Unequal Response to Mobility Restrictions: Evidence from COVID-19 Lockdown in the City of Bogotá.

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In this paper, we study the efficacy of government-mandated mobility restrictions on curbing urban mobility, and estimate the spatial heterogeneity in lockdown compliance. We explore the role of cash subsidies disbursed during lockdown as well as socioeconomic differences across neighborhoods in explaining their unequal response to mobility restrictions. We rely on novel data showing changes in movements at highly disaggregated spatial units in Bogotá, before and during the first wave of the COVID-19 pandemic, matched with data on socioeconomic characteristics as well as data on Non-Pharmaceutical Interventions (NPIs) implemented in the period of analysis. We find that the general lockdown imposed in the city significantly reduced mobility (by about 41pp). When looking at the unequal response across locations, we find that low-income areas, with higher population density, informality and overcrowding, reacted less to mobility restrictions. We also find that cash subsidies were not sufficient to make compliance easier in low-income neighborhoods.

Keywords— mobility, development, inequality, COVID-19, place-based policies.
JEL Codes— R11, R12, I18.

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1 Introduction

Larger and denser cities allow for increased interaction among individuals. While these interactions are the source of productivity-enhancing agglomeration economies , they also increase the risk of disease contagion. The COVID-19 pandemic represents an example, as well as an exogenous shock of great magnitude, dramatically impacting global health and with profound socio-economic and political consequences. In contrast with more highly localized epidemics, like Ebola, COVID-19 quickly acquired a global status, affecting rich and developing countries alike. In response to the pandemic, governments worldwide implemented several Non-Pharmaceutical Interventions (NPIs), including mobility restrictions, to curb the spread of contagions and in some cases to improve the resilience of the health infrastructure.

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In this paper, we study the efficacy of mobility restrictions and direct subsidies on curbing urban mobility. We provide evidence of the unequal response to these policies across different areas of the same city, and how this unequal response depends on socioeconomic differences across within-city locations. Mobility reduction has been one of the main objectives of NPIs and one of the most effective ways to reduce the spread of cases (Glaeser et al., 2020). Consequently, the ability to comply with lockdown largely affects who remains shielded from contagion. We analyze NPIs implemented in Bogotá, Colombia, from March 20th to August 30th, during the first wave of the COVID-19 pandemic, and estimate the extent to which different areas in the city reacted to these policies. We then explore the role of spatial differences in socio-economic factors in explaining this unequal response. While the pandemic's evolution and its diverse and profound consequences are still underway, understanding the heterogeneous impact of measures implemented to date to reduce contagion is essential to guide policy responses in the future.

The pandemic has hard hit Latin America and the Caribbean (LAC) and exacerbated inequality 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). LAC countries implemented several NPIs as the primary tool to contain the COVID-19 pandemic. Governments have banned public gatherings, closed restaurants, and told their residents to stay at home to reduce the virus's contagion speed by reducing mobility and social interaction. Between the virus and the NPIs, the pandemic has brought about unprecedented social and economic shocks too. 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. According to the Colombian National Statistics Department (DANE), by July 2020, around 4 million people had lost their jobs in Colombia, increasing unemployment to 20.2%.[1] Almost 100.000 companies went into bankruptcy despite government subsidies to firms' payrolls and expansion of credit.

Heterogeneous reactions to NPIs can happen as mobility reductions impose a more substantial burden on some households than others. According to Wright et al. (2020), low-income families might have a more difficult time transitioning to teleworking, and lower access to credit and savings availability might hamper compliance of even short lockdowns. For households in the informal sector, safety nets are limited, and compliance is even more costly. Consequently, mobility restrictions may have lower compliance, and more profound economic consequences, in developing 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.[2] Service sector concentrate a high share of informal jobs that are more difficult to be performed from home. According to DANE, informal workers' job loss represents around 52% of the total fall in employment during the pandemic as of June 2020 (DANE, 2020). Similarly, households

[1] Technical bulletin on employment by DANE and be found here:

[2] The National statistics department, DANE, classifies informal workers as those who work in establishments of 5 or fewer workers, unpaid family workers, domestic workers, and self-employed workers, except professional. There is also a high proportion of informal workers who do not contribute to the health and pension systems.

with higher incomes, more access to financial services, and working in formal sectors that can telecommute, are likely to have more options to adjust to confinement measures (Bick et al., 2020; Dingel and Neiman, 2020). These economic realities predict that households of different income levels will have different reactions to the NPIs. In a segregated city, this is reflected in spatial heterogeneity.

To analyze the heterogeneous impact of NPIs, we build a unique dataset combining information on mobility and socioeconomic characteristics at a disaggregated spatial level, with data on NPIs, including lockdown and cash subsidies measures, as well as the evolution of COVID-19 cases. We focus on Bogotá, one of the largest and densest cities in Latin America. Bogotá is well suited for our study. First, it implemented a city-wide lockdown with uniform enforcement throughout the city for more than seven weeks. The country was prominent for having one of the longest lockdowns globally, happening from March 24th to August 31st. Bogotá started it a bit earlier on March 20th. After the general lockdown, some economic sectors were allowed to start operations. Subsequently, the city implemented mobility restrictions in specific within-city areas according to the evolution of cases. We estimate and compare the impact of the city-wide coordinated lockdown with that of localized measures. Second, cash grants or subsidies were distributed for some poor households as a measure to help them stay at home. We analyze the role of these subsidies on mobility restriction compliance. Third, the city presents significant segregation of income over space (Castells-Quintana, 2019), which increases the expected unequal response to lockdown across households and locations in the city.

