14	0.34	0.00	1.00	0.08	0.27	0.00	1.00
	Share Small Firm	0.33	0.47	0.00	1.00	0.31	0.46	0.00	1.00
	Age	33.48	11.22	9.00	92.00	33.64	10.96	13.00	87.00
	Share Long-Term Contract	0.29	0.45	0.00	1.00	0.39	0.49	0.00	1.00
	Woman	0.35	0.48	0.00	1.00	0.36	0.48	0.00	1.00
	Log. Firm Income	12.10	0.65	6.83	14.79	12.31	0.58	6.93	14.30
Large	Log. Wage	12.07	0.73	7.26	14.48	12.10	0.72	7.26	15.28
	Work Same LLM	0.86	0.34	0.00	1.00	0.87	0.34	0.00	1.00
	Share College	0.10	0.30	0.00	1.00	0.08	0.27	0.00	1.00
	Share Small Firm	0.58	0.49	0.00	1.00	0.57	0.49	0.00	1.00
	Age	33.47	10.64	15.00	77.00	33.98	10.82	13.00	84.00
	Share Long-Term Contract	0.49	0.50	0.00	1.00	0.52	0.50	0.00	1.00
	Woman	0.29	0.45	0.00	1.00	0.32	0.47	0.00	1.00
	Log. Firm Income	12.23	0.59	8.35	14.56	12.27	0.58	6.93	14.57
All Markets	Log. Wage	11.96	0.81	7.26	15.19	12.10	0.78	7.26	15.28
	Work Same LLM	0.86	0.35	0.00	1.00	0.86	0.35	0.00	1.00
	Share College	0.12	0.33	0.00	1.00	0.08	0.27	0.00	1.00
	Share Small Firm	0.41	0.49	0.00	1.00	0.42	0.49	0.00	1.00
	Age	33.48	11.03	9.00	92.00	33.79	10.90	13.00	87.00
	Share Long-Term Contract	0.36	0.48	0.00	1.00	0.45	0.50	0.00	1.00
	Woman	0.33	0.47	0.00	1.00	0.34	0.47	0.00	1.00
	Log. Firm Income	12.15	0.64	6.83	14.79	12.29	0.58	6.93	14.57

NOTES: Own calculations using administrative data from the period 2003-2005. Treatment municipalities had metro lines constructed during 2006-2019, while control municipalities did not. Small firms refer to firms of less than 50 employees.

When comparing across labor market sizes, workers who reside in treated municipalities working in small markets exhibit lower average wages compared to their counterpart in control municipalities. While the same is true for large market workers, the gap is smaller for this group than the former. On the other hand, across market sizes and treatment status, there do not appear to be substantial pre-treatment differences in the likelihood of workers remaining employed within the same market.

4 Empirical Analysis

4.1 Defining Local Labor Markets

Previous work on labor market outcomes has often performed analyses at the local labor market level. Since not all workers have access to all jobs in an economy, and not all jobs have access to all workers, it is reasonable to expect labor markets to be segmented into smaller sub-markets. Until recently, researchers have typically used combinations of geography and industry or occupation to delineate these markets. The idea being that a sushi chef that lives in downtown Washington DC is likely to almost only have access to jobs in sushi restaurants in the DC area. This approach, however convenient, has two shortcomings: 1) delineations rely on arbitrary administrative boundaries for regions, industries, and occupations, and 2) this delineations hardly ever change, which implies that the local labor markets defined by them also hardly ever change. The second problem is especially problematic in our case, as we want to study whether transportation infrastructure can effectively blur the the boundaries between previously segregated local labor markets.

More recently, the network of firms implied by job-to-job transitions has been used to infer the structure of the larger market and to group firms into local labor markets (Nimczik, 2023; Jarosch et al., 2024). Using data up to 2005, we construct a weighted directed graph G, where nodes are firms and, edges are job-to-job transitions, and edge weights are the number of transitions. Following Nimczik (2023), we estimate a Stochastic Block Model with k latent local labor markets. Given the graph G and a vector $\vec{z}$ of assignments of firms to communities, the log-likelihood to be maximized

can be shown[4] to be

$$\mathcal{L}(G \mid z) = \sum_{u,v} E_{uv} \ln \frac{E_{uv}}{\delta_u^+ \delta_v^-}$$

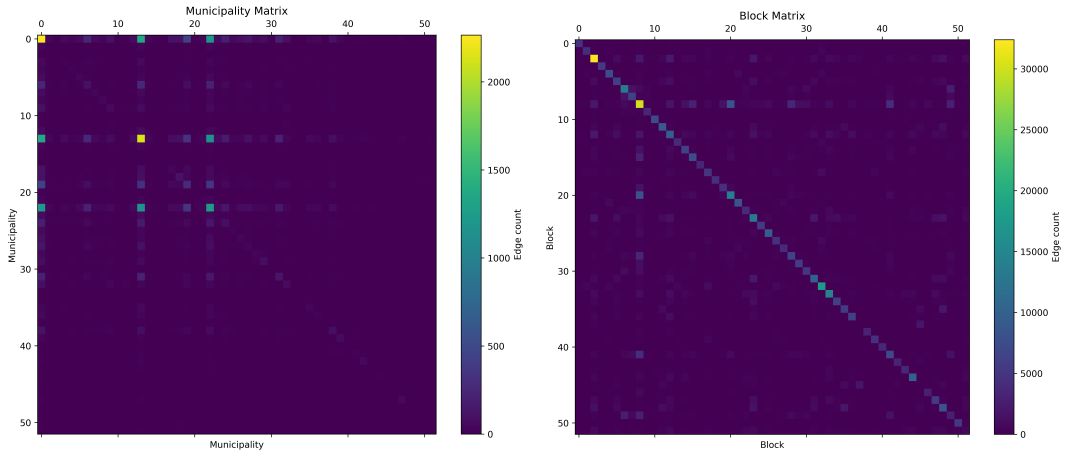
where E_{uv} is the total number of links between communities u and v, and δ_u^+ and δ_v^- are the sum of all in-degrees in community u and the sum of all out-degrees in community v, respectively, and which depends only on the transition counts induced by the partition z. As in Nimczik (2023), we estimate this via approximate maximum likelihood using a greedy algorithm (Peixoto, 2014). A comparative strength of the Stochastic Block Model estimation to infer structure, as opposed to other methods such as the Louvain algorithm (Blondel et al., 2008) or the Newman-Girman algorithm (Girvan and Newman, 2002), is that it can be easily micro-founded[5]. We set the number of latent local labor markets to 104, to reflect a high-skill and a low-skill market per municipality. Jarosch et al. (2024) instead nest the estimation of the SBM inside a modularity maximization algorithm to internally pick the number of latent markets that maximizes the graph modularity. Our results are robust to different choices for k.

