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Socio-economic status and mobility during the COVID-19 pandemic: An analysis of large Latin American urban areas

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Abstract

This study analyzes mobility patterns during the COVID-19 pandemic for 8 large Latin American urban areas. Indicators of mobility by socio-economic status are generated combining georeferenced mobile phone information with granular census data. Higher socio-economic status is consistently associated with more intense reductions in mobility. According to estimated lasso models, an indicator of government restrictions provides the best parsimonious description of these heterogeneous responses. These estimations point to noticeable similarities in the patterns observed across the urban regions. This 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.

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]

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

These changes have important implications for the evolution of the pandemic (Lau et al. 2020, Dhaval et al. 2020, Flaxman et al. 2020), economic activity (Coibon et al. 2020, Mongey et al. 2020) and, more broadly, the wellbeing of different socio-economic groups.

Beyond aggregate descriptions, detailed analyses of mobility patterns can provide useful insights. First, this information can help policy makers identify vulnerable groups and, in this way, improve the allocation of healthcare resources such as testing capacity, prevention campaigns and treatment equipment. Second, this data can also be used to understand the channels that explain contagion dynamics. Third, fine grained data can be used to assess the economic impact and the social toll resulting from the combined effect of the pandemic and restrictions in mobility.

In this work we carry out a detailed analysis of changes in mobility for eight large Latin American urban regions. More specifically, we measure changes in mobility as a function of socioeconomic status (SES). We produce detailed descriptions of differences in the response of mobility. Importantly, our approach allows for comparisons of these patterns across the different regions covered in our analysis.

To implement this analysis, we combine two types of granular data. First, georeferenced 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. The sample period for this data starts in March 1st and ends in June 14th . The eight urban regions covered in this study correspond to the following cities: Bogotá (Colombia), Buenos Aires (Argentina), Guadalajara (Mexico), Guayaquil (Ecuador), México DF (Mexico), Rio de Janeiro (Brazil), Sao Paulo (Brazil) and Santiago de Chile (Chile). According to population statistics, these region include 7 of the 10 largest urban areas in Latin America.

The results provide a coherent picture of the heterogeneous responses in mobility. First, for all urban regions of the study, higher socioeconomic status is associated with more intense reductions in mobility. Furthermore, penalized regressions suggest that an indicator of government restrictions constitutes a convenient resource to describe, in a parsimonious manner, these heterogeneous responses. Finally, the estimated empirical models indicate that, in addition to the previously mentioned qualitative similarities, these heterogeneous responses share similar quantitative characteristics.

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 regions 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 reemerge in subsequent stages of the current crisis or in future instances of similar epidemics.

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 & Neiman 2020, Atchison et al. 2020, Mongey et al. 2020, Chiou & 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. Complementarily, liquidity constraints constitute another important factor (Attanasio & Székely 2000, Cavallo & Serebrisky 2016). Household 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.

This work is related to other studies that have also 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) shows that, in the US, high SES groups reduced mobility faster. Also, for the case of the US and in consistence with the previous study, Wright et al. (2020) reports a negative association between SES economic status and mobility for US counties. Coven & Gupta (2020) shows a similar pattern in New York City. In contrast, Dahlberg et al. (2020) concludes that in the case of Sweden similar reductions are observed for users in different socio-economic groups. Studies analyzing mobility in Israel and France a positive, but modest, association between socioeconomics status and reduction in mobility (Yechezkel et al. 2020, Pullano et al. 2020).

For emerging economies, we only found a couple of studies that analyze changes in mobility by socioeconomic status. Brotherhood et al. (2020) 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 in two parts according to geographic data that identifies slums. Compared to this analysis, our work is able to provide a much more detailed evidence on the relationship between socio-economic status and mobility. Dueñas et al. (2020) 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 is stronger as SES increases. Considering this existent evidence for emerging economies, our study aims to contribute detailed, comprehensive and comparable evidence on the changes in mobility by SES. In this way, we are able to identify empirical regularities that can be conjectured to constitute persistent features that characterize not only the eight regions 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. Extended results are presented in section 4 and the next section concludes.

