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RESEARCH ARTICLE

Socioeconomic status and mobility during the COVID-19 pandemic: An analysis of 8 large Latin American cities*

J. Daniel Aromí† M. Paula Bonel‡ Julián Cristiá§ Martín Llada¶
Luis Palomino‖

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Abstract

This study analyzes mobility patterns during the COVID-19 pandemic for 8 large Latin American cities. Indicators of mobility by socioeconomic status (SES) are generated by combining geo-referenced mobile phone information with granular census data. Before the pandemic, a strong positive association between SES and mobility is documented. With the arrival of the pandemic, in most cases, a negative association between mobility and SES emerges. This new pattern is explained by a notably stronger reduction in mobility by high SES individuals. A comparison of mobility for SES decile 1 vs decile 10 shows that, on average, the reduction is 75% larger in the case of decile 10. According to estimated lasso models, an indicator of government restrictions provides a parsimonious description of these heterogeneous responses. These estimations point to noticeable similarities in the patterns observed across the cities. We also explore how the median distance traveled changed for individuals that travel at least 1 km (the intensive margin). We find that the reduction in mobility in this indicator was larger for high-SES individuals compared to low-SES individuals in 6 out of 8 cities analyzed. The evidence is consistent with asymmetries in the feasibility of working from home and in the ability to smooth consumption under temporary income shocks.

Keywords: mobility; COVID-19; socioeconomic status.
JEL codes: I1, R2, R4.

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†Corresponding author. Universidad de Buenos Aires, Argentina and Universidad Católica Argentina, Argentina. E-mail: aromi.daniel@gmail.com
‡Universidad de Buenos Aires, Argentina
§Inter-American Development Bank, United States of America.
¶Universidad de Buenos Aires, Argentina.
‖Inter-American Development Bank, United States of America.

1. Introduction

The coronavirus pandemic resulted in dramatic changes in mobility patterns across the world. Aggregate indicators of mobility show abrupt and persistent changes in mobility.[1] These changes have important implications for the evolution of the pandemic (Lau et al., 2020; Flaxman et al., 2020; Dave et al., 2020) economic activity (Coibion et al., 2020; Mongey et al., 2021) and, more broadly, the well-being of different socioeconomic groups. In addition, the changes in mobility patterns are expected to be heterogeneous due to differences in the ability to telework, savings and other socioeconomic factors.

In this study, we carry out a detailed analysis of changes in mobility for eight large Latin American cities. More specifically, we measure changes in mobility as a function of socioeconomic status (SES). This dimension is particularly relevant if we consider that Latin America is one of the most unequal regions of the world.[2] In addition, the changes in mobility patterns can be conjectured to be substantial since, by the end of May, Latin America was already one of the regions that were worst-hit by the pandemic.[3] Importantly, this is the first paper that reports changes in mobility by SES across a range of countries using the same data source and standardized procedures. Hence, the quantitative results in the different countries can be compared and summarized in a direct way.

To implement this analysis, we combine two types of granular data. First, geo-referenced mobile phone data is used to measure mobility and to infer the residence of mobile phone users. Then, census data corresponding to small census geographic units, jointly with previously inferred user residence, is used to classify mobile phone users by SES. Our primary metric of mobility reports, for each census geographic unit, the fraction of cell phone users that traveled at least one kilometer in a day. The sample period for this data starts on March 1 and ends on June 14. The eight cities covered in this study include: Bogotá (Colombia), Buenos Aires (Argentina), Guadalajara (Mexico), Guayaquil (Ecuador), México DF (Mexico), Rio de Janeiro (Brazil), Sao Paulo (Brazil) and Santiago de Chile (Chile). Our analysis covers 7 of the 10 largest cities in Latin America.

The results provide a coherent picture of the evolution of mobility patterns around the pandemic. First, before the pandemic, there was a strong positive association between SES and mobility in all cities covered by the study. During this period, the fraction of people that traveled at least one kilometer in a day was 15 percentage points higher for SES decile 10 than for decile 1. Second, during the pandemic, this association was reversed. In this period, the fraction of people that traveled at least one kilometer in a day was 4 percentage points higher for decile 1 than for decile 10. Third, this changing pattern is explained by a notably more intense response of mobility by high SES individuals. For SES decile 1, on average, the fraction of mobile phone users that traveled at least one kilometer in a day fell by 25 percentage points. The drop is markedly stronger in the case of SES decile 10. In this case, the fraction of people that traveled at least one kilometer in a day fell 44 percentage points. As a result, the average reduction in mobility is 75% larger for decile 10. It is important to note that, with some differences in intensity, this heterogeneous response is a feature observed in all cities covered by this study.

To complement the previous results, formal models are used to describe the heterogeneous changes in mobility observed in each city. We estimated lasso models to select, in each city, the indicators that best describe the heterogeneous response in mobility. These estimations consistently select the indicator of government restrictions. In addition, the estimations point to patterns that are also quantitatively similar.

[1] See for example `https://www.google.com/covid19/mobility/`

[2] See for example Alvaredo and Gasparini (2015) and United Nations Department of Economic and Social Affairs (2019)

[3] See PAHO (2020).

In an extension, a similar analysis is carried out for the intensive margin of mobility, that is, the distance traveled by users that move at least one kilometer. In this case, on average, the reduction in this alternative mobility metric is 3 kilometers larger for decile 10 than for decile 1. It is worth noting that in the case of this metric, in the case of Rio de Janeiro and Sao Paolo the negative association between mobility and SES is not observed.

In this way, this study is able to identify empirical regularities or "stylized facts" of the response of mobility to the public health crisis. This pattern can be understood as a prevalent and persistent feature. Hence, beyond the eight cities covered in this study, this type of heterogeneous response is, with high likelihood, an appropriate depiction for other regions with similar socioeconomic characteristics. Also, as long as the identified pattern is a consequence of stable socioeconomic characteristics, this type of heterogeneous response is likely to characterize subsequent stages of the COVID-19 epidemic or future instances of similar crises.

Our analysis focuses on SES since this is one key dimension along which mobility might differ in a substantive manner. First, the opportunity cost of staying at home is a function of whether job-related tasks can be performed remotely (Dingel and Neiman, 2020; Atchison et al., 2021; Mongey et al., 2021; Chiou and Tucker, 2020; Berg et al., 2020; Albrieu, 2020; Gottlieb et al., 2020). As long as work-at-home is more likely adopted in the case of high SES workers, mobility is expected to be linked to socioeconomic status. In addition, liquidity constraints constitute another important factor (Attanasio et al., 2000; Cavallo et al., 2016). Households that are unable to smooth consumption during a temporary shock to income will find that a reduction in mobility is an excessively costly option. Finally, differences in household composition, housing unit characteristics and neighborhood population density can cause differences in mobility. It is worth noting that heterogeneous responses are particularly likely in the case of emerging economies that display significant disparities in work and living conditions.

The current paper is related to studies that have analyzed policy responses and socioeconomic impacts during the COVID-19 pandemic in emerging countries. For example, Benítez et al. (2020) describe how socioeconomic conditions effectiveness of policy responses. Busso et al. (2021) analyze the social protection policies and Alicea-Planas et al. (2021) use self-reported indicators to provide evidence on the determinants of social distancing practices. Campos-Vazquez and Esquivel (2021) use point of sales data to study the impact of the pandemic on consumption levels in Mexico.

More specifically, our work is related to other studies that have analyzed heterogeneous changes in mobility patterns during the COVID-19 pandemic. Most of these studies analyze advanced economies. For example, Ruiz-Euler et al. (2020) show that, in the US, high SES groups reduced mobility faster. Also, for the case of the US and consistent with the previous study, Wright et al. (2020) report a negative association between SES economic status and mobility for US counties. Coven and Gupta (2020) show a similar pattern in New York City. In contrast, Dahlberg et al. (2020) conclude that in the case of Sweden, similar reductions are observed for users in different socioeconomic groups. Studies analyzing mobility in Israel and France find a positive, but modest, association between socioeconomic status and reduction in mobility (Yechezkel et al., 2020; Pullano et al., 2020).

