

Urban Transit Infrastructure: Spatial Mismatch and Labor Market Power*

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Abstract

Does transit infrastructure reduce labor market power? This paper estimates the effects of a large subway expansion on local labor market outcomes in Santiago, Chile. Using a linked employer-employee dataset with spatial information, we estimate the effects of the network expansion on the most-affected workers and firms through a reduced-form analysis. We find changes in work locations and wages consistent with a reduction in firms' labor market power around areas connected to the subway network after the expansion. We then lay out a quantitative spatial equilibrium model where firms behave as oligopsonies in the labor market to calculate the welfare gains from the transit infrastructure expansion. Our model allows us to decompose the welfare gains into i) the efficiency gains through improved matching between workers and firms and ii) the gains from reducing labor misallocation through labor market power responses. The model also provides a framework to analyze the distributional implications of the infrastructure expansion. We find that workers benefit as firm owners see reduced profits and that accounting for labor market power responses amplifies the welfare gains.

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1 Introduction

Urban transit infrastructure projects involve large capital investments, but it is challenging to measure their benefits. How much of the change in neighborhoods targeted by infrastructure expansions is a causal effect on incumbents rather than a change in neighborhood composition? Beyond direct efficiency gains from reduced commuting costs, are there indirect benefits from reduced labor market power now that workers can substitute more easily between jobs? The lack of individual-level panel data when most subway networks around the world were built has posed a challenge when investigating these aspects. This paper aims to answer these questions. We use a unique employer-employee dataset from Santiago, Chile, that allows us to track workers over time. We circumvent the principal challenge faced by the urban economics literature that has assessed the effect of transit infrastructure on wages: worker sorting vs. efficiency gains.¹

First, we test if transit infrastructure gives workers better job opportunities and more bargaining power due to the improved access to labor markets in the city. We compare areas affected by the network expansion to those not affected through a panel event-study leveraging the opening of 84 new subway stations. By combining administrative data on monthly earnings from an unemployment insurance database and data on each worker’s residence location and each firm’s business location, we obtain reduced-form estimates of the effects of improving market access on wages and work locations. Because we include worker and firm fixed effects in our event-study regressions, we estimate the impacts of infrastructure net of any sorting caused by the treatment.

Second, we build a quantitative spatial equilibrium model in which workers commute and firms exert labor market power over workers. The model serves two purposes: One, it allows us to disentangle the channels behind the reduced-form estimates, and two, it provides a tool to quantify the infrastructure expansion’s effect on aggregate welfare and market power. The model is based on [Monte et al. \(2018\)](#) and [Berger et al. \(2019\)](#) that uses the framework from [Atkeson and Burstein \(2008\)](#) to model the market structure. Its main assumption is that firms behave as oligopsonies in the labor market.² Using the model estimates, we quantify the economic impact of transit improvements considering two channels. First, we measure

¹The challenge faced by previous work in the urban economics literature is similar to the one in the literature on labor productivity in low-income countries. Estimates with individual panel data can lead to substantially different policy conclusions. For instance, [Hicks et al. \(2017\)](#) show that including individual fixed effects reduces the estimated urban-rural productivity gaps by as much as 92%.

²The assumption of oligopsonies is similar to assuming different Nash-Bargaining parameters in search models ([Manning, 2021](#)).

the efficiency gains from the infrastructure expansion, accounting for the direct benefits of reducing commuting costs and the indirect effects of changing labor market power. Second, given that one of the biggest concerns of economists right now is the rise of market power and inequality, we measure the effects on the welfare distribution between firms and workers. The aggregate impact of the infrastructure expansion on firms' labor market power can go in either direction. On the one hand, as labor market integration increases, more competition among firms for workers reduces labor market power. On the other hand, larger firms may become bigger, and some firms may exit the market, increasing the wage-setting ability of the most productive firms.

Our reduced-form estimates reveal four facts that motivate our model: 1) After the subway network expands to connect an additional district, workers who experience an improvement in market access commute longer distances and earn higher wages. 2) After the subway network expands to a district, even workers who live in that district and do not switch jobs start earning more. 3) After the subway network expands to a district, firms in that district start hiring workers from farther away but pay the same wages on average. 4) Expansions of the subway network lead earnings to converge across space. Specifically, firms start paying workers wages closer to the average of their sector-education-age group after the subway connects the district where the firm is.

The convergence of earnings across space that we find in fact number 4 suggests that there is heterogeneity in the firm's responses to infrastructure that we find in fact number 3. Firms with little access to workers were paying higher wages to attract them. After being connected, these firms can pay lower wages closer to the city average. In contrast, firms that had access to many workers who were unconnected to other places could pay lower wages and now have to increase them to bring them closer to the city average. The wage equalization we observe is equivalent to the convergence of tradeable-goods prices after trade costs decrease. Moreover, it suggests differentiation of jobs by commuting costs, as theorized by job differentiation models like in [Card et al. \(2018\)](#), which leads to labor market power. Therefore, the previous facts imply that there are potential winners and losers of a city's labor market integration, and that a model is needed to assess the overall gains. The facts also indicate that incorporating labor market power is important to rationalize the gains seen by workers who do not switch jobs and to account for the differentiation of jobs due to commuting costs.

Our model with oligopsonistic firms incorporates this firm heterogeneity. The model's main predictions on the welfare impact of new infrastructure depend on two structural pa-

parameters: the labor supply elasticity across sectors and the commuting supply elasticity specific to firms. First, we describe the model’s limit cases and show that the data conforms to its main predictions. Then, we estimate the model’s key parameters. Last, we simulate an infrastructure expansion and show that the welfare gains from reducing commuting costs are significantly larger when accounting for imperfect labor markets.

Our paper relates to three different strands of the literature. First, it complements the urban economics literature that analyzes the impact of transit infrastructure. Second, it relates to the literature that has studied the causes and consequences of spatial mismatch. Third, it follows a growing literature in labor and macroeconomics analyzing the implications of labor market power.

This paper is closely related to the literature measuring the impact of transportation infrastructure on economic activity. Part of this literature has studied the integration of different regions through railroads, highways, and administrative unification (Alder, 2016; Bartelme, 2015; Donaldson, 2018; Donaldson and Hornbeck, 2016; Faber, 2014; Redding and Sturm, 2008). Other papers have studied property prices and population in cities as a response to various transportation infrastructure improvements (Baum-Snow, 2007; Baum-Snow et al., 2017; Billings, 2011; Gibbons and Machin, 2005; Gonzalez-Navarro and Turner, 2018; Gupta et al., 2020; Kahn et al., 2008; Tsivanidis, 2018; Zárate, 2019). For example, Tsivanidis (2018) measures the welfare gains from Bogotá’s bus rapid transit system using rich data at the census tract level. He shows that when considering general equilibrium effects and reallocation, welfare gains are 20-40% larger than usual estimates based on time savings alone. Our paper contributes to this literature in two ways. First, we use linked employer-employee data, which allows us to obtain more credible reduced-form estimates. Second, we incorporate labor market power into a quantitative spatial equilibrium model, allowing us to analyze the welfare gains from infrastructure-induced labor market power changes.

The paper also contributes to the spatial mismatch literature. This strand of work started with Kain (1968), who argued that low black employment in U.S. cities was partially due to residential segregation. Hsieh and Moretti (2019) estimate that mismatch across cities in the U.S. due to housing constraints lowered population growth by 36% between 1964 and 2009. On the other hand, other papers suggest that local mismatch does not significantly affect employment (Hellerstein et al., 2008; Marinescu and Rathelot, 2018). Closer to the Chilean context, Meneses (2021) studies how the subway network in Santiago expanded educational choices for students, and Carrera and Rojas (2021) finds that having access to the network reduced the harmful effects of displacement to the outskirts from camps near the city center.

Our paper uses a shock to commuting costs to test the importance of mismatch in a city. We find that mismatch plays a role in work decisions, as workers change work locations and earn more when labor market access expands.

Last, we also build on the growing labor market power literature, which has received increasing attention in the last decade (Amodio and De Roux, 2021; Azar et al., 2019, 2017; Berger et al., 2019; Bhaskar et al., 2002; Dube et al., 2020; Felix, 2022; Hershbein et al., 2021; Lamadon et al., 2019; Naidu et al., 2016; Staiger et al., 2010; Tortarolo and Zarate, 2020). We contribute to this literature by quantifying responses to additional labor market integration in a city. Our findings on reduced labor market power due to transportation infrastructure expansion are consistent with those of Brooks et al. (2021), who find reduced labor markdowns after an infrastructure expansion in India that may facilitate migration.

The rest of the paper is structured as follows. Section 2 narrates the process behind the subway expansion, Section 3 describes the different data sources used. Section 4 presents the reduced-form empirical strategy and results, section 5 lays out the model, and section 6 concludes.

2 Context about Santiago’s Subway Expansion

Santiago is Chile’s capital. With a population of 5.6 million, it is home to 30% of the country’s inhabitants. Like many other Latin American cities, it has a central business district (CBD), and other than for a few high-income suburbs, income tends to fall as one moves away from the CBD. Connecting people from the peripheries to jobs downtown has been the main advertised reason behind the creation of new subway lines, since the initial project was devised in 1968. That year, President Eduardo Frei Montalva signed a decree to begin constructing a subway network in Santiago. Figure 1 shows the master plan that was approved, which included five lines covering a large part of Santiago. The first line was inaugurated in 1975, stretching from East to West. Construction continued during the ’80s and ’90s, and by 2000, the network had three lines, shown in Figure 2, panel (a). The network had 52 stations, covering 40 km, and transported almost 1 million passengers daily. Our analysis starts after this, so the network’s extent up to this point is our baseline.

President Ricardo Lagos took office in March 2000 and quickly expressed his intent to expand the subway network. His first announcements were on the short extensions of two existing lines. Then, in 2001, he announced the next expansion. After a lobbying campaign

from the majors of Santiago’s two most populated districts (Puente Alto and Maipú) in the southeast and southwest areas of the city (Cooperativa, 2001), the President announced the construction of Line 4 connecting the downtown and the southeast. Between 2004 and 2006, the extensions to the previous lines and line 4 were inaugurated, extending the network over 70 km. Figure 2, panel (b) shows the network after this construction wave. We refer to this expansion the first wave.

The government announced the second expansion wave in 2005. It included a sizable extension of one of the existing lines to serve the previous contender district, Maipú, in the southeast. The other extension was shorter and aimed at reaching the East of the city, an affluent area where many people work. The stations’ opening took place between 2010 and 2011. Figure 2 panel (c) shows the layout of the extended network.

The third and most recent expansion announcement occurred in October 2010. New Lines 3 and 6 opened in 2017 in 2019, serving the north and the west of the city. Figure 2 panel (d) shows the network’s current state. After the three expansion waves, the network has grown from 52 to 136 stations, 40 to 140 km, and now carries over 2.5 million passengers daily. Figure 3, panel (a) shows the current location of the subway stations in the city’s districts.

Our primary analysis pools the results of the first and second expansion waves in a staggered adoption framework. Nevertheless, the impacts of each expansion wave may show some differences because of other transit system changes that happened over time. The most important of these changes was the creation of Transantiago, an upgraded bus system, in 2007, soon after the first expansion wave ended. Transantiago introduced several changes to the bus system. First, it reduced the number of firms competing in the city’s bus system. Second, it changed bus drivers’ payment schemes. Last, it integrated bus and metro fares to make the Metro the backbone of the transit system.³ Transantiago’s creation should make the impact of the first expansion larger than that of other waves. However, the launch of Transantiago was problematic (Muñoz and Gschwender, 2008), with initial years of low frequency, crowded buses, and overall longer travel times. The initial failure of Transantiago suggests that travel times might not have decreased despite the subway line expansions. In

³Transantiago was a high-profile project that completely changed the logic and functioning of Santiago’s public transit system. The previous system consisted of 8000 buses (serving 380 routes) owned by competing firms which, on average, owned two buses each (Muñoz and Gschwender, 2008). Such fragmentation meant long bus routes and on-street competition between buses. Because drivers received a share of collected fares, they frequently skipped less busy stops. They also did not comply with student fares (30% of the adult fare). Transantiago reduced the number of bus firms to 10, each operating in an area with buses that fed into main “trunk lines” and the Metro. The bus and metro fares were integrated and allowed multiple transitions within 90 minutes, and drivers were not paid based on the fares collected.

the appendix, we show results by wave to see if the effects of the first expansion wave are different.

3 Data

Data sources. We use data from three sources. Our primary data source is an 8% sample of the Unemployment Insurance Database (UID), an employer-employee dataset with monthly earnings for all private sector formal employees starting in October 2002. It also has information on each worker’s date of birth, gender, education, district of residence, and each firm’s sector and the district where it is registered.⁴

Table 1 shows descriptive statistics on workers from the UID from a cross-section of September 2012. We can see that average monthly earnings at this time were USD 1,406⁵. This figure underestimates average earnings since earnings are top-coded at USD 4,860. Only 14% of workers work in their residence district and almost 50% work in firms in one of the three districts with the most jobs. We refer to these three districts as “Downtown” from now on. About 15% of workers have a college degree (2-year technical or 5-year university). Despite this low percentage, the younger cohorts have more educational attainment.

Our second data sources are the 2001 and 2012 Origin-Destination Surveys (OD surveys from now on). These surveys collect the exact coordinates of origin and destination, time, purpose, and transportation mode for thousands of trips in Chile’s Metropolitan Region. They are representative at the district level. We restrict our analysis to the 38 districts included in the 2001 OD Survey. Since the surveys’ purpose is to characterize commuting in Santiago, the included districts should represent an adequate sample to study the effects of the subway expansion. Figure 3, panel (a), shows the 38 districts and the current subway network. Figure 3 panel (b) maps all the origin points of trips from both surveys, which we use in Section 4.

Our third dataset contains the coordinates of each subway station, along with their opening date.

Commuting statistics and infrastructure effects. Table 3 shows statistics on com-

⁴Preliminary results using the full dataset are similar. Unfortunately, the database does not have establishment-level identifiers, so our analysis is at the firm level. Reassuringly, 60% of firms in Chile are small-medium (up to 4 million USD in annual sales), making up 70% of employment. These firms are less likely to be multi-establishment.

⁵Using September 2012 pesos, converted to USD at 486 pesos per dollar.

muting and its evolution between 2001 and 2012. Between these years, commutes increased in time and distance, and they exhibit large differences across districts. The share of public transportation trips increased only slightly, but as expected, subway usage increased by 200%. By 2012 half of all commutes were through the subway in some districts. This increase in subway use is partly due to the expansions, but it could also be due to the change in the bus system detailed in the previous section.