2 Data and methodology

2.1 Mobile phone data and indices of mobility

We constructed mobility indicators based on georeferenced mobile phone data provided by Veraset. This company collects anonymized location data from millions of mobile phones in several 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 in that day. Additionally, we computed an indicator of the intensive margin of mobility that is equal to the median distance traveled by those users that traveled more than one kilometer. Both indicators are calculated for each census unit and day from March 1$^{\text{st}}$ to June 14$^{\text{th}}$.

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 phones 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 during the night 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, we use files "shapefiles" that provide census geographical information. More specifically, these files indicate the perimeter of each census unit. In the first step, we identify the home coordinates for each user based on the most frequent location during the night. After that, we link this home 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 total population. These differences are due to restrictions in data availability. Also, the availability of public "shapefiles" and census data restricts the granularity of the analysis in each city. More details regarding census data are provided in Table A in Annex A.

Table 1 reports descriptive statistics. As shown by population figures, our study covers large urban regions. The varying size of census geographical units can be inferred comparing the population figures to the number of units. There are also differences in the daily average of mobile phones as a fraction of the population.

Table 1: Descriptive statistics

Urban Region[a]	Population[b]	#Census units	#Mobile phones[c]	SES Index[d]	
				Decile 1	Decile 10
Bogotá	7.4	3683	22552	0.37	0.89
Buenos Aires	14.8	12598	87696	0.18	0.86
Guadalajara	4.4	1610	21586	0.13	0.86
Guayaquil	3.0	4886	5316	0.20	0.88
Mexico DF	20.1	4636	119313	0.21	0.83
Rio de Janeiro	11.8	336	100970	0.24	0.83
Sao Paulo	19.7	633	256728	0.25	0.78
Santiago de Chile	7.1	2423	24656	0.56	0.95

[a] Data belongs to the entire metropolitan area, [b] in millions, [c] daily average, [d] SES Index indicates the fraction of people over 25 years old who completed secondary education (over total population over 25 years)

2.2 Additional Data

- **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. In the analysis below, we rescale this index dividing 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 indicators on this matter: daily confirmed cases and daily deaths. We include this information both at the national level and at urban region level. Data was collected from official sources (See Annex A for further details). To implement the analyses, these indicators are first expressed as cases/deaths per million population. Then, we apply a logarithmic transformation.[2]

2.3 Empirical models

We use empirical models to measure and summarize the heterogeneity in the response of mobility. These models are estimated for each urban area. The first class of model specification is given by 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. We consider six different specifications for this indicator. In these models, the heterogeneous response of mobility to the crisis is summarized by the coefficient of the interaction term. The six variables that capture the evolution of the crisis in the alternative model specifications are: Stringency Index, time trend indicator, daily confirmed cases and daily deaths (the last two indicators both at national and urban region level). We estimate these simple models in which one variable is considered at a time, contemplating the difficulties resulting from the high correlation between the indicators.

The second type of model we consider involves penalized regressions in which multiple interactive terms are allowed for as explanatory variables. This type of exercise allows for a parsimonious description of the associations and, at the same time, is informed by

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

a relatively large set of explanatory variables. Further details on model specifications and estimation strategies are described in the sections below.

3 Results

In this section we carry out a detailed analysis of changes in mobility along the extensive margin. This is 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 analysis in this section is divided in two parts. In the first part, we implement a descriptive exploration in which indicators of mobility are computed by SES decile. In the second part, formal empirical models are estimated. These models allow for a more concise and comparable description of the heterogeneous responses of mobility.

3.1 Mobility by socioeconomic decile

We compute daily indicators of mobility by SES decile. These indicators allow for a rich and informative description of heterogeneity in mobility patterns.

As shown in table 2, during the period that preceded the pandemic, the association between socioeconomic status and the fraction of users that move at least 1 kilometer was positive. With differences in intensity, this feature is observed in all large urban areas under study. For example, in the case of Mexico DF, this indicator is on average 0.57 in the case of decile 1 users and 0.82 in the case of decile 10 users. That is, using our suggested interpretation, during normal times, the fraction of people left their home was 25% larger for high SES users. In contrast, a substantially smaller difference is found for Guayaquil. In this case, the difference between the fraction of decile 10 users that leave their home and decile 1 users that leave their home is only 7%.