There exists some contributions that analyze the heterogeneous response in mobility in emergent economies. For the case of Santiago de Chile, Gozzi et al. (2021) and Carranza et al. (2020) report a pattern of heterogeneous response in mobility across the socioeconomic dimension. Brotherhood et al. (2022) study Sao Paulo and Rio de Janeiro in Brazil. The authors find that social distancing, as inferred from mobility data, is positively associated with socioeconomic status. The analysis is generated dividing each city into two parts according to geographic data that identifies slums. Compared to this analysis, our work is able to provide a more comprehensive and, at the same time, more fine-grained evidence on the relationship between socioeconomic status and mobility. Dueñas et al. (2021) study mobility patterns using public transportation data for Bogotá, Colombia. In their study, the authors report that, with the emergence of the crisis, the reduction in mobility becomes more intense as SES increases. Testa et al. (2021) use data from Google Mobility Reports to analyze, at a city level, the determinant of changes in mobility patterns from the cases of the US, Mexico and Brazil.

Our study contributes to this literature on the heterogeneous impact of the pandemic with a focus on emerging economies. It does so by providing a detailed, comprehensive and comparable analysis. In this way, we are able to identify empirical regularities that can be conjectured to constitute persistent features that characterize not only the eight cities that we analyze but also other regions with similar socioeconomic attributes.

The next section presents the data and methodology. The main results are presented in section 3. Results associated with the intensive margin of mobility are presented in section 4 and the following section reports some robustness exercises. The last section concludes.

2. Data and methodology

2.1. Mobile phone data and indices of mobility

We constructed mobility indicators based on geo-referenced mobile phone data provided by the company Veraset. This company collects anonymized location data from millions of mobile phones in all countries in Latin America (and other regions). The data is provided by applications installed on those smartphones. Using this data, we created two mobility indicators.

Our primary indicator is the extensive margin index. It represents the percentage of people that traveled at least one kilometer on a day. This metric is proposed as a way to identify the fraction of people that stay at home. The choice of the threshold allows for a certain low level of mobility that could take place inside the home. A similar strategy can be found in Zhang et al. (2020). It must be noted that each urban area is characterized by a particular spatial structure. This information could be incorporated in the design of indices that are adapted to the features of each neighborhood. This type of extension of beyond the scope of the current work.

Additionally, we computed an indicator of the intensive margin of mobility that is equal to the median distance in kilometers traveled by those users that traveled more than one kilometer. Both indicators are calculated for each census unit and day from March 1 to June 14.

Raw data consists of a database where one observation is a “ping”. A ping is a measurement of the latitude and longitude of a cell phone at a given time. The first step to calculate our daily mobility measures is to define the criteria to determine which mobile phone users will be included each day in our database. We select mobile phones that provide location data on a regular basis for the entire sample period. More specifically, we constructed the database selecting mobile phones (i.e. users) that have at least 4 pings at night (between 6 pm and 10 am) during the period analyzed in at least 30 nights during the whole sample period. In addition, to make sure that data in a specific day is informative of the real distance traveled by the user, each day, we consider the distance traveled by those users that are included in the users database and also meet the requirement of having at least 10 pings during that day. Having established these filters, to estimate the distance traveled by a person during a day, we add the distance between consecutive observations, pings, corresponding to that day.

Mobile phone data is also used to assign users to census units. For this task, as a first step, we identify the home coordinates for each user based on the most frequent location during the night. Then, we use “shapefiles” that provide census geographical information. More specifically, these files indicate the perimeter of each census unit. We link home coordinates to the census unit to which the coordinate belongs. In the final step, indicators of daily mobility for each census unit are computed aggregating the information generated in the previous stages.

Socioeconomic status of each census unit is approximated using educational attainment data. More specifically, the indicator we use is given by the fraction of people over 25 years old that completed secondary education level (high school). This is a widely available indicator that will facilitate comparisons across different countries. Also, it is worth noting that in the analysis below, we work with SES percentiles or deciles, as a result, the indicators are only used to rank different census units.

The SES data is from the respective national population census. The index is slightly different in Mexico DF, Guadalajara and Bogotá. The SES indicators for Mexican cities are calculated for the population that is at least 18 years old. On the other hand, Bogota’s index is calculated as the fraction of people over 25 years that completed secondary education level over the total population. These differences are due to restrictions in data availability. Also, the availability of public “shapefiles” and census data resulted in variability in the granularity of the analysis implemented in each city. More details regarding census data are provided in Table A1 in Annex A.1.

Table 1 reports descriptive statistics. In each case under analysis, the data corresponds to the entire metropolitan area. For simplicity, we will refer to these areas as cities throughout the document. As shown by the population figures, our study covers large cities. The varying size of census geographical units can be inferred by comparing the population figures to the number of units. There are also differences in the number of mobile phones as a fraction of the population.

2.2. Additional Data

We complement the main data already described with the following sources:

- **Stringency index:** The Oxford COVID-19 Government Response Tracker (OxCGRT) is an initiative supported by Oxford University that collects publicly available information on 17 indicators of government responses to COVID-19. We use the Policy Stringency Index that sums up information on those 17 indicators related to containment and closure policies, economic policies and record health system policies. The data is aggregated into a common index reporting a number between 1 and 100. A value of 100 indicates the imposition of a set of very severe measures such as school closings, workplace closings, the prohibition of internal movement and stay-at-home requirements. In the analysis below, we rescale this index dividing it by 100.
- **Infections and deaths:** We understand that mobility decisions are not only related to government measures but also can be related to current sanitary conditions. We select two straightforward

Table 1: *Descriptive statistics*

City	Population	Census units	Mobile phones	SES Index Decile 1	SES Index Decile 10
	(1)	(2)	(3)	(4)	(5)
Bogotá	7.4	3,683	22,552	0.37	0.89
Buenos Aires	14.8	12,598	87,696	0.18	0.86
Guadalajara	4.4	1,610	21,586	0.13	0.86
Guayaquil	3.0	4,886	5,316	0.20	0.88
Mexico DF	20.1	4,636	119,313	0.21	0.83
Rio de Janeiro	11.8	336	100,970	0.24	0.83
Santiago de Chile	7.1	2,423	24,656	0.56	0.95
Sao Paulo	19.7	633	256,728	0.25	0.78

Notes: Column (1) reports population (in millions) according to census data (see Table A1 in Annex for more details). Column (2) indicates the number of census units used in this study. Column (3) is the daily average number of mobile phones included in the data provided by the company Veraset. Columns (4) and (5) indicate, for deciles 1 and 10 respectively, the value of the SES indicator described in Section 2.1.

indicators on this matter: daily confirmed cases and daily deaths. We include this information both at the national level and at the city level. Data was collected from official sources (See Annex A for further details). To implement the analyses, these indicators are expressed as cases/deaths per million population. Also, we apply a logarithmic transformation.[4]

2.3. Empirical models

We use empirical models to measure and summarize heterogeneity in the response of mobility. These models are estimated for each city. The first type of model specification is given by a standard panel fixed effects model where the dependent variable is the mobility indicator and the independent variable is the interaction between SES and a variable that captures the evolution of the COVID-19 crisis. In this way, the heterogeneous response of mobility to the crisis is summarized by the coefficient of the interaction term. We consider six different specifications for the variable that captures the evolution of the crisis: Stringency Index, time trend, daily confirmed cases and daily deaths (the last two indicators both at national and city level). Given the high correlation between the indicators, these univariate models provide valuable insights that are later complemented with the analysis of more complex models.

The second type of model we consider involves lasso regressions in which multiple interactive terms are allowed for as explanatory variables. Highly correlated explanatory variables discourage the implementation of a naive multivariate model that is likely to overfit. Therefore, we implement lasso regressions that result in parsimonious representations of the association between mobility patterns and the different features that characterize the evolution of the health crisis. Further details on model specifications and estimation strategies are described in the sections below.

[4] Formally, let x_t represent the number of deaths or cases, then the indicator used in our analysis is $log(1 + x_t/Population * 10^6)$.

3. Results

In this section, we report the findings of the analysis of changes in mobility along the extensive margin. That is, here we focus on the fraction of mobile phone users that traveled at least one kilometer in that day, our primary indicator of mobility. With some flexibility, it can be interpreted as a proxy of the fraction of the population that practices social distancing by staying at home.

The exercises presented in this section are divided into two parts. In the first part, we study the evolution of the indicators of mobility by SES deciles. This analysis provides an informative description of the heterogeneous responses in mobility. In the second part, formal empirical models are estimated to analyze mobility indicators jointly with indicators of government policies and health outcomes. These models provide additional insights that allow for a more concise and comparable description of the heterogeneous responses of mobility.

