Enhancing Private Transportation: The Positive Spillovers from Santiago's Subway Expansion

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Abstract

In Latin America, where traffic congestion is a significant issue, subway expansions are frequently employed to alleviate traffic woes. Evaluating the efficacy of these investments poses challenges, notably due to the scarcity of real-time data. This study leverages Uber Movement data, which provides insights into daily travel times, to examine the effects of subway expansion on car transportation in Santiago, Chile. We find that the introduction of a new subway line reduces car travel times by an average of 1.1%. Importantly, this positive spillover effect intensifies during peak traffic periods and near existing and newly established subway stations. Our results suggest that the benefits of subway expansions amplify with increasing car density and highlight the synergistic effects of integrated subway investments.

Keywords: Traffic congestion, urban mobility, subway expansion.

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1 Introduction

Effective impact evaluation is crucial yet often hindered by the lack of accessible data. In the realm of transportation policy, the availability of real-time traffic data could significantly enhance assessment accuracy. This challenge is particularly acute in regions like Latin America, where cities are marked by severe congestion, urban sprawl, and rapidly increasing car usage (Bull et al., 2003; INRIX, 2019). For instance, car usage in Santiago, Chile, more than doubled between 2010 and 2020 (INE, 2023). The scarcity of reliable official and satellite data forces these regions to make substantial infrastructure investments without robust technical validation (Yañez-Pagans et al., 2019). Consequently, this data deficit obscures the true impacts of transportation infrastructure projects and exacerbates urban mobility issues by potentially misguiding policy decisions. To counteract these limitations, there is a growing imperative to harness alternative data sources, such as crowd-sourced platforms and other innovative technologies. These tools promise to illuminate the effects of such investments and support more informed decision-making in urban transportation planning.

This paper aims to harness data from Uber Movement[1] to scrutinize the impact of a new subway line in Santiago, Chile. The new subway line connected the Southwest with the more affluent Northeast of Santiago, complementing the already existing subway lines.[2] The inauguration of the subway expansion provides a natural experiment, allowing us to assess changes in travel times and explore potential heterogeneous effects. Unlike impact evaluations of housing prices or firm locations, private transportation cannot adapt or alter its behavior before the expansion, thereby enhancing the identification of causal impacts. Our data encapsulates travel times between various municipalities in Santiago, structured as panel data. This format allows us to track travel times for numerous days before and after the subway opening for each origin-destination pair, including both lower-bound (fastest) and upper-bound (slowest) travel times for each day.

Moreover, the panel structure helps control for unobserved factors at the origin, destination, and origin-pair combination We employ a discontinuous regression framework,

[1] Currently, the data platform is offline. Some of the data is still available at `https://www.kaggle.com/datasets/ishandutta/uber-travel-movement-data-2-billion-trips`.

[2] A map of the new and existing subway lines is available in Online Appendix Figure A.1.

using the subway opening date as a pivotal point, to discern changes in travel times post the initial opening shock. Subsequent analysis of the estimated impacts for each origin-destination pair helps us probe the spatial extent of these effects. Specifically, we investigate whether the impacts are localized to municipalities directly affected by the new subway line or if they propagate throughout the subway network.

Our analysis reveals that the new subway line resulted in an approximate 1.1% reduction in car travel times. This decrease is more pronounced during periods of heavy traffic and not only along the new subway line but also throughout other parts of the city connected by the transportation network. Interestingly, our findings suggest that the returns on subway investments are not diminishing; rather, they indicate that we are far from reaching a point of decreasing marginal returns. These insights are crucial for planning future subway expansions, as they highlight the broad and sustained benefits of such infrastructure investments.

The structure of this paper is organized as follows: Section 2 provides a comprehensive literature review on public transport policy interventions, highlighting previous studies and their relevance to our research. Section 3 details the data sources and methodologies employed to analyze the impacts of the subway expansion. Section 4 discusses both the average results and the variability in impacts across different contexts. Finally, Section 5 offers conclusions and implications drawn from our findings.