Figure 3 compares the modularity of the partition estimated via SBM to that of the partition implied simply by geographical boundaries. As is clear from the two panels, the SBM partition captures the segmentation of the labor market in a much better way than the arbitrary administrative boundaries parition does. The estimated partition is our structure of the labor market in Santiago at the start of our analysis. That is, the markets are constructed with data going up to 2005, and the analysis begins in 2005. As such, we use the structure of the labor market *before* the changes in transport links to see whether there was any significant change attributable to the expansion of the metro.

An advantage of data-driven labor markets is that, while they capture the strong geographic component of traditional local labor markets, they do so without imposing predefined geographical or administrative boundaries. This flexibility allows labor markets to emerge naturally from the data rather than being constrained by ex-ante definitions. Figure 4 illustrates the spatial distribution of selected labor markets, demonstrating their strong geographic component. While *Labor Market 30* and *Labor Market 69* are

[4]See section 3 in Nimczik (2023) for a detailed explanation.
[5]See Appendix B in Nimczik (2023) for a detailed exposition of the micro-foundations.

Figure 3: Adjacency Matrix: Municipalities vs Estimated Communities



NOTES: The left panel shows the adjacency matrix of the job-to-job transitions of college educated workers implied by a partition of firms using administrative boundaries for municipalities. The right panel shows the adjacency matrix of the job-to-job transition of college educated workers implied by the partition of firms estimated via the SBM. For comparison purposes we use *k=municipalities*.

primarily concentrated in the western part of the city, *Labor Market 88* is more widely dispersed across the city. We show in the online appendix a map of every labor market using $k = 104$.

4.2 Wage Markdowns by Market

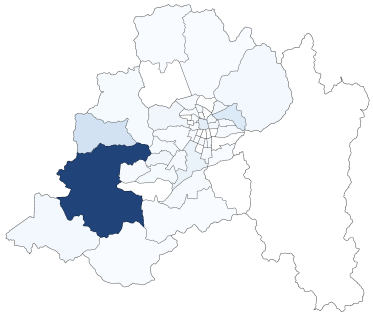
Following the approach developed by Bassier et al. (2022), we estimate markdowns at the local labor market level by estimating separation elasticities. In models of dynamic monopsony, the steady-state elasticity of the labor supply facing a firm can be expressed as two times the separation elasticity (Manning, 2003). Recovering the firm level supply elasticity allow us to estimate the markdown at the local labor market.

Using 3-year rolling time windows, we begin by isolating the firm component of workers wages through a two-way fixed effects model à la Abowd et al. (1999) (hereafter AKM) and Card et al. (2013).

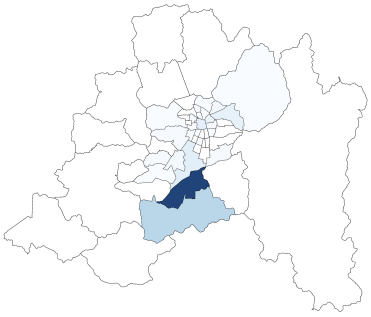
$$w_{ijt} = \theta_j + \theta_i + \tau_t \epsilon_{ijt} \tag{9}$$

Where w_{ijt} is the wage of the worker that works in firm j at time t, and θ_j, θ_i and θ_t are

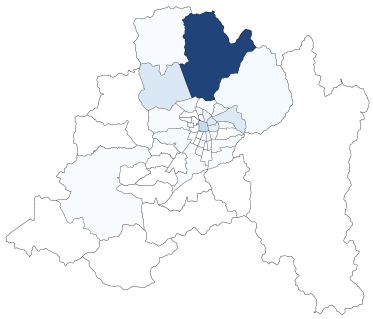
Figure 4: Geography of Labor Markets, before Metro Expansion



(a) Labor Market 30



(b) Labor Market 47



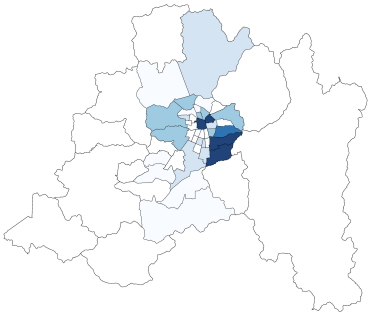
(c) Labor Market 55



(d) Labor Market 69



(e) Labor Market 78



(f) Labor Market 88

NOTES: This figure presents the spatial distribution of a series of Labor Markets maps in the municipalities of Santiago. Municipalities are colored according to the share of firms within each market that are located in the respective municipality. Darker shades indicate higher shares.

the firm, individual and time fixed effect. Then, in equation 9, θ_j represents the firm component of wages clean of workers characteristics, or what is called the firm-wage policy.

