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Rapid Transit, Labor Market, and Business Growth: The case of São Paulo, Brazil

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Dissertação apresentada ao Programa de Pós-Graduação em Economia Aplicada da Universidade Federal de Juiz de Fora como requisito parcial à obtenção do título de Mestre em Economia Aplicada. Área de concentração: Economia Regional e Macroeconomia

Orientador: Prof. Dr. Admir Antonio Betarelli Júnior

Coorientador: Prof. Dr. Ricardo da Silva Freguglia

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RESUMO

Nas últimas duas décadas, a Região Metropolitana de São Paulo recebeu uma série de investimentos em sua rede de transporte coletivo, justificados com base em melhorias de acessibilidade ao conectar indivíduos a postos de trabalho, a instituições de saúde e educação e a atividades de lazer. Mas outra razão para ampliar a rede de transporte são seus desdobramentos na economia por meio do crescimento na atividade das firmas, associado na literatura de economia urbana ao conceito de economias de aglomeração. Para investigar se essas externalidades estão presentes em São Paulo, esta dissertação estima o impacto da nova Linha 4 e da expansão das linhas 2, 9 e 12 no emprego, salários e surgimento de novas empresas, a partir da Relação Anual de Informações Sociais (RAIS). As unidades foram geolocalizadas no nível da empresa e em uma grade espacial de alta resolução e, em seguida, selecionadas com base no tempo de caminhada até as estações por um algoritmo de rotas. O método de diferenças em diferenças (DiD) escalonado foi adotado para capturar diferenças nos resultados de acordo com a data de tratamento. Como as características espaciais também afetam os possíveis resultados, as regiões foram analisadas separadamente e em conjunto. Os resultados gerais apontam para ganhos de 11,3% no emprego e 9% em novas empresas, mas sem ganhos salariais significativos. Não houve mudança na média de trabalhadores por empresa, o que indica que os ganhos de emprego vieram de novas empresas. Os resultados variam entre as linhas, com os maiores impactos ocorrendo na região da linha 9. Além da evidência empírica inédita para São Paulo, a principal contribuição deste trabalho é a elaboração de um referencial para a aplicação do novo DiD escalonado no contexto de políticas de transporte coletivo, com atenção para as características espaciais.

Palavras-chave: Transporte coletivo, economias de aglomeração, mercado de trabalho.

Códigos JEL: R41, J61, O18.

ABSTRACT

In the past two decades, the São Paulo Metropolitan Region received a series of investments in its rapid transit network. They are justified based on improved accessibility, by connecting households to their jobs, health and education institutions, and leisure activities. But a second reason for transit improvement is its wider impact on economic activity, through additional growth in business activity, associated in the urban economics literature with the concept of agglomeration economies. To investigate whether those externalities are present in São Paulo, this thesis estimates the impact of the new Line 4 and the expansion in Lines 2, 9, and 12 on employment, wages, and business growth, using data from the country's employer-employee dataset (RAIS) on formal jobs. Units were geolocated in two stances—at the firm level and a high-resolution spatial grid—and then selected based on walking times to stations by a routing algorithm. A staggered differences-in-differences (DiD) approach was adopted to capture outcome differences based on treatment timing. Since spatial features also affect potential outcomes, regions were analyzed separately and jointly. Overall results point to gains of 11.3 percent in employment and 9 percent in new firms, but no significant wage gains. The average number of workers per firm did not change, indicating that employment gains came from new companies rather than the growth of the existing ones. Results vary between transit lines, with the biggest impacts ocurring in the Line 9 region. In addition to the unique empirical evidence for São Paulo, the main contribution of this work is elaborating a framework for applying the novel staggered DiD in the context of transit policy, paying attention to spatial features.

Keywords: Rapid transit, agglomeration economies, labor market.

JEL Codes: R41, J61, O18.

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1 Introduction

Society does not exist in a vacuum. This rather obvious statement implies that more than a mere grouping of constructions and people, urban spaces are the arena where human life—people's actions and their consequences—takes place. It is no coincidence that the world's greatest cities are where they are and that they have a disproportionate concentration of highly productive and diverse activities. First, the role played by local features such as natural resources in the economy has been investigated since the origins of economic thought, to the point of being a consensual, even trivial fact in present times. Second, distance matters in the sense that it hampers the exchange of goods and ideas, also a concept exhaustively debated from the early works of von Thünen to the New Economic Geography (Krugman, 1991; Marshall, 1890; Von Thünen, 1966).

Negative externalities and other constraints to urban growth are also widely described, as population and density increases can strengthen economic performance as long as infrastructure and built environment catch up. To cite some of the biggest constraints: Lack of housing stock and of affordable options prevent further entry of individuals that could contribute to growth or outbid marginalized groups that cannot keep up with rising prices. Underprovision of amenities such as parks or schools makes urban spaces less desirable to productive agents. Deficient transport provision leads to overcrowded public transit and traffic jams—resulting in longer commutes and higher fatigue—that ultimately have a similar effect of shrinking the city size since some workers become unable or unwilling to partake in the local labor market (Behrens and Robert-Nicoud, 2015; Capello and Nijkamp, 2019; Duranton and Puga, 2004; Eberts and McMillen, 1999; Marshall, 1890; Redding and Turner, 2015; Von Thünen, 1966; White, 1999).

A large body of empirical studies points out increasing returns to density and the role of transport costs as an intermediator. A survey of 300 studies found, on average, that a 10 percent increase in economic density is associated with annual *per capita* welfare gains of US$270 and welfare losses of US$93—over a third of it in congestion costs (Ahlfeldt et al., 2018). Gonzalez-Navarro and Turner (2018) investigated over 600 cities worldwide and found evidence that while subway networks do not increase overall city size, sprawl effects are smaller than for highways; moreover, ridership data suggest a migration from other transport modes. Subways are also a source of positive environmental and health externalities. Gendron-Carrier et al. (2022) analyzed 58 new subways across the globe and for 23 of them, air pollution fell consistently in the years following system openings, especially for the most polluted cities. They also can avoid deaths provoked by respiratory diseases.

In turn, emerging nations face different urban issues than richer countries. While the former may need to focus on requalifying mature, more stable cities (Ahlfeldt et al., 2018), the latter needs to tackle issues such as violence, health diseases, and long commutes in fast-growing cities (Bryan, Glaeser and Tsivanidis, 2020), eventually with higher institutional and monetary constraints that contribute to increasing the lag between urban growth and infrastructure provision

In the Brazilian context, from the 1930s onwards, the country began an intense urbanization process, becoming a mostly urban country in the 1970s (Matos, 2012). Nevertheless, investment in transport infrastructure has failed to keep pace: Between 2011 and 2021, while the country's largest metropolitan regions experienced a seven percent to 20 percent population growth, the motorization rate increased by between 22 percent and 57 percent. Albeit a sign of Brazil's recent progress in promoting wealth for lower-income citizens and a result of government policy directed at the automobile industry (Santos et al., 2015), this trend is also symptomatic of a history of low investment in rapid transit. In all metropolitan regions in the country, the proportion of the population near medium- and high-capacity public transport stations is no more than 20 percent.

To change this reality in the country's biggest metropolitan regions, investments in the order of R$ 454 billion (in 2024 values) are necessary to provide public transport networks to attend to commuting needs and make progress towards decarbonization policies; 65 percent of this amount concentrated in São Paulo, Rio de Janeiro, and Belo Horizonte (Santos et al., 2015). Although the country's history of low investment in rapid transit is the result of fiscal restrictions and policies that prioritized the automobile, there have been efforts to include public transport in the federal budget since the 2000s, especially after Brazil was announced as the host of the 2014 World Cup. However, several projects have not evolved due to the lack of solid studies for their implementation: In part, this scenario results from a lack of studies and indicators at the national level on urban mobility (Santos et al., 2015).

This thesis aims to evaluate the impact on wages, employment, and business creation of rapid transit expansion in the São Paulo Metropolitan Region (RMSP)—the largest metropolitan area in Brazil, second in Latin America, and seventh in the world (United Nations, 2019), with over 20 million inhabitants. From 2006 to 2019, RMSP gained 31 new rapid transit stations in 62 kilometers, distributed in eight different lines. Four of them are analyzed (lines 2, 4, 9, and 12) covering the 2006-2014 period and although they were constrained to limits of the capital, some of them are close to other municipalities in RMSP, which were also included.

Data comes from the official government employer-employee dataset covering formal job relationships from 2003 to 2017 and building a counterfactual scenario based on firms farther away from transit stations. After geolocating addresses, firms are selected to compose the panel under the treatment category if their walking distance to a new station is up to 30 minutes. Those between 31 and 60 minutes are part of the control group and the remainder are not included. Walking times are calculated using the `r5r` routing algorithm, based on the paths provided by OpenStreetMap. The analysis is conducted at two levels: at the firm and at a spatial hexagonal grid with 10-hectare cells.

Two estimation techniques under the difference-in-differences (DiD) category are employed to recover the impacts: the standard two-way fixed effects (TWFE) in the static and dynamic (event study) version, for reference, and the novel staggered approach of Callaway and Sant'Anna (2021b). The latter has the advantage of being free from cross-period contamination, an issue that arises in TWFE settings, as Goodman-Bacon (2021) pointed out. This is possible since separate parameters are estimated both over time and for each treatment cohort (defined by the time units get treated). Besides, the parallel trends assumptions are less strict than in TWFE and other estimators. This accommodates situations such as when the potential outcome of treated and untreated units do not follow the same path before the intervention but then do follow due to exogenous factors in the economic environment.

In large urban agglomerations, urban dynamics vary between different regions (White, 1999), which in turn affects local labor markets. To deal with spatial heterogeneity, five different models are estimated, one for each line and another for all of them, enabling comparisons between regions, in addition to the two levels of analysis (firm and hexagon). The group-time parameters are analyzed in three aggregation schemes: an overall parameter for the whole period, average effects by cohort, and average effect by length of exposure regardless of cohort.

Interest in analyzing the impact public transit provision has increased over the past decades, especially following the availability of geolocated microdata on job relationships (Credit, 2019; Vickerman, 2017), following the DiD framework, but with varying results. Insignificant impacts were found for the Uppsala, Sweden (Åslund, Blind and Dahlberg, 2017), Charlotte, USA (Canales, Nilsson and Delmelle, 2019), and Los Angeles, USA (Severen, 2023); while negative impacts following an exogenous service cut was identified in New York, USA (Tyndall, 2017) and positive results of service expansion are notably found in Latin America, such as BRT expansion in Lima, Peru (Scholl et al., 2018) and BRT, LRT, and Subway expansion in Rio de Janeiro, Brazil (Campos, 2019).

Outside econometrics, computable general equilibrium (CGE) analysis for the São Paulo subway (Haddad et al., 2015) pointed to positive economic benefits related to the network in the productive system of the city, the state, and the country. More recently, structural models simulating integrated labor and real estate markets have shown significant welfare benefits related to rapid transit, such as the Ahlfeldt model applied by Tsivanidis (2019) for the BRT network of Bogotá, Colombia.

This study's overall findings at the hexagon level resonate with the Latin American body of literature for increases in employment (estimated at 11.3 percent) and the number of firms (9 percent), whereas the lack of impacts on wages is more aligned with the European case. The biggest differences arise at the firm level and when lines are disaggregated: negative impacts were found for the average wage in firms near Line 2 (-1.98 percent) and the average number of workers in firms close to Line 12 (-7.23 percent). However, employment at the hexagon level did not change for the latter, suggesting a compositional change on the distribution of average workers per firm.

The contribution of this thesis is twofold. First, it provides evidence on how local transit policy performed in generating outcomes out of rapid transit expansion. Moreover, the case of São Paulo is worth analyzing not only for the city's importance in the local and global economies but also as it presents a unique case of commitment (albeit with shortcomings) in rapid transit deployment throughout the last five decades, especially in the Latin American context. Since the inauguration of the city's first subway line in 1974 and the restructuring of suburban rails in the 1990s-2000s period, the metropolitan area now enjoys a 372-kilometer network that carried over 7.9 million daily passengers, as of 2019 (CPTM, 2020), highlighting its role in integrating the region's labor market.

Second, this thesis expands the applied econometrics and place-based policies literature in general, but especially in urban economics, by applying the novel staggered DiD framework developed by Callaway and Sant'Anna (2021b). This approach has two advantages over the traditional two-way fixed effects (TWFE) static DiD and dynamic (event study) methodologies applied in the studies mentioned above. First, they consider a one-time intervention, either with two periods (pre- and post-treatment) in the static case or in periods relative to treatment in the dynamic case. This is not the case in São Paulo and in many cities worldwide, where transport infrastructure is implemented gradually. In these stances, TWFE estimators are subject to contamination due to heterogeneity in treatment timing; for instance, it may be the case that the first treated regions benefit relatively more from transit expansion than the latter ones in terms of labor market outcomes. The staggered DiD method addresses this heterogeneity by dividing groups according to their treatment period, allowing more precise estimates of local impacts. To this date, no other study has used the staggered approach in evaluating transit policy.

A final contribution regards the research design concerning treatment selection. While other works delimit treatment regions inside distance buffers, this thesis uses isochrones, which are calculated using real paths between a firm and a station, and therefore provides more precise delimitation of the study area, preventing incorrect selection of a firm for the treatment and control group.

1.1 Structure of the thesis

Chapter 2 first provides a review of the main theories in urban economics briefly exposed in this introduction, with the aim of sustaining the proposed hypothesis with the current paradigm in urban economics. First, Section **2.1.1** focuses on the fundamentals of agglomeration economies that establish a transmission channel from changes in accessibility to the analyzed outcomes. Second, theories on business location decision are exposed in Section **2.1.2** to help outline how firms respond to changes in accessibility. Moving the focus to the studied area, Section 2.2 provides a brief history of urban development and transit policy in the São Paulo Metropolitan Region, defining properly the rapid transit systems analyzed and what lines have been implemented.

Next, Chapter 3 starts by detailing the employer-employee dataset used (3.1), the methodology used to separate data in space (3.2), and how individuals are aggregated into firms and firms into hexagons depending on each outcome (3.3). These sections are directly linked to the identification strategy explained in the next chapter (4), where a brief discussion on the issues with TWFE estimation is presented in Section 4.1 and followed by the Callaway and Sant'Anna (2021b) model in Section 4.2. After building a theoretical case and establishing the required hypothesis and empirical strategy, results are presented in Chapter 5 accompanied by a discussion linking estimates with theory. Chapter 6 concludes this thesis with final remarks and policy implications. Appendices A and B and Annex B are presented after the references.

2 From Rapid Transit to Economic Growth: Establishing the Link

This chapter explores the relationship between investment in rapid transit and economic growth in the first section, focusing on labor market transmission channels and business location decisions, according to the body of literature on urban economics. They are not intended to be used as formal models but rather an investigation on the mechanisms of agglomeration economies. It is followed by background information on rapid transit, land use, and economic development in the São Paulo Metropolitan Region. The final section concludes the chapter with a review of recent applied works that attempt to establish the link between rapid transit and economic development, summarizing their key aspects and how they are related to this thesis.

2.1 Theoretical Grounds

It is a well-established fact in economic theory that space is neither homogeneous nor irrelevant: certain activities tend to concentrate in space, and there are economic benefits associated with density, known as agglomeration economies (Behrens and Robert-Nicoud, 2015; Duranton and Puga, 2004; Redding and Turner, 2015). These gains are limited, among other factors, by how difficult it is to reach other individuals and firms; therefore, transport lies at the core of agglomeration economies. An efficient transport network can leverage production; a congested one can put a constraint on it to the point of completely offsetting agglomeration economies (Eberts and McMillen, 1999; White, 1999).

These forces affect the economy indirectly through locational decisions and firm performance (Neumark, Zhang and Wall, 2006), which are also affected by other aspects such as land value, wage structure, and overall macroeconomic conditions.

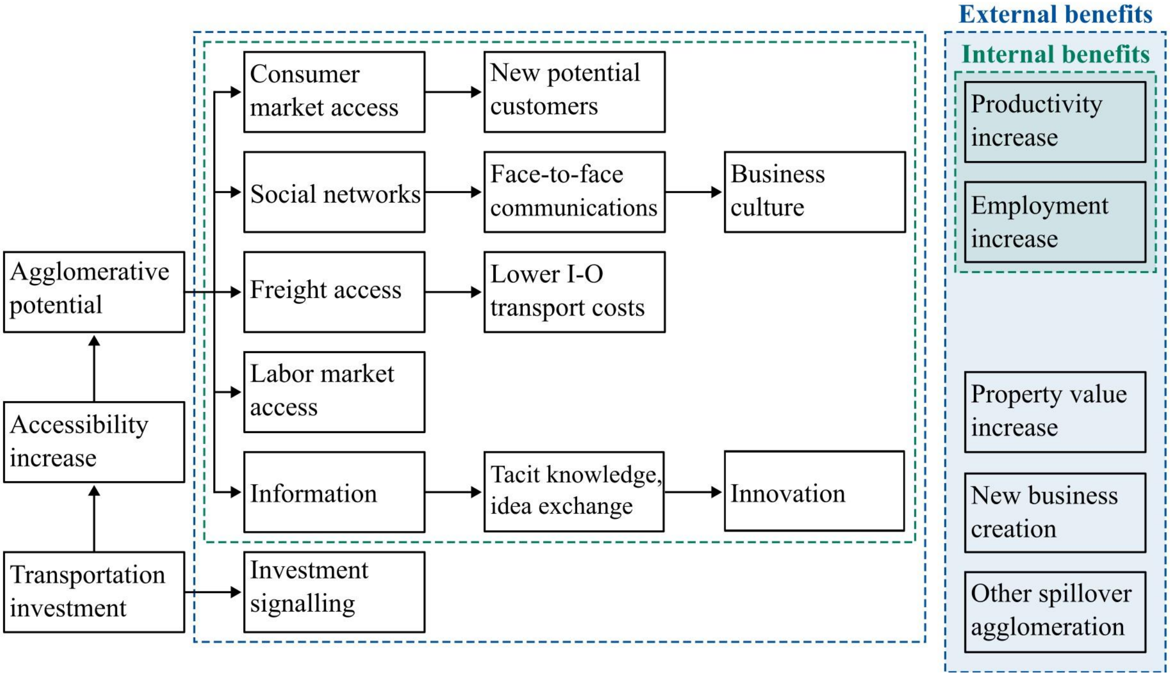
Figure 1 below illustrates the links from transport infrastructure to economic development found in the literature. While the main transmission channel relies on accessibility increases, new transport infrastructure also signals to agents which regions are prioritized by the government in terms of urban transformation; as a result, some economic growth (especially real estate development) can stem from signaling rather than changes in accessibility (Credit, 2019). This is a purely external benefit (i.e., external to the firm), whereas agglomeration economies imply that accessibility-led gains (e.g., larger consumer market) are also enjoyed by the rest of the agents in a connected urban system.

To understand how changes in the public transport system affect labor market outcomes, this chapter focuses the foundations behind agglomeration economies (**2.1.1**) and on the drivers of locational decisions (**2.1.2**).

2.1.1 Agglomeration economies

Economic theory interprets the city from different points of view. But from a historical perspective, agglomeration economies lie behind the main theories in urban economics since the early works of von Thünen (1966) and Marshall (1890) and gave rise to theories of regional economics—such as Christaller's Central Place Theory (Christaller and Baskin, 1966) and Krugman's New Economic Geography (Krugman, 1991)—and urban economics, that is, focused on issues at the city scale. Both regional and urban economics are deeply interconnected, just as macro and microeconomics; for instance, the debate on industry clustering—Marshall's externalities, after Marshall (1890)—versus diversity of activities—Jacobs' externalities, after Jacobs (1969)—is at the core of both fields.

Figure 1: Diagram of theoretical connections between transport investment, agglomeration benefits, and property value increases



Source: Adapted from Credit (2019).

Urban economics can be further subdivided into two branches of literature that differ on their main driver of urban development: land use or agglomeration's role in agent decision-making. The first one is the set of land use theories combining agglomeration economies, transport costs, and the classical microeconomics utility framework. Literature departed from models with an atomic, exogenous central business district (CBD) at the geographical center of a circular region because of their ease of mathematical tractability and evolved into more complex, polycentric models with multiple possible equilibria (White, 1999). This CBD shape was not an arbitrary decision; rather, it is a stylized fact based on the history of urban development, as cities in the developed world began to grow at a central location, generally close to a port. This is deeply linked to transport and construction technology: In a time when the only available transport modes were walking, horse-powered vehicles, and boats, workers could commute more easily to a central location than elsewhere, whereas goods should either be consumed locally (delivered by horse or men) or shipped to other regions —which was best done by boat, and later on by train since the mid-19th century (O'Sullivan, 2012).

The canonical AMM Model derived from the works of Alonso (1964), Mills (1972), and Muth (1975), for instance, considers endogenous (and homogeneous) households who face the tradeoff between living close to the CBD (minimizing their commuting costs) or consuming more land, at the expense of living far from the city center. As its main result, the model predicts that cities' density and land value gradients have an exponential decay departing from the CBD (Brueckner, 1987).

Other models with endogenous firms, multiple equilibria, and other extensions, such as that of Fujita and Ogawa (1982), provide better approximations of actual urban structures but do not change the main takeaways. These models have been used as the basis for a strand of empirical literature attempting to capture economic advantages in space through land values (Credit, 2019; Vickerman, 2008), such as real estate capitalization of rapid transit expansion. Nevertheless, land values are not a perfect measure of accessibility externalities because they also change in response to other factors, such as zoning restrictions (Vickerman, 2008; White, 1999).

Moreover, assuming that all markets have constant returns to scale and are perfectly competitive (and therefore have equal marginal costs) is a necessary condition for land values to be a perfect measure of locational advantages, but in reality, increasing returns to scale and imperfect competition are commonplace—indeed, increasing returns are one of the foundations behind the New Economic Geography (Krugman, 1991). This allows different markets to reap different benefits from locational advantages (Vickerman, 2017), and therefore, specific markets such as real estate cannot be used as a proxy to measure the overall transit externalities.

The second branch consists of theoretical models that build upon the mechanisms broadly described by Marshall (1890)—sharing, matching, and learning—and develop microfoundations for agglomeration economies, such as Henderson (1974) and Duranton and Puga (2004), whose structural equations describe labor market equilibrium across different industries and spatial equilibrium in either a single city or multiple cities. These models are used as the theoretical foundation for econometric analysis of agglomeration economies, deriving reduced-form equations from the structural ones that can be estimated (Redding and Turner, 2015).

In the last two decades, especially since the mid-2010s, general equilibrium models using household, firm, and transport microdata became increasingly popular to estimate counterfactual and ex-ante analyses of urban policies, such as studies in the informal housing market (Pereira, 2022) and public transit provision (Tsivanidis, 2019) using the framework developed by Ahlfeldt et al. (2015). Despite their flexibility and ability to generate multiple spatial equilibria, which is useful in policy evaluation and project appraisal (Redding and Turner, 2015), they rely on static coefficients, mostly obtained from different contexts and regions (Vickerman, 2017), and that do not respond to changes in transport costs (Vickerman, 2008).

The three main mechanisms behind agglomeration economies—sharing, matching, and learning—can all be related to transport improvements, as detailed by Chatman and Noland (2011) and Duranton and Puga (2004), in different degrees. The sharing mechanism occurs when industries or the whole region share the monetary costs of indivisibles and the risks of engaging in specialization. In the first one, density dilutes costs of capital-intensive infrastructure, either directly (such as a high taxpayer base to finance public goods) or indirectly (when greater demand enables private investments); it is, therefore, more an enabler of rapid transit expansion than a consequence of it. This endogeneity issue can be circumvented by assuming that (i) the sharing of indivisibles is constant across a local labor market and (ii) a metropolitan region constitutes a single labor market.

Risk sharing in entrepreneurial decisions happens when a greater concentration of consumers allows investors to innovate or invest in niche products, also increasing diversification (Jacobs, 1969; Chatman and Noland, 2011). This form of risk sharing could be indirectly captured through changes in the number of firms as a response to transit expansion, both in quantity and diversity of activities. In labor markets, workers share the risks of acquiring specialized knowledge with firms. Greater firm density incentivizes workers to specialize, based on expected higher wages and a smaller perception of unemployment risk (Duranton, 1998; Duranton and Puga, 2004; Eberts and McMillen, 1999).

The matching mechanism is deeply related to labor pool sharing. While firms prefer workers with a specific set of abilities, they cannot always find such workers and, therefore, face a production constraint limited to their current workers' skills. In an urban environment, a good match depends on accessibility levels. Defining accessibility broadly as the potential to reach opportunities distributed in space (Páez, Scott and Morency, 2012), cities with low access to job opportunities face a poorer match, as some specialized workers are not able to reach the jobs that would benefit from their skills. Improved transit networks, therefore, can match skilled workers with niche job positions, for which they are rewarded with better salaries.