During the pandemic, a very significant reduction in mobility is observed. As shown in figure 1, the indicators of mobility display strong downward trends starting in mid-

March. By the end of March a new regime of low mobility is reached. The reduction in mobility is more intense for Guayaquil and Buenos Aires. This is consistent with the strict lockdowns imposed in the respective countries.

The daily indicator of mobility shows that, as conjectured, heterogeneous responses constitute prevalent feature. As shown in table 2, in all cases under study, the drop in mobility is significantly larger for high SES users. For example, in Buenos Aires, the fraction of decile 1 users that traveled at least 1 km fell 31% from 0.69 pre-pandemic to 0.38 during the pandemic. In contrast, for decile 10 users, this indicator fell 53% from 0.85 to 0.32. In Rio de Janeiro, the fraction of decile 1 users that traveled at least 1km fell 20% from 0.72 pre-pandemic to 0.52 during the pandemic, while this indicator fell 46% from 0.85 to 0.20 for decile 10 users.

A more detailed description of the evolution of mobility is provided in figure 1. For example, this figures show that in the cases of Rio de Janeiro and Santiago de Chile, the heterogeneity in the response is particularly noticeable starting in May. In contrast, in the case of Guayaquil, the heterogeneity in the response is more intense during April, a period in which the sanitary crises was particularly strong.

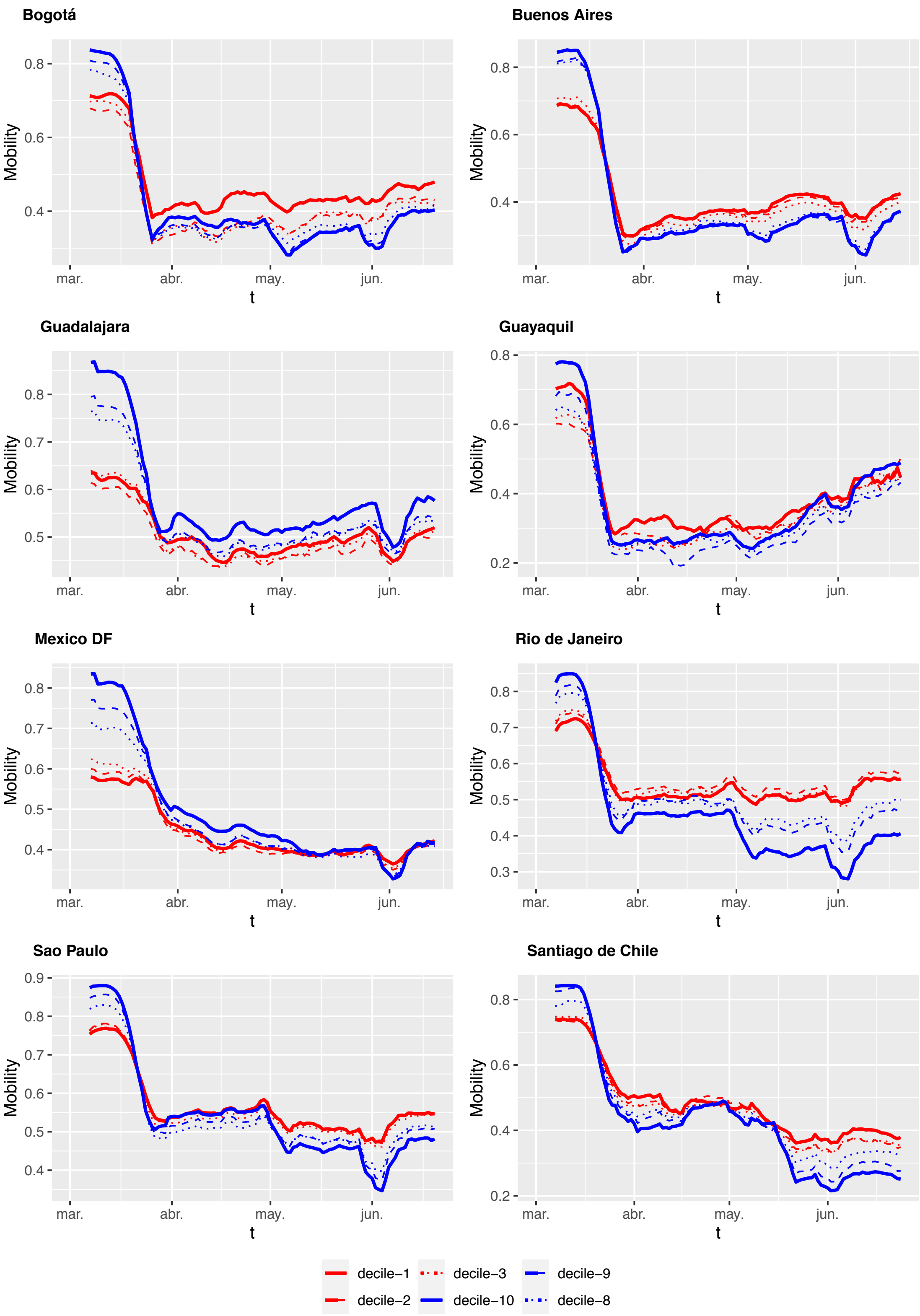
According to this descriptive analysis, higher socioeconomic status is consistently associated with more intense reductions in mobility. This evidence is consistent with important differences in the opportunity cost of staying at home. More specifically, this difference can be explained by differences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

