The impact of commuter market access on a city's structural density: evidence from a substantial investment in transport infrastructure*

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Abstract

This paper studies the impact of investments in urban highways and subway stations on a city's structural density. We use microdata from Santiago, Chile, to analyze the effect of the inauguration of six urban highways and several subway stations in the mid-2000s on the floor to area ratio (FAR). We find that the average elasticity of the FAR to market access is 0.84 for all land use. This elasticity relies heavily on residential construction, with a FAR to accessibility elasticity of 0.48. Blocks whose residents belong to the poorer four income quintiles drive the previous result. Our findings provide some evidence that wealthy homevoters find ways to limit residential development near their residences, limiting the positive welfare effects of urban transport infrastructure.

Keywords— Transport and Land Use, Transport Economics, Transport Policies

1 Introduction

Transport infrastructure has a long-standing relationship with density patterns in cities and their development and growth. Lower commuting costs allow workers to live further away from their workplace to take advantage of lower prices of dwellings and possibly better access to amenities. In today's context of increased urbanization and climate crisis, understanding the effects of transport infrastructure in the shape of cities is crucial for promoting sustainable development.

Governments, especially in developing countries, spend a significant share of the GDP on urban transportation infrastructure, mainly road and rail transport. While both types of infrastructure provide better accessibility to people and firms, they vary in their effects on city growth. For example, while urban highways are often correlated with a city's sprawl, subways are commonly associated with urban density (Redding and Turner, 2015; Duranton and Puga, 2014, 2015).

This paper aims to shed light on the effects of transport infrastructure on the spatial allocation of economic activity. In particular, unlike most previous literature, it studies the impact of increased market access on a city's structural density, i.e., on its floor area ratio. We use a detailed dataset that includes the built-up surface at the Chilean Internal Revenue Service (SII) block-level, henceforth blocks or SII blocks. To uncover causal relations, we

*Preliminary and incomplete working paper exploit a substantial investment in urban transport infrastructure in Santiago, Chile. Between 2001 and 2010, the subway network increased by 36 percent (over 53 km), and over 200 km of urban highways were built.

To study the effects of increased market access, we use the variation in accessibility due to the new urban transport infrastructure's opening. Considering a band of three km around the new infrastructure, we work with a sample of around 35,000 blocks with an average size of 9,000 square meters.[1] In the spirit of Gibbons et al. (2019), we argue that by using this network-based accessibility index and controlling for location and infrastructure fixed effects, we control for the non-random location of the transport infrastructure. There is vast reduced-form evidence regarding the effects of transport infrastructure on intracity outcomes and the spatial distribution of activity. Investment in highways decentralizes population (Baum-Snow, 2007; Redding and Turner, 2015; Garcia-López et al., 2015; Baum-Snow et al., 2017) and manufacturing activity (Baum-Snow et al., 2017), and induces employment growth (Duranton and Turner, 2012). On the other hand, an investment in subways also causes population decentralization, although to a lesser extent than highways (Gonzalez-Navarro and Turner, 2018), and increases employment in suburban areas (Mayer and Trevien, 2017).[2]

A growing body of research on quantitative models studies the distribution of economic activity (see Redding and Rossi-Hansberg (2017) for a recent review). Among these, Tsivanidis (2019), Zárate (2019), and Heblich et al. (2020) focus on the effect of transport infrastructure on outcomes within cities. A relevant contribution of this strand of literature is to show that a gravity equation in commuting flows characterizes a wide array of urban models. In these models, floor space prices are a function of income by workplace for commercial use and income by residence for residential use (Heblich et al., 2020). In particular, Tsivanidis (2019) shows that commuter market access (CMA) summarizes the effect of the transportation network and directly determines outcomes such as population, employment, and prices.

Our study provides two main results. First, we find that a ten percent increase in CMA induces a 8.4 percent increase in the total floor area ratio (FAR), explained by a 4.8 percent increase in the residential FAR. Second, we find an increase in CMA does not affect the FAR in blocks whose residents belong to the richest income quintile. The overall effect is explained by the elasticities of FAR for the areas that belong to the first four quintiles. Preliminary analysis shows that baseline regulation is relatively stringent in the wealthiest quintile. This situation could be due to high-income residents' lobbying power to use urban regulation to block residential developments.

Our paper contributes to the empirical literature on the spatial distribution of economic activity in several ways. While Baum-Snow (2007),Garcia-López et al. (2015),Baum-Snow et al. (2017), Gonzalez-Navarro and Turner (2018), and Baum-Snow (2020) study decentralization of population in cities due to transport infrastructure changes, they do so by using two aggregate zones for the city, namely city center and suburbs. In this sense, our work is more closely related to Tsivanidis (2019), who studies the effect of the Bus Rapid Transit (BRT) system TransMilenio in Bogotá using data at the census tract level (which is around 12 times larger than the SII blocks in our data). Tsivanidis (2019) shows that commuter market access significantly affects real estate prices, employment, worker spatial reallocation, and welfare.

We depart from the literature by focusing on the floor to area ratio as the outcome and using micro-level data. First, our outcome may respond differently to shocks, where prices and population may react faster because of the mobility of these types of capital. Second, the granular level allows for providing a broader picture by looking at the heterogeneity of the effects. The quantitative models usually have one type of agent and floor space is computed by assuming a floor space production function and market-clearing conditions under perfect competition.[3] Tsivanidis (2019) is an exception as he models low- and high-skilled workers; however, he finds that the transport infrastructure did not affect the amount of floor space.

We also contribute to the literature by considering two types of infrastructure, subways, and highways, that increased accessibility for transit and cars. The nature of the highway network is also novel, as most of the literature

[1]As the treatment has a continuous form, there are no discrete treatment and control groups.