A broad field of literature dedicated to this topic gave rise to the spatial mismatch hypothesis (SMH), according to which poor and low-skilled workers, especially ethnical minorities, face bigger difficulties in finding jobs that match their ability due to being spatially segregated from those opportunities (Gobillon, Selod and Zenou, 2007). Among the main reasons for the SMH is a higher reliance on public transport since many underprivileged groups are less able to afford automobiles. When job accessibility by public transport is low, individuals are not able to reach a large portion of a region's job positions. Moreover, even if they find it feasible to commute once they have a job, transport costs in the job search process can be high enough to offset the expected payout of finding a job. In contrast, improvements in the public transit network can facilitate the process of job search, increasing employment for underprivileged, spatially segregated groups (Gobillon, Selod and Zenou, 2007; Chatman and Noland, 2011).

The third mechanism, learning, concerns the diffusion of knowledge that is specific to urban environments. While many skills are acquired through formal education, others are developed by contact with coworkers; in addition, another manifestation of the learning mechanism is when innovations spread from one company to another due to workforce migration or informal communication of peers who work in different companies.

Knowledge spillovers act differently according to industry. Some might require physical proximity, such as learning by copying a competitor's behavior (White, 1999), whereas in others, knowledge spillovers occur in-company; therefore, proximity to similar companies is not a requirement. These phenomena are dependent on space and communications technology. While working from home, video calls, and instant messages have facilitated the diffusion of information between distant individuals, physical proximity still plays a key role in knowledge spillovers (Glaeser and Cutler, 2021). For instance, a form of knowledge spillover that is relevant but hard to find empirically takes place in informal meetings, such as happy hours or lunches, that are facilitated in denser, walkable urban environments, as they enhance encounters (Credit, 2019).

To summarize, the sharing, matching, and learning mechanisms indicate that a greater density of firms and individuals tends to yield greater outcomes compared to less dense regions. Altogether, agglomeration economies can be seen as increasing returns to the density of jobs and firms (White, 1999; Vickerman, 2008). While some benefits are industry-specific (localization economies), such as higher productivity due to learning from a competitor's behavior, others affect the whole region, (urbanization economies), such as industry linkages related to sharing input suppliers—Table 1 depicts agglomeration economies according to their mechanism and scope.

Table 1: Types of agglomeration economies by source and scope

Source	Localization economies	Urbanization economies
Labor market pooling	Access to specialized labor market	Cost benefits from access to a larger labor market
Input/output sharing	Access to specialized suppliers	Cost benefits from access to customers
Knowledge spillover	Industry-specific	Between different industries or from scientific environment

Blue: Marshall's externalities; green: Jacobs' externalities.
Source: Adapted from de Bok and van Oort (2011).

Benefits derived from input sharing tend to be most easily identified in manufacturing industries that face large fixed costs, but the learning mechanism impacts mostly service industries that are dependent on information and face-to-face contact—such as education, consulting, and information technology (IT)—, and matching benefits mainly the industries with higher requirements for specialized labor, which can also outbid the others (by offering higher wages) to retain workers that match their requirements.

These mechanisms are hardly isolated, which makes it difficult to estimate them separately in econometric analysis. Transport network upgrades in region i deepen agglomeration potentials by making it easier to reach i from different regions in the network and vice-versa; in other words, by increasing firms' consumer market access and laborers' job market access. This effect also propagates in the whole network, affecting origin-destination pairs not related to i. The outcome is generally a combination of positive spillover to regions deeply connected to the treated node i and a comparative advantage loss for other parts, which changes agents' optimal localization decision and thus can lead to a reorganization of economic activity in space. These diffuse effects require paying attention to what effect is being recovered in econometric estimation (Vickerman, 2008, 2017; Redding and Turner, 2015; Credit, 2019).

2.1.2 **Location decision**

Since the widespread adoption of trucks and cars in the first half of the 20th century, cities departed from the monocentric paradigm described in the introduction of this section to a more complex arrangement with multiple centralities, a trend which was also leveraged by new industrial organization paradigms and the rise of telecommunications technologies such as the internet. This phenomenon was observed both in developed and developing countries. In the United States, land use sprawled dramatically since the 1950s, and while residential uses comprise most of the land outside of downtown, all economic activities faced significant decentralization (Baum-Snow, 2007; Glaeser and Kahn, 2004; Gordon and Lee, 2015; White, 1999). Davanzo et al. (2011) highlights that in peripheral countries, metropolization also started following a monocentric pattern, departing from a central city and reaching neighbor municipalities to form a continuous urban tissue, but later on evolved into dispersed patterns. In the Brazilian case, urbanization intensified in the 1950s, but only at the end of that century, it started to follow a more dispersed pattern that, nonetheless, concentrated along main transport corridors between centralities (Davanzo et al., 2011).

To understand how cities can diverge from the monocentric structure and the role played by transport and accessibility in this process, it is necessary to look at the forces behind a firm's location choice. White (1999) lists six main factors: wages, commuting and shipping costs, land value, agglomeration economies, and technology. First, if a firm decides to locate at a suburban site closer to where workers live, then it might be able to reduce wages while maintaining a worker's net income fixed since their commuting costs would fall.

Transport modes, nevertheless, have different implications on the extent to which a firm can succeed in attracting workers by relocating to the suburbs: If all workers commute by car, then every household inside a roughly circular region centered on the new plant location can find it attractive, to the limit that the reduced wage completely offset commuting savings. This happens because car routes are point-to-point, and driving costs, especially fuel, are more directly related to distance.

If individuals face congestion, this increases the opportunity costs of commuting, which can reduce the radius of the area where individuals are willing to work outside the CBD. But if instead workers rely on a public transport network constrained to a few corridors, then the locus of households benefited by a suburban firm relocation has a very different shape: it is constrained in a buffer around transport nodes. In a city where all transit routes pass through downtown, only the workers living around the closest route to the new firm (and between the plant and the CBD) are willing to work there; as for all the other nodes, the CBD is a closer location.

While in practice modal shares are less extreme, some cities do have a more predominant transport mode, either homogeneous or by income group; in both cases, if a firm decides to reduce wages to a level slightly superior to their workers' savings on commuting, they might attract more workers while still saving on labor costs. Shipping costs, in turn, are more relevant to manufacturing industries since moving goods is a relatively bigger part of their operation than for services. In this case, a suburban site closer to highway exits or airports can not only save transport costs by being closer to the city's ports of exit but also by avoiding congestion at a crowded central location (White, 1999). Glaeser and Kahn (2004) consider transport costs (both of goods and people) as the biggest force behind suburbanization trends, arguing that even with the associated traffic congestion, automobiles and trucks reduce dramatically these costs compared to public transport and shipping by boats or rail (which require large facilities), both by their speed and point to point nature: this rationale is consonant with the labor sharing mechanism.

In the Brazilian context, on the monetary side of transport costs, firms might face a cost reduction if this means spending fewer bus tickets in a worker's monthly *vale transporte*[1], which is a labor cost reduction without implying a direct wage cut. In summary, transport shapes accessibility, which is the ease of getting to a desired destination. For manufacture and trade, it is the ease of product delivery, be it at a regional scale or locally for the last mile. For trade and services that rely on human contact, it is the customers' access to business/consumption opportunities. But for all industries, it is also the workers' access to job opportunities.

[1] Public transport vouchers are compulsory offered by Brazilian firms to their employees, but are not considered as part of their monthly wage (Brasil, 1987).

Assuming the stylized fact that land is cheaper farther from downtown, industries that need a large horizontal space have an additional incentive to locate outside of the CBD. White (1999) argues that when public transport is the dominant mode, firms are attracted to transit corridors since they provide better accessibility to workers. At the same time, this accessibility advantage makes those regions more attractive to households, which implies higher land values, so companies may have fewer incentives to relocate due to cheaper land. In contrast, car-oriented cities provide more relocation options: since workers can drive directly to the plant, its location is not limited to being near transit corridors; therefore, moving to a cheaper region might be a viable option.

The role played by agglomeration economies in the firm's locational choice depends both on the industry-specific relevance of these mechanisms and their distribution within a city. In broad terms, industries that benefit more from agglomeration economies have more incentives to locate where they can find such benefits. Factories can be attracted to cities with similar companies, where they share inputs and labor, whereas retail activities might be motivated to cluster since this attracts customers who want to compare options (Eberts and McMillen, 1999; White, 1999; De Bok and Van Oort, 2011; Credit, 2019), giving rise to Marshall's externalities.

In contrast, for some firms, diversity is a more important driver of agglomeration benefits. As Jacobs (1969) states, interaction between players of different sectors can foster cross-industry knowledge spillover and innovation. In both cases, on the intraurban scale, if agglomeration economies are higher in a particular location, firms have an incentive to locate there. For instance, if the CBD has better accessibility and thus provides higher labor-sharing agglomeration economies, locations elsewhere are less attractive. But if a new highway or rapid transit line enhances labor sharing far from downtown and this benefit is high enough to offset an eventual higher land value (compared to another suburban location with no public transport improvement), this region would attract firms that benefit from labor sharing.

As for technology, the mass adoption of telephones, the fax machine, and computers since the last decades of the past century made the physical presence of workers less necessary in activities across many industries, leading companies to outsource activities such as call centers to countries with cheaper labor or even to allow working from home as early as the 1990s White (1999). However, producer services (B2B) industries still benefit from proximity when tacit knowledge is important; for instance, business meetings with potential clients. While retail locations with ease of access and high foot traffic are seen as important factors, the emergence of online shopping also seems to have affected it negatively. Some activities still demand physical contact, such as dentist appointments, and experience-based services, such as cafes: these industries are expected to value prime locations more, as they are less easily substituted for online services.

Other key factors for the location decision are network effects and firm-level attributes. First, an established socio-spatial network of stakeholders, including customers and suppliers, may attract business to specific locations. This is particularly important in the case of an existing firm, in which case it will seek a new place as close as possible (given its relocation needs) to its original site. Firm-level attributes matter to relocation in the sense that its unique capabilities and assets, including its knowledge base, dictate its success. Older firms have a greater stock of knowledge, while newer ones need to accumulate it. Larger firms have the resources and scale to acquire knowledge but they also tend to ossify their procedures and knowledge, which slows their growth (De Bok and Van Oort, 2011). Firms that experienced growth in the past years are likely to expand in space, whereas firms going through a rough period can shrink to adapt; therefore, performance history has a role in relocation decisions.

2.2 The São Paulo Metropolitan Region

Home to around 22 million inhabitants across 39 municipalities (11.5 million of them in the capital), the São Paulo Metropolitan Region (RMSP[2]) is among the ten most populous urban areas in the world. The region is the core of what has been considered the rise of Brazil's first megalopolis, known as the Paulista Macrometropolis[3], ranging from Campinas to the port city of Santos, in the north-south direction, and from Sorocaba to São José dos Campos in the west-east direction (Davanzo et al., 2011). In 2011, this region was responsible for 79% of the state's GDP, 65% of its freight movements, and 95% of the commuting flows (Davanzo et al., 2011). The metropolization process in course began with industrial sprawl from the capital to the interior of the state, especially since the 1980s, following main transport axes towards previously dynamic centralities such as Campinas and Jundiaí (Santos et al., 2011).

Despite its unique development process, São Paulo shares some key aspects with other Brazilian cities that reflect national trends and paradigms of economic development, land use, and transport organization (Faissol, Moreira and Fereira, 1987). Figure 2 illustrates the urbanization process in Brazil, which gained track in the 1950s and was initially restricted to Rio de Janeiro and São Paulo: The former, for being then the federal capital and therefore concentrating administrative services; the latter, for its rising industry. In the 1960s, they were the only cities in the country with more than one million inhabitants (Davanzo *et al.*, 2011).

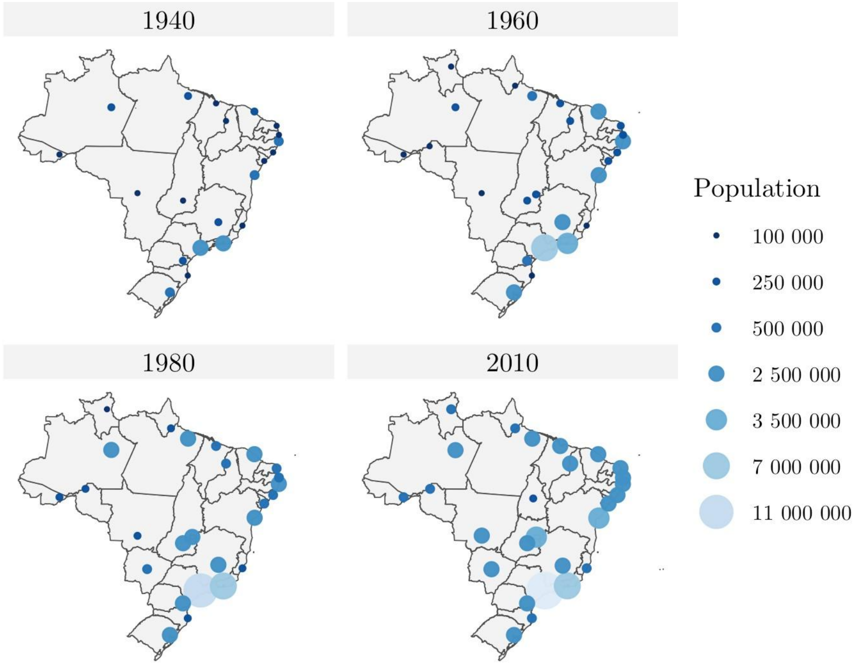
By the 1970s, urbanization was spread across all major capitals throughout the country, albeit concentrated in the South and Southwest regions (also known as Brazil's "center-south"). The urban transformation was driven by industrialization, which concentrated

[2] Região Metropolitana de São Paulo

[3] Macrometrópole Paulista

in those regions for historical reasons, infrastructure availability, political decisions, and migration. In that decade, the federal government created Brazil's first metropolitan regions (Davanzo et al., 2011), of which two were first-order metropolises—Rio de Janeiro and São Paulo—and six were second-order (Motta, Mueller and Torres, 1997).

Figure 2: Population evolution in Brazilian capitals



Source: Own elaboration.

Explaining the entirety of Brazilian urban development exceeds the scope of this thesis, but it is fair to say that the center-south region was the main stage of economic development since the 19th century. This historical process largely influenced infrastructure development: In 1898, 82% of the country's railways were in the center-south (68% in the present-day Southeast); in 1954, the center-south still concentrated 71% of the railways, 53% of which in the Southeast (IBGE, 1954; Silva, 1954); the first electricity plants were also in that region, and so on. Political decisions in the form of industrial policy and the establishment of large industrial facilities (e.g., oil refineries and steel industries) were also mostly focused on the center-south (Faissol, Moreira and Fereira, 1987; Motta, Mueller, and Torres, 1997; Davanzo *et al.*, 2011).

The 1980s represented a turning point in Brazilian urbanization: growth decelerated in the capital cities, whereas medium-sized ones assumed the lead, giving rise to a polycentric network of cities along transport axes (Motta, Mueller and Torres, 1997; Davanzo *et al.*, 2011). In the center-south and parts of the Northeast, this was due to industrial sprawl into the interior of the states, whereas in the Center-West, North, and parts of the center-south, it was led by agribusiness development (Davanzo *et al.*, 2011). In the meantime, inside metropolitan regions, growth started to occur mostly in the outskirts of the central city (Motta, Mueller, and Torres, 1997), a process that persists to this day and is marked by informal settlements and poorer neighborhoods, lacking infrastructure and generally facing higher commuting times (Pereira et al., 2019a).

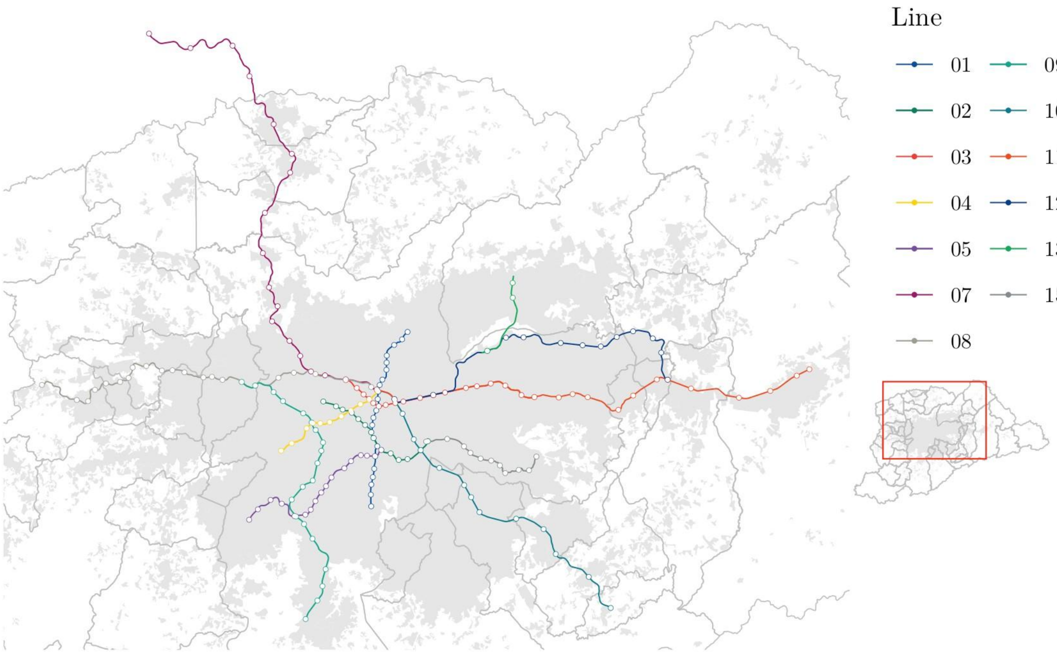
2.2.1 **Transit Policy in São Paulo**

São Paulo has a long history of railway investment that go back to the second half of the 19th century with the first interurban services—precursors of the modern regional metro (CPTM). Figure 3 displays the current, under construction, and planned rapid transit lines in the region, along with city borders and the urban footprint (in gray).

Only line 7-Ruby crosses metropolitan limits, reaching Jundiaí. Lines 1–5 and 15, future lines 6 and 17 (under construction), and planned lines 16, 19, and 20 are property of Companhia do Metropolitano de São Paulo (CMSP, mostly known as Metrô) and are the type of service commonly labeled as “metro”, “underground”, or “subway”—that is, service with frequent headways (up to 90 seconds in rush hour), closer stops and inside a dense urban core—although they are not necessarily entirely underground and mix both monorail (lines 15 and 17) and heavy rail modals.

Lines 7–13 are the property of Companhia Paulista de Trens Metropolitanos (CPTM), which falls in the regional metro category. On one hand, these lines reach farther portions of the metropolitan region and feature more spaced stations and longer lines, when compared to subway services. On the other hand, headways are as frequent as four minutes in the rush hour and 30 minutes in the rest of the day in some lines, whereas the North American archetype of a commuter rail features less frequent services. Table 2 summarizes the key aspects of each line.

Figure 3: São Paulo Metropolitan Rail Network in 2023



Source: Own elaboration.

Both Metrô and CPTM are owned by the state government and are fully fare-integrated, but they have different origins. CPTM was founded in 1996 resulting from the merger of suburban lines operated by federal and state agencies [4]. This reorganization process was followed by modernization, bringing CPTM lines closer to the regional metro paradigm with newer trains, modern signaling, and expansion, mostly through infill stations in the East Zone (line 11-Coral) and along the Pinheiros

[4] At the federal level, those were the *Rede Ferroviária Federal S/A* (RFFSA, extinct), *Companhia Brasileira de Trens Urbanos* (CBTU, still operating in other states), and at the state level, the *Ferrovias Paulistas S/A* (FEPASA, extinct).

River (line 9-Emerald), this one adjacent to the city's new financial district that began to rise in the 1980s and is now the city's main employment center.

Table 2: Rapid transit lines in São Paulo as of 2023

Line	Opening date	Owner	Operator	Stations	Extension (km)	Peak headway
1-Blue	Sep. 1974	Metrô	Metrô	23	20.2	125 sec.
2-Green	Jan. 1991	Metrô	Metrô	14	14.7	128 sec.
3-Red	March 1979	Metrô	Metrô	18	22	119 sec.
4-Yellow	May 2010	Metrô	ViaQuatro (PPP)	11	12.8	100 sec.
5-Lilac	Oct. 2002	Metrô	ViaMobilidade (PPP)	17	19.9	171 sec.
7-Ruby	Feb. 1867	CPTM	CPTM	19	62.7	6 min.
8-Diamond	1875	CPTM	ViaMobilidade (PPP)	22	41.6	6 min.
9-Emerald	1957	CPTM	ViaMobilidade (PPP)	19	35.1	4-7 min.
10-Turquoise	Feb. 1867	CPTM	CPTM	14	38	6 min.
11-Coral	1890	CPTM	CPTM	16	50.5	4-8 min.
12-Sapphire	1934	CPTM	CPTM	13	39	6-8 min.
13-Jade	March 2018	CPTM	CPTM	3	12.2	20 min.
15-Silver	August 2014	Metrô	Metrô	11	14.6	180 sec.

Sources: CPTM (2023), CMSP(2023).
Notes: Line 13 includes hourly Airport Express service. All lines are heavy rail, except Line 15 (monorail).

Many of CPTM's lines, especially lines 7, 11, and 12, have had regular urban passenger service since as early as the late 19th century, following some of the country's oldest railways. Historically, urban development first began along this axis, which to this date concentrates on very dense neighborhoods surrounded by trade, services, and industrial activities (IBGE, 1954; Santos *et al.*, 2011).

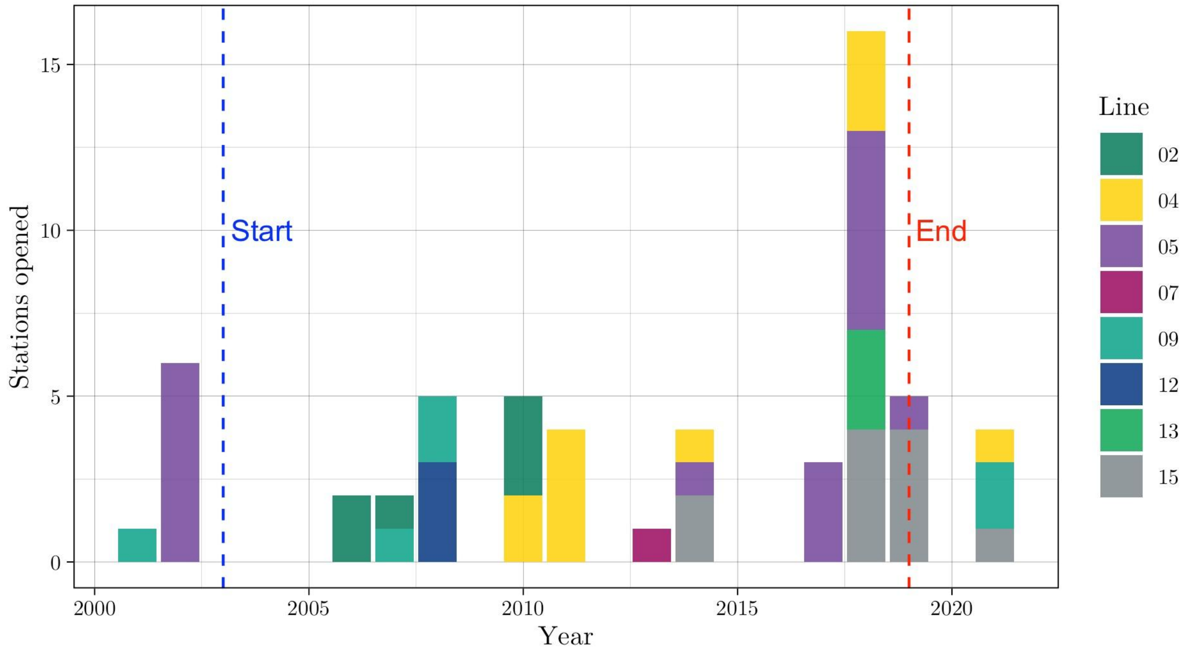
In turn, Metrô was founded in 1968 as a traditional subway service, initially restricted to the state capital's boundaries and with a planned network of four lines, most of which correspond to modern-day lines 1–4. The first line opened in 1971 and the network went through continuous expansions in the following decades. To this date, the Metrô network is still restricted to the capital limits; nevertheless, line 2-Green is expected to reach Guarulhos (the second largest city in the region) before 2030, and projects such as line 4's west expansion and new lines 19 and 20 are expected to be operating before 2040 in neighbor cities of Taboão da Serra, Santo André, and São Bernardo do Campo. Currently, Metrô's lines 4 and 5 are operated through public-private partnerships (PPP), as well as CPTM's lines 8 and 9. Lines 6 and 17, currently under construction, will also be privately operated.