3.1. Mobility by socioeconomic decile

For each city covered in the study, we compute daily indicators of mobility by SES decile. In the first analysis below, mobility indicators are summarized for two sample periods: "Pre-pandemic" (between March 5 and 11, the week prior to the announcement of the pandemic by the WHO) and the "Pandemic" period (between April 1 and June 14).

Table A2 reports the mean value of mobility indicators before and during the pandemic period for SES deciles 1 and 10. Our analysis documents three "stylized facts". First, before the pandemic, there was a strong positive association between SES and mobility in all cities covered by the study. On average, the fraction of people that traveled at least one kilometer in a day was 15 percentage points higher for SES decile 10 than for decile 1. It is worth noting that there are differences in the intensity of this positive association. In the case of Mexico DF and Guadalajara, the difference in the indicator of mobility by SES is between 23 and 25 percentage points. These are the largest differences for the sampled cities. In contrast, the smallest difference is 7 percentage points and corresponds to the case of Guayaquil.

Second, during the pandemic, the association between SES and mobility was reversed. On average, during this period, the fraction of people that traveled at least one kilometer in a day was 4 percentage points higher for decile 1 than for decile 10. For a notable example, in the case of Rio de Janeiro, during the pandemic period, the indicator of mobility was 13 percentage points higher for SES decile 1 than for decile 10. The two Mexican cities are the only two exceptions. As previously indicated, in those cases, before the pandemic, there was a very strong positive association between mobility and SES. While the sign of the association during this pandemic did not change, a very noticeable reduction in the strength of this association is observed in these two cities.

Finally, when we combine the information corresponding to both periods, a robust pattern emerges. In all cities under study, the response in mobility is noticeably more intense in the case of high SES individuals. For SES decile 1, on average, the fraction of mobile phone users that traveled at least one kilometer fell from 69 to 44 percent compared to a reduction from 84 to 40 percent for the decile 10. As a result, the average reduction in mobility was 75% larger for decile 10. Remarkably, for three cities, Guadalajara, Mexico DF and Rio de Janeiro, the reduction in mobility for decile 10 is more than two times the reduction observed in the case of decile 1.

To gain additional insights, a more detailed description of mobility patterns is provided in figure 1. The indicators of mobility displayed strong downward trends starting in mid-March. By the end of March, a new regime of low mobility was reached. The reduction in mobility was more intense for Guayaquil and Buenos Aires. This large reduction is explained by the strict lockdowns imposed in the respective countries (Aromi et al., 2020).

Under the new regime, the difference in mobility by SES decile changes in a noticeable manner. In this more detailed description, we can distinguish changes in mobility patterns that took place after April 1, that is, well after the WHO declared the pandemic. For example, in the case of Guayaquil, the heterogeneity in the response becomes less visible after April, that is, after the period in which the sanitary crises was particularly severe in that city.[5] Starting in May, as the most severe stage of the crises was left behind, the upper decile are seen to increase their mobility at a rate that was faster than what is observed in the case of lower SES deciles. In contrast, in the cases of Rio de Janeiro and Santiago de Chile, where the worst stages of the crisis arrived later, the heterogeneity in the response is particularly noticeable starting in May. In the models estimated in the following section, we analyze the links between mobility patterns and indicators of the evolution of the pandemic.

According to the evidence reported above, higher socioeconomic status is consistently associated with more intense reductions in mobility. This evidence is consistent with important differences in the opportunity cost of staying at home. More specifically, this difference can be explained by differences in the ability to adopt work-from-home practices and differences in the ability to smooth temporary shocks in current income.

3.2. Empirical models

To complement the analysis of the previous section, we document associations between mobility measures and indicators of the evolution of the pandemic. In particular, we estimate models that provide parsimonious descriptions of the heterogeneous responses in mobility.

In these models, the response of mobility to indicators of the evolution of the pandemic is allowed to differ as a function of SES percentiles. First, we report results from univariate regressions. Next, we report multivariate models estimated using lasso regressions.

3.2.1 Univariate Panel Models

Let Mov_{ut} stand for the weekly indicator of the extensive margin of mobility for census unit u in week t and let $Percentile_u$ be the socioeconomic percentile of the census geographical unit u. Also, let $Shock_t$ represent a variable that captures the evolution of the pandemic at a weekly frequency. Then, the univariate panel model is given by:

$$Mov_{ut} = \alpha + \mu_u + \mu_t + \beta[Shock_t * Percentile_u] + \epsilon_{ut} \tag{1}$$

[5](Dube and Jd, 2020) provide a brief description of the evolution of the epidemic in Guayaquil.

Where μ_u and μ_t are census unit and week fixed effects, respectively and ϵ_{ut} is the error term. The parameter of interest is the coefficient of the interactive term: β. A negative value for this parameter indicates a stronger reduction in mobility as SES increases.

We consider six specifications for the indicator of the evolution of the pandemic: the Stringency Index, Time Trend, Regional Cases, Regional Deaths, National Cases and National Deaths. "Time Trend" counts the number of weeks since the declaration of the COVID-19 pandemic by the WHO. It is proposed considering that, as the costs associated with social distancing accumulate, there might exist a heterogeneous trend in mobility patterns. The other indicators of the evolution of the pandemic were described in the data section. In all cases, an increment in the indicator can be interpreted as an increment in the severity of the crisis triggered by the COVID-19 pandemic.

The estimated models provide a consistent picture of the heterogeneous response of mobility to the evolution of the pandemic. Independently of the indicator under consideration, the estimated coefficients are in all cases negative, that is, higher socioeconomic status is associated with a more intense drop in mobility as the crisis turns more severe. Tables A3 and A4 summarize the estimations for the alternative models.

In addition to the coincident sign, the estimated coefficients point to quantitative similarities in the association observed across the eight sampled cities. This is particularly noticeable in the case of the Stringency Index. In the case of five cities, the estimated coefficient for the interaction term is approximately -0.003. The estimated value is between -0.002, for the cases of Mexico City and Guadalajara, and -0.004, for the case of Rio de Janeiro. These values provide a concise description that summarizes the main features of the heterogeneous responses of mobility to the pandemic.

To facilitate the interpretation of the estimated models, we consider the case of Buenos Aires and the stringency index. In this city, the mean stringency index during the Pre-pandemic period was 0.16, while its average value increased to 0.93 during the pandemic period, that is, the difference in mean values between these periods is 0.77. Also, the estimated coefficient for the interaction term is -0.003. As a result, when the response in mobility of percentile 5 versus percentile 95 is compared, the estimated difference in the response is 21 percentage points (-0.003 x 0.77 x [95-5]). This estimated heterogeneous response coincides with what was reported in the previous section. In other words, simple models emerge as convenient tools to summarize the change patterns in mobility.

Similar conclusions are observed when we consider the models that incorporate a time trend in the interaction term. As in the previous case, the estimated coefficients are negative and statistically significant. Also, the estimated coefficients are quite similar across the cities.

In the case of specifications that incorporate indicators of health outcomes, the estimated coefficients for different cities are not as similar to each other as in the previously analyzed specifications. To an important extent, these differences reflect the very distinct health outcomes that were observed in the different regions during the sample period. At the same time, this difference across cities could reflect the absence of a solid relationship between mobility patterns and the evolution of health outcomes.

Summarizing, the estimated association is robust to changes in the model specification. On the other hand, it must be noted that additional insights can result from a joint evaluation of the diverse set of indicators. We turn to this task in the following subsection.

3.2.2 Lasso regressions

In the previous section, we considered a series of univariate panel data models that incorporate only one indicator of the evolution of the pandemic at a time. These exercises indicate a robust pattern between SES and changes in mobility. The joint analysis of these indicators can be presumed to result in a more informative account of heterogeneous responses in mobility. Nevertheless, it must be noted that the six indicators used in these exercises are highly correlated. As a consequence, a naive estimation of a multivariate model could result in a noisy representation of the association between mobility patterns and the different features that characterize the evolution of the health crisis.

