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The effect of dynamic lockdowns on public transport demand in times of COVID-19: Evidence from smartcard data

Benjamin Gramsch\textsuperscript{a,d,*}, C. Angelo Guevara\textsuperscript{b,a}, Marcela Munizaga\textsuperscript{b,a}, Daniel Schwartz\textsuperscript{c,a}, Alejandro Tirachini\textsuperscript{b,a}

\textsuperscript{a} Instituto Sistemas Complejos de Ingeniería, Av. República 701, Santiago, Chile
\textsuperscript{b} Civil Engineering Department, Universidad de Chile, Blanco Encalada 2002, Santiago, Chile
\textsuperscript{c} Industrial Engineering Department, Universidad de Chile, Av. República 701, Santiago, Chile
\textsuperscript{d} Institute for Transport Planning and Systems, ETH Zürich, Stefano-Franscini-Platz 5, Zürich, Switzerland

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\textbf{ABSTRACT}

Governments around the globe have taken different measures to tackle the COVID-19 pandemic, including the lockdown of people to decrease infections. The effect of such a strategy on transport demand is important not only for the current pandemic but also to understand changes in transport use and for future emergencies. We analyse a 2019–2020 database of smartcard data of trips from the city of Santiago, Chile, which followed a dynamic lockdown strategy in which its municipalities were temporarily restricted. We use this variation over time across municipalities to study the effect of lockdowns on public transportation using trips on buses and metro, accounting for the variation of municipalities that were under lockdown in a given day. We found a decrease of 72.3% at the beginning of the pandemic when schools suspended in-person classes, while the dynamic lockdowns reduced public transport demand by 12.1%. We also found that the effect of lockdowns decreased after the fifth week of their application, suggesting a short-term effectiveness of such policy to reduce mobility. Regarding sociodemographic effects, we found that lockdowns have a stronger impact on reducing public transport demand in municipalities with a larger proportion of the elderly population (2% additional reduction per 1% increase in the share of the elderly population) and high-income households (16% additional reduction for 1000 USD increase in GDP per capita).

\section{1. Introduction}

The global pandemic caused by the virus SARS-CoV-2, and the subsequent preventive measures, have produced significant changes in the structure of urban mobility worldwide (De Vos, 2020). One of these changes is issues concerning shared modes that might be associated with a source of risk during the trip, which increases negative attitudes towards public transport (Sharifi and Khavarian-Garmsir, 2020; Basnak et al., 2022). These changes have affected many aspects of urban transport systems and patterns, such as a reduction of trips to the Central Business District (CBD), increasing the dispersion of daily activities (Nian et al., 2020); or a reduction of distance travelled (Fatmi, 2020); and a change in traffic accidents (Aloi et al., 2020). However, the main effect of the COVID-19 pandemic has been a reduction of the overall travel demand in every affected city. The most affected mode is public transport, which, independent of the type of sanitary measures taken by governments, has seen a sudden and large reduction of demand due to its perceived risk of contagion (Tirachini and Cats, 2020).

Countries have reacted in different ways to the COVID-19 pandemic regarding mobility restrictions. In Australia, the approach was to adjust the confinement depending on the prevalence of the virus, with increases in the lockdown severity based on the number of daily infections. During the full lockdown, which started on March 30th, the main affected service was public transport, whose demand fell from 15% of the total trips to 7%, replaced mainly by active transport, which increased from 7% to 14% of the total trips, while 15% of the households had not made any changes in their commute nor were planning to do so (Beck and Hensher, 2020). Budapest had a different approach to the pandemic, based on a limited curfew in which people were only able to leave their home for work, shopping, and jogging but without strict enforcement. These measures also have produced a decrease in the share of public transport in urban mobility. While urban mobility was reduced...
by 51% overall, public transport usage reported an average drop of 80%, with a peak of 90% the second week after the first measure, reducing its participation from 43% to 18% of the total trips (Bucksy, 2020). The Netherlands used a system called “intelligent lockdown”, in which people were urged to leave their homes as little as possible. While restaurants, schools, and other “contact professions” were closed, people were allowed to move freely as long as they kept a distance of 1.5 m to others. This approach reduced the average number of trips per person from 8 to 3.6 trips every three days with a special reduction in public transport use (90%) and car use (80%) (de Haas et al., 2020). Lastly, in Sweden, which used a herd immunity approach, Jenelius and Cebeaucer (2020) studied the effect of COVID-19 on public transport in the three largest regions of the country between March and May 2020. They find a decrease of 60% in public transport use in Stockholm while in Västra Götaland the decrease was 40%, with slow increases from mid-April. This decrease has been mainly from a reduction in the number of active public transport travellers as the number of trips per traveller stayed relatively stable. The authors suggest a drastic change of mobility patterns by abandoning public transport and replacing it mainly with private cars and, to some extent, bikes.

For this paper, we count with a large database of smartcard transactions for trips made in the public transport system of the city of Santiago, per mode (bus and metro), location, time, and date. Santiago is composed of 34 municipalities. The Chilean government decided to implement a strategy of “dynamic lockdowns” at the municipality level. These dynamic lockdowns were applied and shifted per municipality on a weekly basis and are, arguably, the more far-reaching non-pharmaceutical governmental measure to reduce virus spreading, as they severely restrict citizens’ freedom of movement. Even though there was no random assignment of these lockdowns applied in Santiago, there was an important variation on which municipality was under lockdown each week, creating a quasi-experiment on urban public transport mobility response to the treatment. Besides, we count with a large and granular database of public transport demand constructed from smartcard data at the level of each bus stop, using the methodology developed by Munizaga and Palma (2012), for the years 2019 and 2020. We use this information to model the effects of dynamic lockdown on public transport demand, and control for a series of seasonal and trend factors to identify the effect of dynamic lockdowns. We examine the average effect of dynamic lockdowns, its effect over time, and how it may have affected different municipalities (heterogeneous effect). We also conduct a falsification test for robustness. We find that the strategy of dynamic lockdowns reduces on average the public transport demand in all modes of transport. However, there was a strong temporal effect as dynamic lockdowns have a decreasing effect as time passes. After the fifth week, there are no distinguishable differences compared to non-lockdown municipalities. The results also suggest a dissimilar effect between modes of transport. Results show that bus use fell in a higher proportion than metro use due to the lockdowns. The lockdown also has a heterogeneous effect depending on the socioeconomic characteristics of the municipalities, higher-income municipalities tend to reduce more their use of public transport, as well as municipalities with a higher percentage of elder individuals.

