The (unequal) impacts of COVID-19 on mobility in Latin America and the Caribbean[*]

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Abstract

The COVID-19 pandemic has generated a worldwide health crisis that has forced most countries to take social distancing measures to try to slow down COVID-19 contagion. Those measures have included closing schools and non-essential businesses, restricting people's mobility, and the imposition of mandatory stay-at-home orders. We study the impacts of the pandemic on traffic volume, traffic congestion and public transit use in several cities in Latin America and the Caribbean, and document sharp decreases in mobility, even prior to official social distancing measures were taken. We show that the reductions in mobility are heterogeneous by time of day, type of fare (for public transit), and by proxies for socio-economic status of the drivers and public transit users, as well as by a city's economic structure (as measured by firm size and sector). As cities are slowly re-opening and allowing more activities, those heterogeneous patterns are exacerbated, with clear evidence that more disadvantaged individuals are increasing their mobility at a faster rate.

Keywords: COVID-19; coronavirus; traffic; traffic congestion; public transit; social inequality; Latin America and the Caribbean
JEL Codes: O0**;** R0; R4

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1. Introduction

The COVID-19 pandemic has generated a worldwide health crisis that has forced most countries to take measures to slow down COVID-19 contagion. Those measures have included closing schools and non-essential businesses, restricting people's mobility, and the imposition of mandatory stay-at-home orders (Hale et al., 2020, present detailed country-specific data). The Inter-American Development Bank (IDB) and IDB Invest created the online IDB and IDB Invest Coronavirus Impact Dashboard, to track in real time the impacts of the pandemic, including measures of traffic volume, traffic congestion, public transit use, people mobility, air quality and COVID-19 cases. The data show a clear pattern of immediate reduced mobility as measured by traffic congestion, public transit use, and human mobility (Coronavirus Impact Dashboard Team, 2020a; Aromi, Cristiá and Izquierdo, 2020), and an improvement in air quality for cities with more stringent social distancing measures (Coronavirus Impact Dashboard, 2020b), but also suggest that mobility is increasing again[1], as well as that air quality gains may have been transitory.

In this paper we study the impacts of the pandemic on different mobility measures (traffic volume, traffic congestion, and public transit use) in several cities in Latin America and the Caribbean (LAC). We document sharp decreases in mobility, even prior to official social distancing measures were taken, and show that the reductions in mobility, regardless of the measure, are heterogeneous by city, day of the week and time of the day. We also find unequal impacts when using different proxies for socio-economic status. To conduct the analysis we exploit: (i) traffic volume data from the Buenos Aires metropolitan area relying on highway tolls high-frequency data and show that there is heterogeneity associated to the socio-economic status of the drivers (as proxied by the socioeconomic characteristics of areas surrounding corridors within the metropolitan area); (ii) a measure of traffic congestion using data from the community-driven navigation app Waze and find heterogeneity in traffic congestion impacts by the socio-economic status of different areas/cells of the metropolitan areas; and (iii) a measure of public transit use based on official trips data and find heterogeneity of impacts by type of fare, and other proxies for socio-economic status of the public transit users and public transit stations. In addition we conduct an analysis in Mexico City showing that impacts are differential by economic structure, as measured by firm size and sector.

As cities are slowly re-opening and allowing more activities, heterogeneous patterns are exacerbated, with clear evidence of more disadvantaged individuals increasing mobility at a faster rate. Our results are consistent with evidence on the type of jobs that are plausible to be continued through telework under stay-at-home orders (Yasunov, 2020), which indicates that in the U.S. lower-wage workers are up to three times less likely to be able to work from home than higher-wage workers. They are also consistent with findings on the heterogeneous impacts of the COVID-19 crisis for the U.S., based on data on mobility reductions by location-based measures of income distribution (Valentino-DeVries, Lu, and Dance, 2020).

This paper adds to a growing literature studying the impacts of the COVID-19 pandemic on consumption spending patterns (Baker et al., 2020), economic activity (Sampi Bravo and Jooste,

[1] These mobility patterns are consistent with those from other sources of mobility data, like Google's COVID-19 Community Mobility Reports, and Apple's COVID-19 Mobility Trends Report.

2020), heterogeneity of job losses (Cho and Winters, 20202), pollution (Breathe Londong, 2020; Brodeur, Cook and Wright, 2020; Coronavirus Dashboard Team, 2020b; Persico and Johnson, 2020;), traffic accidents (Brodeur et al., 2020; Oguzoglu, 2020), among other dimensions.

2. Data[2]

We rely on different sources of data for traffic volume, traffic congestion, and public transit.

2.1. Traffic volume data

We measure traffic volume for the access highways to the City of Buenos Aires (Argentina), using high-frequency toll-based data. We obtain measures of traffic volume at the hourly level, and at the toll-station level from AUSA, the toll operator in Buenos Aires. The data is available on the City of Buenos Aires' open data website, and is updated monthly. Traffic volume used in the analysis is computed from the three main tolls of the Buenos Aires highway network, Illia, Avellaneda and Dellepiane, which accounted jointly for 86% of all AUSA tolls in 2019.[3]

2.2. Traffic congestion data

The IDB Group has an agreement with Waze through the Waze for Cities Program. The agreement provides us with access to aggregate-level information originating from a continuous feed every two minutes from the Waze app. This feed provides information on traffic jams and user alerts. The data on traffic jams are passively generated while the Waze app is running on a user's device (i.e., even if the user is not actively using it). Combining that information for all Waze users ("Wazers") in the area, Waze identifies whether at any given geographic point traffic is slowing down (with respect to the expected speed under no-jam conditions, or "free-flow").[4] The jam data is composed of jam lines (which can change over time) measured at different time intervals. Given the crowd-sourced nature of the data, it cannot be determined if fluctuations in jam line activity are due to actual changes in traffic conditions or due to fluctuations in the number of active Wazers. As we show in Appendix Figure A1, evidence from Buenos Aires supports the notion that changes in jam activity are generally due to actual changes in traffic volume.

Using the Waze data, we can calculate a measure we call Traffic Congestion Intensity (TCI) for any given area (polygon or cell) for any time period. At every time interval i at which the data is

[2] This section relies heavily on Inter-American Development Bank and IDB Invest (2020), which details the data and methodology used in the IDB and IDB Invest Coronavirus Impact Dashboard (https://www.iadb.org/en/topics-effectiveness-improving-lives/coronavirus-impact-dashboard).

[3] The Illia toll is located on the north highway axis (Illia Highway). This axis extends to the Buenos Aires Metropolitan Area through the Acceso Norte Highway. In 2019, it represented 26% of all AUSA tolls. The Avellaneda toll is located on the west highway axis (Perito Moreno Highway). This axis extends to the Buenos Aires Metropolitan Area through the Acceso Oeste Highway. In 2019, it represented 37% of all AUSA tolls. The Dellepiane toll is located on the southwest highway axis (Dellepiane Highway). This axis extends to the Buenos Aires Metropolitan Area through the Ricchieri Highway. In 2019, it accounted for 23% of all AUSA tolls.