The literature on NPIs, mobility, and COVID-19 has increased exponentially. A large majority of papers to date have focused on developed countries (Dave et al., 2020) and on cross-city or cross-country comparisons (see Brodeur et al. (2020) for a survey). Barnett-Howell and Mobarak (2020) discuss the differences in trade-offs between the benefits and costs of social distancing experienced by developing and developed countries, highlighting the benefits of studying countries of different income levels to fully understand dynamics and policy consequences. We extend this analysis by analyzing locations of different income levels within a developing city. One strand of the literature has analyzed the socioeconomic determinants of lockdown compliance at a large scale by comparing regions of developed and developing countries (Bargain and Aminjonov, 2020; Askitas et al., 2020), comparing US counties Wright et al. (2020), and comparing cities (Ruiz-Euler et al., 2020; Garcia-Lopez and Puga, 2020) with low and high income levels. Maire (2020) studies the role of income in influencing compliance with mobility restrictions, and showing that these restrictions are more effective in higher-income countries. Our paper contributes to the literature by evaluating the unequal response to mobility restrictions across neighborhoods within a large city in the developing world, and by providing an analysis of potential socio-economic factors behind this unequal response. We look not only at income levels, but also at other factors, including housing infrastructure, overcrowding, education and demographics. By analyze the sectoral composition of the workforce, we also contribute to the literature connecting teleworking capabilities and lockdown compliance (Papanikolaou and Schmidt, 2020).[3] Finally, we further contribute to the literature by analyze the role of cash subsidies in enhancing lockdown compliance. Cash-subsidy programs were implemented in many countries and cities but have been less commonly studied. To the best of our knowledge, one exception being the study by Baker et al. (2020), which finds that the 2020 CARES Act quickly accelerated household spending. This was particularly strong for households with either lower incomes and or greater income drops due to the pandemic, which highlights the importance of studying such programs in lower income areas. Arndt et al. (2020), for South Africa, show how these types of subsidies have even determined who experiences nutritional problems due to lack of food access. Wright et al. (2020) find a significant impact of local stimulus injections on increased social distancing and provide a theoretical foundation for this result that hinges on the relative higher cost of staying at home for lower income households and foregoing income due to this compliance. They find that, for every additional dollar per capita a county received in the US, mobility temporarily declined by over 1 percent.

Our findings suggest a significant impact of the general lockdown on mobility, with an average reduction higher than 40 percentage points. By contrast, we find that the effect of location-specific restrictions on mobility decline is less than 1/10th of the generalized lockdown impact. We found no evidence that the subsidies program implemented was sufficient to improve the compliance with lockdown measures. Looking across neighborhoods, we find considerable heterogeneity in their responses to mobility restrictions. Key neighborhood characteristics explain this heterogeneity. In particular, we find that neighborhoods with lower income, higher population density and high informality rates tend to comply less. Overcrowding, measured as households per unit and persons per room, is also associated with lower compliance to mobility restrictions.

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 pandemic in Bogotá, the NPIs implemented, and the association between mobility and COVID cases. In Section 4, first, we estimate the effect of NPIs on mobility. Then, we estimate neighborhood-specific responses to NPIs and explain these using neighborhood's socioeconomic characteristics. Finally, section 5 concludes and derives policy implications from the results.

2 Data

We use tracked mobility as our primary outcome to measure the impact of the different NPIs implemented. NPIs were aimed directly at reducing urban mobility and, thus, reductions in mobility are the best measure of their efficacy.

We rely on mobile phone tracked movements to determine time spent outside of home. Mobility has a strong

[3] See for also Dingel and Neiman (2020) and Palomino et al. (2020), showing that lockdown and social distance measures implemented in Europe generate unequal increases in poverty and wage inequality.

connection with COVID-19 cases. For instance, Glaeser et al. (2020), using zip code data across five U.S. cities, estimate that total cases per capita decreased by 19% for every 10% percentage point fall in mobility. When controlling for endogeneity concerns, this elasticity becomes 25% and increases to 30% when controlling for neighborhoods' unobserved characteristics. Despite heterogeneity across cities, this qualitative relationship remains uncontested, justifying the focus on mobility when studying the pandemic, and our use of mobility as the main outcome variable.[4]

Our phone mobility data comes from Grandata, a data laboratory focused on progressing the fields of Artificial Intelligence, Machine Learning, and Data Privacy.[5] 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 associated with the user's location at different points in time. The location of this ping is related to a hash of the MADID (Mobile Advertising ID). The average number of geolocation events per user per day is 130. In Bogotá, residency is determined as the location where the user was present more often in an initial baseline period during nighttime hours. The residence location is assigned to a hexagon with a diameter (of the hexagon's circumscribed circle) of 40 meters. The location hexagons follow the Geohash location system.[6] Mobility events are classified as inside or outside of the home depending on whether they are geolocated outside or inside this residence hexagon. Those users who have had less than ten daily events, for example because the mobile phone remained off for a long time, or for whom the data did not capture an entire day because all their pings have happened in less than 8 hours, were filtered out. All events that occurred within the user's residency are deleted, and traffic is determined by the number of events classified as occurring outside of the residence.

The dataset provides the percentage differences in events carried out by mobile users between any date and a baseline date, set on March 2, 2020. Since lockdowns began in Bogotá on March 20th, this data allows us to measure their mobility impact with respect to the baseline date set before restrictions. 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.