During the 2003-2019 period, 52 new stations were inaugurated (31% increase), adding around 62 kilometers to the network, a 20% increase in length. CPTM extended line 9 southbound, added infill stations in lines 7 and 12, and opened a new link to Guarulhos International Airport (line 13). Most of the expansion, however, was carried out by Metrô: first, an eastbound extension of Line 2, reaching CPTM line 10 in 2011. Second, the new Line 4 started its operations in 2010 in a roughly four kilometers stretch linking Paulista Station (connection to Line 2), in Paulista Avenue, to the north end of Faria Lima Avenue. Both are dense avenues oriented towards retail, services, and offices.

While Paulista was the epicenter of economic dynamism during the 1980s—representing the first wave of migration from the historical city center to a new CBD—since the 1990s and especially in the 2000s, Faria Lima took its role as the city's financial district (Lores, 2017); nevertheless, its north end was still less developed when it received a Line 4 station in 2010. In the following year, the line expanded north to Luz, at the core of the historical downtown, and southwest to Butantã, a neighborhood characterized by high-income single-family households but also institutions such as Universidade de São Paulo (USP): One of the country's biggest universities, with almost

100 thousand alumni. In the following years, three infill stations were inaugurated[5], in addition to a westbound expansion to Morumbi in 2018, a mostly single-family residential neighborhood, and the current terminus station Vila Sônia, in 2021.

Figure 4: Rapid transit expansion in RMSP between 2001 and 2022



Source: Own elaboration.
Note: Dashed lines indicate the time frame analyzed (2003-2018).

Two other significant openings in the period were line 5 expansion and the new monorail line 15. Line 5 opened in 2002 with five kilometers, linking the southern neighborhood of Capão Redondo to CPTM's line 9. In 2014, a northeast-bound expansion began with one new station, followed by three new stations in 2017, seven new stations in 2018 (reaching its current length), and one infill station in 2019. This expansion represented a great accessibility improvement to the southwest portion of the city, historically underserved of public transport and characterized by low and middle-income households, by connecting it to the southern portion of the city's new financial district and to lines 1 and 2 in the center-east region, also an important employment subcenter.

[5] 2014: Fradique Coutinho; 2018: Higienópolis-Mackenzie and Oscar Freire.

As most of this expansion took place in 2018, not only long-run benefits cannot be measured yet, but also short-run ones are hard to infer due to lack of available data, especially since the 2020 pandemic changed transport dynamics and resulted in the government delaying the release of employer-employee data for the following years.

Finally, line 15 started operating in 2014 between to adjacent stations, as a trial service, gaining five additional stations in 2018 (four more in 2021, outside the analyzed period). Line 15 is still expanding and is the city's first monorail service. It reaches the southernmost portion of the East Zone, also a densely populated region lacking rapid transit service until Line 15's arrival. The west terminus connects to Line 2 and a further westbound station will reach Line 10, in addition to another westbound expansion—two additional stations in 2.6 kilometers expected to enter service in 2025, in addition to another four stations along seven kilometers still in project phase.

2.3 Previous studies

This section consists of a methodology-focused review of the empirical literature, with emphasis on recent econometric and general equilibrium approaches. It was only in the last two decades of the twentieth century that empirical analysis linking infrastructure and economic development began to be done consistently (Gramlich, 1994; Vickerman, 2008); however, generally focused on investment in highways in the USA (Credit, 2019). Starting with the seminal work of Aschauer (1989), the first studies analyzed macroeconomic variables, such as aggregate investment, without distinguishing by type of investment.

These studies suffered from problems that difficulted to establish a causal relationship. As Vickerman (2008) points out, there are econometric problems of serial correlation and endogeneity: as much as we want to estimate the influence of infrastructure investment on economic growth, there is also reverse causality, in that better economic performance drives these investments. The spatial nature of investments can also imply spatial dependence and spillover to other regions, so not considering these effects can also lead to biased results.

From the 1990s onwards, studies at the regional level began to incorporate panel data techniques with fixed effects, which control for unobserved heterogeneity, mitigating some of the problems listed. In the 2010s, the greater availability of microdata—i.e. socio-economic information at the level of the individual and the company, not just geographical aggregates—allowed several studies to establish a more direct relationship between specific urban interventions and variables such as productivity, employment, and economic activity (Credit, 2019; Deng, 2013; Vickerman, 2008).

Following the modern econometrics approach (Angrist and Pischke, 2009), recent applications pay attention to research design concerns, such the establishment of treatment and control groups or the use of instrumental variables to filter endogeneity (Redding and Turner, 2015). Some articles managed to successfully distinguish between growth and reorganization. Baum-Snow (2007) determined the area of the historical CBD (1950) and calculated the population change related to highway construction, finding that while Metropolitan Statistical Areas (MSAs) grew around 72 percent in the period and CBDs' populations declined around 17 percent. That way, most of the 17 percent decrease in the average CBD population is associated with highway construction.

Although not related to transport provision, Mayer, Mayneris, and Py (2017) provide an insightful approach to distinguishing growth from organization. They analyzed the impact of special business districts on firm creation in French cities; as the program was implemented in three waves, they were able to make spatial and temporal differentiation. Mayer, Mayneris, and Py (2017) found out that although receiving a special district does not divert growth from one city to another —third-wave cities, treated in 2007, were not affected in 2004 when second-wave cities received their special districts— most business creation within each city is due to relocation from the rest of the city to the new zone.

A crescent number of works on the difference-and-differences (DiD) framework. In the land values research branch, Gibbons and Machin (2005) estimated the effect of getting closer to a station with the inauguration of the Docklands Light Rail system in London. Postcode units (10 to 15 homes) within two kilometers of a new station in a straight line are considered treated, while postcodes further away from the rest of the city are in the control group. They found that real estate prices increase on average two percent per kilometer of distance to a new station. They also ran a cross-section analysis for comparative purposes, finding a three times higher increase: this evidences the power of the DiD and similar strategies in filtering selection bias.

After the opening of a light rail transit (LRT) system in Charlotte, USA, Billings (2011) estimated a four percent increase in the value of single-family homes, while condominiums were appreciated by 11 percent, and no difference was found for commercial properties. Units were selected if they were up to one mile (1.6 km) from the station. A highlight of that study is the design of test and control groups: the control group is made up of units that should, but did not receive treatment: properties near two other proposed branches.

As for studies focused on labor market outcomes, Canales, Nilsson, and Delmelle (2019) also analyzed Charlotte's first LRT, but on employment levels. Although, like Billings (2011), they use planned lines as a control group, data are aggregated at the neighborhood level, and the catchment radius is smaller (a quarter mile). The authors did not find significant effects, which they attribute to the line passing mostly through regions that already had the highest job density (as well as the highest salaries) prior to the intervention. Drawing a parallel to Billings (2011), the authors consider that transit policy in Charlotte was more focused on urban requalification than on improving accessibility to underprivileged portions of the city.

Åslund, Blind, and Dahlberg (2017) used the DiD matching estimator to recover the impact on wages and employment of the introduction of a regional train in the Uppsala region (Sweden) in the 1990s, in a ten-year panel. A good aspect of this study is that it considers individuals at their residency rather than at their workplace. Treated individuals are those living in a statistical region whose centroid is up to 4.5km away from a new station but no farther than 10km from downtown Uppsala, whereas the control group contains individuals far away from the new corridor but with high commuting rates to downtown.

They did not find a significant overall effect, with the exception of the subgroup of non-Western migrants, precisely those who are most dependent on public transport and have lower average incomes. They argue, nevertheless, that the small size of this subsample reduces the confidence of the estimates. Åslund, Blind, and Dahlberg (2017) also speculate that the result may have been insignificant due to the high motorization share and the pre-existence of a public transport network; thus, the investment may not have represented a significant gain in accessibility.

Tyndall (2017) analyzed the exogenous reduction in commuter train service in New York City, USA, caused by Hurricane Sandy in 2012. His DiD strategy included controls for regional trends and considered as a treatment group the districts affected by the R Line closure in 2013, while the rest of the city served as a control. The unit of analysis is the Public Microdata Use Area (PUMA)—an aggregated spatial unit, but whose boundaries are, argue the author, close enough to the limit of Line R's catchment area.

While the unemployment rate followed a downward trend from 2010 to 2012 in both groups, in 2013, it fell for the control districts but rose for the affected ones, leading to the conclusion that the R-line closure negatively affected employment.

Regarding the Lima (Peru) BRT, Scholl et al. (2018) used a DiD strategy to analyze the impact of the network introduction on employment (formal and informal), work hours, and monthly wages, using a household survey. They initially hypothesized that individuals living along feeder lines would benefit more than those closer to the trunk lines since the formers were already the ones best served by public transport prior to the BRT. The results went in the opposite direction, showing positive benefits near the trunks—a 3.9 percentage points increase in employment, 19 percent in hours worked, and 32 percent in monthly income—and no impact near the feeder lines. Their model also included temporal lags, which suggested that the impacts started shortly after the intervention. This interpretation should be done with caution, since leads and lags in a two-ways fixed effects model can suffer from contamination from other periods (De Chaisemartin and D'Haultfœuille, 2020; Goodman-Bacon, 2021).

Since data is geolocated at the neighborhood level, the research design of Scholl et al. (2018) delimited treatment groups using the linear distance from the neighborhood's centroid to the transit lines. Treated individuals live in a neighborhood no farther than 1.5km from a line, a measure based on an origin-destination (O-D) survey that pointed out that this threshold is the maximum walking distance to transit for 99% of the respondents. In turn, the control group is delimited by neighborhoods between 2 and 6 kilometers from the corridors, therefore leaving a 500-meter buffer between treatment and control groups.

In the regional scale, Castro, Almeida, and Lima (2021) analyzed the impact of road paving on the economic output of small towns in the state of Minas Gerais, Brazil, using a spatial DiD strategy. Following the "yet-to-be-treated" approach, the control group was constituted by cities that were expected to receive road paving, but whose works were delayed. Data was analyzed in two periods: 2000, prior to any investment, and 2010, when some roads were already paved. They found no significant effect, arguing that either not enough time had passed since many cities were treated short of 2010, or that increased accessibility actually results in wealth transfer from these smaller towns to bigger municipalities: the "two-way road" effect, also noted on Vickerman (2008). The first case is yet more evidence of the average treatment effect being smoothed by not considering group-time heterogeneity, while the second relates to the issue of growth versus reorganization, also reported by Mayer, Mayneris, and Py (2017) and Behrens and Robert-Nicoud (2015).

Under the fixed effects panel data strategy, Matas et al. (2020) analyzed the impact of the development of the Spanish high-speed train (*Alta Velocidad Española* — AVE) network on job creation in the country. The authors analyzed a wide time frame (1995 to 2017), which allows them to capture medium- to long-term effects. In addition, they distinguished business creation in four different economic sectors, which provides more detail regarding which activities benefited most from the investments. The absence of microdata for the period prior to the mid-2000s limited the authors to study the economic impact at the provincial level; however, since AVE is a regional network, this is relatively less of a problem than in the urban scope. The authors identified heterogeneous results: (i) not all provinces experienced relevant growth due to the implementation of the AVE, and (ii) more developed provinces, such as Barcelona, were the most benefited by the development of the network.

Historical and planned routes have gained popularity since the 2010s as instruments for infrastructure provision. Garcia-López, Holl, and Viladecans-Marsal (2015) used a First-Differences (FD) approach to measure the change in central city population in

Spain resulting from changes in the highway network and historical instruments, concluding that each highway declines the population of central Barcelona by 5 percent.

Computable General Equilibrium (CGE) and Land-Use Transport Integration (LUTI) models have also been used to estimate wider economic impacts (Vickerman, 2017), often combined with an econometric approach. A notable work in this field is Ahlfeldt et al. (2015), which used the division of Berlin after World War II as an exogenous variation in the urban spatial equilibrium. Using location, population, land rent, and employment data in three years—1936, 1986, and 2006—and a first-differences regression, they concluded that the Berlin Wall caused the CBD to migrate to West Berlin, whereas unification reversed this process. Properties closer than 250 meters to a subway station in 1936 were less devalued after the division than those farther from a station. A general equilibrium model was then estimated with point data and discrete locational choice, yielding similar results to the econometric model but with the advantage of providing welfare and reorganization analyses.

Campos (2019) adopted a similar approach. She investigated the economic impacts of transit investments in Rio de Janeiro (Brazil) for the 2014 World Cup and the 2016 Olympics. In addition to econometric analysis, she used a variation of Ahlfeldt's model with heterogeneous agents to simulate a counterfactual non-investment scenario, which allowed her to calculate the estimated benefit in commuting time savings after urban interventions.

In the first analysis, the author combined firm microdata with the 2010 Population Census and estimated the impact of the interventions on wages, employment level, and new business creation, adopting the difference-in-differences framework. Using a spatial grid of 100 square meters, Campos (2019) considered the regions within 1.75 km of the inaugurated stations as treated, in concentric 250m rings, and the rest of the city as a control group, estimating the effects for the different rings and considering different income levels, economic activities, and which mode of transit was used (BRT, tram, or subway).

The study evidenced a spatial decay—the further away from the station, the lower the impact—and an uneven distribution, as more educated individuals benefited more from urban interventions. Subway also appears to generate a bigger impact than BRT since the spatial decay is less intense for the latter, and no impact was detected for the LRT, which the author attributes to the lines being inaugurated only two years before the final period.

Another study using Ahlfeldt's is Tsivanidis (2019), who studied the effects of the BRT in Bogotá, Colombia, considering different worker income and economic activity groups, using a general equilibrium strategy. He identified increases in social welfare and economic activity that were greater than the cost of implementing the network; nonetheless, the estimated benefits were unequal, being greater for more educated workers. Tsivanidis (2019) also expanded the model with a transport choice model, where agents decide whether to own a car or not and, in the positive case, can choose between public transit and private automobiles when commuting to work.

The great heterogeneity in the results of the studies surveyed indicates that regional characteristics do limit the extent to which transit improvements can foster agglomeration economies. Among other factors, the previous size of the network, their effectiveness in providing accessibility gains, and land use can be the reason behind a null effect, often combined.

Accessibility gains may feature marginally decreasing returns; therefore, an addition to an already robust transit system provides fewer economic benefits than the first lines (Chatman and Noland, 2011; Deng, 2013). Even a completely new system may not enhance accessibility, therefore rendering no utility (Vickerman, 2008; Credit, 2019), e.g. in a highly car-dependent environment and in the absence of additional investments such as feeder bus routes.

Land use matters in the sense that mature portions of a city can benefit relatively less from transit improvements—as was the case for Charlotte (Canales, Nilsson and Delmelle, 2019) but not for Rio de Janeiro (Campos, 2019)—but at the same time, density and transport provision are highly associated, so it is difficult to separate those two aspects of urban development. Zoning might also prevent growth in any region that faces density constraints (Combes and Gobillon, 2015; Redding and Turner, 2015), so lack of growth in mature regions can be a result of lack of available space rather than lack of demand.

Research design choices also lead to different results, even for studies that share the same methodology. While the most recent ones delimit treatment and control groups, they use different distance thresholds, ranging from 400 meters (Canales, Nilsson and Delmelle, 2019) to 4.5 kilometers (Åslund, Blind and Dahlberg, 2017). More so, few of them are geolocated at the individual level, an issue also raised by Credit (2019): this can weaken identification since units are regarded as lying at the same distance to the stations, which is the region's centroid; thus, the bigger the region, the bigger the error potential. On the bright side, around half of the evidence related to labor market effects analyzes individuals at their residences, a better measure than looking at the workplace since it measures the impact of public transport more directly.

Time can also affect estimates in two ways: by length of exposure to treatment and by heterogeneities between groups treated in different periods. The first case is considered in some studies with the inclusion of time lags (only Scholl et al. (2018) regarding labor markets), but if the second heterogeneity source is present, those time dummies have a limited capability of recovering estimates due to the contamination issue.

Considering these research design and estimation issues, the strategy adopted in this thesis has three main differences from the surveyed literature. First, catchment areas are delimited using a routing algorithm through real paths—more precise than the straight-line distance—although the issue of an arbitrary threshold persists.

Second, identifying individuals at their residences would only be possible through the origin-destination survey, which has a decennial frequency and thus compromises the identifying assumptions, or using a household survey designed to be representative at the state level, compromising inference for the metropolitan level. In turn, the employer-employee dataset in use is an annual database containing the whole population of formal workers in the country. Therefore, its advantages related to inference and identification of the timing of the interventions overcome its limitations.

Third, the econometric strategy is where this thesis differs the most from the literature. Since treatment time is not equal for all units, this heterogeneity is modeled through the staggered setup of Callaway and Sant'Anna (2021b), which analyzes each treatment cohort separately and over time in a way that does not suffer from the contamination on TWFE lags. The underlying hypothesis is that groups treated earlier from rapid transit expansion since marginal accessibility gains are higher, and if the most demanded regions are attended first. To deal with spatial heterogeneities, each transit line is analyzed separately, similar to the distinction between trunk and feeder corridors made by Scholl et al. (2018).

3 Data

This chapter explores the database used in this thesis. Anticipating the discussion on the identification strategy, special attention is given to how units are selected for treatment or control and the two aggregation levels: at the firm and at a hexagonal grid in space.

3.1 Employer-employee dataset

The main data source for this study is RAIS[6], an employer-employee dataset of the Brazilian Ministry of Labor and Employment (*Ministério do Trabalho e Emprego* — MTE). RAIS provides information in two formats: An annual establishments base, informing for each unit its number of employees, economic sector (*Classificação nacional de atividades econômicas* — CNAE, similar to North America's NAICS), and location data such as the firm's address, postal code, and the neighborhood. The second is a job contracts database, also per year, listing for each contract both personal data on workers (e.g., age, ability degree, gender) and information on wages and contracts. Individuals can be listed more than once per year, either when they change jobs or if they have multiple formal job relationships.

Despite RAIS' comprehensive detailing, there is no information on the worker's residence. This limits the range of possible analysis, as it is not possible to determine if the analyzed transit improvements improved job accessibility for specific workers. Still, it provides more fine-grained data both in space and time, since the available

[6] *Relação anual de informações sociais*, lit. Annual Relation of Social Informations. The usage of this data was authorized by the university's Committee in Research Ethics. The process can be validated on the website plataformabrasil.saude.gov.br/login.jsf, by clicking on *Confirmar Aprovação pelo CAAE ou Parecer* and typing 70141623.5.0000.5147 on the option *Número do CAAE*.

alternative—the Origin-Destination Survey—is aggregated in large tracts and has a decennial frequency.

The dataset was filtered to remove firms with less than two employees since they mostly consist of self-employed individuals under the different Brazilian variations of a single-member limited liability company. The selected time window starts in to focus on recent transit investments and ends in 2017 due to a change in data methodology in 2019[7], to limit the study to the pre-pandemic period, and avoid contamination from stations inaugurated in 2018 near Line 2. Another adjustment concerns treatment timing: firms near stations that opened between July and December of year t begin treatment in year $t+1$, since RAIS data is annualized. A map locating the new stations according to the adjusted dates is available in Figure 12 of Annex A.

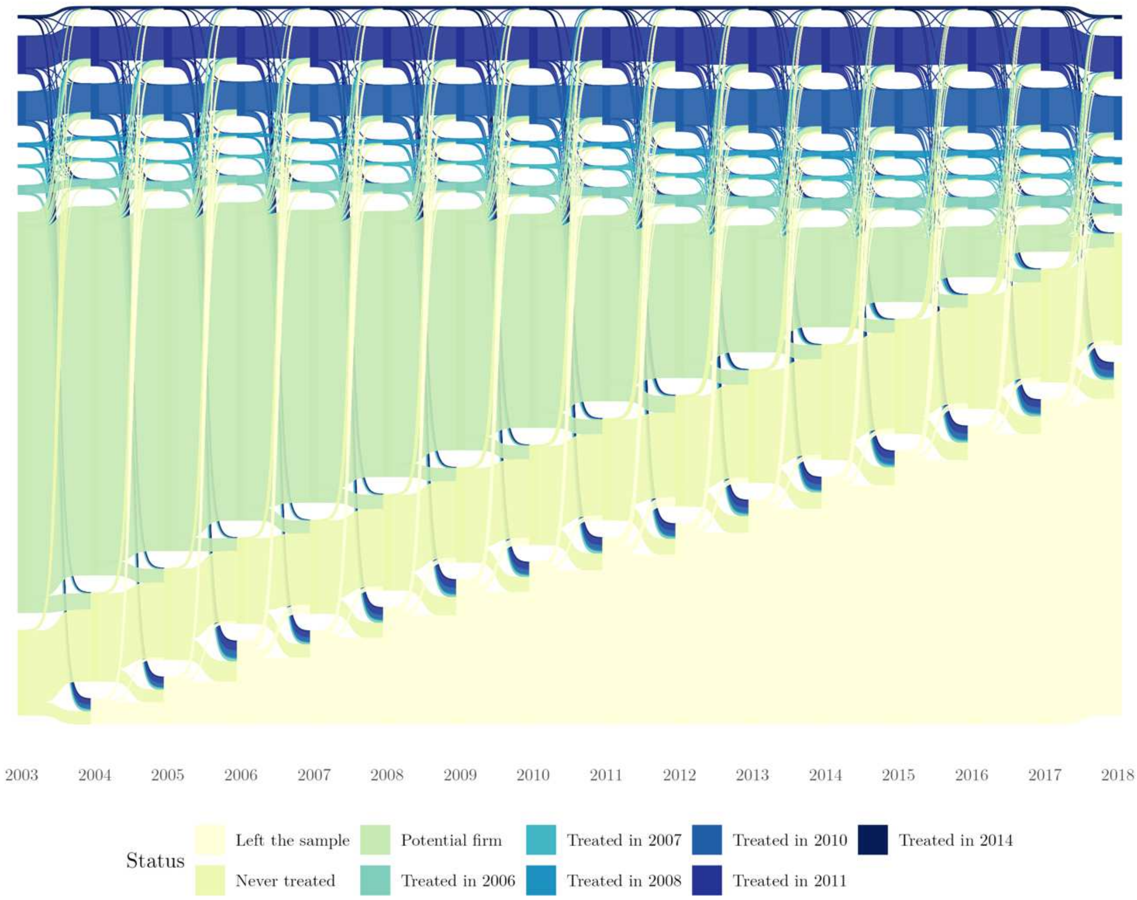
Figures 13 and 14 of Annex A show average firm employment and inflation-adjusted hourly wage, for each treatment cohort. Except for firms treated in 2011 near Line 4, visual inspection suggests parallel trends for level employment. Upon visual inspection, a striking effect can be noted for 2006, in Line 2, and 2008, near Line 9. As for hourly wages, all series are mostly positive despite inflation adjustment, indicating that workers in RMSP enjoyed a great purchase power increase during this period. In turn, all cohorts follow a similar path, pointing towards no salary differential for treated units.

In such a long panel, it is usual that firms and workers come and go—some companies go extinct, workers retire or get unemployed, new businesses are created, and

[7] From 2019 onwards, firms do not fill an annual RAIS form anymore, but rather the base is constructed by the ministery based on *e-Social*, a new platform that consolidates all labor data filled out by the firms. Despite increasing the number of workers and allegedly mitigating filling errors, there is a break from the previous series because some variables (like education level and race) because they are filled out differently (BRASIL, 2020)

individuals who were children at the beginning of the study enter the workforce. Figure 5 displays firm flows on time—leaving and (re)entering the panel—but also in space, migrating from firms in different catchment areas.

Figure 5: Firm migration flows in space and time.



Source: Own elaboration.

For instance, the line connecting the third to the first chunk (from top to bottom) indicates firms moving from a region close to a station that opened in 2010 to another region in the catchment area of a station that opened in 2014. Besides the business life and death movements, migration between different treatment regions represents a small fraction of total flows.

3.2 Geolocation and catchment area

A prerequisite to correctly identifying the impact of transit expansion is to pay attention to the spatial extent of the effects, as economic agents closer to the treatment (i.e., the stations) tend to benefit more from it than those farther away. Applied works deal with this issue by distinguishing treatment and control groups in space so that treated units are close enough to the stations that some impact can still be recovered but control ones are far enough not to be contaminated by spillover effects. The most classical strategy of this kind is the “rings method”, where a circular region around the station composes the treatment group and a surrounding annulus serves as treatment. This strategy was found in Campos (2019), Scholl et al. (2018), Åslund, Blind, and Dahlberg (2017) among the surveyed literature. Alternatively, planned transit routes have been suggested by Redding and Turner (2015) as a counterfactual. The idea behind this is that although transit planning is not random, corridors eligible for mass transit hold similar characteristics.