Motivated by this concern, we evaluate this multivariate association using lasso regressions. Under penalized or regularized regression methods, the loss function has two terms. The first term is the traditional sum of squared errors. The second term is a penalty term that increases with model complexity. Under this methodology, the analyst needs to specify the weight for this second term. In this study, we implement a theory-driven penalization methodology that controls for overfitting and produces parsimonious estimated models regularized by theory-driven penalization parameters (Belloni et al., 2012, 2016). The estimation was implemented using Stata package “lassopack” described in Ahrens et al. (2020) [6]

We estimate multivariate models with census units and week fixed effects and six interaction terms, one for each indicator of the evolution of the pandemic. Following the notation and structure used in the univariate case, the model is given by:

$$Mov_{ut} = \alpha + \mu_u + \mu_t + \sum_{i=1}^{I} \beta_i [Shock_{iut} * Percentile_u] + \epsilon_{ut} \tag{2}$$

Where i is used to index the six indicators used in the univariate analysis above. Table A5 shows the estimated models for each city. It must be noted that, as is common practice when implementing lasso regression methods, the independent variables were standardized. [7]

Results from the lasso regressions suggest that the indicator of government restrictions constitutes a convenient tool to describe, in a parsimonious manner, these heterogeneous responses. The estimated coefficients corresponding to this indicator are negative. Furthermore, in only three cities, the estimated model incorporates an additional variable. However, in each of those cases, the estimated coefficient for those additional variables is small compared to the coefficient corresponding to the Stringency Index. These estimations indicate that the Stringency Index emerges as the most informative variable when it comes to describing heterogeneity in mobility responses. Additionally, the value of the estimated coefficients of these estimations highlight the similarities in the documented patterns across the eight cities of the analysis.

[6] In the estimation, we used command ”rlasso” and set the options so that loss function did not penalize the coefficients associated to fixed effects.

[7] Each regressor was standardized subtracting its sample mean and dividing the difference by its sample standard deviation.

The selection of the Stringency Index in the lasso regression exercises can be rationalized by analyzing the trajectory of this index and mobility for two representative cities. Figure 2 shows these trajectories for Buenos Aires and Rio de Janeiro. In both cases, the changes in mobility patterns that take place in the second half of March coincide with sharp increments in the Stringency index. This factor emerges as the main reason why the Stringency index is selected in the multivariate models of mobility patterns. Later, during the pandemic period, the link between changes in mobility patterns and the index of government policies is not so clear. While in the case of Rio de Janeiro, a tightening of government policies during late April and early May are seen to coincide with increments in the mobility gap between low and high SES deciles, in the case of Buenos Aires, during the same period, a similar change in mobility patterns coincided with a relaxation of government restrictions.[8]

4. Extended analysis: the intensive margin

Our main analysis focuses on the extensive margin of mobility. That is, we focus on the fraction of people that move at least one kilometer in a day or, following the interpretation we informally suggested, the fraction of people that leave their home. There is a second metric, related to the intensity of mobility, that can be derived from the primary indicator. In this section, we analyze the evidence related to this indicator: the median distance in kilometers traveled by users that traveled at least one kilometer. While assessing the evidence presented below, it is worth keeping in mind that this metric is a secondary indicator that is affected by the variation in the fraction of users with low levels of mobility. In other words, it can be interpreted as the evidence on the residual variation once we take into account the main factor associated with the extensive margin.

4.1. Mobility by socioeconomic decile

Table A6 shows indicators of the intensive margin of mobility by socioeconomic decile. As in the case of the indicator of the extensive margin of mobility, for all cities under analysis, the COVID-19 pandemic is associated with important reductions in median distance traveled.

With respect to heterogeneous responses in mobility, in the case of this secondary metric, the findings can be summarized through three observations. First, there are 5 cities in which there was a negative SES-mobility gradient in the pre-pandemic period. As before, we see that the cities that display a different pattern are the Mexican cities but now Guayaquil is also in that group. Second, for all cities, there is a negative SES-mobility gradient in the pandemic period. Third, for five cities, the reduction in percentage points was larger for high versus low SES deciles.

Out of the five cities in which the response is more intense for decile 10, the largest differences are observed in Mexico City (9 percentage points) and Guadalajara (6 percentage points). In contrast, in the case of Buenos Aires, no noticeable difference in the intensive margin of mobility is found. While the difference is small, in the case of Rio de Janeiro and Sao Paulo, the reduction is larger for decile 1. In other words, in contrast to the analysis of the extensive margin of mobility, in the case of the intensive margin, the differences in the response are not as consistent across the cities.

[8]The regressions presented in Table A5 were repeated for the sample period that starts in April 1 and end in June 14. The results suggest that neither variables used as indicator of the evolution of the pandemic has information useful that explain the evolution of the indicators of mobility

4.2. Empirical models

4.2.1 Univariate models

We follow the same methodology used in the analysis of the extensive margin of mobility to measure the heterogeneous response of intensity of mobility. We estimate univariate panel data models in which mobility is a function of an indicator of the evolution of the health crisis interacted with the SES indicator. More specifically, the indicator of the intensive margin of mobility of geographic unit u in week t (Mov_{ut}) is a function of the product of $Shock_t$ and $Percentile_u$. The variable $Shock_t$ is one of the six indicators of the evolution of the public health crisis: Stringency Index, Time trend, Regional Cases, Regional Deaths, National Cases or National Deaths.

Table A7 reports the estimated coefficients for the different cities and alternative specifications of the model. In the case of the Stringency Index, we find a negative and statistically significant coefficient in five cities. That is, in those cases, the reduction in mobility becomes more intense as SES increases. In contrast, in one case (Sao Paulo), a positive and statistically significant association is found. In other words, in the case of the intensive margin of mobility, when different cities are compared, the observed patterns are not as consistent as observed in the case of the extensive margin of mobility. This variation is corroborated when other indicators of the evolution of the health crisis are considered.

4.2.2 Lasso regressions

As in the previous section, we implement lasso regressions to estimate multivariate models that incorporate six indicators of the evolution of the health crisis. As in the case of the analysis of the extensive margin of mobility, the selected models include a small set of interaction terms. In five cases, the selected models include the Stringency Index with a negative estimated coefficient. In the case of Guayaquil no interaction term is included in the selected specification. In the cases of Rio de Janeiro and Sao Paulo, a small but positive association is estimated for an interaction term associated with deaths.

These estimations provide further support to previous findings established for the case of the primary indicator of mobility. First, the Stringency Index emerges as a valuable indicator that allows for a parsimonious description of changes in mobility patterns. Second, this index points to negative associations between mobility and SES during the health crisis. On the other hand, it must be noted that the evidence for this secondary indicator is not as one-sided as the evidence reported for the primary indicator of mobility.

5. Robustness

The main findings presented above were generated using rich data provided by the firm Veraset and using a specific methodology. In this section, we explore the robustness of these findings to using alternative data sources and methodologies.

First, one important issue is the data source we used to construct the mobility metrics. To which extent would the conclusion still hold under alternative data sources? One prominent alternative source of mobility data is Google´s COVID-19 Community Mobility Reports. This data source has been used widely to document changes in mobility at the national level. Unfortunately, for Latin America, this data source only provides mobility statistics at the national, province/state, and city level. Consequently, this data source cannot be used for the analysis carried out in this paper which required mobility statistics at census-track level. Still, we can check the correlation between the mobility indicator constructed using the data from the firm Veraset and indicators included in Google´s COVID-19 Community Mobility Reports. Performing such analysis we found a very strong association between the index used in the current study and the six different indices reported by Google (see table A9).

Another aspect that needs to be considered is the methodology used to construct the indicators of mobility. In particular, the indicators were constructed restricting the sample to mobile phone users that we classified as "active users." To which extent are the mobility metrics sensitive to selecting active users as opposed to using all users? To examine this issue, we computed the series for the indicator of the extensive margin of mobility without restricting the sample to active users. The correlation between the baseline index and the index under the alternative specification is very high for the eight urban areas suggesting that results are robustness to this methodological decision (see table A9). Additionally, we estimated the model in which the Stringency Index is the shock variable using the index of mobility without applying any filter. The estimated coefficient for the interaction term is very close to the estimated value under the baseline methodology (see table A10).

In the baseline exercises SES was approximated using an indicator constructed using data on educational attainment. This choice was based on availability and comparability reasons. Nevertheless, a reasonable concern deals with potential variation in the results under alternative socioeconomic indicators. Taking advantage of the existence of an index of multidimensional poverty at the census unit level, we explore this methodological decision for the case of Bogotá. First, we classified census units using an index of multidimensional poverty. We then, generated percentile values for each census unit and compare these values with those from the baseline educational-based SES metric. We found that the correlation between these two SES measures is 0.87 suggesting that the main findings are robust to the choice of the SES indicator. In addition, the percentiles associated with the alternative socioeconomic indicator were used to estimate a model in which the Stringency Index is the shock variable that is interacted with the SES percentile. The estimation indicates an association that that is similar but slightly weaker than the association estimated in the baseline exercise. The estimated coefficient in this alternative exercise is -0.0026.