Table 2: Mobility by decile

	Pre-Pandemic		Pandemic		Mobility reduction		Dif
Urban Region	Decile 1	Decile 10	Decile 1	Decile 10	Decile 1	Decile 10	
Bogotá	0.71	0.83	0.43	0.35	-0.28	-0.48	-0.20
Buenos Aires	0.69	0.85	0.38	0.32	-0.31	-0.53	-0.22
Guadalajara	0.63	0.86	0.48	0.53	-0.15	-0.33	-0.18
Guayaquil	0.71	0.78	0.35	0.33	-0.36	-0.45	-0.09
Mexico DF	0.57	0.82	0.4	0.42	-0.17	-0.40	-0.23
Rio de Janeiro	0.72	0.85	0.52	0.39	-0.20	-0.46	-0.25
Sao Paulo	0.77	0.88	0.53	0.49	-0.24	-0.39	-0.16
Santiago de Chile	0.74	0.84	0.43	0.36	-0.30	-0.48	-0.18

Note: the "Pre-pandemic" figures correspond to the week that preceded the declaration of the pandemic by the WHO (March 5th through 11th. The data for the "Pandemic" period corresponds to April 1st through June 14th.

Figure 1: Extensive margin



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

3.2 Empirical models

Can we generate informative and concise descriptions of the rich evidence explored above? With this objective in mind, we estimate simple models that provide low-dimensional representations of the heterogeneous response of mobility.

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:

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

Where μ_u and μ_t are fixed effects by census unit and by week 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 possible 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 practices accumulate, there might exist a heterogeneous trend in mobility patterns. The other indicators of the pandemic were presented in the data section.

Tables 3 and 4 summarize the estimations for the alternative models. The results are consistent with the observations made in the previous section. When the Stringency Index is used as the indicator of the evolution of the pandemic, in all cases, the estimated coefficient is negative and statistically significant. That is, the response to more restrictive government policies is stronger as SES increases. It is important to observe that the estimated coefficients are quite similar across urban areas (between -0.002 and -0.004).

The largest estimated coefficient corresponds to Rio de Janeiro. Qualitatively similar results are observed for 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 urban areas.

