Is COVID-19 The Great Equalizer? Heterogenous Impact of Non Pharmaceutical Interventions in a Metropolitan Area.

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Abstract

The capacity of areas within a city to comply with mobility restrictions aimed at curbing the COVID-19 epidemic is crucial to the local dynamics of the disease. In this paper, we study the efficacy of policies implemented to restrict mobility and their impact on the COVID-19 expansion, and how this impact depends on socioeconomic differences across within-city locations. To do so, we rely on unique and novel data showing changes in movements at highly disaggregated spatial levels. We use data from Bogotá to explore the relationship between Non-Pharmaceutical Interventions (NPI's), people's mobility and the expansion of the COVID 19 pandemic. Bogotá implemented a general lockdown, followed by district-specific restrictions and subsidies. We find that the general lockdown imposed in the city significantly reduced mobility (by about 47%). By contrast, the marginal impact of district-specific restrictions and subsidies is found to be small. When looking at heterogeneous impact across locations, we find that poorer locations, with higher share of informal workers, as well as those where households have deficient infrastructure, reacted significantly less to mobility restrictions.

Keywords— mobility, development, inequality, COVID-19, place-based policies.

JEL Codes— R11, R12, I18.

1 Introduction

Larger and denser cities allow for an increased interaction among individuals. While this interaction is the source of productivity enhancing agglomeration economies[1], it also increases the risk of disease contagion. This became evident with the rapid spread of the coronavirus disease 2019 (COVID-19) in large cities. The COVID-19 pandemic represents an exogenous shock of great magnitude, with a dramatic impact for global health, as well as with profound socioeconomic and political consequences. In contrast with more highly localized epidemics, like Ebola, COVID-19 quickly acquired a global status, affecting rich and poor countries alike. Policies aimed at preventing the spread of

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[1]for example Duranton (2016) show the main determinants of this agglomerations for Colombia, highlighting that this agglomerations were stronger for the informal sector in this country

the virus have affected daily activities for everyone. This widespread impact led to the discussion of COVID-19 as the great equalizer in media: it transcends income, prestige; we are all at risk. Celebrities declaring from bathtubs with rose petals that COVID-19 affects us equally[2] is an ironic example of a view that was widely propagated, especially at the beginning of the pandemic (UN, 2020).

This paper provides evidence against this view by showing the unequal impact of response policies across different areas of the same city. In particular, we show the unequal ability of different within city locations to reduce movement outside of home. Mobility reduction has been one of the main objectives of Non-Pharmaceutical Interventions (NPIs) as well as one of the most effective ways to reduce spread of cases (Glaeser et al., 2020). Consequently, the ability to comply with NPIs aimed at reducing mobility largely affects who remains shielded from contagion. If some areas of the city are systematically less protected by the NPIs, they are bound to be more affected by the disease. We analyze NPIs implemented in Bogotá, Colombia, estimate the extent to which different areas in the city reduced their mobility as a result to lockdown, and analyze the characteristics that may explain this heterogeneous reaction across locations. While the evolution of the pandemic, as well as its diverse and profound consequences, is still underway, understanding the heterogeneous impact of measures implemented to date to reduce contagion is essential to guide policy responses.

Latin America and the Caribbean (LAC) has been hard hit by the pandemic. The pandemic is expected to exacerbate problems of inequality and social conflict in the region (Alderson and Doran, 2014; Villareal-Villamar and Castells-Quintana, 2020). Multiple reports have raised alarms about the severity of the situation in the region (CEPAL et al., 2020). In face of the pandemic and as it was done in many other world regions, LAC countries implemented several NPIs as the main tool to contain the COVID-19 pandemic. Governments have banned public gatherings, closed restaurants, and told their residents to stay at home, aiming at reducing the speed of contagion of the virus by reducing mobility and social interaction. Between the virus and the NPIs, the pandemic has brought about unprecedented social and economic shocks. The drop in economic activity is of such magnitude that, it is expected that by the end of 2020, LAC GDP per capita will experience a 10-year setback. In Colombia, one of the countries mostly impacted by the pandemic, by July 2020 around 4 million people had lost their jobs, increasing unemployment to 20.2%. Almost 100.000 companies went into bankruptcy despite government subsidies to firms' payrolls and expansion of credit.

Heterogeneous reactions to NPIs may be expected as mobility reductions might impose a stronger burden on some households than others. For households with lower savings and insecure income, such as those in the informal sector, safety nets are limited and, thus, complying with mobility restriction measures is difficult, as subsistence depends on daily work. In this line, mobility restriction are expected to have more profound consequences in devel-

[2] See article in https://www.cnn.com/2020/03/23/entertainment/madonna-coronavirus-video-intl-scli/index.html

oping countries, where incomes are lower and informality is higher. In Colombia, informality has been persistent, with 47% of the population classified as informal as of 2019. [3] Informal workers in the country represent around 60% of the total fall in employment during the pandemic (as of July 2020). Wright et al. (2020) has shown how low income households might have a more difficult time transitioning to teleworking, and how lower access to credit and availability of savings might hamper compliance of even short NPIs. Similarly, households with higher incomes, more access to financial services and working in formal sectors that have the ability to telecommute, are likely to have more options to adjust to confinement measures. This is the documented case, for example, in the United States (Bick et al., 2020; Dingel and Neiman, 2020). These economic realities predict that households of different income levels and occupations will have different reactions to the NPIs. Consequently, spatial segregation predicts different areas of the city will also have different reactions to NPIs.

To analyze the heterogeneous impact of NPIs, we build a unique dataset with information on mobility, COVID-19 cases, and socioeconomic characteristics at a disaggregated spatial level, as well as data on NPIs, including lockdown and subsidies measures. We focus on Bogotá, as one of the largest and densest cities in Latin America. Bogotá is well suited for our study. First, Bogotá implemented a general lockdown with uniform enforcement throughout the city initially and then lifted it 5 weeks later. Then, implemented location specific lockdown. This allows us to estimate and compare the impact of city wide coordinated lockdown and localized measures. Second, cash grants or subsidies were distributed for some poor households. This allows us to check the role of these subsidies on enhancing of mobility related NPIs. Third, the city presents large segregation of income over space (Castells-Quintana, 2019), which makes the expected heterogeneous reaction to mobility NPIs by households discussed before more salient and more closely reflected in heterogeneous reactions across city areas.

The literature on NPIs and COVID-19 has increased exponentially. However, most papers to date have focused on developed countries and in cross city or cross country comparisons (see Brodeur et al. (2020) for a recent survey). An important recent contribution on the topic was given by Ascani et al. (2020) finding for Italy that the specialization in economic activities that are geographically concentrated increase contagion. However, previous papers have studied the relevance of city structure (i.e. density) on disease rates and effectiveness of NPIs in cross-sectional analysis (Dave et al., 2020). This paper contributes by evaluating the heterogeneous impact of NPIs within a large city in the developing world. We also provide an analysis of the role of intra-urban differences in socioeconomic characteristics in the effectiveness and costs of NPIs compliance. Some of these characteristics, like the presence of fridges at home and the number of households living in the same house, are potentially of particular importance to explain heterogeneous effects across low and high income groups. We also complement the evaluation of mobility restriction

[3]DANE defines informal households using firm size and affiliation to the social security system in health and pensions system. Informal workers are workers occupied in establishments of 5 or fewer workers, who are not professionals. In addition, this definition includes as informal, unpaid family workers, and domestic workers

NPIs, by considering the impact of household subsidies, not only on their temporal but also spatial variation. These programs are present in many countries and cities, but often absent from studies.