2 Literature Review

The literature surrounding the externalities of public transportation consistently underscores that subway expansions provide multifaceted benefits. These include reduced pollution levels (Li et al., 2019; Lu et al., 2018), spurred employment growth (Jin and Kim, 2018), and elevated property values in areas gaining improved subway access (Bae et al., 2003; Costa et al., 2022). Nevertheless, a primary aim of such expansions is to alleviate traffic congestion—a chronic challenge in major urban centers (Gu et al., 2021; Xu et al., 2010). These infrastructure enhancements often boost public transportation adoption, potentially reducing reliance on private vehicles and encouraging residential shifts towards neighborhoods served by new subway lines.

Research on the externalities of public transportation was initially concentrated in developed nations. For instance, Anderson (2014) used a regression discontinuity design to assess the impact of a public transport worker strike in Los Angeles, revealing a substantial increase in congestion during peak hours. Similarly, Monzón et al. (2013) examined the effects of a high-speed rail expansion in Spain, noting significant improvements in accessibility, though with notable spatial heterogeneity.

In contrast, recent studies in developing regions, particularly in China, provide fresh insights. Yang et al. (2018) applied a regression discontinuity approach to explore subway expansions in Beijing, uncovering a significant reduction in traffic congestion. Concurrently, Gao et al. (2019) found a decrease in travel times in Shenzhen attributed to urban trail enhancements. Furthermore, Xie (2016) and Zhang et al. (2017) observed reduced car usage linked to new subway lines. Gu et al. (2021) utilized a difference-in-differences approach to assess the impact of new subway lines in Chinese cities, reporting an increase in car velocity during rush hours, especially near subway lines. However, the spatial uniformity of this impact varies, with roads farther from subway lines experiencing smaller increases in velocity.

Research on urban transport policies in Latin America remains sparse, yet several studies provide insightful findings. Martinez et al. (2020) and Oviedo et al. (2019) evaluate the effects of new bus rapid transit (BRT) and subway systems in Lima, Peru on labor market participation. These studies highlight significant improvements in connectivity, as evidenced by reduced travel times from peripheral areas to the city's central historical, financial, and educational hubs. In Colombia, Tsivanidis (2018) investigates the "TransMilenio" BRT system in Bogota, initiated in 2000, uncovering a positive impact on employment access, particularly for residents outside the urban core.

Further south, Hernandez (2018) reports similar benefits from transportation improvements in Uruguay. Conversely, Pereira et al. (2019) explores the socio-spatial impacts of transport expansion in Rio de Janeiro, Brazil, prompted by the World Cup and Olympic Games, finding that these enhancements disproportionately benefited wealthier populations.

In Chile, Zegras and Hannan (2012) analyzed the impact of the Santiago subway expansion in 2001 on individual transportation choices. Their findings indicate that living within 500 meters (0.31 miles) of a subway station decreases the likelihood of owning a vehicle by 0.4%. Moreover, proximity to new subway stations correlates with a significant 3.1 percentage point increase in employment rates and access to higher-quality schools (Asahi, 2016; Herskovic, 2020; Asahi and Pinto, 2022), underscoring the transformative effects of subway accessibility on urban mobility and socioeconomic opportunities."

Although existing research sheds some light on transportation policies in Latin America, the scarcity of data significantly hampers comprehensive analysis, particularly regarding the heterogeneity of outcomes from subway investments. This gap is critical considering the substantial investments funneled into transportation infrastructure, which require detailed inputs for accurate cost-benefit calculations. Moreover, effective policy assessments need to pinpoint specific spatial regions that benefit from these improvements, a crucial step given the prevalent issue of high spatial segregation across Latin American cities. Thus, enhancing data availability and methodological approaches in transportation studies is vital for generating more precise and actionable insights.

3 Data and Methodology

3.1 Uber Movement

We derive daily car travel times from the Uber Movement dataset for Santiago in 2020, recognized for its accuracy in reflecting real-time traffic conditions (Sun et al. (2020); Tarduno (2021)). This dataset aggregates average travel durations across all Uber rides between Santiago's 32 municipalities, following the methodology described by Uber Movement (Uber-Movement, 2019). It is important to note, however, that not all origin-destination pairings are included; data for routes with insufficient trips or drivers are systematically omitted to ensure reliability.