If the subway expansion affected the labor market, it should have reduced commuting times. We use the 2001 and 2012 Origin Destination Surveys to evaluate this. Table 2 shows trip-level regressions of commuting time on a “treated” dummy. This dummy equals one if the district or zone where the trip started saw a reduction of its average distance to the closest subway station larger than 50%, controlling for distance to work.⁶ Column 1 analyzes these effects at the district level, defining treatment by the district of origin and using ‘district of origin-district of destination’ fixed effects. Column 2 replicates the analysis at the zone level, dividing Santiago into approximately 400 rectangular zones. Both regressions compare similar trips in 2001 and 2012 and examine how a change in the distance to subway stations affected commuting times, controlling for distance and overall increases in commuting time. We see that in both specifications, trips from places that received better access to the subway network experienced a 6% reduction in commuting times relative to places which did not. These results are unsurprising yet fundamental to believe that the expansion of the subway network could have affected the labor market. We explore the labor market effects in the next section.

4 Reduced-form Evidence

4.1 Empirical Strategy

We first present reduced-form evidence on the subway expansion’s impact on affected workers and firms. Thanks to the UID, we can control for worker fixed effects in our estimations, avoiding the problem of worker sorting present in most previous attempts at estimating the effects of transit infrastructure.

We first combine the 2001 and 2012 OD surveys to have a representative sample of work trips from each district. We take the origin coordinates of these trips, shown in Figure 3,

⁶Appendix Table A.1 performs a similar analysis but using the distance of the trip origins and destinations as a continuous variable.

panel (b), and calculate the distance to the closest subway station that has been opened so far for each month. We then take a district-level average of these distances for each month, obtaining an average minimum distance to the subway for each month, a measure of access to the subway network. We consider the month with the largest percentage reduction in the average minimum distance as the event period for each district. For simplicity of exposition and precision of our estimates, we group all 198 months in our sample into groups of 6 months, and therefore the semester in which the event month is in is the event semester.⁷ All thirty-eight districts experience some reduction in distance to the subway between 2002 and today, with different intensities. Figure 4 shows which the treated districts and the average reduction in the distance for three of the event-semesters and overall.

We estimate the following specification relating outcomes to the subway expansion:

$$y_{idt} = \alpha + \beta_{-5-} T_{dt}^{-5-} \times I_d + \sum_{k=-4}^8 \beta_k T_{dt}^k \times I_d + \beta_{9+} T_{dt}^{9+} \times I_d + \lambda_i + \delta_t + \varepsilon_{idt}, \quad (4.1)$$

where y_{idt} is the outcome of worker i , who lives in district d , in month t . The coefficients λ_i are worker fixed effects, and δ_t are month fixed effects. The variables T_{dt}^k are district-level event-time dummies, which range from 4 semesters prior to 8 semesters after each event. We exclude the semester prior to the semester of the event to have it as the baseline. Following the literature on panel event study estimation (Freyaldenhoven et al., 2021; Schmidheiny and Siegloch, 2019), we bin the event-time dummies beyond this range in T_{dt}^{-5-} and T_{dt}^{9+} , and estimate β_{-5-} and β_{9+} but do not present them in the results. Each event-time dummy is interacted with I_d , which is the percentage reduction in the average minimum distance to the subway that took place in the event.⁸ This scales each event by the intensity of its treatment, and the interpretation of each coefficient is the effect of a 100% reduction in the distance to the subway. Last, we allow for correlation in the error terms ε_{idt} within each district.

Recent work has highlighted the problems that event-study designs have in the presence of dynamic and heterogeneous treatment effects (Abraham and Sun, 2018; Borusyak and Jaravel, 2017). Suppose the first wave of expansions (2004-2006) caused a change in trend in an outcome rather than a jump in levels. In that case, this could lead to an implicit estimation

⁷Although we refer to them as semesters, they are not calendar semesters because the sample does not begin in January 2002.

⁸Each district-month has an average minimum distance to the subway network $MD_{d,t}$, so $I_d = \max_t \left\{ \frac{MD_{d,t} - MD_{d,t-1}}{MD_{d,t-1}} \right\}$

of a negative effect on the subsequent waves (because districts treated in the first wave act as controls when estimating the effects for the other waves), leading to a miss-estimated zero effect. To deal with this, we estimate equation (4.1) interacting all event-time dummies and month fixed effects with a wave categorical variable. This interaction means we estimate the effects separately (but in the same regression to estimate covariances between coefficients) for each wave. We then average the effects across waves, weighting by the share of workers affected by each wave. Since the third wave happened late in our sample, we excluded it from our analysis. Another advantage of estimating the effect separately for each wave is that we only exploit variation in timing within each wave. Using only within-wave variation reduces endogeneity concerns if the timing of openings within each wave is orthogonal to the trends in the outcome variables.

4.2 Results

We summarize the reduced-form evidence into four main facts that serve as motivation for our model. Recall that the event-study coefficients are the effect of a 100% decrease in the distance to a subway station. The weighted average reduction of distance in our sample is 42%. Therefore, for the discussion, we scale the coefficients by 0.42 to represent the effect for the average worker:

***Fact 1:** After the subway network expanded to a district, workers who lived in that district started working farther away and earning more.*

To measure the effect on the distance to work, we calculate the average commuting time by public transportation between districts using the 2001 OD survey, so they are measured before the subway expansion and should only be interpreted as distance. A positive effect of infrastructure expansion on these travel times implies that workers started commuting to districts further away –as measured by pre-expansion travel time–, but does not necessarily imply commuting time increases. Alternatively, we measure the distance to work as the euclidean distance between the centroids of worker’s residence district and the firm’s registration district. We use the average distance inside each district for workers who work in the same district where they live.

Figure 5, panel (a) shows the coefficients estimated in equation (4.1) using the log of this pre-expansion travel time to work as the outcome. We do not see statistically significant pre-trends, and we find a persistent increase of almost 1% in this outcome. Panel (b) looks at the effects on the distance to work. Even though this measure of distance is coarse, we

see similar results. Both of these measures are very noisy since we only see a change in the outcome for a worker if they switch jobs to an entirely different district. The dynamic effect in both panels is not surprising since not all workers search for jobs each period. As natural turnover happens, more workers in affected districts start considering jobs further away, and the average distance to work in the district starts increasing. These effects suggest that the subway expansion did influence workplace decisions.

Figure 6, panel (a) shows the effect on log monthly earnings. Workers' earnings increase slightly over 1% four years after the subway expansion. Including worker fixed effects allows us to rule out the possibility of this effect arising from higher-earnings workers moving to the affected districts. One way to interpret these results is that some workers could have taken higher-paying jobs before the subway expansion, but did not due to high commuting costs. With the new infrastructure reducing these costs, workers can now take those jobs and experience higher earnings.

***Fact 2:** After the subway expands to a district, workers who lived in that district and did not switch jobs started earning more.*

The results in Figure 6, panel(a), and Figure 5 show that workers affected by the infrastructure expansion start earning more and that this effect may be coming from changes in worker's place of work. Nevertheless, we expect that workers who do not change their place of work should benefit from the infrastructure expansion. Because the substitutability between jobs in different locations has increased, models of job differentiation such as [Card et al. \(2018\)](#) would predict a decrease in the labor market power of firms. Recent work by [Caldwell and Harmon \(2019\)](#) suggests that an increase in the value of outside options can be enough to cause an increase in earnings without the worker having to change jobs. Both of these previous papers suggest that reducing commuting times could increase earnings for workers who do not change jobs.

To test this prediction, we estimate equation (4.1) with worker-firm fixed effects instead of worker fixed effects. In practice, this specification estimates the changes in earnings for "stayers" since it exploits changes in earnings within each worker-firm pair. Panel (b) in Figure 6 shows the results. We see a similar effect as the ones in panel (a), although the point estimates are slightly smaller. These results are consistent with wage effects from reduced labor market power.

There may be alternative explanations for these wage increases not associated with the changes in outside options from reduced commuting costs. For example, the infrastructure

expansion may have induced changes in the local labor supply and the composition of the labor force. To the extent that the expanded infrastructure increased the labor supply of high-productivity workers, wages could increase. The reduced commuting and trade costs could also boost agglomeration externalities, increasing earnings. Last, the infrastructure expansion may stimulate local economic activity at station construction sites, boosting local wages. While we can distinguish between these mechanisms in the model, we only attempt to rule them out in the reduced-form analysis. Figure 7 presents estimates that include both worker-firm fixed effects and district-of-firm-sector-month fixed effects. This model compares stayers who work in the same district and sector but experience subway expansions at different times in their district of residence. We see an effect of a similar magnitude to Figure 6, panel (b). If changes in wages were because of a shift in the labor supply curve, we would expect wages for all workers in a district-sector cell to change, instead of only the wages of those who experienced an increase in connectivity to other jobs. Moreover, if the effects came from local economic activity changes or agglomeration effects, we would expect to see them for all the workers in the same district of work and sector, and not only for those workers whose commuting costs decreased.

Another alternative explanation is that reduced commuting times either increased the productivity or hours of work of stayers. Both of these could translate into higher earnings. To test this hypothesis, we split the sample into two: residence-workplace pairs with high commuting time reductions, and residence-workplace pairs with low commuting time reductions. We do not have data on commuting times after the subway expansion, so we simulate the commuting time reductions using the network analysis tool in ArcMap. We fix a residence district and simulate the commuting time reduction to all other districts when the residence district receives a subway expansion. We then assign the residence-workplace pairs with below-median simulated commuting time reduction to the low-reduction sample and the rest to the high-reduction sample. We repeat this process for every residence district. To validate that our sample split based on simulated commuting time reductions is meaningful, we estimate the effect of the subway expansion on the probability of working in a district in the high-reduction sample. Figure 8, panel (a) shows the results. After the subway expands to a district, workers are more likely to start working in high-reduction districts. This result suggests that our sample split properly selects the most and least affected location pairs.

We then estimate the event study with worker-firm fixed effects for the low-reduction sample. If the effect came from workers who experience a sizable reduction in commuting time to their jobs (who should be in the high-reduction sample), we should expect smaller or

null effects. Figure 8, panel (b) shows that this is not the case, suggesting that the reduction in commuting times to their current job is not what is driving the results for stayers.

***Fact 3:** After the subway network expands to a district, firms in that district start hiring from further away, but they pay the same on average.*

We estimate a modified version of equation (4.1), including firm fixed effects and defining the event using the distance to the subway in the firms' districts. Figure 9, panel (a), shows that firms start employing workers from further away after the event. Four years after their access to subways improves, firms are employing workers who, on average, live 3% further away than before the subway arrived in their district. Panel (b) looks at the effects on how much firms pay their workers. Although there does not seem to be a change in average wages, the large standard errors suggest the presence of heterogeneity.

***Fact 4:** Earnings converge across space.*

Firms start paying workers wages closer to the average wage of their sector-education-age group after the subway connects the district where the firm is. This wage convergence results from firms facing an upward-sloping labor supply curve. The firms with little access to workers are potentially paying high wages to attract them. After these firms are connected to more workers thanks to the subway expansion, they can pay lower wages. On the other hand, the firms that have access to many workers because these workers are unconnected to other places can pay lower wages. After their district is connected, their labor market power decreases, and they need to pay higher wages. Overall, we expect the gap between a firm's workers' earnings and their group average to decrease unambiguously. To see this, we compute the average earnings for each sector-education-age group every month and take each worker's monthly earnings difference with this group average.⁹ We estimate equation (4.1) with the log of the absolute value of that difference as the dependent variable. Figure 10 shows that this is the case. The gap is reduced by approximately 4% two years after the subway arrives at a firm's district.

4.3 Robustness

Time Aggregation: To have a better visualization of the pre-trends, Appendix Figures A.1 - A.4 show the main results aggregating months in groups of 3 instead of 6. Our results display the same patterns as the main results using 6-month aggregations.

⁹We divide educational attainment into four categories: no high school, high school, tertiary technical degree, and tertiary university degree. We classify age in 5-year bins.

Stacked difference-in-differences: There could still be the concern that within-wave, we are using early-treated districts as controls for later-treated ones, a problem highlighted by [Abraham and Sun \(2018\)](#). To address this, we re-estimate the effects using a stacked difference-in-differences specification. For each wave, we consider districts with a treatment intensity below 30% as “pure” controls. Then, we estimate event studies for each treatment cohort against the corresponding controls and aggregate the results according to the number of workers in each regression.¹⁰ This estimation compares districts treated with high intensity vs. low intensity and not districts with similar treatment intensity but differences in treatment timing. With this specification, we can control for differential pre-trends in the regressions on earnings by estimating pre-treatment trends for each treatment-cohort and partialling them out of the full panel, as suggested in [Bhuller et al. \(2013\)](#); [Goodman-Bacon \(2021a,b\)](#). This specification has 13 treated districts and five controls in the first wave, and six treated districts and four controls in the second wave. Appendix Figures [A.5 - A.7](#) show the main results from this estimation. They suggest that problematic definitions of control groups are not driving our results.

Using another region as a control: Another possible concern with our main estimates is the possibility of spillovers across space. The districts we use as controls are likely to be benefiting from the subway expansion as well. For example, a new subway line might not reduce the minimum distance from a particular district to the subway. However, it may still create a faster route to a specific part of the city from that district, reducing commuting times for some workers. With such spillovers, our primary regression may underestimate the benefits of receiving access to the subway network.

To tackle this concern, we compare the districts in Santiago to 33 districts from the Bio Bio region, where Concepción, Chile’s third largest city, is located.¹¹ We estimate event studies for each treatment cohort against all control districts. Then, we aggregate the results from each cohort according to the share of workers in each, interacting the treatment intensities with the event-time dummies and partialling out pre-treatment linear trends on the earnings regressions. Unfortunately, we do not have travel times between districts for any region outside of Santiago; therefore, we can only look at the Euclidean distance between districts.

Figures [12 - 14](#) shows the results from this analysis. The regression with worker fixed

¹⁰In practice, we generate a dataset for each comparison, stack the datasets, and then estimate an event-study regression interacting the worker fixed effects and the month fixed effects with dummy variables by dataset.

¹¹Valparaíso, Chile’s second-largest city, also built new railway stations during the analysis period, and therefore is not an ideal control.

effects and the regression with worker-firm fixed effects both show effects that are larger than those from the within-Santiago analysis. These results suggest that the main analysis may underestimate the effects of the infrastructure expansion due to spillover effects.

Randomization inference: We cluster standard errors at the district level in the main analysis. With a small number of districts, our hypotheses test may not have the correct size [Bertrand et al. \(2004\)](#); [Cameron and Miller \(2015\)](#). For robustness, we probe the main results using randomization inference. We take the 38 districts, randomize the 38 timing-intensity pairs across them, and estimate the same specification on log wages. [Figure 11](#) shows the results. Following [Abadie et al. \(2010\)](#), we square each coefficient and compute the average squared coefficient pre and post-event. Finally, we calculate the ratio between this post and pre measures. The actual estimates have the 3rd largest ratio out of 60 permutations, putting them in the top 5%. This position means that if the treatment were meaningless, there would be less than a 5 percent chance of seeing a trend break of the magnitude we are seeing.