We then regress separations on these estimated firm-wage policies separately for each local labor market to obtain a separation elasticity for each market. The result is a yearly estimate of separation elasticities for every local labor market. We then obtain estimates of the labor supply elasticity ϵ^L, which in models of dynamic monopsony is equal to $\epsilon^L = -2 \times s$, where s is the separation elasticity. Then, we back out the wage markdown in equilibrium using equation 10.

$$md = \frac{1}{1 + \epsilon^L} \tag{10}$$

Appendix B1 covers this procedure in detail. Figure 11 in Appendix C2, shows the average markdown estimated across local labor markets per year, which is around 32 percent in the year 2002 and declines steadily to approximately 25 percent in 2019.

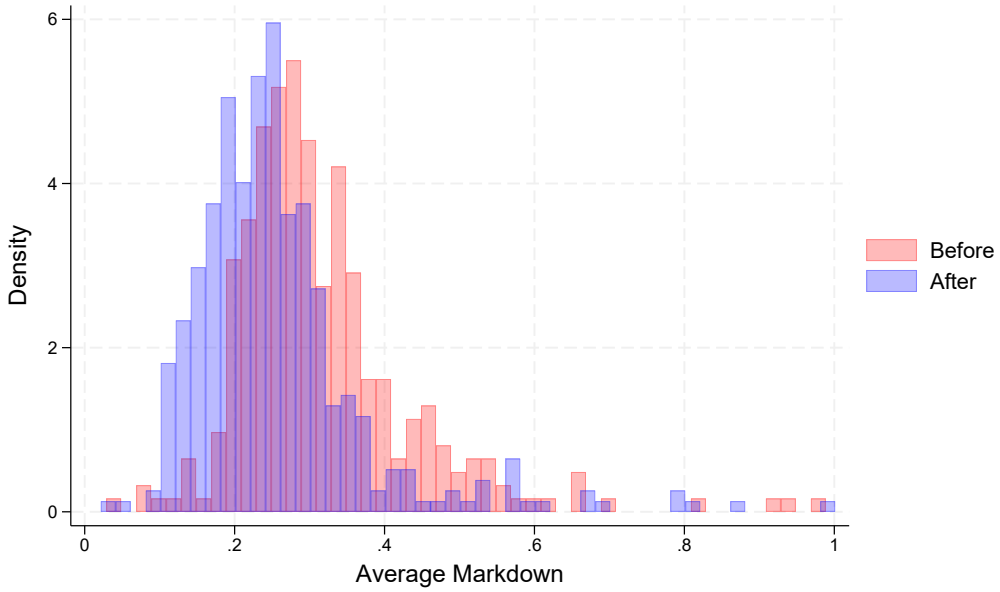
Figure 5 shows the distribution of labor market markdowns before and after the metro expansion. The markdown distribution after the expansion is clearly shifted to the left compared to the distribution before the expansion

4.3 Identification Strategy

Our empirical approach exploits the massive expansion of the Santiago Metro system during the 2000s and 2010s to identify the effects of a reduction in commuting costs on labor market structure. The methodology follows a staggered difference-in-differences (DiD) framework, using quasi-experimental variation from the phased introduction of metro lines and stations to estimate causal effects. Ideally, we would compare workers randomly assigned to metro accessibility with those without access. However, since metro construction follows urban planning decisions rather than random allocation, we implement a staggered DiD approach, treating municipalities that receive metro access later as a valid control group.

The first metro line opened in 1975, and the system has expanded over time, with the latest line constructed in 2023. We focus on the period 2006-2019 for two reasons: First,

Figure 5: Markdown Distribution



NOTES: This figure presents the distribution of labor market markdowns before and after the metro expansion, considering $k = 104$ labor markets. *Before* refers to earlier than 2006, while *After* includes 2016 and later.

we construct local labor market definitions using data from 2003-2005 which we fix over the entire period of study. Second, starting in 2020, with the onset of COVID-19, the dynamics of the labor markets changed significantly due to the widespread adoption of remote work. As explained in detail in Section 3.1, the staggered expansion of the metro system connected large residential areas to job-dense zones. The average commuting time in municipalities that gained access to a metro line decreased as a result of its construction. Figure 10, in Appendix C1, shows a timeline of treatment adoption at the municipality level. Eighteen out of the 52 municipalities in the metropolitan region had a metro line at the start of the study period. Our variation comes from the opening of new lines in nine municipalities at different points in time. By the end of our period of study, there are 25 municipalities that serve as pure control units.

We define our treatment variable T_m, which takes a value of one if a worker i resides in a municipality m with access to a metro station and zero otherwise. To formally test for differential pre-treatment trends and estimate the dynamic effects of metro expansion, we use an event study specification:

$$y_{imt} = \alpha + \sum_{j=-10}^{-2} \beta_j T_m \mathbf{1}[t = j] + \sum_{k=0}^{10} \beta_k T_m \mathbf{1}[t = k] + \phi_t + \phi_i + \gamma X_{ijt} + \varepsilon_{imt} \quad (11)$$

where y_{imt} represents the outcome of interest. We consider the following two outcomes: log-wages and an indicator that equals 0 if worker i, resident in m, makes a job-to-job transition to a firm in a labor market different than the previous one at time t, and 1 otherwise. The variable T_m is a dummy variable indicating whether municipality m has access to a newly constructed metro line. The coefficients β_k capture the post-treatment effects, while β_j estimate potential pre-treatment trends to test for parallel trends. The terms ϕ_t and ϕ_i represent time and individual fixed effects, respectively. Additionally, X_{ijt} is a vector of worker- and firm-level time-varying controls.