Our research analyses public transport demand trends inferred from smartcard data during the COVID-19 pandemic under lockdown measures. The scientific and policy relevance of this research is twofold. The first lies in contributing to understanding the response of the population to different types of mobility restrictions. Having access to detailed and extensive trip-level public transport demand in a large metropolitan area during this process is a unique powerful tool to analyse the effects of such non-pharmaceutical measures on reducing mobility. We are interested in uncovering both modal and temporal differences in demand adaptation to the new situation. For example, the temporal evolution of public transport demand in a prolonged lockdown could provide evidence about people’s reaction to this type of mobility restriction. In particular, we hypothesise that this type of measure may become less effective over time as restraining people at home for long periods can present several economic and personal difficulties. The second scientific and policy contribution of our work lies in providing evidence of the potential post-COVID situation of public transport systems. In the medium-term, a potentially significant problem for public transport in the post-lockdown period is related to public transport being perceived as poorly adapted to post-pandemic conditions. This perception will create an unhealthy reputation that could be transferred into lower demand levels even when the risk of COVID-19 contagion is heavily reduced or non-existent (Tirachini and Cats, 2020). However, current research points to the use of face masks, ventilation of vehicles while running, and traveling in silence (not talking among passengers) as key elements to greatly reduce the risk of COVID-19 contagion in public transport (Tirachini and Cats, 2020; Moreno et al., 2021). Early evidence on the post-lockdown after the first wave in Europe clearly showed that public transport demand recovered more slowly than car and cycling demand (see, e.g., Orro et al. (2020) for Spain and Molloy et al. (2020) for Switzerland). A sustained reduction in public transport demand has consequences for the sustainability of mobility patterns, the financial viability of public transport systems, and the social equity of the transport system as a whole (Tirachini and Cats, 2020). Therefore, understanding patterns of public transport demand today could provide glimpses of how the situation will look in the recovery phase and guide public policy responses to restore the role of public transport in satisfying mobility needs in the near future.

It should be noted that this article does not assume that there is any causality between the use of public transport and COVID-19 infections or deaths. The logic of our research thesis is that the usage of public transport serves as an indicator of global mobility, which in turn is related to human gatherings (occurring anywhere), which may explain the spread of the pandemic. For this reason, the authority seeks to curb human gatherings with measures such as lockdowns and, in this research, we can examine the relative success of this measure based on the use of public transport.

The rest of the paper is organised as follows. Section 2 provides background on our case study, including the evolution of the COVID-19 pandemic and the Chilean government response to reduce community contagion. In Section 3, the specific data used for this research is described. Section 4 presents the empirical strategy and the results of the study. In Section 5, discussion and conclusions are presented.

2. The COVID-19 pandemic in Chile

As there was no exact formula to prevent the virus from spreading, almost every country has taken different measures to control it. Following a herd immunity strategy in Sweden (Korhonen and Granberg, 2020) to an aggressive tracking of new cases in Singapore and strict lockdowns in China (Lu et al., 2020). The measures Chile took during the year 2020 can be divided into four periods: First Measures, Dynamic Lockdown, Total Lockdown, and Re-Opening. The first measures started on March 16th, 2020 (at the beginning of the school year), and included: suspension of in-person classes of kindergarten, schools, and universities; prohibition to visit elderly care centres; restrictions on public gatherings to a capacity limit of 200 people; and compulsory 14 days quarantine for people arriving from foreign countries, and a curfew from...
10 p.m. to 5 am\(^1\). The government also recommended implementing remote work when possible and giving workplace flexibility to employees\(^2\). The period of Dynamic Lockdowns consisted of temporary lockdowns at the municipality or even half-municipality level. Every week the government announced which municipalities had to start or finish their lockdowns. The decision was taken depending on the amount of new daily contagion and positivity rates, and the number of beds available at critical care units in hospitals. During these local lockdowns, people could get out of home a maximum of two times a week with a valid permit issued by the local police and only for essential activities, such as shopping for groceries and medicines or elderly care. Disobeying these measures could risk fines of 1250 USD or up to 540 days of jail for repeat offenders. The dynamic lockdown period was first implemented on March 26th starting with six municipalities. During the following weeks, the central government decreed new lockdowns in some municipalities and lifted previously established lockdowns in others. The Total Lockdown started on May 15\(^3\) and consisted of the same restrictions and enforcement but at a city level. Lastly, the re-opening period started on July 28th consisting of lifting the lockdowns depending on the evolution of the pandemic on a municipality level, while opening restaurants, stores, and gyms. By September 28th all municipalities were no longer under strict lockdown (see Fig. 1).

In Santiago, private car use has steadily increased in the past decades. For example, between 2001 and 2012, there has been an increase of 41% in the number of households that own at least one car, which goes concurrently with a decrease in public transport mode share from 30.1% to 23.7% in the same period (SECTRA, 2014), making Santiago the 7th most congested city in Latin America (26th worldwide\(^4\)). As one of the countries that are part of the Paris climate agreement 2015, Chile has been committed to achieve GHC neutrality by 2050, which implies reducing car use and promoting the use of public transport. Furthermore, the Chilean Nationally Determined Contribution (2020), establishes a commitment to reduce black carbon emissions by at least 25% by 2030, and to decrease private car transport by the transfer to public transport and bicycle. These goals could only be achieved if the country provides better public transport and cycling conditions, that would effectively allow reducing car use in the city. However, the COVID-19 pandemic has generated a trend in the opposite direction.

The first study analysing the impact of the pandemic in urban mobility in the city of Santiago was developed by Astroza et al. (2020), with data collected through an online convenience sample of self-reported trips, focused on mobility during the first week of restrictions, on March 2020. The authors show that public transport is the mode with the largest loss of demand during the pandemic, especially metro usage, and that the reduction in trips is more pronounced for high-income people. They also found other socioeconomic factors that affect the change in public transport use such as education, gender and age, evidencing some of the social implications of the COVID-19 pandemic in the Chilean context. Later, Basnak et al. (2022) estimates an increase for the discomfort of passenger crowding in public transport in Santiago due to the COVID-19 pandemic, where the actual level of discomfort (measured as an increased in the value of travel time savings) depends on whether passengers wear face masks. Our research complements the study of Astroza et al. (2020) for the city of Santiago by using extensive and granular revealed preference data inferred from smartcards, which could be considered almost as a census of the system for two years.