In this study, the rings method is adopted, but using isochrones (the maximum area that can be reached in a given time) instead of buffers to distinguish firms between treatment and control. Isochrones are calculated using the city’s road layout and therefore consider physical barriers, irregular streets, and topography in the walking time. Figure 6 below gives a real example of this situation for Pinheiros Station in Line 4. The red circle is the equivalent of a 2000-meter buffer, while shaded areas are equivalent to different isochrones. A research design that uses buffers instead of isochrones assumes implicitly that two firms at opposite sides of the river, but at the same linear distance from the station, have the same ability to reach it. In turn, since isochrones are calculated using the street layout, they provide a better measure of accessibility to transit.

Either when using buffers or isochrones, the threshold is an arbitrary choice[8] and can vary from 2 kilometers (Campos, 2019) to 10 kilometers (Åslund, Blind, and Dahlberg, 2017). In this study, preliminary regressions were analyzed with isochrones ranging from five to 60 minutes, increasing the limit to five more minutes per model. The smallest isochrones (5-10 min) had too few samples to provide adequate inference, whereas there was no significant difference in outcomes between 15 and 30 minutes; in turn, between 30 and 60 minutes the effects are null. Hence, the 30-minute isochrone was selected as the treatment group catchment area and the 31- to 61-minute isochrone as the control group.

Using official data on rapid transit networks (São Paulo, 2018, 2019, 2022, 2023), an algorithm was created in R to define each station's catchment area, using the package `r5r` (Pereira et al., 2021). These areas are then subdivided according to their treatment status, using custom functions compiled by the author in the package `spatialops` (Alvarenga, 2024). As many stations' catchment areas overlap—especially in the most economically active regions—the next steps deal with this by further subdividing each station catchment.

The initial strategy classified stations as either always-treated (A), first-treatment (B), or never-treated (C). All firms in category A were already inside a station's catchment area before transit expansion, but they can be subdivided into A'— where no additional treatment happened—and AB, those close enough to a new station to fall inside two catchment areas. This strategy was motivated by the concern that AB firms are impacted by transit expansion differently than B firms, on one hand, and that using

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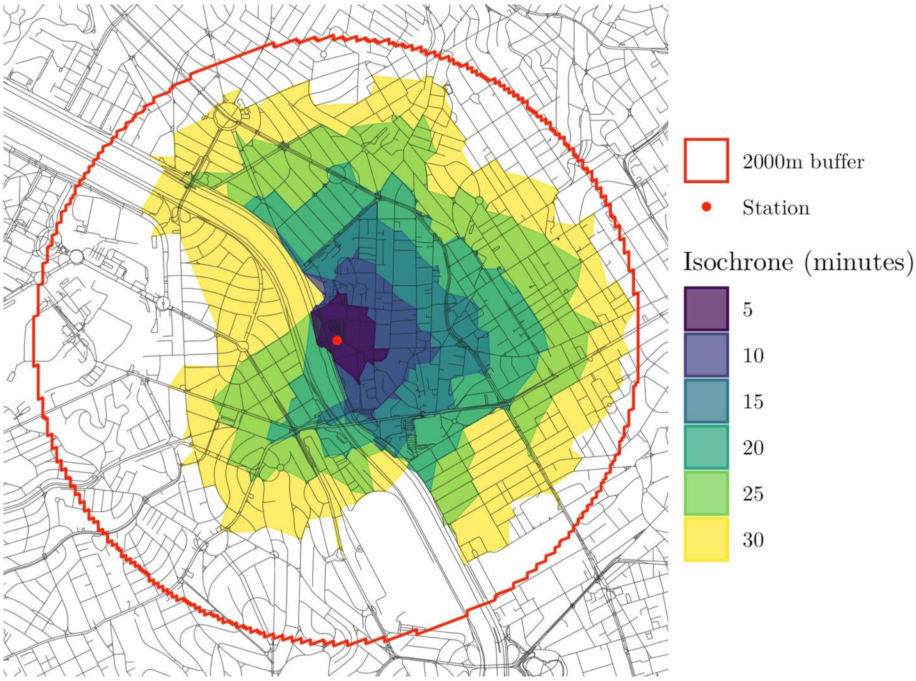
[8] One exception is Butts (2023), which implements a buffer choice method through parametric regression for a static DiD model.

A' as a counterfactual for B masks the treatment effect since they can also benefit from a network expansion elsewhere due to network effects.

Figure 6: Isochrones around Pinheiros Station



Source: Own elaboration.

In this sense, a transitive property $A \succ B \succ C$ is considered. If region i falls inside a never-treated and a treated catchment area, it is considered as treated; furthermore, if it also falls inside an always-treated area, it cannot be considered a new treatment area. First, the algorithm distinguishes for each category their strict portions, that is, $A^{'} :=$ $A - B \cup C$ and similarly for B and C. Next, exclusive intersections are calculated as $ABC := A \cap B \cap C$, $AB := A \cap B - ABC$ (and its pairwise equivalents), leading to the sets

$$\begin{aligned} A" := A' + AC &\rightarrow \text{Always treated,} \\ C' &\rightarrow \text{Never treated} \\ B" := B' + BC &\rightarrow \text{First treatment,} \\ D := AB + ABC &\rightarrow \text{Additional treatment.} \end{aligned}$$

Despite the robustness advantage of this strategy, one main drawback is that it limits severely the number of observations in data. A great portion of Line 4's catchment area falls in the additional treatment category, especially its central portion and the intersection with lines 9 and 2, to the point that almost no station was left to analyze for the 2003-2018 period. The same applies to Line 2 since its eastbound expansion (2006-2011) lies between the catchment areas of Lines 1 and 10. Applying that stricter definition of treatment, what is left to analyze are extensions to the CPTM network, which happened mostly in areas previously underserved by transit: Three stations in Line 9's 2008 southbound expansion, another three infill stations in Line 12 inaugurated in 2008 and 2009, and an infill station in Line 7 (2013).

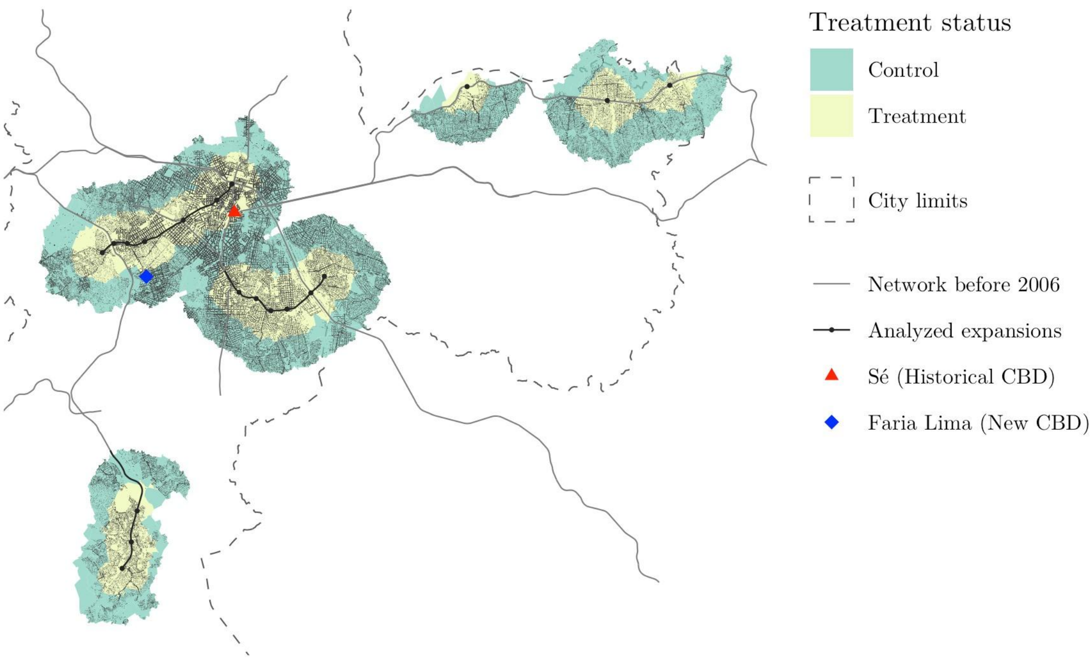
Instead, the preferred approach was to ignore the distinction between A and B, changing the transitivity order to $B \succ A \sim C$. In other words, every part of A and C that intersect with B are considered as treated, whereas both never-treated and previously treated regions are considered as controls. While, as recognized above, this strategy may render more modest impact measures, it enables the study of the two major expansions to the network in the period, lines 2 and 4.

The resulting study area comprises four different lines (2, 4, 9, and 12) with disconnected expansions, in the sense that their catchment areas do not overlap[9]. The single infill station inaugurated in Line 7 was dropped from the analysis since the number of surrounding firms is too small to provide adequate inference. As for Line 5, the single station opened in 2014 was discarded for the same reason, while the 2017-2018 expansion was dropped since not only are they too close to the end of the period, but the northernmost stations overlap with Line 2's expansion. São Paulo-Morumbi station in Line 4 was discarded since it opened in 2018, the last year selected for analysis. Finally, the time window was restricted to 2016, especially to prevent

[9] Although Line 4 and Line 2 share an interchange station, Line 2's expansion between 2006 and 2011 happened in the opposite direction

contamination from Line 5 into the results of Line 2. Although there are 39 cities in the metropolitan region, only four of them intersect with the stations' catchment area in 60-minute isochrones: São Paulo, Guarulhos, Itaquaquecetuba, and São Caetano do Sul. In practice, as Figure 7 reveals, only a minority of them are outside of the capital, where all the stations that opened in the period are.

Figure 7: Catchment areas for each line according to treatment status



Source: Own elaboration.

The addresses of all firms registered in the period in these cities were geolocated using the ArcGis (ArcGIS, 2024) and HERE (HERE, 2024) APIs through the R package `tidygeocoder` (Cambon et al., 2021), retrieving latitude and longitude coordinates. They were cleaned in R using regular expressions (regex) to circumvent typing errors and other inconsistencies since the information is imputed by firms and is subject to human error. This cleaning process enabled more adequate geolocation and a better match between firms and addresses through the years, reducing the amount of double-geolocated addresses. The total number of locations was above 800 thousand addresses, which can represent more than one firm: not only some companies move, but a single address can hold multiple firms (e.g., office towers). This process resulted in the catchment areas in Figure 7. Each geolocated firm is represented by a small point in the map: In denser regions, they are close enough to resemble the road layout.

3.3 Data aggregation

Four outcomes are analyzed in this study. At the firm level, employment and hourly wage; at a spatial level, the number of firms and employment. The first aggregation provides fine-grained information on the firms' labor market response to transit expansion at the demand side, e.g. by contracting more employees or increasing their salaries in response to increased productivity. In turn, zooming out of the firm via spatial aggregation helps to address impacts on a wider scale, especially by looking at the relative growth or decline in a region's number of firms after transit expansion. Analyzing the number of jobs at a regional scale also helps in understanding if there are significant employment gains near new stations even if, on average, firms do not change their number of workers (or even if the average decreases).

There is a delicate balance between aggregation and the precision provided by microdata. The more spatially aggregated data is, the fewer observations are in the sample, resulting in higher standard errors and less reliability. Any aggregation scheme is subject to the modifiable areal unit problem (MAUP), recognized in the geography literature since Openshaw (1983). MAUP occurs when considerably distinct microdata (firms, in this case) are aggregated at a higher level that disregards these differences, leading to measurement errors (Openshaw, 1983). This study uses the H3 grid, an open-source hexagonal grid developed by Uber available in R package `h3jsr` (O'Brien, 2023). While not eliminating MAUP, this grid potentially provides more accurate results than administrative borders and is increasingly being adopted in different works. One example is Pereira et al. (2019b), which investigated the distributional effects of BRT expansion in Rio de Janeiro and concluded that using census tracts and traffic zones as the basic spatial units leads to different conclusions on welfare gains than using a finer spatial grid, the latter with more precise results. From the different resolution levels available, the smallest one (level 9) was chosen, and each hexagon cell has a 10-hectare area, which translates into a few blocks in most parts of the city.

Table 3 shows the number of observations for the firms and hexagon panels, subdivided by each line's catchment area. In the latter, roughly 70 percent of the hexagons are never treated. Line 4 has the most number of hexagons (847), followed by Line 2 (736)— in both cases, more than double that of Line 9 (368)— whereas Line 12's catchment area has 604 hexagons. It is also worth noting that treated hexagons for lines 9 and 12 are almost half of their counterparts for lines 2 and 4 and that there is a small overlap in the never-treated groups of lines 2 and 4 (23 hexagons). In the firms' panel, the only region with more treated than never treated units is that of Line 4; however, this untreated group is the largest of all, roughly tenfold the size of the never-treated group for Line 9.

Table 3: Number of observations per treatment status and aggregation level

(continued on next page)

Group	Hexagons	Firms	Hexagons (%)	Firms(%)
Line 2				
Never treated	539	42440	70	68
Treated	230	19559	30	32
Line 4				
Never treated	551	52802	65	41
Treated	296	76750	35	59

Group	Hexagons	Firms	Hexagons (%)	Firms(%)
Line 9				
Never treated	262	5483	71	59
Treated	106	3844	29	41
Line 12				
Never treated	464	10217	77	72
Treated	140	3980	23	28

Source: Own elaboration.

4 Identification strategy

Under the potential outcomes framework, the adequate way of recovering the causal effect of a policy depends on establishing a counterfactual for the treated group: the trajectory their outcome would follow in the absence of treatment. But since the counterfactual for each treated unit is by definition unknown, a common strategy is to rely on another group that has not been submitted to treatment and then compare the difference in the evolution of their outcomes; this is, as will be shown later, the intuition of the parallel trends assumption. If the counterfactual is well-established, then this discrepancy is attributed to the event that changed the treated units' trajectory (Angrist and Pischke, 2009; Cunningham, 2021).

Different techniques can be used to measure this effect. Assuming that the established control group is an adequate counterfactual for the treated group in the analyzed period, the differences-in-differences framework (DiD) is a suitable option to recover the impact of transit expansion in labor market outcomes. As the literature developed since the late 2010s shows, models based on the two-way fixed effects specification can generate misleading interpretations if treatment effects are heterogeneous either between units treated at different periods or over time; in such cases, researchers need to address treatment timing directly (Borusyak, Jaravel and Spiess, 2022; Callaway and Sant'Anna, 2021b; De Chaisemartin and D'Haultfœuille, 2020; Goodman-Bacon, 2021; Marcus and Sant'Anna, 2021; Sun and Abraham, 2021).

This chapter exposes the main concerns related to the DiD setup when using two-way fixed effects (TWFE). Next, the technique chosen to deal with heterogeneity in this study—the Callaway and Sant'Anna (2021b) staggered DiD model—is introduced, describing its main assumptions for correct identifications, estimation procedures, and aggregation techniques.

4.1 Standard difference-in-differences methods

The canonical 2x2 DiD model considers two periods, pre- and post-intervention, and two groups, treated and never-treated. It can be calculated by different methods, such as a double difference in means, or by an ordinary least squares (OLS) estimation,

$$Y_{it} = \alpha + \alpha_{it} \cdot treated_i + \alpha_t \cdot post_t + \beta^{DiD} \cdot treated_i \times post_t + u_{it}, \tag{4.1}$$

where α is the intercept, $treated_i$ is one for the treated units, $post_t$ is one for all units in the post period, and u_{it} is the error term. If the never-treated group is an adequate counterfactual, then the average treatment effect on the treated (ATT) is correctly identified by β^{DiD} in this setup (Goodman-Bacon, 2021). An implicit assumption in the 2x2 DiD is that treatment occurs at the same time for all units, after *pre* and up to the *post* period. In practice, applied policies roll out at different periods, as is the case in this study since stations are inaugurated gradually between 2006 and 2012. In such cases, a common approach is to include time and individual dummies while still running a pooled OLS, a method known as two-way fixed effects (TWFE):

$$Y_{it} = \alpha_i + \alpha_t + \beta_{TWFE} \cdot D_{it} + u_{it}, \tag{4.2}$$

where $D_{it} = treated_i \times post_t$. The advantage of the TWFE method would be rendering a more precise ATT, captured by β^{TWFE}, since α_i filters individual characteristics constant in time and α_t captures common trends that affect all units in the same manner from one period to another, such as macroeconomic conditions.

Interpreting β^{TWFE} as a causal treatment parameter depends on strong assumptions on homogenous treatment (Borusyak, Jaravel, and Spiess, 2022). As De Chaisemartin and D'Haultfœuille (2018), De Chaisemartin and D'Haultfœuille (2020), Goodman-Bacon (2021), and others point out, this parameter consists of a weighted average of several 2x2 DiDs in the form of β^{DiD} from Equation 4.1. Goodman-Bacon (2021) demonstrates that if there are K treatment groups and one never-treated group, then β^{TWFE} is an average of K^2 β^{DiD}s made up of comparisons between each group, weighted by group size and the variance of D_{it}[10]. An important finding from the Bacon decomposition is that early-treatment units are part of the control group for later-treated ones since their treatment status does not change after they are treated. This means that if treatment effect is not null for early-treated groups, their effects are subtracted from those of later-treated groups, leading to an underestimated overall ATT if they are positive and an overestimated effect if they are negative.

To illustrate this implication in the light of this study, suppose that stations that opened in 2006 have a positive impact on employment in the treated firms compared to the never-treated ones since it is the first treated group. Since for every group ℓ treated after 2006 there is a 2x2 DiD between ℓ and $g = 2006$, the ATT for these groups is net of the (positive) effect found in 2006, to the extent that it can be negative even if there is a positive effect for ℓ if it is smaller than the one found for $g = 2006$. Thus, β^{TWFE}contains negative or softened estimates of the true treatment effect, and their weight on the overall estimate is higher when there are few or no never-treated units and when the number of later treated units is high relative to early- and never-treated groups. Goodman-Bacon (2021) also showed that the variance of D_{it} is the highest for units treated in the middle of the period, increasing their weight on the overall ATT regardless of their subsample size. In practice, for the analyzed 2003–2016 period, this gives more weight to firms treated in 2009 and 2010—the latter also has a great share of the total sample since most stations in the dense Line 4 area opened in 2010.

[10] The full decomposition and its proof is outside of the scope of this thesis and can be found on Goodman-Bacon (2021)

If more than two periods are available, another strategy available is the event study (ES), which details the evolution of the outcome relative to treatment time by including leads and lags in Equation 4.2. Similar to the notation used in Callaway and Sant'Anna (2021b), let $T = \{-K, \ldots, 0, \ldots L\}$ be the time window centered around treatment (in $t = 0$), G_i the period when a unit is treated, and $e, t \in T$. Then,

$$Y_{it} = a_i + \alpha_t + \sum_{e=-K}^{-2} \delta_e^{anticip} \cdot D_{it}^e + \sum_{t \geq g}^{T} \beta_e^{ES} \cdot D_{it}^e + u_{it}, \tag{4.3}$$

In this case, $D_{it}^e = \mathbf{1}\{t - G_i = e\}$; in words, D_{it}^e is one for i at time t if treatment happened e periods prior to t or will occur e periods in the future. The first sum gives treatment leads and at least two of them are excluded to avoid multicollinearity and are commonly used as evidence of parallel trends holding in the pre-treatment period when their coefficients are statistically zero (Sun and Abraham, 2021). The second sum yields separate ATTs for every year a unit is treated, in contrast with the overall β^{TWFE} from Equation 4.2.

This specification would allow the researcher to recover treatment heterogeneity in time, but it still relies on assuming all group cohorts are affected by treatment in the same manner. Returning to the previous example, this would be the case if even though firms treated in 2006 had a bigger ATT in 2010 than in 2008, it is statistically the same as the ATT found in 2013 for units treated in 2011. However, as Sun and Abraham (2021) demonstrated by decomposing β_e^{ES}, even if treatment is homogeneous between cohorts, these estimates cannot be interpreted as dynamic treatment effects because they can be contaminated by other periods. This also applies to treatment leads, so their coefficients are not informative of pre-trends even if they are zero.

To summarize the main takeaways from this discussion, static and dynamic (event study) DiD techniques using two-way fixed effects can render contaminated estimates (i) due to treatment effect heterogeneities between cohorts and (ii) if treatment changes in time (in the static case), since the TWFE parameter is a weighted average of comparisons between the analyzed groups. In addition, using the leads from an ES-TWFE model as a test for parallel trends in the pre-intervention periods is incorrect, as they are also a weighted average containing post-treatment estimates. On the bright side, if such heterogeneities are adequately handled in the research design, there are adequate ways to measure policy impact under the difference-in-differences framework.

Covering all available techniques would be out of the scope of this study; instead, the remainder of this section focuses on the Callaway and Sant'Anna (2021b) staggered DiD. This setup was chosen for six main reasons. First, it deals with heterogeneity through a group-time average treatment effect, $ATT(g,t)$, whereas the typical ES-TWFE only deals with $ATT(t)$. Other methods also consider cohort-specific ATTs; for instance, Sun and Abraham (2021) allow a general cohort specification of which staggered treatment timing is a particular setting, and De Chaisemartin and D'Haultfœuille (2020) can be implemented in fuzzy designs where treated and untreated units coexist in a same cohort.

Second, parallel trends in Callaway and Sant'Anna (2021b) can hold after conditioning on pre-treatment covariates, while other techniques assume unconditional parallel trends for the outcome. Third, as highlighted by Marcus and Sant'Anna (2021), parallel trends assumptions (PTAs) in Callaway and Sant'Anna (2021b) are weaker. If one uses both never-treated and not-yet-treated units as controls, De Chaisemartin and D'Haultfœuille (2020) and Sun and Abraham (2021) require parallel trends to hold in the pre-treatment period between all eventually treated cohorts (in addition to the never-treated group), while in Callaway and Sant'Anna (2021b) they do not need to hold for the first treated group. Parallel trends still need to hold in the post period; however, the weaker assumptions in Callaway and Sant'Anna (2021b) can accommodate situations where PTA does not hold before treatment but then do hold after it, e.g. when economic conditions were different between groups before intervention.

Still regarding PTAs, Callaway and Sant'Anna (2021b) also allow a study design where only never-treated units act as controls. In such setting, the PTA is even less strict, since no treated groups need pre-trends to hold. Fourth, the doubly-robust estimation procedure available in Callaway and Sant'Anna (2021b) is less sensible to model misspecification.

Fifth, the bootstrap technique used in Callaway and Sant'Anna (2021b) provides an overall confidence interval that can be used for simultaneous inference of all $ATT(g,t)$s; in contrast, the commonly used pointwise CIs are not suited for joint significance tests. Finally, the sixth reason is that while De Chaisemartin and D'Haultfœuille (2020) focus on an overall estimate like the static DiD and Sun and Abraham (2021) on event study parameters, the Callaway and Sant'Anna (2021b) strategy has different aggregation schemes ranging from a single overall estimate to individual $ATT(g,t)$s, allowing one to look at the results from different perspectives and to shed light into multiple policy implications.

Besides the staggered DiD model, static TWFE DiDs and ES-TWFE models are also estimated for comparison with the main results. In both cases, five models are estimated for each outcome: one for each transit line and one overall model encompassing all interventions. The static DiD models follow Equation 4.2 with the addition of control variables. Let $t = \{2003{,}2016\}$ for the model encompassing all lines and when Line 2 results are estimated separately, $t = \{2005{,}2017\}$ for Line 4, $t = \{2003{,}2014\}$ for Line

9, and $t = \{2003{,}2015\}$ for Line 12. Periods were chosen such that there are four years before and after interventions[11]. Then, for firm i and when i is the average hourly wage,

$$\begin{aligned} \ln(Y_{it}) = firm_i + year_t + D_{it} + ind\_b2b_{it} + \\ size\_micro_{it} + size\_small_{it} + u\_it, \end{aligned} \tag{4.4}$$

where $firm_i$ and $year_t$ are the fixed effects, ind_b2b_{it} is an indicator equal to one for firms classified as business-to-business (B2B)[12], and $size\_micro_{it}$ and $size\_small_{it}$ are firm size dummies following the national classification provided by the Brazilian Service of Support to the Micro and Small Businesses (*Serviço Brasileiro de Apoio às Micro e Pequenas Empresas* — Sebrae), available in SEBRAE... (2013, p. 17) and freely translated to English in Table 10 of Annex A.