Overall, our reduced-form results are pretty intuitive. A reduction in commuting costs appears to integrate labor markets, leading to new worker-firm matches and the convergence of earnings across space. When workers gain access to the subway network, they are more likely to take a job further away, at a higher wage because these locations may be more productive than the locations nearby. On the other hand, our results also suggest that even workers who do not switch jobs obtain earnings gains, which do not result from by higher productivity or working more hours. Different mechanisms that can explain this result: larger agglomeration forces, shifts in the labor supply curves, and changes in the bargaining power of firms and workers. In addition, our complementary analysis suggests that there are spillover effects. To disentangle these channels and to be able to estimate the overall welfare gains of transit infrastructure, we develop a model of oligopsonistic firms that considers all these mechanisms in the next section.

5 Model

This section develops a quantitative spatial equilibrium model with oligopsonistic labor markets. The model has two objectives. First, it provides a framework to explain the economic forces driving the reduced-form results. Second, it allows us to compute the welfare effects of transit improvements through different margins in the labor market. We focus on the effect on wages and rent-sharing parameters between firms and workers. We split the welfare effects of infrastructure expansion into i) the efficiency gains of transit improvements

through improved matching between firms and workers and ii) the gains from reduced factor misallocation across firms. We also use the model to measure how the new infrastructure modifies the distribution of surpluses between firms and workers due to the changes in labor market power.¹²

5.1 Labor supply

There is a set of locations \mathcal{I} within a closed city, \mathcal{S} sectors and \mathcal{F} firms where $\mathcal{F} = \cup_s \mathcal{F}_s$ and \mathcal{F}_s represents the set of firms in each sector. Workers allocate their wages, net of commuting costs, towards consumption at a price P and housing at a price r_i . Consumption prices do not vary across the city, but housing prices depend on location. The utility of a worker ω who lives in i , works in location j , sector s , and firm f is:

$$U_{\omega i j s f} = u_i \epsilon_{\omega i j (f) s (f) f} \left(\frac{C_\omega}{\alpha} \right)^\alpha \left(\frac{H_\omega}{1 - \alpha} \right)^{1 - \alpha},$$

where C_ω is a consumption aggregator, and H_ω is the amount of housing. The parameter $1 - \alpha$ represents the expenditure share in housing, u_i is an amenity parameter, and the variable $\epsilon_{\omega i j (f) s (f) f}$ is an idiosyncratic shock. Given the preferences, indirect utility is given by:

$$V_{\omega i j s f} = \frac{u_i w_{j(f) s (f) f} d_{i j (f)}^{-1} \epsilon_{\omega i j (f) s (f) f}}{P^\alpha r_i^{1 - \alpha}}. \quad (5.1)$$

Here, the wages $w_{j(f) s (f) f}$ are wages paid per efficiency unit. The parameters $d_{i j} \geq 1$ are iceberg commuting costs and represent the decrease in efficiency units of labor from commuting. We assume that the idiosyncratic shock $\epsilon_{\omega i j (f) s (f) f}$ affects efficiency units and comes from a Nested Fréchet distribution with two nests: sector and firm. Conditional on this shock, each agent makes two decisions: the sector to work in and the firm within each sector-location. Letting ϵ denote the vector of all the shocks $\epsilon_{\omega i j (f) s (f) f}$, the CDF distribution of ϵ follows an extreme value type II (Fréchet) distribution and is given by:

$$H(\epsilon) = \exp \left[- \sum_s B_{i s (f)} \left(\sum_f B_{j (f) s (f)} \epsilon_{i j (f) s (f) f}^{-\beta} \right)^{\frac{\kappa}{\beta}} \right], \quad \text{with } \kappa \leq \beta \quad (5.2)$$

¹²The model can be easily extended for different types of workers and to allow migration across locations within the city that, for now, we have assumed fixed.

where the parameters β and κ capture the shocks' dispersion in each nest.¹³ These parameters capture how substitutable jobs are in the two nests. The parameter β represents how easy it is for workers to substitute jobs across firms within each sector, and the parameter κ measures how easy it is to substitute between jobs across sectors.¹⁴ On the other hand, the parameters $B_{is(f)}$ and $B_{j(f)s(f)}$ are scale parameters that capture amenity or productivity shocks in sector s and firm f . For simplicity, we assume that there is no migration within the city.¹⁵

Given the properties of the Fréchet distribution, following [McFadden \(1978\)](#) that the share of workers that are living in i , who decide to work in firm f from sector s at district j is:

$$\lambda_{ij(f)s(f)f} = \frac{B_{is} W_{is}^\kappa}{\underbrace{\sum_{s'} B_{is'} W_{is'}^\kappa}_{\text{Prob. of working in sector } s}} \frac{B_{j(f)s(f)f} w_{js(f)f}^\beta d_{ij}^{-\beta}}{\underbrace{\sum_{f' \in \mathcal{F}_s} B_{j'(f')s'(f')} w_{j'(f')s'(f')f'}^\beta d_{ij'(f')}^{-\beta}}_{\text{Prob of working in } jf \text{ conditional on working in } s}}, \quad (5.3)$$

where $W_{is} \equiv \left(\sum_f B_{j(f)s(f)} w_{j(f)s(f)}^\beta d_{ij}^{-\beta} \right)^{\frac{1}{\beta}}$ is a wage index for each combination of sector and residence location. It also represents the expected wage conditional on choosing a sector to work in each location i . To simplify the notation, we drop the dependency of j and s on the firm index f from now on.

5.2 Labor demand

We assume a wage posting model as in [Card et al. \(2018\)](#), where firms post wages per efficiency unit and workers decide where to provide labor depending on the idiosyncratic shock and commuting costs. However, while [Card et al. \(2018\)](#) assume a monopsonistic market structure, we follow [Berger et al. \(2019\)](#) assuming an oligopsonistic market structure.¹⁶ Although it would be hard to provide evidence for this assumption from our current dataset because we do not observe evidence of strategic interactions, the literature has shown that this may be the case in several labor markets. Work from [Staiger et al. \(2010\)](#) showed

¹³We fix these parameters for both nests, but we could also assume that these parameters vary within each nest as in [Zárate \(2019\)](#).

¹⁴We will show that this parameter also governs the labor supply elasticity when firm when firms behave like oligopsonies in the labor market.

¹⁵To incorporate migration we could add a nest that depends on a migration elasticity parameter.

¹⁶[Berger et al. \(2019\)](#) follow [Atkeson and Burstein \(2008\)](#) and [Edmond et al. \(2015\)](#) and assume this market structure to have a tractable framework to analyze market power responses.

strategic interaction in the nurses' labor market, and recent work by [Arnold \(2019\)](#) shows evidence of these interactions in the US.

We assume that there are several potential entrants M_{js} into each sector and location that draw their productivity from a Pareto distribution $G(A)$. The production function for each firm f in j, s is:

$$Y_{jsf} = A_{jsf}L^\gamma, \quad 0 < \gamma < 1. \quad (5.4)$$

Here A_{jsf} is a productivity parameter specific to each firm f that operates in location j and sector s .¹⁷ The parameter γ represents decreasing returns to labor. To simplify things, we will assume that all firms produce a homogeneous good, and there are no trade costs within the city, meaning the good is freely tradeable. This assumption implies that the price index for the consumption aggregator does not vary across locations. We normalize the price of this good to 1. Then, the firm f 's problem is:

$$\max_w \pi_{jsf} = Y_{jsf} - w_{jsf}L_{jsf}, \quad (5.5)$$

where $L_{jsf} = \sum_i L_{ijsf}$. Each firm posts a wage, assuming it affects wages in the entire city but only within each sector s .¹⁸ Maximizing profits, we obtain that the wage posted by firm f is:

$$w_{jsf} = \left(\frac{\epsilon_{jsf}}{1 + \epsilon_{jsf}} \right) MRPL_{jsf}. \quad (5.6)$$

This equation means that the wage of each firm is a function of the labor supply elasticity (LSE) and the marginal revenue product of labor. The LSE varies across firms:

$$\epsilon_{jsf} = \sum_i \theta_{ijsf} [\lambda_{ijsf|s}\kappa + (1 - \lambda_{ijsf|s})\beta], \quad (5.7)$$

where θ_{ijsf} corresponds to the share of workers from firm f that live in i . This parameter corresponds to a rent-sharing parameter that captures how firms and workers share the marginal revenue product of labor. On the other hand, the parameter $\lambda_{ijsf|s}$ represents the

¹⁷We are abstracting from external economies of scale, which the urban literature has shown to be important. This simplification is because we want to identify the pro-competitive effects of transit improvements on labor market power in the model.

¹⁸An analogous assumption is that there is a continuum of sectors.

share of workers from location i who work in firm f , conditional on working in sector s . The share of the MRPL that is given to the worker is $\frac{\epsilon_{jsf}}{1+\epsilon_{jsf}}$.

We compare our model with that of Berger et al. (2019) to ease interpretation. In our case, residence locations i represent different local labor markets. All firms compete for workers in each market, and LSE each firm faces is a linear combination of the elasticities from each market. For instance, notice that the model replicates the case of Berger et al. (2019) when $d_{ij} \rightarrow \infty$ for all $i \neq j$, or the case in which the local labor market is the entire city and $d_{ij} = 1$ for all $i, j \in \mathcal{I}$. We now proceed to analyze extreme cases.

5.3 Extreme Cases

In this section, we analyze market power and the effects of reducing commuting costs –as expected from the subway expansion– under extreme case such as $\beta \rightarrow \infty$, $d_{ij} = 1 \forall i, j$; and $d_{ij} \rightarrow \infty \forall i \neq j$.

Lemma 1: *Assume that firm f' has higher productivity than firm f'' within sector s and location j , $A_{jsf'} > A_{jsf''}$. Then firm f' has more labor market power than firm f'' in each local labor market i .*

The result follows from the fact that in each local labor market i , more productive firms within each sector s and location j have a higher share of workers, that is, $\lambda_{ijsf'}|_s > \lambda_{ijsf''}|_s$. For all local labor markets i , $\frac{\partial \epsilon_{ijsf}}{\partial \lambda_{ijsf}|_s} \leq 0$ given the assumption that $\kappa \leq \beta$. On the other hand, it is easy to show that all firms within the same j, s have the same share of workers living in i θ_{ijsf} for all local labor markets i since this parameter is only a function of commuting costs. Combining these two results, we obtain that more productive firms face lower LSEs than less productive firms and, as a consequence, exert more labor market power.

Lemma 2: *If there is more than one firm in sector s and $\beta \rightarrow \infty$, firms do not have labor market power, and the model behaves as a model of perfect competition.*

This result follows from Card et al. (2018). If there is more than one firm in sector s , given that firms are differentiated, in each local labor market i , firm f has a share of workers lower than one. Then the LSE ϵ_{ijsf} goes to infinity, implying that the markdown goes to 1. Thus, in this case, the model replicates the perfectly competitive equilibrium in the labor market.

Lemma 3: *In the case in which $d_{ij} \rightarrow \infty$ firms only operate in the local labor market in which $i = j$ and exert the highest level of market power.*

This result follows from the fact that firm f will have the largest labor share $\lambda_{ijsf|s}$ when $i = j$. Then, the lowest LSE is obtained when $\theta_{jsf} = 1$ which is exactly the case in which $d_{ij} \rightarrow \infty$. Because there is a one-to-one correspondence between the LSE and the markdown, firm f exerts the highest level of market power in this case.

Lemma 4: *With a fixed number of firms, reductions in commuting costs d_{ij} decrease labor market power for all firms.*

This result is a consequence of the previous lemmas. There are two effects. On the one hand, the increase in commuting costs d_{ij} reduces λ_{ijsf} and θ_{ijsf} in the locations in which firms have more market power because some workers of local labor market i reallocate to other areas of the city. On the other hand, there is an increase in $\lambda_{i'jsf}$ and $\omega_{i'jsf}$ in the local labor markets i' in which firms have less market power. Combining the two results, we obtain an increase in the LSE ϵ_{jsf} , and labor market power for all firms decreases.

In the next section, we look at welfare in the model in equilibrium and decompose this welfare into components attributed to different model mechanisms.

5.4 Welfare Decomposition

From the properties of the extreme value type II shocks, the average wage or workers' welfare in each location i is given by:

$$W_i = \left(\sum_s W_{is}^\kappa \right)^{\frac{1}{\kappa}}$$

Following [Holmes et al. \(2014\)](#) and [Asturias et al. \(2019\)](#), we can decompose the welfare in each location i using the following formula:

$$U_i = \underbrace{W_i^{PC}}_{\text{Efficiency term}} \times \underbrace{MD_i}_{\text{Average Markdown}} \times \underbrace{\left(\frac{W_i}{W_i^{PC} MD_i} \right)}_{\text{Allocative efficiency}}, \quad (5.8)$$

where W_i^{PC} is the wage index in location i under perfect competition, MD_i is a term that captures the average markdown of workers from location i face, and W_i is the wage index if firms behave as oligopsonies. Then, the first term captures the direct effects of the infrastructure. In particular, this term captures how much the improvements reduce the spatial mismatch between firms and workers. The second term captures the aggregate effect on

market power; on average, the change of market power at the aggregate level. Finally, the third term captures the misallocation channel, which corresponds to whether the infrastructure reduces the dispersion of market power across establishments leading to higher or lower efficiency gains.

5.5 Key Predictions in the Data

There are some key predictions from the model that we can test in the data.

First of all, one of the key features of our model is the functional form of the LSE to the firm, which we repeat for convenience:

$$\epsilon_{jsf} = \sum_i \theta_{ijsf} [\lambda_{ijsf|s}\kappa + (1 - \lambda_{ijsf|s})\beta].$$

It is a standard result that the markdown on wages is higher when the LSE to the firm is low. Our model, through the incorporation of multiple labor markets and oligopsonistic competition between firms, provides a specific conjecture on what this elasticity depends on: the shares θ_{ijsf} and $\lambda_{ijsf|s}$. Recall that θ_{ijsf} is the share of workers within firm f who live in location i , and $\lambda_{ijsf|s}$ is share of workers from location i who work in firm f , conditional on working in sector s . Intuitively, a firm that hires from many different labor markets will have a higher LSE than a firm that employs a larger share of a specific labor market since those workers represent a larger share of the firm’s employment.

We test if the model-implied labor supply elasticity is associated with lower markdowns, as measured by higher wages after controlling for firm fixed effects. To calculate the model-implied elasticity, we fix $\kappa = 1.5$ and $\beta = 7$ following previous estimations of these parameters in the literature.¹⁹ We then regress monthly earnings on the model-implied LSE, controlling for firm size, firm fixed effects, and month fixed effects. Table 4, column 1, shows the results. It shows that a more elastic LSE is associated with higher wages within the same firm. Column 2 uses worker fixed effects instead of firm fixed effects. It shows that the same worker earns more in a firm with a higher LSE, controlling for firm size.

Another way to test this model prediction is to use a decomposition a la [Abowd et al. \(1999\)](#). This way, we obtain a firm effect for each firm, net of worker and time effects. These firm effects can represent higher productivity but also higher rent-sharing. The first column

¹⁹See [Zárate \(2019\)](#) and [Galle et al. \(2017\)](#) for κ and [Kline et al. \(2019\)](#) for β .

of table 5 presents the results of a regression (employment weighted) relating the firm fixed effects on the LSE, controlling for a fixed effect for the average firm size (in bins of 5). With this set of controls, this specification compares firms of the same size but with a different average composition of workers. We see that firms with a more elastic LSE have larger firm effects, consistent with having less labor market power and sharing a larger share of profits.