Our findings suggest a significant impact of the general lockdown on mobility, with a reduction of around 47 per cent. By contrast, the marginal impact of district-specific restrictions is found to be less than 1/10th of the impact of the generalized lockdown. We found no evidence that the subsidies program implemented was sufficient to improve the compliance of city areas to the mobility NPIs. When estimating the area specific reaction/compliance to the lockdown, we find large variation across locations. This variation is explained by some key neighborhood characteristics. We find that overall poorer neighborhoods, as well as those with a large share of workers in informal sectors, showed lower reaction to the lockdown. Areas with a larger share of households working in manufactures, in which some are day laborers, also complied less. Other differences in social structure, like marriage status, and access to home appliances, like a fridge at home, explained some of the variation across locations. In sum, we find that while lockdown measures may have been effective in reducing mobility in all areas of the city, their impact was not homogeneous across locations.

The remainder of the paper is organized as follows. Section 2 describes the data. Section 3 presents some basic stylized facts about the COVID-19 epidemic in Bogotá, the NPIs implemented, and the association between mobility and cases. In Section 4, we estimate the effect of NPIs on mobility. We use the neighborhood specific estimated impact of the NPI and explain its variation in a second stage using neighbourhood' socioeconomic characteristics. Finally, section 5 concludes and derives policy implications from the results.

2 Data

2.1 COVID-19 cases

COVID-19 daily cases were obtained for a period covering March through October 2020, from the Bogotá's Secretariat of Health. 70% of the cases reported patient's residence address. We geocoded this address and aggregated at the Zoning Planning Unit level (UPZ for their acronym in Spanish). The UPZs are urban areas smaller than the districts but larger than a neighborhood, as discussed below. Bogotá is divided into 110 planning units (UPZ)[4], which are the smallest unit of analysis for urban planning and zoning in the city. Despite their urban policy role, UPZ are heterogeneous. UPZs areas range from 0.8km^2 to 9.2km^2. Their population ranges from 63 to 262K. The database contains the date on which the symptoms started, and the date of the diagnosis provided by a laboratory result. Additionally, there is information about the age and gender of the person.

[4]Another administrative division of the city are the *localidades* or districts. Each district contains several UPZ and Bogotá has 19 districts

2.2 Mobility

Our ultimate interest is in the disease incidence. However, we use tracked mobility as the main outcome to measure the impact of lock down measures. The reasons are two-fold. First, using cases has multiple challenges as testing is not random and uniform, affecting disease prevalence measurement (Niehus et al., 2020; Badr et al., 2020). In Colombia the distortions, especially at the beginning of the pandemic, were large because there were large waiting lists for tests due to a shortage of locations to process them, which furthered distances true disease prevalence and cases detected. Second, the lock down NPIs were aimed directly at reducing mobility. Reductions in mobility are the best measure of their efficacy.

We use mobile phone tracked movements to determine time spent outside of home. Despite testing issues mentioned above, mobility has shown to have a strong connection with proved cases, especially in developed contries. Glaeser et al. (2020), using zip code data across five U.S. cities, estimate that total cases per capita decrease by 19% for every 10% percentage point fall in mobility. When controlling for endogeneity concerns, this elasticity becomes 25% and even increases to 30% when controlling for unobserved characteristics of neighborhods. Despite, heterogeneity across cities, this qualitative relationship remains uncontested, justifying the focus on NPIs to address the pandemic, as well as our use of mobility as the main outcome variable. [5]

Our phone mobility data comes from Grandata, a data laboratory focused on progressing the fields of Artificial Intelligence, Machine Learning, and Data Privacy.[6] The United Nations Development Programme (UNDP) in Latin America and the Caribbean and GRANDATA produced this data that tracks people's frequency of movements outside of their homes. Mobile phones generate pings or events which are associated with the user's location at different points in time. The location of this ping is associated with a hash of the MADID (Mobile Advertising ID).

The average number of geolocation events per user per day is 130. The place of residency is determined as the location where the user was present more often in an initial baseline period during nighttime hours. The place of residence is assigned to an hexagon with a the diameter (of the hexagon's circumscribed circle) of 40 meters. The location hexagons follow the Geohash location system.[7] Mobility events are classified as inside or outside of home depending on whether they are geolocated outside or inside of this residence hexagon. Those users that have had less than 10 daily events, for example because the mobile phone remained off for a long period of time, or for whom a full day was not captured because all their pings have happened in less than 8 hours, are filtered out. All events that happened within the user's residency are deleted and traffic is determined by the number of events classified as occurring outside of the residence.

[5] We were able to establish a positive and significant statistical relationship for our own sample.

[6] Mobility data aggregates are accessible in covid.grandata.com/

[7] Geohash is a public domain geocode system invented in 2008 by Gustavo Niemeyer. This system encodes a geographic location into a short string of letters and digits. All locations follow a hierarchical spatial data system dividing space into a grid.

The dataset provides the percentage differences in events carried out by mobile users between any date and a baseline date, set in March 2 2020. Since stay-at-home NPIs began in Bogotá in March 20th. We use the aggregate event count at the census tract level for all tracts in Bogotá metropolitan area. We use the percentage growth with respect to the baseline date in each census tract, and average these daily growths for the UPZs to get a measure at that geographical aggregation level.

2.3 Socioeconomic characteristics

We use the metropolican 2017 household level survey, called the Multipropósito Survey, carried out by the National Statistics Department of Colombia (DANE). This survey includes data on labor market, housing conditions, poverty and demographic characteristics. Household level data is representative at the UPZ level for 73 out of the 112 UPZs.

Table 1 presents some descriptive statistics of the aggregate cases, as well as some key socioeconomic variables. The COVID-19 cases varied between 151 in San Isidro Patios-Chapinero at the east of the city up to 7,040 in El Rincon-Suba in the northwest. The change in mobility shows large differences across UPZs as well. In addition, UPZs differ in many socioeconomic dimensions: Poverty, income, labor market outcomes (unemployment rate and informality), sectors of employment, average years of education, demographics (share of population above 51 years old, and share of married), infrastructure characteristics (overcrowding and if the household had a fridge) and some scale characteristics (density and population).

2.4 Subsidies

The city government implemented another NPI, called Bogotá Solidaria, which consisted in giving subsidies to citizens in extreme poverty, moderate poverty and vulnerable population, including people in informality (709.000 households). Subsidies data comes from the city official program website[8].