In our study, we focus on the daily average travel time between each pair of Santiago's 32 municipalities as our dependent variable. This analysis spans 19 business days before and 21 after the opening of Line 6 on November 2, 2017. Theoretically, all combinations of origin and destination among the 32 municipalities yield $(32 \times 32) - 32 = 992$ possible pairs. However, after excluding data for pairs lacking sufficient information, we effectively analyze 925 pairs. Over the 40 business day period, this amounts to 37,000 observations in total.[3]

Table 1 presents the descriptive statistics of our dataset, detailing the travel times before (first row) and after (second row) the subway line's expansion, as well as aggregate statistics for the entire period (third row). Our preliminary analysis suggests a modest improvement in travel efficiency. Specifically, the average travel time decreased from 21.2 to 20.9 minutes post-expansion, reflecting a 1.4% reduction. Additionally, the standard deviation of travel times fell by 2.3%, suggesting a more uniform travel experience across different routes. Notably, when examining the bounds[4] of travel times provided by Uber Movement, the fastest trips among each origin-destination pair (lower bound) saw a minimal decrease of 0.07 minutes, whereas the longest trips (upper bound) experienced a more substantial reduction of 0.54 minutes, highlighting the policy's heterogeneous impacts.

Table 1: Descriptive statistics of travel times (minutes) for 925 Pairs of Municipalities

Trip	Date range	N	Mean	SD
Average	Before 02/11/2017	16,650	21.22	9.820
	After 02/11/2017	20.350	20.99	9.583
	All sample	37,000	21.09	9.691
Lower bound	Before 02/11/2017	16,650	14.21	7.570
	After 02/11/2017	20,350	14.14	7.510
	All sample	37,000	14.17	7.537
Upper bound	Before 02/11/2017	16,650	32.18	12.704
	After 02/11/2017	20,350	31.64	12.074
	All sample	37,000	31.88	12.364

3.2 Methodology

In theory, the introduction of a new subway line is expected to alleviate vehicular congestion via two primary mechanisms. First, subway openings often lead to time savings in commuting by making neighborhoods with new stations more appealing for economic activities and residential development (Baum-Snow et al., 2005). Second, by enhancing the public transportation infrastructure, subway openings naturally reduce the reliance on private vehicles and buses (Vuk, 2005). Given the specific characteristics

[3]Onlin Appendix Figure A.2 illustrates the distribution of these travel times, providing a visual understanding of the data.

[4]Sadly, the Uber-Movement (2019) does not detail what the bounds are exactly.

of our data, our analysis will primarily focus on the latter mechanism.

To discern the immediate effects of the subway line inauguration, we treat its launch as an exogenous event introducing a sharp temporal discontinuity for car commuters. This approach allows us to attribute causal interpretations to our findings under the assumption that the event is isolated, occurring on a specific date without coinciding with other significant disruptions (Yang et al., 2018), and that commuters do not alter their behaviors in anticipation of the subway opening. One inherent challenge in our identification strategy is the widespread impact of the subway expansion across the entire city, eliminating the possibility of a directly comparable 'untreated' group. To address this, we employ a regression discontinuity design, utilizing travel data from 19 days prior to and 21 days following the subway's introduction. Our approach involves extrapolating pre-intervention data to create a synthetic control group, thereby facilitating a robust comparison post-introduction. The formal modeling of our data is structured as follows:

$$y_{ijt} = \beta_0 + \beta_1 timepre_t + \beta_2 subway_t + \beta_3 timepost_t + u_{ijt} \tag{1}$$

In our regression model, y_{ijt} represents the travel time in minutes for a journey from origin i to destination j on day t. The model is structured to disentangle the effects of the subway line inauguration on travel times through the following parameters: β_0 sets the baseline average travel time; $timepre_t$ is a continuous variable counting down to the inauguration, capturing the trend leading up to the subway opening with β_1 reflecting this pre-event slope; $subway_t$ is a binary indicator that switches on during the post-inauguration phase, with β_2 measuring the immediate impact on travel times; $timepost_t$ counts the days following the inauguration, allowing β_3 to measure changes in the post-opening period.

The parameter of primary interest, β_2, is designed to capture the direct, short-term impact of the subway's introduction, isolating this effect from long-term trends. However, this focus on immediate impacts implies certain limitations. For instance, β_2 might underestimate the true effect if commuters delay transitioning from road to subway transport in the days immediately following the subway's opening. Moreover, β_2 is not equipped to capture the longer-term implications of the subway expansion, such as those stemming from the economic relocation phenomena detailed in (Baum-Snow et al., 2005), which could significantly alter travel patterns over time.