To match with our socio-economic data, we aggregate these daily growths at the level of Zoning Planning Units (UPZs for their acronym in Spanish). UPZs are the smallest unit of analysis for urban planning and zoning in the city. There are 112 UPZs in the 19 districts (i.e., "localidades") of the Bogotá.[7] These UPZs are urban areas smaller than districts but larger than a neighborhood. Despite their urban policy role, UPZs are very heterogeneous; For instance, UPZs areas range from 0.8km^2 to 9.2km^2. Their population ranges from 63 to 262K.

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

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

[6]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.

[7]Another administrative division of the city are the *localidades* or districts

An initial concern with our data is how representative phone mobility is of people's total mobility.[8] This boils down to smartphone penetration. Recent data shows this is very high in Colombia, with 84.5% of households having at least one smartphone at home in Bogotá (according to DANE). These households use these devices for around 4.3 hours daily, while 85% of the population state they never leave their phones at home. This supports the use of smartphone technologies to track population mobility. Warren and Skillman (2020) confirm the *fair* sampling of devices in this data source. A collection of apps collects the movement pings on the phone. This assuages the concern that some apps might be biased to collect behavior more or less related to movement (for instance, if the data vendor only used pings from a navigation application, those will capture more distance traveled than an app used at home). Another significant caveat to the accuracy of the statistics we present here is related to systematic sampling errors. This is equivalent to asking whether phone tracking and phone penetration are homogeneous across our spatial units of analysis (i.e., the UPZs). Grandata has a random sampling of mobile phones in the smaller available Geohash hexagons (which have a circumscribed circle with a diameter of 40 meters). These units are significantly smaller than the UPZs (the smallest (average) UPZ has an area equivalent to an associated circle with a diameter of 0.58 (2.05) km). This ensures comparable coverage across all UPZs. The final concern is heterogeneity in smartphone penetration across UPZs. The Multipropósito Survey indicates high penetration across all UPZs despite significant differences in socioeconomic indicators. [9] Finally, a potential correction for coverage heterogeneity is taken by using growth with respect to an initial date. We measure change to the initial condition in each UPZ and then compare the evolution cross-sectionally. As long as the coverage differences across UPZs are constant over time and that the captured movement represents the mobility in the UPZ, the effects we are interested in would be well-identified.

In Figure 1 in each set of vertical dots, each dot represents the average, 5th, 25th, 75th, and 95th percentiles of the change of mobility in a given week. Week zero, the week of reference, includes the day in which mobility change is zero (March 2^{nd}, 2020). Lockdown started in week 2. Positive values indicate increases in mobility with respect to the reference week and negative values show a decline. Figure 2 maps the change in mobility by UPZ. Together, both figures show that mobility fell in all UPZs after lockdown, although with noticeable heterogeneity across locations. These figures indicate that some areas began mobility reduction even before the lockdown. The city's wealthiest areas, located in the east, had higher mobility reductions than other areas. People living in these places were able to work from home, had better support networks in case of emergencies, and were more adapted to comply with the national government's measures. 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 mobility reductions. In these areas, most people do not have

[8] Couture et al. (2021) show that smartphone mobility data are representative of movement patterns in the US similar to conventional survey data.

[9] The average UPZ has 64% of households with smartphones. Penetration ranges between 37% and 85% across the UPZs distribution.

formal jobs; mandatory lockdown means no income whatsoever for these households. The city concentrated cash 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 worsened by week 15, compared to baseline.