Finally, we analyze whether the modelling assumption that there is a linear relationship between the interaction term and the mobility metric. This choice is motivated by parsimony but might miss important nonlinear features. To address this concern, a nonlinear model was fitted for the case of Bogotá. In this model, for each SES decile, we estimate a different coefficient that captures the relationship between the shock variable (Stringency Index) and mobility. Figure 4 presents the estimated coefficients under this model. Results indicate that there is a monotonic and approximately linear relationship between the shock variable and mobility suggesting that the parsimonious baseline model is a satisfactory approximation.

Taken together, the exercises described in this section indicate that the main findings reported in the paper are robust to changes in data sources, the definition of the variables and model specification.

6. Conclusion

In this study, we estimated the link between SES and the response of mobility to the COVID-19 pandemic. The analysis suggests that there is a common pattern in the eight cities in Latin America under study. In all cases, higher SES is associated with a more intense reduction in mobility. A comparison of mobility between the SES decile 1 and decile 10 shows that, on average, the reduction is 75% larger in the case of decile 10. According to estimated lasso models, an indicator of government restrictions provides a parsimonious description of these heterogeneous responses. The analysis of the intensive margin of mobility provides leads to similar conclusions.

The detailed evidence we report can be used as an input in analyses of the health outcomes during the COVID-19 pandemic. Also, the regularities reported in this study allow for a better characterization of the economic impact and a more precise representation of the distribution of the welfare costs associated with the COVID-19 pandemic.

These estimations point to noticeable similarities in the patterns observed across the cities. This evidence is consistent with common underlying socioeconomic factors. Two plausible factors are given by substantial asymmetries in the feasibility of work-from-home and uneven ability to smooth consumption under temporary income shocks.

This study characterized mobility patterns considering two aspects of mobility: the extensive margin and intensive margin. One interesting path for future research involves an analysis of mobility in terms of activities such as work, shopping and leisure. Another related aspect that was not considered in the current study is the use of mass transport and changes in residence. These extensions can result in further insights regarding the heterogeneous response of mobility during the COVID-19 pandemic.

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A. Appendix

A.1. Census Data

Table A1: *Census data description and sources*

City	Census Data Census unit level	Census year	Source
Bogotá	Secci´on urbana	2018	DANE
Buenos Aires	Radio Censal	2010	INDEC
Guadalajara	AGEB	2010	INEGI
Guayaquil	Sector	2010	INEC
Mexico DF	AGEB	2010	INEGI
Rio de Janeiro	Area de ponderaçãó	2010	IBGE
Santiago de Chile	Zona censal	2017	INE
Sao Paulo	Area de ponderaçãó	2010	IBGE

A.2. Sanitary Conditions Data

- **Bogotá:**
  National level & city level: Colombia National Health Institute Dashboard.
  https://www.ins.gov.co/Noticias/Paginas/Coronavirus.aspx.

- **Buenos Aires:**
  National level & city level: Ministry of Health of the Nation.
  http://datos.salud.gob.ar/dataset/covid-19-casos-registrados-en-la-republicaargentina.

- **Guadalajara:**
  National level & city level: Secretary of Health
  https://coronavirus.gob.mx/datos/

- **Guayaquil:**
  National level & city level: Ministry of Public Health
  https://www.gestionderiesgos.gob.ec/informes-de-situacion-covid-19-desdeel-13-de-marzo-del-2020/

- **Mexico DF:**
  National level & city level: Secretary of Health
  https://coronavirus.gob.mx/datos/

- **Rio de Janeiro:**
  National level: Oxford University Coronavirus Government Response Tracker
  https://www.bsg.ox.ac.uk/research/research-projects/coronavirus-governmentresponse-tracker
  City level: Rio de Janeiro State COVID-19 Dashboard
  http://painel.saude.rj.gov.br/monitoramento/covid19.html

- **Sao Paulo:**
  National level: Oxford University Coronavirus Government Response Tracker
  https://www.bsg.ox.ac.uk/research/research-projects/coronavirus-governmentresponse-tracker
  City level: São Paulo State Department of Health Dashboard
  https://www.seade.gov.br/coronavirus/

- **Santiago de Chile:** National level city level: Chilean Government COVID-19 Dashboard
  https://www.gob.cl/coronavirus/

A.3. Tables and Figures

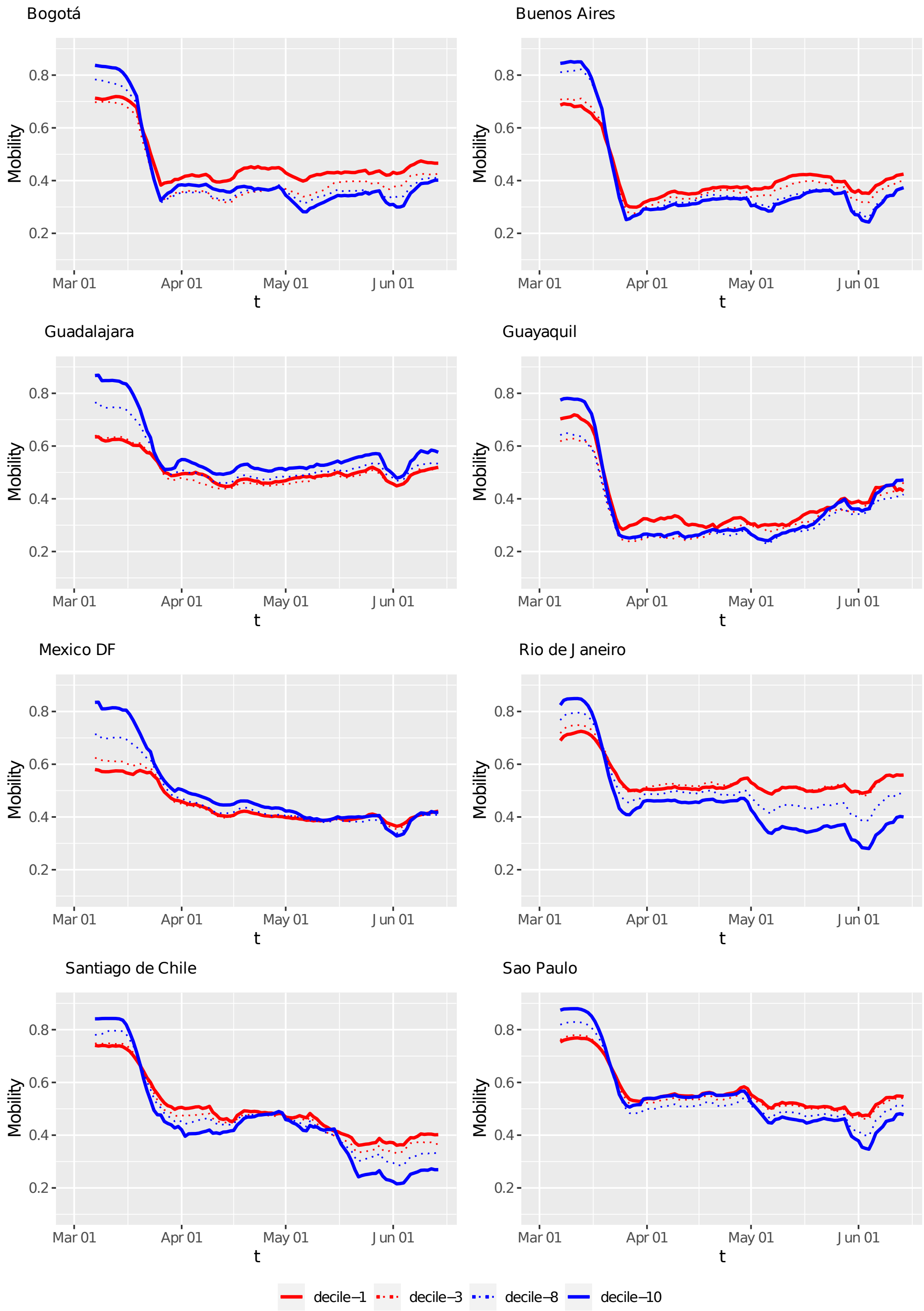


Figure 1: *Share of individuals traveling more than 1 km in a day by SES*

Note: weekly averages for days $t - 6$ through t.