The model predicts that reducing commuting costs should decrease the labor market power of firms and the cross-sectional dispersion of markdowns because of wage convergence across space. Columns 2 and 3 of Table 5 test this prediction. Both columns show the results of a regression identical to column 1, but after estimating two separate AKM models. Column 2 uses wages and firm effects from an AKM model estimated using data from 2002-2006, and column 3 uses wages and firm effects from 2012-2016. We see that in the 2002-2006 period, before most of the new subway expansions happened, LSE correlates strongly with the firm effects. However, the relationship was no longer statistically significant during 2012-2016. This change in the relationship is consistent with the change in the distribution of LSEs across firms over time. In 02-06, the average LSE (weighted by employment) was 6.83, with a 0.35 standard deviation and an interquartile range of 6.86-6.99. In 12-16, the average LSE was 6.88, with a standard deviation of 0.28 and an interquartile range of 6.9-6.99. Therefore, the reduced correlation between LSE and wages in the 12-16 period may be due to considerably less variation in LSEs. The lower dispersion of LSEs after the subway expansion is consistent with the model’s predictions.

Last, Figure 15 shows the correlation between firm size and the firm fixed effects in both periods. In 02-06, the relationship is flatter, consistent with more labor market power. Larger firms do not pay higher wages (net of worker characteristics). In the 12-16 period, we see a steeper relationship between firm size and firm effects, consistent with a smaller markdown and a higher pass-through of the firms’ rents to workers’ wages.

5.6 Model Quantification

In this section, we quantify and analyze the welfare implications of reducing commuting costs across the different locations within Santiago. Consistent with the model, we show that i) there is an important reduction in labor market power and ii) the welfare implications of transit improvements are larger when we consider the effect of market power in the labor market. For instance, welfare increases between 20%-50% relative to models with no heterogeneous labor market power across firms such as [Tsivanidis \(2018\)](#) and [Ahlfeldt et al. \(2015\)](#).

We also show that workers gain more after the transit shock to the detriment of firm owners. These results are robust to different values of the model's main parameters.

5.6.1 Model Inversion

We invert the model to recover amenity and productivity parameters. Specifically, with data on wages, the number of workers in each firm, and the number of residents in each location, we can solve the labor supply and labor demand to recover the scale parameters.

Amenity parameters: We recover firm amenity parameters using the total number of workers that work in each firm. Conditional on working in sector s , and using data on wages, we match the number of workers in firm f with the labor supply and recover the amenity parameters. Let L_{jsf}^{data} be the share of workers from sector s that work on firm f . From equation (5.3), this share must equal:

$$L_{jsf}^{data} = \sum_i \frac{B_{jsf} w_{jsf}^\beta d_{ij}^{-\beta}}{\sum_{f' \in \mathcal{F}} B_{j'(f')s'(f')f} w_{j's'(f')f}^\beta d_{ij'}^{-\beta}}.$$

This equation has a unique solution for the vector of amenity parameters B_{jsf} . After knowing these scale parameters we construct the wage indices for each sector and residence location, $W_{is} = \left(\sum_{f \in \mathcal{F}_s} B_{jsf} w_{jsf}^\beta d_{ij}^{-\beta} \right)^{\frac{1}{\beta}}$. Then we can match a sector amenity parameter specific to each residence location. Let L_{is}^{data} be the share of workers in location i who work in sector s . We solve the following system of equations for the amenity parameters B_{is} :

$$L_{is}^{data} = \frac{B_{is} W_{is}^\kappa}{\sum_{s'} B_{is'} W_{is'}^\kappa}.$$

These amenity parameters represent labor supply shifts that are not explained by the wage indices.²⁰

Productivity parameters: We follow a similar procedure to recover the productivity parameters using the labor demand. In particular, we match the number of workers in the data with the ones implied by the model. First, given the parameters κ and β and the shares of workers in each firm, we can use equation (5.7) to calculate the labor supply elasticities. Then, given a value of γ , we find the productivity parameters by solving the following system of equations:

²⁰In both equations the parameters are only identified up to a constant (Ahlfeldt et al., 2015), so we need to normalize one of the scale parameters B_{jsf} and B_{is} .

$$L_{jsf}^{\text{Data}} = \left[\gamma \left(\frac{\epsilon_{jsf}}{1 + \epsilon_{jsf}} \right) \frac{A_{jsf}}{w_{jsf}} \right]^{\frac{1}{1-\gamma}}.$$

After knowing the scale parameters, we can simulate counterfactual scenarios of transit infrastructure expansions by varying the iceberg commuting cost parameters d_{ij} in the model.

5.6.2 Calibration of Commuting Costs

To calibrate the commuting costs, we follow the standard method from [Ahlfeldt et al. \(2015\)](#). In particular, we parametrize the iceberg commuting costs as a function of travel times using the following equation:

$$d_{ij} = \exp(\delta t_{ij}),$$

where δ is a parameter that transforms travel times into commuting costs and t_{ij} is the travel time from location i to location j . For δ , we use a value of 0.01, a standard value used in the literature ([Ahlfeldt et al., 2015](#)). To calculate travel times across locations, we randomly sample 1000 points in the city. We then calculate the distance between every two points using the network analysis tool in ArcMap. We then average the travel times over location pairs to estimate t_{ij} . To simulate counterfactual scenarios with the subway expansion, we calculate these travel times before and after the subway expansion.²¹

5.7 Estimation of the Main Parameters

To adjust the model to the data, we need to estimate two main parameters that determine labor supply elasticities and the effects of transit improvements on labor market power. These two parameters are β , which captures how easy it is for workers to substitute jobs across firms in the city, and κ , which captures how easy it is to substitute sectors within each residential area.

To estimate β , we use the method of moments. Following [Ahlfeldt et al. \(2015\)](#), we set β to match the standard deviation of the log wage distribution in the pre-period. The reason behind using this moment is that β determines the cross-sectional variance of wages across firms and places. As β increases, because of the Fréchet distribution assumption,

²¹We take a weighted average across the different transportation modes. Using this average implicitly assumes that the preferences for transportation modes follow a Cobb-Douglas structure.

the dispersion of the idiosyncratic shock is lower. As a result, the wage dispersion across establishments is also lower. To estimate the variation in wages that is coming from the model we proceed in three different steps. First, we estimate a gravity equation for different transportation modes regressing commuting flows with travel times in each location:

$$\ln \lambda_{ijm} = \mu t_{ijm} + \gamma_{ij} + \gamma_{im} + \gamma_{jm},$$

where λ_{ijm} is the population share in location i that commute to location j using transportation mode m , and t_{ijm} is the travel time from location i to location j using mode m . The coefficient of interest is μ , and to include the zeros, we estimate the gravity equation through PPML. The parameter μ measures how sensitive are commuting flows to changes in travel times, and it captures two different terms. First, the commuting elasticity β that captures how easy is to substitute jobs across firms in the city, and a second parameter δ that transforms travel times to commuting costs $d_{ij} = \exp(\delta t_{ij})$. When we invert the model, we just need to know μ to recover an adjusted wage distribution that we use to calculate the standard deviation of the log wage distribution predicted by the model. In particular, using the employment measure in each sector, we can recover an adjusted measure ω by solving the following equation:

$$L_{jsf}^{\text{Data}} = \sum_i \frac{B_{jsf} \omega_{jsf} \exp(-\mu t_{ij})}{\sum_{f' \in \mathcal{F}} B_{j'(f')s'(f')f} \omega_{j's'f'} \exp(-\mu t_{ij})},$$

Once we recover the adjusted wage distribution ω , we minimize the following moment condition:

$$E \left[\frac{1}{\beta^2} (\ln \omega^2) \right] - \sigma_w^2 = 0, \tag{5.9}$$

Table 6 reports the coefficients of the gravity equation. Overall, we find a value of μ of around 0.035. Figures 16 and 17 plot the moment condition for different values of β and κ . Overall, we find a labor supply elasticity across establishments of around 8.2, which is consistent with the findings from Berger et al. (2019) and Felix (2022).

For the second parameter, we use the structure of the model. We assume that the model holds at two points in time to obtain model-implied equations in time differences. First, note that from equation (5.3), the share of workers working in sector s conditional that they live

in location i is:

$$\lambda_{is|i} = \frac{B_{is}W_{is}^\kappa}{\sum_{s'} B_{is'}W_{is'}^\kappa}.$$

Taking logs on both sides and a first difference across time, we get:

$$\Delta \ln \lambda_{is|i} = \kappa \Delta \ln W_{is} + \Delta \ln B_{is}. \quad (5.10)$$

This equation can be estimated by linear regression of $\lambda_{is|i}$ on $\ln W_{is}$ to obtain an estimate of κ . The term ΔB_{is} is a structural residual that captures changes in the amenity parameter B_{is} –which captures how attractive a sector is for workers in a given residential location– over time. Because we do not observe the amenity parameters, and their change in time may be correlated with wages, we estimate (5.10) by instrumental variables. We use the following moment condition:

$$E[\Delta B_{is} \cdot \Delta Z_{is}] = 0,$$

where Z_{is} corresponds to an instrument that is uncorrelated with the error term of equation 5.10. We obtain different estimates of κ from two different instruments.

First, we build an instrument at the sector level using a leave-out mean of the wage bill in location i . In particular, for each sector s and location i , our first instrument ΔZ_{is} corresponds to:

$$\Delta Z_{is} = \log \left(\sum_{f \in s, j \neq i} w_{j(f)s(f)f,2016} L_{j(f)s(f)f,2016} \right) - \log \left(\sum_{f \in s, j \neq i} w_{j(f)s(f)f,2004} L_{j(f)s(f)f,2004} \right), \quad (5.11)$$

where f indexes firms. The idea of this shock is to capture changes in productivity level in sector s that affect the wage index W_{is} but are uncorrelated with the error term, in particular, amenities. The exclusion restriction implies that changes in the wage bill within the same sector of other locations only affect the sector decision of workers through the wage index.

In the presence of spatial correlation of this wage bill shock across locations, the instrument would not satisfy the exclusion restriction. For an alternative estimate, we build a second instrument using the wage bill of the same sector but in the Bio-Bio region outside

of Santiago. In particular, the second instrument ΔZ_{ist} corresponds to:

$$\Delta Z_{is} = \log \left(\sum_{f \in s} w_{Bio,s(f)f,2016} L_{Bio,s(f)f,2016} \right) - \left(\sum_{f \in s} w_{Bio,s(f)f,2004} L_{Bio,(f)s(f)f,2004} \right), \quad (5.12)$$

where the location index Bio represents the Bio-Bio region. The identification assumption is that, on average, changes in the wage bill in sector s in the Bio-Bio region capture only productivity shocks that are uncorrelated with changes in the amenities in location i in Santiago.

Table 7 presents the results of our regressions to estimate κ . Panel A reports the results for the leave-out mean instrument and Panel B using the wagebill in the Bio-Bio region. The odd columns presents the results of the reduced form and the even columns of the first-stage. Since the instruments are productivity shocks by sector, we cannot include sector fixed effects in these estimations, but we include location fixed effects to capture specific trends. We find that both the employment shares at the sector level and the wage index are positively correlated with productivity shocks. We find a value of κ –which measures the labor supply elasticity across sectors– between 2.2 and 2.7. This parameter goes in line with some of the findings of the literature. For example, Galle et al. (2017), and Zárata (2019) find a labor supply elasticity across sectors of 2 for the US and Mexico City. The value is slightly larger than the one found by Berger et al. (2019) that analyzes the effect of labor market power in the US on local labor markets.

For the other parameters, we use values from the literature. Table 8 shows the values we use for the counterfactuals.

5.8 Counterfactual Results

Welfare Analysis: First, we analyze the welfare effects of the subway expansion. Figure 18 presents the main results. In panel (a), we plot the distribution of markdowns before and after the shock to study markdown heterogeneity, which is the main determinant of the effect on welfare (Hsieh and Klenow, 2009). In panel (b), we plot the welfare effects under perfect competition and consider markdown responses for different values of β holding κ fixed at 3. In general, the counterfactuals imply that the subway expansion generated welfare gains between 2% and 7% of real income, depending on the parameter values. The welfare gains increase when we consider markdown responses. For example, in the case of $\beta = 8$, our

preferred value, the welfare gains increased by around 55%. Under perfect competition, the welfare gains are 1.9%, but when we consider markdown responses, the welfare gains are 3.1%. This increase is higher as the difference between κ and β grows. This amplification in the welfare gains occurs because dispersion of markdowns decreases with the subway expansion. In panel (a), in the pre-period, the markdowns' standard deviation was 2.44%, while in the post-period, it was 2.40%.

Distributional Effects: Figure 19 plots the main effects in terms of redistribution between firms and workers. In panel (a), we plot the effect on the average markdown for different values of β . The markdown coefficient increases between 2% with a $\beta = 5$ to 10% with a $\beta = 10$. Increases in the markdown coefficient imply higher wages and lower markdown levels. The reduction in markdowns implies that the transit infrastructure expansion significantly affects firms' rent-sharing parameters. In the baseline case setting $\beta = 8$, the average fraction of the MRPL given to the worker is 0.80, and the transit shock increases this fraction to 0.85. Therefore, the transit shock increased the bargaining power of workers by a substantial amount.

Similarly, in panel (b), we plot the effects on the aggregate income variables: the aggregate wage bill, the firms' profits, and the total income (the sum of the two). In general, we observe that workers gain more from the transit improvements to the detriment of firms as the commuting elasticity specific to each firm, β , increases. For example, with a $\beta = 8$, aggregate labor income increases by around 4%, while firm-owners lose 6% of operational profits. Nevertheless, the aggregate effect on total income is positive, around 2%.

Overall, the counterfactual results suggest two main conclusions. First, regarding efficiency, the results imply that considering markdown responses amplify the welfare gains from transit infrastructure by a considerable proportion. This result is robust to different values of the commuting elasticity, β . For instance, in the most conservative case, the welfare gains increase by 16%. Second, regarding redistribution, the results suggest that workers gain more from the transit shock to the detriment of firms since average labor market power decreases with the transit shock.

6 Conclusions

This paper studies a large subway expansion in Chile using linked employer-employee data with geographical information on workers and employers. Using an event study framework,

we show four effects on the labor market of a subway expansion: 1) After a subway expands to a district, workers from that district start working further away and earning more; 2) After a subway expands to a district, workers from that district who do not switch jobs start earning more; 3) After a subway expands to a district, firms in that district start hiring from farther away, but pay the same wages on average; and 4) Earnings converge across space: specifically, firms start paying workers closer to their sector-education-age average after the subway connects the firm's district.