[2]There is also substantial evidence that property prices increase in the vicinity of highways (Levkovich et al., 2016; Theisen and Emblem, 2020) and subways (Gibbons and Machin, 2005; Ahlfeldt, 2013; Bowes and Ihlanfeldt, 2001).

[3]For example, Heblich et al. (2020) assumes that the quantity of floor space is a constant elasticity function of land values.

focuses on interstate highways or urban segments of interstate highways. Santiago's urban highway network was planned to provide better connectivity within the city, presenting a new angle to research regarding accessibility within a city and urban transport infrastructure.

2 Background and Data

We study the effect of a substantial investment in transport infrastructure in the Greater Santiago Area (henceforth, Santiago) between 2001 and 2010. During this decade, Chile's per capita GDP increased almost twofold from 9,937 USD to 18,129 USD (OECD, 2017), transitioning from a middle-income country to a high-income country (World Bank, 2019). Santiago accounts for more than 40 percent of the country's population and GDP (Banco Central, 2017).

Santiago is located in a valley, has an extension of approximately 838 km^2 (INE, 2014), slightly larger than New York City, and in the studied period (2001 to 2010) experienced a population increase of 17.4 percent, from 6,061,185 to 7,112,808 inhabitants (INE, 2017). During that same period, Santiago experienced a reallocation of the economic activity with a significant expansion of employment towards the north-east of the city (Truffello and Hidalgo, 2015), densifying that part of the city (Caballero, 2018). Santiago is also the place where most of the high-income and skilled workers live. Chile's Gini coefficient in 2000 was 0.55. Santiago's Gini coefficient has been relatively similar in the last two decades (Asahi, 2015). In 2009, Chile was within the 12 percent most unequal countries according to the Gini coefficient (Asahi, 2015).

2.1 Data

We obtain the data for built-up surface from the Chilean National Taxing System (Servicio de Impuestos Internos, SII). The SII categorizes built-up surfaces into different land uses and disaggregates such information at the SII block-level for 2001 and 2010. The land uses include commercial, educational, residential, industrial, and services.[4] This study focuses on residential and commercial space, which we define as the aggregation of services, and commercial land uses. The sample studied are those blocks located in the urban limit, within a 3km radius of a new subway station or an urban highway entry or exit. We winsorized the top .1 percent top FAR and changes in FAR values. This is 144 blocks, which is a 0.32 percent of all blocks.

We use Chile's 2002 population census carried out by the Chilean Census Bureau (Instituto Nacional de Estadisticas, INE) to derive the socioeconomic covariates at the SII block-level. Lastly, for proximity covariates such as distance to subways, urban highways, and the CBD, we calculate the distance from the transport infrastructure to each block's centroid using GIS tools.

The dataset used to characterize the urban regulation consists of 94,240 lots in eleven Municipalities of Santiago, around 9,400 blocks, between January 1997 and April 2019. This data was elaborated by an interdisciplinary team of the Escuela de Gobierno, Economics Department, and the Engineering Department of the Pontificia Universidad Católica de Chile with some inputs provided by TocToc, a real estate company, all based on information obtained by the transparency law from the municipalities (decrees, municipal ordinances, and communal regulatory plans).

This unique dataset contains the description of height in meters, floor area ratio regulation, building coverage ratio, and regulation on population density. Additionally, we consider the difference between regulation and the built floor area ratio as a real estate potential, as it assesses the percentage of available space for building.

The sample of blocks for the Greater Santiago Area has 45,041 blocks, from which 44,493 blocks are within Santiago's urban limit (INE, 2014). This sample remains constant in the study period, consisting of 36 municipalities that, on average, include 865 blocks.

[4]The land use purposes are commerce, education, residential, industrial (industrial and mining activity), services (including public administration, offices, and health), a category named as not considered (that includes vacant land, agricultural land, forests, and everything not defined and without information), and others (including hotel, motel, sports and recreation, cult and others) (Suazo, 2017).

3 Framework and empirical specification

The classic monocentric city model developed by Alonso (1964), Mills (1967), and Muth (1969) considers a linear monocentric city, where housing and land are allocated endogenously through competitive bidding. This model considers commuting costs that increase linearly with distance to the central business district (CBD). The remainder of the residents' income is consumed in housing and a numeraire good. In the residential equilibrium, if a resident moves marginally away from the CBD, she experiences an increase in commuting costs and therefore must experience a decrease in the housing consumption cost (Duranton and Puga, 2015). The tension between proximity to the CBD and prices, known as the Alonso-Muth condition, translates into a negative price gradient from the CBD.

Subsequent studies have extended the model to include multiple land uses, agglomeration and negative externalities, provision of amenities, among others. A recent strand of literature has advanced the understanding of the internal city structure by generalizing the relationship between the density of development and access to transportation infrastructure (see, e.g., Ahlfeldt et al., 2015a). Accounting for agglomeration, congestion externalities, amenities, and production, a class of urban models has shown that a single measure of accessibility summarizes the effect of a city's entire transit network on any location (Tsivanidis, 2019). The measure, usually referred as commuter market access (CMA), reflects access to jobs and considers the commuting times from a location to all others weighted by employment.[5]

Equation (1) shows the cross-section intracity model that is typically used to assess the impact of a transport infrastructure opening on outcomes such as prices and population density. In this study, we seek to estimate the effect of commuter market access Θ_{it} on floor area ratio (FAR).

$$\text{FAR}_{it} = \alpha_{it} + \beta \cdot \Theta_{it} + \gamma_i + \delta_t + \epsilon_{it} \tag{1}$$

where our geographical unit of analysis is the block i, and t is the year.