Table A2: *Fraction of individuals traveling more than 1 km in a day by SES decile*

City	Pre-Pandemic			Pandemic			Mobility reduction		
	Dec. 1	Dec. 10	Dif.	Dec. 1	Dec. 10	Dif.	Dec. 1	Dec. 10	Dif.
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Bogotá	0.71	0.83	0.12	0.43	0.35	-0.08	-0.28	-0.48	-0.20
Buenos Aires	0.69	0.85	0.16	0.38	0.32	-0.06	-0.31	-0.53	-0.22
Guadalajara	0.63	0.86	0.23	0.48	0.53	0.05	-0.15	-0.33	-0.18
Guayaquil	0.71	0.78	0.07	0.35	0.33	-0.02	-0.36	-0.45	-0.09
Mexico DF	0.57	0.82	0.25	0.40	0.42	0.02	-0.17	-0.40	-0.23
Rio de Janeiro	0.72	0.85	0.13	0.52	0.39	-0.13	-0.20	-0.46	-0.25
Santiago de Chile	0.74	0.84	0.10	0.43	0.36	-0.08	-0.30	-0.48	-0.18
Sao Paulo	0.77	0.88	0.11	0.53	0.49	-0.04	-0.24	-0.39	-0.16
Average	0.69	0.84	0.15	0.44	0.40	-0.04	-0.25	-0.44	-0.19

Notes: The "Pre-pandemic" figures correspond to the week that precedes the declaration of the pandemic by the WHO (March 5 through 11). Data for the "Pandemic" period corresponds to April 1 through June 14. Columns (1) and (2) report the mean value of the mobility index before the pandemic for SES deciles 1 and 10. Column (3) indicates the difference between Columns (1) and (2). Columns (4) and (5) report the mean value of the mobility indicators throughout the pandemic period. Column (6) indicates the difference between Columns (4) and (5). Columns (7) and (8) report mobility reduction by decile. Column (9) indicates the difference in mobility reduction across deciles.

Table A3: *Univariate models*

City	Stringency Index	Time Trend	N
Bogotá	-0.0034*** (0.0001)	-0.0171*** (0.0004)	47,132
Buenos Aires	-0.0031*** (0.0001)	-0.0157*** (0.0004)	184,592
Guadalajara	-0.0017*** (0.0001)	-0.0081*** (0.0010)	23,091
Guayaquil	-0.0026*** (0.0002)	-0.0097*** (0.0013)	51,302
Mexico DF	-0.0023*** (0.0001)	-0.0146*** (0.0005)	68,221
Río de Janeiro	-0.0041*** (0.0002)	-0.0187*** (0.0003)	5,040
Santiago de Chile	-0.0025*** (0.0002)	-0.0136*** (0.0004)	27,803
Sao Paulo	-0.0029*** (0.0001)	-0.0123*** (0.0002)	9,495

Note. The table reports the estimated coefficient for the interaction term of a model in which mobility by SES percentile is a flexible function of an indicator of the evolution of the pandemic. The specification incorporates census unit and week fixed effects. The mobility indicator is the fraction of people that traveled at least one kilometer in a day (extensive margin). Column 2 incorporates the Stringency index as the indicator of the evolution of the pandemic. Column 3 uses the time trend variable as the indicator of the evolution of the pandemic, which counts the number of weeks since the declaration of the COVID-19 pandemic by the WHO. Column 4 shows the number of observations. Sample: eight large Latin American cities at weekly frequency. Robust and clustered standard errors at geographical unit level in parentheses. *p<0.1; **p<0.05; ***p<0.01

Table A4: *Univariate models*

City	Regional Cases	National Cases	Regional Deaths	National Deaths	N
Bogotá	-0.00058***	-0.00049***	-0.00238***	-0.00141***	47,132
	(0.00003)	(0.00003)	(0.00003)	(0.00014)	
Buenos Aires	-0.00050***	-0.00067***	-0.00224***	-0.00461***	184,592
	(0.00001)	(0.00002)	(0.00007)	(0.00013)	
Guadalajara	-0.00022***	-0.00030***	-0.00037***	-0.00042***	23,091
	(0.00004)	(0.00003)	(0.00009)	(0.00006)	
Guayaquil	-0.00058***	-0.00060***	-0.00079***	-0.00106***	51,302
	(0.00005)	(0.00005)	(0.00007)	(0.00010)	
Mexico DF	-0.00048***	-0.00054***	-0.00063***	-0.00088***	68,221
	(0.00002)	(0.00002)	(0.00002)	(0.00004)	
Río de Janeiro	-0.00050***	-0.00046***	-0.00065***	-0.00112***	5,040
	(0.00002)	(0.00002)	(0.00003)	(0.00005)	
Santiago de Chile	-0.00029***	-0.00050***	-0.00063***	-0.00060***	27,803
	(0.00005)	(0.00003)	(0.00009)	(0.00004)	
Sao Paulo	-0.00036***	-0.00033***	-0.00062***	-0.00071***	9,495
	(0.00001)	(0.00002)	(0.00001)	(0.00003)	

Note. The table reports the estimated coefficient for the interaction term of a model in which mobility by SES percentile is a flexible function of an indicator of the evolution of the pandemic. The specification incorporates census unit and week fixed effects. The mobility indicator is the fraction of people that traveled at least one kilometer in a day (extensive margin). We consider four possible specifications for the indicator of the evolution of the pandemic: the Regional Cases (column 2), National Cases (column 3), Regional Deaths (column 4) and National Deaths (column 5). Column 6 shows the numbers of observations. Sample: eight large Latin American cities at weekly frequency. Robust and clustered standard errors at geographical unit level in parentheses. *p<0.1; **p<0.05; ***p<0.01

Table A5: *Lasso regressions*

City	Stringency Index	Regional Cases	National Cases	Regional Deaths	National Deaths	Time Trend	F Statistic	p-value
Bogotá	-0.0029	-	-	-	-	-	5.6	0.00
Buenos Aires	-0.0025	-	-	-	-	-	42.40	0.00
Guadalajara	-0.0012	-	-	-	-	-	12.62	0.00
Guayaquil	-0.0017	-0.0001	-	-	-	-	12.65	0.00
Mexico DF	-0.0017	-	-	-	-	-	28.45	0.00
Rio de Janeiro	-0.0026	-	-	-	-0.0003	-	11.80	0.00
Santiago de Chile	-0.0020	-	-	-	-0.0001	-	19.45	0.00
Sao Paulo	-0.0022	-	-	-	-	-	16.09	0.00

Note. The table reports the estimated coefficient for the interaction term of a model in which mobility by SES percentile is a flexible function of an indicator of the evolution of the pandemic. The specification incorporates census unit and week fixed effects. The mobility indicator is the fraction of people that traveled at least one kilometer in a day (extensive margin). We consider six possible specifications for the indicator of the evolution of the pandemic: the Stringency Index (column 2), Regional Cases (column 3), National Cases (column 4), Regional Deaths (column 5), National Deaths (column 6) and Time Trend (column 7). Column 8 and 9 show the F-Statistic and p-value from a test of the joint significance of the regressors, respectively. Sample: eight large Latin American cities at weekly frequency. lasso regressions were used, with robust and clustered standard errors at geographical unit level in parentheses. *p<0.1; **p<0.05; ***p<0.01