Table 3: Univariate models

Urban Region	Stringency Index	Time Trend	N
Bogotá	-0.003***	-0.0001***	47132
	(0.0001)	(0.00001)	
Buenos Aires	-0.003***	-0.0002***	184592
	(0.0001)	(0.000004)	
Guadalajara	-0.002***	-0.0001***	23091
	(0.0001)	(0.00001)	
Guayaquil	-0.003***	-0.0001***	51302
	(0.0002)	(0.00001)	
Mexico DF	-0.002***	-0.0001***	68221
	(0.0001)	(0.00001)	
Río de Janeiro	-0.004***	-0.0002***	5040
	(0.0001)	(0.00004)	
Sao Paulo	-0.003***	-0.0001***	9495
	(0.00007)	(0.00003)	
Santiago de Chile	-0.003***	-0.0001***	27803
	(0.0001)	(0.00003)	

Robust and clustered standard errors at geographical unit level in parentheses. *p<0.1; **p<0.05; ***p<0.01

Table 4 describes the estimation for model specifications that incorporate indicators of health outcomes in the interactive term. More specifically, we consider statistics of cases and deaths at the regional and national level. In all cases, the estimations indicate more intense reductions in mobility as SES increases. This heterogeneity in the response to the crisis is statistically significant. On the other hand, the estimated coefficients for different urban regions 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 variance could reflect the absence of solid relationship between mobility patterns and the evolution of health outcomes.

The estimated models suggest that the association between changes in mobility and SES can be captured by simple models. The estimated association is robust to changes in the model specification. On the other hand, we would like to explore methodologies in which this diverse set of indicators of the evolution of the pandemic can be considered simultaneously to uncover advantageous representation of mobility patterns. We turn to this task in the following subsection.

3.2.2 Penalized 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. 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 results in a very 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 estimate this multivariate association using penalized 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 associated with more complex models. Under this methodology, the analyst needs to specify the weight associated with this second term . In this study, we implement a theory driven penalization methodology that controls for overfitting and produces parsimonious estimated models (Belloni et al. 2012, 2016). One benefit of this strategy is consistent model estimation. We use stata package “lassopack” described in Ahrens et al. (2020).

Table 4: Univariate models

Urban Region	Regional Cases	Regional Deaths	National Cases	National Deaths	N
Bogotá	-0.0006***	-0.002***	-0.0005***	-0.001***	47132
	(0.00003)	(0.0001)	(0.00003)	(0.0001)	
Buenos Aires	-0.0005***	-0.002***	-0.0007***	-0.005***	184592
	(0.00001)	(0.00007)	(0.00002)	(0.00013)	
Guadalajara	-0.0002***	-0.0004***	-0.0003***	-0.0004***	23091
	(0.00004)	(0.00009)	(0.00003)	(0.00006)	
Guayaquil	-0.0006***	-0.001***	-0.0006***	-0.001***	51302
	(0.00005)	(0.00007)	(0.00005)	(0.0001)	
Mexico DF	-0.0005***	-0.001***	-0.0005***	-0.0009***	68221
	(0.00002)	(0.00002)	(0.00002)	(0.00004)	
Río de Janeiro	-0.0005***	-0.0007***	-0.0005***	-0.001***	5040
	(0.00002)	(0.00003)	(0.00002)	(0.00005)	
Sao Paulo	-0.0004***	-0.0006***	-0.0003***	-0.0007***	9495
	(0.00001)	(0.00002)	(0.00001)	(0.00003)	
Santiago de Chile	-0.0003***	-0.0006***	-0.0005***	-0.0006***	27803
	(0.00005)	(0.0001)	(0.00003)	(0.00004)	

Robust and clustered standard errors at geographical unit level in parentheses. *p<0.1; **p<0.05; ***p<0.01

We estimate multivariate models that include six interaction terms, one for each indicator of the evolution of the pandemic. Table 5 shows the estimation of these models for each urban region. It must be noted that, as is common practice when implementing penalized regression methods, the independent variables are standardized.

Penalized regressions suggest that the indicator of government restrictions constitutes a convenient resource to describe, in a parsimonious manner, these heterogeneous responses. In consistence with the previously reported results, the estimated coefficients corresponding to this indicator are negative. Furthermore, in only three urban areas, 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 key variable when it comes to describe the heterogeneity in mobility responses. Additionally, the value of the estimated coefficients of these estimations highlight the similarities in the documented patterns across the eight urban regions of the analysis.