One of our key outcomes of interest is whether a worker transitions to a different labor market following metro expansion. We define a transition between labor markets as a move from a firm in one local labor market to a firm in another, using the estimated partition of firms into markets using data up to 2005. This approach ensures that we capture changes in job accessibility rather than simple firm turnover. That is, job-to-job transitions within a labor market are not considered.

The literature has recently discussed that unrestricted treatment effect heterogeneity can bias traditional staggered event-study designs when estimating equations such as equation 11 using the traditional two-way fixed effects models (Borusyak et al. (2021), Roth et al. (2022) and Sun and Abraham (2021)). Our main results, present estimates using both the standard dynamic event study method and the imputation method by Borusyak et al. (2021). While the second method is robust to dynamic treatment effect heterogeneity, we remove always treated municipalities avoiding the *forbidden comparison* as discussed by the authors of the imputation method. The results using both methods are similar. The main assumptions of our empirical strategy are:

- **Conditional Parallel Trends**: In the absence of metro construction, the wages and labor mobility of workers living in treated areas would have evolved in parallel to those of areas that did not have metro lines constructed at the same point in time, conditional on the size of their local labor market.

- **No Anticipation**: Workers in treated areas do not change their behavior in terms of labor market outcomes in anticipation of metro construction.

While we rule out anticipation effects, as workers cannot benefit from using the metro until it is completed, we test for pre-treatment trends by estimating the coefficients β_j from equation 11. Following the theoretical predictions of our model, we separate our results by market size. By implementing these empirical strategies, we aim to provide credible estimates of the impact of improved transit infrastructure on labor market mobility and wage determination.

4.4 Empirical Results

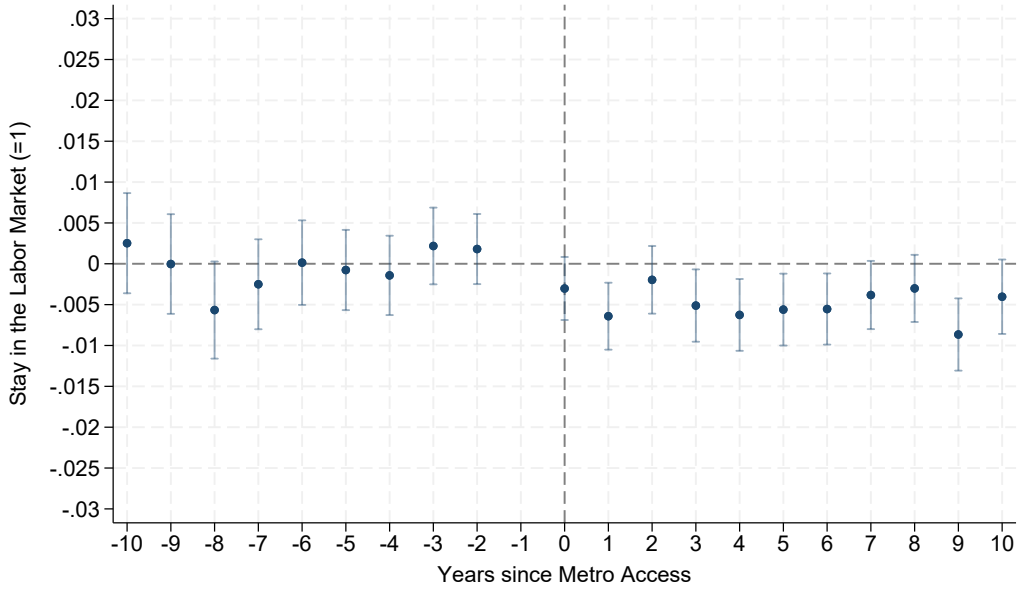
Figure 6 presents the estimated coefficients from equation 11 on mobility out of small markets. We find that the introduction of new metro lines significantly reduces the probability of workers remaining employed within the same labor market, and that this change is persistent over time. This finding is consistent with the predictions from the theory: reduced costs of providing labor to other labor markets leads to a higher probability of moving across markets.

Figure 7 illustrates the results for large labor markets. In contrast to the previous cases, the estimated effect of Metro access on staying working in the same municipality falls initially, but then goes back to the previous level. This suggests that in large labor markets, where job density and competition are high before the introduction of the metro, there are smaller gains to be made from increased accessibility. This result is consistent with theoretical and empirical work on spatial economics (Redding, 2024).

In addition to the effects on cross-market job-to-job flows, we examine the impact of metro expansion on wages across different labor market sizes. The event study design presented in Figures 8 and 9 estimates the effects of treatment on log-wages in small and large labor markets, respectively.

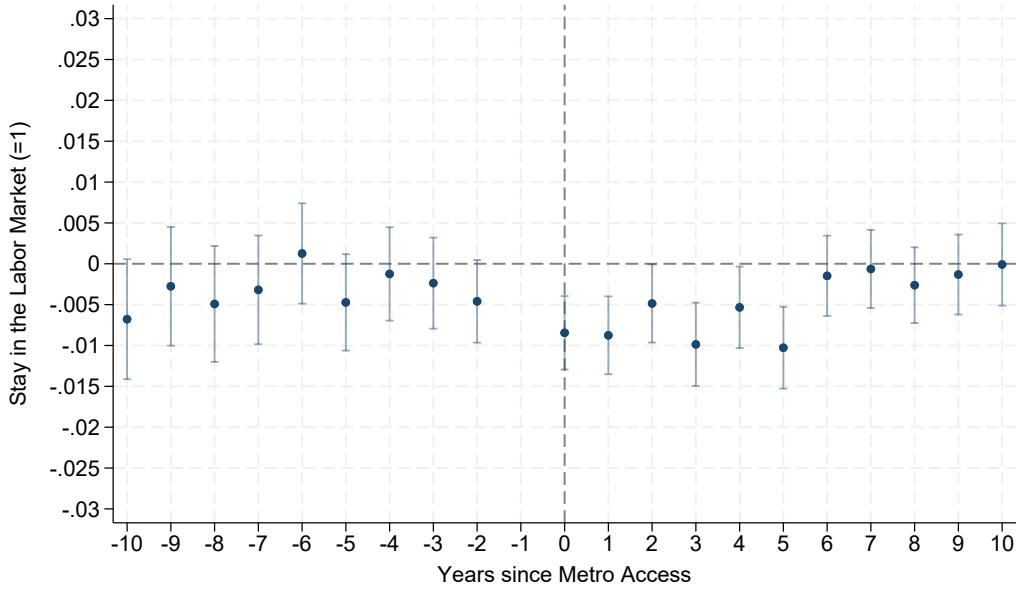
Figure 8 shows that in small markets, the introduction of new metro lines leads to higher wages. In years following the introduction of new infrastructure, small labor markets see wage increases of up to 10 percent. This result is consistent with the first prediction of our model, which is that in small, relatively less competitive markets, the reduction of cross-market transition costs leads to a reduction in labor market