Fig. 2 illustrates the lockdown timeline in Santiago, showing different periods of the pandemic from week 1 (From March 23rd to 29th), when the first 7 municipalities entered the lockdown, until week 18 of dynamic lockdown (From September 28th to October 4th) when one last municipality was still on lockdown. The lockdown period in Santiago lasted 28 weeks in total, but as we are interested in identifying the effect of the dynamic lockdowns, we consider as week 9 the first week after the full lockdown is over and so on. The figure includes only some weeks of this period as not every week had seen changes in the spatial distribution of the lockdowns. The figure shows that the first municipalities to enter the lockdown were located at the north-east sector of the city for three weeks. After that period the southern locations started their lockdown followed by the centre and north part of the city. By week 7 most of the city was already under lockdown. It is important to notice that downtown Santiago was the only municipality to be in lockdown from week 1 until full lockdown. The opening period started with the ending of the lockdown for the north-east sector, moving towards the west and, by week 17, the last 8 municipalities were under lockdown. The closing and opening period lasted 8 and 10 weeks respectively.

3. Study area and data

To analyse the impact of dynamic lockdowns on public transport demand, this study is conducted in the Santiago Metropolitan area, which is 680 km\(^2\) in size, is compounded of 34 municipalities, and is served by an integrated public transport system known as Transantiago (see Munizaga & Palma 2012). This system includes 382 different bus routes, seven metro lines and a train line (metrotren) which connects the city centre with other localities outside the Santiago Metropolitan Area. All these public transport modes are integrated into a fare system that operates with a pre-paid smartcard (Bip!), which is the only payment

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system available (no cash, no season tickets available). The system as a whole served 5.5 million trips, during a normal day in the pre-Covid period. Observed trips can have up to five trip legs on any combination of the three modes available: bus, metro and metrotrén. The fare structure is such that the fare depends on the mode used to travel (bus, metro or train) and on the time of day (peak, valley, off peak), but not on the distance travelled. The data used in this paper is collected through the platform ADATRAP (Munizaga et al., 2016; Gschwender et al., 2016), which collects the data automatically generated by the daily use of the public transport system including buses’ location (GPS signal every 30 s) and the payment transactions made by the public transport users when boarding a bus or entering a metro station. After applying some methods developed by them to enrich the data, a database is obtained, that contains detailed information for each trip, including trip origin, services used, estimated travel time and destination. For this study, we used the daily trips at municipality level, and from March to September 2019 and 2020. This period captures both closing and opening process of the lockdown in 2020.

For the following section, we consider trips during business days and from 5 a.m. to 10 a.m. The latter condition is used to capture the morning trip, and avoid return trips. Previous studies show that morning trips enable making the assumption that the origin of the trip is from the municipality of residence of the individual (Amaya et al., 2018). After filtering the data, there are 8,122 valid observations which consider the number of daily trips for each municipality. For the socioeconomic characterization of the municipalities, we have used the information from CASEN survey made by the Ministerio de Desarrollo Social y Familia de Chile the year 2017. As the survey respondents cannot be identified within the smartcard database, we use the socio-demographic information as an aggregate descriptor at municipality level.

4. Empirical strategy and results

4.1. Average effects

We begin with a descriptive analysis of the main impact of the COVID-19 pandemic on public transport demand. Fig. 3 shows the number of daily public transportation trips per thousand inhabitants for 2019, without the pandemic (in red), and 2020, with the pandemic (in blue). Data from the year 2020 shows an abrupt decline in public transport trips as soon as the government implemented the first measures (mainly, suspension of in-person classes). Daily trips diminished by 72.3% compared to the same weeks in 2019 and 61.3% compared to the last week of “normality” in 2020. Then, demand decreased even more in late-March, when dynamic lockdowns started in the first municipalities. In April, daily trips started to increase. Then mobility decreased again at the beginning of May when lockdowns started to affect a large part of the city due to an increase in contagion rates. For the same reason, in mid-May, the authorities determined a lockdown in all municipalities. For this period, Fig. 3 shows a low and steady level of daily trips. However, trips started to increase slowly at the end of July, as lockdowns started to be less effective since presumably people got tired of being at home or could not comply with the lockdown anymore due to financial reasons. As authorities slowly lifted lockdowns in municipalities at the end of July, daily trips increased at levels higher than before the first measures started with the pandemic.

To examine the difference in daily trips between municipalities with and without lockdown, Fig. 4 shows the average daily public transport trips from municipalities under lockdown compared to those that were not under lockdown on a specific day. Therefore, this figure shows the variation on average daily trips depending on the dynamic lockdowns.

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5 Information del sistema | Red Metropolitana de Movilidad [Website]. http://www.red.cl/acerca-de-red/informacion-del-sistema.
6 March is the month in which full activity begins after the summer holidays.
7 Agencia Aton. (2020, September 25). Alcalde de Renca: “La cuarentena hace varias semanas muestra que no es efectiva” [Newspaper]. 24horas.CL. https://www.24horas.cl/coronavirus/alcalde-de-renca-la-cuarentena-hace-varias-semanas-muestra-que-no-es-efectiva-4464840.
8 La Tercera. (2020, July 3). Hartos de la pandemia: La fatiga emocional y mental que se apodera de la crisis [Newspaper]. https://bit.ly/3JDdBKF.
Before March 26th, there was no lockdown, and between May 15th and July 28th, all municipalities were under lockdown – i.e., on those periods, there are no differences among municipalities. More importantly, Fig. 4 shows that lockdowns reduced the number of public transport trips initially. Then, around the beginning of May, it seems that lockdowns lost effectiveness. An apparent opposite pattern is shown in the first two weeks of August (although when we later control for other variables in the regression models, we did not find a sizable difference).

Because seasonal effects and other factors may confound the previous descriptive analysis, we estimate the effect of dynamic lockdowns on public transportation demand using a regression analysis framework. We take advantage that municipalities under lockdowns varied almost every week, and municipalities could be under lockdown for a short period, then their lockdown was lifted, and then they went back to being under lockdown. The identification of the effect of dynamic lockdowns arises from this variation over time for each municipality compared to the changes in lockdown from other municipalities. Equation (1) shows the main model:

\[ \ln(V_t) = X_{it}\beta + \tau L_{it} + \gamma C_{it} + \epsilon_t \]  

(1)

where \( V_t \) is the ratio of the number of trips generated from municipality \( i \), on all public transport modes, over the total population of the municipality during day \( t \); \( L_{it} \) indicates whether municipality \( i \) is under lockdown on day \( t \) (=1, 0 if not); \( C_{it} \) indicates whether first measures decreed by the government started (=1 after March 15th, 0 before); \( X_{it} \) includes year, month and weeks fixed effects, day-of-the-week dummies, and municipalities fixed effects to control for municipalities’ time-invariant characteristics. \( \epsilon_t \) is the error term. We use robust standard errors clustered at the municipality level (see Bertrand et al., 2004). The average treatment effect of dynamic lockdowns is provided by \( \tau \). Because the dependent variable is in natural logarithm, \( \tau \) should be interpreted as the variation in trips by \( (\exp(\tau)-1)\times100\% \).