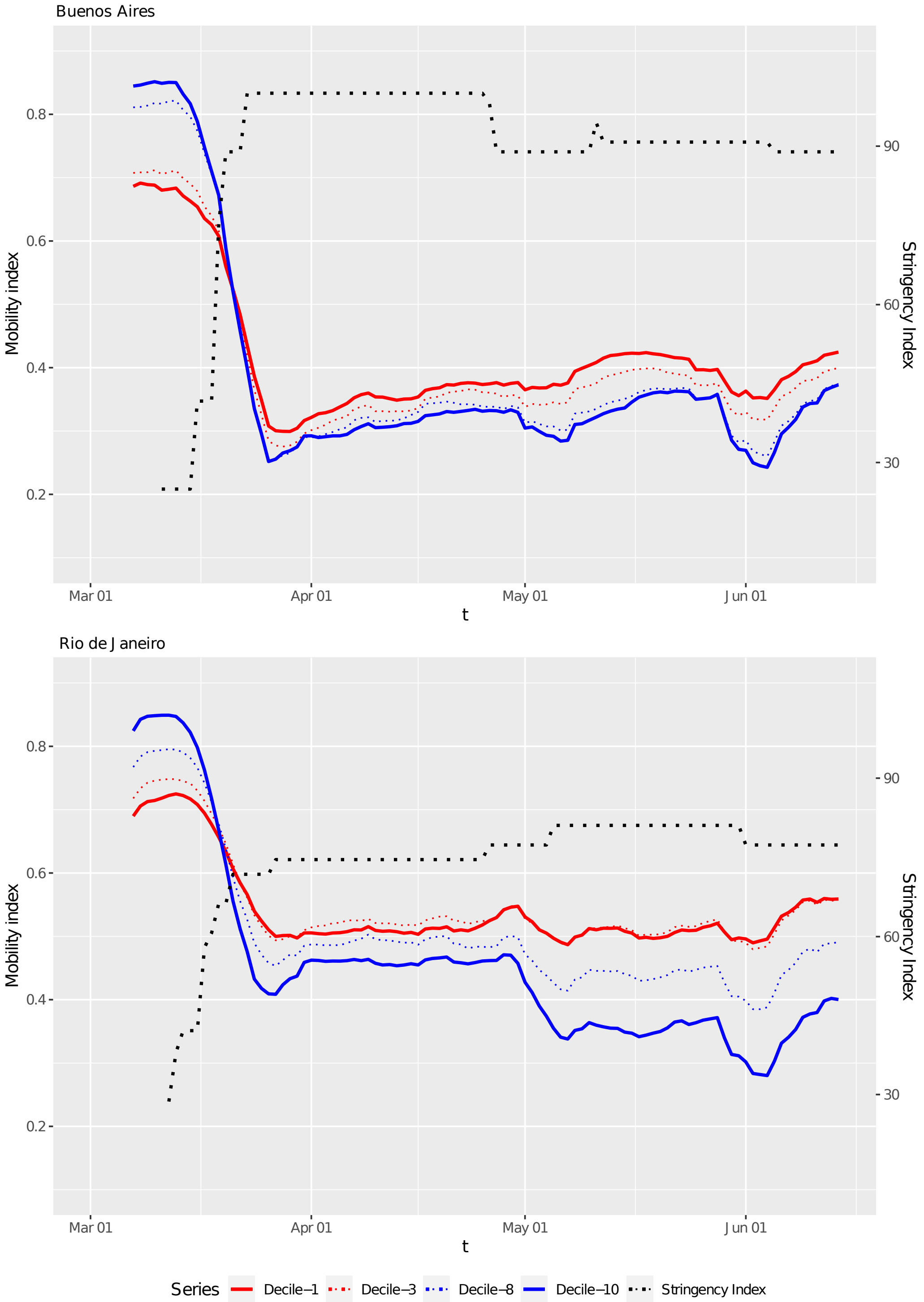


Figure 2: *The Extensive Margin and the Stringency Index*

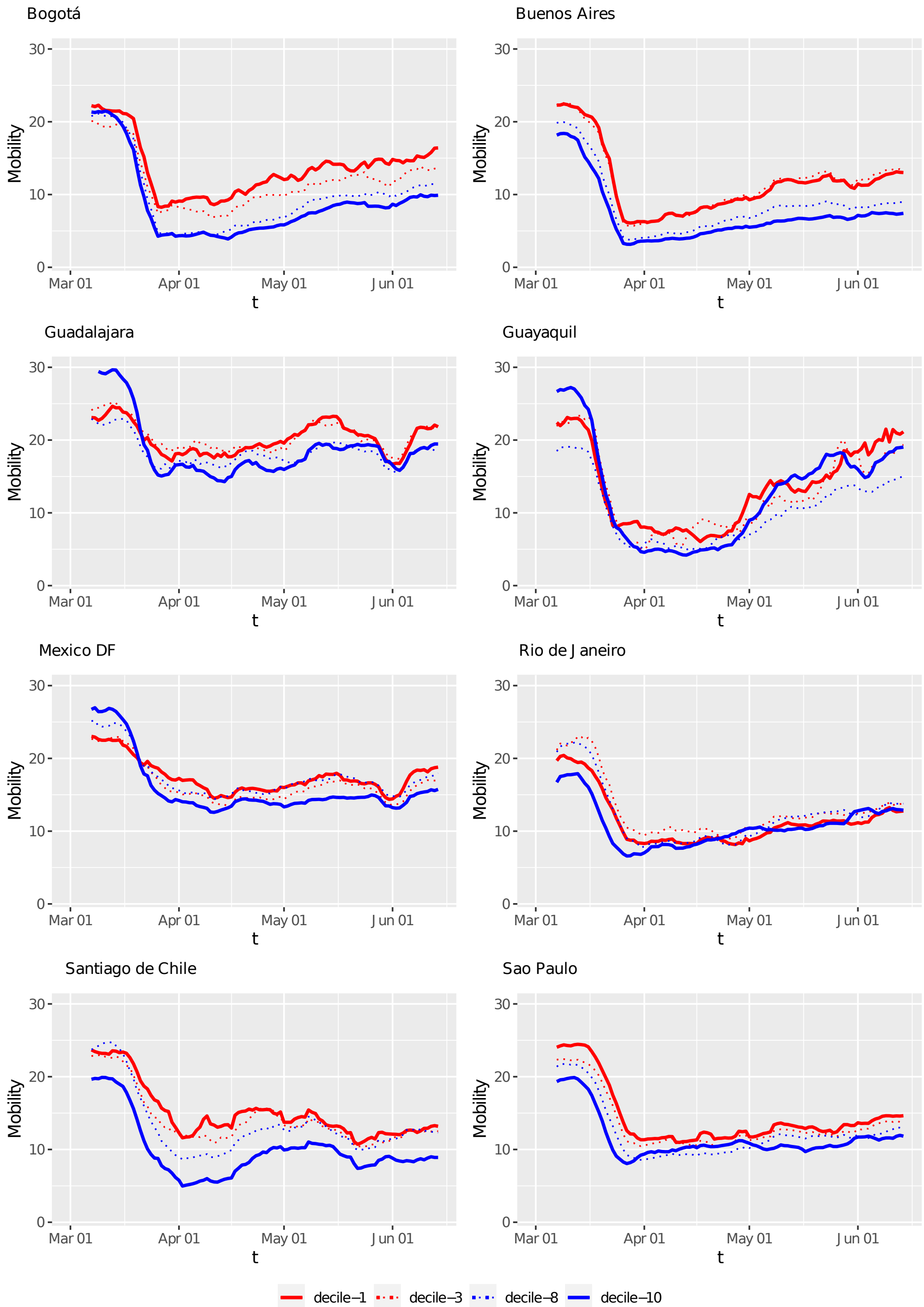
Note: weekly averages for days $t-6$ through t.

Table A6: *The Intensive Margin of Mobility by SES decile*

	Pre-Pandemic			Pandemic			Mobility Reduction		
City	Dec. 1 (1)	Dec. 10 (2)	Dif. (3)	Dec. 1 (4)	Dec. 10 (5)	Dif. (6)	Dec. 1 (7)	Dec. 10 (8)	Dif. (9)
Bogotá	22	20	2	13	7	6	-9	-13	-5
Buenos Aires	22	18	4	10	6	4	-12	-12	-0
Guadalajara	23	29	-6	20	17	3	-3	-12	-9
Guayaquil	23	27	-4	13	12	1	-10	-15	-5
Mexico DF	23	27	-4	16	14	2	-7	-13	-6
Rio de Janeiro	20	18	2	10	10	0	-10	-7	3
Santiago de Chile	23	20	3	13	9	4	-10	-11	-2
Sao Paulo	24	20	4	13	9	4	-12	-11	1
Average	23	22	0	14	11	3	-9	-12	-3

Notes: This table shows indicators of the intensity margin of mobility for SES deciles 1 and 10. The metric is expressed in kilometers. The “Pre-pandemic” figures correspond to the week that precedes the declaration of the pandemic by the WHO (March 5 through 11). The data for the “Pandemic” period corresponds to April 1 through June 14. Columns (1) and (2) report the mean value of indicators of mobility before the pandemic for SES deciles 1 and 10. Column (3) indicates the difference between Columns (1) and (2). Columns (4) and (5) report the mean value of indicators of mobility for the pandemic period. Column (6) indicates the difference between Columns (4) and (5). Columns (7) and (8) include the mobility reduction for each decile represented by the difference between Columns (1) and (4), and (2) and (5), respectively. Column (9) indicates the difference in mobilty reduction by decile represented by the difference between Columns (7) and (8).