Redding and Turner (2015) summarize the standard inference problems in cross-section specifications such as the model in Eq. (1). First, the transport infrastructure is not located randomly. Second, in the presence of general equilibrium effects of transport infrastructure, separating spillovers from other location time-varying factors requires additional assumptions.

We partially address the first problem by studying the first difference version of equation (1). By doing so, we control for all blocks time-invariant unobserved characteristics and, at the same time, we are able to control for pre-determined baseline variables (X_{i0}).

$$\Delta FAR_i = \beta \cdot \Delta \ln \Theta_i + \phi \cdot X_{i0} + \delta + \Delta\epsilon_i \tag{2}$$

Still, if changes in the transport infrastructure (hence, in commuter market access) are correlated with changes in the time varying unobservables $\Delta\epsilon_i$, our estimates would still be biased. This would happen if, for example, planners locate the new subway lines based on expected structural density trends.

In absence of reliable instrumental variables for the new infrastructure, such as planned routes or historical routes, we deal with the potentially endogenous location of the infrastructure differently. First, we use a continuous variable (the change in CMA) and focus only on blocks that are close to the infrastructure (within 3km). Second, we control for location within the city through dummies that reflect the different areas of the city, and for distance to the nearest subway station in 2001 and to the main roads. Therefore, we identify the effect by looking at changes in accessibility, conditional on being in a targeted zone in a specific part of the city.

This is also the approach and argument put forward by Gibbons et al. (2019) to estimate the effects of new road infrastructure on employment and labor productivity in Britain. As they argue, it is key to use small geographical

[5] A similar measure summarizes the effect of transportation infrastructure to firms, reflecting access to workers.

units of analysis and controlling for proximity to the infrastructure. For example, two blocks at the same distance of a new highway ramp could experience significantly different changes in accessibility, for example, by being on different sides of the highway. We identify the impact of accessibility from this type of variation rather than from comparing areas that are near and far from the infrastructure. The following section provides suggestive evidence that the new infrastructure induces quasi-random changes in commuter market access within targeted areas.

For the second issue described in Redding and Turner (2015), we argue that the general equilibrium effects and the difficulty of separating spillovers from other location-specific time-varying factors are less of a concern for two reasons. First, the treatment is continuous; thus, the identification is not based on differences between a treated and a control group. Second, our measure, which is based on quantitative urban theory, captures the entire effect of the improvements on outcomes, considering all mechanisms (including general equilibrium effects).

Lastly, there is a third issue; the changes in CMA rely on using endogenous outcomes, such as post-treatment employment. To deal with this, following Tsivanidis (2019), we instrument for the change in market access by keeping labor outcomes and modal shares fixed at previous levels (more details in Section 3.1). In this way, we isolate the effect of travel time changes induced by the new infrastructure.

3.1 Accessibility index

As discussed above, the accessibility measure that we use is known as market access and it captures access to markets and opportunities in the city (Donaldson and Hornbeck, 2016; Gibbons et al., 2019). Following Ahlfeldt et al. (2015b), we use the following functional form for the market access:

$$\Theta_{it} = \sum_{j \neq i} \exp(-\beta \cdot T_{ijt}) \cdot w_{jt} \tag{3}$$

Market access for a block i is a weighted sum of the proximity to all destinations j at time t, where proximity is a decreasing function of the minimum commuting times, T_{ijt}. The weight factor w_{jt} should reflect that well-paid jobs are more important and therefore is usually a function of wages (Tsivanidis, 2019).

Ideally, we would have liked to use the wages by location by firms in greater Santiago at least for the baseline period (2001). However, to the best of our knowledge, such data does not exist. As a proxy for employment density, we use the built-up surface for commercial land use at time t as the weight in equation (3). Last, we use 0.01 as our β parameter based on the estimations by Ahlfeldt et al. (2015b) and Tsivanidis (2019).

As discussed above, the weights at the post-treatment year are mechanically endogenous. We instrument the change in market access $\Theta_{i\,2010} - \Theta_{i\,2001}$ for the change in market access when the weights are fixed at a predetermined level. To provide an additional source of exogeneity to the accessibility measure, we construct the weights using data from 1990. However, because we only have aggregated data for 1990, we use Chile's Estraus zones as the spatial unit of destination. These zones were constructed by the Ministry of Planning to analyze transport systems in the main cities of the country. For the Santiago Metropolitan area, there are 618 Estraus zones (see Niehaus et al., 2016, for details); consequently, for each of the approximately 35,000 blocks we calculate the market access considering 618 destinations weighted by their commercial floorspace.

3.1.1 Travel times

To compute the commuter market access in equation (3), we need to compute the minimum travel time between origin-destination pairs for each of the available modes, namely car, buses and subway. We also need to account for the fact that in different areas of the city, modes are used with different intensity. For example, a highway in areas in which the predominant mode is public transport should have a less significant impact than a subway line. To account for this, we also need to estimate a mode choice model to aggregate over modes.

To construct the minimum travel times for each block i to the 618 Estraus zones, we compute the origin-destination cost matrix using ArcGIS's Network Analysis Tools. We adapt the 2017 pre-census street network and the subway networks from the Observatory of cities of the Pontificia Universidad Católica de Chile (Observatorio de Ciudades UC), considering alterations to the urban highway network and subway network, as to replicate their versions in 2010 and 2001.[6] The speed parameters used are those documented in official reports of average travel speed for every transportation mode (SECTRA, a,b). For our baseline scenario, the average speed is 34 km/h for car trips, 23 km/h for public transportation (buses), 35km/h for subway trips, and 4km/h for walking. These speeds also apply to our 2010 network, except for the urban highways that have an average traveling speed of 60km/h. This information comes from Santiago's 2001 Mobility Survey (in Spanish, *Encuesta de Movilidad*) for the morning peak period. To account for access and waiting times for buses, we add four minutes to each bus trip as the bus network is extremely dense and buses stopped almost at every corner in 2001. For subway trips, the walking time is given by the network analysis tool.