[8]Data can be found in https://rentabasicabogota.gov.co/

Variable	Mean	Std. Dev.	Min	Max
Covid-19 cases	1,866	1,367	151	7,040
Total subsidies	4,260	4,548	6	18,981
Mobility change	-0.3	0.2	-0.7	0.2
Hshlds below poverty (%)	15	10	1	55
Income per cap *(pesos)*	1,200,000	818,904	305,881	4,100,000
Labor market variables				
Unemployment rate (%)	8.1	2.3	2.0	14.4
Informality rate (%)	37.2	11.5	15.0	63.6
Sector variables				
Shr Doctors (%)	0.7	0.8	0.0	3.2
Shr Construction (%)	2.6	1.3	0.8	6.6
Shr Health (%)	2.8	0.8	0.9	4.8
Shr Manufacture (%)	5.6	1.8	2.5	10.2
Shr Transportation (%)	4.5	1.2	1.9	8.0
Shr Education (%)	2.7	1.5	0.6	8.3
Shr Hotels/Rest (%)	2.2	0.8	0.5	4.8
Education *(years)*	4.30	1.14	3.00	6.00
Demographics characteristics				
Shr 0-13 yrs (%)	17.7	4.4	8.6	29.3
Shr older 65 yrs (%)	7.5	3.1	2.5	13.9
Shr married (%)	21.5	7.5	10.1	41.5
Infrastructure variables				
Overcrowding	1.05	0.07	1.00	1.37
Fridge at home (%)	94	4	86	100
Scale variables				
Density	31,751.26	33,609.87	6,046.708	284,357.3
Population	80,821	54,298.88	1,0940	262,013

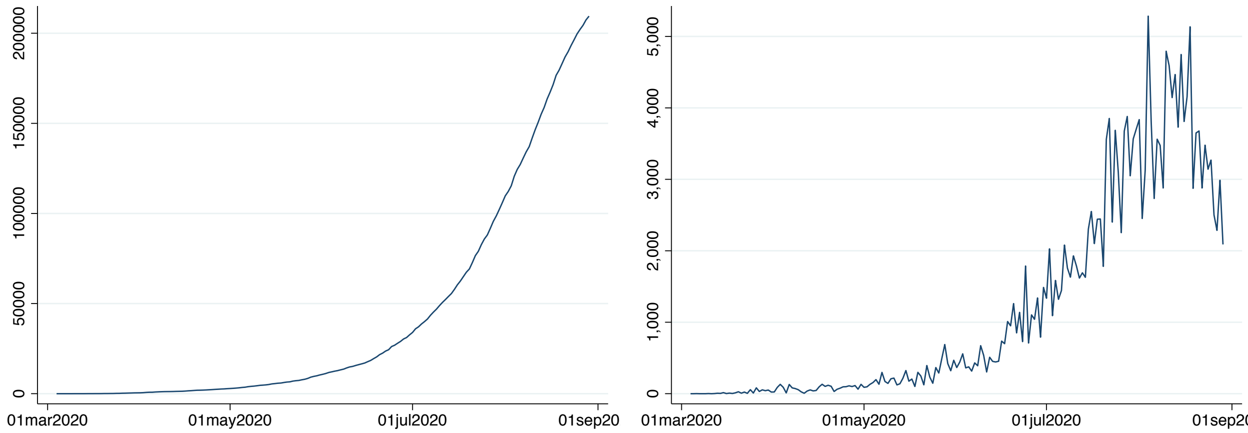
Table 1: UPZ Summary Statistics. Descriptive statistics of the 73 UPZs for which sociodemographic data are available in the Multipropósito survey are presented.

3 The COVID-19 Pandemic in Bogotá

The very first reported cases of COVID-19 in the country happened in Bogotá on March 6^{th}. According to the city's administration between January and February more than 210,000 people came into the country from Europe or the USA where the virus was already circulating through air travel. [9] The lack of international travel restrictions are blamed for a rapid spread of the virus.

As of November 30^{th}, there have been 374,074 COVID-19 cases, which have led to 8,505 deaths. [10] The evolution

[9]The city government provides information in the report of https://Bogotá.gov.co/mi-ciudad/ingreso-de-viajeros-a-colombia
[10]This information is reported daily by the Ministry of Health and Social Protection at: https://www.ins.gov.co/Noticias/Paginas/Coronavirus.aspx



(a) Cumulative COVID-19 cases

(b) Daily COVID-19 cases

Figure 1: The COVID-19 pandemic in Bogotá.

of cases in the city are shown in Figure 1. Among the positive cases, 51.29% were women and the average age is 39 years old.

Spatial distribution of confirmed cases showed in Figure 2 describe the uneven nature of Covid cases. Spatial distribution of cases slightly follows poverty distribution. These poor areas saw more cases and are also the ones which experienced more mobility since before the pandemic, had higher population densities and worse household infrastructure. The south and southwest of the city were heavily impacted by the virus, including,as well as some districts of the northwest.

3.1 Non Pharmaceutical Interventions

Restrictions to mobility

lock down measures were decreed by local governments at the beginning of the pandemic. The city government was the first to announce a mandatory stay at home drill for the period of March 20^{th} to 23^{th} . This announcement was followed by a presidential declaration of a national lock down, which began on March 24^{th} at midnight and was planned to end on April 12^{th} at midnight. As cases surged, the lock down was extended to April 27^{th}. During this lock down only sectors considered fundamental were able to work including transportation, food provision, healthcare and deliveries, some banks and notaries were partially open also.

After April 27^{th} the government allowed the reopening of activities of the construction and manufacturing sectors; companies were allowed to resume operations under the surveillance and authorization of local governments. lock down was extended for the general public until May 11^{th}.

After the first lock down was lifted cases surged. The city started implementing localized lock downs by district.

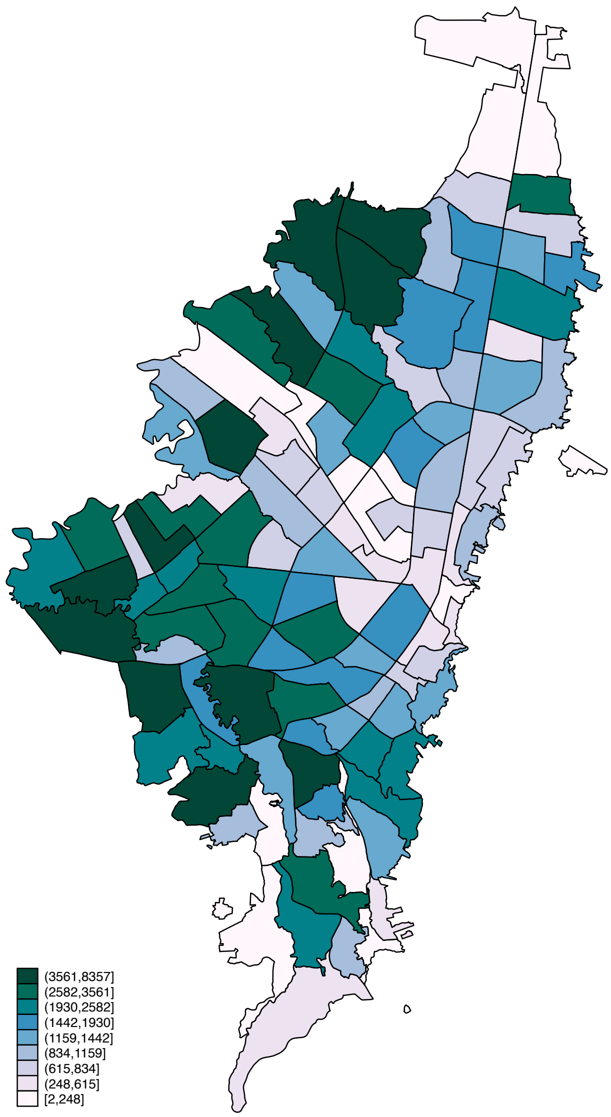


Figure 2: Aggregate number of cases registered by UPZ for the 30 week period starting in March 2, 2020.