Figure 3: *The Intensive Margin of Mobility by SES Decile*



Note: weekly averages for days $t - 6$ through t.

Table A7: *Univariate models*

City	Stringency Index	Time Trend	Regional Cases	National Cases	Regional Deaths	National Deaths	N
Bogotá	-0.0693***	-0.0014***	-0.0084***	-0.0056***	-0.0342***	-0.0113	45,095
	(0.0075)	(0.0004)	(0.0014)	(0.0015)	(0.0067)	(0.0063)	
Buenos Aires	0.0069	-0.0012***	-0.0046***	-0.0055***	-0.0193***	-0.0358***	184,592
	(0.0044)	(0.0002)	(0.0008)	(0.0010)	(0.0037)	(0.0074)	
Guadalajara	-0.0628***	-0.0027***	-0.0054*	-0.0107***	-0.0106*	-0.0151***	23,091
	(0.0081)	(0.0006)	(0.0024)	(0.0021)	(0.0058)	(0.0040)	
Guayaquil	-0.0341**	0.0003	-0.0093**	-0.0052*	-0.0087*	-0.0027	51,302
	(0.0126)	(0.0008)	(0.0030)	(0.0031)	(0.0049)	(0.0067)	
Mexico DF	-0.0518***	-0.0025***	-0.0088***	-0.0093***	-0.0098***	-0.0129***	68,221
	(0.0048)	(0.0004)	(0.0011)	(0.0013)	(0.0016)	(0.0024)	
Río de Janeiro	0.0173	0.0019***	0.0047***	0.0052***	0.0071***	0.0127***	5,038
	(0.0122)	(0.0004)	(0.0013)	(0.0010)	(0.0016)	(0.0020)	
Santiago de Chile	-0.0303***	0.0010	0.0006	0.0006	0.0074*	-0.0085**	27,735
	(0.0090)	(0.0005)	(0.0011)	(0.0013)	(0.0029)	(0.0027)	
Sao Paulo	0.0373***	0.0017***	0.0058***	0.0050***	0.0111***	0.0101***	9,473
	(0.0069)	(0.0002)	(0.0007)	(0.0006)	(0.0013)	(0.0013)	

Note: The table reports the estimated coefficient for the interaction term of a model in which mobility by SES percentile is a flexible function of an indicator of the evolution of the pandemic. The specification incorporates census unit and week fixed effects. The mobility indicator is the median distance in kilometers traveled by users that traveled at least one kilometer (intensive margin). We consider six possible specifications for the indicator of the evolution of the pandemic: the Stringency Index (column 2), Time Trend (column 3), Regional Cases (column 4), National Cases (column 5), Regional Deaths (column 6) and National Deaths (column 7). Column 7 shows the numbers of observations. Sample: eight large Latin American cities at weekly frequency. Robust and clustered standard errors at geographical unit level in parentheses. $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Table A8: *Lasso regressions*

City	Stringency Index	Regional Cases	National Cases	Regional Deaths	National Deaths	Time Trend	F Statistic	p-value
Bogotá	-0.0308	-	-	-	-	-	4.14	0.00
Buenos Aires	-0.0017	-	-	-	-	-	5.83	0.00
Guadalajara	-0.0341	-	-	-	-	-	7.51	0.00
Guayaquil	-	-	-	-	-	-	3.15	0.01
Mexico DF	-0.0355	-	-	-	-	-	10.51	0.00
Rio de Janeiro	-	-	-	-	0.0056	-	5.73	0.00
Santiago de Chile	-0.0177	-	-	-	0.0018	-	5.45	0.00
Sao Paulo	-	-	-	0.0067	-	-	7.83	0.00

Note. The table reports the estimated coefficient for the interaction term of a model in which mobility by SES percentile is a flexible function of indicators of the evolution of the pandemic. The specification incorporates census unit and week fixed effects. The mobility indicator is the median distance in kilometers traveled by users that traveled at least one kilometer (intensive margin). We consider six possible specifications for the indicator of the evolution of the pandemic: the Stringency Index (column 2), Regional Cases (column 3), National Cases (column 4), Regional Deaths (column 5), National Deaths (column 6) and Time Trend (column 7). Column 8 and 9 show the F-Statistic and p-value from a test of the joint significance of the regressors, respectively. Sample: eight large Latin American cities at weekly frequency. lasso regressions were used, with robust and clustered standard errors at geographical unit level in parentheses. *p<0.1; **p<0.05; ***p<0.01

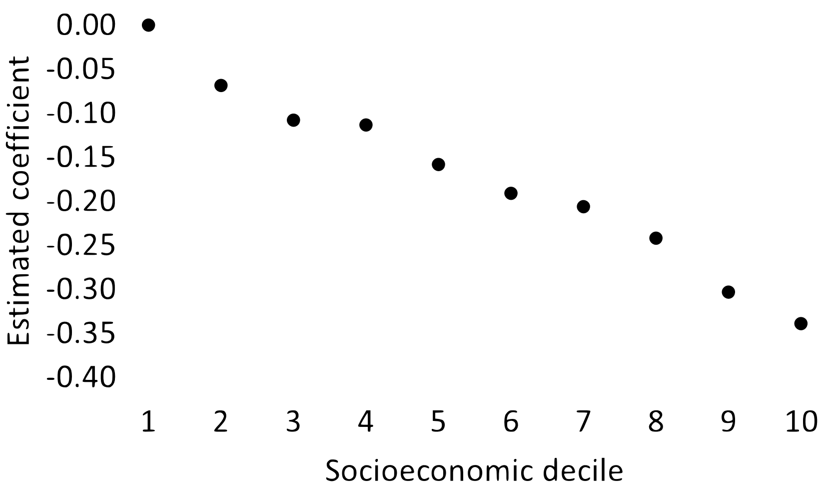


Figure 4: *Estimated coefficients for nonlinear model (Bogotá)*

Note: the coefficient for decile 1 is set equal to zero, all other coefficients indicate the difference in the response versus decile 1.

Table A9

Table 9: Correlation of the indicator of the extensive margin of mobility with other metrics

	Bogotá	Buenos Aires	Guadalajara	Guayaquil
Google Mobility Reports				
retail	0.953	0.954	0.934	0.951
grocery	0.873	0.875	0.780	0.869
parks	0.916	0.889	0.928	0.931
transit	0.949	0.963	0.943	0.962
worplace	0.860	0.894	0.681	0.790
residential	-0.866	-0.929	-0.808	-0.832
Veraset no filter	0.980	0.952	0.943	0.993

	Mexico DF	Rio de Janerio	Sant. de Chile	Sao Paulo
Google Mobility Reports				
retail	0.952	0.916	0.913	0.899
grocery	0.912	0.611	0.921	0.595
parks	0.944	0.894	0.921	0.807
transit	0.931	0.898	0.913	0.886
worplace	0.778	0.764	0.846	0.711
residential	-0.833	-0.816	-0.839	-0.788
Veraset no filter	0.968	0.952	0.946	0.982

Note: Veraset no filter is the indicator of the extensive margin of mobility when no ”active users” filter is applied.

Table A10

Table 10: Estimated coefficients under alternative specifications

Region	Mobility index	Coef	St. Dev.	Dif.
Bogotá	original	-0.0034	(0.0001)***	0.0002
	no filter	-0.0036	(0.0001)***	
Buenos Aires	original	-0.0031	(0.0001)***	0.0002
	no filter	-0.0033	(0.0000)***	
Guadalajara	original	-0.0017	(0.0001)***	0.0002
	no filter	-0.0019	(0.0000)***	
Guayaquil	original	-0.0026	(0.0002)***	0.0001
	no filter	-0.0027	(0.0000)***	
México DF	original	-0.0023	(0.0001)***	0.0001
	no filter	-0.0024	(0.0000)***	
Rio de Janeiro	original	-0.004	(0.0002)***	0.0003
	no filter	-0.004	(0.0002)***	
Sant. de Chile	original	-0.0025	(0.0001)***	0.0001
	no filter	-0.0026	(0.0001)***	
Sao Paulo	original	-0.0029	(0.0001)***	0.0000
	no filter	-0.0029	(0.0001)***	

Note: The estimated coefficients correspond to the estimated the model in which the Stringency Index is the shock variable. ”no filter” refers to the indicator of the extensive margin of mobility when no ”active users” filter is applied.