A primary challenge in our analysis is distinguishing the effects of the subway opening from other concurrent changes that could influence travel times, such as traffic increases due to special events or the completion of unrelated construction projects (Yang et al., 2018). Specifically, our estimates could be biased if there is an unexpected shift in the error term, u_{ijt}, that coincides with the subway's inauguration.[5] To address these concerns, we have refined our model to include a comprehensive set of controls: daily dummies for each weekday, origin-destination pairs, and their interactions, thus capturing both routine and unique variations in travel times.

By applying this model to each distinct trip ij, and incorporating weekday-specific variables, we enhance the granularity of our analysis. This methodological rigor allows us to dissect the subway's impact on travel dynamics across Santiago with greater precision. Furthermore, it enables us to compute changes in travel times for every origin-destination pair, thereby facilitating an exploration of factors that predict variations in the subway's effects, such as the existing proximity to subway facilities within each municipality.

4 Results

This section delineates the outcomes of our comprehensive analysis. Initially, we detail the overarching findings regarding the average travel times impacted by the new subway line. Subsequently, we delve into the nuanced effects stratified by trip length, illuminating how distance influences the observed changes. Finally, we explore and identify key predictors that significantly influence the magnitude and direction of the subway's effects on travel times.

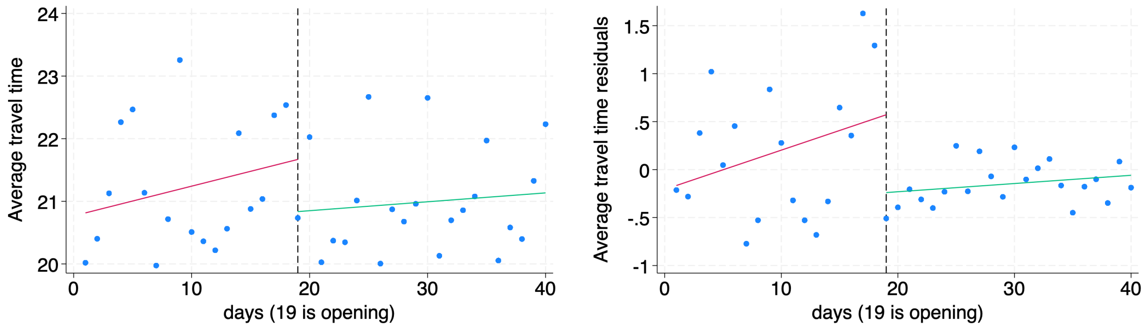
4.1 Average travel times

Initially, we analyze the changes in average travel times. As previously discussed, this analysis leverages the sharp discontinuity observed in travel times subsequent to the inauguration of the new subway line. This effect is visually represented in Figure 1(a), which illustrates the daily evolution of average travel times. Assuming a linear progres-

[5]This shift may also stem from how the time variable is structured in our model.

sion pre- and post-event, there is a noticeable reduction in travel times immediately following the subway's opening (as evidenced by the divergence between the trend lines on day 19). This observable decline indicates a beneficial short-term impact of the subway on surface travel times, although considerable variability in travel times persists.

Figure 1: Scatterplots of Uber Movement's average travel times (minutes) and residuals



(a) Sample averages

(b) Residuals after weekday FE

To enhance the clarity of the observed effect, we have adjusted the data to remove typical daily fluctuations associated with weekdays. Specifically, Figure 1(b) displays a scatter plot of the daily average residuals, which have been adjusted by employing fixed effects for each weekday. This visualization clearly illustrates a reduction in travel times subsequent to the subway's inauguration. Not only does the average travel time show a noticeable decrease, but the distribution of residuals also appears more concentrated, indicating a more consistent travel experience across the network after the new subway line became operational.