Table 1 shows the estimated effect of dynamic lockdowns on public transport demand using Equation (1), for three models. Model I only considers \( L_{it} \) and no controls for the first measures implemented neither the time fixed effects. Model II adds \( C_{it} \). Model III includes time fixed effects (all models include municipalities fixed effects). More important, all results show that there is a significant impact of the lockdown in the use of public transport. Without any control variable, the Model I shows that trips decreased by 70.3% compared to the year before. However, as shown by Model II, most of this massive effect comes down to 19.6% when accounting for the first measures applied at the beginning of the COVID-19 pandemic (including school closures and voluntary mobility restrictions), which after a few weeks coincide with dynamic lockdowns. In model III controlling for any difference correlated to timely effects, the average and overall effect of dynamic lockdowns is a reduction of 12.1% of daily trips. To complement this analysis, Table 2 presents a variation of model III. In this case the dependent variable \( V_{it} \) in Equation (1) is built using the number of trips attracted by municipality \( i \), i.e., the number of trips that have municipality \( i \) as a destination. Thus, the estimates in Table 2 indicate the effect of the lockdowns on the trips attracted by the municipality under lockdown. Results show that the effect of the lockdowns on the destination is more than 56% larger than those on the origin (Table 1). This may occur because, upon being affected by a lockdown, work places tend to close down and other trips attracted by a municipality have a

| Table 1 | Dynamic lockdowns average effect. |
|---------|----------------------------------|
|          | I                      | II                      | III                      |
| Lockdown | -1.214***               | -0.218***               | -0.129**                 |
|          | (0.043)                 | (0.036)                 | (0.036)                  |
|          | < 0.001                 | < 0.001                 | < 0.001                  |
| First Measures | -1.550***               | -1.318***               | -0.757***                |
|          | (0.048)                 | (0.054)                 | (0.058)                  |
|          | < 0.001                 | < 0.001                 | < 0.001                  |
| Time Fixed Effects | No                  | No                     | Yes                     |
| Observations | 5470                 | 5470                   | 5470                    |

All columns show robust standard errors between parenthesis and \( p \)-values in italic.

| Table 2 | Dynamic lockdowns effect on destination municipality. |
|---------|--------------------------------------------------------|
|          | I                      | II                      | III                      |
| Lockdown | -1.181***               | -0.309***               | -0.230**                 |
|          | (0.059)                 | (0.040)                 | (0.042)                  |
|          | < 0.001                 | < 0.001                 | < 0.001                  |
| First Measures | -1.355***               | -1.102***               | -0.595***                |
|          | (0.057)                 | (0.055)                 | (0.057)                  |
|          | < 0.001                 | < 0.001                 | < 0.001                  |
| Time Fixed Effects | No                  | No                     | Yes                     |
| Observations | 5465                 | 5465                   | 5465                    |

All columns show robust standard errors between parenthesis and \( p \)-values in italic.

This model is similar to a difference-in-difference approach, in which a treated group is compared over time to a non-treated group. However, in our case, treated units (i.e., municipalities under lockdown) changed over time, providing a greater sort of variation to examine the effect of lockdowns – a municipality can be under lockdown one day and without lockdown on another. A similar approach has been used for examining the causal effect of policies in diverse domains, such as food labeling (Araaya et al., 2023), housing eviction (Kroeger and La Mattina, 2020), and residential waste (Alacevich et al., 2021).

Results are also very similar when controlling for daily contagions cases in the rest of analyses.

Because governmental authorities announced lockdowns for each municipality 3 or 4 days before lockdowns took place, we also examined the effect on trips for the days before the lockdown took place (without the weekends), in Appendix 1, as some people may not have differentiated between announcement and enforcement of lockdowns. We found a much smaller effect – i.e., the reduction in trips is more strongly associated with the lockdown and not to its announcement.

\[ p < 0.10, *p < 0.05, **p < 0.01, ***p < 0.001 \]
large range of possible alternative destinations that act as proper substitutes. Therefore, the trips may still be performed, but to elsewhere. Consequently, the trips generated by a municipality, there are no proper substitutes, reflecting on a relatively smaller effect of the lockdowns. Nevertheless, the results based on destinations should be taken with caution because how the information on trips is built from the smartcards uses an algorithm that approximates users’ destination by using the origin of their next trip (Munizaga and Palma, 2012). This result complements the following analyses, which are based on trips generated in each municipality.

Table 3 shows the effect of dynamic lockdowns by mode (i.e., trips using only metro, only bus, and intermodal trips combining bus and metro). For this, we used Equation (1) but define $V_\text{p}$ as the ratio of the number of trips on each respective mode. We control for the first measures and the time fixed effects. Results show that the effect of first measures was larger for metro than for buses, in line with what is reported by Astroza et al. (2020).

Regarding lockdowns, trips by all public transport modes suffered a reduction, but the effect was larger for the buses (25.2%) than for the metro (10.6%). This dichotomy may be explained in part by socioeconomic differences. Metro users were more likely to switch to other travel modes (e.g., cars or bikes) or to work from home, as they have a higher income than average bus users (SECTRRA, 2014), and likely reacted quicker to the first measures that included voluntary confinement. On the contrary, bus users with lower income may be forced to travel and would stop doing so only when lockdowns were in place. Additionally, as metro users already experienced a large reduction in trips with the decree of the first measures, it becomes more difficult for that mode to reduce its levels even further. In addition, there is a fare evasion effect that affects the estimation of bus, metro and combined-mode trips differently. In Santiago, there is significant fare evasion in buses, while in Metro it is almost negligible (Munizaga et al., 2020). Metro stations have turnstiles and guards that enforce payment, and in buses the driver does not play such a role, and even though some buses have turnstiles near the front door, which is used for boarding, users might jump over the turnstile or enter through the back door to avoid payment. During the pandemic, some drivers would purposely open the back door to allow passengers to board the bus without crowding the bus entrance area, and minimise the contagion risk for drivers themselves. This practice might have increased fare evasion, but no fare evasion measurements were made during the pandemic.