The model for the number of workers follows the same structure of Equation 4.4 except for the removal of the size dummies since they are potential colliders. The choice of the B2B industry is backed by the theoretical framework. In this sector, input and output transport play a minor role than in manufacturing and construction; hence, location decisions are more driven by access to consumer markets and workers than the ease of transporting goods. This also applies to consumer services and to retail—since sold goods do require transport, but this aspect is less determinant to location than for manufacture. Differently from those B2C (business-to-consumer) industries, B2B relies less on proximity to residences, and therefore, accessibility plays a major role in labor market access than in consumer market access. A binary variable for B2C industries was included initially, but since most firms in the sample are either B2B or B2C, there were collinearity issues when estimating some of the models.

[11] The exception is Line 2, since reliable data is availabe since 2003 and the first intervention took place in 2006

[12] The list of economic activities classified as B2B can be found in Table 9 of Appendix A

At the hexagon level, the number of firms and of workers follow Equation 4.4 with the difference that control variables are calculated as proportions relative to the total number of firms in the hexagon. The event study models follow Equation 4.3 with the addition of control variables in the same logic of the static models and t encompassing all periods in the aforementioned intervals but centered around treatment date.

4.2 Staggered DiD

In this section, before describing the identifying assumptions and the estimation methods for the Callaway and Sant'Anna (2021b) staggered setup, the notation is introduced following the authors. Let $\mathcal{T}$ be the number of periods, $t = \{1, \ldots, \mathcal{T}\}$ a particular period, Y_{it} the outcome for the firm or hexagon i observed in t, D_{it} an indicator equal to one if i is treated in period t, X the vector of covariates for the baseline period, and G the period when a unit becomes treated. For never-treated units, $G = \infty$. G_g is equal to one for all units that begin treatment in period g and let $\bar{g}$ be the maximum G: since never-treated observations are used in this study, $\bar{g} = \infty$. Let $\mathcal{G}$ be the support of G excluding $\bar{g}$, i.e., all treatment periods but the last one. Finally, let the generalized propensity score for the probability, in time s, of a unit being treated since period g be $p_{g,s}(X) = P[Gg \ = \ 1|X, G_g + (1 - D_s)(1 - G_g) \ = \ 1]$. In addition to this probability being conditional on pre-treatment covariates, for the never-treated groups, $(1 - Ds)(1 - Gg) = 1$.

4.2.1 Identification assumptions

The Callaway and Sant'Anna (2021b) method relies on five assumptions: staggered treatment, random sampling, limited treatment anticipation, conditional parallel trends, and overlap. Treatment is absorbing under the first assumption, meaning that units do not change their treatment status after they become treated and no unit is treated in the first period. The intuition behind absorbing treatment is that treatment has a long-lasting impact. Intuitively, this is the case for policies such as education programs since they tend to have a permanent impact on an individual. However, firms that change their address to any area that is untreated or treated in a different period were removed from this study since, despite being treated in the first place, moving to a different location implies accessibility changes, which alters the impact of transit expansion in the target outcomes.

Random sampling assumption means that $\{Y_{i1}, \ldots, Y_{iT}, X_i, D_{i1}, \ldots, D_{it}\}_{i=1}^{n}$ is an independent and identically distributed (iid) random sample from a large population. There are no restrictions on temporal dependency of the outcome path or on randomness of treatment allocation and potential outcomes.

The third assumption differs from most DiD applications since anticipation is allowed as long as it is known. Let $\delta \geq 0$ be the anticipation limit. The unit index i is omitted, following the original, to simplify the notation. Then, under the potential outcomes framework,

$$\mathbb{E}[Y_t(g)|X, G_g = g] = \mathbb{E}[Y_t(0)|X, G_g = g] \forall g \in \mathcal{G}, t \in \{1, \ldots, T\}, t - g < \delta. \tag{4.5}$$

In words, the outcome observed in periods before $g - \delta$ is the potential outcome in the absence of treatment, since despite being treated in g, units are already affected since $g - \delta$. In this study, δ is assumed to be zero for all outcomes: some anticipation periods (up to three years) have been tested with no resulting significance; therefore, the simpler $\delta = 0$ was chosen.

There are two parallel trends assumptions under Callaway and Sant'Anna (2021b). In this thesis, the not-yet-treated units are part of the control group along with the never-treated ones. In this case, the $ATT(g, t)$s are properly recovered when in addition to parallel trends after treatment, the observed outcomes between all eventually treated (except the first) and the never treated group is the same in the previous period:

$$\begin{aligned} &\mathbb{E}[Y_t(0) - Y_{t-1}(0) | X, G_g = g] = \mathbb{E}[Y_t(0) - Y_{t-1}(0) | X, D_s = 0, G_g = 0] \\ &\forall g \in \mathcal{G}, (s,t) \in \{2, \dots, T\} \times \{2, \dots, T\}, t \geq g - \delta, t + \delta \leq s < \bar{g}. \end{aligned} \tag{4.6}$$

The proof that this PTA does not require pretrends holding for the first group can be found in Marcus and Sant'Anna (2021).

Finally, the overlap assumption states that a positive fraction of units begins treatment in g and that $p_{g,t}$ is uniformly bounded away from one, a standard assumption in conditional DiD methods adapted to the staggered setting:

$$\forall t \in \{2, \dots, \mathcal{G}\} \exists\, \varepsilon > 0 : P(G_g = 1) > \varepsilon, p_{g,t}(X) < 1 - \varepsilon. \tag{4.7}$$

4.2.2 Estimation, aggregation, and inference

Under those five assumptions, the group-time average treatment effect $ATT(g,t)$ can be nonparametrically identified through three methods: inverse probability weighting (*ipw*), outcome regression (*or*), or doubly robust (*dr*), a combination of the previous two. In short, *ipw* weighs outcome difference relative to the baseline period ($\Delta Y :=$ $Y_t - Y_{g-\delta-1}$) by the probability of an unit being treated at that given time and its covariates, relying on $p_{g,s}(X)$ being correctly modeled. In turn, *or* subtracts from ΔY the population outcome regression (conditional on X) for the control group, and thus depends on the outcome evolution for the control group being correctly modeled.

According to Theorem 1 in Callaway and Sant'Anna (2021b), under the *dr* method only one of the two conditions above needs to be met, rendering more robust estimators; therefore, this is the procedure chosen in this study. Nonetheless, if assumptions 1–4 are satisfied, Callaway and Sant'Anna (2021b) demonstrates that the three estimators are identical.

Let the population outcome regression when not-yet-treated (ny) units are part of the control group be $m^{ny}_{g,t,\delta}(X) := \mathbb{E}\left[Y_t - Y_{g-\delta-1} \middle| X, D_{t+\delta} = 0, G_g = 0\right]$. The parameter of interest in the doubly-robust setting is

$$ATT^{dr}_{ny}(g,t;\delta) = \mathbb{E}\left[\left(\frac{G_g}{\mathbb{E}[G_g]} - \frac{\frac{p_{g,t}(X)(1-D_{t+\delta})(1-G_g)}{1-p_{g,t+\delta}(X)}}{\mathbb{E}\left[\frac{p_{g,t+\delta}(X)(1-D_{t+\delta})(1-G_g)}{1-p_{g,t+\delta}(X)}\right]}\right) - \left(Y_t \; - \; Y_{g-t+\delta} - m_{g,t+\delta}(X)\right)\right] \tag{4.8}$$

The first step for obtaining $ATT^{dr}_{ny}(g,t;\delta)$ is estimating $p(\cdot)$ and $m(\cdot)$ according to the parametric estimators as demonstrated in Callaway and Sant'Anna (2021b). Next, these estimates are plugged into the sample analog of Equation 4.8. These procedures and the following aggregation are all available in the R package `did` (Callaway and Sant'Anna, 2021a).

In each analysis, there are $g \cdot t$ group-time average treatment effects, resulting in 544 total estimates[13] since there are four outcomes and five analysis schemes (overall and each transit line separately). For better interpretation, they are aggregated in three different schemes: overall measures (compared with the static DiD), overall measures by treatment cohort, and effect by length of exposure (compared with ES-TWFE).

From the least to the most aggregated (the reverse order of presentation), the length of exposure parameters are summarized across all treatment groups. These estimates are balanced so that only units that have experienced treatment for at least six periods

[13] Sum of the last column in Table 8 of Appendix A

are used. As Callaway and Sant'Anna (2021b) demonstrate, direct comparison of parameters in time is contaminated by differences in group composition and in each group's weight in the event study aggregation; however, balancing can eliminate such nuisances. The parameter is given, for periods $e = t - g \in \{-6, \dots, 6\}$, by

$$\theta_{es}^{bal}(e; 6) = \sum_{g \in \mathcal{G}} \mathbf{1}\{g + 6 \leq \mathcal{T}\} ATT(g, g + e) P(G = g | G + 6 \leq \mathcal{T}). \tag{4.9}$$

The second aggregation scheme is useful in understanding how treatment effect differs by group cohort. The parameter averages $ATT(g, t)$s separately for each g:

$$\theta_{sel}(\tilde{g}) = \frac{1}{\mathcal{T} - \tilde{g} + 1} \sum_{t=\tilde{g}}^{\mathcal{T}} ATT(\tilde{g}, t). \tag{4.10}$$

Instead of a simple mean of all $ATT(g, t)$s, the overall parameter is a simple average of the $\theta_{sel}(\tilde{g})$s: this reduces the influence that length of exposure and group size have in the overall measure, while still being comparable to static DiDs:

$$\theta_{sel}^{O} = \sum_{g \in \mathcal{G}} \theta_{sel}(g)\, P(G = g | G \leq \mathcal{T}). \tag{4.11}$$

After estimation and aggregation, inference for the θ parameters above is done using a bootstrap procedure. Details are available in Callaway and Sant'Anna (2021b). In short, an influence function estimates the vector of $ATT(g, t)$s; then, for each iteration, the bootstrap algorithm calculates t-tests for the parameters. After B iterations, $\hat{c}_{1-\alpha}$ is constructed as the $(1 - \alpha)$-quantile (e.g., the 95th percentile) of the t-tests distribution so that the confidence interval is given by

$$\hat{C} = \left[\widehat{ATT}_{dr}^{ny}(g, t; \delta) \pm \hat{c}_{1-\alpha} \underbrace{\widehat{\Sigma}(g, t)^{-1/2} n^{-1/2}}_{\text{standard error}} \right], \tag{4.12}$$

where the standard error is clustered at the firm or at the hexagon in their respective panels. In the case of event study plots, the same bootstrap procedure can be applied to pre-treatment estimates. Differently from the ES-TWFE case, these estimates do not contaminate post-treatment $ATT(g,t)$s nor are contaminated by then. Therefore, as suggested by Marcus and Sant'Anna (2021), pre-treatment t-tests can be used for placebo tests and as evidence against parallel trends, if they turn out to be significant.

5 Results and Discussion

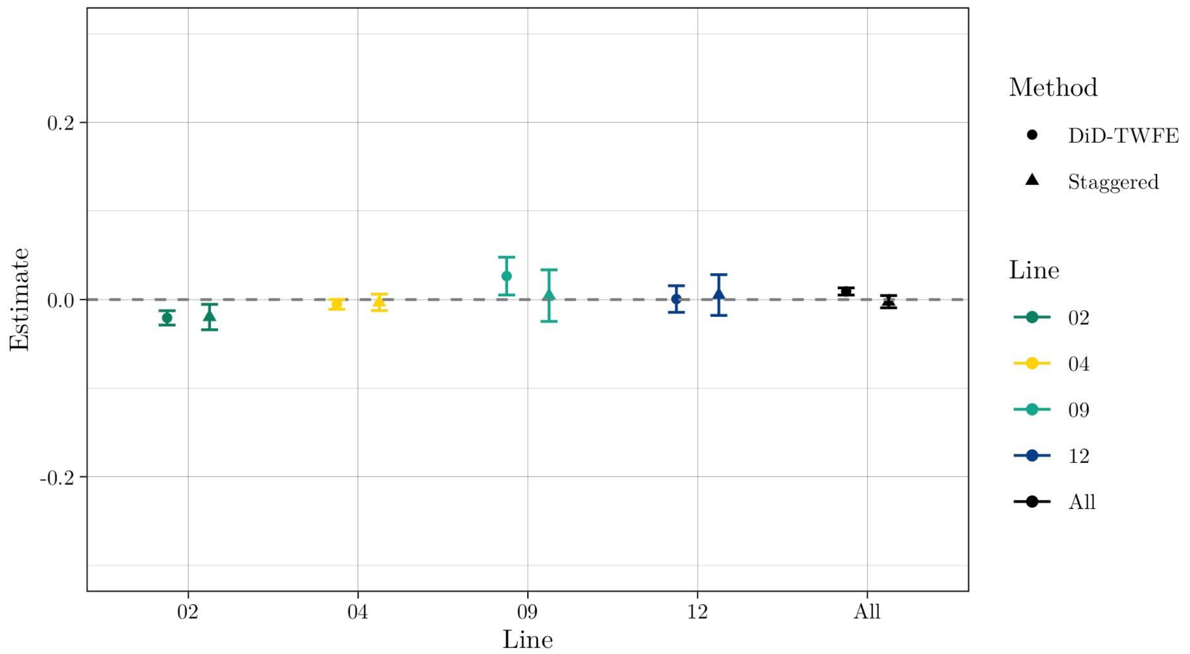
The next paragraphs explore results in detail and establish a connection with the theoretical grounds. For each outcome, a graph is presented showing the overall impact based on the DiD-TWFE (Equation 4.2) and staggered DiD (Equation 4.8 and Equation 4.11) methods; next, overall ATTs for the staggered approach are dismembered by cohort (Equation 4.10). For conciseness, event study plots comparing ES-TWFE (Equation 4.3) and staggered (Equation 4.9) approaches are registered in Appendix B; besides ATTs, they also contain pre-treatment estimates. Confidence bands are reported for the 95% significance level; all results are presented as natural logarithms but converted to percentages when mentioned in the text by subtracting one from its exponential.

5.1 Average hourly wage

Figure 8 shows the overall impact on wages at the firm level. What strikes the most is the negative and significant result for Line 2, indicating a 1.98 percent reduction after the opening of subway stations in both the staggered and TWFE estimates. In contrast, results are positive for Line 9 (at 2.5 percent using TWFE); nonetheless, the staggered estimate fails to reject the null: despite both estimates having similar standard errors, the effect is closer to zero for the staggered one. Lines 4 and 12 are both nearly zero in both models.

In the joint model (“All”), there is a marginal but significant effect in the TWFE case and a negative but insignificant estimate for the staggered setup; however, both are very close. Given the small confidence bands, there is not much variance in wage growth within regions, albeit they are about twice as large for Lines 9 and 12 (which have fewer units in any treatment group).

Figure 8: Average impact of transit expansion on hourly wage at the firm level



Source: Own elaboration.

Table 4 uncovers differences between cohorts that are not visible in the overall parameters. Line 2's overall significance comes mostly from firms close to stations that opened in 2007 and 2010 since they are the only cohorts with relevant estimates, at respectively -5.16 percent and -3.44 percent. When lines are aggregated, $g = 2010$ has no significance and is softened—it even becomes positive, even though the (insignificant) coefficient for $g = 2010$ for Line 4 alone is also negative.

In contrast, $g = 2009$ changes sign (becomes negative) and thus has twice the magnitude just by changing the comparison group (since only Line 12 is treated in 2009), although still close to zero (from -0.7 percent to 0.7 percent). Pre-trends are all zero (figures 15–19, panel b of Annex A) except for $t = -5$ in Line 4.

This can be thought of as a minor problem since outcomes are statistically equal on average between treatment and control for $t = \{-6, -4, -3, -2\}$; however, it can also indicate a placebo test failure. Line 4 opened in 2010 with two stations in a core section

(Paulista and Faria Lima) followed by expansions towards downtown (Luz) and the west (Butantã) in the next year two years[14]; therefore, it is possible that each time cohort follow different outcome paths due to their urban dynamics.

Table 4: Impact of transit expansion on average firm wage, by cohort

Cohort	All lines	Line 2	Line 4	Line 9	Line 12
Average	-0.002	-0.02*	-0.003	0.004	0.005
	[-0.007, 0.002]	[-0.031, -0.008]	[-0.011, 0.004]	[-0.026, 0.035]	[-0.016, 0.027]
2006	-0.014	-0.013	-	-	-
	[-0.035, 0.007]	[-0.033, 0.007]	-	-	-
2007	-0.049*	-0.053*	-	-	-
	[-0.092, -0.006]	[-0.093, -0.012]	-	-	-
2008	-0.014	-	-	0.004	0.004
	[-0.035, 0.007]	-	-	[-0.026, 0.035]	[-0.024, 0.033]
2009	-0.007	-	-	-	0.007
	[-0.063, 0.049]	-	-	-	[-0.037, 0.052]
2010	0.001	-0.035*	-0.009	-	-
	[-0.013, 0.015]	[-0.063, -0.007]	[-0.023, 0.006]	-	-
2011	-0.003	-0.011	0.01	-	-
	[-0.024, 0.018]	[-0.034, 0.012]	[-0.03, 0.05]	-	-
2012	0.002	-	0	-	-
	[-0.007, 0.012]	-	[-0.01, 0.01]	-	-
N	204867	61999	127019	9327	14197

[14] See Figure 12, Annex A

SE Clusters	by: Firm	by: Firm	by: Firm	by: Firm	by: Firm

Source: Own elaboration.
Notes: confidence interval reported in brackets; * = significant at 5%.

Looking at group-time average treatment effects for Line 4 in the lowest level of detail, the yearly $ATT(g,t)$s, pre-treatment parallel trends are violated for $g = 2012$ (Fig. 20 of Appendix A), which corresponds to firms and hexagons around stations República and Luz. Both stations, in addition to offering connections to several other lines in the network, are inserted in the historical CBD, a dense region with a high concentration of jobs that, despite losing part of its dominance to other business districts since the mid-20th century, still experienced relatively higher growth in comparison with never-treated and not-yet-treated regions in the Line 4 region, up until 2006 (firm employment) and 2007 (firm wage).

The result for Line 2 is not matched in the literature since the positive effects on wages are either nonexistent (e.g., Åslund, Blind and Dahlberg (2017)) or positive, particularly in Latin American contexts (Campos, 2019; Scholl et al., 2018; Tsivanidis, 2019). Looking for reasons for this result on the theory, one of the transmission channels from transit expansion into wages is through productivity, in which case wage reductions could indicate productivity loss and the lack of significance suggests no productivity gains or no pass-trough into wages, i.e., productivity being completely absorbed by the employer.

Alternatively (or in addition to this effect), commute savings might be captured by the employer through smaller wages, while still resulting in a positive or null utility change for workers. A similar reasoning is found in Vickerman (2008), when describing the two-way road effect applied on wages on a regional scale: the increase in labor supply resulting from greater accessibility reduces wage pressure, while the contrary happens if firms elsewhere outbid local firms for their workers[15]. In the three cases, however, the sticky nature of wages—among other factors, in observance to the Brazilian labor legislation—suggests that the reduction perceived in Line 2 region stems not from wage cuts but rather from new employment relationships, that could either be a substitution of previous, better-paid workers, or result from new employers receiving less and thus bringing the average down.

5.2 Employment

At first glance, Figure 9 points to similar results for the two methods, but great variability between regions. The lowest values are registered for Line 12: impacts are negative in both methods, but under the staggered method, it reaches -7.23 percent and is significant. Similar to wages, results are the highest for Line 9 (at roughly 5 percent for TWFE and 4 percent for the staggered method), albeit none are significant; the same applies for Lines 2 and 4 and in aggregate.

Cohorts in Table 5 do not differ from the overall results: Group 2008 is significant for line 12 (-8.52 percent) and offsets Line 9's positive effect (3.67 percent but not significant) when all lines are considered, leading to a negative and significant impact of -5.26 percent for $g = 2008$.

Event study plots on panel (a) of figures 15–19 show virtually no fluctuation for all lines aggregated and for lines 2 and 4; in contrast, a crescent (but still non significant) trend is perceived for Line 9 up to the fourth year, when it breaks monotonicity and starts to fall, and the opposite movement is noted for Line 12. Pre-parallel trends are

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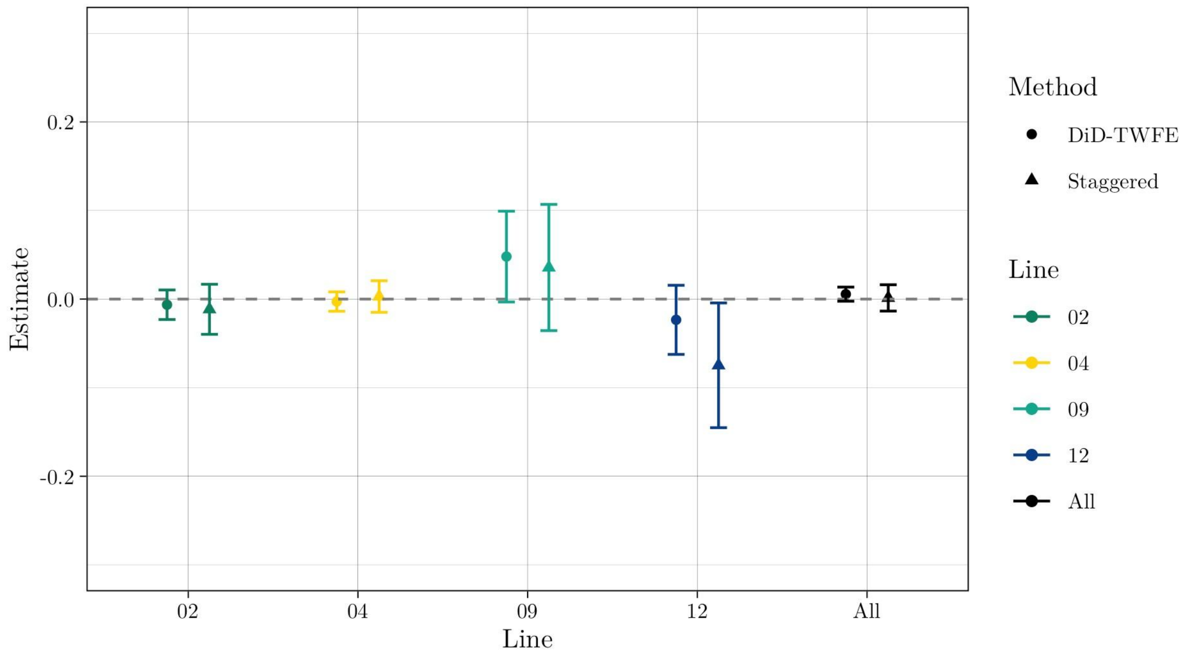
[15] Adapting to the intraurban context, the latter argument only makes sense for the set of individuals that used to work near their houses, as mentioned previously in the Line 12 case.

present in all scenarios but near significance for Line 12 in $t \leq -4$, albeit converging to zero.

Figure 9: Average impact of transit expansion on employment at the firm level



Source: Own elaboration.

The lack of meaningful results in most regions might suggest that transit investments did not translate into accessibility gains that increase the labor market pool or enable firms to be reached by more customers. This hypothesis needs to be considered with caution since accessibility is not modeled in this study, and available data look at individuals at their workplaces, not residences. Another possibility is that additional labor supply was absorbed by entrant firms rather than established ones: results for the number of firms at the hexagon level will help to investigate this hypothesis.

For lines 2 and 4, two other possible explanations are high motorization rate in those regions, as was the case of Uppsala (Åslund, Blind and Dahlberg, 2017), and the fact that those regions were already important job centers prior to intervention, in the same line of Canales, Nilsson and Delmelle (2019).

As for the negative and significant impact estimated for Line 12 region, how is it possible that new train stations decreased the average number of workers per firm? One can then think of the "two-way road" effect: the same accessibility gains that increases accessibility *to* a place also increases accessibility *from* it (SACTRA, 1999; Vickerman, 2008). In other words, if the three new infill stations in Line 12 increased the labor pool for the surrounding firms, residents nearby also gained access to a wider range of employment possibilities and thus might have exchanged from employment in a local business to other firms elsewhere along the network, which could also indicate a greater firm-worker match. Yet, a simpler explanation and along the lines of the last paragraph is that new firms may employ less workers, bringing the average down. This is also intuitive assuming that new businesses are in a earlier development stage and, therefore, have fewer employees.