Finally, in 2007 there was a renewal of Santiago's public transport system, which included a fare integration for buses and the subway, changing the decision-making process of individuals traveling on public transportation. Due to this change, public transport users in 2010 could travel by bus, walk to the subway, or take the bus to the subway for roughly the same price. Therefore, in the post-treatment year, 2010, we allow for the combination of both modes; we consider the same 4 minutes of waiting in the bus stop (Díaz et al., 2004), and an additional 4.9 minutes of transfer between modes (Guo and Wilson, 2011).

3.1.2 Aggregation by mode

We compute T_{ijt} in Eq. (3) as the weighted average of travel times by mode, using a predicted modal share for commuting trips as weights:

$$T_{ijt} = \sum_{r \in \{\text{car,bus,subway}\}} \omega_{ijt}^{r} \cdot t_{ijt}^{r} \tag{4}$$

Following Ahlfeldt et al. (2015b), we estimate a mode choice model using the modal split observed in the corresponding year in each of the 36 municipalities of Santiago's 2001 and 2012 Mobility Survey.[7] For each of the modal share observations we need to construct a travel time by mode that is representative of the municipality for each period. To do this, we use the travel times by mode obtained before using the GIS Software. For each block in a municipality m, we average travel times over all destinations and then average over blocks in that municipality. This provides a single travel time for each mode in each municipality for each period.

We then estimate the logit regressions in Eqs. (5)-(7) that explain the mode share of journeys in each municipality as a function of the average difference in driving times by car and bus (equation (5)), car and subway (equation (6)), and subway and bus (equation (7)).

$$ln(\frac{car_m}{bus_m}) = \beta_1 + \beta_2 \Delta_m^{cb} + \epsilon_m \tag{5}$$

$$ln(\frac{car_m}{subway_m}) = \beta_3 + \beta_4 \Delta_m^{cs} + \epsilon_m \tag{6}$$

$$ln(\frac{subway_m}{bus_m}) = \beta_5 + \beta_6 \Delta_m^{sb} + \epsilon_m \tag{7}$$

$$subway_m + bus_m + car_m = 1 \tag{8}$$

In these equations, m indexes municipalities, car_m is the share of journeys undertaken by car, $subway_m$ is the share of journeys undertaken by subway, and bus_m is the share of journeys undertaken by bus. Δ_m^{kl} is the average difference in travel time between modes k and l: car and bus in Eq. (5), car and subway in Eq. (6), and subway and bus in Eq. (7).

The weights used for each mode and each origin-destination pair, ω_{ijt}^{r} in Eq. (4), are the predicted modal shares of trips from the origin (block) to the destination (Estraus zone). Our estimated model delivers these modal shares

[6] As we are studying blocks within the urban limit, all modifications of peripheral roads are not a problem for our network.
[7] The survey is representative only at the municipality level, so we cannot estimate a more disaggregated model.

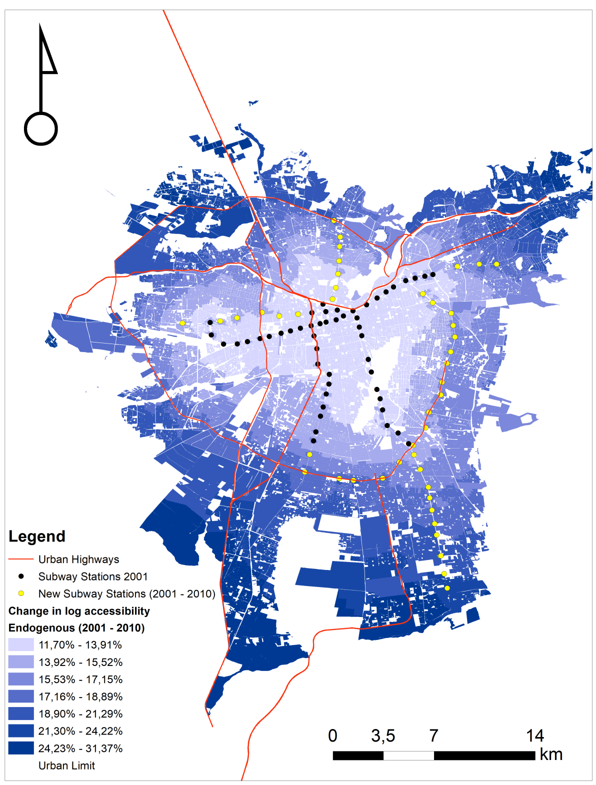
when evaluated the travel times by mode obtained with the GIS system as described in Section 3.1.1. Because the post-treatment weights are mechanically endogenous, as mentioned in Section 3.1, the weights for our instrument are also fixed at a predetermined level, using the information of 2001.

3.2 Predicted market access

The accessibility index described in Eq. (3) increases when travel times decrease. Changes in log accessibility from 2001 to 2010, for those blocks located within the urban limit and within the first 3 kilometers from a new subway station or an urban highway entry or exit. On average, accessibility improved by 43.36%, with a standard deviation of 3,80%, a median of 42.77%, and a 90th percentile of 49.10%. Changes in accessibility are similar amongst socioeconomic quintiles, with the lowest quintile experiencing an increase in accessibility of 43.31%. The second, third, and fourth quintile increased their accessibility in 42.99%, 43.74%, and 43.93%. Last, in the wealthiest quintile accessibility changed by 42.85%.