Subsequently, we applied various iterations of equation (1) to quantify the subway's impact. Table 2 delineates these results. Column (1) presents elementary Ordinary Least Squares (OLS) estimates, omitting any sophisticated treatment of the error term. Here, the observed coefficient suggests a modest reduction in travel times by 0.23 minutes, equivalent to a 1.1% decrease, though this effect is not statistically significant. This lack of significance can be attributed to the basic error term modeling. To refine our analysis, Column (2) incorporates weekday fixed effects, as depicted in Figure 1(b). This adjustment yields a more pronounced decrease in travel times by 0.309 minutes, translating to a 1.5% reduction, which achieves statistical significance at the 10% level.

Continuing our analysis, Column (3) of Table 2 incorporates a control for trip

Table 2: Estimates of subway effect on travel times (minutes)

VARIABLES	(1) travel time	(2) travel time	(3) travel time	(4) travel time
Subway is open	-0.230	-0.309*	-0.309**	-0.309***
	(0.161)	(0.163)	(0.120)	(0.0293)
Trend before opening	0.0281**	0.0213*	0.0213**	0.0213***
	(0.0116)	(0.0121)	(0.00893)	(0.00212)
Trend after opening	0.0202*	0.0131	0.0131	0.0131***
	(0.0109)	(0.0109)	(0.00801)	(0.00195)
Trip distance kms.			0.949***	
			(0.00711)	
Constant	20.98***	20.27***	7.944***	20.27***
	(0.123)	(0.156)	(0.138)	(0.0286)
Observations	37,000	37,000	37,000	37,000
R-squared	0.000	0.006	0.464	0.970
Weekday FE	No	Yes	Yes	Yes
Origin-destination FE	No	No	No	Yes

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

distance, significantly enhancing the regression model's fit. While the key coefficient concerning the subway's effect remains unchanged—highlighting that our identification hinges on temporal rather than spatial variations—it achieves enhanced statistical significance at the 5% level. Additionally, the coefficient for trip distance is highly significant, marked at the 1% level. Advancing to Column (4), we include fixed effects for each origin-destination pair to meticulously account for the unique attributes of each journey in our dataset. This comprehensive control boosts the model's R-squared close to unity, markedly reducing standard errors. The coefficients remain consistent with our earlier models, and the significance of the subway opening effect strengthens, now significant at the 1% level.

In conclusion, our findings consistently indicate a modest reduction in average travel times, as corroborated through both simple graphical analyses and rigorous statistical testing. These reductions, while slight, are significant, underscoring the positive impact of the new subway line on surface travel dynamics.

4.2 Heterogeneity analysis

While we have documented a general reduction in travel times, the effects of the new subway line may be more pronounced during periods of heavy traffic. In less congested conditions, the decrease in vehicular volume likely has only a marginal impact, primarily constrained by traffic signals rather than congestion. To further explore these dynamics, our analysis will differentiate between conditions of varying traffic intensity. Utilizing the Uber Movement data, which provides both lower and upper-bound travel times for each origin-destination pair daily, we can assess whether the subway's impact varies with traffic flow. Specifically, upper-bound travel times correspond to peak traffic hours, while lower-bound times reflect periods of lighter traffic. This distinction will allow us to discern whether the subway's benefits are amplified under heavier traffic conditions.

Table 3 presents our findings on the varying effects of the subway opening across different traffic conditions. The reduction in travel times for lower-bound trips, which represent faster journey times, is modest at 0.15 minutes and attains statistical significance at the 10.4% level. In stark contrast, the impact on upper-bound travel times, which correspond to slower trips, is more substantial. Our analysis shows a reduction of 0.571 minutes for these trips, suggesting a notably larger benefit during peak traffic periods. This result confirms that the new subway line has a more pronounced positive effect when traffic conditions are slower, as evidenced by the significant influence of trip distance on travel time. Overall, these findings highlight that slower trips, specific to each origin and destination, experience the most significant improvements following the subway's inauguration.