These facts suggest an integration of the labor market which should yield efficiency gains and reduced labor market power from reduced differentiation between employers. We develop a commuting model with oligopsonistic firms where each firm's labor market power on the workforce's composition and where firms who dominate specific labor markets can apply a higher markdown if that labor market represents a large share of its employees. The model also predicts that reductions in commuting costs should reduce this measure of labor market power and the dispersion of markdowns, yielding indirect efficiency gains through better labor allocation. We provide evidence that the model's measure of labor supply elasticity to the firm correlates negatively with markdowns. After the subway expansion the average markdown and dispersion of markdowns decreased. Finally, we simulate the model to show that incorporating labor market power suggests gains in the order of 20-50% larger than models without it.

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Table 1: UID Descriptive Statistics - September 2012

Variable	Mean	Std. Dev.	Min.	Max.
Monthly Earnings (USD)	1,406	1,206	66	4,860
Age	37.4	11.17	16	93
Female	0.39	0.49	0	1
HS Complete	0.82	0.38	0	1
College Complete	0.15	0.36	0	1
Works in District of Residence	0.13	0.33	0	1
Works Downtown	0.5	0.5	0	1
N	108,889			

Notes: Descriptive statistics from the Unemployment Insurance Dataset. A cross-section of September 2012.

Table 2: Relationship between distance to subway and work-commuting times

	(1)	(2)
	ln(Trip Duration)	ln(Trip Duration)
Improved Access to Subway	-0.057** (0.025)	-0.065*** (0.019)
N	17455	10898
R2	0.53	0.62
OD District FE	Yes	No
OD Zone FE	No	Yes
Distance Control	Yes	Yes
Year FE	Yes	Yes
Std Errors	Cl at OD-District	Cl at OD-Zone

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Notes: These regressions use data from the 2001 and 2012 Origin-Destination surveys. OD District FE are fixed effects for each pair of origin-destination districts. OD Zone FE divide Santiago into 400 rectangular zones, and are fixed effects for each pair of origin-destination zones. Only work trips that use public transportation at some stage are included in this sample. “Improved Access to Subway” is a dummy equal to 1 if the district or zone saw its average distance to the closest subway station reduced by more than 50%. Results are robust to using a different cutoffs or the continuous measure of the reduction in distance to the closest subway station.

Table 3: Commuting in Santiago

Variable	Mean		District-level Min–Max	
	2001	2012	2001	2012
Commuting Time (min)	36.67 (25.3)	47.92 (29.5)	22.1–51	27.8–68.6
Commuting Distance (km)	7.27 (6.2)	8.5 (7)	3.5–13.3	4.1–14.4
Used Public Transport	0.49 (0.5)	0.54 (0.5)	0.19–0.67	0.19–0.81
Used Subway	0.08 (0.27)	0.25 (0.43)	0.01–0.22	0.05–0.51
N	18,143	17,331	38	38

Notes: This table shows evolution in commuting patterns in the 38 included districts using the Origin Destination Surveys of 2001 and 2012. Columns 3 and 4 show the minimum and maximum district-level averages

Table 4: Relationship between LSE and earnings

	(1)	(2)
	ln(Earnings)	ln(Earnings)
ln(LSE)	0.27** (0.12)	0.69*** (0.2)
ln(Firm Size)	-0.06*** (0.003)	0.02*** (0.004)
N	52,308,062	52,315,973
R2	0.51	0.63
Firm FE	Yes	No
Worker FE	No	Yes
Time FE	Yes	Yes
Std Errors	Cl at Firm	Cl at Firm

Robust standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Notes: Two-way fixed effects regressions of monthly earnings on the model-implied measure of labor supply elasticity for each firm.

Table 5: Relationship between LSE and firm effects

	(1)	(2)	(3)
	Firm Effect	Firm Effect	Firm Effect
ln(LSE)	0.16** (0.07)	0.5*** (0.07)	-0.1 (0.11)
N	54,435,127	6,937,539	21,189,593
R2	0.12	0.1	0.1
Firm Size FE	Yes	Yes	Yes
Std Errors	Cl at Firm	Cl at Firm	Cl at Firm
Time Period	02-16	02-06	12-16

Robust standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Notes: Regressions of firm effects on the model's measure of labor supply elasticity to the firm. Firm effects are estimated from using an AKM-style regression. Column 1 is from an AKM of the entire sample. Column 2 from an AKM of 2002-2006, and column 3 an AKM of 2012-2016.

Table 6: Commuting gravity equations

VARIABLES	(1)	(2)	(3)	(4)
	$\ln \lambda_{ijm}$	$\ln \lambda_{ijm}$	$\ln \lambda_{ijm}$	$\ln \lambda_{ijm}$
time_{ij}	-0.035*** (0.002)	-0.038*** (0.003)	-0.039*** (0.003)	-0.042*** (0.003)
Transportation mode fe	X			
Origin fe	X		X	
Destination fe	X	X		
Origin-mode fe		X		X
Destination-mode fe			X	X
Observations	3,328	3,328	3,328	3,328
Pseudo R-squared	0.148	0.157	0.163	0.171

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Notes: This table reports the results of a gravity equation in which we relate commuting flows in the city with travel times for different transportation modes. We estimate this equation through PPML to include the zeros.

Table 7: Results: Estimation labor supply elasticity across sectors

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Instrument leave-out mean						
Variables	$\Delta \ln \lambda_{is}$	$\Delta \ln W_{is}$	$\Delta \ln \lambda_{is}$	$\Delta \ln W_{is}$	$\Delta \ln \lambda_{is}$	$\Delta \ln W_{is}$
$\Delta \ln Z_{is}$	0.839*** (0.079)	0.381*** (0.099)	0.838*** (0.080)	0.398*** (0.105)	0.841*** (0.079)	0.390*** (0.102)
Constant	-1.780*** (0.171)	0.351 (0.230)	-1.778*** (0.172)	0.310 (0.243)	-1.763*** (0.258)	0.515* (0.259)
Observations	755	755	755	755	755	755
R-squared	0.374	0.076	0.405	0.206	0.381	0.137
Implied κ		2.20		2.11		2.16
Panel B: Instrument Bio-Bio region						
Variables	$\Delta \ln \lambda_{is}$	$\Delta \ln W_{is}$	$\Delta \ln \lambda_{is}$	$\Delta \ln W_{is}$	$\Delta \ln \lambda_{is}$	$\Delta \ln W_{is}$
$\Delta \ln Z_{is}$	0.699*** (0.128)	0.257* (0.138)	0.696*** (0.131)	0.266* (0.144)	0.700*** (0.128)	0.261* (0.139)
Constant	-1.456*** (0.272)	0.642* (0.321)	-1.448*** (0.278)	0.619* (0.334)	-1.453*** (0.317)	0.797** (0.331)
Observations	756	756	756	756	756	756
R-squared	0.323	0.042	0.354	0.170	0.329	0.102
Implied κ		2.72		2.62		2.68
Comuna fe			X	X	X	X
Controls					X	X

Standard errors in parentheses

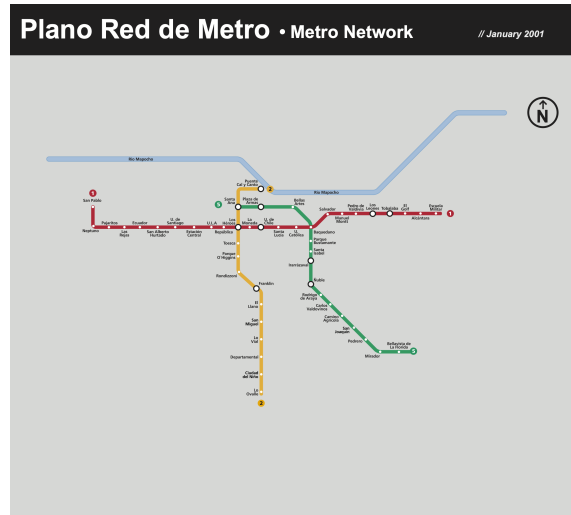
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Notes: This table reports the results for the estimation of κ . We estimate a labor supply equation relating the employment share by sector with a wage index. In panel A, we report the results in which we use as an instrument the leave-out mean of the wage bill by sector, and in panel B using the wage bill in the Bio Bio region.

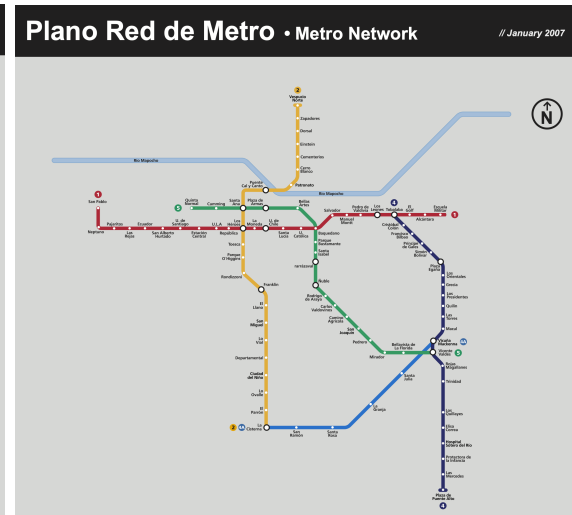
Table 8: Parameters

Parameter	Interpretation	Value
κ	Elasticity of substitution across sectors	2.2
β	Elasticity of substitution across firms within a sector	5-10
γ	Decreasing returns to scale	0.9
Commuting costs	Travel times	$\exp(\delta t_{ij})$

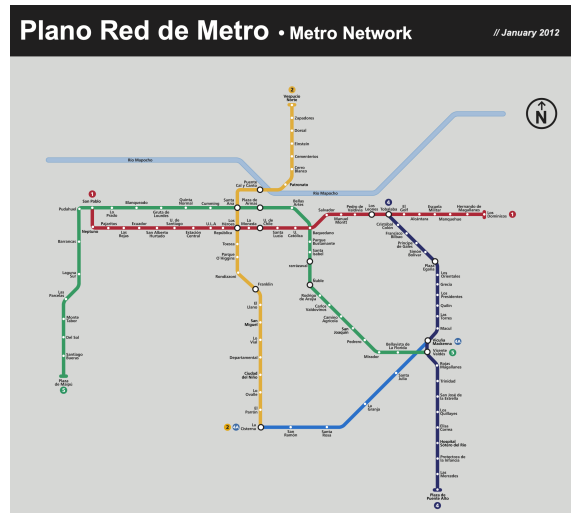
Figure 2: Subway Expansions after 2001



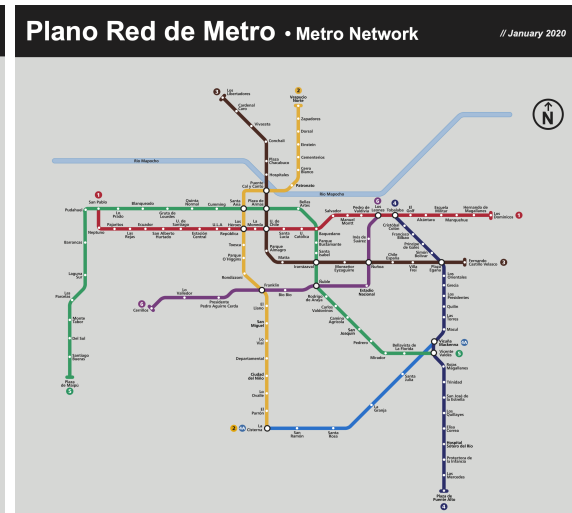
(a) Jan 2001



(b) Jan 2007



(c) Jan 2012



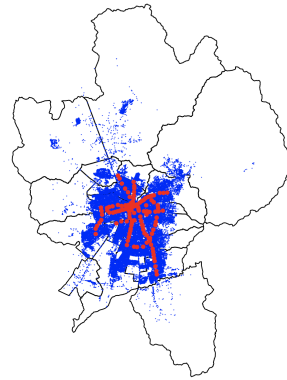
(d) Jan 2020

Notes: Evolution of Santiago's subway network.

Figure 3: Districts in Sample



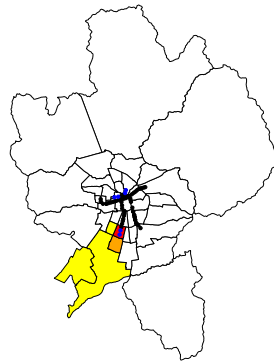
(a) Districts and Subway Stations



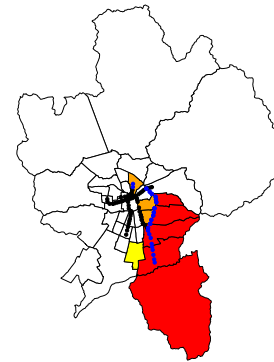
(b) OD Surveys Origin Points

Notes: Maps of the 38 districts included in our sample. Panel A shows the subway stations up to date, and Panel B also shows the Origin-Destination Survey points used to create representative work trips sample.

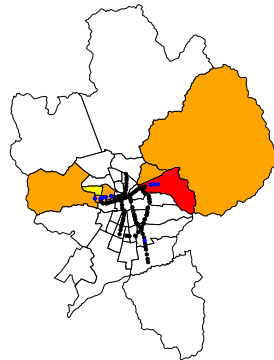
Figure 4: Treatments Visualization



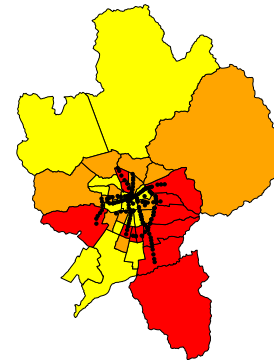
(a) Treated in 2004



(b) Treated in 2006



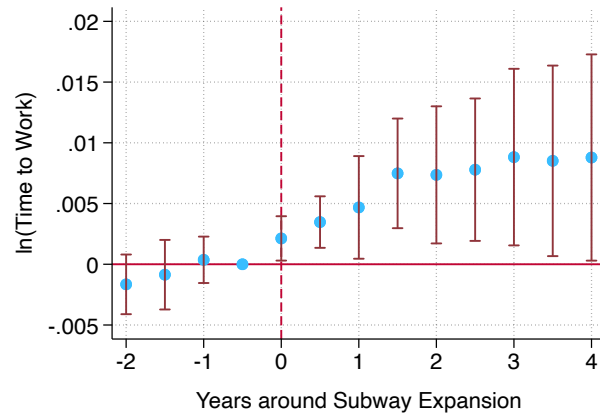
(c) Treated in 2010



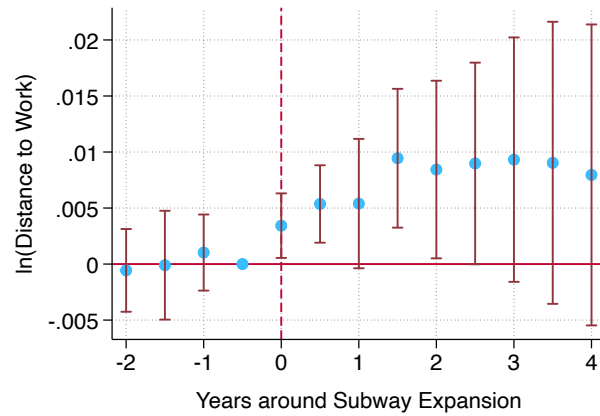
(d) All Treatments

Notes: Black dots are existing subway stations. Blue dots are new subway stations. Districts in yellow reduced their distance to the subway by less than 25%, those in orange by 25-50%, and those in red by over 50%.