Figure 1 show the change in market access using 1990 commercial floorspace (the instrumental variable) and the endogenous change using the 2001 and 2010 commercial floorspace, respectively. In these panels, darker colors stand for larger changes in accessibility, varying within the treated area. The scattering that can be observed in these figures is expected for these types of indexes (Gibbons and Machin, 2005), and it provides a visual representation of the variation in the space.

Figure 1: Change in log accessibility (2001 - 2010) using 2010 and 2001 destination weights



Notes: The figure presents the change in log accessibility index from 2001 to 2010 using 2010 and 2001 accessibility weights. The sample studied are areas located in the urban limit, within a 3km radius of a new subway station or an urban highway entry or exit.
Source: Own elaboration. Maps use built-up land from the Chilean Internal Revenue Service (SII) and geo-referenced information on subways and urban highway from the Observatory of cities of the Pontificia Universidad Católica de Chile (Observatorio de Ciudades UC), and the 2017 pre-census street shapefile.

4 Results

Tables and figures in this section report the coefficients from the regression of floor area ratio (FAR) on the market access. As our first-difference regression in equation (2) has the change in FAR level as the outcome, we divide the coefficients by the mean baseline FAR to interpret them as elasticities. The sample used in all specifications consists of blocks inside the urban limit within 3 km of a new subway stations or an entry or exit of an urban highway.

4.1 Main Results

Results for the reduced form specification described in equation (2) show that a one percent increase in our measure of market access increases the overall FAR by 0.98 percent. It also shows that for residential FAR, the elasticity is 0.50 percent (results are available upon request in the full-size paper). While the increase in prices due to improved accessibility has been extensively documented, its impact on floorspace is far less studied. To the best of our knowledge, there is no direct evidence of this elasticity that we can use to compare with our findings. However, our resulting elasticities can be interpreted further by noting that it can be written as the product of the price elasticity of floor space and the elasticity of prices to market access changes.[8] Using the average price elasticity of floor space of 3 obtained by (Baum-Snow, 2020), our results imply a elasticity of prices to market access of 0.33 for all land uses and 0.17 for residential floorspace, which is in the range of previous estimations.[9]

Table 2 shows the results when we instrument the change in log accessibility from 2001 to 2010 with the change in log accessibility using data from 1990 to compute the (employment) destination weights and from 2002 to obtain the mode-specific travel time weights. Elasticities in Panel A's columns 1 and 2 are from the second stage, which are practically the same as the OLS coefficients in the reduce form. For all land uses, FAR to market access elasticity is 1.00 percent, and for residential land use is 0.55 percent. Panel B shows the results of the first stage of the endogenous market access on the instrument. The coefficient shows that a one percent increase in our instrument increases in 1.02 percent the endogenous accessibility measure.

We are in the presence of a strong instrument, as the Kleibergen-Paap rk Wald F statistic is 234824, well above the Stock-Yogo Critical Value for one endogenous variable of 16.38. Additionally, we assess for exogeneity of the specification with the Durbin-Wu-Hausman test. For all land uses, the p-value is 0.04, rejecting the exogeneity hypothesis; on the other hand, for residential land use, the p-value is 0.26, not rejecting the null hypothesis of exogeneity.

Table 1: OLS Results: Effects of accessibility on floor area ratio (2001-2010).

	(1) Total	(2) Residential
$\Delta \ln(Acc._{2010-2001})$	0.84^{***}	0.48^{***}
	(0.20)	(0.15)
Observations	34730	34730
R^2	0.05	0.03
F	77.35	82.14

Standard errors in parentheses

Notes: Table reports coefficients and robust standard errors from block-level regression, divided by the mean value of FAR in 2001. Variable $\Delta \ln(Acc._{2010-2001})$ is the change in log accessibility index from 2001 to 2010 using 2010 and 2001 accessibility weights. The sample studied are areas located in the urban limit, within a 3km radius of a new subway station or an urban highway entry or exit. Regressions in each column control for log accessibility 2000, log distance to main roads (Alameda, Ruta 5, and Vespucio), nearest subway station in 2001, Region controls which are dummies for whether the block is in the North, West, East, Center, South or South-West part of the city, and the baseline socioeconomic quintile of the block. Regression in column 1 shows results for all land uses, and column 2 shows results for residential land use.

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

[8] This is, $\epsilon^{\text{FAR}}_{\text{market access}} = \epsilon^{\text{FAR}}_{\text{price}} \cdot \epsilon^{\text{price}}_{\text{market access}}$

[9] Tsivanidis (2019), for example, finds an elasticity of 0.4

Table 2: IV Results: Effects of accessibility on floor area ratio (2001-2010)

	(1) Total	(2) Residential
Panel A: Two-Stage Least Squares		
$\Delta \ln(Acc._{2010-2001})$	1.00***	0.55***
	(0.20)	(0.16)
Observations	34730	34730
R^2	0.05	0.03
Wu-Hausman F(1,34713)	4.13 (p = 0.04)	1.25 (p = 0.26)
Panel B: First Stage		
$\Delta \ln(Acc._{1990})$	1.02***	
	(0.00)	
Observations	34730	
R^2	0.99	
Kleibergen-Paap rk Wald F statistic	234824	
Stock-Yogo weak ID test CV (10%)	16.38	