Figure 6: Employment and Metro Network Expansion - Small Labor Markets



NOTES: This figure presents the estimated dynamic effects of the metro network expansion on the probability of staying in the same labor market in the case of small labor markets. The horizontal axis represents the years relative to metro access, while the vertical axis indicates the probability of staying in the labor market. The estimates are based on the event study specification from equation 11.

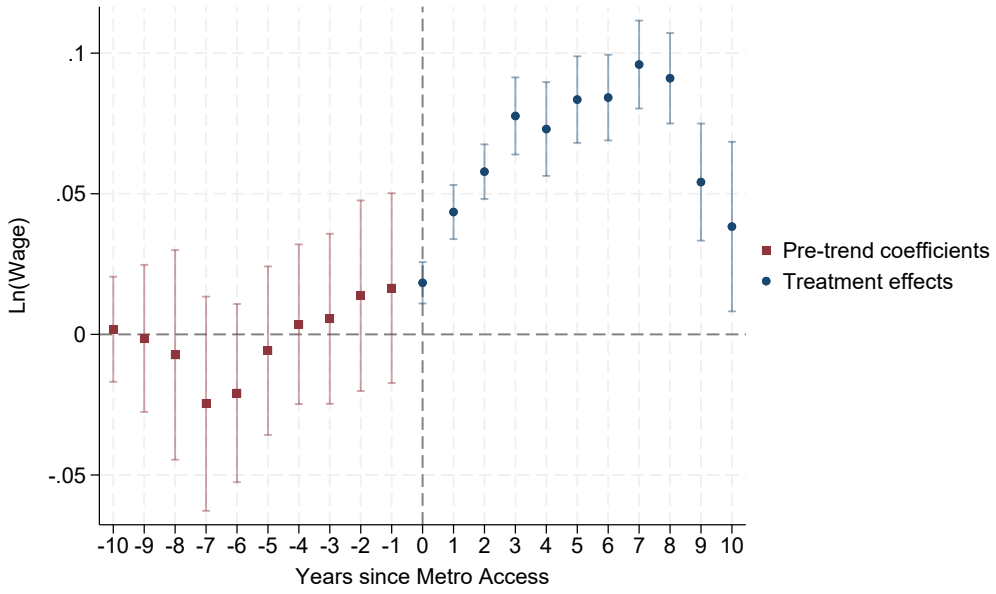
Figure 7: Employment and Metro Network Expansion - Large Labor Markets



NOTES: This figure presents the estimated dynamic effects of the metro network expansion on the probability of staying in the same labor market in the case of large labor markets. The horizontal axis represents the years relative to metro access, while the vertical axis indicates the probability of staying in the labor market. The estimates are based on the event study specification from equation 11.

power and an increase in wages. The magnitude of the wage response aligns well with findings from other studies on labor market integration (Manning and Petrongolo, 2017; Tsivanidis, 2022).

Figure 8: Wages and Metro Introduction - Small Labor Markets

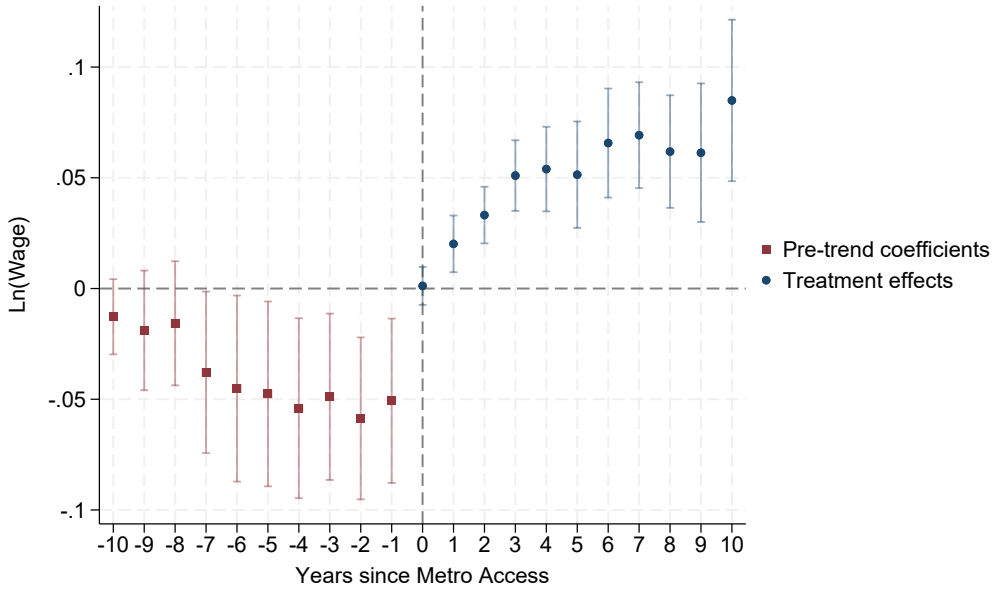


NOTES: This figure presents the estimated dynamic effects of the metro network expansion on the log wage of the workers from small labor markets. The horizontal axis represents the years relative to metro access, while the vertical axis indicates the log of the wage. The estimates are based on the event study specification from equation 11.