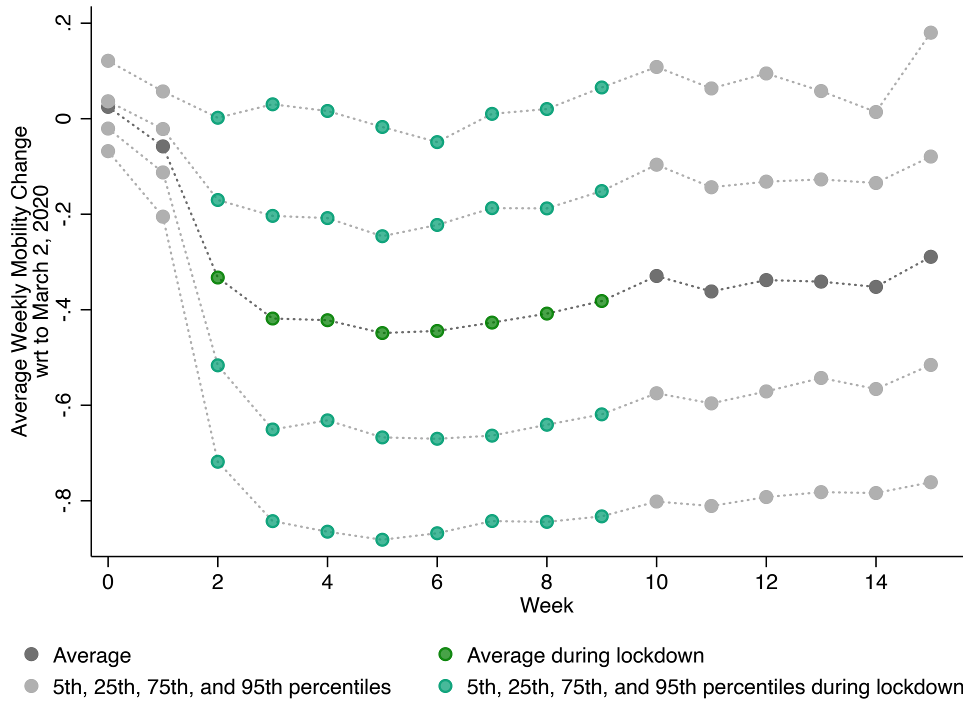
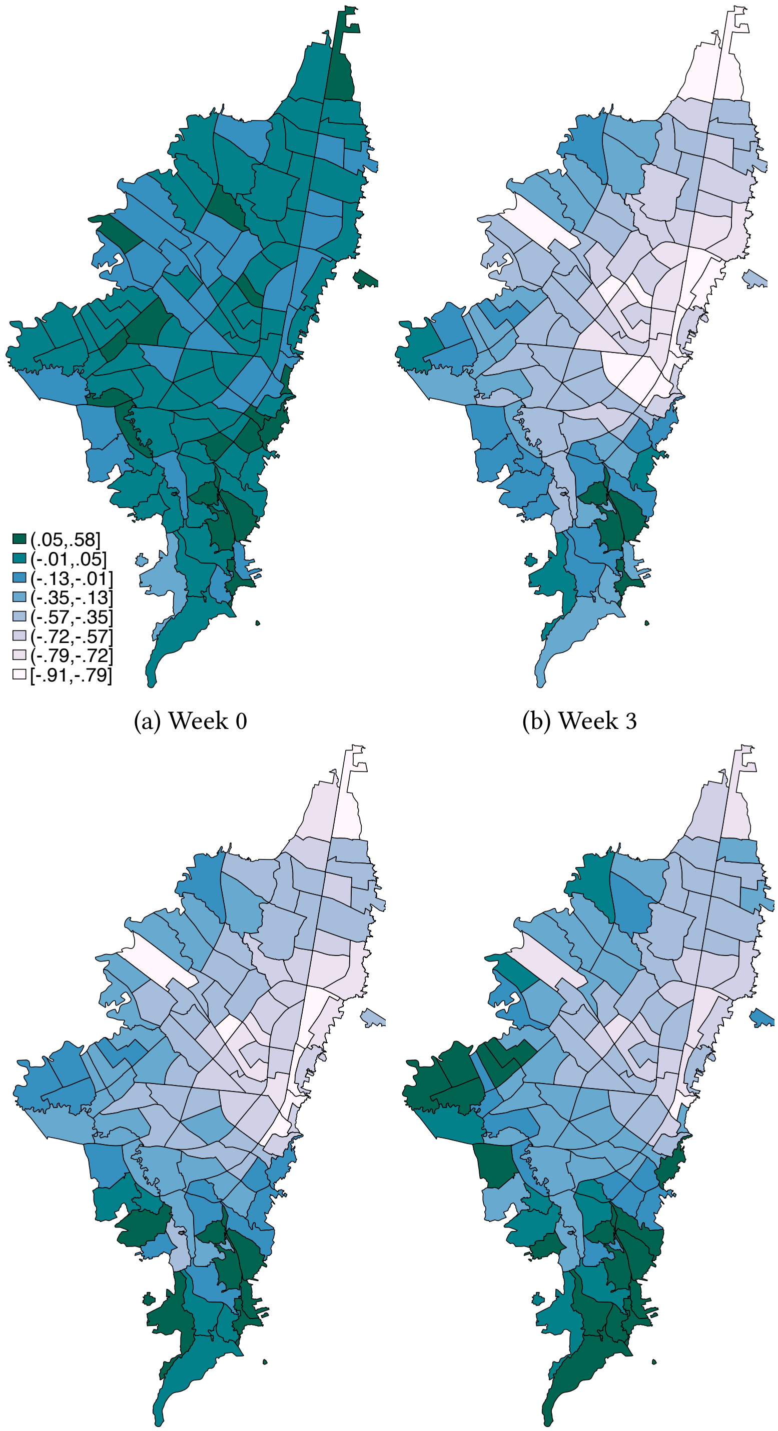


Figure 1: Average and percentiles of UPZ weekly mobility change wrt to March 2, 2020.



(a) Week 0 (b) Week 3

(c) Week 9 (d) Week 15

Figure 2: 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. Week 1 is the week previous to the general lockdown. Week 3 is the first after lockdown. Week 9 is the last week before the lockdown lift.

Source	Variable	Mean	Std. Dev.	Min	Max
Bogota Health Dpt	Covid-19 cases	1,866	1,367	151	7,040
Bogota City Gov	Total subsidies	4,260	4,548	6	18,981
Grandata	Mobility change	-0.3	0.2	-0.7	0.2
Multipurpose Household Survey	*Poverty*				
	Hshlds below poverty (%)	15	10	1	55
	Income per cap *(dollars)*	315	215	80,3	1076,3
	Education	9.0	0.7	7.3	10.5
	Labor market				
	Unemployment rate (%)	8.1	2.3	2.0	14.4
	Informality rate (%)	37.2	11.5	15.0	63.6
	Sector				
	Shr Health (%)	5.8	1.5	2.8	9.1
	Shr Construction (%)	5.7	3.1	1.5	14.9
	Shr Commerce (%)	19.2	4.3	8.6	30.3
	Shr Manufactures (%)	11.9	4.1	4.5	20.4
	Shr Transportation (%)	9.6	2.7	3.5	16.4
	Shr Education (%)	5.5	2.8	1.8	14.8
	Shr Hotels/Rest (%)	4.7	1.7	1.1	10.2
	Shr Finance (%)	3.5	1.7	0.7	7.1
	Shr Real Estate (%)	17.5	3.6	11.1	28.7
	Shr Government (%)	5.9	3.7	0.7	19.0
	Shr Community Serv. (%)	4.6	1.2	2.1	9.0
	Shr Domestic Serv. (%)	1.8	1.3	0.1	6.4
	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				
	Mobile Internet (%)	64.0	11.1	36.7	85.1
	Cooking stove (%)	96.8	1.9	90.3	99.6
	Fridge (%)	94.3	3.9	85.7	99.9
	Overcrowding				
	Person/rooms	1.55746	0.167691	1.2373	1.96384
	Hhlds/unit	1.04582	0.07359	1	1.37432
Census	*Scale*				
	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: Descriptive statistics for the UPZs in our estimation sample.