To further investigate traffic variations, we analyze the impact of subway expansion on days with varying overall traffic levels. We accomplish this by applying quantile regression, a method pioneered by Koenker and Bassett Jr (1978), which allows us to estimate the subway's effects across different travel time quantiles, conditioned on distance. Specifically, we conduct analyses at the 25th, 50th, and 75th quantiles to capture the differential impacts across typical, lighter, and heavier traffic days respectively. To ensure accurate estimation of standard errors, we employ the MCMC approach to classical estimation as described by Chernozhukov and Hong (2003). This method involves

Table 3: Estimates of subway effect on lower bound, upper bound, 25th quantile, 50th quantile, 75th quantile of travel times (minutes)

VARIABLES	(1) lower bound	(2) upper bound	(3) 25th quantile	(4) 50th quantile	(5) 75th quantile
Subway is open	-0.150	-0.571***	-0.148	-0.227**	-0.360***
	(0.0916)	(0.162)	(0.102)	(0.105)	(0.130)
Trend before opening	0.00922	0.0433***	-0.00186	0.0109	0.0291***
	(0.00674)	(0.0123)	(0.00748)	(0.00754)	(0.00979)
Trend after opening	0.00960	0.0162	0.00468	0.00784	0.0132
	(0.00616)	(0.0106)	(0.00679)	(0.00748)	(0.00869)
Trip distance kms.	0.757***	1.116***	0.877***	1.189***	1.274***
	(0.00522)	(0.00966)	(0.00469)	(0.00547)	(0.00799)
Constant	3.902***	15.92***	4.138***	4.449***	8.316***
	(0.105)	(0.185)	(0.0993)	(0.114)	(0.154)
Observations	37,000	37,000	37,000	37,000	37,000
R-squared	0.483	0.402	-	-	-
Weekday FE	Yes	Yes	Yes	Yes	Yes

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

using a Markov Chain Monte Carlo (MCMC) technique with a thinning parameter of 2, a burn-in of 5,000 simulations, and a chain size of 20,000.

The results, as depicted in columns (3)-(5), span the 25th, 50th, and 75th quantiles of the conditional distribution of travel times. A notable observation from these results is the increasing magnitude of the trip distance coefficient across higher quantiles, indicating that these represent slower trips with longer durations. The findings corroborate the visual insights from Figure 1(b), which illustrated a decrease in travel times predominantly in the upper range of the distribution. Specifically, at the 25th quantile, the effect is not statistically significant, reflecting minimal change. In contrast, the median (50th quantile) shows a statistically significant reduction in travel times by 0.227 minutes at the 5% level, a more modest decrease compared to the average effect previously discussed. The most substantial impact is observed at the 75th quantile, with a decrease of 0.36 minutes, confirming that the benefits of the subway expansion are most pronounced during periods of heavier traffic. This pattern supports the hypothesis that the positive spillovers from subway expansions are enhanced under conditions of higher traffic congestion.

4.3 Predictors of the effects

To further delve into the spatial variability of the subway's impact, we separately estimated equation (1) for each one of the 32 origin-destination combinations, thereby generating specific effect estimates for each trip. While these estimates are inherently noisy due to the relatively small sample size for individual routes, they remain unbiased. To analyze the spatial predictors of these effects, we conducted a simple OLS regression across different origin-destination pairs. Notably, the distribution of the estimates is skewed to the left and centered around a negative impact, indicating that most routes experienced beneficial effects from the new subway line.[6] Furthermore, a Kurtosis test, drawing on the methodology from D'Agostino et al. (1990), confirms the rejection of symmetry in the distribution, underscoring the predominance of negative effects across the trips.

To explore the localized impacts of travel time reductions, we hypothesized that municipalities hosting new subway line stations might experience more significant decreases, aligning with findings from Gu et al. (2021). To evaluate this, we conducted a regression analysis, assessing the relationship between travel time changes and the presence of a new subway station in either the origin or destination municipalities. As shown in column (1) of Table 4, the results confirm our hypothesis: trips originating from municipalities with a new line exhibit a larger reduction in travel times by 0.12 minutes, while those destined for these municipalities see an even greater decrease of 0.15 minutes. Moreover, our analysis indicates a positive correlation between trip length and the extent of travel time reduction, suggesting that longer journeys benefit more substantially from the proximity to the new subway infrastructure.

Additionally, we investigated whether the presence of existing subway stations within municipalities could either diminish or enhance the effects of new stations, suggesting potential decreasing or increasing returns due to complementarities. To examine this, we included variables indicating the prior presence of subway lines in column (2) of our analysis. The results reveal that the coefficients for these variables are negatively significant and exceed 0.10, while the impact of the new subway stations is only marginally reduced. Specifically, for a typical 13 km trip—the average distance

[6] Online Appendix Figure A.3 shows the distribution of the estimated effects.