4.2. Effect over time

The previous analysis showed a relevant average effect associated with the dynamic lockdowns. To examine how this effect varies over time – which should be relevant based on Fig. 4 – we estimate the dynamic lockdown’s weekly effect based on Equation (2).

$$\ln(V_t) = X_t \beta + T_t L_t + \sum \rho_j T_j + \sum \alpha_j T_j + \gamma C_t + \varepsilon_t$$

where, in addition to the variables defined in Equation (1), $T_j$ indicates whether day $t$ belongs to dynamic lockdown week $j$ ($= 1, 0$ if not), from the first week of dynamic lockdown ($j = 1$) to the last week of dynamic lockdown ($j = 17$). This variable is included as interaction with $L_t$ to examine the effect of lockdown overtime, and as main effect to control for the effect over time not associated with a municipality being in lockdown. Our estimate of interest is $\rho_j$ which indicates the average treatment effect of the dynamic lockdown for each week.

Fig. 5 shows $\rho_j$ for each week. It indicates that the effect of dynamic lockdowns on public transport demand decreases after a few weeks. In the first week, municipalities in lockdown had 59.0% fewer trips than municipalities not in lockdown. This difference started to shrink every week. For example, in the fourth week, municipalities in lockdown had 20.7% fewer trips than those not in lockdown. After the sixth week, there was almost no sizable difference. This pattern was very similar in all travel modes (see Appendix 6 and Appendix 7). This result is consistent with data, based on connection to telecommunication infrastructure, showing that people’ mobility increase after several weeks of lockdown (Olivares et al., 2020). The hypotheses behind this result are multiple: financial, social or personal needs. Several behavioural changes reflected this greater mobility despite lockdowns: some businesses started to open as “sellers of essential products”, starting on April 17th, 2020 public employees had to go back to work in their offices, and people started to use more permits.

### Table 3
Dynamic lockdowns average effect by modes of transport.

|                   | I          | II         | III        |
|-------------------|------------|------------|------------|
| **Lockdown**      |            |            |            |
| Bus               | -0.290***  | -0.112**   | -0.130**   |
| (0.036)           | (0.039)    | (0.037)    |
| <0.001            | 0.009      | 0.001      |
| **First Measures**| -1.107***  | -1.428**** | -1.453**** |
| (0.043)           | (0.080)    | (0.060)    |
| <0.001            | <0.001     | <0.001     |
| **Time Fixed Effects** | Yes       | Yes        | Yes        |
| Observations      | 5355       | 3893       | 5466       |

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$, **** $p < 0.001$. All columns show robust standard errors between parenthesis and $p$-values in italic.

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12 This data analysis excludes the weeks that all municipalities were under lockdown (the “total lockdown” phase, because it does not provide any variation). For completeness, Appendix 5 shows results, including these weeks. The effect of dynamic lockdown is overestimated, as expected, as when all municipalities were in lockdown, the number of trips was very low.

13 We have excluded week 18 of the analysis that included only the first two days of the week with one municipality under lockdown.

14 Part of the larger average reduction in trips by bus than by metro is due to an upward trend in the re-opening phase of lockdowns that differed between these two modes.

15 La Tercera. (2020, October 3). Permisos temporales suben 25% pero se mantienen bajo el millón en la previa del primer fin de semana de la RM en desconfinamiento. [Newspaper] https://bit.ly/3R83PZr.
The estimated trend in public transport demand due to the lockdowns has to be seen with caution because, even though there is sufficient variation across and within municipalities, the dynamic lockdown order was not random. For example, the effect may be triggered by the fact that the wealthier municipalities, in the north-east part of the city, were the first to be affected by lockdown at the beginning of the dynamic lockdown strategy. Therefore, the estimated effect reflects a particular form of dynamic lockdown correlated to municipalities’ characteristics. Also, north-east municipalities were the first ones to have their lockdown lifted in the opening phase. Households in these municipalities can more easily substitute public transportation, work from home, and do online shopping (Carranza et al., 2022). This issue is explored in the analysis of heterogeneous effects, presented next.

4.3. Heterogeneous effect

We examine heterogeneous differences associated with the dynamic lockdowns, by results by age and income, since those shows have shown to be relevant factors related to risk perception and COVID-19 contagion. For this, we use municipalities’ characteristics based on the proportion of the elderly population (over 65 years old), income per capita (average US$ in thousands using the 2019 conversion rate), and the population’s proportion under the poverty line. Similar to Equation (1), we estimate:

$$\ln(V_t) = X_t \beta + \tau_{it} + \sigma_{iy} \times S_t + \gamma C_t + \epsilon_{it}$$

(3)

where we add $S_t$, which indicates the socioeconomic variables described above (elderly, income per capita and poverty) interacted with the term $\tau_{it}$. Therefore, $\sigma$ indicates the heterogeneous effect of dynamic lockdowns. Results are shown in Table 4.\textsuperscript{16}

Table 4 shows that municipalities’ reduction of public transport demand associated with the dynamic lockdown is more pronounced in municipalities with a larger proportion of the elderly population (e.g., each additional 1 percent in the proportion of elderly in a municipality, decreases trips by 2 percent approximately). This result was expected because older people have a higher risk of contagion and get seriously ill, as well as younger people living with elders may have tried to avoid trips that may have spread the disease at home. In addition, the elderly population can have more flexible hours, and people over 75 years old were requested to be at home from the start of the first measures, regardless of their place of residence. Table 4 also shows the differences in socioeconomic characteristics. In municipalities with a higher income per capita and lower poverty level, dynamic lockdowns reduce more public transport demand than in municipalities with a lower income per capita and higher poverty level. As mentioned above, higher-income municipalities have more alternatives to replace public transport, work from home, or bear a job loss than people living in poorer municipalities.\textsuperscript{17}

4.4. Falsification test

As a robustness analysis, we conduct a falsification test imputing the same first measures and dynamic lockdown strategies used in 2020, in same weekdays of the previous year (2019), when there was no lockdown whatsoever. For example, the first lockdown started on a Thursday of the 13th week of 2019. Therefore, the first falsification lockdown starts on a Thursday of the 13th week of 2019. We used the same estimation described in Section 4.1. Because there were no lockdowns in 2019, no effect should be expected on trips, so this analysis serves as a test for identifying of the dynamic lockdown effect provided in the previous sections.

Table 5 shows the results of the falsification test. A falsification test for the average treatment effect using simulated dynamic lockdowns in 2019.