[4] A "no congestion scenario" does not necessarily imply that there is no traffic on a specific road. This is because while congestion is obviously correlated with the volume of vehicles, the relationship between speed and volume is not linear. Even when congestion is reduced to zero there may still be vehicles driving on the road.

analyzed (in this case, every 5 minutes) and for every polygon, p, we calculate a measure of total jam length, $\mathrm{L_{ip}}$, by adding the lengths of all jam lines[5] j in the polygon in that time interval:

$$\mathrm{JAM_{ip}} = \sum \mathrm{L_{jip}}. \tag{1}$$

The TCI measure for a period t (hour, day, etc.) adds up all the total jam lengths across all intervals in the period t:

$$\mathrm{TCI_{pt}} = \sum \mathrm{JAM_{ip}}. \tag{2}$$

The TCI summarizes both the extent of jams in the street network of a polygon (e.g., a metropolitan area) and their duration, because jam lengths are counted at each time interval i. For example, if in metropolitan area A and metropolitan area B the same 10 jam lines are formed in a day, each 150 meters long, we would have a measure of 1,500 meters jammed in both A and B during the day. However, if jams in A have a duration that is double the duration in B, the TCI for A would be double the TCI for B. The TCI is not particularly useful as a point-in-time measure, but it is useful to capture changes in jam intensity over time for a fixed-size polygon.

For the IDB and IDB Invest Coronavirus Impact Dashboard, we calculate TCI changes for over 60 metropolitan areas in LAC, adapting the OECD-EC methodology to identify metropolitan areas (Dijkstra and Poelman, 2012). For details see Inter-American Development Bank and IDB Invest (2020). In this paper we concentrate the analysis on the TCI for four metropolitan areas: Bogotá (Colombia), Buenos Aires (Argentina), Lima (Peru) and São Paulo (Brazil).

2.3. Public transit use data

We rely on four different data sources to measure public transit in the cities of Bogotá, Lima, and São Paulo (Brazil), plus an index of public transit use for 17 cities in Argentina, Brazil, Chile, Colombia, Mexico, Peru, and Uruguay generated by Moovit. Below we provide a more detailed description of each data source.

1. Bogotá BRT and bus system: We use data on individual validations (i.e., each ticket card swipe) at stations for the BRT Transmilenio and for the SITP buses (when boarding the bus). We obtain the data from Transmilenio's open data website. We can identify each individual bus ride during the day and when a full, subsidized or over-62 years old fare is used.

2. Lima BRT: We use data on daily validations (i.e., ticket card swipes at stations) for the BRT Metropolitano. We obtain the data from the Instituto Metropolitano PROTRANSPORTE de Lima of the Municipality of Lima. Validations are registered at the point of entry into the system. We collect daily data by hour and stop.

3. São Paulo Bus System: We use data on daily validations (i.e., ticket card swipes and single cash paid tickets in the buses) for the São Paulo Bus System. We obtain the data from the Secretaria Municipal de Mobilidade e Transportes of the Municipality of São Paulo. The data

[5] We exclude from the analysis jam lines with a value of *traffic congestion level* in the Waze data equal to 5 (blocked) which refers to streets that are closed to traffic.

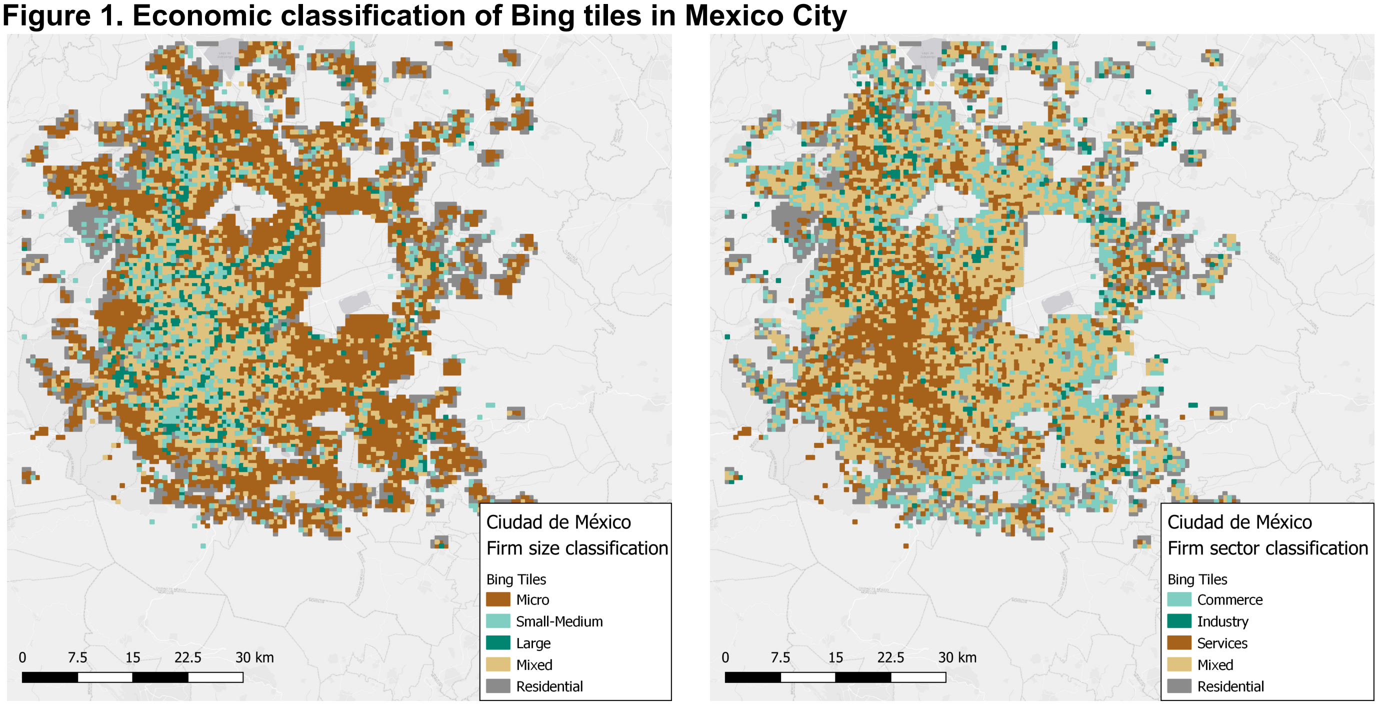
is at the bus line level, and it is reported daily. We can identify when a full, free (no students) and student (free and paid) fare is used.

4. Public Transit Index (Moovit): The public transit app Moovit generates the Moovit Public Transit Index for almost 100 cities across the world, of which 17 cities are in LAC, in Argentina (Buenos Aires), Brazil (Belo Horizonte, Brasilia, Campinas, Curitiba, Fortaleza, Porto Alegre, Recife, Rio de Janeiro, Salvador, São Paulo), Chile (Santiago), Colombia (Bogotá), Mexico (Guadalajara, Mexico City), Peru (Lima) and Uruguay (Montevideo). The index captures the usage of the Moovit app to plan public transit trips.

2.4. Population change data

We rely on data provided by Facebook through their Movement Range Maps to study the movement of population post-coronavirus crisis in Mexico City, classifying units of measure (Bing tiles[6]) by the economic activity of the tile (either by looking at firm size or firm sector), based on up-to-date economic activity data. Figure 1 presents the economic classification by Bing Tiles of Mexico City. In the left we show the classification by firm size, while in the right we show the classification by economic sector. Mixed indicates that there is no dominant category, and residential areas are also indicated.

Figure 1. Economic classification of Bing tiles in Mexico City



Note: Authors' elaboration based on Mexico's National Statistical Directory of Economic Units (Directorio Estadístico Nacional de Unidades Económicas, DENUE), https://www.inegi.org.mx/temas/directorio/.