Standard errors in parentheses

Notes: Panel A reports coefficients and robust standard errors from block-level second stages in the two-stage least squares regressions, divided by the mean value of FAR in 2001. Panel A's column 1 shows results for all land use, and column 2 shows results for residential land use. The endogenous regressor in Panel A for both regressions is $\Delta \ln(Acc._{2010-2001})$ which is the change in log accessibility index from 2001 to 2010 using 2010 and 2001 accessibility weights. The instrument for both regressions is $\Delta \ln(Acc._{1990})$, which is the change in log accessibility index from 2001 to 2010 using 1990 accessibility weights. Panel B reports the coefficient of the first stage regression of the endogenous measure of accessibility, $\Delta \ln(Acc._{2010-2001})$, on the instrument, $\Delta \ln(Acc._{1990})$. The Stock and Yogo (2005) weak-identification critical value for one endogenous regressor (assuming i.i.d. errors) and a 10% maximal bias of the IV estimator relative to OLS at the 5% level is 16.38. We compare this critical value with the Kleibergen-Paap Wald F-statistic. The sample studied are areas located in the urban limit, within a 3km radius of a new subway station or an urban highway entry or exit. Regressions in each column control for log accessibility 2000, log distance to main roads (Alameda, Ruta 5, and Vespucio), nearest subway station in 2001, Region controls which are dummies for whether the block is in the North, West, East, Center, South or South-West part of the city, and the baseline socioeconomic quintile of the block.

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

We perform a series of robustness checks that are summarized in this Section. In a nutshell, we test the robustness of our results by considering different sub-samples, using alternative measures of accessibility and by including additional covariates. All the results are available upon request in the full-size paper.

4.2 Testing for pre-treatment trends

The main concern with our identification strategy is the potential endogeneity due to non-random infrastructure allocation. A typical mechanism of endogeneity is that governments assign improvements in transportation infrastructure based on differential growth trends. For example, they could be implemented to enhance the cities' growing areas or assist municipalities that are declining.

To address this issue, we test for pre-existing trends. Because 2001 is the earliest version of this dataset that includes square meters built at a block-level, we cannot test if the treatment is correlated with pre-treatment trends using the same level of disaggregation. Instead, we use the information on FAR at the level of "Estraus" zones. These zones are approximately 600 and the aggregate information on the floorspace by land use is made available by the Transport Planning Authority in Santiago (Programa de Vialidad y Transporte Urbano, SECTRA). This dataset is used for transportation planning and is available from 1990.

A second consideration for the test of pre-treatment trends is that our key variable, market access, captures the effects of the transportation infrastructure directly through travel times, but also through changes in employment that affect the relevance of each destination. Therefore, the standard test of regressing changes in the outcome (FAR) in the pre-treatment period (from 1990 to 2000) on changes in log-accessibility in the study period (2001 to 2010) is problematic. As we use commercial floorspace as the proxy for employment, the pre-treatment trends in floor area ratio are mechanically correlated with the change in accessibility because the dependent variable is constructed using floorspace in 2000 and the key variable floorspace in 2001. To avoid ambiguous results, we use the instrumental variable to study the pre-treatment trends.

Table 3 shows the results of the regression of changes in FAR between 1990 to 2000 on the changes in accessibility due to the travel time changes caused by infrastructure built between 2001 and 2010, but using data from 1990 to weight destinations. The control variables are the same as those used in Table 1. Columns 1 and 2 show the coefficients for the FAR for all land uses and residential use, respectively. The results are not statistically different from zero at the conventional levels, suggesting that there is no correlation between the improvements in the transportation infrastructure and trends in floor area ratio before their inaugurations. Our test therefore suggests that the non-random allocation of the infrastructure should not be a major concern.

4.3 Heterogeneity

We take advantage of the micro-scale of our data to study two important sources of heterogeneity: socioeconomic status and initial density (initial FAR). For the analysis, we interact our key variable $\Delta ln(acc)$ with an indicator for five equally sized groups (quintiles) based on the baseline (pre-determined) value of the variable.

Figure 2 summarize the results of the heterogeneity of the effect of changes in market access by socioeconomic level and 3 the heterogeneity with respect to initial structural density, i.e., the initial floor area ratio. Both analyses reveal a crucial result: the average effect of increased accessibility masks that there is a large group of blocks where increased commuter market access does not impact the residential floorspace. Figure 2 reveals that for the richest quintile the impact of increased market access is not statistically different from zero. Figure 3

The lack of impact of increased market access on the floorspace in the blocks that belong to the richest quintile may be due to a number of reasons. One possibility is that there is substantial preference heterogeneity; however, it is unlikely that it could lead to such extreme outcome. A second possibility is that there is an unobserved variable correlated with high-income that causes the result. A natural candidate is regulation, if high-income individuals are able to limit growth by enforcing height or FAR regulation. Finally, it is possible that these blocks are strongly developed before the transportation improvement, and the redevelopment that could increase the available residential

Table 3: Testing for pre-treatment trends (1990-2000)

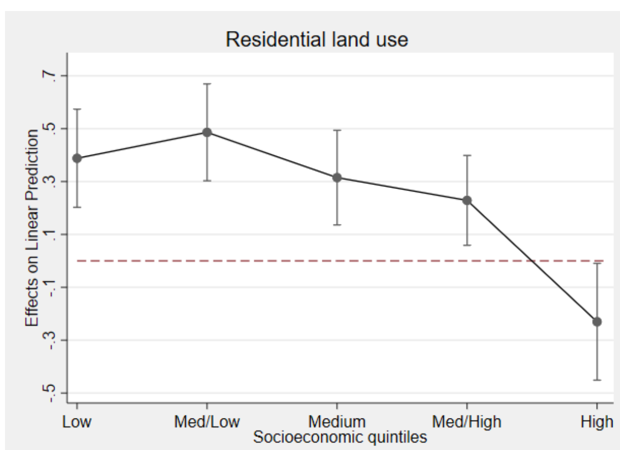
	(1) Total	(2) Residential
$\Delta \ln(Acc._{1990})$	0.98	-4.09
	(1.95)	(2.60)
Observations	508	508
R^2	0.32	0.22

Standard errors in parentheses

Notes: Table reports coefficients divided by the mean value of FAR in 1990 from Estraus level regression and robust standard errors. Variable $\Delta \ln(Acc._{1990})$ is the change in log accessibility index from 2001 to 2010 using 1990 accessibility weights. The sample studied are areas located in the urban limit, within a 3km radius of a new subway station or an urban highway entry or exit. Regressions in each column control for log accessibility 2000, log distance to main roads (Alameda, Ruta 5, and Vespucio), nearest subway station in 2001, Region controls which are dummies for whether the block is in the North, West, East, Center, South or South-West part of the city, and the baseline socioeconomic quintile of the Estraus zone. Regression in column (1) shows results for all land uses, and column (2) shows results for residential land use.