Table 5

|                      | I     | II    | III    |
|----------------------|-------|-------|--------|
|                      | Elderly | Income | Poverty |
| Falsification lockdown | 0.003  | 0.003 | 0.006  |
|                      | (0.006) | (0.006) | (0.006) |
|                      | 0.668  | 0.601 | 0.274  |
|                      | (0.003) | (0.003) | (0.001) |
| Falsification first Measures | 0.040*** | -0.006 | 0.068*** | 0.062*** |
|                      | (0.003) | (0.003) | (0.001) |
|                      | <0.001 | 0.101 | <0.001 |
|                      | <0.001 | <0.001 | <0.001 |
| Time Fixed Effects Observations | Yes | Yes | Yes |
|                      | 2278 | 2271 | 1660 |
|                      | 2278 | 2271 | 1660 |

\* $p < 0.10$, \*\* $p < 0.05$, \*\*\* $p < 0.01$, \*\*\*\* $p < 0.001$.

- Elderly and poverty are measured as the percentage of people over 65 years old and below the poverty line in a municipality, respectively. Income is measured as the average income in a municipality in US Dollars. All columns show robust standard errors between parenthesis and $p$-values in italic.

\textsuperscript{16} The main effect of $S_t$ is captured by the municipalities’ fixed effect. $\tau$ would indicate the effect of lockdown in municipalities with only young people, no income and no people under the poverty line. Therefore, $\sigma$ is the relevant estimate for this analysis.

\textsuperscript{17} Appendix 8 shows the heterogeneous effect over time. This analysis suggests that the reduction in trips lasted a few more weeks for municipalities with a relatively higher proportion of the elderly population, not much difference by income over time, and lasted for several weeks more for municipalities with a smaller proportion of people below the poverty line. Also, Appendix 9 shows the effect over time using the number of trips that have municipality as a destination. We also examined the effect of lockdown on the travelled distance without observing any effect, showing that the reduction of ridership in the destination is probably due to a decrease in the total ridership and not due to a change in the destination itself.
the start of the academic year in Chile. More importantly, all falsification lockdown effects are very unlikely different from zero. In Appendix 11, we also show the falsification test over time. Even though there are very few significant differences (with positive signs), we can conclude that the falsification test results can robustly rule out seasonally or yearly spurious effects on the main results shown in the previous regressions.

5. Discussion and conclusion

During the year 2020, city lockdowns have been used to control the Covid-19 pandemic worldwide. In Chile, this measure was implemented dynamically, at the municipality level, depending on how the prevalence of the virus in the community evolved over the weeks. This variation in time and space created a quasi-experiment on urban public transport mobility response to the lockdowns, which we study by examining smartcard transaction data from Santiago’s public transport system from 2019 to 2020. We complement the analysis by examining the correlation between sociodemographic attributes (such as average income and proportion of elderly people per municipality) and the effectiveness of dynamic lockdowns. The lockdown approach to the pandemic has divided opinions on its adequacy to fight the virus and its long-term consequences. As of today, many countries have seen a second, third, or even fourth peak of contagion of the virus, forcing its population to re-enter lockdowns. This paper contributes to understanding the changes in people’s behaviour towards public transport and helps to generate relevant information for policymakers in the use of different strategies to tackle the spread of a virus during a pandemic. Besides allowing the analysis of the effect of dynamic lockdowns, our study also gives some insights on the long-term implications that the COVID-19 pandemic may have for public transport demand.

We distinguish between two main actions affecting the public transport demand during the analysis period: the first measures implemented by the government at the beginning of the pandemic (mainly in-person classes suspension and voluntary confinement), and the dynamic lockdowns implemented at a municipality level. First measures reduced the use of public transport by 72.3%, relative to the year 2019 (without COVID), while the lockdowns reduced, on average, the public transport demand by 12.1%. There is also an impact of the lockdowns on the destination with an effect of more than 56% compared to the origin, as incidence continues after the pandemic, there may be a long way until we can see public transport reaching pre-pandemic demand levels.

We finalize detailing some of the possible limitations of our study. The first limitation is that the information on mobility that we have corresponds only smart card transactions. This implies that any fare evasion, for whatever reason, is not captured in the data, and it cannot be assured that those events occur randomly. In general, evasion is more present on buses and where household income is lower (Guarda et al., 2016). Besides, as it was discussed before, the decision to allow entrance by the rear door on buses by the end of March may have played a role in the by-mode differences in the responses detected. The second possible limitation, also related to the available data on mobility, comes from the fact that smartcard transactions in Santiago’s public transportation system occur only at boarding and thus alighting and trip chains have to be inferred from later transactions from the same smartcard. This raises the potential problem of missing trip legs or even confounding trips between different users if the smartcard is shared by different individuals. A discussion on the conditions under which these errors may arise is detailed in Munizaga et al. (2014). Although it cannot be claimed that such limitations occur randomly, there is no clear reason to think that they may affect the conclusions reached in this study. Another potential limitation on the analysis developed is related to a possible endogeneity in the treatment, which in this case would imply that the change in trips is not only due to dynamic lockdowns. Because an ideal randomized experiment cannot be implemented, we used a falsification test to rule out confounding factors due to seasonal and time trends. However, specific municipalities’ characteristics may still be correlated to the treatment (e.g., it may be more effective to start the dynamic lockdown strategy with certain municipalities). This needs to be considered if a dynamic lockdown strategy is implemented.

CRediT author statement

Benjamin Gramsch: Conceptualization, methodology, formal analysis, investigation, writing - original draft, visualization, data curation.

C. Angelo Guevara: Conceptualization, methodology, resources, writing - review & editing, supervision, funding acquisition.

Marcela Munizaga: Conceptualization, methodology, resources, writing - review & editing, supervision, funding acquisition, supervision.

Daniel Schwartz: Conceptualization, methodology, formal analysis, investigation, writing - review & editing, supervision, funding acquisition, supervision.

Alejandro Tarchini: Conceptualization, methodology, writing - review & editing, supervision, funding acquisition.
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Appendix

Appendix 1
Dynamic lockdown effect with days before lockdown.

|                      | Origin   | Destination |
|----------------------|----------|-------------|
| Lockdown             | -0.135***| -0.232***   |
| (0.037)              | (0.044)  |
| <0.001               | <0.001   |
| First Measures       | 1.311*** | -1.099***   |
| (0.549)              | (0.056)  |
| <0.001               | <0.001   |
| Days before lockdown | -0.059*  | -0.032      |
| (0.029)              | (0.035)  |
| 0.049                | 0.358    |
| Time Fixed Effects   | Yes      | Yes         |
| Observations         | 5470     | 5465        |

*p < 0.10, *p < 0.05, **p < 0.01, ***p < 0.001.