[6] Bing tiles are determined by the Bing Maps Tile System, which render maps in tiles of 256 x 256 pixes. For more details see: https://docs.microsoft.com/en-us/bingmaps/articles/bing-maps-tile-system.

3. Methodology

Our analysis relies on studying the changes in different mobility measures, as explained below. We analyze those changes by city (and areas within a city), hour of the day, day of the week, type of fare (for public transit), and by different proxies for socio-economic status (SES). The next sub-section explains succinctly the different ways in which we proxy for SES for each type of data and city, while the following sub-section specifies our empirical model.

3.1. Definition of socio-economic status

To quantify the heterogeneous impacts of COVID-19 by SES we generate proxy measures for SES within different part of the cities. Our hypothesis is that impacts on mobility in areas of relatively lower SES will be less pronounced (and the return to normalcy faster) due to the nature of the jobs associated to a lower SES, which are probably less susceptible of being conducted at home or teleworking.

We use highly disaggregated data from population censuses across countries and other data sources on income (mostly from household surveys) to classify the relevant unit of observation (details for each case below) in three socioeconomic status: Low, Middle, and Hight income, or Mixed when there is no dominant socioeconomic status. We also classify areas as non-residential when appropriate.

For public transportation, the relevant unit of observation is the one related to the validations level of aggregation. When we have validations by stations, the station is the relevant unit and is classified according to the socioeconomic status of its surrounding area. In the cases where we have data at the bus line level, the whole line is classified. For that, we use the whole line surroundings, attributing the major socioeconomic status of this area to the bus line.

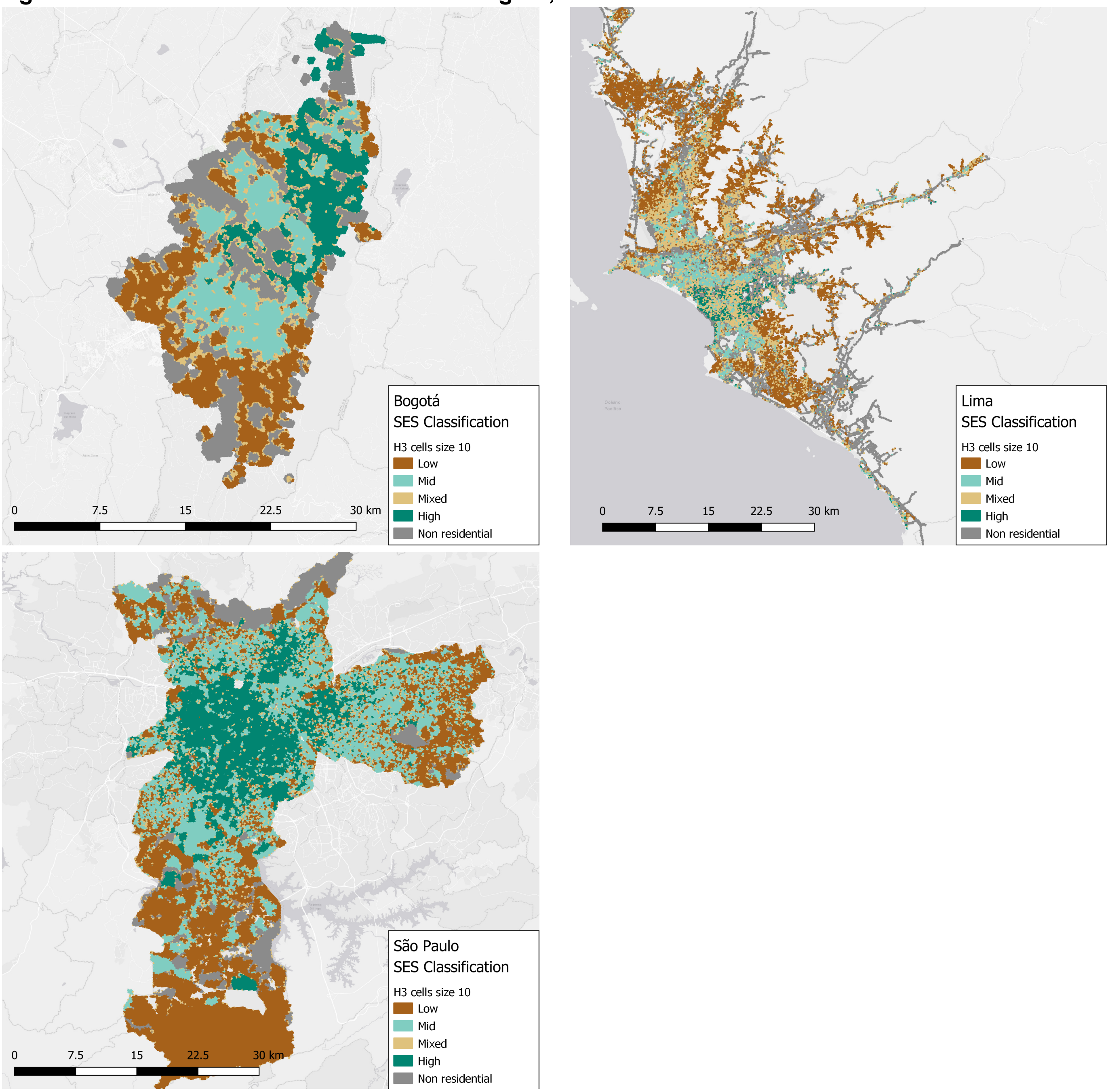
For the traffic congestion intensity analysis, we divide the cities into H3 cells[8], the relevant unit of analysis in this case. We then classify each cell in terms of socioeconomic status based on census or other available information and calculate the TCI within each cell. Figure 2 presents the SES classification of the three cities of interest, Bogotá, Lima and São Paulo by SES, using H3 cells.

For traffic volume in Buenos Aires the units of analysis are the tolls across certain highways. For them, we characterize the socioeconomic level of the people who are expected to use the tolls and therefore the different highways that go into the City of Buenos Aires. In particular we use census data on the population that lives between 5 km and 30 km along the highways. This helps us determine the population areas that are expected to be most influenced by and that are closer to the different highways (see Appendix Figure A2). Since the national census does not directly measure income, we use the CAPECO area index as a proxy. This index is constructed using the relationship between the years of formal education of all income earners in the household and the total number of household members (see Appendix Figure A3). As a result, we obtain a continuous numerical indicator that varies between zero (when there is no earner of income in

[8] H3 cells are a hexagonal hierarchical geospatial grid system developed by Uber, to analyze sub-areas of the world. This grid system has the advantage of quickly splitting areas in grids, and allowing to efficiently assign points to those grids, worldwide, at different grid sizes ("resolutions"). For more details see https://eng.uber.com/h3/.

the household or the earners do not have formal education) and a maximum value that depends on the extension of the current formal education system and the number of adults in a household that have an income.

Figure 2. SES classification of H3 cells in Bogotá, Lima and São Paulo



Note: Authors' elaboration based on SISBEN classification (Bogotá), 2017 population census data (Lima) and 2010 population census (São Paulo).