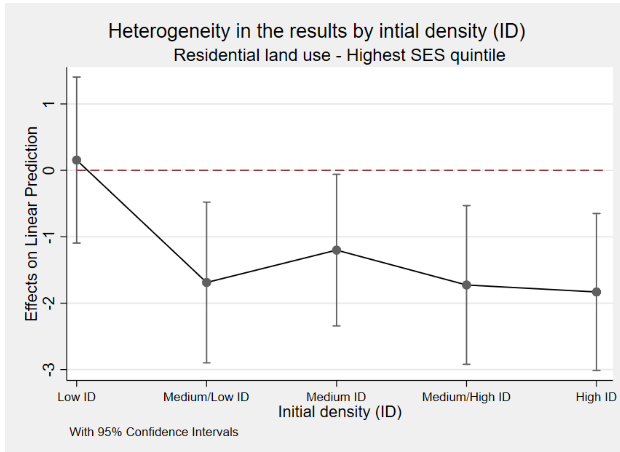
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Figure 2: Heterogeneity in the results for residential land use - Socioeconomic status



Notes: Figures present the coefficients (main effect and interacted term) from block-level regression, divided by the mean value of FAR in 2001. Variable $\Delta \ln(Acc._{2010-2001})$ is the change in log accessibility index from 2001 to 2010 using 2010 and 2001 accessibility weights. This variable interacts with the baseline socioeconomic quintile of the block to study heterogeneous effects. The sample studied are areas located in the urban limit, within a 3km radius of a new subway station or an urban highway entry or exit. Regressions in each panel control for log accessibility 2000, log distance to main roads (Alameda, Ruta 5, and Vespucio), nearest subway station in 2001, and Region controls which are dummies for whether the block is in the North, West, East, Center, South or South-West part of the city.

Figure 3: Heterogeneity in the results for residential land use - Initial Density



Notes: Figures present the coefficients (main effect and interacted term) divided by the mean value of FAR in 2001 from block-level regression. Variable $\Delta \ln(Acc._{2010-2001})$ is the change in log accessibility index from 2001 to 2010 using 2010 and 2001 accessibility weights. This variable interacts with the initial floor area ratio of the block (expressed in quintiles) to study heterogeneous effects. The sample studied are areas located in the urban limit, within a 3km radius of a new subway station or an urban highway entry or exit. Regressions in each panel control for log accessibility 2000, log distance to main roads (Alameda, Ruta 5, and Vespucio), nearest subway station in 2001, Region controls which are dummies for whether the block is in the North, West, East, Center, South or South-West part of the city, and the baseline socioeconomic quintile of the block.

floorspace is prohibitively costly. Among these three possibilities, the latter may also apply for the heterogeneous results with respect to initial structural density as the lack of impact appears only on the most developed blocks. In the following subsection we explore the role of regulation in shaping the results.

4.4 Initial Density in the highest socioeconomic quintile

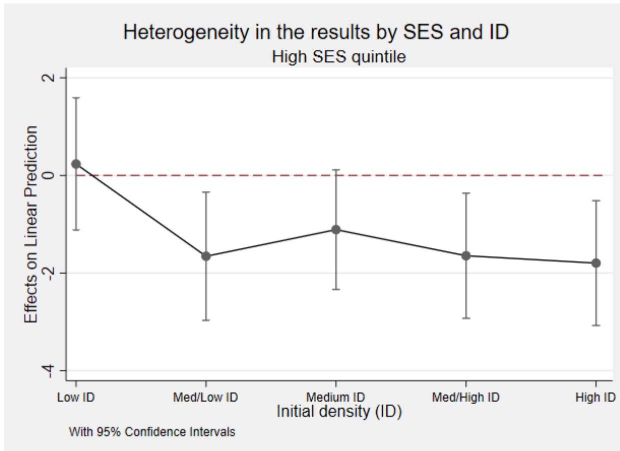
One possible reason for the results found in Figure 2 for the highest socioeconomic quintile is due to saturation in the supply of built-up residential land. Focusing just on blocks in the highest socioeconomic quintile, we assess the difference in changes in accessibility by quintiles of initial density, mirroring the exercise in Figure 3. A downward slope should appear if this hypothesis is true, where blocks with low initial density have higher effects than those with high initial density. Results in Figure 4 show that this is not the case, as elasticities amongst all density quintiles are relatively similar.

4.5 Allocation of economic activities

Another possible explanation for the results found in Figure 2 for the highest socioeconomic quintile is a trade-off between the residential and commercial built-up land. To assess this hypothesis, we reproduce the reduced form specification in Eq.(2) using as dependent variable commercial built-up land. Figure 5 shows results of the heterogeneity of the effects of changes in market access by socioeconomic level considering only blocks with built-up land in 2001 within the sample studied.