4 Extended analysis: the intensity margin

Our main analysis focuses on the extensive margin of mobility. That is, we focus on the fraction of persons that move at least one kilometer or, following the interpretation we informally suggested, the fraction of people that leave their home. There is second metric, related to the intensity of mobility, that can be derived from the primary indicator. In this section we analyze the evidence related this indicator: the median distance traveled by users that traveled at least one kilometer. While inspecting the analyses presented below, it is worth keeping in mind that the intensive margin metric is a secondary metric that is affected by the variation the fraction of users with low levels of mobility.

Table 5: Penalized regressions

Urban Region	Stringency Index	Regional Cases	Regional Deaths	National Cases	National Deaths	Time Trend	F Statistic	p-value
Bogotá	-0.003	-	-	-	-	-	5.6	0.00
Buenos Aires	-0.002	-	-	-	-	-	42.4	0.00
Guadalajara	-0.001	-	-	-	-	-	12.62	0.00
Guayaquil	-0.002	-0.0001	-	-	-	-	12.65	0.00
Mexico DF	-0.002	-	-	-	-	-	28.45	0.00
Rio de Janeiro	-0.003	-	-	-	-0.0003	-	11.80	0.00
Sao Paulo	-0.002	-	-	-	-	-	16.09	0.00
Santiago de Chile	-0.002	-	-	-	-0.0001	-	19.45	0.00

Robust and clustered standard errors at geographical unit level in parentheses. *p<0.1; **p<0.05; ***p<0.01

4.1 Mobility by socioeconomic decile

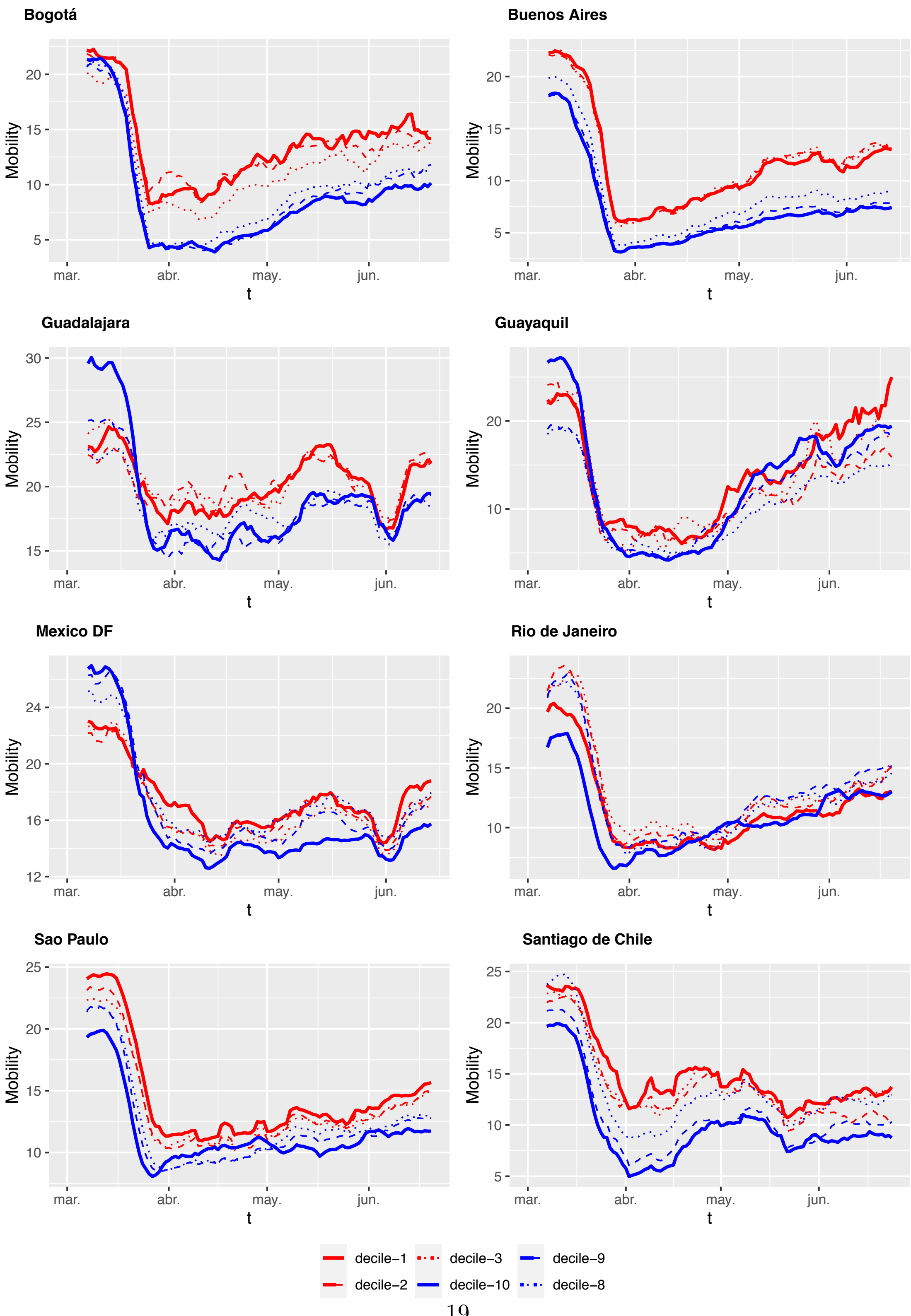
Table 5 shows indicators of the intensity of mobility by socioeconomic deciles. As in the case of the indicator of the extensive margin of mobility, the health crisis is associated with important reductions in median distance traveled. The analysis of the reduction in median distance traveled by SES indicates that in five urban regions, the reduction in mobility is stronger for decile 10. In the case of Buenos Aires no noticeable difference is observed. 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 contrasts to the analysis of the extensive margin of mobility, in the case of the intensive, the differences in the response are not as uniform across the different urban areas.