3.2. Empirical model

Our approach estimates a flexible fit that includes a series of weekly dummies that capture the adjustment phase following the pandemic announcement made by the WHO[10]. Although WHO's announcement of pandemic was somehow expected at some point in March, we rely on the sudden nature of the virus spread itself as the source of external variation used to estimate the causal effect of COVID-19. Unlike the evaluation of a policy, we expect that the pandemic declaration to be unrelated to any previous trends in mobility. WHO declared pandemic on March 11, 2020, well before most Latin American countries introduced severe mobility restrictions. In our specification, we consider the week from March 9 to 15, 2020, as week 0 when the effects of COVID-19 on mobility became apparent.

$$y_{\mathrm{it}} = \lambda_i + \gamma_{\mathrm{d}} + \gamma_m + \alpha t + \beta_k M_k + \varepsilon_{it}. \tag{3}$$

We estimate this equation for each city using daily data, where $y_{i\mathrm{t}}$ is the mobility outcome of interest (e.g. number of public transit validations or TCI) for the unit of analysis i in day t; λ_i is a fixed effect for the unit of analysis i (e.g. bus stop or bus line for validations, and H3 cell for TCI or highway for traffic volume); γ_d are dummies for each day of the week; γ_m are month dummies; t is a linear time trend, and α its associated coefficient; ; T_t is a dummy variable that takes the value of 1 after a given breakpoint in the series, which could be date when the World Health Organization (WHO) declared COVID-19 a pandemic or else idiosyncratic dates by city based on their government-mandated social-distancing measures and the dates when they were taken; and ε_{it} is the error term. The impact of COVID-19 on mobility is captured by the coefficient β resulting from the interaction of the time trend and T_t. The interpretation of β would be the average percentage change in the mobility measure in the city as consequence of the irruption of the COVID-19 pandemic. We also estimate a flexible specification of (3) in which we allow β to vary over time.

To explore the heterogenous impacts of COVID-19 on mobility we re-express equation (3) as:

$$y_{\mathrm{it}} = \lambda_i + \gamma_{\mathrm{d}} + \gamma_m + \alpha t + \theta_{jk} \sum_{\mathrm{j}} (Z_j M_k) + \varepsilon_{it}, \tag{4}$$

where π_{ji} is a vector of j socioeconomic status and θ_j captures impact of COVID-19 in the mobility measure of group j. As before, this model can be more flexible, allowing the θ_j coefficients to vary over time. In further heterogeneity analysis we explore differential impacts by time-of-day, day-of- the-week, proximity to the date of WHO pandemic proclamation, and by proximity to different social distancing measures taken by the city and/or country.

4. Preliminary results

[10] Similar approaches have been used to study the effect of driving restrictions. See Gallego, Montero, and Salas (2013).

In this version of the paper we include only descriptive statistics under the stylized facts sub-section, and initial results for TCI regressions from estimating equations (3) and (4) for Bogotá and Lima. In a subsequent version of the paper we will include the results for additional cities, mobility measures, and heterogeneity analyses.

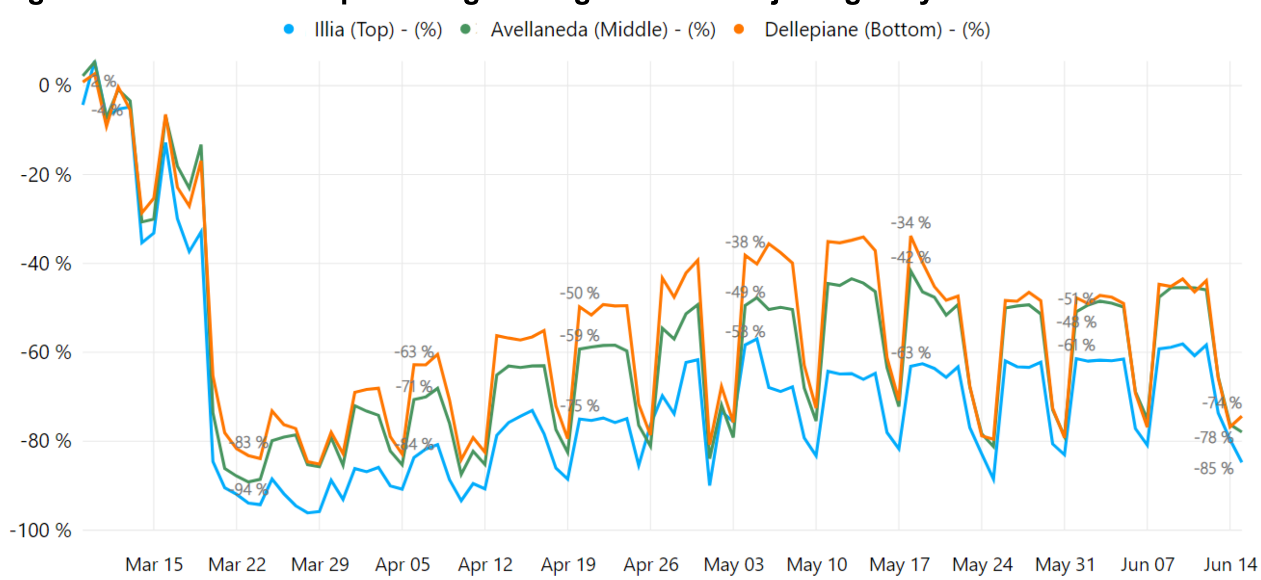
4.1. Stylized facts

We present stylized facts on the impacts of COVID-19 for three measures of mobility we consider: traffic volume, traffic congestion intensity (TCI) and public transit use. In all cases the baseline period to calculate the percentage changes in the mobility measure is the week of March 2 to 8, 2020, when there were very few declared cases of COVID-19 in the region. When presenting daily percentage changes, those are calculated comparing same days of the week (i.e., comparing Mondays against Monday March 2, Tuesdays against Tuesday March 3, etc.). For details see Inter-American Development Bank and IDB Invest (2020).

- **Traffic volume**

Figure 3 shows the daily percentage change in traffic volume in the three major highways that lead to the City of Buenos Aires. Each of them ends in a toll station where traffic volume is measured. Considering the classification by SES conducted, Illia in the north represents incoming inflow of vehicles from mostly well-off areas, Avellaneda from the East, represents vehicle inflow from middle income areas, and Dellepiane from the south, represents incoming inflow from low-income areas. Figure 3 suggests that the initial drop in traffic volume was somewhat larger for well-off areas, but the recovery starting in May has been slower in those areas. The difference between well-off areas and low-income areas is on weekdays over 20 pp.

Figure 3. Traffic volume percentage change in three major highways in Buenos Aires

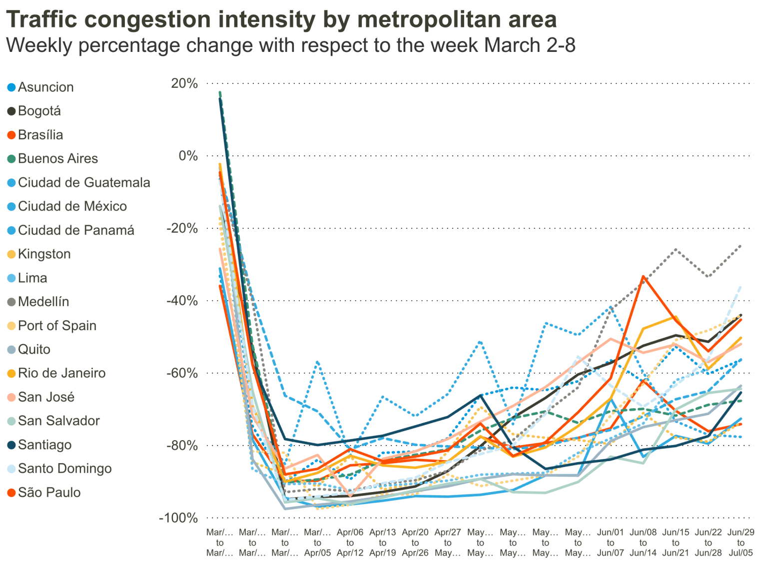


Note: Authors' elaboration based on data from AUSA. Percentage change against the week of March 2-8.