Table 4: Predictors of subway effects

VARIABLES	(1) subway effect	(2) subway effect	(3) subway effect
Trip distance kms.	-0.0232***	-0.0231***	-0.0231***
	(0.00564)	(0.00561)	(0.00564)
Origin already had subway		-0.101*	-0.101*
		(0.0613)	(0.0614)
Origin has new subway line	-0.120**	-0.0993*	-0.0920
	(0.0579)	(0.0591)	(0.0698)
Destination already had subway		-0.187***	-0.187***
		(0.0607)	(0.0607)
Destination has new subway line	-0.147**	-0.107*	-0.0997
	(0.0587)	(0.0599)	(0.0723)
New subway at both origin and destination			-0.0364
			(0.112)
Constant	0.0531	0.196**	0.195**
	(0.0685)	(0.0782)	(0.0782)
Observations	925	925	925
R-squared	0.028	0.040	0.040

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

in our dataset—the reduction in travel times is 0.104 minutes. This reduction is amplified by 0.305 minutes if the trip starts from a municipality with both an existing and a new subway line. Similarly, if the destination municipality has both types of stations, the effect increases by 0.391 minutes. These findings suggest the absence of decreasing returns and point towards synergistic effects from cumulative subway infrastructure.

Lastly, we considered whether our model's structure might inherently preclude the observation of decreasing returns by using separate dummies for origin and destination. To address this, column (3) introduces a variable representing a direct new subway connection between origin and destination. While the incorporation of this variable increases the standard errors, the coefficient associated with the new subway connection is slightly negative and not statistically significant. Consequently, we find no evidence to support the notion of diminishing returns from subway investments; the spillover effects appear consistent regardless of direct connectivity.

5 Conclusions

Latin American cities have long grappled with severe traffic congestion, leading to substantial investments in subway infrastructure to mitigate these challenges. Traditionally, the absence of detailed intertemporal travel time data has significantly hampered the effective evaluation of such investments. In this study, leveraging the comprehensive Uber Movement dataset, we have systematically analyzed the impact of the 2017 subway expansion in Santiago, Chile, on surface travel times. Our findings not only underscore the effectiveness of subway expansions in reducing congestion but also demonstrate a methodological framework that can be applied to evaluate transportation investments across various urban settings.

Our research corroborates earlier findings, notably those concerning subway expansions in Chinese cities, which demonstrate significant reductions in travel times (Yang et al., 2018; Gao et al., 2019). Specifically, we found that the recent subway expansion in Santiago, Chile, decreases average car travel times by approximately 0.309 minutes for trips that typically last 21.2 minutes. While this reduction might appear modest, it masks underlying heterogeneity. Notably, the positive impacts of the subway expansion are more pronounced in areas with heavier traffic and in proximity to both new and existing subway stations. These observations suggest that subway infrastructure exhibits strong complementarities, enhancing the network's overall efficiency, rather than yielding decreasing returns.

Our study underscores the necessity of accounting for externalities and network effects in public transportation investments, particularly those identified within our study's parameters. A notable contribution of this research is the demonstration of how our methodology, leveraging openly accessible data, can be adapted to assess public transportation investments in different urban contexts. This adaptable approach fosters more informed and data-driven urban transport planning policies, enhancing the precision and efficacy of future infrastructure developments.