Table 5: Impact of transit expansion on employment at the firm level, by cohort

Cohort	All lines	Line 2	Line 4	Line 9	Line 12
Average	0.001	-0.012	0.003	0.036	-0.075*
	[-0.009, 0.012]	[-0.036, 0.013]	[-0.012, 0.017]	[-0.034, 0.105]	[-0.138, -0.012]
2006	0.017	0.013	-	-	-
	[-0.023, 0.058]	[-0.031, 0.058]	-	-	-
2007	-0.089	-0.078	-	-	-
	[-0.18, 0.002]	[-0.167, 0.011]	-	-	-
2008	-0.054*	-	-	0.036	-0.089*
	[-0.106, -0.001]	-	-	[-0.039, 0.11]	[-0.165, -0.012]
2009	-0.026	-	-	-	-0.029
	[-0.161, 0.108]	-	-	-	[-0.156, 0.099]
2010	0.012	-0.013	0	-	-

Cohort	All lines	Line 2	Line 4	Line 9	Line 12
	[-0.01, 0.034]	[-0.087, 0.062]	[-0.024, 0.025]	-	-
2011	-0.022	-0.03	-0.011	-	-
	[-0.068, 0.025]	[-0.086, 0.026]	[-0.093, 0.072]	-	-
2012	0.009	-	0.006	-	-
	[-0.013, 0.03]	-	[-0.017, 0.028]	-	-
N	204867	61999	127019	9327	14197
Clusters	by: Firm	by: Firm	by: Firm	by: Firm	by: Firm

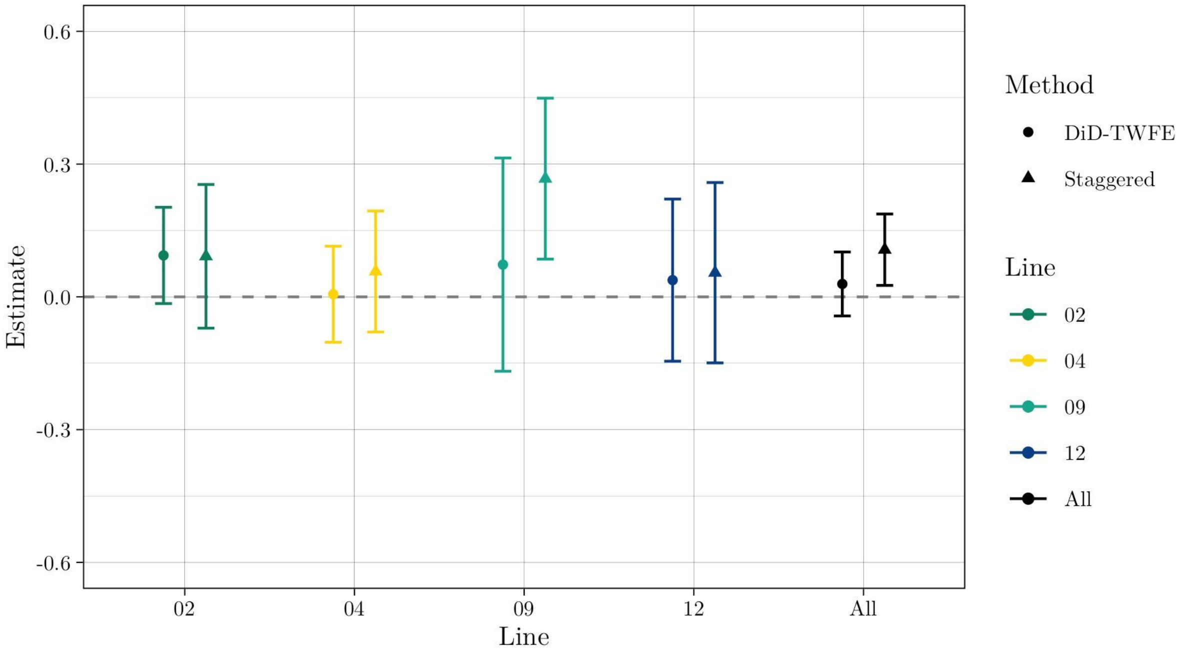
Source: Own elaboration.
Notes: confidence interval reported in brackets; * = significant at 5%.

Zooming out to the hexagon level, overall are positive and significant for Line 9, at 30.6 percent, and all lines jointly, at 11.3 percent. The biggest difference from firm-level results occurs at Line 12, where results are positive: this indicates that a reduction in firm-level average employment was compensated by business creation.

Group ATTs in Table 6 are all positive, but only $g = 2008$ has significance. Despite some estimates suggesting strong employment effects—mostly positive and one negative, which is $g = 2009$ for Line 12)—, there is great variability. The estimated impact on hexagon employment for $g = 2011$ among all lines, the parameter is centered on 5.34 percent but goes from -16.14 percent to 32.18 percent; for Line 2 and $g = 2007$ it reaches 21.53 percent, but CI goes from -1.09 percent to 49,33 percent.

Employment evolution over time follows mostly positive and crescent paths (except for Line 12 as well). In special, estimates for the fifth and sixth year after treatment for Line 9 are significant, at roughly 40 percent job growth, but on the edge of significance. Overall results, though, are not different from zero at an yearly basis.

Figure 10: Average impact of transit expansion on employment at the hexagon level



Source: Own elaboration.

The contrast between firm-level and hexagon-level estimates of employment provide additional support to the hypothesis that the decrease observed in some regions at the firm level does not mean less employment in general, but rather a composition change resulting from new players employing less workers.

Table 6: Impact of transit expansion on employment at the hexagon level, by cohort

Cohort	All lines	Line 2	Line 4	Line 9	Line 12
Average	0.107*	0.092	0.057	0.267*	0.055
	[0.042, 0.171]	[-0.058, 0.241]	[-0.054, 0.169]	[0.09, 0.444]	[-0.172, 0.281]
2006	0.059	0.043	-	-	-
	[-0.106, 0.224]	[-0.132, 0.219]	-	-	-
2007	0.143	0.195	-	-	-
	[-0.07, 0.357]	[-0.011, 0.401]	-	-	-
2008	0.283*	-	-	0.267*	0.168

Cohort	All lines	Line 2	Line 4	Line 9	Line 12
	[0.115, 0.451]	-	-	[0.071, 0.463]	[-0.159, 0.495]
2009	-0.127	-	-	-	-0.24
	[-0.458, 0.204]	-	-	-	[-0.532, 0.053]
2010	0.071	0.263	0.056	-	-
	[-0.077, 0.22]	[-0.686, 1.213]	[-0.094, 0.205]	-	-
2011	0.052	0.047	0.037	-	-
	[-0.176, 0.279]	[-0.297, 0.39]	[-0.322, 0.396]	-	-
2012	-0.017	-	0.072	-	-
	[-0.216, 0.183]	-	[-0.187, 0.331]	-	-
N	2552	768	837	367	603
Clusters	by: Hexagon	by: Hexagon	by: Hexagon	by: Hexagon	by: Hexagon

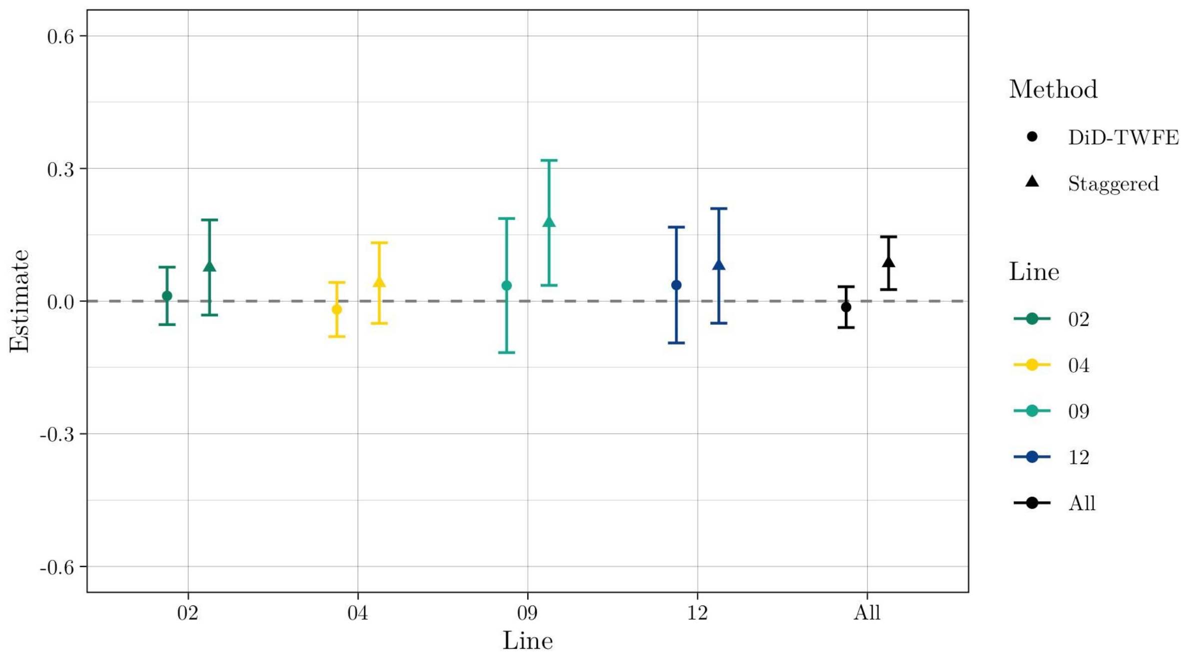
Source: Own elaboration.
Notes: confidence interval reported in brackets; * = significant at 5%.

5.3 Business growth

In the most aggregated form, the 2006-2012 Metrô and CPTM expansion resulted in 8.98 percent more jobs for the treated hexagons. All individual overall estimates for the staggered approach are positive but significant only for Line, 9 at 19.36 percent. The aggregated results are in line with the findings for Rio de Janeiro (Campos, 2019) after the inauguration of subway stations for firms between 750 and 1000 meters from a station. BRT inauguration in Lima (Scholl et al., 2018) also caused business growth, at roughly 32 percent.

By cohort, all parameters in Table 7 are positive with two exceptions: $g = 2009$ for Line 12 and $g = 2012$ for the joint analysis. Both cohorts belong to only one project (Line 12 and Line 4, respectively) and when analyzed separately, estimates are positive, just as happened for $g = 2009$ for the average wage. Line 2 presents large effects for all groups except $g = 2006$, but are only significant for $g = 2007$ at 18.77 percent. Once again, confidence intervals are too large, indicating a high variability of results among hexagons. Aggregating all lines, groups 2007 and 2008 remain significant.

Figure 11: Average impact of transit expansion on firm growth at the hexagon level



Source: Own elaboration.

The role played by length of exposure varies between lines, as indicated by panel (c) of the figures 15–19 of Appendix A. Just as in the case of hexagon employment, a crescent trend is noted for lines 2 and 9, although with no significance for individual $ATT(g,t)$s; for lines 4 and 12, this pattern is reverted respectively in the third and fourth years after treatment. Considering all lines together, the overall trend is positive, crescent, and significant from the third year onwards. On one hand, estimates are more moderate than those recovered for Line 9 and more aligned with the ones from Line 2; on the other hand, analyzing all lines at the same time provides more precision through smaller standard errors, leading to significant estimates.

Recalling the drivers of firm location decision, public transport attracts firms to a location if its accessibility gains allow firms to save labor and shipping costs, attract more customers (at the retail sector), enjoy a greater labor pool and employ better matched workers. At the same time, land value and go in the opposite direction, as regions with good accessibility tend to be more expensive, and so does technology, since they can make proximity less essential for a firm's activity.

Applied in the context of this study, either transit expansion did not improve access to workers and consumers in the regions served by lines 2, 4, and 12, or land values offset these benefits. The latter is a plausible possibility, in particular, for Line 4. Its core section was already dense prior to intervention, and, therefore, less land is available for development.

Additional pressure can come from zoning restrictions; however, it exceeds the scope of this thesis[16]. By the same logic, the two-digit growth in number of business experienced in the surroundings of Imigrantes station (Line 2, $g = 2007$) and in the southbound expansion of Line 9 can reflect not only increased agglomerative potential in those regions led by new stations, but also cheaper land, in the case of Line 9.

When these results are compared with firm-level outcomes, the positive estimates support the hypothesis that lower average wages and employment per establishment stem from entrant firms, but the lack of significance precisely in the regions where those firm-level results were observed (Line 12 and most of Line 2) go in the opposite direction.

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[16] In the 2014 zoning code, restrictions were eased for development around rapid transit stations, while increasing limits on other parts of the city (São Paulo, 2014)

Table 7: Impact of transit expansion on firm growth at the hexagon level, by cohort

Cohort	All lines	Line 2	Line 4	Line 9	Line 12
Average	0.086*	0.076	0.041	0.177*	0.08
	[0.043, 0.129]	[-0.018, 0.17]	[-0.039, 0.121]	[0.037, 0.317]	[-0.052, 0.211]
2006	0.073	0.04	-	-	-
	[-0.029, 0.176]	[-0.091, 0.171]	-	-	-
2007	0.162*	0.172*	-	-	-
	[0.031, 0.292]	[0.032, 0.311]	-	-	-
2008	0.201*	-	-	0.177*	0.122
	[0.095, 0.307]	-	-	[0.043, 0.311]	[-0.051, 0.295]
2009	0.035	-	-	-	-0.03
	[-0.193, 0.262]	-	-	-	[-0.232, 0.172]
2010	0.045	0.192	0.046	-	-
	[-0.066, 0.156]	[-0.333, 0.716]	[-0.067, 0.16]	-	-
2011	0.031	0.04	0.014	-	-
	[-0.115, 0.177]	[-0.168, 0.248]	[-0.223, 0.251]	-	-
2012	-0.017	-	0.047	-	-
	[-0.148, 0.114]	-	[-0.153, 0.248]	-	-
N	2552	768	837	367	603
SE Clusters	by: Hexagon	by: Hexagon	by: Hexagon	by: Hexagon	by: Hexagon

Source: Own elaboration

Notes: confidence interval reported in brackets; * = significant at 5%.

6 Final remarks

This thesis investigated the impact of rapid transit expansion between 2006 and 2014 in the labor market of São Paulo, one of the biggest metropolises in the world, using special techniques to deal with heterogeneities in space and time. Rapid transit expansion is often defended on the basis of expected growth on employment, wages, and establishments, but there is no structured evaluation of these expectations once the investments are made. During this period, five rail lines were improved and two new ones were inaugurated. Four of them were analyzed: eastbound expansion in the subway (Metrô) Line 2, the new subway Line 4, infill stations in regional metro (CPTM) Line 12, and the southbound expansion in CPTM Line 9. Their impact on labor market and business growth varies more between regions than between the time a region is treated. In particular, results were the most positive for Line 9 and absent in the highly-anticipated Line 4.

There are multiple transmission channels from rapid transit expansion labor market outcomes, linking accessibility gains with localization (industry-specific) and urbanization (region-specific) economies that can result in greater labor supply, increased market access, and higher productivity through better firm-worker match. These mechanisms are interconnected and cannot be disentangled in the reduced-form models used in this study; however, they serve as guidance to interpret the results.

Considerable challenges are imposed when trying to recover causal estimates in this context. Endogeneity of treatment selection was a prime concern that guided the research design from its beginnings, by establishing an adequate counterfactual for the treated regions through a control group. This was done by selecting treatment areas that do not overlap and using as control the annulus surrounding treated regions. In addition, catchment areas were delimited via isochrones calculated using real walk paths instead of a buffer with uniform radius, reducing measurement error in treatment selection.

The selected estimation technique was the difference-in-differences technique, a workhorse of empirical estimation, that poses its own challenges. To deal with treatment heterogeneity in treatment timing, the estimation procedure incorporated the staggered method of Callaway and Sant'Anna (2021b) that circumvents the contamination issue that arises in the standard two-way fixed effects technique and renders detailed estimation per treatment cohorts and length of exposure. Space is another font of heterogeneity since regions have intrinsic characteristics that affect their response to transit improvements. This concern was addressed by running separate analyses for each transit line and in conjunction.

The findings of this thesis portray different scenarios depending on the outcome, region, and treatment cohort, but some patterns arise in space and time. Most of the positive and significant impacts take place in the surroundings of Line 9's 2008 south expansion; in contrast, the central, denser, and wealthier Line 4 region saw no relevant effects. This goes in the opposite direction of recent empirical evidence for Latin America, since the impact on labor market outcomes was greater for either wealthier regions or better-paying jobs (which often are at the same place) in Bogotá (Tsivanidis, 2019), Lima (Scholl et al., 2018), and Rio de Janeiro (Campos, 2019).

One caveat in the latter case is that wealthier regions were also the ones that received subway expansion, whereas the less privileged ones were served by BRT, which makes it difficult to disentangle whether greater outcomes stem from the different infrastructures or socioeconomic characteristics. Scholl et al. (2018) predicted bigger impacts for regions that previously had worse public transport coverage, which did not happen in that study. In turn, this hypothesis is fulfilled in this study, since, by all metrics, the most benefited region is the most isolated one in the network, the extreme south region of the capital.

Over time, most group-time ATTs follow a monotonic path, either increasing for positive impacts or decreasing in the negative case, but not exponentially. In other words, outcomes evolve and then plateau, but the impact is persistent (when significant). Recovered estimates also differ between treatment cohorts, which points toward the relevance of the staggered design. One might suppose that groups treated earlier benefit more from the intervention if their units have more incentive to self-select for treatment since transit expansion is generally planned and executed following a priority order where most demanded regions are connected first—therefore, the first treatment groups would accrue higher labor market benefits from transit expansion. Despite differences in ATT between treatment cohorts, they do not follow a pattern. One possible explanation is assuming that the most important network links were those already existent prior to 2006, when the study began.

As theorized by Chatman and Noland (2011) and supported by evidence from Uppsala (Åslund, Blind and Dahlberg, 2017), the impact of transport infrastructure expansion depends on the level of maturity of the network; in other words, the benefits have diminishing returns. The rapid transit network in São Paulo is far from covering the entirety of the metropolitan region; in fact, coverage has always been bigger in the urban core and in a few corridors along regional railways from over a century ago. In this sense, the two biggest expansions in the 2006-2015 period took place precisely in central places that were already served by rapid transit (albeit not necessarily in an ideal level), which can be a reason for the insignificant effects found for Line 4 and most of Line 2. In contrast, the Line 9 expansion served the extreme south of the capital, which was underserved by rapid transit since the suppression of rail service in the late 1980s.

Two counterintuitive results found were the decrease in average workers per firm for Line 12 and in average hourly wage for parts of Line 2. In both cases, the simplest explanation is that entrant firms employ less individuals and pay less, thus bringing down the average. This idea is backed up by the growth in the number of firms and employment at the more aggregated hexagon level, albeit not always significant. Another possibility is that improved accessibility allowed residents to exchange workplaces from local firms to other companies along the network (the "two-way road" effect), thus decreasing local activity, but this hypothesis requires caution since there is no data on worker residence and it may be too strong to assume that the number of workers living close to their jobs was big enough to generate such negative and significant estimates.

More than answers, this thesis provokes two questions to aid future policymaking. First, is transit expansion merely catching up with urban development or promoting it? Since 2014, the zoning code of the capital explicitly ties density to transit corridors, in a 600-meter buffer around mass transit stations and 200-meter along low/medium capacity corridors, where double the floor-area ratio (FAR) is allowed (São Paulo, 2013, 2014). The effect of this legislation is probably not captured by this study, since the analyzed period ends in 2017, when few real estate ventures developed under the new legislation were inaugurated; instead, it mostly reflects the 2004 zoning code (São Paulo, 2004), which had more restrict FARs.

Second, which regions should be prioritized for the next interventions? Pereira, Schwanen and Banister (2017) argue that if a society wishes to reduce social exclusion (and specifically transport-related social exclusion)—as appears to be the Brazilian case, given the social contract implied in the country's Constitution—transport planning should meet minimum accessibility standards, especially for disadvantaged communities, to mitigate inequalities. In addition to accessibility, this study proposes that the project's transformation potential on labor market outcomes should be analyzed as well. The fact that Line 9 south expansion—which serves a lower to middle class portion of São Paulo and with the 8th worst HDIs in the city[17]—had such a large impact on business and employment growth suggests that rapid transit expansion has potential to transform the scenario of underprivileged communities.

This thesis can be extended in several ways. To begin with, a migration analysis tracking individual workers and firms in space could provide additional robustness to distinguish growth from reorganization (Behrens and Robert-Nicoud (2015)) and give more insight into the proposed explanations. An intersection with the 2022 Census microdata (gradually being released as of May 2024) and previous editions would be helpful in conducting a welfare analysis into the interventions' potential to reduce social inequalities, given income and household characteristics. Inasmuch as the results obtained here are limited to a partial equilibrium context, a quantitative spatial model integrating land use, labor markets, and accessibility modeling such as the Ahlfeldt model (Ahlfeldt et al., 2015) could enhance welfare analysis in a general equilibrium context and help to integrate land use and transport planning.

[17] Data compiled by Rede Social de Cidades (2024) using data from the 2000 and 2010 IBGE Censuses and SABESP, the water and sewage company of São Paulo

References

AHLFELDT, G. *et al.* Demystifying compact urban growth. 2018.

AHLFELDT, G. M. *et al.* The Economics of Density: Evidence From the Berlin Wall. **Econometrica**, v. 83, n. 6, p. 2127–2189, 2015.

ALONSO, W. **Location and land use: toward a general theory of land rent**. Cambridge/Mass: Harvard Univ. Press, 1964.

ALVARENGA, A. B. **spatialops: Spatial operations that comes in handy**. , 2024.

ANGRIST, J. D.; PISCHKE, J.-S. **Mostly harmless econometrics: an empiricist's companion**. Princeton: Princeton University Press, 2009.

Anuário do trabalho na micro e pequena empresa. . [s.l.] Serviço Brasileiro de Apoio às Micro e Pequenas Empresas; Departamento Intersindical de Estatística e Estudos Socioeconômicos, 2013. Disponível em: <https://sebrae.com.br/Sebrae/Portal%20Sebrae/Anexos/Anuario%20do%20Trabalho%20Na%20Micro%20e%20Pequena%20Empresa_2013.pdf>. Acesso em: 27 apr. 2024.

ARCGIS. **Geocoding service—ArcGIS REST APIs | ArcGIS Developers**. Esri, , 2024. Disponível em: <https://developers.arcgis.com/rest/geocode/api-reference/overview-world-geocoding-service.htm>. Acesso em: 22 apr. 2024

ASCHAUER, D. A. Is public expenditure productive? **Journal of Monetary Economics**, v. 23, n. 2, p. 177–200, Mar. 1989.

ÅSLUND, O.; BLIND, I.; DAHLBERG, M. All aboard? Commuter train access and labor market outcomes. **Regional Science and Urban Economics**, v. 67, p. 90–107, 1 Nov. 2017.

BAUM-SNOW, N. Did Highways Cause Suburbanization? **The Quarterly Journal of Economics**, v. 122, n. 2, p. 775–805, 1 May 2007.

BEHRENS, K.; ROBERT-NICOUD, F. Agglomeration Theory with Heterogeneous Agents. In: **Handbook of Regional and Urban Economics**. [s.l.] Elsevier, 2015. v. 5p. 171–245.

BILLINGS, S. Estimating the value of a new transit option. **Regional Science and Urban Economics**, v. 41, n. 6, p. 525–536, 1 Nov. 2011.

BORUSYAK, K.; JARAVEL, X.; SPIESS, J. **Revisiting Event Study Designs: Robust and Efficient Estimation**. Rochester, NY, 19 Apr. 2022. Disponível em: <https://papers.ssrn.com/abstract=2826228>. Acesso em: 25 apr. 2024

BRASIL. 7619. Lei nº 7.619, de 30 de Setembro de 1987. . 30 Sep. 1987.

BRASIL. **Substituição da captação dos dados da RAIS pelo eSocial e aspectos metodológicos da RAIS 2019**. Brasília: Ministério da Economia, 26 Oct. 2020.

BRUECKNER, J. K. The structure of urban equilibria: A unified treatment of the muth-mills model. In: **Handbook of Regional and Urban Economics**. [s.l.] Elsevier, 1987. v. 2p. 821–845.

BRYAN, G.; GLAESER, E.; TSIVANIDIS, N. Cities in the Developing World. **Annual Review of Economics**, v. 12, n. 1, p. 273–297, 2020.

BUTTS, K. JUE Insight: Difference-in-differences with geocoded microdata. **Journal of Urban Economics**, Special Issue: JUE Insight Shorter Papers. v. 133, p. 103493, 1 Jan. 2023.

CALLAWAY, B.; SANT'ANNA, P. H. C. **did: Difference in differences**. , 2021a. Disponível em: <https://bcallaway11.github.io/did/>

CALLAWAY, B.; SANT'ANNA, P. H. C. Difference-in-Differences with multiple time periods. **Journal of Econometrics**, v. 225, n. 2, p. 200–230, Dec. 2021b.

CAMBON, J. *et al.* tidygeocoder: An R package for geocoding. **Journal of Open Source Software**, v. 6, n. 65, p. 3544, 2021.