To explore the role of socio-economic characteristics, we match our mobility data with data from the metropolitan 2017 household-level survey, called the *Multipropósito* Survey, and carried out by the National Statistics Department of Colombia (DANE). This survey includes data on the labor market, housing conditions, poverty, and demographic characteristics. [10] Information about households and individuals is representative at the UPZ level for 73 out of the 112 UPZs. Information about households and individuals is representative at the UPZ level for 73 out of the 112 UPZs [11]

Beyond mobility restrictions, the city government implemented another measure. They put together a data base called *Bogotá Solidaria en casa*, consisting of self-reported people in need and using geographic information about poverty and other socioeconomic conditions, they ranked reported individuals and assigned subsidies to those in extreme poverty, moderate poverty, and considered vulnerable, including people in informality, reaching 709.000 households until September 2020. Subsidies data comes from the city official program website.[12]

Although our focus is on mobility, we also look at the evolution of COVID-19 cases. However, using data on cases has multiple challenges, as COVID testing is not random and uniform, affecting disease prevalence measurement (Niehus et al., 2020; Badr et al., 2020). Besides, in Colombia, the distortions, especially at the beginning of the pandemic, were large because there were long waiting lists for tests processing due to a shortage of locations able to process them.[13] With these caveats, we explore the connection between mobility reduction and the evolution of cases. We use COVID-19 daily cases from Bogotá's Secretariat of Health. 70% of the cases reported the patient's residence address. We geocoded this address and aggregated it at the UPZ level. The database contains the date on which the symptoms started and the laboratory result's diagnosis.

Table 1 presents some descriptive statistics at the UPZ level. Variables gather information about Covid cases, change in mobility, subsidies, demographics, labor market, household infrastructure, and sector-of-employment specific data. Starting with COVID-19 cases, we can see large heterogeneity across locations, from 151 in San Isidro Patios-Chapinero, at the east of the city, up to 7,040 in El Rincon-Suba, in the northwest. This reflects how the pandemic's effects affected differently each of the locations within the same city. The possibility to stay at home is likely to be one of the main factors for this heterogeneous impact. Regarding mobility, as it can be seen, there were important differences across locations: while the average reduction in mobility during the entire period for poorer zones was around 7%, in more affluent zones it was 55%.[14] Regarding subsidies, we also see high heterogeneity across UPZs:

[10] Poverty measures and some labor market variables (such as informality, employment and unemployment) calculated at the individual level using Multipropósito survey were obtained from http://www.sdp.gov.co/gestion-estudios-estratégicos/estudios-macro/encuesta-multiproposito/encuesta-multiproposito-2017

[11] The survey also has information for 17 aggregations of UPZ, however with this information is not possible to recover all UPZs, furthermore given the sample design of these aggregations, when fractioning them, the representativeness is compromised

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

[13] Some papers in the literature rely on SIR and SIR augmented models to account for under reporting of cases (Chudik et al., 2021).

[14] We took the average of the five wealthiest and five poorer UPZs for this calculation.

city authorities gave more subsidies to poorer UPZs. And, as it can be seen, there are significant differences in terms of income. This is also reflected looking at incidence of monetary poverty. Usme and Ciudad Bolivar districts, with a combined population of more than 1 million people, and located in the south of the city, far away from the business center, are among the poorest areas. Labor market outcomes are also quite heterogeneous. Informality in poorer UPZs is higher than 47%, while in more affluent UPZs is below 20%. We find a similar pattern in unemployment: in poorer areas it can be as high as 14.4%, while in the more affluent zones as low as 2%. Regarding economic sectors of employment, richest UPZs concentrate workers who can do their jobs at home and health workers essential to contain the virus. For instance, the share of jobs in the education and healthcare sectors is positively correlated with per capita income, with a correlations of 0.7. By contrast, poorer UPZs concentrated more workers with less possibility of teleworking. The richest UPZs have a higher concentration of workers in education (9%), public (12%) and financial sectors (6%), while in the poorest UPZs these workers represent less than 2%. There is also a larger proportion of construction workers in the poorest UPZs, around 11%, compared to less than 3% in the richest ones. Regarding demographics, it is also important to note that the population is much younger in poorest UPZs. In the wealthiest 5 UPZs, for instance, 10% of the population is above 65 years, while this is only 5% in the poorest UPZs. Finally, poorer UPZs are also denser and more overcrowded, have fewer years of education, and have worse housing infrastructure.