- **Traffic congestion intensity**

Figure 4 reports the weekly percentage changes in TCI based on Waze data when compared to the week of March 2 to 8. It also shows the clear overall and sharp initial reduction in traffic congestion for multiple metropolitan areas in LAC and the increase in congestion starting in May, as social distancing measures have been slowly being lifted in many metropolitan areas. There is, however, a fair amount of heterogeneity across cities (within and across countries) both in terms of the initial decrease and in terms of the return of congestion.

Figure 4. TCI weekly percentage change in selected LAC metropolitan areas



Note: Based on Waze data. Percentage change against the week of March 2-8. For daily changes and for more cities see the *IDB and IDB Invest Coronavirus Impact Dashboard*.

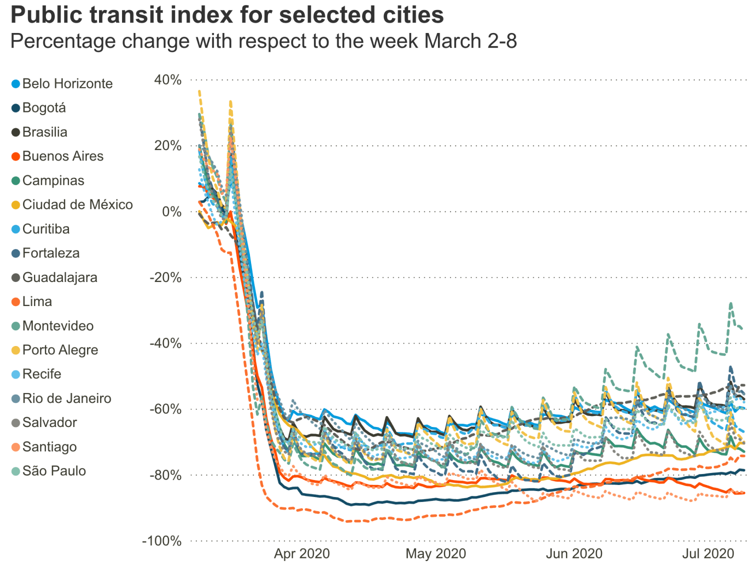
- **Public transit use**

Similar as with traffic volume in Buenos Aires, and traffic congestion for many LAC metropolitan areas, the evidence shows a large reduction in public transit use for many cities in LAC (as measured by planned trips in the Moovit app) and by actual trips in the four cities of interest, since the start of the COVID-19 pandemic. Figure 5 shows for 17 LAC cities the percentage change in Moovit's public transit index. The patterns are quite similar to those captured by the TCI measure, with across city heterogeneity in an initial sharp drop, and a slow increase over time, in particular starting in May, for some cities. Overall the index seems to stay flatter over time, compared to the TCI measure.

The data on actual validations (trips) for Bogotá, Lima and São Paulo suggest a similar story, as shown in Figure 6. We can see Bogotá's bus and BRT systems separately as well as Lima's BRT and Sao Paulo's bus system. It is quite remarkable that the data from an app capturing the intent to use public transit (planned trips) matches so well the overall trends of actual public transit use in the cities. Ridership decreased dramatically either following stay-at-home orders or being cautious. São Paulo had a smaller but still impressive decrease of 70% in late March compared to the week before the pandemic, even though the city did not impose as restrictive stay-at-home orders as Lima and Bogotá did. In cities with strict stay at home orders the ridership fell between

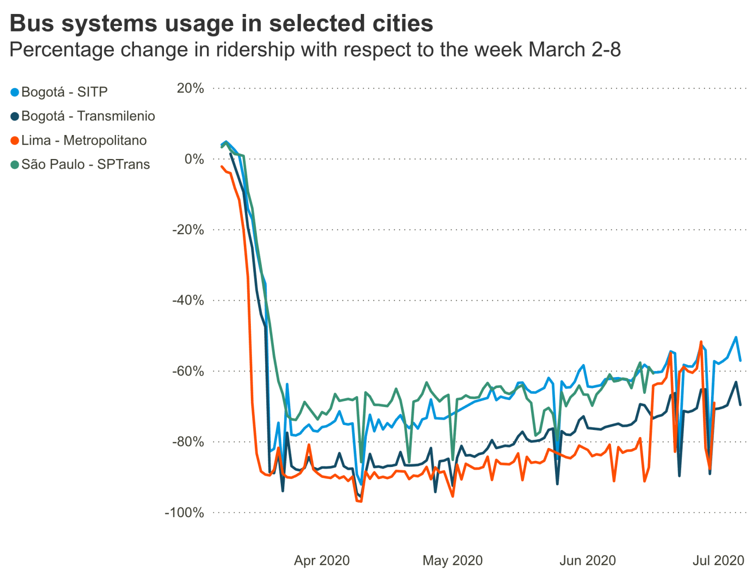
80% and 90% in late March. Two months after the pandemic declaration by WHO we can see small rises in ridership, but still far from the levels prior to the crisis.

Figure 5. Public transit index percentage change in selected LAC cities



Note: Public transit index elaborated by Moovit, measuring use of the app for planning public transit trips. Percentage changes measured against the week of March 2-8.