On May 30^{th}, the first one was implemented for Kennedy district for two weeks from June 1^{st} June 14^{th}. Afterwards lock downs for Ciudad Bolivar, Engativá and Bosa districts followed. This districts were closed until June 30^{th}. On July 13^{th}, Ciudad Bolivar, San Cristobal, Rafael Uribe, Chapinero, Santa fe, Usme, Martires and Tunjuelito started lock down until July 26^{th}. These district-based lock down continued until August 30^{th}. Figure 10 and **??** shows the district-based lock down time line.

Poverty is concentrated in five districts: Bosa (6%), Ciudad Bolivar (8,7%), Kennedy (4,8%), Usme (8,9%) and Rafael Uribe (6,5%). These places seem to be among the least compliant with non-pharmaceutical interventions, as show in figure 5. We will test this more rigorously in our empirical work.

Subsidies

From March to September more than 350.000 households receive at most three disbursements from the city's government. Total amount in each payment was COP$160,000 (USD$42) per household for people classified as vulnerable and COP$240,000 (USD$63) for those classified as poor. The subsidy amount was small. According to DANE the extreme poverty line is $170.000 (USD$44.6) per person per month, this is the monetary amount necessary to buy food to ingest 2,100 calories per day. Virtually all UPZs in Bogotá had households that received subsidies. There we areas with a higher concentration of subsidies, mainly those in the south and southwest, and a couple of lower income neighborhoods in the northwest as shown in Figure 3.

The subsidies in our data were disbursed in three $waves$ starting in April 29th, May 21th and July 21th. Combining disbursements done by the government and the city each wave got to more than 230,000 people. Not all the households received transfers in all $waves$.

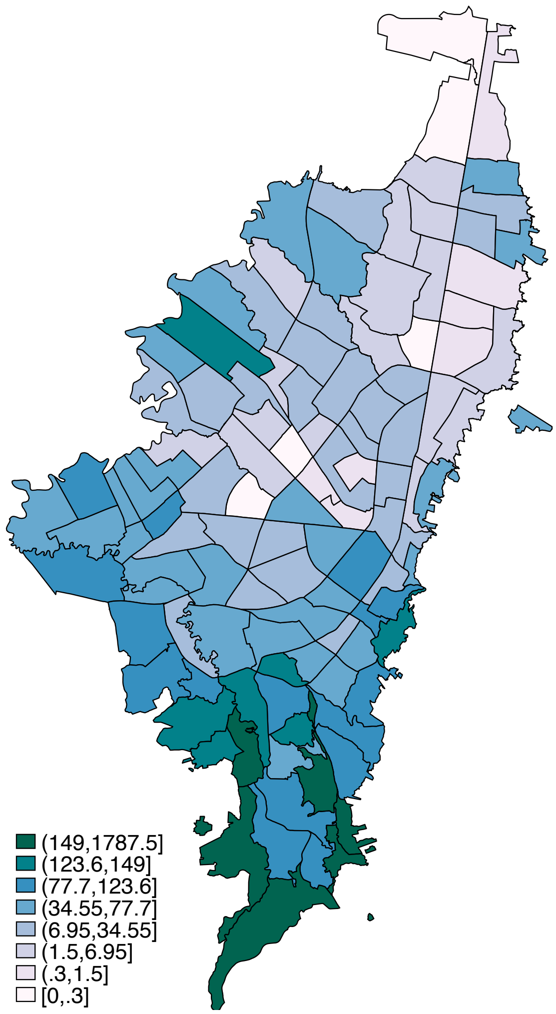


Figure 3: Number of Subsidies (per 100 inhabitants) by UPZ

3.2 Mobility and COVID-19 cases

We now explore the relationship between mobility and cases. Figure 4 shows the association between the growth in mobility and the evolution in COVID-19 cases, relying on a binned scatterplot (see footnote 11) and controlling for week and UPZ fixed effects. Negative numbers in mobility refer to percentage decline with respect to the baseline date. The vertical axis shows the percent change of cases between weeks. As shown, larger falls in mobility are associated with slower increases in cases.

Figure 5 shows that mobility fell in all UPZs after lock down (week 3), although with noticeable heterogeneity. The wealthiest areas of the city, located in the east, had the higher reductions in mobility compared to other areas. People living in these places were able to work from home, had better support networks in case of emergencies