Figure 5: The Effect of Subway Expansion on Workers: Where to work



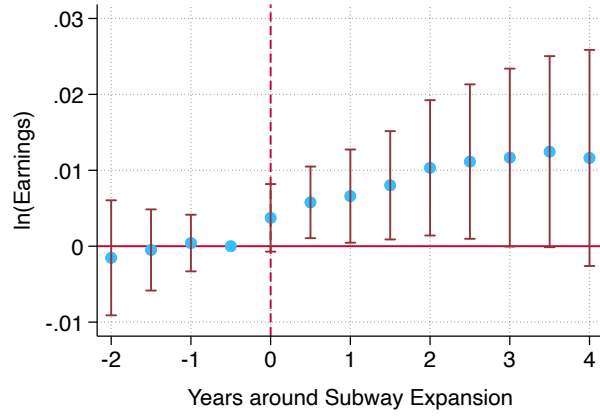
(a) Time to Work



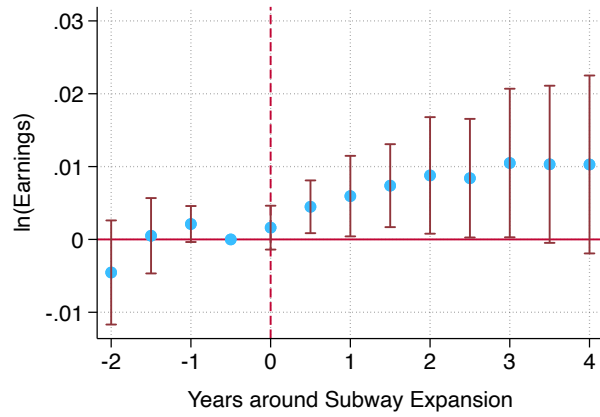
(b) Distance to Work

Notes: Event Study results on distance and time to work. Time to work is estimated before any subway expansion, and therefore is just another measure of distance, does not necessarily imply longer commutes. Coefficients are scaled by 0.42 to represent the effect on the average worker.

Figure 6: The Effect of Subway Expansion on Workers: Earnings



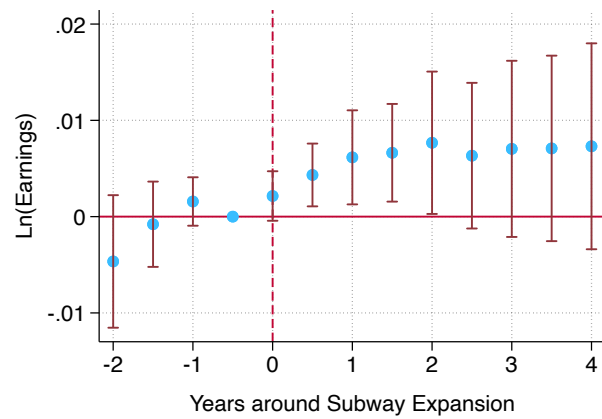
(a) Earnings



(b) Earnings - Stayers

Notes: Event Study results on earnings. Panel A using worker fixed effects, Panel B using worker-firm fixed effects. Coefficients are scaled by 0.42 to represent the effect on the average worker.

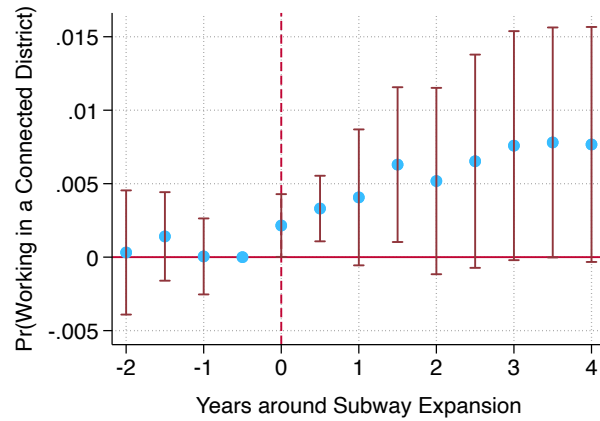
Figure 7: The Effect of Subway Expansion on Workers: Ruling out Labor Supply



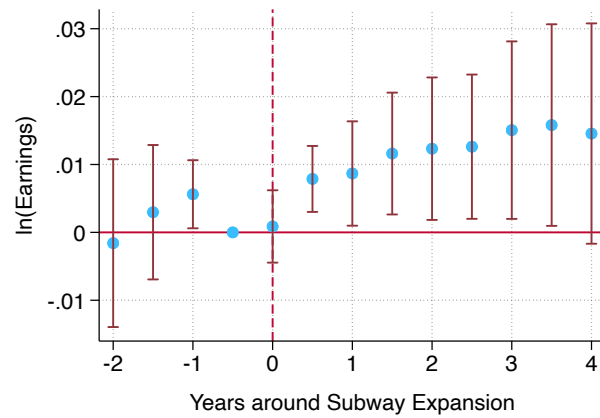
(a) Earnings - Stayers - District of Firm x Sector Fixed Effects

Notes: This event study includes Worker x Firm fixed effects, and Month X District of Firm x Sector fixed effects. Coefficients are scaled by 0.42 to represent the effect on the average worker.

Figure 8: The Effect of Subway Expansion on Workers: Worker Flows and Earnings of Unconnected



(a) Worker Flows

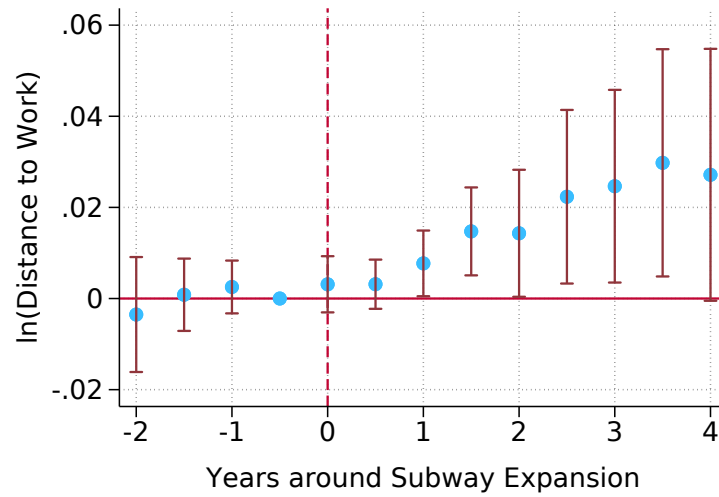


(b) Earnings - Stayers - Unconnected

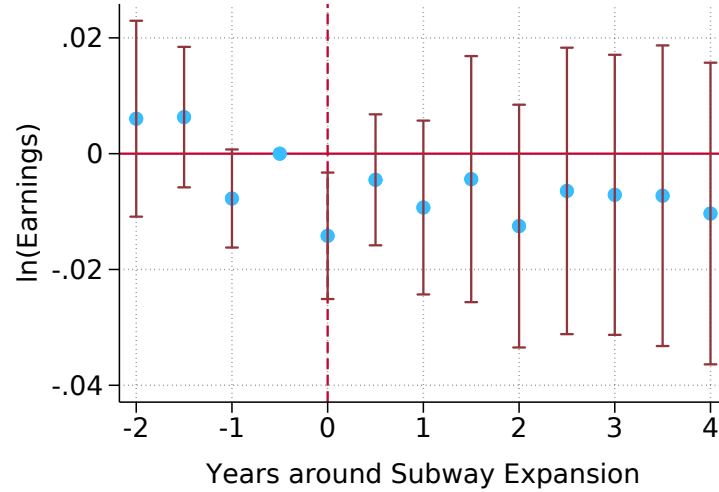
Notes: For each treated district, we simulate commuting times before and after the treatment to all other districts. Then divide destination districts into above and below the median for each treated district. Above the median districts are referred to as connected districts, below the median as unconnected. Panel

A shows that workers are more likely to work in connected districts, and Panel B shows that results on earnings using worker-firm fixed effects hold even for workers who are working in districts that did not get connected. Coefficients are scaled by 0.42 to represent the effect on the average worker.

Figure 9: The Effect of Subway Expansion on Firms



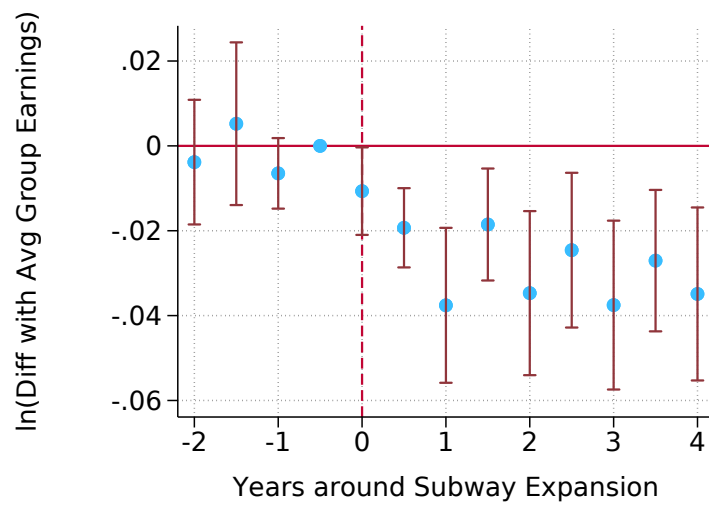
(a) Distance to Work



(b) Earnings

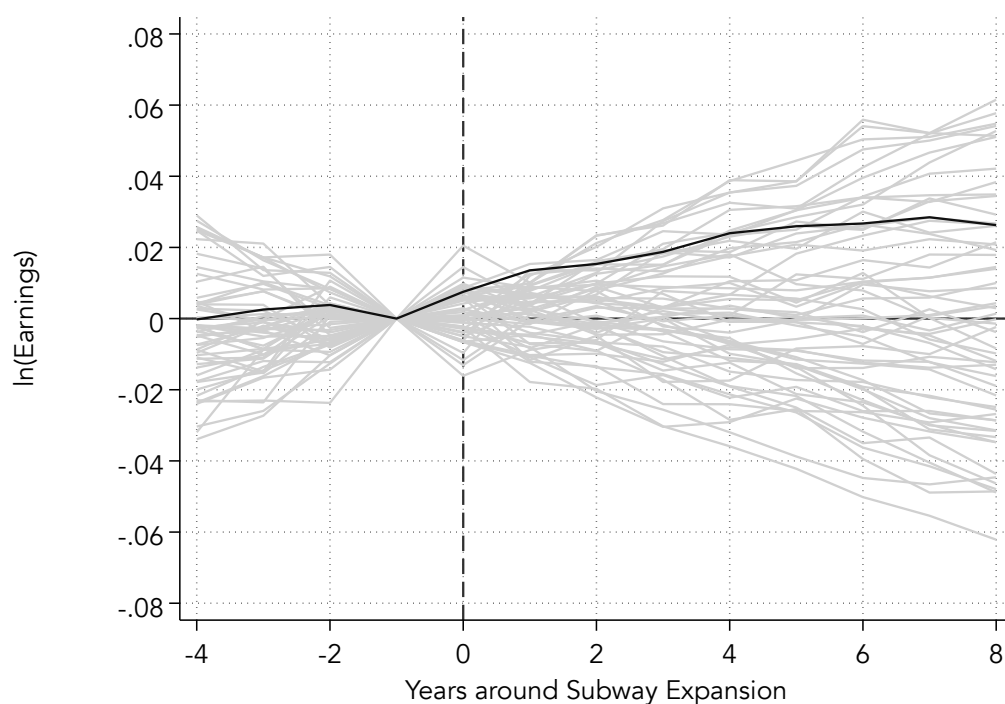
Notes: Event Study results on firms. So the treatment is when the district where the firm is located gets the subway expansion, and regressions are estimated with firm fixed effects. Coefficients are scaled by 0.42 to represent the effect on the average worker.

Figure 10: Convergence of earnings



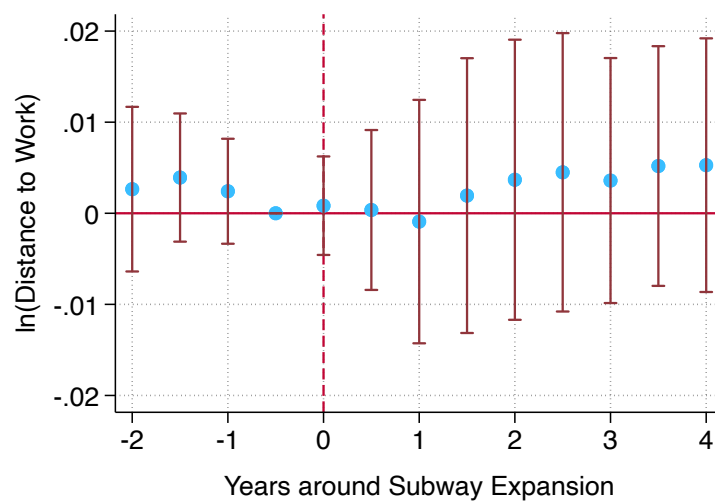
Notes: Each month we calculate sector-education-age average earnings. Then we calculate the difference of each worker's monthly earnings with this group average, and run the event study on the log of the absolute value of this difference, from the firms' perspective with firm fixed effects. We see that when the subway reaches the district of a firm, the gap between its worker's earnings and each worker's group average decreases. Coefficients are scaled by 0.42 to represent the effect on the average worker.

Figure 11: The Effect of Subway Expansion on Earnings: Permutation Test



Notes: We take the 38 treatment timing-intensity pairs and randomize them across the 38 districts, and estimate the event study on earnings of workers. We repeat this 60 times, and plot the results. The break in the trend is in the top 5%.