Figure 9 shows the estimated effects on wages in large labor markets. It is clear that parallel trends in wages do not hold for large markets in this setting. While wages seem to increase after the introduction of metro, the violation of the parallel trends assumption makes inference difficult in this case. This heterogeneity in wage responses across market sizes highlights the complementarity of spatial frictions and labor market competition. In smaller, relatively uncompetitive markets, the introduction of new metro lines increases competition for workers from firms in other markets, leading to upward wage adjustments. In contrast, in larger labor markets, where firms already face strong competitive pressures, the additional reduction in commuting costs does not have a clear effect on wage-setting dynamics.

Together, our results suggest that increased geographical access through public transport infrastructure generate positive effects especially on previously segregated and

Figure 9: Wages and Metro Introduction - Large Labor Markets



NOTES: This figure presents the estimated v effects of the metro network expansion on the log wage of the workers from large labor markets. The horizontal axis represents the years relative to metro access, while the vertical axis indicates the log of the wage. The estimates are based on the event study specification from equation 11.

small markets. Wages increase significantly and so does mobility to other markets. The latter finding contributes to the broader literature on labor market segmentation. Previous work has discussed the shortcomings of using administrative boundaries as delineations of labor markets, which often overstate labor market integration (Manning and Petrongolo, 2017). We point at something deeper: changes in transportation infrastructure that significantly alter the cost of providing labor across labor markets can change the structure of the market itself. This is reflected by the change in the rate of job-to-job transitions across previous labor market delineations.

Our theoretical model predicts that a reduction in cross-market transition costs leads to increased competition for workers in small labor markets, which leads to higher wages and lower wage markdowns. We have already documented that the metro expansion had this positive effect on wages in small markets. Now we turn to markdowns.

Armed with our yearly estimates of markdowns at the local labor market level μ_{zt} (for market z and year t), and assigning treatment to markets based on the most common municipality of the firms in said market, we implement a static staggered difference-in-differences (DiD) strategy at the labor market level. We shift from a fully dynamic specification to a static model, as our unit of analysis is labor markets rather than individuals, and the limited number of observations restricts our ability to estimate period-specific coefficients. While this choice improves statistical power, it also limits our ability to capture post-treatment dynamics.

Following Equation (11), we define $T_z\mathbf{1}[k \geq 0]$ as an indicator variable that takes the value of 1 if the metro network was introduced in labor market z at time t, and 0 otherwise. k is equal to the difference between the year of the Metro access and the actual time t. To focus on the effects of small (or local) Labor Markets we introduce S_z, a dummy variable that takes the value of 1 if the labor market was classified as small in the reference period (2005 or earlier). A Labor Market is thus considered treated if it received metro network expansion and was initially small, as our theory predicts a reduction in markdowns for small markets. The following equation is estimated:

$$\mu_{zt} = \alpha + \beta \times T_z\mathbf{1}[k \geq 0] \times S_z + \phi_t + \phi_z + T_z\mathbf{1}[k \geq 0] + \varepsilon_{zt} \tag{12}$$

where β captures the effect of metro network expansion on markdowns in labor markets that were initially small. We include time fixed effects ϕ_t to control for macroeconomic trends, and labor market fixed effects ϕ_z to account for unobserved, time-invariant labor market characteristics.

Table 2 presents the results from estimating Equation (12). We find that markdowns on small markets decrease significantly following a metro network expansion, with an estimated reduction of 10.8 percentage points. Conversely, markdowns in large markets do not show a statistically significant change. This result is consistent with the theoretical prediction of our model.

Table 2: Regression results for markdowns

	(1)
	Labor Market Markdown
After Metro [=1] x Small Labor Market [=1]	-0.108**
	(0.0426)
After Metro [=1] x Large Labor Market [=1]	-0.0274
	(0.0404)
Labor Market FE	Yes
Time FE	Yes
N	208

Note: Standard errors in parentheses. $*p < 0.1$, $**p < 0.05$, $***p < 0.01$. The table reports the results for β from equation 12. The specification includes both fixed effect by Labor Market and Time.

5 Conclusions and Discussion

We build a simple theoretical model of segmented labor markets that generates three testable predictions about the consequences of a reduction in cross-market transition costs. The predictions state that wages increase, wage markdowns decrease, and the probability of taking a job in a different market increases, for workers previously in small and uncompetitive markets. We then use the massive expansion of the metro system in Greater Santiago to test these predictions and find that the introduction of new metro lines increased wages by up to 10 percent in small markets, decreased wage markdowns by up to 10 percentage points in small markets, and decreased the probability of staying in the current labor market by up to 1 percent.

Our findings challenge the implicit assumption that local labor markets are fixed and independent of policy, often made by previous studies. Moreover, they provide a clear link between transportation friction and labor market power: fragmented labor markets due to barriers to mobility are an endogenous source of labor market power.

Our conclusions have important policy implications for urban planning. Well-targeted investments in public transportation infrastructure can serve as a tool to enhance labor market competition, reduce monopsony power, and increase wages.

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Appendix

A: Model Appendix

TO BE COMPLETED.