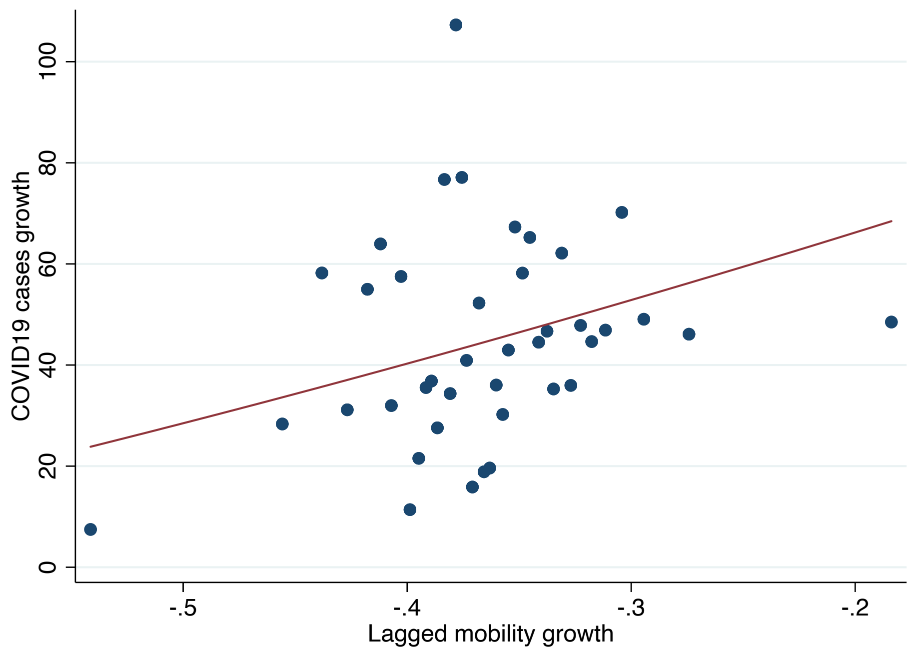


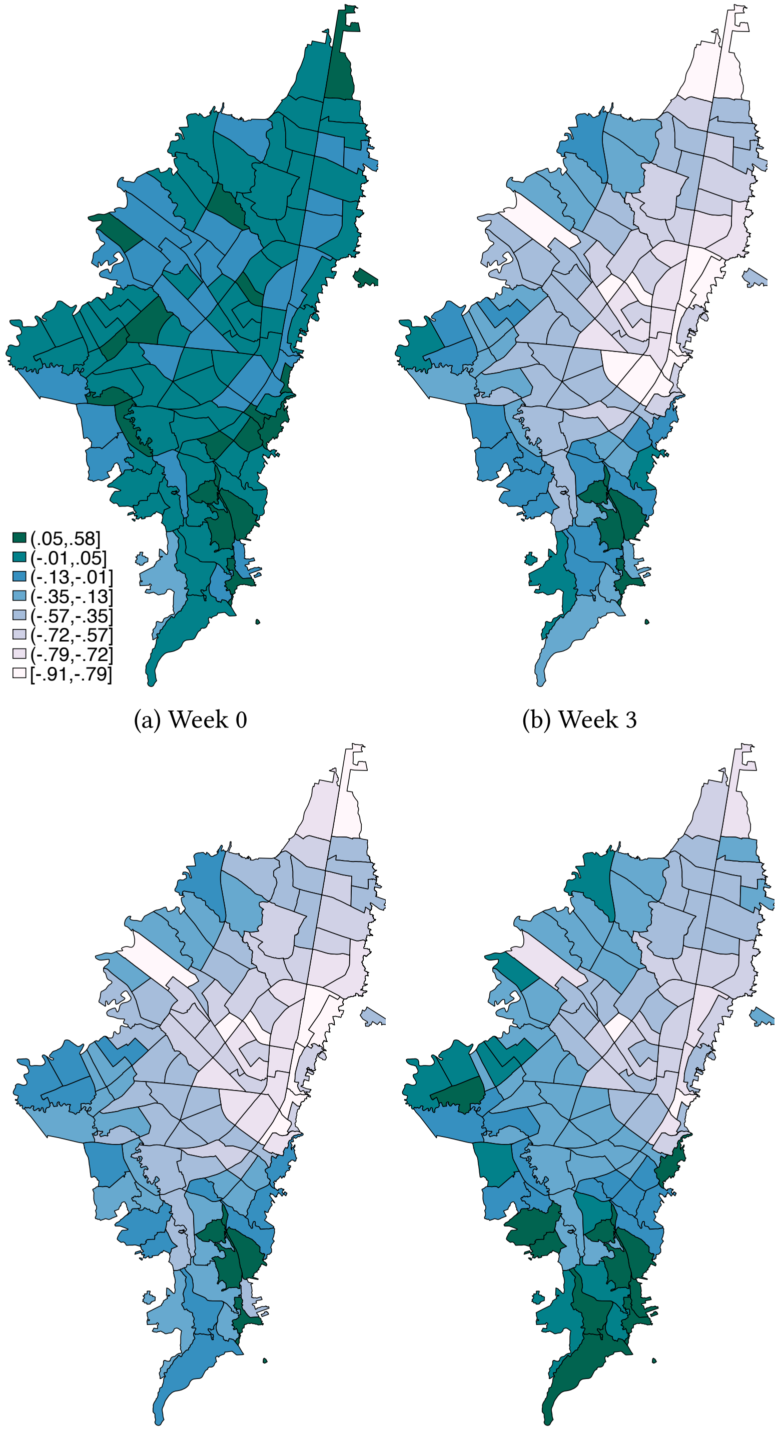
Figure 4: Binned scatterplot showing the relationship between COVID-19 cases and fall in mobility. Binscatter groups all observations in 40 quantiles for simplicity of presentation. The scatter controls for week and UPZ fixed effects. Values in the horizontal axis refer to mobility fall with respect to the baseline date of March 2, 2020, and are lagged one week with respect to cases.

and were therefore more adapted to comply with the measures imposed by the national government. Reductions in mobility last until week 15. In the meantime, in the south of the city, where poorer UPZs are located, we can find the lowest reductions in mobility. In these areas, most of the people do not have formal jobs; mandatory lock down means no income whatsoever for these households. The city centered the subsidies in these poor areas in part to help them to stay at home. High mobility at the south of the city persisted in week 3 to 6 and got worse by week 15 from baseline week.

As a first exploratory analysis of the role of lock down in mobility, in Figure 6 we show the relationship between the general lock down and mobility, controlling for week and UPZ fixed effects. [11] Measurements in this graph are made in a weekly basis. The value of the horizontal axis denotes the share of days under lock down in the considered week. Negative numbers in the vertical axis refer to mobility drops with respect to the baseline date of March 2^{nd}, 2020. As it can be seen, the fall in mobility was significantly larger during weeks with a higher proportion of days

[11] Figure 6 show binned scatterplots. These are a convenient way of observing the relationship between two variables, or visualizing OLS regressions. Binned scatterplots are a non-parametric method of plotting the conditional expectation function (which describes the average y-value for each x-value). Chetty et al. (2014) highlights an example and discussed interpretation of these plots. To generate the binned scatterplot, we group the x-axis variable into equal-sized bins, computes the mean of the x-axis and y-axis variables within each bin, then creates a scatterplot of these data points. We use a linear fit line using OLS and control for covariates before plotting the relationship.

that were under lock down.



(a) Week 0 (b) Week 3

(c) Week 6 (d) Week 15

Figure 5: Mobile phone mobility growth. The map shows the average weekly percentage growth rate with respect to the baseline date (March 2, 2020). Week number is determined relative to the baseline week.

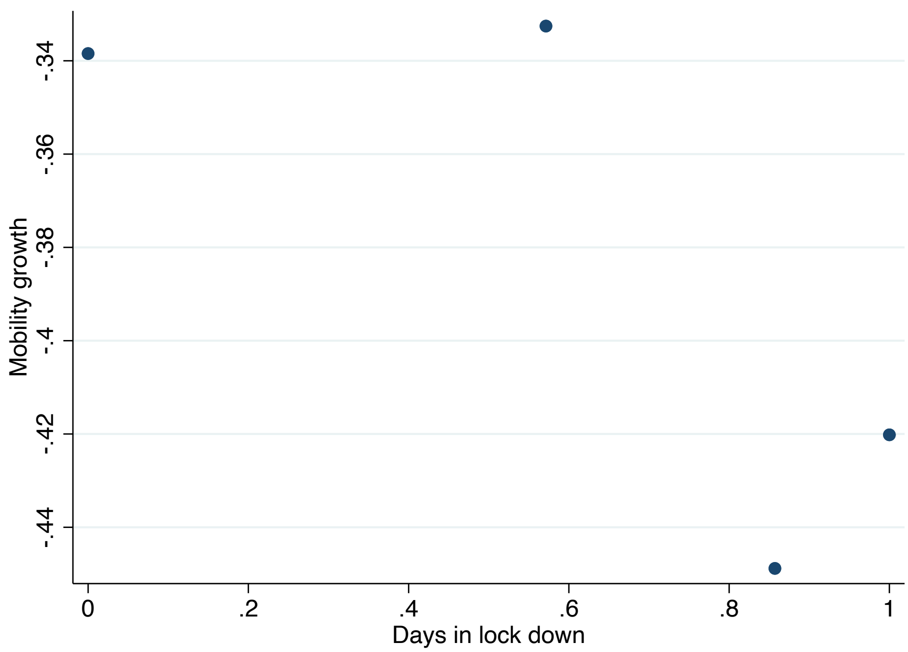


Figure 6: Binned scatterplot showing change in mobility during different levels of lock down. Negative numbers in the vertical axis refer to mobility drops with respect to the baseline date of March 2^{nd}, 2020. The scatter controls for week and UPZ fixed effects.