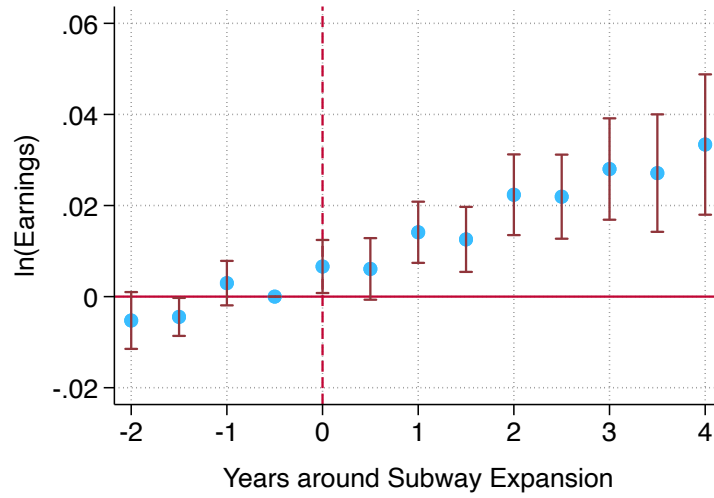
Figure 12: Another region as control: Where to Work



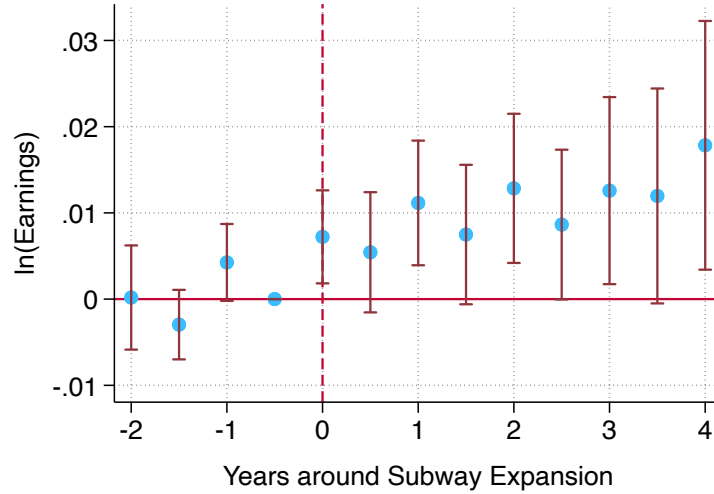
(a) Distance to Work

Notes: Stacked Dif-in-Dif using districts from the Bio-Bio region as controls. Coefficients are scaled by 0.42 to represent the effect on the average worker.

Figure 13: Another region as control: Earnings



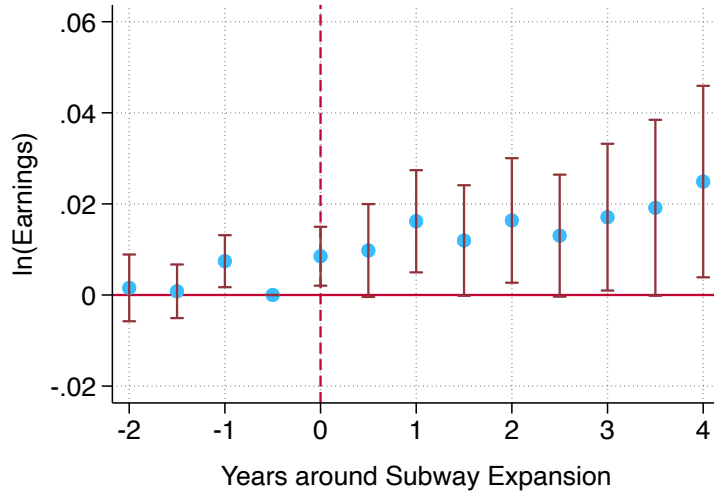
(a) Earnings



(b) Earnings - Stayers

Notes: Stacked Dif-in-Dif using districts from the Bio-Bio region as controls. Panel A uses worker fixed effects, while Panel B includes worker-firm fixed effects. Coefficients are scaled by 0.42 to represent the effect on the average worker.

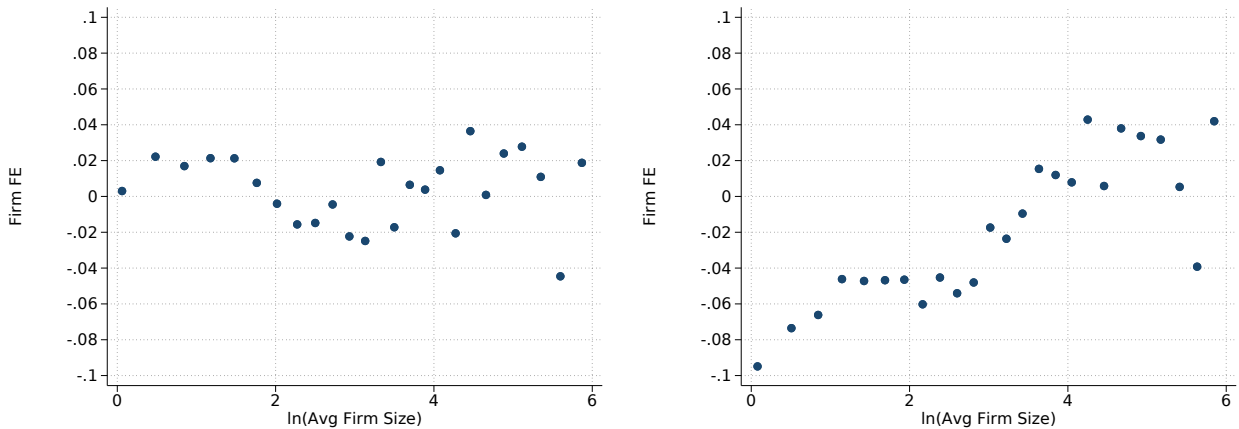
Figure 14: Another region as control: Earnings (Robustness)



(a) Ruling out hours/productivity

Notes: Stacked Dif-in-Dif using districts from the Bio-Bio region as controls. The regression includes worker-firm fixed effects, and only includes workers who work in districts that were not connected by the new subway line. Coefficients are scaled by 0.42 to represent the effect on the average worker.

Figure 15: Relationship between firm size and firm fixed effect

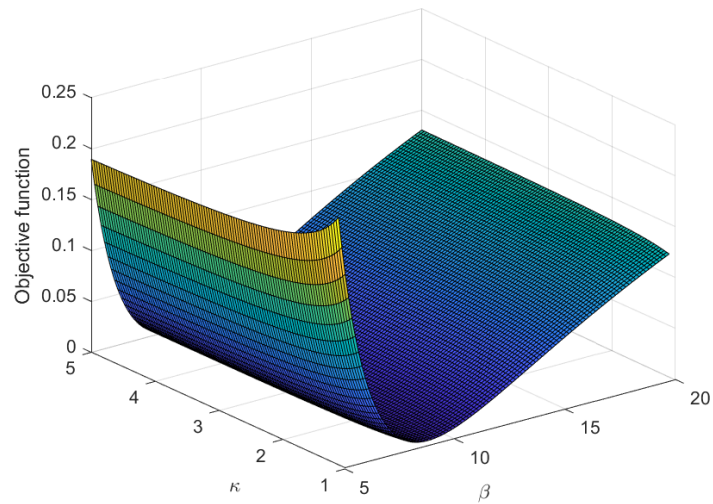


(a) 02-06

(b) 12-16

Notes: We estimate an AKM model for 2002-2006 and 2012-2016. Then do an employment-weighted binscatter of firm effects on $\ln(\text{average firm size})$ during each period, controlling for firm's district fixed effects.

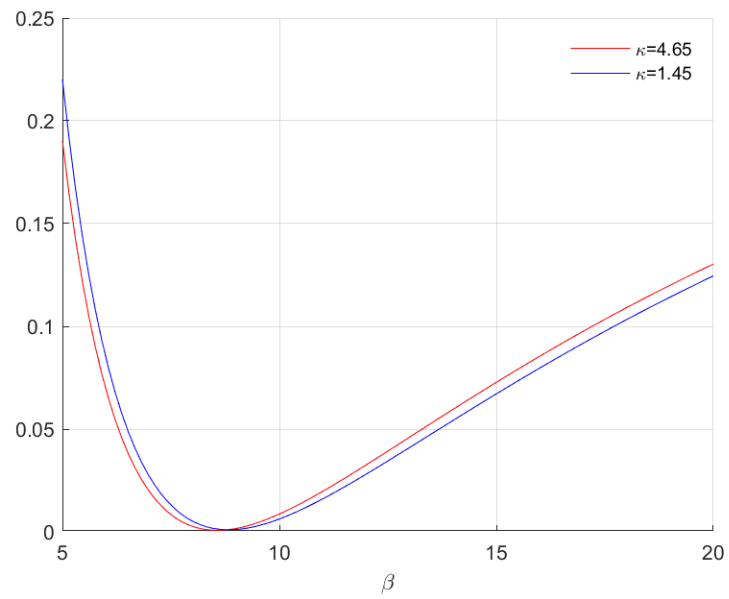
Figure 16: Objective Function-GMM



(a) Objective function

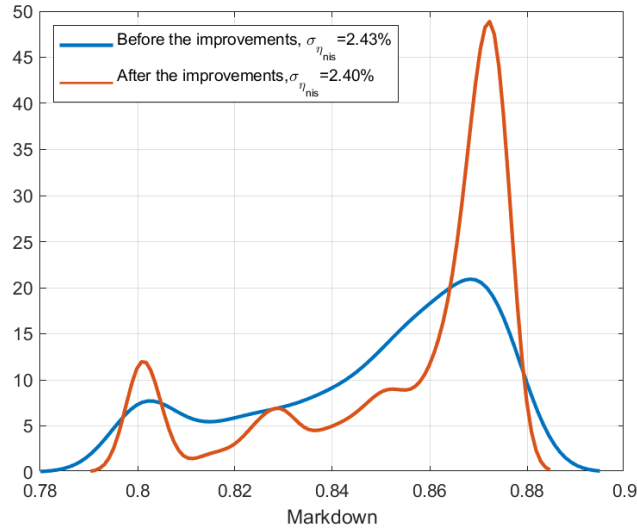
Notes: This figure plots the objective function of the GMM approach to estimate the main parameters of the model.

Figure 17: Objective function-constant κ

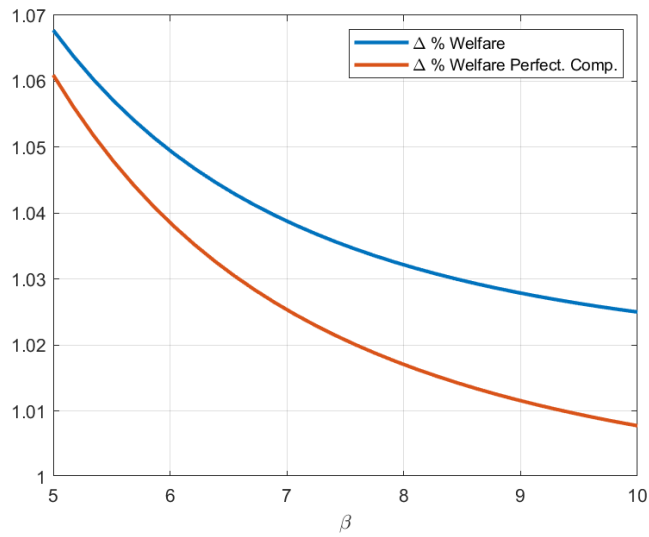


Notes: This figure plots the objective function for constant values of κ .

Figure 18: Simulation of the subway expansion: Welfare



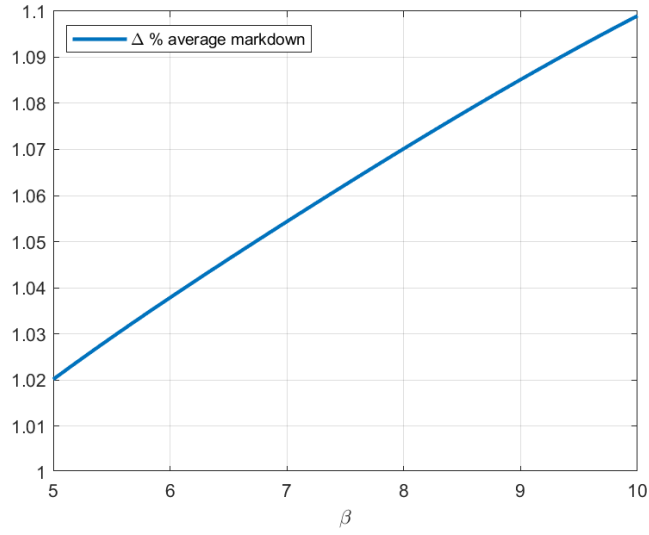
(a) Markdown



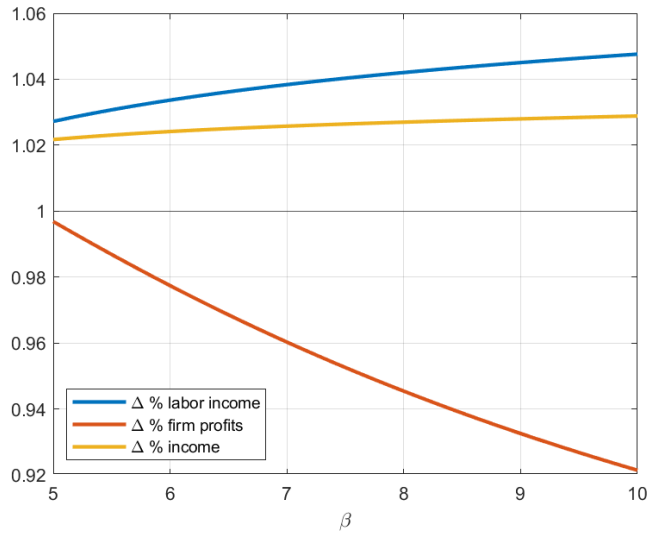
(b) Markdown percent

Notes: In panel A we simulate how the distribution of markdowns before and after the shock with $\kappa = 3$, and $\beta = 10$. In Panel B we show the change in welfare for different values of β .

Figure 19: Simulation of the subway expansion: Distributional Effects



(a) % Change markdown



(b) % Change in income

Notes: In Panel A we simulate how welfare changes when reducing commuting costs. In Panel B we simulate what % of the change in welfare is due to reduced variation in markdowns.

Appendix

Table A.1: Relationship between distance to subway and commute duration

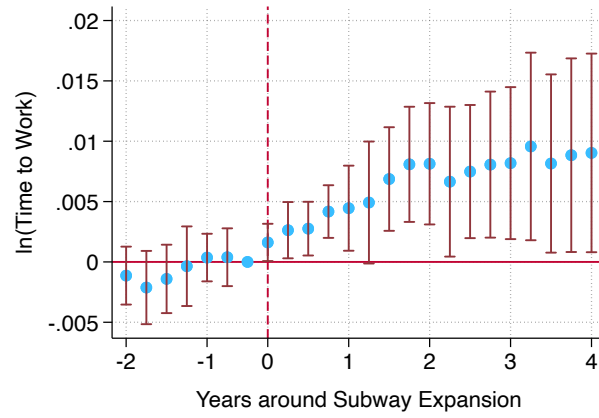
	(1)	(2)	(3)	(4)
	ln(Trip Duration)	ln(Trip Duration)	ln(Trip Duration)	ln(Trip Duration)
ln(Trip Distance)	0.20*** (0.024)	0.096** (0.048)	0.19*** (0.023)	0.093* (0.048)
ln(Distance of O to Subway)	0.072*** (0.0076)	0.077*** (0.0083)		
ln(Dist of O to Subw + Dist of D to Subw)			0.12*** (0.011)	0.098*** (0.010)
N	18417	14148	18417	14148
R2	0.55	0.66	0.55	0.66
OD District FE	Yes	No	Yes	No
OD Zone FE	No	Yes	No	Yes
Time FE	Yes	Yes	Yes	Yes
Std Errors	Cl at OD-District	Cl at OD-Zone	Cl at OD-District	Cl at OD-Zone

Standard errors in parentheses

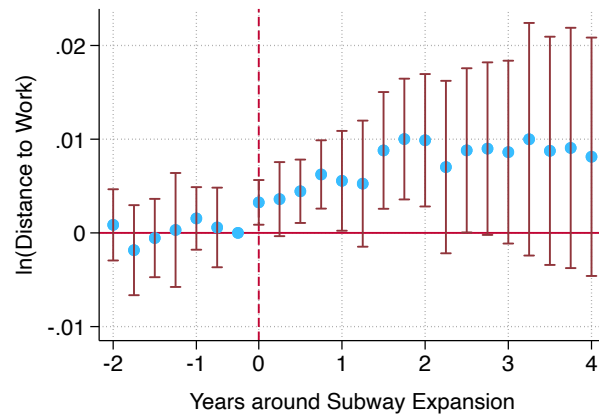
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Notes: These regressions use data from the 2001 and 2012 Origin-Destination surveys. OD District FE are fixed effects for each pair of origin-destination districts. OD Zone FE divides Santiago into 400 rectangular zones, and is a fixed effect for each pair of origin-destination zones. Only work trips that use public transportation at some stage are included in this sample. Dist of O to Subway is the euclidian distance from the trip-origin to the subway, and Dist of D to Subway is the euclidian distance from the trip-destination to the subway.