A1: Proof of Proposition 1

We have the equilibrium conditions:

$$\left(\frac{\alpha}{w_A}\right)^{\frac{1}{1-\alpha}} = \mu_A \frac{\exp(w_A)}{\exp(w_A) + \exp(w_B - \theta)} + \mu_B \frac{\exp(w_A - \theta)}{\exp(w_A - \theta) + \exp(w_B)} \tag{13}$$

and

$$\alpha \left[1 - \left(\frac{w_A}{\alpha}\right)^{\frac{1}{\alpha-1}}\right]^{\alpha-1} \frac{\partial L_B}{\partial w_B} = 1 - \left(\frac{w_A}{\alpha}\right)^{\frac{1}{\alpha-1}} + w_B \frac{\partial L_B}{\partial w_B}, \tag{14}$$

where

$$\frac{\partial L_B}{\partial w_B} = \mu_A \frac{\exp(w_B + w_A + \theta)}{[\exp(w_B) + \exp(w_A + \theta)]^2} + \mu_B \frac{\exp(w_B + w_A + \theta)}{[\exp(w_B + \theta) + \exp(w_A)]^2}. \tag{15}$$

We define

$$F(w_A, w_B, \theta) = 0, \quad G(w_A, w_B, \theta) = 0. \tag{16}$$

Differentiating implicitly,

$$\frac{dF}{d\theta} = \frac{\partial F}{\partial w_A}\frac{dw_A}{d\theta} + \frac{\partial F}{\partial w_B}\frac{dw_B}{d\theta} + \frac{\partial F}{\partial \theta} = 0, \tag{17}$$

$$\frac{dG}{d\theta} = \frac{\partial G}{\partial w_A}\frac{dw_A}{d\theta} + \frac{\partial G}{\partial w_B}\frac{dw_B}{d\theta} + \frac{\partial G}{\partial \theta} = 0. \tag{18}$$

Rearranging,

$$\begin{bmatrix} \frac{\partial F}{\partial w_A} & \frac{\partial F}{\partial w_B} \\ \frac{\partial G}{\partial w_A} & \frac{\partial G}{\partial w_B} \end{bmatrix} \begin{bmatrix} \frac{dw_A}{d\theta} \\ \frac{dw_B}{d\theta} \end{bmatrix} = - \begin{bmatrix} \frac{\partial F}{\partial \theta} \\ \frac{\partial G}{\partial \theta} \end{bmatrix}. \tag{19}$$

Solving for $\frac{dw_B}{d\theta}$ using Cramer's rule,

$$\frac{\partial w_B}{\partial \theta} = -\frac{\begin{vmatrix} -\frac{\partial F}{\partial \theta} & \frac{\partial F}{\partial w_B} \\ -\frac{\partial G}{\partial \theta} & \frac{\partial G}{\partial w_B} \end{vmatrix}}{\begin{vmatrix} \frac{\partial F}{\partial w_A} & \frac{\partial F}{\partial w_B} \\ \frac{\partial G}{\partial w_A} & \frac{\partial G}{\partial w_B} \end{vmatrix}}. \tag{20}$$

To ensure $\frac{\partial w_B}{\partial \theta} > 0$, we verify the sign of the determinants explicitly:

For the denominator,

$$\begin{vmatrix} \frac{\partial F}{\partial w_A} & \frac{\partial F}{\partial w_B} \\ \frac{\partial G}{\partial w_A} & \frac{\partial G}{\partial w_B} \end{vmatrix} = \left(\frac{\partial F}{\partial w_A} \frac{\partial G}{\partial w_B} - \frac{\partial F}{\partial w_B} \frac{\partial G}{\partial w_A} \right) > 0, \tag{21}$$

For the numerator,

$$\begin{vmatrix} -\frac{\partial F}{\partial \theta} & \frac{\partial F}{\partial w_B} \\ -\frac{\partial G}{\partial \theta} & \frac{\partial G}{\partial w_B} \end{vmatrix} = \left(-\frac{\partial F}{\partial \theta} \frac{\partial G}{\partial w_B} + \frac{\partial G}{\partial \theta} \frac{\partial F}{\partial w_B} \right) < 0, \tag{22}$$

Thus, we conclude:

$$\frac{\partial w_B}{\partial \theta} > 0. \quad \text{Q.E.D.} \tag{23}$$

A1: Proof of Proposition 2

The markdown in market B is defined as:

$$MD_B = \frac{MPL_B}{w_B} = \frac{\alpha L_B^{\alpha-1}}{w_B}$$

Taking the derivative with respect to θ:

$$\frac{\partial MD_B}{\partial \theta} = \frac{\alpha(\alpha-1) L_B^{\alpha-2} \frac{\partial L_B}{\partial \theta} w_B - \alpha L_B^{\alpha-1} \frac{\partial w_B}{\partial \theta}}{w_B^2}$$

From equilibrium condition that $L_B = 1 - (\frac{w_A}{\alpha})^{\frac{1}{\alpha-1}}$, we have:

$$\frac{\partial L_B}{\partial \theta} = -\frac{1}{\alpha - 1}(\frac{w_A}{\alpha})^{\frac{2-\alpha}{\alpha-1}}\frac{\partial w_A}{\partial \theta}$$

From Proposition 1, we know that $\frac{\partial w_B}{\partial \theta} > 0$. Furthermore, since market A clears competitively, $\frac{\partial w_A}{\partial \theta}$ is positive but small as it only adjusts through equilibrium effects. Substituting these into the markdown derivative:

$$\frac{\partial MD_B}{\partial \theta} = \frac{\alpha}{w_B^2}\left[(\alpha - 1)L_B^{\alpha-2}\left(-\frac{1}{\alpha - 1}(\frac{w_A}{\alpha})^{\frac{2-\alpha}{\alpha-1}}\frac{\partial w_A}{\partial \theta}\right)w_B - L_B^{\alpha-1}\frac{\partial w_B}{\partial \theta}\right]$$

The first term in brackets is positive but small (as $\frac{\partial w_A}{\partial \theta}$ is small), while the second term is negative and larger in magnitude (as $\frac{\partial w_B}{\partial \theta}$ is larger from Proposition 1). Therefore:

$$\frac{\partial MD_B}{\partial \theta} > 0$$

Thus, as θ decreases, the markdown decreases, which completes the proof. Q.E.D.