Figure 6. Public transit use percentage change in Bogotá, Lima and São Paulo

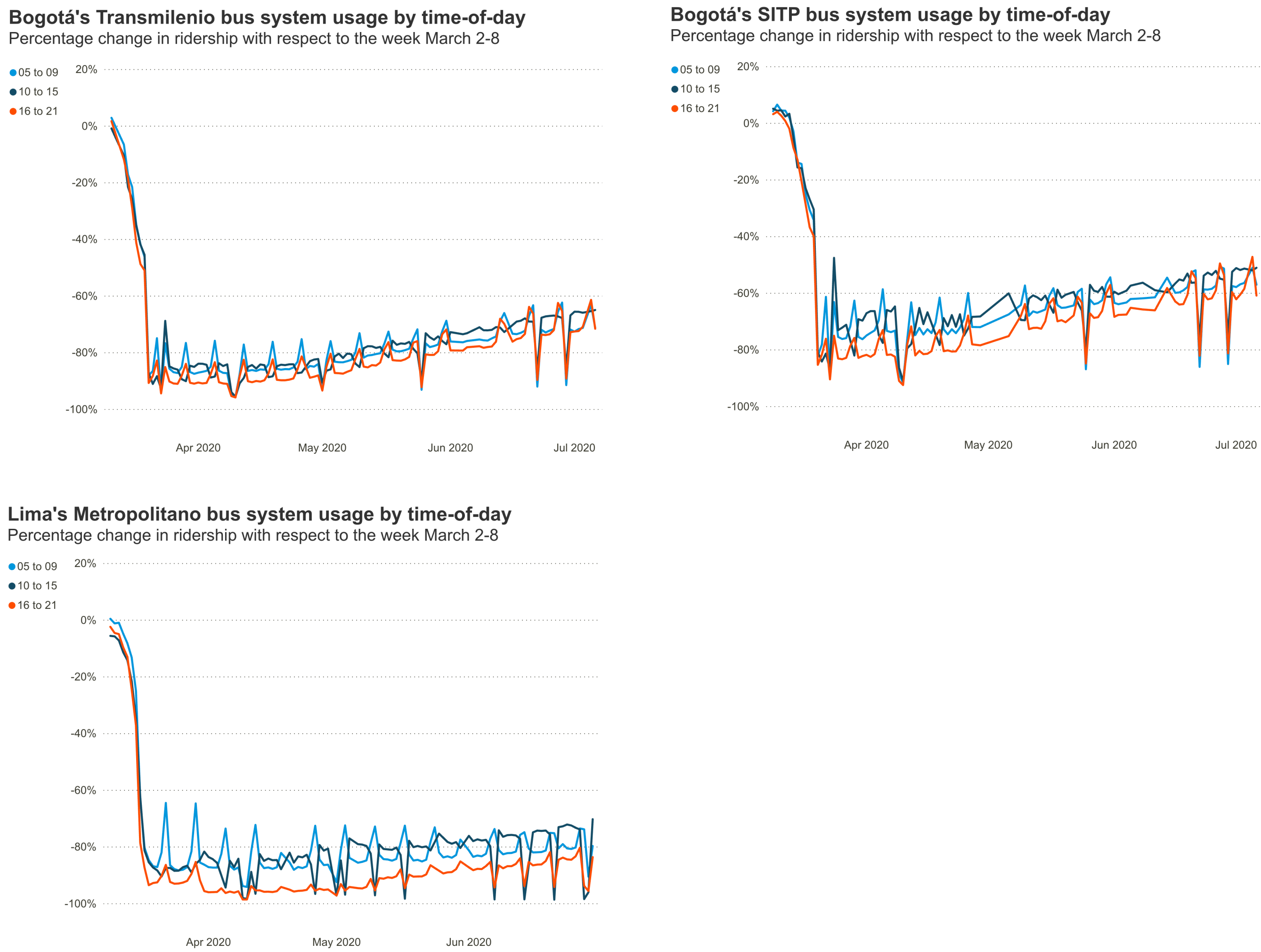


Note: Public transit use based on validation (trips) data from each system. Percentage changes measured against the week of March 2-8.

The validation data (when available) allows us to also analyze transit use changes by time of the day, fare type, and socio-economic status. Figure 7 presents the time of the day analysis for Bogotá and Lima (there is no time-of-day data for São Paulo). In both cities public transit use decrease is smaller in the morning and mid-day, with a larger decrease in the afternoon/evening.

This suggests that there may be a change in behavior where people avoid using public transit during the afternoon and evening. In the case of Lima, we could explain this due to the mandatory curfew imposed at night but in Bogotá there was no such curfew in place.

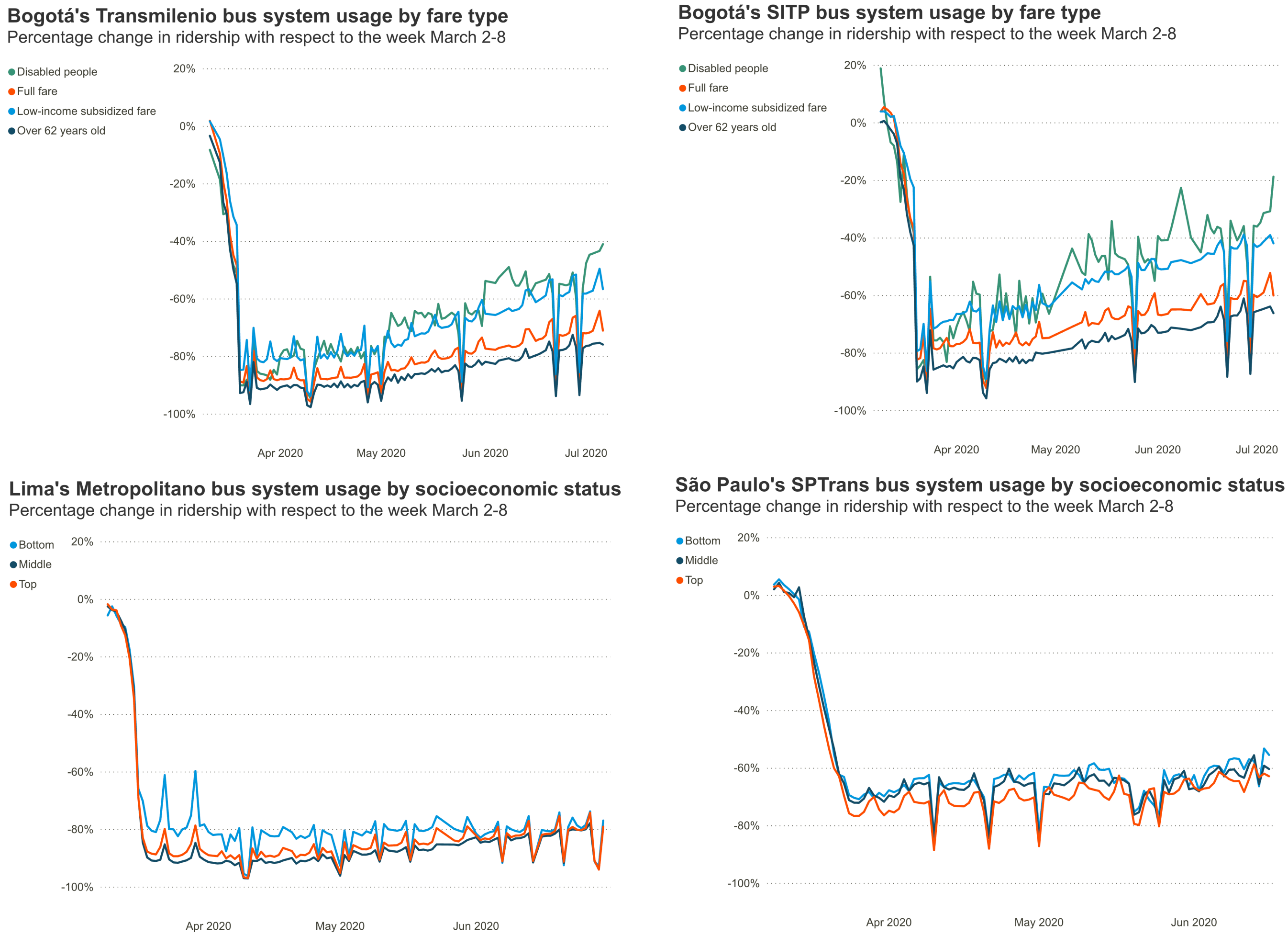
Figure 7. Public transit use change by time-of-day in Bogotá and Lima



Note: Public transit use based on validation (trips) data from each system. Percentage changes measured against the week of March 2-8. There is no time-of-day information for the São Paulo bus system.

Figure 8 presents transit use changes for the three cities with different splits of the data that serve as a first approximation to the SES heterogeneity analysis that will be conducted with cell-based data, using equation (4). The left and right top panels in the Figure show the changes in transit use in Bogotá, by fare type. It is clear that the decrease in transit use has been larger for individuals over 62 years old, consistent with the stricter social distancing measures for adults over 60 years old in the city. In the bottom we show splits for SES categories for Lima and São Paulo.