Figure A.1: Trimesters: Where to work



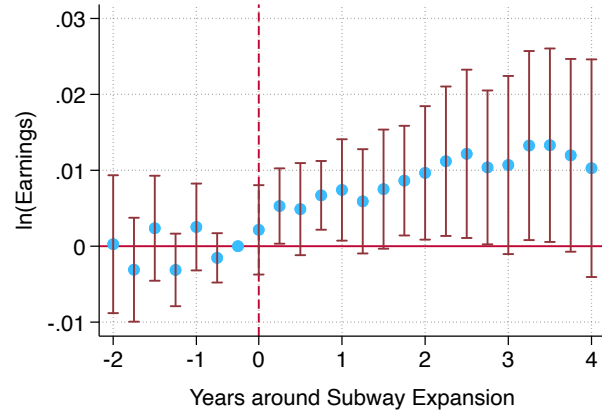
(a) Time to Work



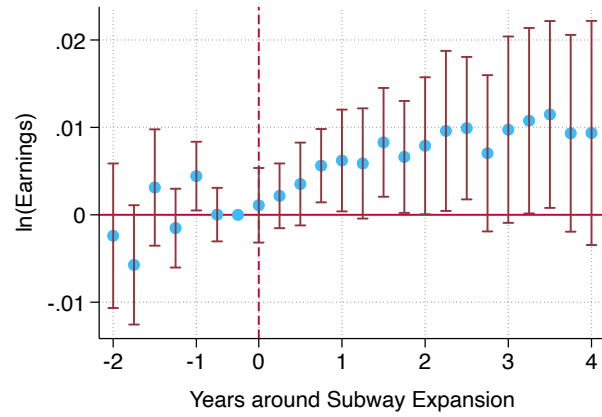
(b) Distance to Work

Notes: Event Study results on distance and time to work. Time to work is estimated before any subway expansion, and therefore is just another measure of distance, does not necessarily imply longer commutes. Coefficients are scaled by 0.42 to represent the effect on the average worker.

Figure A.2: Trimesters: Earnings



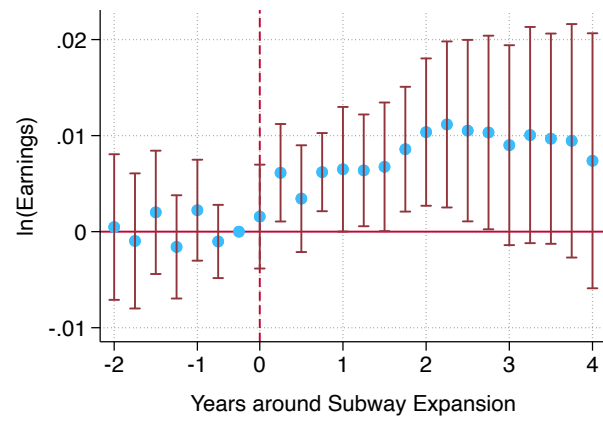
(a) Earnings



(b) Earnings - Stayers

Notes: Event Study results on earnings. Panel A using worker fixed effects, Panel B using worker-firm fixed effects. Coefficients are scaled by 0.42 to represent the effect on the average worker.

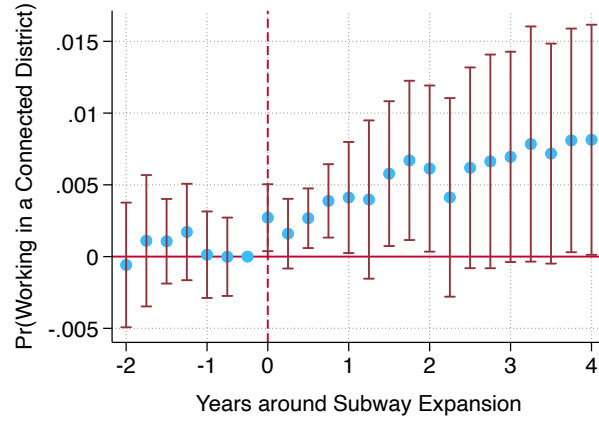
Figure A.3: Trimesters: Ruling out Labor Supply



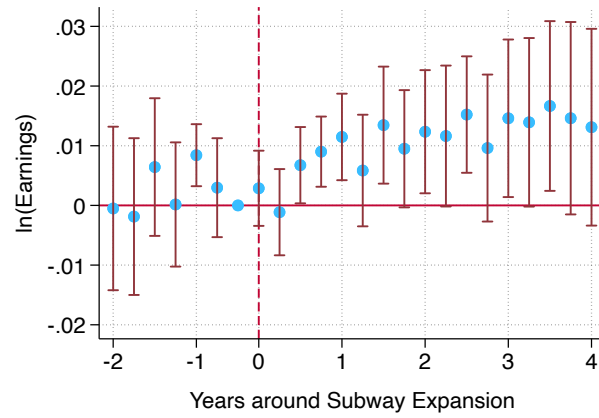
(a) Earnings - Stayers - District of Firm x Sector Fixed Effects

Notes: This event study includes Worker x Firm fixed effects, and Month X District of Firm x Sector fixed effects. Coefficients are scaled by 0.42 to represent the effect on the average worker.

Figure A.4: Trimesters: Worker Flows and Earnings of Unconnected



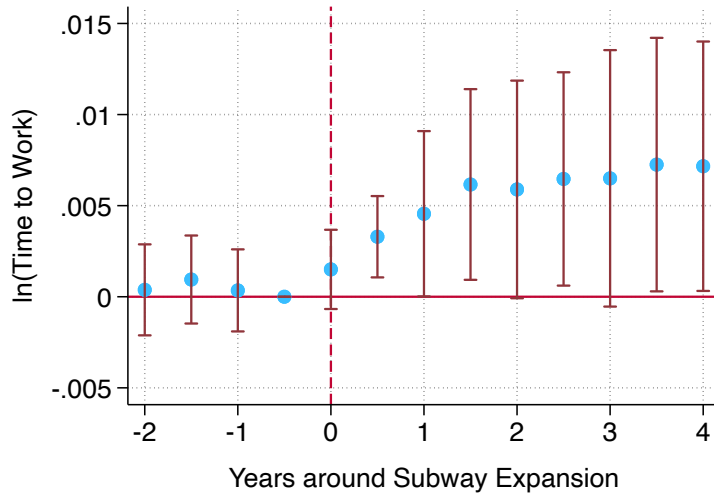
(a) Worker Flows



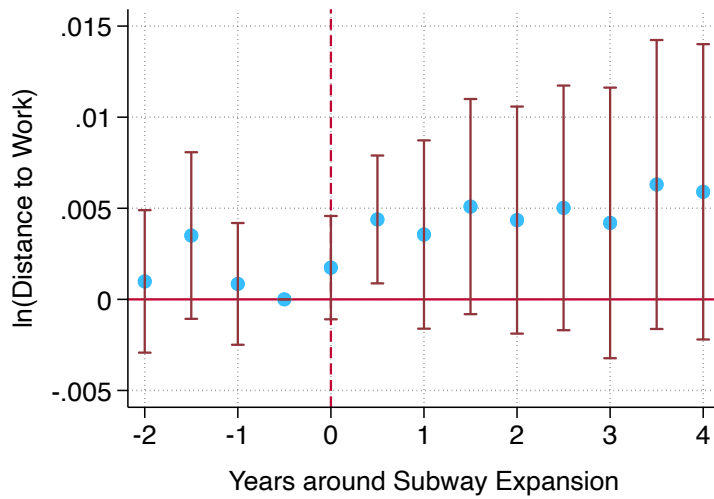
(b) Earnings - Stayers - Unconnected

Notes: For each treated district, we simulate commuting times before and after the treatment to all other districts. Then divide destination districts into above and below the median for each treated district. Above the median districts are referred to as connected districts, below the median as unconnected. Panel A shows that workers are more likely to work in connected districts, and Panel B shows that results on earnings using worker-firm fixed effects hold even for workers who are working in districts that did not get connected. Coefficients are scaled by 0.42 to represent the effect on the average worker.

Figure A.5: Stacked Dif-in-Dif: Where to Work



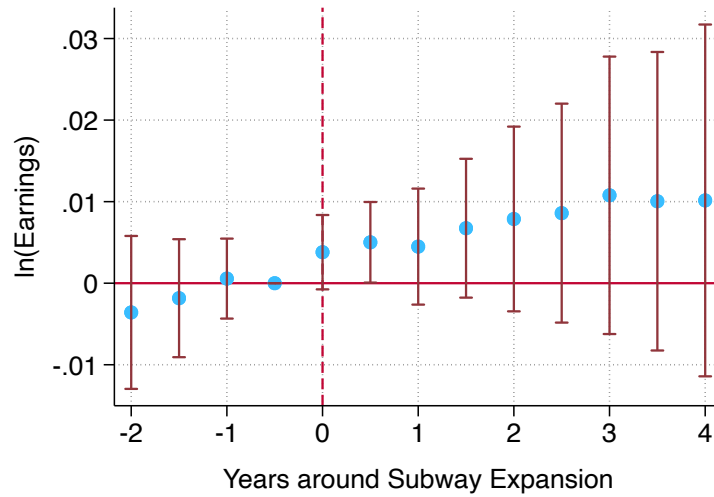
(a) Time to Work



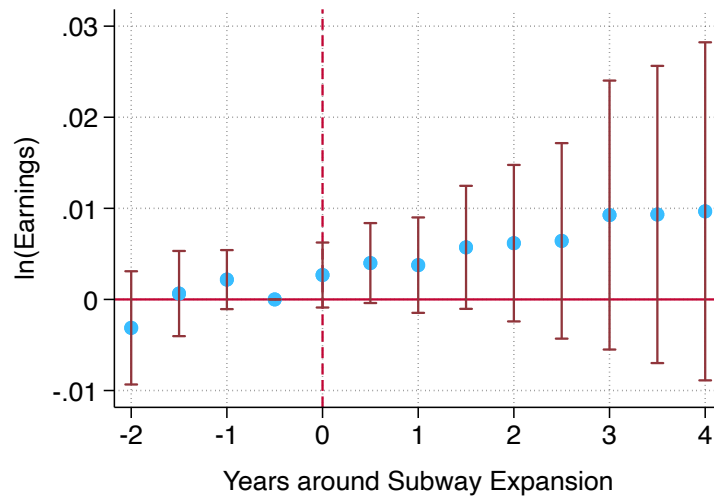
(b) Distance to Work

Notes: Stacked Dif-in-Dif using districts within wave with under 30% treatment intensity as controls for the treated districts in the wave. Coefficients are scaled by 0.42 to represent the effect on the average worker.

Figure A.6: Stacked Dif-in-Dif: Earnings



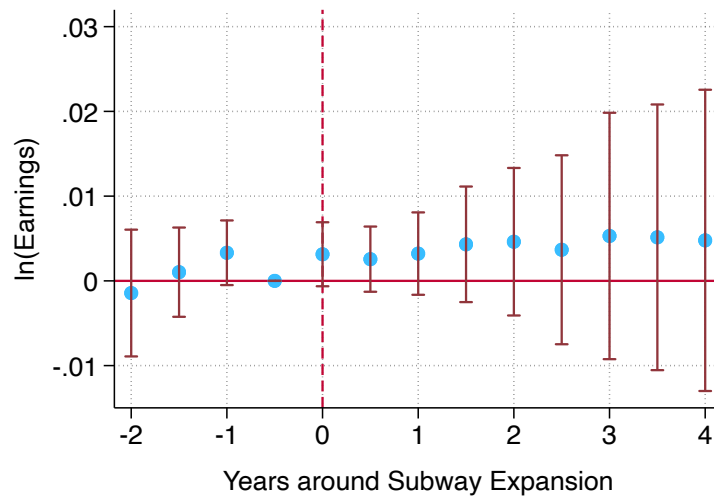
(a) Earnings



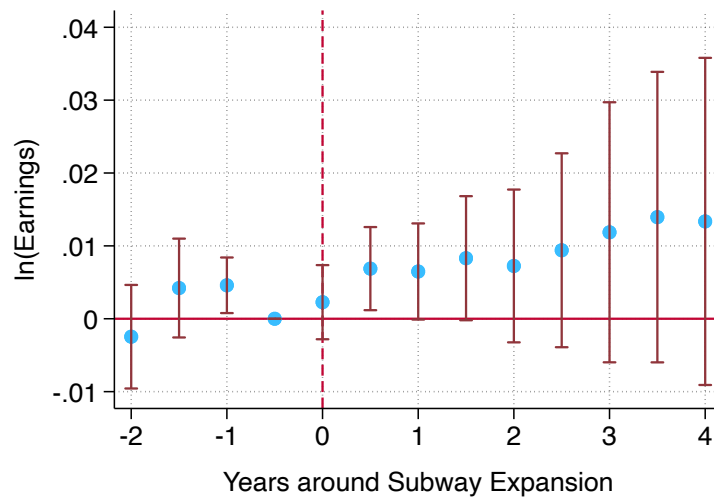
(b) Earnings - Stayers

Notes: Stacked Dif-in-Dif using districts within wave with under 30% treatment intensity as controls for the treated districts in the wave. Panel A uses worker fixed effects, while Panel B includes worker-firm fixed effects. Coefficients are scaled by 0.42 to represent the effect on the average worker.

Figure A.7: Stacked Dif-in-Dif: Earnings (Robustness)



(a) Ruling out labor supply



(b) Ruling out hours/productivity

Notes: Stacked Dif-in-Dif using districts within wave with under 30% treatment intensity as controls for the treated districts in the wave. Both Panel include worker-firm fixed effects. Panel A also includes firm's district-month fixed effects instead of only month fixed effects. Panel B only includes workers who work in districts that were not connected by the new subway line. Coefficients are scaled by 0.42 to represent the effect on the average worker.