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Online Appendix

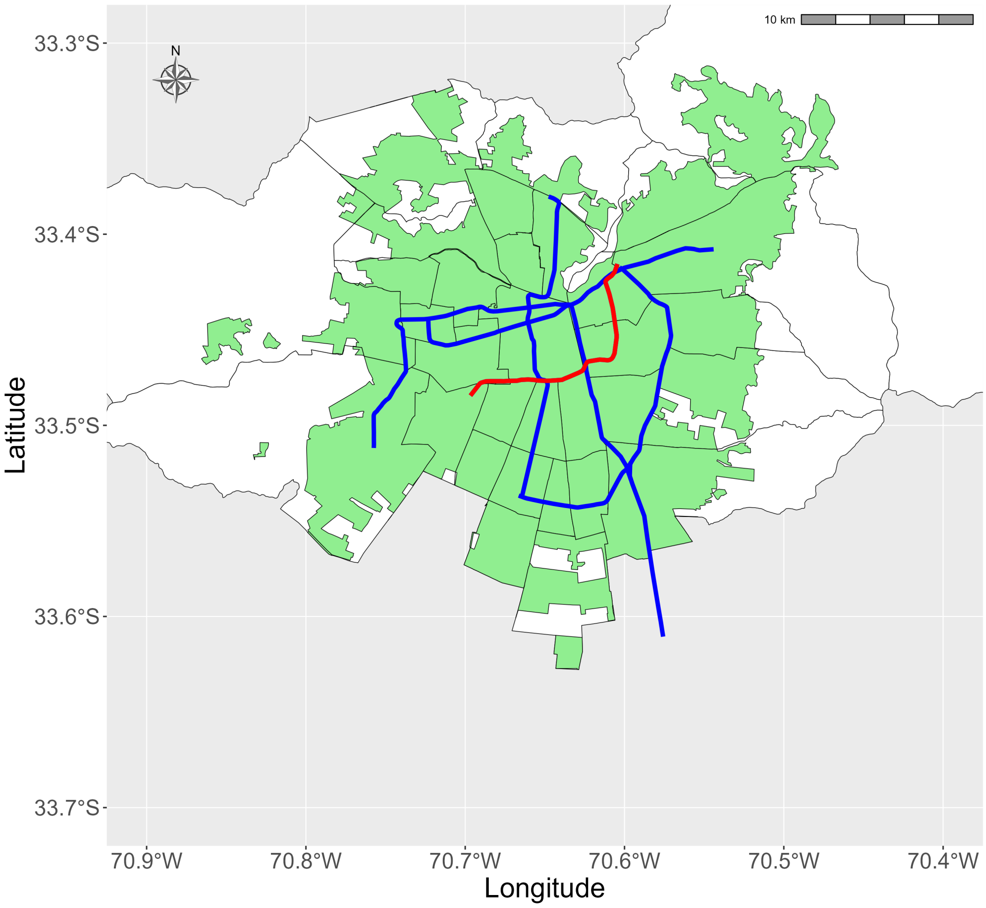

Figure A.1: Geographical Distribution of Santiago City's Subway Network.

Note: Red line is subway line 6. Blue lines are the rest of the subway network. Green is urban areas. The white background is the 32 municipalities of the "Gran Santiago". Source: Own elaboration.

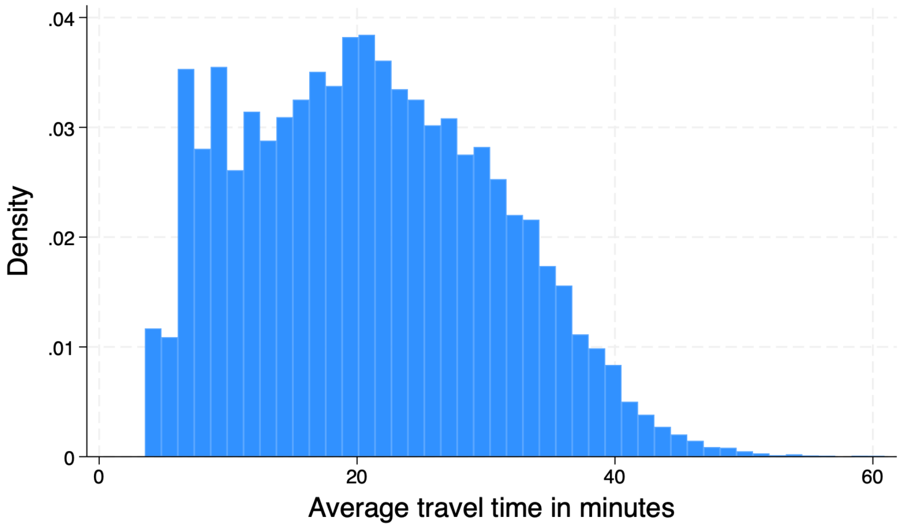

Figure A.2: Distribution of travel times between municipalities in minutes

Figure A.3: Distribution of subway opening effect' estimates