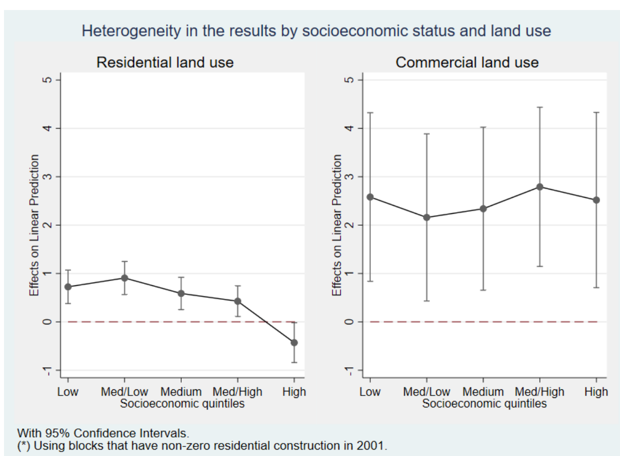
Residential results are similar to those found in Figure 2, while commercial land use results show positive and statistically significant elasticities for all socioeconomic quintiles. These results indicate that commercial land use reacts to changes in accessibility. Still, due to the homogeneity in the results by socioeconomic quintile, they do not allow us to conclude about substitution mechanisms between land uses in the block of the highest socioeconomic quintile.

Figure 4: Heterogeneity in the results for residential land use and blocks in the highest socioeconomic quintile - Initial Density



Notes: Figures present the coefficients (main effect and interacted term) from block-level regression, divided by the mean value of FAR in 2001. Variable $\Delta \ln(Acc._{2010-2001})$ is the change in log accessibility index from 2001 to 2010 using 2010 and 2001 accessibility weights. This variable interacts with the initial floor area ratio of the block (expressed in quintiles) to study heterogeneous effects. The sample studied are areas located in the urban limit, within a 3km radius of a new subway station or an urban highway entry or exit, and in the highest socioeconomic quintile. Regressions in each panel control for log accessibility 2000, log distance to main roads (Alameda, Ruta 5, and Vespucio), nearest subway station in 2001, and Region controls which are dummies for whether the block is in the North, West or East part of the city.

Figure 5: Heterogeneity in the results by socioeconomic status and land use



Notes: Figures present the coefficients (main effect and interacted term) from block-level regression, divided by the mean value of FAR in 2001. Variable $\Delta \ln(Acc._{2010-2001})$ is the change in log accessibility index from 2001 to 2010 using 2010 and 2001 accessibility weights. This variable interacts with the baseline socioeconomic quintile of the block to study heterogeneous effects. The sample studied are areas located in the urban limit, within a 3km radius of a new subway station or an urban highway entry or exit, and that in 2001 they had no construction in residential land use. Regressions in each panel control for log accessibility 2000, log distance to main roads (Alameda, Ruta 5, and Vespucio), nearest subway station in 2001, and Region controls which are dummies for whether the block is in the North, West or East part of the city. The first panel show results for residential land use, while the second shows results for commercial land use.

4.6 The role of regulation

To understand the role of regulation in shaping the distribution of economic activity, we use a unique dataset that details the maximum FAR and height of every block in a subsample of 11 municipalities. With this subsample we can control for the presence of regulation and study its role in the heterogeneity of the effects of market access on FAR.

To understand the role of the regulation on the changes in FAR, we provide additional analysis. One option is that regulation is stringent in blocks in the highest socioeconomic quintile. Preliminary analysis shows that baseline regulation is relatively low in the wealthiest quintile. Table 4 shows average values of REP for residential land use, regulation of floor area ratio, and regulation in height, all at our baseline levels. These statistics show lower average values for the fifth quintile relative to all four indicators.

Table 4: Average regulation indicators by socioeconomic quintile at baseline

	(1)	(2)	(3)
	$\text{REP}_{Residential}$	FAR	Height
Total	76.82	4.06	41.81
	(1818.51)	(4.48)	(46.42)
Lowest quintile	143.00	4.67	44.51
	(62.13)	(0.09)	(0.92)
Medium/Low quintile	72.58	4.35	42.94
	(24.93)	(0.09)	(0.90)
Medium quintile	99.45	4.84	49.79
	(51.27)	(0.12)	(1.33)
Medium/High quintile	54.83	6.14	64.90
	(34.02)	(0.19)	(2.05)
Highest quintile	4.64	1.70	22.38
	(0.54)	(0.06)	(0.59)

Standard errors in parentheses

Notes: Table reports mean and standard errors of the initial real estate potential of the block (REP) of residential land use (column 1), initial floor area ratio regulation (column 2), and initial height regulation (column 3). The sample studied are areas from a subsample of 11 municipalities with data on regulation, located in the urban limit, within a 3km radius of a new subway station or an urban highway entry or exit.

5 Summary and conclusions

This paper studies the effects of the inauguration of subway stations and urban highways on floor-are ratio (FAR). A one percent increase in our measure of market access increases the FAR by 0.84 percent. For residential land use, FAR elasticity with respect to market access is 0.48.

We take advantage of our data's micro-scale to study two sources of heterogeneity: the residents' socioeconomic status, and the initial density of the block. The effect of increased market access on the floor area ratio is significant in both economic and statistical terms in blocks whose residents belong to the first four income quintiles. By contrast, the effect mentioned above is non-significant both in economic and statistical terms for blocks whose residents belong to the richest income quintile. We hypothesise that this heterogeneity is partially due to high-income residents' high lobbying power that enables them to use urban regulation to block residential and commercial developments induced by urban transport infrastructure.

Our results imply that the welfare effects of investments in urban infrastructure are possibly lower in blocks whose residents belong to the wealthiest income quintile relative to the remaining blocks. In turn, our results imply that an exciting area for future research is to understand the mechanisms through which high-income residents block residential developments through regulation.

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