3 The COVID-19 Pandemic in Bogotá

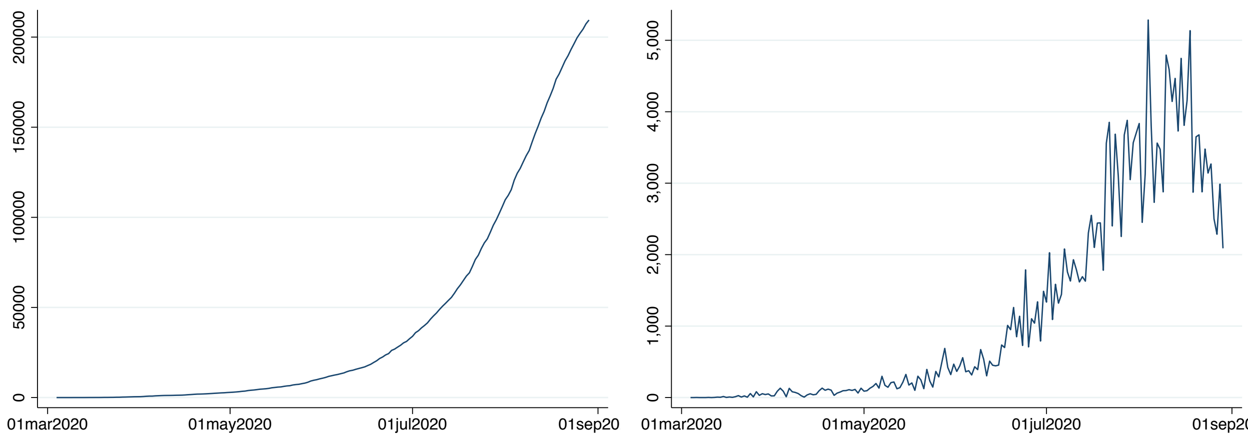
In this section, we provide a quick overview of the context of the first wave of the pandemic in the city of Bogotá, as well as the different NPIs implemented (at the city and district level). We also provide an initial exploration of mobility evolution and the connection between mobility reductions and the evolution of COVID-19 cases.

The first reported case of COVID-19 in the country happened in Bogotá on March 6^{th}. However, according to the city's administration, more than 210,000 people came into the country from Europe or the USA, where the virus was already circulating through air travel between January and February.[15] The lack of international travel restrictions is blamed for the rapid spread of the virus. As of November 30^{th} 2020, there was 374,074 COVID-19 cases, which led to 8,505 deaths.[16] The evolution of cases in the city are shown in Figure 3. Among the positive cases, 51.29% were women, and the average age is 39 years old.

The spatial distribution of cases describes the uneven nature of Covid-19 and slightly follows poverty distribution (see Figure A.1 in Appendix). Poor areas saw more cases and are also the ones with fewer mobility declines. They

[15] The city government provides information in the report of https://Bogotá.gov.co/mi-ciudad/ingreso-de-viajeros-a-colombia

[16] 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 3: The COVID-19 pandemic in Bogotá.

also had higher population densities and worse household infrastructure.

3.1 Non-Pharmaceutical Interventions

Lockdowns

The Bogotá government was the first to announce a lockdown drill for March 20^{th} to 23^{th}. This announcement was followed by a national lockdown presidential declaration, which began on March 24^{th} at midnight and was planned to end on April 12^{th} at midnight. As cases surged, the lockdown was extended to April 27^{th}. During this lockdown, 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 national government allowed the reopening of activities of the construction and manufacturing sectors; companies were allowed to resume operations under local governments' surveillance and authorization. Bogotá stayed closed for two more weeks while they approved the companies that will start operations after visiting them to verify safety protocols. Lockdown was extended for the general public until May 11^{th}.

After the first city-level lockdown was lifted, cases surged. The city started implementing localized restrictions by district. On May 30^{th}, the first one was implemented for Kennedy district for two weeks from June 1^{st} to June 14^{th}. Afterward, restrictions for Ciudad Bolivar, Engativá, and Bosa districts followed. These 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 lockdown until July 26^{th}. These district-level restrictions continued until August 30^{th}. Figure A.2 and A.3 show the district-level restrictions timeline.

As a first exploratory analysis of lockdown in mobility, we show the relationship between the general lockdown and mobility in a binned scatterplot in Figure A.4. Measurements in this graph are made weekly. The value of the horizontal axis denotes the share of days under lockdown 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. The fall in mobility was significantly larger during weeks with a higher proportion of days under lockdown, which indicates that the measures may have had an association with the decline in mobility. In Section 4, we assess the effect of lockdowns on mobility relying on econometric analysis.

Subsidies

More than 350.000 households receive at most three disbursements from the city's government from March to September. The 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 for Bogotá is $176.602 (USD$46.8) per person per month.[17] This line represents the monetary amount necessary to buy enough 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 (see Figure A.5 in Appendix).

The subsidies in our data were disbursed in three *waves* starting in April 29^{th}, May 21^{th} with beneficiaries and July 21^{th} with 118,823, 108,220 and 127,532 payments respectively. 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 $waves$.

3.2 Mobility and COVID-19 cases

As mentioned before, the relationship between mobility and COVID-19 cases has been widely established. In Bogotá, as simple exploration also suggests that COVID-19 cases are associated with mobility. We run a regression of one week lagged mobility on COVID-19 cases, controlling for week and UPZ fixed effects, and find a significant elasticity of mobility to cases of 1.23. This suggests that a drop in mobility of 1% is associated with a decline in the growth of cases of 1.23%. Results are provided in Figure A.6 in Appendix.[18]

But working with COVID-19 cases is difficult, as discussed.[19] Besides these difficulties, our focus on mobility stems from an interest in place based policies. One of the contributions of the paper is to analyze the compliance

[17] Exchange rate used was 3809,523 colombian pesos(COP) per us dollar(USD)

[18] Figures A.4 and A.6 in Appendix 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, compute the mean of the x-axis and y-axis variables within each bin, then create a scatterplot of these data points.