CAMPOS, M. C. DE. **Urban Mobility, Inequality and Welfare in Developing Countries: Evidence from 2016 Olympics in Rio de Janeiro**. Tese de Doutorado—Rio de Janeiro, Brazil: Pontifícia Universidade Católica do Rio de Janeiro, 25 Feb. 2019.

CANALES, K. L.; NILSSON, I.; DELMELLE, E. Do light rail transit investments increase employment opportunities? The case of Charlotte, North Carolina. **Regional Science Policy & Practice**, v. 11, n. 1, p. 189–202, Mar. 2019.

CAPELLO, R.; NIJKAMP, P. (EDS.). **Handbook of regional growth and development theories**. Revised and extended second edition ed. Cheltenham, UK Northampton, MA, USA: Edward Elgar Publishing, 2019.

CASTRO, L. S. D.; ALMEIDA, E.; LIMA, J. E. D. Transporte e crescimento econômico : o caso do Proacesso em Minas Gerais. **Pesquisa e Planejamento Econômico (PPE)**, n. v. 51, n. 02, p. 145–178, 15 Aug. 2021.

CHATMAN, D. G.; NOLAND, R. B. Do Public Transport Improvements Increase Agglomeration Economies? A Review of Literature and an Agenda for Research. **Transport Reviews**, v. 31, n. 6, p. 725–742, 1 Nov. 2011.

CHRISTALLER, W.; BASKIN, C. W. **Central places in southern Germany**. Englewood Cliffs, N.J.: Prentice-Hall Englewood Cliffs, N.J., 1966.

COMBES, P.-P.; GOBILLON, L. The Empirics of Agglomeration Economies. In: **Handbook of Regional and Urban Economics**. [s.l.] Elsevier, 2015. v. 5p. 247–348.

CPTM. **Relatório Integrado da Administração 2019**. São Paulo: Companhia Paulista de Trens Metropolitanos, 2020. Disponível em: <https://www.cptm.sp.gov.br/esg-consciente/Governanca/Paginas/Relatorio-da-Administracao-RIA.aspx>. Acesso em: 1 nov. 2023.

CREDIT, K. Accessibility and agglomeration: A theoretical framework for understanding the connection between transportation modes, agglomeration benefits, and types of businesses. **Geography Compass**, v. 13, n. 4, p. e12425, Apr. 2019.

CUNNINGHAM, S. **Causal inference: the mixtape**. New Haven ; London: Yale University Press, 2021.

DAVANZO, A. M. Q. *et al.* Metropolização e rede urbana. In: **Dinâmica urbano-regional: rede urbana e suas interfaces**. 1. ed. Brasília: Ipea, 2011. p. 486.

DE BOK, M.; VAN OORT, F. Agglomeration economies, accessibility and the spatial choice behavior of relocating firms. **Journal of Transport and Land Use**, v. 4, n. 1, p. 5, 11 May 2011.

DE CHAISEMARTIN, C.; D'HAULTFŒUILLE, X. Two-Way Fixed Effects Estimators with Heterogeneous Treatment Effects. **American Economic Review**, v. 110, n. 9, p. 2964–2996, Sep. 2020.

DENG, T. Impacts of Transport Infrastructure on Productivity and Economic Growth: Recent Advances and Research Challenges. **Transport Reviews**, v. 33, n. 6, p. 686–699, Nov. 2013.

DURANTON, G.; PUGA, D. Micro-foundations of urban agglomeration economies. In: HENDERSON, J. V.; THISSE, J. F. (Eds.). **Handbook of regional and urban economics**. Handbook of regional and urban economics. [s.l.] Elsevier, 2004. v. 4p. 2063–2117.

EBERTS, R. W.; MCMILLEN, D. P. Agglomeration economies and urban public infrastructure. In: **Handbook of Regional and Urban Economics**. Applied Urban Economics. [s.l.] Elsevier, 1999. v. 3p. 1455–1495.

FAISSOL, S.; MOREIRA, L. L.; FEREIRA, M. L. O Processo de urbanização brasileiro : uma contribuição à formulação de uma política de desenvolvimento urbano/regional. **Revista Brasileira de Geografia**, v. 49, n. 2, p. 57–116, 1987.

FUJITA, M.; OGAWA, H. Multiple equilibrium and structural transition of non-monocentric urban configurations. p. 36, 1982.

GARCIA-LÓPEZ, M.-Á.; HOLL, A.; VILADECANS-MARSAL, E. Suburbanization and highways in Spain when the Romans and the Bourbons still shape its cities. **Journal of Urban Economics**, v. 85, p. 52–67, Jan. 2015.

GENDRON-CARRIER, N. *et al.* Subways and Urban Air Pollution. **American Economic Journal: Applied Economics**, v. 14, n. 1, p. 164–196, Jan. 2022.

GIBBONS, S.; MACHIN, S. Valuing rail access using transport innovations. **Journal of Urban Economics**, v. 57, n. 1, p. 148–169, 1 Jan. 2005.

GLAESER, E. L.; KAHN, M. E. Sprawl and Urban Growth. In: HENDERSON, J. V.; THISSE, J.-F. (Eds.). **Handbook of Regional and Urban Economics**. Cities and Geography. [s.l.] Elsevier, 2004. v. 4p. 2481–2527.

GOBILLON, L.; SELOD, H.; ZENOU, Y. The Mechanisms of Spatial Mismatch. **Urban Studies**, v. 44, n. 12, p. 2401–2427, 1 Nov. 2007.

GONZALEZ-NAVARRO, M.; TURNER, M. A. Subways and urban growth: Evidence from earth. **Journal of Urban Economics**, v. 108, p. 85–106, Nov. 2018.

GOODMAN-BACON, A. Difference-in-differences with variation in treatment timing. **Journal of Econometrics**, v. 225, n. 2, p. 254–277, Dec. 2021.

GORDON, P.; LEE, B. Spatial structure and travel: trends in commuting and non-commuting travels in US metropolitan areas. In: HICKMAN, R. *et al.* (Eds.). **Handbook on Transport and Development**. [s.l.] Edward Elgar Publishing, 2015.

GRAMLICH, E. Infrastructure investment: A review essay. **Journal of Economic Literature**, v. 32, n. 3, p. 1176–96, 1994.

HADDAD, E. A. *et al.* The underground economy: Tracking the higher-order economic impacts of the São Paulo Subway System. **Transportation Research Part A: Policy and Practice**, v. 73, p. 18–30, Mar. 2015.

HENDERSON, J. V. The sizes and types of cities. **The American Economic Review**, v. 64, n. 4, p. 640–656, 1974.

HERE. **Geocoding and Search API v7 API Reference**. HERE Global B. V., , 2024. Disponível em: <https://www.here.com/docs/bundle/geocoding-and-search-api-v7-api-reference/page/index.html>. Acesso em: 22 apr. 2024

IBGE. **I Centenário das ferrovias brasileiras**. Rio de Janeiro: SERGRAF do IBGE, 1954.

JACOBS, J. **The economy of cities**. [s.l.] Random House, 1969.

KRUGMAN, P. Increasing returns and economic geography. **Journal of Political Economy**, v. 99, n. 3, p. 483–99, 1991.

LORES, R. J. **São Paulo nas alturas: a revolução modernista da arquitetura e do mercado imobiliário nos anos 1950 e 1960**. São Paulo, SP: Três Estrelas, 2017.

MARCUS, M.; SANT'ANNA, P. H. C. The Role of Parallel Trends in Event Study Settings: An Application to Environmental Economics. **Journal of the Association of Environmental and Resource Economists**, v. 8, n. 2, p. 235–275, 1 Mar. 2021.

MARSHALL, A. **Principles of economics; an introductory volume**. (1920) ed. London: Macmillan, 1890.

MATAS, A.; RAYMOND, J. L.; ROIG, J. L. Evaluating the impacts of HSR stations on the creation of firms. **Transport Policy**, v. 99, p. 396–404, Dec. 2020.

MATOS, R. Migração e urbanização no brasil. **Revista Geografias**, p. 7–23, 2012.

MAYER, T.; MAYNERIS, F.; PY, L. The impact of Urban Enterprise Zones on establishment location decisions and labor market outcomes: evidence from France. **Journal of Economic Geography**, v. 17, n. 4, p. 709–752, Jul. 2017.

MILLS, E. S. **Studies in the structure of the urban economy**. Baltimore: Published for Resources for the Future by Johns Hopkins Press, 1972.

MOTTA, D. M. DA; MUELLER, C. C.; TORRES, M. DE O. **A dimensão urbana do desenvolvimento econômico-espacial brasileiro**. Brasília: Instituto de Pesquisa Econômica Aplicada (Ipea), Dec. 1997. Disponível em: <http://repositorio.ipea.gov.br/handle/11058/2389>. Acesso em: 11 oct. 2022.

MUTH, R. F. **Urban economic problems**. New York: Harper & Row, 1975.

NEUMARK, D.; ZHANG, J.; WALL, B. Where the Jobs Are: Business Dynamics and Employment Growth. **Academy of Management Perspectives**, v. 20, n. 4, p. 79–94, 2006.

O'BRIEN, L. **h3jsr: Access uber's H3 library**. , 2023. Disponível em: <https://CRAN.R-project.org/package=h3jsr>

OPENSHAW, S. The Modifiable Areal Unit Problem. In: **Concepts and techniques in modern geography**. Norwich: Geo Books, 1983.

O'SULLIVAN, A. **Urban economics**. 8th ed ed. New York, NY: McGraw-Hill/Irwin, 2012.

PÁEZ, A.; SCOTT, D. M.; MORENCY, C. Measuring accessibility: positive and normative implementations of various accessibility indicators. **Journal of Transport Geography**, v. 25, p. 141–153, Nov. 2012.

PEREIRA, A. N. A. **Informal housing, spatial spillovers, and labor market access in Brazil**. Master Thesis—Rio de Janeiro, Brazil: Pontifícia Universidade Católica do Rio de Janeiro, 11 Apr. 2022.

PEREIRA, R. H. M. *et al.* Desigualdades socioespaciais de acesso a oportunidades nas cidades brasileiras – 2019. **http://www.ipea.gov.br**, 2019a.

PEREIRA, R. H. M. *et al.* Distributional effects of transport policies on inequalities in access to opportunities in Rio de Janeiro. **Journal of Transport and Land Use**, v. 12, n. 1, 11 Oct. 2019b.

PEREIRA, R. H. M. *et al.* r5r: Rapid realistic routing on multimodal transport networks with R5 in R. **Findings**, 2021.

PEREIRA, R. H. M.; SCHWANEN, T.; BANISTER, D. Distributive justice and equity in transportation. **Transport Reviews**, v. 37, n. 2, p. 170–191, 4 Mar. 2017.

REDDING, S. J.; TURNER, M. A. Transportation Costs and the Spatial Organization of Economic Activity. In: **Handbook of Regional and Urban Economics**. [s.l.] Elsevier, 2015. v. 5p. 1339–1398.

REDE SOCIAL DE CIDADES. **Rede de esgoto (domicílios sem ligação com a rede de esgoto) de São Paulo, SP**. Disponível em: <https://www.redesocialdecidades.org.br/br/SP/sao-paulo/regiao/capela-do-socorro/rede-de-esgoto-domicilios-sem-ligacao-com-a-rede-de-esgoto>. Acesso em: 17 may. 2024.

SACTRA. **Transport and the economy**. London: Standing Advisory Committee on Trunk Road Assessment, 1999. Disponível em: <https://www.ffue.org/wp-content/uploads/2016/08/SACTRA_Full-report.pdf>.

SANTOS, R. T. DOS *et al.* Demanda por investimentos em mobilidade urbana no Brasil. **BNDES Setorial**, n. 41, p. 179–134, Mar. 2015.

SANTOS, S. M. M. DOS *et al.* São Paulo: dinâmica urbano-regional do estado. In: **Dinâmica urbano-regional: rede urbana e suas interfaces**. 1. ed. Brasília: Ipea, 2011. p. 486.

SÃO PAULO. LEI Nº 13.885 DE 25 DE AGOSTO DE 2004. . 25 Aug. 2004.

SÃO PAULO. **Coeficiente de Aproveitamento**. Government webpage. Disponível em: <https://gestaourbana.prefeitura.sp.gov.br/novo-pde-coeficiente-de-aproveitamento/>. Acesso em: 17 may. 2024.

SÃO PAULO. 16.050. LEI Nº 16.050 DE 31 DE JULHO DE 2014. . 31 Jul. 2014.

SÃO PAULO. **Metrô - Estação**. Geosampa, , 30 Nov. 2018. Disponível em: <https://geosampa.prefeitura.sp.gov.br/PaginasPublicas/_SBC.aspx>. Acesso em: 27 apr. 2023

SÃO PAULO. **Trem Metropolitano - Estação**. Geosampa, , 7 Feb. 2019. Disponível em: <https://metadados.geosampa.prefeitura.sp.gov.br/geonetwork/srv/por/catalog.search;jsessionid=6A16949E35221CBF3E8B8D22F13CE067#/metadata/6ee9af1d-d343-4fd2-b2ab-18d4a6556aba>. Acesso em: 27 apr. 2023

SÃO PAULO. **Metrô Projeto - Estação**. Geosampa, , 2022. Disponível em: <https://geosampa.prefeitura.sp.gov.br/PaginasPublicas/_SBC.aspx>. Acesso em: 27 apr. 2023

SÃO PAULO. **Trem Metropolitano Projeto - Estação**. Geosampa, , 11 May 2023. Disponível em: <https://metadados.geosampa.prefeitura.sp.gov.br/geonetwork/srv/por/catalog.search;jsessionid=6A16949E35221CBF3E8B8D22F13CE067#/metadata/65df3022-5086-45f8-80b3-fcb92f861eaf>. Acesso em: 27 apr. 2023

SCHOLL, L. *et al.* **A Rapid Road to Employment? The Impacts of a Bus Rapid Transit System in Lima**: IDB Working Paper Series. [s.l.] Inter-American Development Bank, Dec. 2018.

SEVEREN, C. Commuting, Labor, and Housing Market Effects of Mass Transportation: Welfare and Identification. **The Review of Economics and Statistics**, v. 105, n. 5, p. 1073–1091, 13 Sep. 2023.

SILVA, M. M. F. Um Guia ferroviário brasileiro do fim do século XIX. **Revista Brasileira de Geografia**, v. 16, n. 2, p. 254–266, 1954.

SUN, L.; ABRAHAM, S. Estimating dynamic treatment effects in event studies with heterogeneous treatment effects. **Journal of Econometrics**, v. 225, n. 2, p. 175–199, Dec. 2021.

TSIVANIDIS, N. The Aggregate and Distributional Effects of Urban Transit Infrastructure: Evidence from Bogotá's TransMilenio. Feb. 2019.

TYNDALL, J. Waiting for the R train: Public transportation and employment. **Urban Studies**, v. 54, n. 2, p. 520–537, Feb. 2017.

UNITED NATIONS, D. OF E. AND S. A., Population Division. **World urbanization prospects 2018: Highlights**. ST/ESA/SER.A/421 ed. New York: United Nations, 2019.

VICKERMAN, R. Transit investment and economic development. **Research in Transportation Economics**, v. 23, n. 1, p. 107–115, Jan. 2008.

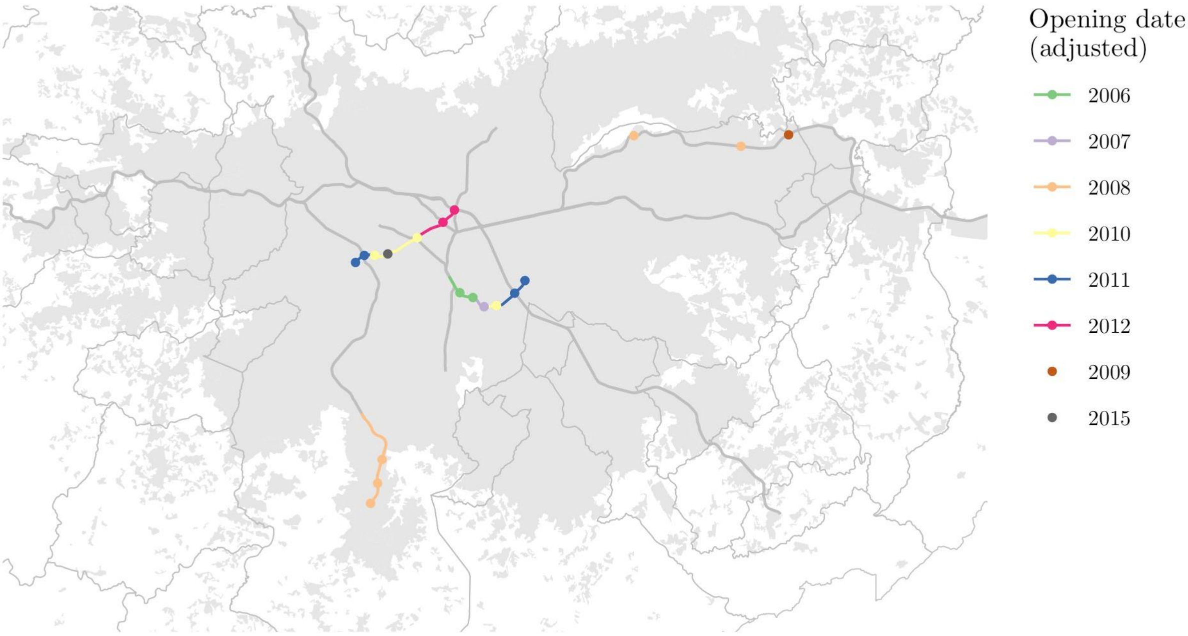
VICKERMAN, R. Beyond cost-benefit analysis: the search for a comprehensive evaluation of transport investment. **Research in Transportation Economics**, v. 63, p. 5–12, Aug. 2017.

VON THÜNEN, J. H. **Von thuñen's "isolated state": An english edition**. Oxford: Pergamon Press, 1966.

WHITE, M. J. Urban areas with decentralized employment: Theory and empirical work. In: **Handbook of Regional and Urban Economics**. Applied Urban Economics. [s.l.] Elsevier, 1999. v. 3p. 1375–1412.

APPENDIX A – Auxiliary data

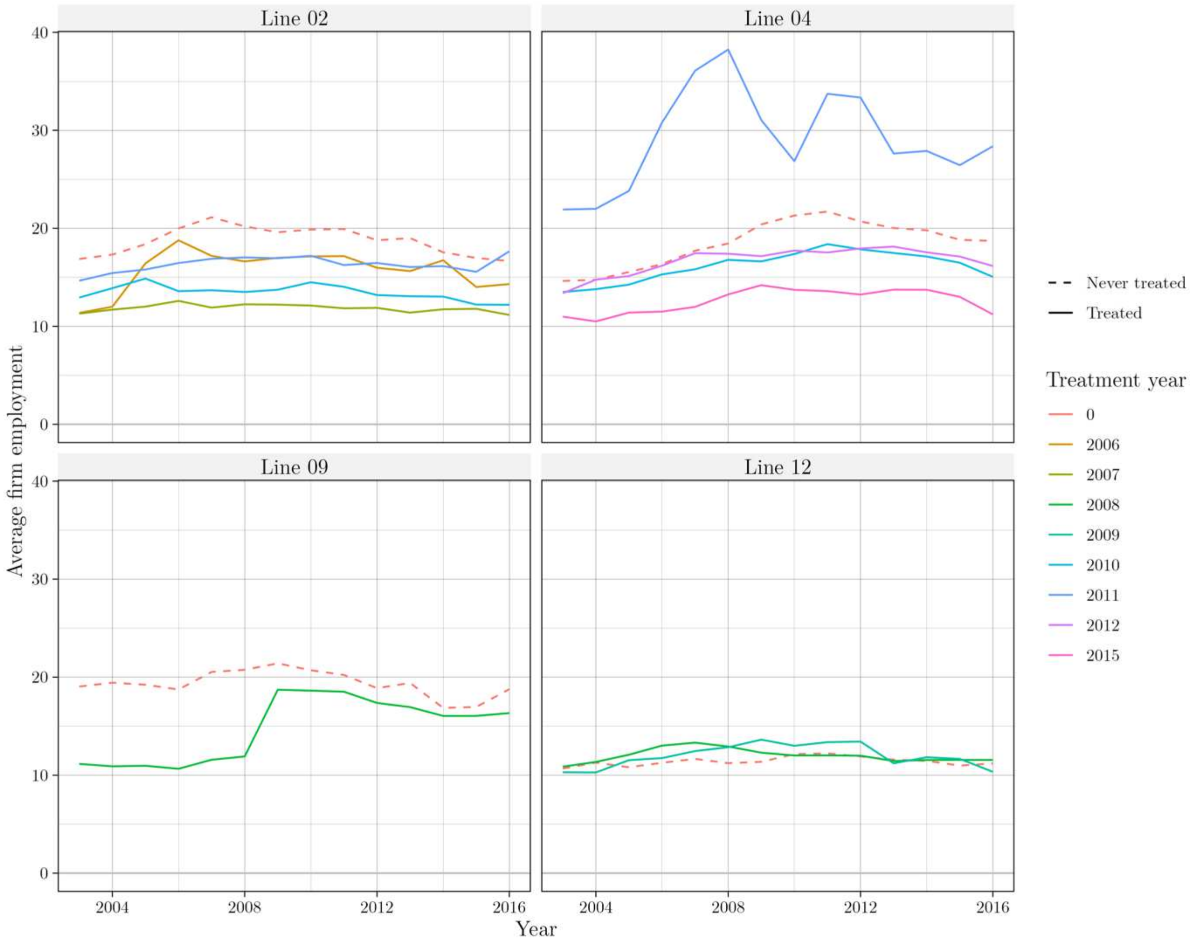
Figure 12: Location of new stations opened in the 2006-2016 period



Source: Own elaboration.

Note: Stations inaugurated between July and December of year t have their opening dates adjusted to t+1.

Figure 13: Average firm employment over time for each line's catchment area.



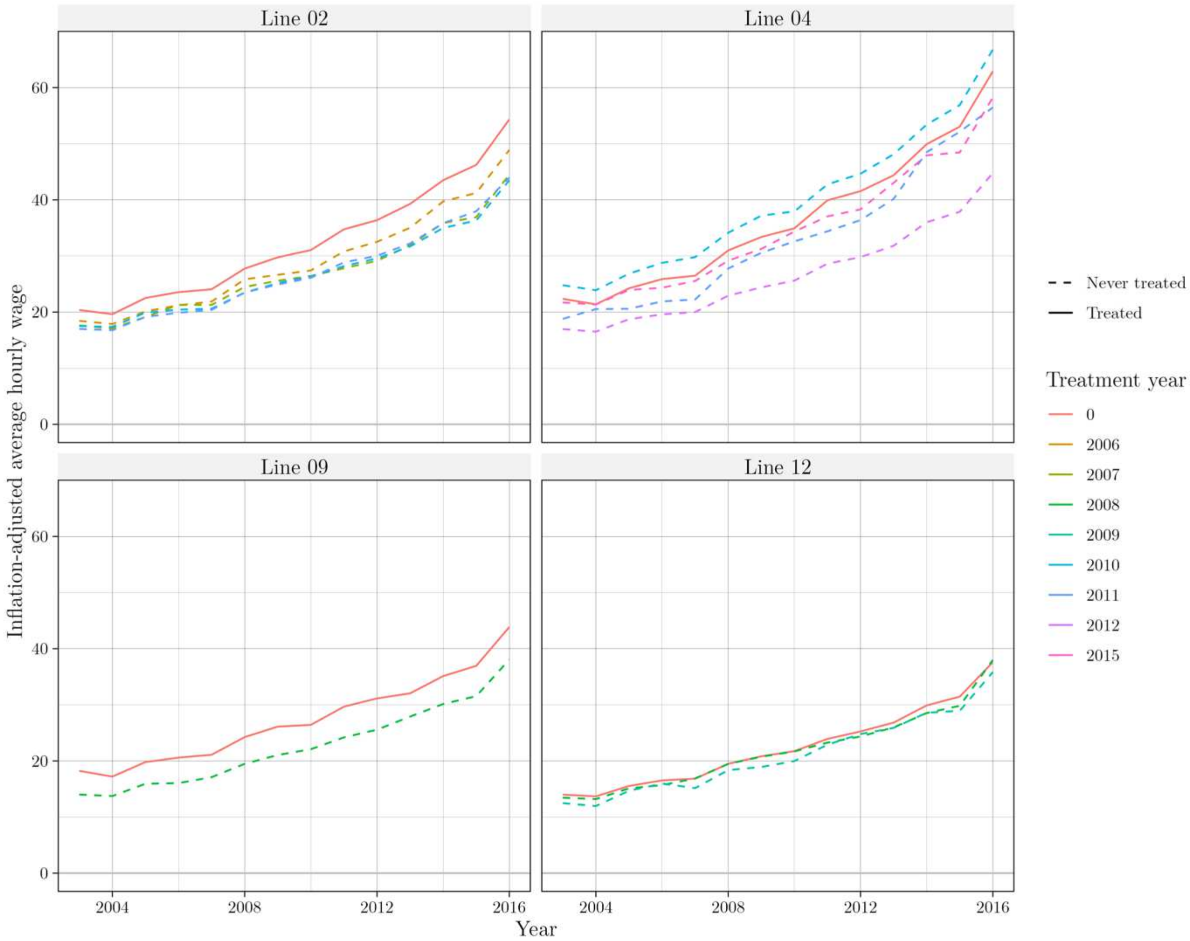
Source: Own elaboration.