All columns show robust standard errors between parenthesis and p-values in italic.

Appendix 2. Change in demand for bus respect to first two weeks of March 2020.

Appendix 3. Change in demand for metro respect to first two weeks of March 2020.
Appendix 4. Change in demand for intermodal trips (bus & metro respect to first two weeks of March 2020.)

Appendix 5
Dynamic lockdowns average effect including full lockdown effect.

|               | I          | II         | III         | IV          |
|---------------|------------|------------|-------------|-------------|
| All Modes     | -1.388***  | -1.172***  | -1.493***   | -1.531***   |
| (0.057)       | (0.046)    | (0.081)    | (0.061)     |
| First Measures| -0.268***  | -0.418***  | -0.234***   | -0.259***   |
| (0.034)       | (0.033)    | (0.033)    | (0.035)     |
| Time Fixed Effects | Yes | Yes | Yes | Yes |
| Observations  | 8122       | 7954       | 5733        | 8118        |

\* p < 0.10, *p < 0.05, **p < 0.01, ***p < 0.001.
All columns show robust standard errors between parenthesis and p-values in italic.

Appendix 6. Lockdown’s weekly average effect in public transport
**Appendix 7**

Dynamic lockdowns weekly effect.

|                | I       | II       | III      | IV       |
|----------------|---------|----------|----------|----------|
|                | All Modes | Bus | Metro | Bus & Metro |
| Lockdown       | -0.025  | -0.027  | 0.083   | -0.020   |
|                | (0.050) | (0.042) | (0.060) | (0.055)  |
| Week 1 × Lockdown | -0.892**  | -1.068*** | -0.952*** | -0.696***  |
|                | (0.081) | (0.093) | (0.111) | (0.068)  |
| Week 2 × Lockdown | <0.001  | <0.001  | <0.001  | <0.001   |
|                | (0.100) | (0.104) | (0.162) | (0.077)  |
| Week 3 × Lockdown | -0.362**  | -0.539*** | -0.414*  | -0.211*   |
|                | (0.113) | (0.119) | (0.176) | (0.094)  |
| Week 4 × Lockdown | -0.212*** | -0.284*  | -0.321*  | -0.169*   |
|                | (0.117) | (0.127) | (0.162) | (0.093)  |
| Week 5 × Lockdown | 0.057   | 0.033   | 0.052   | 0.080    |
| Week 6 × Lockdown | <0.001  | <0.001  | <0.001  | <0.001   |
| Week 7 × Lockdown | 0.032   | 0.041   | 0.053   | 0.092    |
| Week 8 × Lockdown | 0.173   | 0.112   | 0.065   | 0.248    |
| Week 9 × Lockdown | 0.080   | 0.084   | 0.067   | 0.433    |
| Week 10 × Lockdown | 0.146   | 0.110   | 0.067   | 0.373    |
| Week 11 × Lockdown | 0.178   | 0.097   | 0.132   | 0.391    |
| Week 12 × Lockdown | 0.143   | 0.045   | 0.077   | 0.144    |
| Week 13 × Lockdown | 0.198   | 0.067   | 0.040   | 0.427    |
| Week 14 × Lockdown | 0.080   | 0.084   | 0.085   | 0.107    |
| Week 15 × Lockdown | 0.364   | 0.579   | 0.795   | 0.771    |
| Week 16 × Lockdown | 0.160   | 0.063   | 0.035   | 0.127    |
| Week 17 × Lockdown | 0.123   | 0.430   | 0.703   | 0.432    |
| First Measures | -0.010   | -0.010   | -0.010   | -0.010    |
|                | (0.078) | (0.079) | (0.091) | (0.159)  |
|                | 0.098   | 0.129*  | 0.020   | 0.029    |
|                | (0.082) | (0.067) | (0.060) | (0.122)  |
|                | 0.083   | 0.053   | 0.015   | 0.016    |
|                | (0.072) | (0.059) | (0.047) | (0.096)  |
|                | 0.259   | 0.377   | 0.749   | 0.875    |
|                | (0.083) | (0.052) | (0.123) | (0.099)  |
|                | 0.571   | 0.251   | 0.722   | 0.546    |
|                | (0.082) | (0.019) | (0.044) | (0.087)  |
| Time Fixed Effects | <0.001  | <0.001  | <0.001  | <0.001   |
| Observations   | 3570    | 3535    | 3893    | 5466     |

*p < 0.10, *p < 0.05, **p < 0.01, ***p < 0.001.

All columns show robust standard errors between parenthesis and p-values in italic.
Appendix 8
Dynamic lockdowns weekly effect including socioeconomic variables.