Figure 8. Public transit use change by fare type and SES in Bogotá, Lima and São Paulo



Note: Public transit use based on validation (trips) data from each system. Percentage changes measured against the week of March 2-8.

Figure 8 represents a first approximation to SES heterogeneity impacts. We can see that subsidized fares for Bogotá, low-income BRT stations in Lima[15] and low SES bus lines in São Paulo[16] have a smaller decrease in ridership after the start of the pandemic, and a faster increase

[15] Using data from the population census and ENAHO we estimate he average income within the census track based on its demographic composition. From ENAHO data for Metropolitan Lima for the period 2016-2018 we calculate monthly income cells by gender, industry (3 digit SIC code), occupation (3 digit SOC code), education (uneducated or primary, secondary, and tertiary), age categories (18-25, 26-30, 31-35, 36-40, 40-45, 46-50, 51-55, 56-60, and 61-60 years of age). Using the same demographic variables available in the census data, we project income for everyone living in the census, and then aggregate at the census track level. Finally, using information from the 1,348 census tracks within the radius of all BRT stops we then aggregate monthly income at the stop level and classify them into three categories.

[16] For Sao Paulo public transport SES analysis, our primary source of information is the Brazilian Census Data from 2010 (IBGE, 2010), where we have data at Census Tract (CT) level on the number of people over ten years old by income categories measured in minimum wages (m.w.). Based on this information, we classify each CT by SES. To harmonize the unit of observation among cities, we split the city area into H3 cells. Then, for Sao Paulo, we match the CT with the H3 cells, and, using the same majority rule used for the other analyses, we attribute an SES to each H3 cell. Finally, to classify bus lines by SES, we intersect each bus line itinerary with the H3 cells, identifying the cells the itinerary crosses and their neighbor cells, including all them in the set of H3 cells of the bus line. Having this set of H3 cells, we define the bus line SES classification applying the same majority rule used before.

in ridership two months into the pandemic. This is consistent with the findings for traffic volume in Buenos Aires. Based on the nature of their jobs, those with a lower SES have a harder time following stay-at-home orders and rely on public transit to make it to their workplace.

- **Population changes**

We conduct an analysis of population changes at different times of the day (in 8-hour intervals) as provided by Facebook's movement range maps. Using the classification presented in Figure 1, we show in Figure 9 that there are unequal population movements compared to the pre-crisis period by firm size (top) and firm economic sector (bottom).

Figure 9. Population changes by economic structure in Mexico City

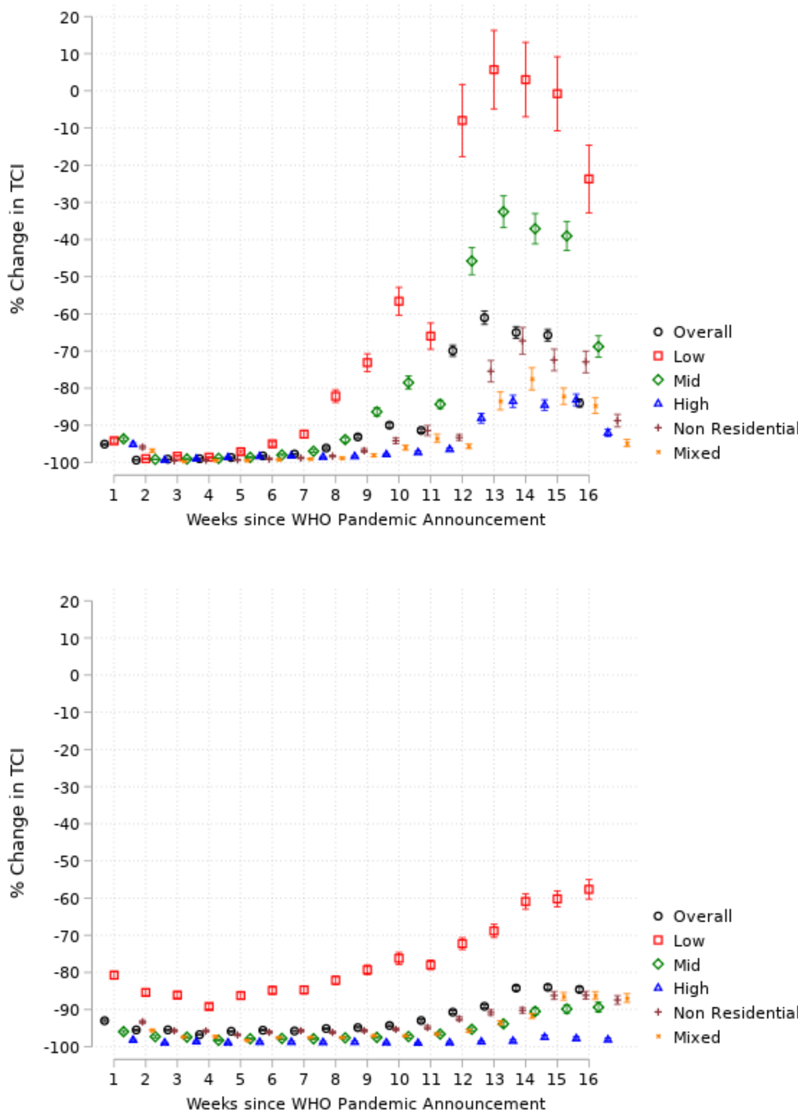
Note: Authors' elaboration based on population changes in Facebook's Movement Range Maps.

4.2. Traffic congestion intensity regression analysis

We estimate equations (3) and (4) for the TCI measure. The coefficients from these regressions are presented in Figure 10 for Bogotá (top) and Lima (bottom). The figure shows clearly that the low SES areas are those that have seen TCI trend toward the pre-crisis values, in particular for

Bogotá. This confirms the analysis in the prior section indicating that low SES individuals are less likely to be able to follow social distancing guidelines.