Table 8: Number of estimated group-time average treatment effects

Intervention	Cohorts	Periods	Outcomes	ATTs
Line 2	4	11	4	176
Line 4	3	7	4	84
Line 9	1	9	4	36
Line 12	2	9	4	76
All	7	11	4	176

Source: Own elaboration.

Figure 14: Average firm real hourly wage over time for each line's catchment area.



Source: Own elaboration.
Note: adjusted for inflation using IPCA – Índice de Preços ao Consumidor Amplo.

Table 9: Industry aggregation scheme (continued on next page)

Section	Division	Sector Name (CNAE 1.1)	Industry
A	01	Agricultura, pecuária e serviços relacionados	Agri and extractives
A	02	Silvicultura, exploração florestal e serviços relacionados	Agri and extractives

Section	Division	Sector Name (CNAE 1.1)	Industry
B	05	Pesca, aqüicultura e serviços relacionados	Agri and extractives
C	10	Extração de carvão mineral	Agri and extractives
C	11	Extração de petroleo e serviços relacionados	Agri and extractives
C	13	Extração de minerais metalicos	Agri and extractives
C	14	Extração de minerais não-metalicos	Agri and extractives
D	15	Fabricação de produtos alimenticios e bebidas	Manufacture and utilities
D	16	Fabricação de produtos do fumo	Manufacture and utilities
D	17	Fabricação de produtos têxteis	Manufacture and utilities
D	18	Confecção de artigos do vestuário e acessórios	Manufacture and utilities
D	19	Preparação de couros e fabricação de artefatos de couro, artigos de viagem e calçados	Manufacture and utilities
D	20	Fabricação de produtos de madeira	Manufacture and utilities
D	21	Fabricação de celulose, papel e produtos de papel	Manufacture and utilities
D	22	Edição, impressão e reprodução de gravações	Producer services, offices, and innovation

Section	Division	Sector Name (CNAE 1.1)	Industry
D	23	Fabricação de coque, refino de petroleo, elaboração de combustíveis nucleares e produção de álcool	Manufacture and utilities
D	24	Fabricação de produtos químicos	Manufacture and utilities
D	25	Fabricação de artigos de borracha e de material plástico	Manufacture and utilities
D	26	Fabricação de produtos de minerais nãometálicos	Manufacture and utilities
D	27	Metalurgia básica	Manufacture and utilities
D	28	Fabricação de produtos de metal - exclusive máquinas e equipamentos	Manufacture and utilities
D	29	Fabricação de máquinas e equipamentos	Manufacture and utilities
D	30	Fabricação de máquinas para escritório e equipamentos de informatica	Manufacture and utilities
D	31	Fabricação de máquinas, aparelhos e materiais elétricos	Manufacture and utilities
D	32	Fabricação de material eletronico e de aparelhos e equipamentos de comunicações	Manufacture and utilities
D	33	Fabricação de equipamentos de instrumentação médico-hospitalares, instrumentos de precisão e opticos, equipamentos para automação indústrial, cronometros e relogios	Manufacture and utilities
D	34	Fabricação e montagem de veiculos automotores, reboques e carrocerias	Manufacture and utilities
D	35	Fabricação de outros equipamentos de transporte	Manufacture and utilities

Section	Division	Sector Name (CNAE 1.1)	Industry
D	36	Fabricação de móveis e indústrias diversas	Manufacture and utilities
D	37	Reciclagem	Manufacture and utilities
E	40	Eletricidade, gás e água quente	Manufacture and utilities
E	41	Captação, tratamento e distribuição de água	Manufacture and utilities
F	45	Construção	Construction
G	50	Comércio e reparação de veiculos automotores e motocicletas; e comércio a varejo de combustíveis	Trade and consumer services
G	51	Comércio por atacado e representantes comerciais e agentes do comércio	Trade and consumer services
G	52	Comércio varejista e reparação de objetos pessoais e domésticos	Trade and consumer services
H	55	Alojamento e alimentação	Trade and consumer services
I	60	Transporte terrestre	Producer services, offices, and innovation
I	61	Transporte aquaviário	Producer services, offices, and innovation
I	62	Transporte aéreo	Producer services, offices, and innovation
I	63	Atividades anexas e auxiliares dos transportes e agências de viagem	Producer services, offices, and innovation
I	64	Correio e telecomunicações	Producer services, offices, and innovation

Section	Division	Sector Name (CNAE 1.1)	Industry
J	65	Intermediação financeira	Producer services, offices, and innovation
J	66	Seguros e previdência complementar	Producer services, offices, and innovation
J	67	Atividades auxiliares da intermediação financeira, seguros e previdência complementar	Producer services, offices, and innovation
K	70	Atividades imobiliarias	Producer services, offices, and innovation
K	71	Aluguel de veiculos, máquinas e equipamentos sem condutores ou operadores e de objetos pessoais e domésticos	Producer services, offices, and innovation
K	72	Atividades de informatica e serviços relacionados	Producer services, offices, and innovation
K	73	Pesquisa e desenvolvimento	Producer services, offices, and innovation
K	74	Serviços prestados principalmente as empresas	Producer services, offices, and innovation
L	75	Administração pública, defesa e seguridade social	Institutions, health, and education
M	80	Educação	Institutions, health, and education
N	85	Saude e serviços sociais	Institutions, health, and education
O	90	Limpeza urbana e esgoto e atividades relacionadas	Institutions, health, and education

Section	Division	Sector Name (CNAE 1.1)	Industry
O	91	Atividades associativas	Institutions, health, and education
O	92	Atividades recreativas, culturais e desportivas	Trade and consumer services
O	93	Serviços pessoais	Trade and consumer services
P	95	Serviços domésticos	Trade and consumer services
Q	99	Organismos internacionais e outras instituições extraterritoriais	Institutions, health, and education

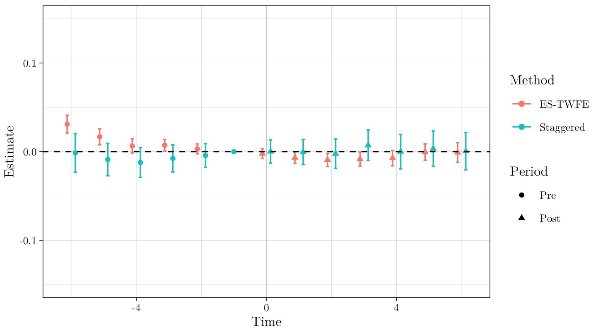
Source: Own elaboration.

Note: Older CNAE 1.1 was used instead of the more recent CNAE 2.0 for compatibility with data from the 2003-2007 period.

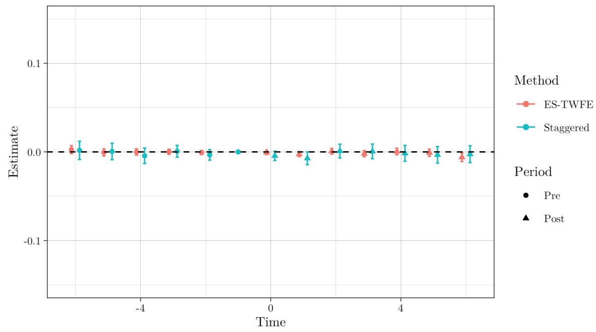
APPENDIX B – Additional estimates

Figure 15: Average effect on outcomes by length of exposure for all transit lines

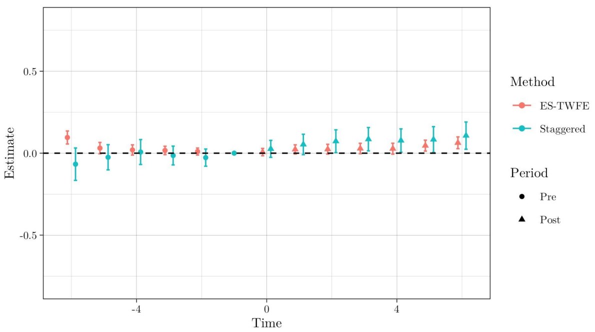
Panel (a): Number of jobs, firm level



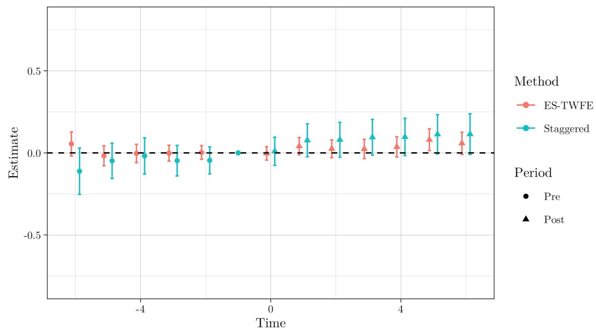
Panel (b): Avg. hourly wage, firm level



Panel (c): Number of firms, hexagon level



Panel (d): Number of jobs, hexagon level

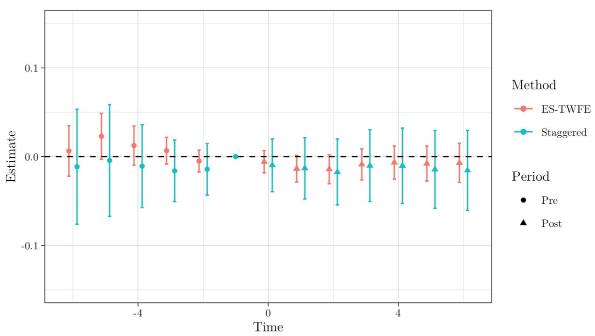


Source: Own elaboration.

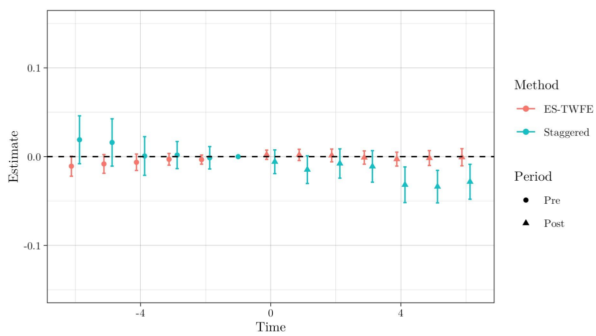
Notes: Time and estimates are relative to opening year ($t = 0$); events were balanced to keep only units submitted to at least six years of treatment.

Figure 16: Average effect on outcomes by length of exposure for Line 2

Panel (a): Number of jobs, firm level

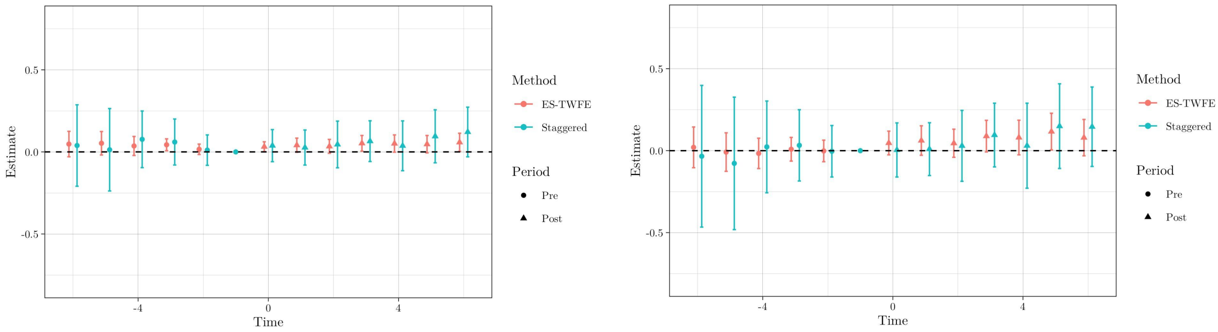


Panel (b): Avg. hourly wage, firm level



Panel (c): Number of firms, hexagon level

Panel (d): Number of jobs, hexagon level

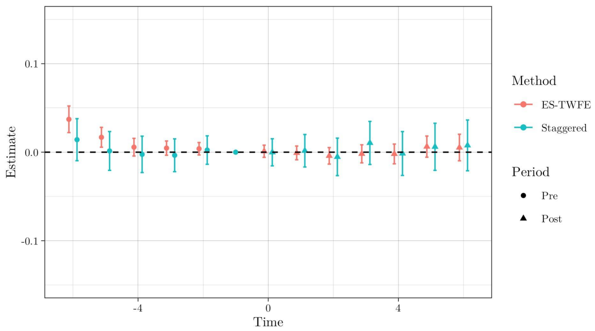


Source: Own elaboration.

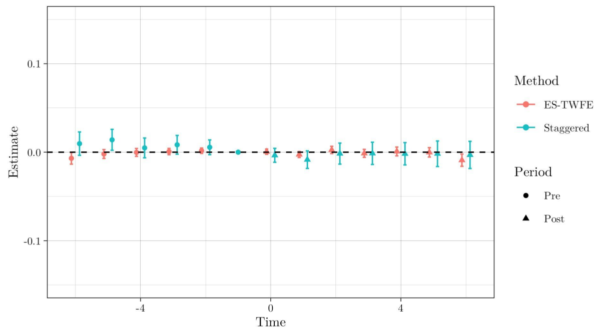
Notes: Time and estimates are relative to opening year ($t = 0$).

Figure 17: Average effect on outcomes by length of exposure for Line 4

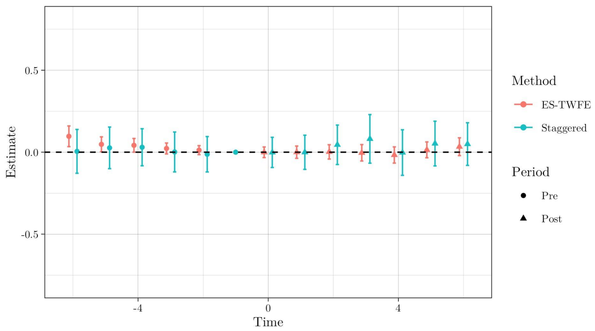
Panel (a): Number of jobs, firm level



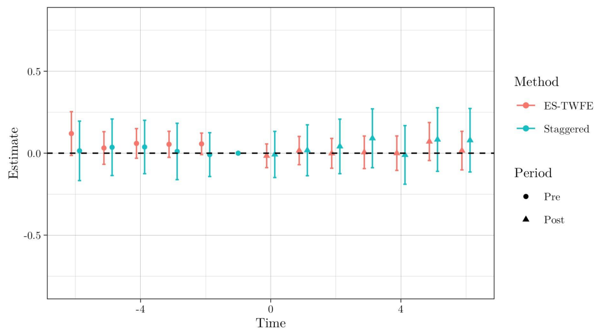
Panel (b): Avg. hourly wage, firm level



Panel (c): Number of firms, hexagon level



Panel (d): Number of jobs, hexagon level

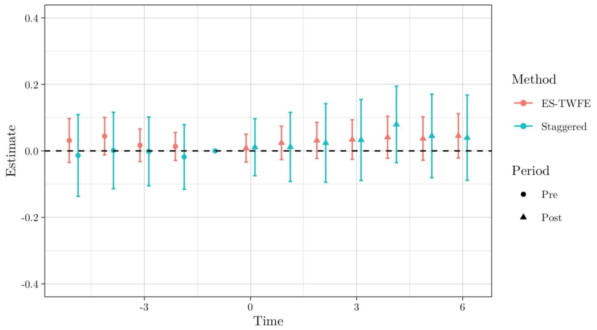


Source: Own elaboration.

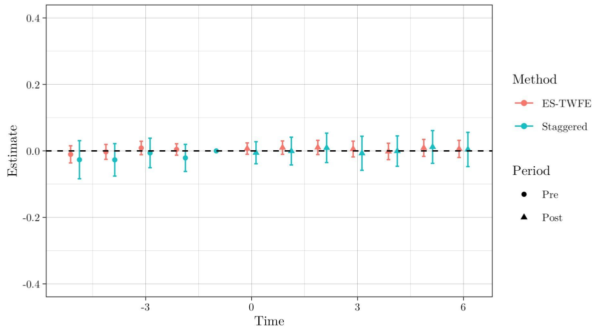
Notes: Time and estimates are relative to opening year ($t = 0$); events were balanced to keep only units submitted to at least six years of treatment.

Figure 18: Average effect on outcomes by length of exposure for Line 9

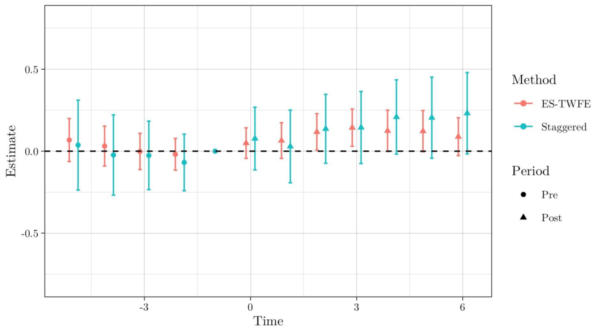
Panel (a): Number of jobs, firm level



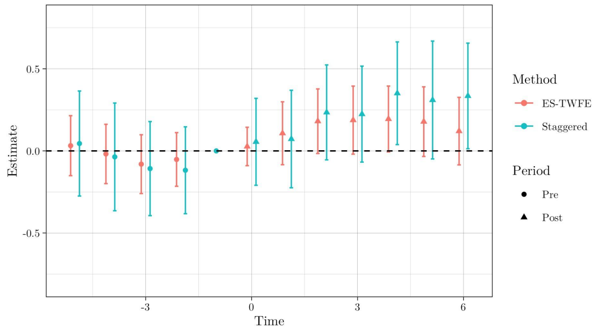
Panel (b): Avg. hourly wage, firm level



Panel (c): Number of firms, hexagon level



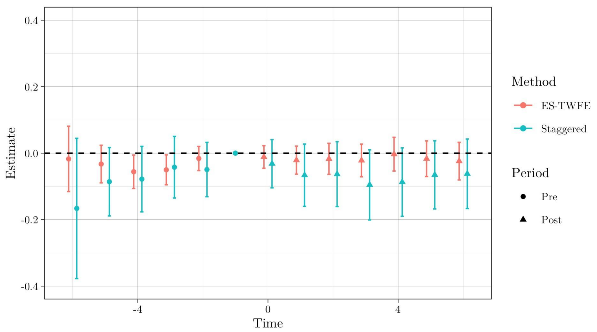
Panel (d): Number of jobs, hexagon level



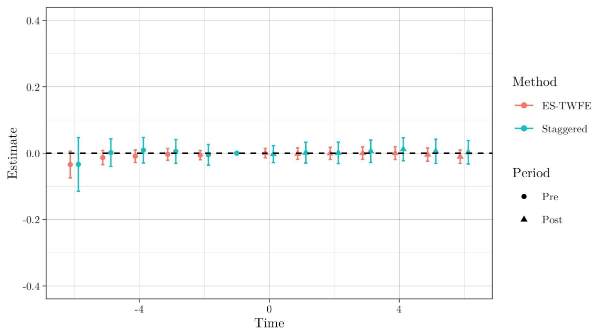
Source: Own elaboration.
Notes: Time and estimates are relative to opening year ($t = 0$); events were balanced to keep only units submitted to at least six years of treatment.

Figure 19: Average effect on outcomes by length of exposure for Line 12

Panel (a): Number of jobs, firm level

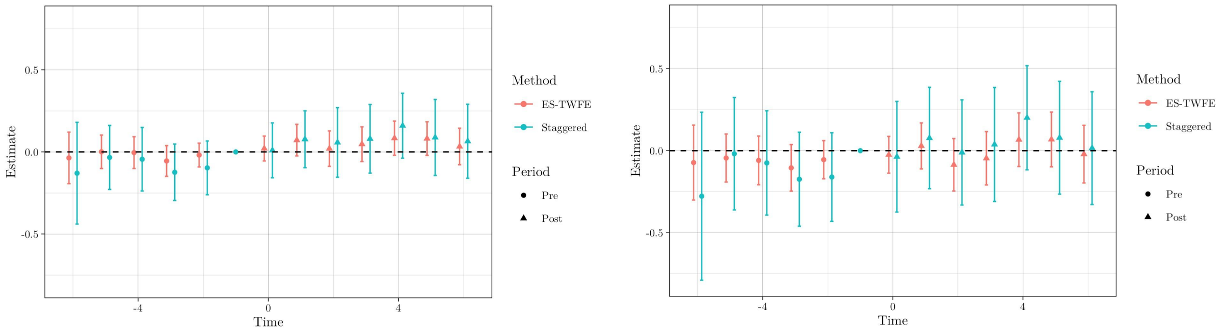


Panel (b): Avg. hourly wage, firm level



Panel (c): Number of firms, hexagon level

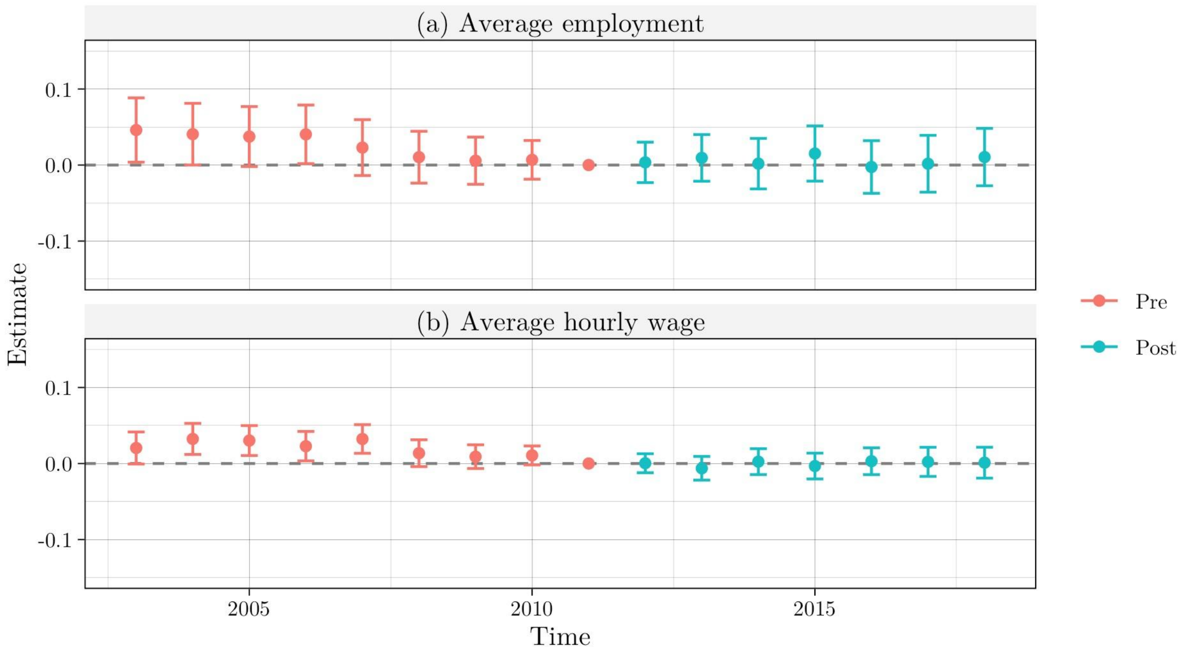
Panel (d): Number of jobs, hexagon level



Source: Own elaboration.

Notes: Time and estimates are relative to opening year ($t = 0$); events were balanced to keep only units submitted to at least six years of treatment.

Figure 20: Event study plots for units around Line 4 treated in 2012, firm-level outcomes



Source: Own elaboration.

ANNEX A – Supplementary tables

Table 10: Firm size classification by industry according to the number of workers

	Number of workers per industry	
Size	Manufacture	Retail and Services
Micro	Up to 19	Up to 9
Small	Between 20 and 99	Between 10 and 49
Medium	Between 100 and 499	Between 50 and 99
Large	500 or more	100 or more

Source: Adapted from SEBRAE (2013)