[19] Additional issues include the unobserved rate of adoption of additional measures, like masks, that will affect how social contact is reflected in case growth. There is also disagreement in the optimal lag to use to link mobility and cases (estimated between 7 and 28 days) (Nie et al., 2020).

of a city-wide policy that has significant heterogeneity in adoption. This is important in and of itself. This, together with the established importance of mobility as a way to reduce the disease incidence, and the measurement issues, motivates our choice of mobility as the primary dependent variable.

4 Empirical analysis

To analyze in more depth the impact of mobility restrictions on the evolution of mobility, we estimate different specifications of the following difference-in-difference type equation:

$$\ln \mathrm{M}_{it} = \eta \mathrm{LockDown}_t + \sum_i \beta_i \mathrm{LockDown}_t \gamma_i + \alpha \text{District Specific LockDown}_{it} + \gamma_i + \tau_t + \epsilon_{it} \tag{1}$$

Observations are week and UPZ combinations. M_{it} is the mobility change with respect to the baseline in the week t for UPZ i; $\mathrm{LockDown}_t$ is an indicator for the city-wide initial lockdown. γ_i and τ_t are UPZ and week fixed effects, respectively. η captures the effect of the general lockdown on mobility, and β_i are parameters that measure the unequal response by UPZ to the city-level lockdown. In some specifications, we include District Specific lockdown_{it}, which take a value of 1 when lockdown measures are implemented in the district of UPZ i. α is the average effect of district-specific restrictions. Recall there are multiple UPZs in each district and that the district-specific lockdowns came after the general lockdown with no time overlap. For robustness, in some specifications we further include UPZ-specific time trends $\gamma_i \times \tau_t$.

In a second stage, we use the estimated coefficients $\hat{\beta}_i$ to analyse the role of UPZ's socio-economic characteristics in explaining the unequal response to lockdown across UPZs, as specified in Equation (2):

$$\hat{\beta}_i = \mathbf{P}_i \theta_1 + \mathbf{L}_i \theta_2 + \mathbf{D}_i \theta_3 + \mathbf{S}_i \theta_4 + \mu_i \tag{2}$$

P_i, L_i, D_i and S_i are vectors of variables measuring UPZ's aggregate poverty, labor market, demographics, infrastructure, and other characteristics, as presented in Table 1. The θ parameters explain the role of the initial socio-economic characteristics in explaining the heterogeneity in the mobility changes across UPZs as a reaction to the general lockdown.

4.1 The impact of lockdown on mobility

Using our weekly panel, we start by looking at the impact of general lockdown measures on mobility estimated through parameter η in Equation 1. Table 2 shows the results. In columns 1 to 3 we include UPZ fixed effects, while in columns 4 to 6 we further include week fixed effects. Once we control for UPZ and week fixed effects (see column

5), results suggest a decrease of around 41 percentage points in mobility compared to baseline mobility (week 0). This average effect lowers but stays relatively high even a week after the lockdown (see column 6). The coefficient for the week before lockdown shows that even before the implementation of mobility restrictions, voluntary reductions of mobility are detected (see column 4).

	Percentage change in mobility						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Week before lockdown	0.30***			-0.08***			
	(0.02)			(0.01)			
Lockdown		-0.20***			-0.41***		-0.56***
		(0.01)			(0.03)		(0.02)
Week after lockdown			0.01			-0.35***	
			(0.01)			(0.03)	
R-squared	0.191	0.278	0.000	0.605	0.605	0.605	0.722
Observations	1456	1456	1456	1456	1456	1456	1456
UPZ FEs	✓	✓	✓	✓	✓	✓	✓
Week FEs				✓	✓	✓	✓
UPZ Specific Lockdown Effect							✓

Robust standard errors reported in parenthesis. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 2: The impact of general lockdown on mobility

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

In Table 3, we include district-specific lockdowns in the setup of Equation 1. Both general and district-specific lockdowns cause a decline in mobility. However, after controlling for the general lockdown's impact and its persistence (week effects in column 2 and time trends in column 3), the district-specific restrictions' the effect is minor.

	Percentage change in mobility			
	(1)	(2)	(3)	(4)
General Lockdown	-0.10***	-0.41***	-0.47***	-0.48***
	(0.01)	(0.03)	(0.03)	(0.03)
District-specific Lockdown	-0.08***	-0.01**	-0.02***	-0.00
	(0.01)	(0.01)	(0.00)	(0.01)
R-squared	0.105	0.552	0.606	0.608
Observations	2912	2912	2912	2912
UPZ FEs	✓	✓	✓	✓
Week FEs		✓	✓	✓
UPZ Specific trend			✓	
Lockdown heterogeneous effect				✓

Robust standard errors reported in parenthesis. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3: Impact of general and localized lockdown on mobility

Another NPI implemented in Bogotá was the disbursement of cash subsidies, as explained before. These were aimed at helping poor households make up for lost income and enhancing lockdown compliance. In Table 4 we explore the role of subsidies. To do so, we extend Equation 1 to include subsidies per capita. Results in column two show that subsidies are correlated with more, rather than less, mobility. One possible interpretation is that these cash transfers increased traffic through their effect in increasing purchasing power. Baker et al. (2020) find that the 2020 CARES Act, which delivered subsidy checks to US households, quickly accelerated household purchases, with spending increasing by $0.25 to $0.40 per dollar of stimulus during the first weeks. This was particularly strong for households with lower incomes and greater income drops due to the pandemic. With lower access to online purchases in a context of low income, this additional consumption could be reflected in additional traffic, hence lower compliance of the lockdown. However, when we interact subsidies with the general lockdown (see column 3), capturing the compliance induced by subsides when the general lockdown was in place, the coefficient is not statistically significant.