Figure 10. Traffic congestion intensity estimated changes



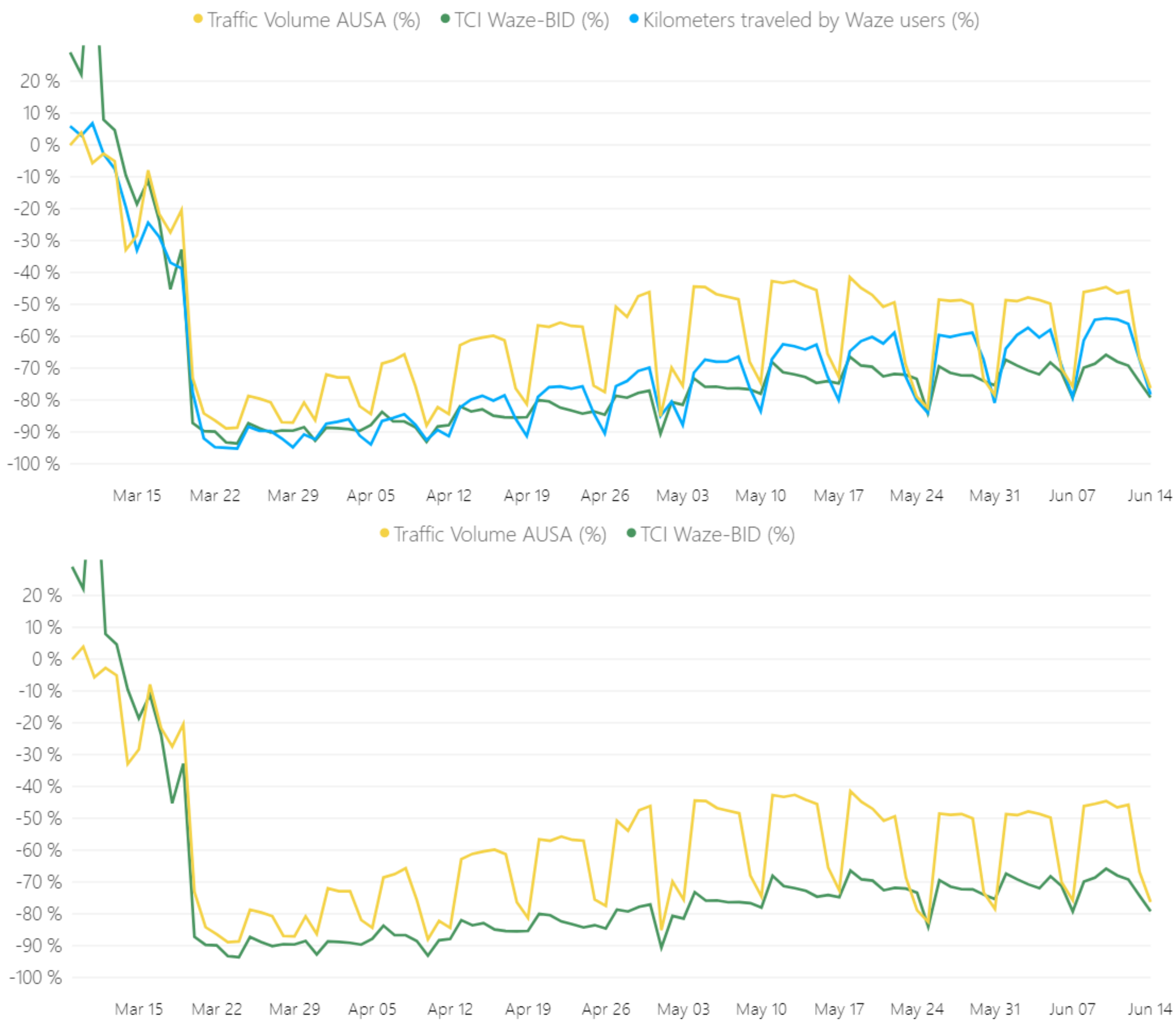
Note: The figures show the coefficients (expressed as percentage changes) from estimating equation (3) (for overall changes) and equation (4) (for changes by SES groups), using the Inverse Hyperbolic Sine (IHS) transformation of TCI as the dependent variable. The vertical lines show 95% confidence intervals.

5. Preliminary conclusion

In this paper we study the impacts of theCOVID-19 pandemic on different mobility measures (traffic volume, traffic congestion, public transit use, and population changes) in several cities in Latin America and the Caribbean (LAC). We document sharp decreases in mobility, even prior to official social distancing measures were put in place, and show that the reductions in mobility, regardless of the measure, are heterogeneous by city, day of the week and time of the day. We also find unequal impacts when using different proxies for socio-economic status. More disadvantaged populations not only reduced their mobility less than better off populations, but also returned to (possibly) work earlier. This could imply higher risks of COVID-19 contagion for the workers, and their families, and is consistent with evidence that COVID-19 deaths are higher for more disadvantaged groups (probably not only caused by differential mobility patterns, but also by worse living conditions, less susceptible of allowing social distancing). We also find differential impacts by firm size and economic sector. This is a preliminary version of the paper, which will be extended to more cities, and refined measures of economic activites.

Appendix

Figure A1. Buenos Aires. Percentage change in TCI v. traffic volume



Note: The figures shows the percentage change in TCI for the Buenos Aires metropolitan area and for the access highways to the City of Buenos Aires. It highlights how the traffic congestion intensity measure captures patterns that are very similar to those of observed traffic volume.

Figure A2. Buenos Aires. Highways areas of influence

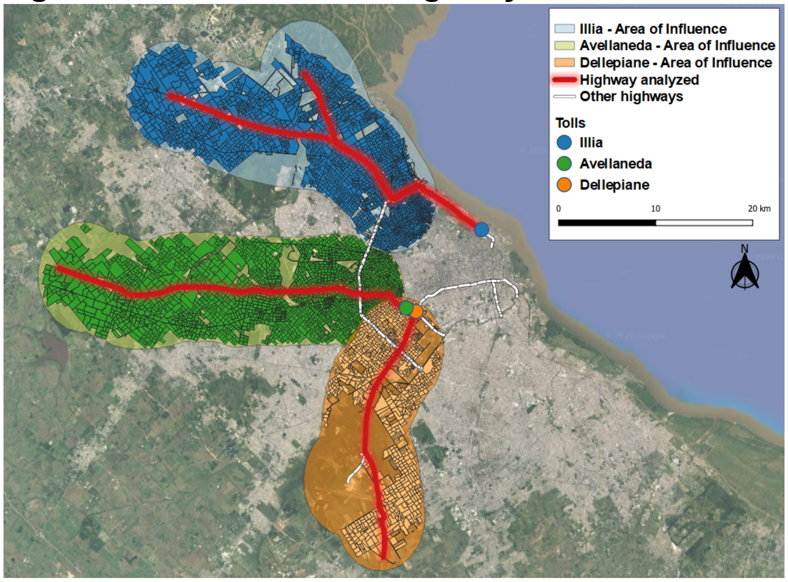
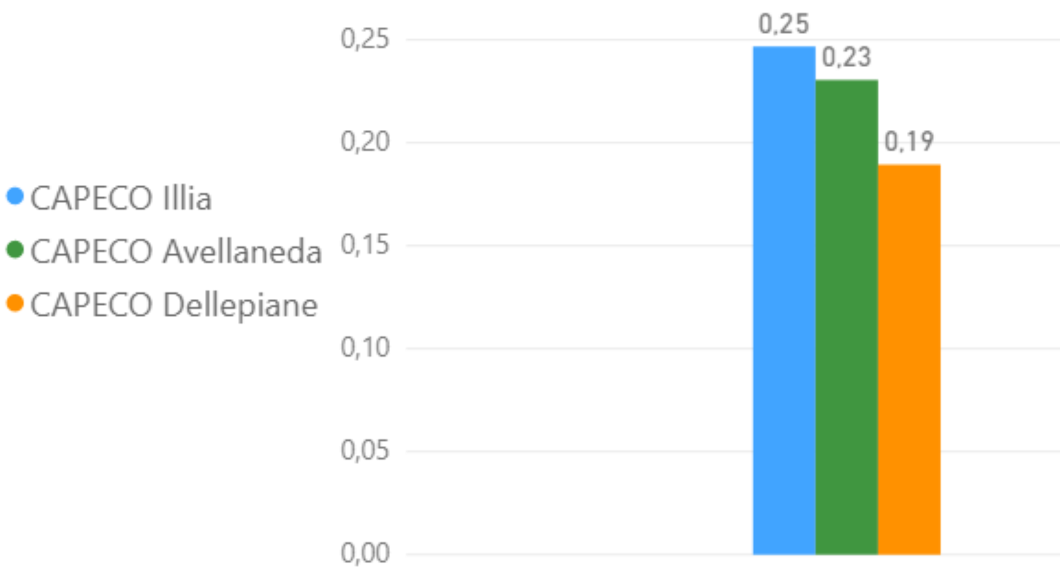


Figure A3. Buenos Aires. CAPECO Index by highways



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