A3: Proof of Proposition 3

The probability of working in A for workers of type B is

$$P_{i(B),A} = \frac{\exp(w_A - \theta)}{\exp(w_A - \theta) + \exp(w_B)}$$

Taking the derivative with respect to θ:

$$\frac{\partial P_{i(B),A}}{\partial \theta} = \frac{-\exp(w_A - \theta)\exp(w_B)\left(1 + \frac{\partial w_B}{\partial \theta}\right)}{[\exp(w_A - \theta) + \exp(w_B)]^2}$$

From Proposition 1, we know that $\frac{\partial w_B}{\partial \theta} > 0$. Therefore, the numerator is negative and: $\frac{\partial P_{i(B),A}}{\partial \theta} < 0$ Thus, as θ decreases, the probability of workers of type B choosing market A increases.

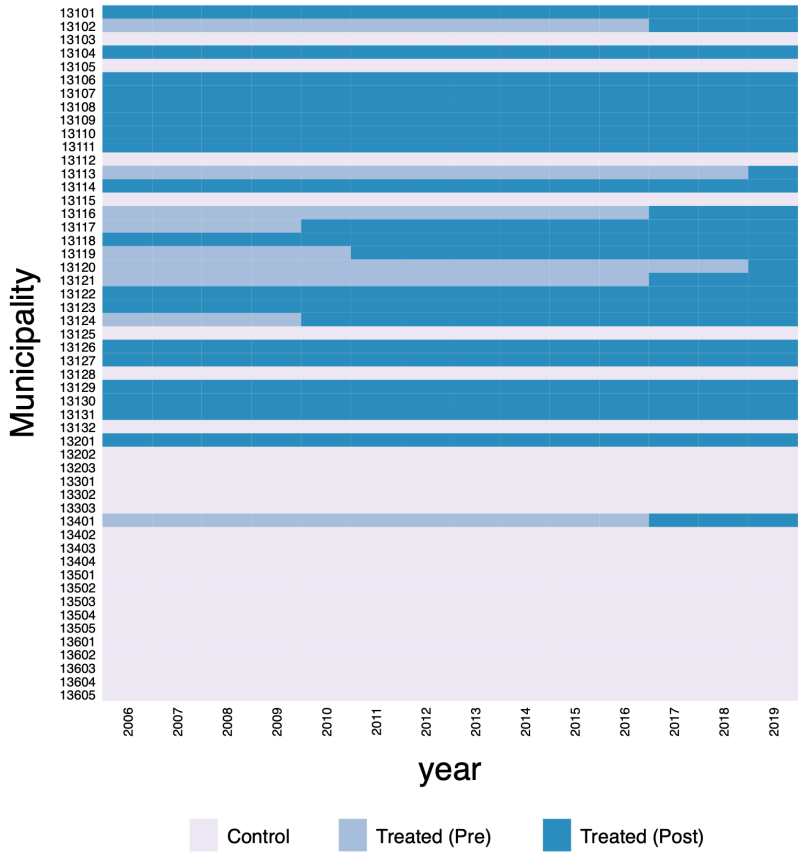
B: Data Appendix

B1: Wage Markdowns by Market

C: Additional Figures

C1: Staggered Treatment Timeline

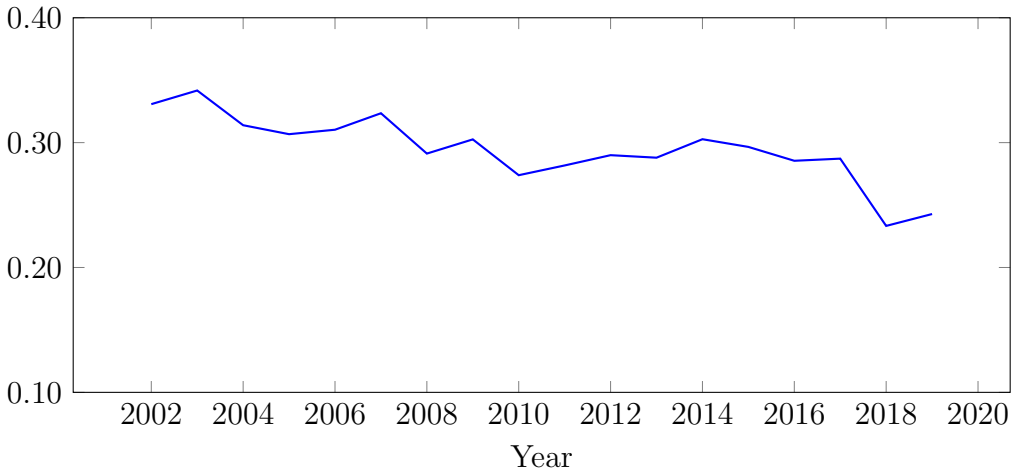
Figure 10: Timeline of construction of metrolines by Municipality



Note: This figure illustrates the timeline of metro line construction across different municipalities. Treated workers are those that lives in municipalities where metro was already built, while control are those who Metro have not been built yet. The figure highlights variation in construction timing, which is used for identification in the analysis.

C2: Weighted Average Markdown Estimated by Year

Figure 11: Evolution of Weighted Average Markdowns in Santiago



Notes: The figure shows the weighted average of the estimated wage markdowns by year.