4 The impact of NPIs on mobility: empirical analysis

To analyze in more depth the impact of the general lock down on mobility we estimate different specifications of the following diff-in-diff type general equation:

$$\ln M_{it} = \gamma_i + \tau_t + \eta LockDown_t + \alpha LockDownDistrict_{it} + \sum_i \beta_i LockDown_t + \epsilon_{it} \quad (1)$$

Observations are week and UPZ combinations. M_{it} is mobility in the week t for UPZ i; $LockDown_t$ and $LockDownDistrict_{it}$ are diff-in-diff type treatment dummies that take a value of 1 when lock down measures are implemented. η captures the effect of the general lock down on mobility, α the effect of district specific lock down[12] which came after the general lock down; γ_i and τ_t are UPZ and week fixed effects respectively. β_i are parameters that measure the relative effectiveness of the NPIs in the different UPZs of the city. For robustness, in some specifications we further include UPZ-specific time trends.

In a second stage, we analyze these estimated coefficients $\hat{\beta}_i$ and test which variables explain their cross-sectional variation, as specified in equation (2):

$$\hat{\beta}_i = \theta_1 P_i + \theta_2 L_i + \theta_1 D_i + \theta_1 S_i + \mu_i \quad (2)$$

P_i, L_i, D_i and Sc_i are vectors of variables measuring UPZ's aggregate poverty, labor market, demographics, infrastructure and other characteristics presented in Table 1. Thus, we are able to explore the differential impact of lockdown measures across the different locations of the city using their initial socio-economic characteristics.

4.1 The impact of lock down on mobility

Using our weekly panel, we start by looking at the impact of general lock down measures on mobility, aiming to estimate parameter η in equation 1. We measure lock down as 0 or 1 depending on whether there was lock down or not that week. Table 2 shows the results. As we can see, the week before general lock down mobility was higher compared to other weeks. By contrast, the weeks of lock down, as well as the week after lock down, mobility was lower and similar in magnitude (see columns 1 to 3). Once we control for UPZ and week fixed effects, results suggest a decrease of around 47% in mobility, compared to baseline mobility (week 0). This average effect stays unchanged even a week after the lock down.

[12] recall there are multiple UPZs in a district

	(1)	(2)	(3)	(4)	(5)	(6)
Week before lockdown	0.30***			-0.08***		
	(0.02)			(0.01)		
Lockdown		-0.11***			-0.47***	
		(0.01)			(0.03)	
Week after lockdown			-0.12***			-0.47***
			(0.01)			(0.03)
R-squared	0.194	0.072	0.031	0.613	0.613	0.613
Observations	1344	1344	1344	1344	1344	1344
UPZ FEs	✓	✓	✓	✓	✓	✓
Week FEs				✓	✓	✓

Standard errors in parentheses

Robust standard errors reported in parenthesis.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 2: The impact of general lock down on mobility

In Table 4 in the Appendix, we check the robustness of our results to measuring lock down continuously from 0 to 1 depending on share of days within of the week affected, with 1 being full lock down the whole week. We also check result to the inclusion of time trend and to the inclusion of UPZ-specific trends. In all cases, we find a significant reduction of mobility due to lock down. Finally, we perform a simple placebo test by generating random assignment of lock downs across weeks and UPZs. As expected we find no significant effect of the placebo.

In Table 3, we explore the potential impact of district-specific lock down beyond the impact of the general lock down. As the Table shows, in lock down weeks, either general lock down or district-specific restrictions, mobility was lower than before NPIs were implemented (see column 1). However, controlling for the impact of the general lock down and its persistence (week effects in column 2 and time trends in column 3), the marginal effect of the district-specific restrictions was minor. The general lock down effect is significantly larger.

	(1)	(2)	(3)	(4)
Lockdown	-0.08***	-0.47***	-0.51***	-0.53***
	(0.01)	(0.03)	(0.03)	(0.03)
Localized lockdown	-0.06***	-0.02**	-0.01	-0.02**
	(0.01)	(0.01)	(0.01)	(0.01)
R-squared	0.051	0.553	0.606	0.575
Observations	2912	2912	2912	2912
UPZ FEs	✓	✓	✓	✓
Week FEs		✓	✓	✓
UPZ Specific $trend$			✓	
Lowckdown heterogeneous effect				✓

Standard errors in parentheses

Robust standard errors reported in parenthesis.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3: Impact of general and localized lock down on mobility

4.2 Exploring the role of subsidies

Another NPI implemented in Bogotá, as discussed before, was the disbursement of subsidies. These were given as a mechanism to help poor and vulnerable people to make up for the income they were not receiving due to the lock down, and also to help them to comply with the restrictions imposed. In Table 5 we explore the role of subsidies. In particular, we want to check whether our results of the impact of lock down is robust to the inclusion of subsidies. We perform the same regression of Table 2 (column 6) and Table 3 (column 4) including the total number of subsidies or alternatively subsidies per capita. When we only include the general lock down, subsidies seem to have had an important effect, and showing an interesting no linearity in Column 5. This non-linearity may suggest that only for high enough disbursement of subsidies mobility may have been reduced. However, once we also control for district-specific restrictions, subsidies are no longer statistically significant (see Column 6). By contrast, the coefficient of the general lock down is highly significant and consistent in value across all the specifications. Overall, subsidies are not effective for reducing mobility, according to our calculations the minimum amount of total weekly subsidies by UPZ with which the effect on mobility start to be negative are around 3,633. Only 4 UPZs receive that amount of subsidies in a specific week.

4.3 The role of socioeconomic characteristics

In this section, we explore the role of socioeconomic characteristics in potentially explaining the heterogeneous impacts on mobility across locations (and given the close relationship between mobility and cases showed before).

Results in column 5 of Table 4 show a sizeable increase in the coefficient of lock down from -47% to -57% once we take into account UPZ-specific lockdown effects, suggesting significant differential effects of lockdown measures across locations. We recover these differential effects on the change in mobility for each location (i.e. β_i coefficients from equation 1). Thus, our recovered β_i compare, for every location of the city, mobility between weeks that were part of the lockdown and weeks that were not, controlling for the average impact of lockdown and taking into account the first 12 weeks of NPIs.These differential effects are shown in Figure 7. The pattern of differential impacts is different from the one explored in the descriptive part of the paper (Figure 5). Some locations lowered their mobility already before the lockdown and therefore the impact of lockdown was small. For the rest of locations, we also see a clear pattern of lower impact of lockdown in locations in the south and west of the city, as well as near the city´s business district center (in the east of the city).

We now rely on specifications given by Equation 2, and explore how different socioeconomic characteristics may explain these differential impacts of lockdown on mobility across locations in Bogotá. We present results of in Figure 8, which shows graphically the main results of Table 6 and 7 (in appendix). We find that locations´s socioeconomic characteristics are indeed significant to partially explain the differential impact of lockdown across locations of the city. The impact of lockdown on mobility was smaller in those areas with lower income and higher informality rate. We also find that areas with higher shared of married population showed more compliance with the lockdown. Additionally, areas with a higher share of households with a refrigerator also showed more compliance with lockdown. [13] These results give evidence that the poorer neighborhoods were less able to comply with the mandatory restrictions and kept a relatively higher mobility, even during the generalized lockdown.