Table 6: Mobility by decile

	Pre-Pandemic		Pandemic		Mobility Reduction		Dif
Urban Region	Decile 1	Decile 10	Decile 1	Decile 10	Decile 1	Decile 10	
Bogotá	22	20	13	7	-9	-13	-5
Buenos Aires	22	18	10	6	-12	-12	-0
Guadalajara	23	29	20	17	-3	-12	-9
Guayaquil	23	27	13	12	-10	-15	-5
Mexico DF	23	27	16	14	-7	-13	-6
Rio de Janeiro	20	18	10	10	-10	-7	3
Sao Paulo	24	20	13	9	-12	-14	2
Santiago de Chile	23	20	13	9	-10	-11	-2

Note: the "Pre-pandemic" figures correspond to the week that preceded the declaration of the pandemic by the WHO (March 5th through 11th. The data for the "Pandemic" period corresponds to April 1st through June 14th.

Figure 2: Intensive Margin



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

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 $Percentile_u$. Where $Shock_t$ 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 7 reports the estimated coefficients for different urban regions and alternative specification of the model. In the case of the Stringency Index we find a negative and statistically significant coefficient. That is, in those cities the reduction in mobility becomes more intense as higher 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 urban regions are compared, the observed patterns are not as similar. This differences can also verified when other indicators of the evolution of the health crisis are considered.

4.2.2 Penalized regressions

As in the previous section, we implement penalized 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 to 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 valu-