|            | I | II | III | IV | V  | VI |
|------------|---|----|-----|----|----|----|
|            | Older | Younger | More income | Less income | Less poor | Less poor |
| Lockdown   | 0.049 | -0.083 | 0.170* | -0.088* | -0.092* | 0.329** |
|            | (0.039) | (0.056) | (0.071) | (0.048) | (0.047) | (0.096) |
| Week 1 × Lockdown | -0.954*** | -0.825*** | -1.007*** | -0.708*** | -0.696*** | -1.164*** |
|            | (0.088) | (0.102) | (0.111) | (0.057) | (0.055) | (0.101) |
| Week 2 × Lockdown | -0.571*** | -0.358* | -0.658*** | -0.195** | -0.192** | -0.903*** |
|            | (0.114) | (0.123) | (0.143) | (0.061) | (0.059) | (0.137) |
| Week 3 × Lockdown | -0.445** | -0.249 | -0.577** | (...) | (...) | -0.693*** |
|            | (0.112) | (0.198) | (0.153) | (...) | (...) | (0.146) |
| Week 4 × Lockdown | -0.52* | -0.094 | -0.382* | -0.235** | -0.250** | -0.49** |
|            | (0.150) | (0.108) | (0.185) | (0.081) | (0.082) | (0.179) |
| Week 5 × Lockdown | -0.404** | -0.135 | -0.183 | -0.322** | -0.343** | -0.293+ |
|            | (0.136) | (0.131) | (0.143) | (0.102) | (0.104) | (0.162) |
| Week 6 × Lockdown | -0.462** | -0.009 | -0.193 | -0.165 | -0.222 | -0.265 |
|            | (0.148) | (0.135) | (0.157) | (0.153) | (0.153) | (0.170) |
| Week 7 × Lockdown | -0.0483 | -0.252* | -0.031 | -0.051 | -0.362** | -0.495** |
|            | (0.068) | (0.128) | (0.108) | (0.103) | (0.101) | (0.098) |
| Week 8 × Lockdown | 0.052 | 0.176 | -0.129+ | 0.148 | 0.169 | -0.346** |
|            | (0.057) | (0.104) | (0.066) | (0.148) | (0.150) | (0.108) |
| Week 9 × Lockdown | 0.115 | -0.044 | -0.141 | (...) | (...) | -0.257* |
|            | (0.105) | (0.098) | (0.165) | (...) | (...) | (0.086) |
| Week 10 × Lockdown | 0.119 | -0.064 | -0.148 | (...) | (...) | -0.261** |
|            | (0.101) | (0.099) | (0.164) | (...) | (...) | (0.085) |
| Week 11 × Lockdown | 0.111 | -0.076 | -0.147 | (...) | (...) | -0.240** |
|            | (0.087) | (0.098) | (0.171) | (...) | (...) | (0.077) |
| Week 12 × Lockdown | 0.062 | -0.059 | -0.180 | -0.089 | -0.099 | -0.269** |
|            | (0.075) | (0.097) | (0.180) | (0.068) | (0.070) | (0.072) |
| Week 13 × Lockdown | 0.059 | 0.240 | -0.042 | -0.096 | 0.330 | -0.266** |
|            | (0.079) | (0.250) | (0.074) | (0.067) | (0.346) | (0.074) |
| Week 14 × Lockdown | 0.000 | 0.167 | -0.053 | 0.023 | 0.198 | -0.315** |
|            | (0.058) | (0.174) | (0.037) | (0.093) | (0.177) | (0.077) |
| Week 15 × Lockdown | 0.004 | 0.173 | (...) | 0.019 | 0.120 | -0.253** |
|            | (0.029) | (0.169) | (...) | (0.070) | (0.127) | (0.060) |
| Week 16 × Lockdown | -0.015 | 0.174 | (...) | -0.006 | 0.142 | (...) |
|            | (0.144) | (0.173) | (...) | (0.067) | (0.134) | (...) |
| Week 17 × Lockdown | 0.042 | -0.097 | 0.035 | (...) | (...) | +0.007 |
|            | (0.096) | (0.144) | (0.063) | (0.116) | (0.001) | (0.001) |
| First Measures | -1.046*** | -1.035*** | -1.066*** | -1.022*** | -1.010*** | -1.089*** |
|            | (0.047) | (0.087) | (0.059) | (0.072) | (0.069) | (0.059) |
| Time Fixed Effects | Yes | Yes | Yes | Yes | Yes | Yes |

Observations: 2736 2734 2252 3218 3379 2091

*p < 0.10, *p < 0.05, **p < 0.01, ***p < 0.001.
All columns show robust standard errors between parenthesis and p-values in italic.
Appendix 9. Lockdown’s weekly average effect in destinations with public transport

Appendix 10
Dynamic lockdowns average effect using year 2020.

|        | I     | II    | III   | IV    |
|--------|-------|-------|-------|-------|
|        | All Modes | Bus | Metro | Bus & Metro |
| Lockdown | -0.127*** | -0.115*** | -0.231*** | -0.115** |
|         | (0.033)   | (0.018) | (0.034) | (0.037) |
| First Measures | -0.925*** | -0.918*** | -1.012*** | -0.955*** |
|         | (0.042)   | (0.089) | (0.037) | (0.037) |
| Time Fixed Effects | Yes | Yes | Yes | Yes |
| Observations | 3192 | 2233 | 3084 | 3188 |

*p < 0.10, **p < 0.05, ***p < 0.01.
All columns show robust standard errors between parenthesis and p-values in italic.

Appendix 11
Falsification test for the weekly effect using simulated dynamic lockdowns in 2019.

|        | I     | II    | III   | IV    |
|--------|-------|-------|-------|-------|
|        | All Modes | Bus | Metro | Bus & Metro |
| Lockdown | -0.002 | 0.006 | -0.010 | -0.000 |
|         | (0.010) | (0.017) | (0.012) | (0.012) |
| Week 1 × Lockdown | -0.005 | -0.002 | -0.003 | -0.019* |
|         | (0.011) | (0.022) | (0.013) | (0.011) |
| Week 2 × Lockdown | -0.015 | -0.030 | -0.007 | -0.019 |
|         | (0.013) | (0.022) | (0.013) | (0.013) |
| Week 6 × Lockdown | 0.011 | -0.010 | -0.005 | 0.048 |
|         | (0.027) | (0.016) | (0.016) | (0.073) |
| Week 7 × Lockdown | 0.026 | -0.007 | -0.003 | 0.090 |
|         | (0.034) | (0.018) | (0.019) | (0.098) |
| Week 9 × Lockdown | 0.049* | -0.000 | 0.040* | 0.088* |
|         | (0.020) | (0.027) | (0.019) | (0.041) |
| Week 10 × Lockdown | 0.020 | 0.995 | 0.040 | 0.04 |
|         | (0.013) | (0.018) | (0.015) | (0.022) |
| Week 11 × Lockdown | 0.004 | -0.001 | 0.014 | -0.004 |
|         | (0.011) | (0.018) | (0.014) | (0.021) |
| Week 12 × Lockdown | 0.747 | 0.604 | 0.225 | 0.958 |

(continued on next page)
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### Appendix 11 (continued)

| I | II | III | IV |
|---|---|---|---|
| All Modes | Bus | Metro | Bus & Metro |
| Week 13 × Lockdown | 0.008 | -0.003 | 0.030* | 0.005 |
| | (0.012) | (0.018) | (0.014) | (0.021) |
| Week 14 × Lockdown | -0.009 | -0.010 | 0.013 | -0.007 |
| | (0.014) | (0.015) | (0.012) | (0.012) |
| Week 15 × Lockdown | -0.012 | -0.002 | -0.002 | -0.006 |
| | (0.017) | (0.014) | (0.010) | (0.009) |
| Week 17 × Lockdown | -0.006 | -0.013 | 0.004 | -0.012 |
| | (0.006) | (0.010) | (0.011) | (0.008) |
| First Measures | 0.072*** | 0.113*** | 0.012** | 0.096*** |
| | (0.004) | (0.012) | (0.004) | (0.007) |
| Time Fixed Effects | <0.001 | <0.001 | 0.006 | <0.001 |
| Observations | 2278 | 1660 | 2271 | 2278 |

*p < 0.10, **p < 0.05, ***p < 0.01, ****p < 0.001. All columns show robust standard errors between parenthesis and p-values in italic.
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