[13]There is a high correlation between the socioeconomic variables presented in Table 1, in some cases the correlation between two variables within the same category can be greater than 0.7 and even across categories the association is high.

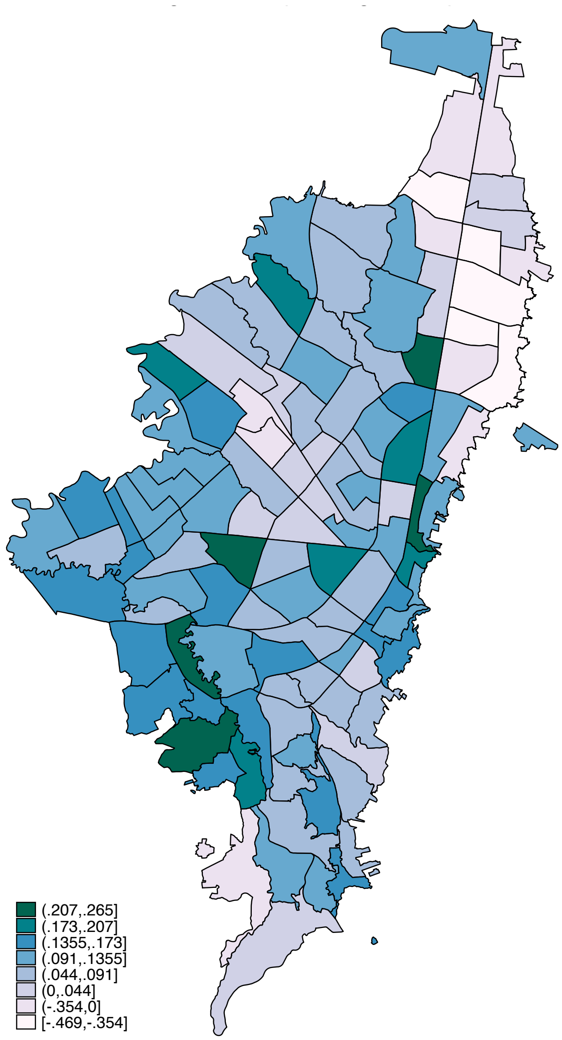


Figure 7: UPZ relative reaction to the general lock down. The values for each UPZ come from the coefficients that allow for a heterogeneous response to the general lock down (the β_i in equation 1).

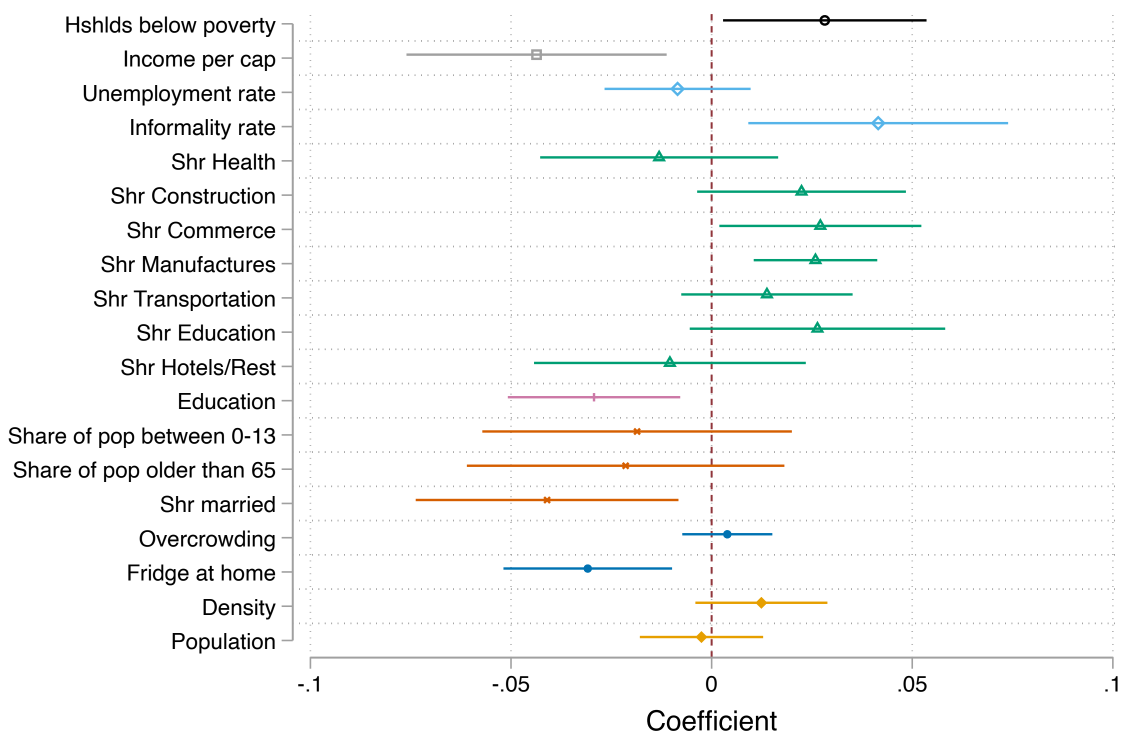


Figure 8: Results from the second stage regressions that explain the heterogeneous reaction tot he general lock down across UPZz. Coefficients shown here are equivalent to the θs from equation 2. Each group of coefficients, identified by color and marker, come form a separate regression. Details are found in Table X in the appendix.

5 Discussion and conclusions

In this paper, we have studied the effect of NPIs on mobility (in terms of *foot traffic*), in a large city in the developing world, namely the city of Bogotá. It implemented a wide range of measures, including a general lock down, location-specific restrictions and the disbursement of subsidies. We have analysed the impact of these measures at a detailed spatial level, looking at differences across locations within the city. We have very heterogeneous spatial effects within the city and those effects are explained by some of the socioeconomic characteristics of each UPZ To do so, we relied on a unique and novel dataset merging localized data on cases, mobility, socioeconomic characteristics and policies implemented during the pandemic. We have found that the generalized lock down reduced mobility in around 47% according to our most preferred specification. And the effect of the general lock down on mobility is even bigger when we look at the UPZ specific fixed effects. We have also found that additional localized restrictions had small marginal affects on mobility.

Our findings also show that poorer neighborhoods were less able to comply with the mandatory restrictions and kept a relatively higher mobility, even during the generalized lock down. In this line of thinking, we found that socioeconomic factors had influence the differential impact of lock down on mobility that we see across locations. The impact of lock down was smaller in those areas with lower income and higher informality rate. Similarly, compliance with lock down was lower in areas with higher share of people in the manufacturing and commerce sectors. Subsidies were not effective to reduce mobility. According to our results it is necessary to give a much higher number of subsidies by UPZ. These follow a non-linear relationship with mobility that starts to be negative when more than 3,633 subsidies a week are delivered while the average delivered per week was 102. However, subsidies per-capita are not significant once we take into account the general an localized lock downs.

In aggregate, our results show that the current pandemic was worse for poorer locations of the city; the romantic view that the pandemic would make us more equal shows to be a fallacy. Richer locations were better prepared for such an exogenous negative shocks. In developing cities like Bogotá, where inequalities are already high, the unequal impact of the Covid pandemic is at the same time reflecting and aggravating the reality of socially fractured urban areas. Addressing this urgent challenge has become more evident than ever. Understanding differences in the response to policies can be very useful for a better targeting of public spending and government interventions during and after the critical period of a pandemic.