Table 7: Univariate models

Urban Region	Stringency Index	Time Trend	Regional Cases	Regional Deaths	National Cases	National Deaths	N
Bogotá	-0.07***	-0.001***	-0.008***	-0.03***	-0.006***	-0.01	45095
	(0.01)	(0.0004)	(0.001)	(0.007)	(0.001)	(0.006)	
Buenos Aires	0.007	-0.001***	-0.005***	-0.019***	-0.005***	-0.036***	184592
	(0.004)	(0.0002)	(0.001)	(0.004)	(0.001)	(0.007)	
Guadalajara	-0.063***	-0.003***	-0.005*	-0.011*	-0.011***	-0.015***	23091
	(0.008)	(0.0006)	(0.002)	(0.006)	(0.002)	(0.004)	
Guayaquil	-0.034**	0.0003	-0.009**	-0.009*	-0.005*	-0.003	51302
	(0.013)	(0.0008)	(0.003)	(0.005)	(0.003)	(0.007)	
Mexico DF	-0.052***	-0.003***	-0.009***	-0.01***	-0.009***	-0.013***	68221
	(0.005)	(0.0004)	(0.001)	(0.002)	(0.001)	(0.002)	
Río de Janeiro	0.017	0.001***	0.005***	0.007***	0.005***	0.01***	5038
	(0.01)	(0.0004)	(0.001)	(0.001)	(0.001)	(0.002)	
Sao Paulo	0.037***	0.002***	0.006***	0.01***	0.005***	0.01***	9473
	(0.01)	(0.0002)	(0.0007)	(0.001)	(0.0006)	(0.001)	
Santiago de Chile	-0.03***	0.001	0.001	0.007*	0.001	-0.009**	27735
	(0.01)	(0.001)	(0.001)	(0.003)	(0.001)	(0.003)	

Robust and clustered standard errors at geographical unit level in parentheses. *p<0.1; **p<0.05; ***p<0.01

able indicator that allows for parsimonious descriptions mobility patterns. Second, this index points to negative associations between mobility and SES during the health crisis. On the other hand, the evidence for this secondary indicator is not as one-sided as the evidence reported for our primary indicator of mobility.

Table 8: Penalized regressions

Urban Region	Stringency Index	Regional Cases	Regional Deaths	National Cases	National Deaths	Time Trend	F Statistic	p-value
Bogotá	-0.03	-	-	-	-	-	4.41	0.00
Buenos Aires	-0.002	-	-	-	-	-	5.83	0.00
Guadalajara	-0.034	-	-	-	-	-	7.51	0.00
Guayaquil	-	-	-	-	-	-	3.15	0.006
Mexico DF	-0.035	-	-	-	-	-	10.51	0.00
Rio de Janeiro	-	-	-	-	0.006	-	7.73	0.00
Sao Paulo	-	-	0.007	-	-	-	7.83	0.00
Santiago de Chile	-0.02	-	-	-	0.002	-	5.45	0.00

Robust and clustered standard errors at geographical unit level in parentheses. $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

5 Conclusion

In this work we estimated the association between SES and the intensity of the reduction in mobility in response to the COVID-19 pandemic. The analysis suggest that there is a common pattern in the eight regions under study. In all cases, higher SES is associated with a more intense reduction in mobility.

The evidence we report can constitute an input in analyses of to the evolution of the 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.

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Annex A: Data

A.1 Census Data

Table A: Census Data description and sources

Urban Region	Census Data		
	Census unit level	Census year	Source
Bogotá	Sección 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	Área de ponderação	2010	IBGE
Sao Paulo	Área de ponderação	2010	IBGE
Santiago de Chile	Zona censal	2017	INE

A.2 Sanitary Conditions Data

- **Bogotá:**

  National level & Urban region level: Colombia National Health Institute Dashboard

  https://www.ins.gov.co/Noticias/Paginas/Coronavirus.aspx

- **Buenos Aires:**

  National level & Urban region level: Ministry of Health of the Nation
  http://datos.salud.gob.ar/dataset/covid-19-casos-registrados-en-la-republica-argentina

- **Guadalajara:**

  National level & Urban region level: Secretary of Health
  https://coronavirus.gob.mx/datos/

- **Guayaquil:**

National level & Urban region level: Ministry of Public Health
https://www.gestionderiesgos.gob.ec/informes-de-situacion-covid-19-desde-el-13-de-marzo-del-2020/

- **Mexico DF:**

  National level & Urban region 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-government-response-tracker

  Urban region 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-government-response-tracker

  Urban region level: São Paulo State Department of Health Dashboard

  https://www.seade.gov.br/coronavirus/

- **Santiago de Chile:**

  National level & Urban region level:Chilean Government COVID-19 Dashboard

  https://www.gob.cl/coronavirus/