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A Appendix

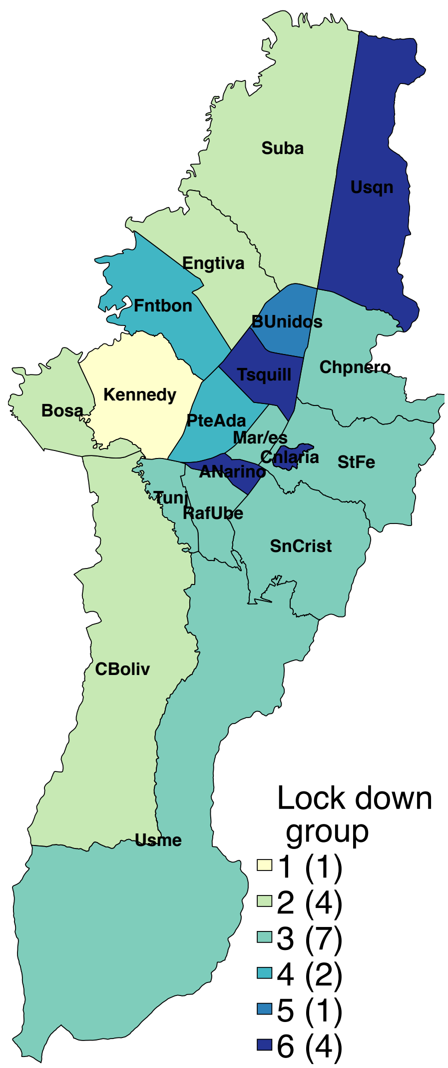

Figure 9: After the first general lock down from March 20 to April 12, 6 localized stay at home orders were implemented by districts. Figure 10 show specific dates and districts in each group G1 to G6. This map shows districts included in each group. The number in the bracket indicates how many districts are in each group. Some districts went through more than one lock down. They are associated with the group with which they experienced their earlier lock down.

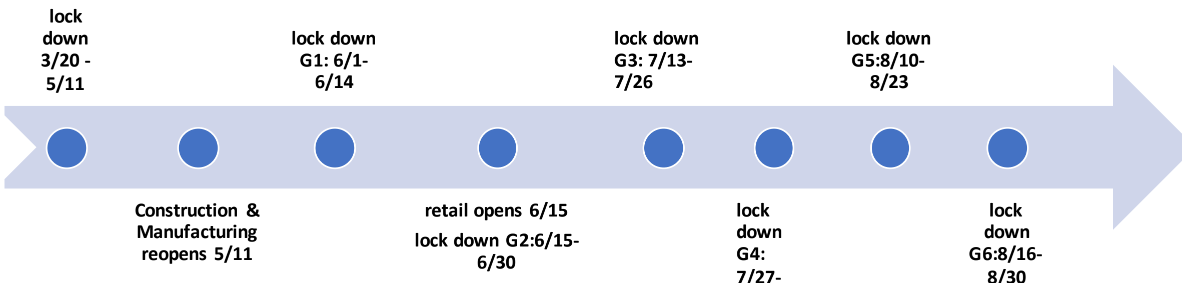

Figure 10: After the first general lock down from March 20 to April 12, 6 localized stay at home orders were implemented by districts, shown in the timeline as groups G1 to G6. The districts included in each were the following: **G1:**Kennedy; **G2:**Ciudad Bolívar, Suba Engativa y Bosa; **G3:**Ciudad Bolívar, San Cristóbal, Rafael Uribe, Chapinero, Santa Fe, Usme, Los Mártires and Tunjuelito; **G4:**Bosa, Kennedy, Puente Aranda, and Fontibón; **G5:**Suba, Engativá, and Barrios Unidos; **G6:** Usaquén, Chapinero, Santa Fe, La Candelaria, Teusaquillo, Puente Aranda, and Antonio Nariño. Some districts went through more than one lock down.

	(1)	(2)	(3)	(4)	(5)	(6)
Lockdown (continuous)	-0.55***					
	(0.03)					
Lockdown		-0.47***	-0.47***	-0.63***	-0.57***	
		(0.03)	(0.03)	(0.02)	(0.03)	
Placebo						-0.01
						(0.01)
R-squared	0.613	0.613	0.613	0.786	0.634	0.786
Observations	1344	1344	1344	1344	1344	1344
UPZ FEs	✓	✓	✓	✓	✓	✓
Week FEs	✓	✓	✓	✓	✓	✓
trend			✓			
UPZ specific *trend*				✓		✓
UPZ specific lock down effect					✓	

Standard errors in parentheses

Robust standard errors reported in parenthesis.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4: Impact of lock downs on mobility

	(1)	(2)	(3)	(4)	(5)	(6)
Lockdown	-0.47***	-0.47***	-0.47***	-0.47***	-0.47***	-0.47***
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
Localized lockdown			-0.02**			-0.02**
			(0.01)			(0.01)
Number of subsidies by UPZ	0.00***	0.00***	0.00***			
	(0.00)	(0.00)	(0.00)			
Subsidies squared		-0.00***	-0.00***			
		(0.00)	(0.00)			
Subsidies per capita				1.29***	4.84**	0.57
				(0.45)	(1.96)	(0.53)
Subsidies per capita squared					-16.39**	-0.27
					(6.66)	(1.38)
R-squared	0.626	0.638	0.561	0.616	0.622	0.554
Observations	1344	1344	2912	1344	1344	2912
UPZ FEs	✓	✓	✓	✓	✓	✓
Week FEs	✓	✓	✓	✓	✓	✓

Standard errors in parentheses

Robust standard errors reported in parenthesis.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 5: Exploring the role of subsidies

	(1)	(2)	(3)	(4)
Hshlds below poverty	0.03*			
	(0.02)			
Income per cap		-0.04**		
		(0.02)		
Unemployment rate			-0.01	
			(0.01)	
Informality rate			0.04**	
			(0.02)	
Shr Health				-0.01
				(0.02)
Shr Construction				0.02
				(0.02)
Shr Commerce				0.03*
				(0.02)
Shr Manufactures				0.03***
				(0.01)
Shr Transportation				0.01
				(0.01)
Shr Education				0.03
				(0.02)
Shr Hotels/Rest				-0.01
				(0.02)
R-squared	0.069	0.164	0.112	0.190
Observations	73	73	73	73

Standard errors in parentheses

Robust standard errors reported in parenthesis.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 6: Impact socioeconomic characteristics on fixed effects (continued in table 7)

	(1)	(2)	(3)	(4)
Share of pop between 0-13		-0.02		
		(0.02)		
Share of pop older than 65		-0.02		
		(0.02)		
Shr married		-0.04**		
		(0.02)		
Overcrowding			0.00	
			(0.01)	
Fridge at home			-0.03**	
			(0.01)	
Density				0.01
				(0.01)
Population				-0.00
				(0.01)
R-squared	0.074	0.137	0.087	0.012
Observations	73	73	73	73

Standard errors in parentheses

Robust standard errors reported in parenthesis.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 7: Impact socioeconomic characteristics on fixed effects (continued from table 6)