Finally, in column 4, we allow for potential non-linearities by introducing the square of subsidies per capita. As it can be seen, the interaction between linear and square subsidies with lockdown are not statistically significant. When general lockdown was not in place, our results suggest the importance of the magnitude in the number of subsidies disbursed: only a high level of subsidies appear as potentially decreasing mobility. According to estimates, for subsidies to decrease mobility, the amount of per capita weekly subsidies by UPZ should have been much higher than the actually disbursed. Only 2 UPZs (Parque Entrenubes y El Mochuelo) appear to have received the minimum amount needed.[20] This explains why our findings may be contrary to the findings of Wright et al. (2020). The amount

[20]There are caveats on this prediction of the threshold of subsidies, precisely because we observe very few UPZs with this level

of the each of the 2020 CARES Act subsidy check disbursed in the US corresponds to around 5% of the annual income of the median household (assuming a family of 4). By contrast, the subsidies distributed in Bogotá only corresponded to a 0.6% of the annual income of the median household in Colombia.

	Percentage change in mobility			
	(1)	(2)	(3)	(4)
Lockdown	-0.41***	-0.41***	-0.41***	-0.42***
	(0.03)	(0.03)	(0.03)	(0.03)
Lockdown × Subsidies/cap			-0.09	-0.68
			(0.22)	(1.39)
Lockdown × Subsidies/cap^2				-0.57
				(5.40)
Subsidies/cap		1.11***	1.16***	4.84**
		(0.34)	(0.29)	(2.00)
Subsidies/cap^2				-13.26**
				(6.01)
R-squared	0.605	0.609	0.609	0.615
Observations	1456	1456	1456	1456
UPZ FEs	✓	✓	✓	✓
Week FEs	✓	✓	✓	✓

Table 4: Exploring the role of subsidies

4.2 The role of socioeconomic characteristics on the unequal response to lockdown

So far, our analysis has shown a very consistent and robust impact of the general lockdown in reducing mobility in Bogotá. In this section, we now explore the role of socioeconomic characteristics in explaining the heterogeneous response to lockdown measures across within-city locations. We recover differential effects on the change in mobility for each location (i.e., β_i coefficients from Equation 1). Recall the dependent variable in these regressions is the change in mobility in the UPZ with respect to the baseline week. The estimated β_is 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, η, and taking into account the first 12 weeks of NPIs. These results correspond to column 7 of Table 2 where we obtain a fall in the average mobility of 56.5pp after the general lockdown was established. $\hat{\beta}_i$ therefore gives the additional percentage growth or decline in mobility with respect to the average effect of the

of subsidies. Hainmueller et al. (2019) suggest do not make predictions outside of the common support.

lockdown. These differential effects are shown in Figure 4.[21]

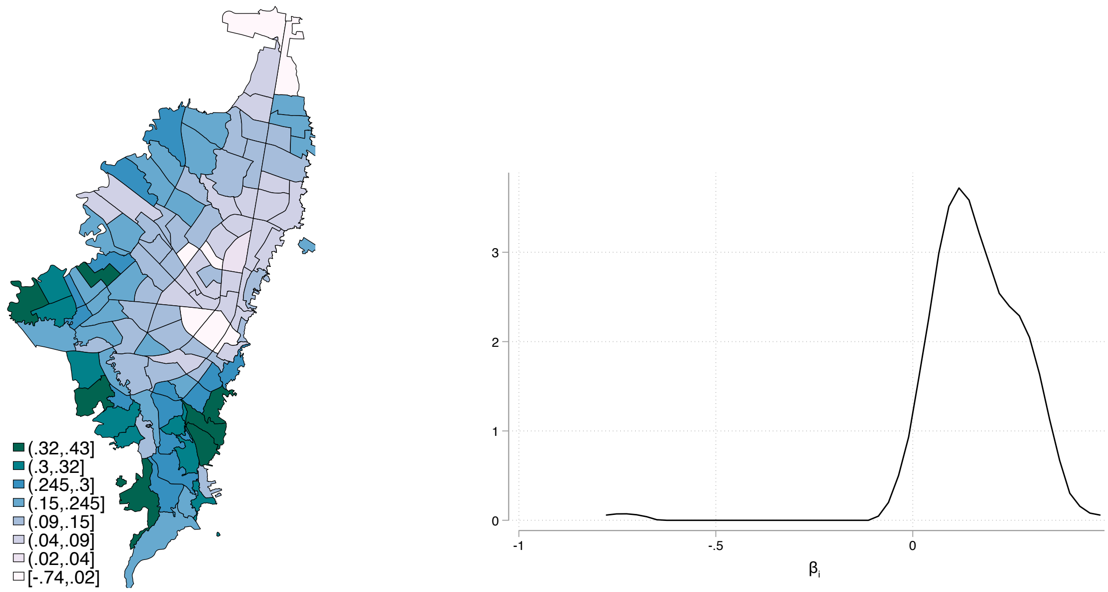


Figure 4: UPZ relative reaction to the general lockdown. The values for each UPZ come from the coefficients that allow for a heterogeneous response to the general lockdown (the β_i in equation 1).

The left panel of Figure 4 shows the $\hat{\beta}_i$ point estimates in the city map, and the right panel shows the distribution of these estimates. The strongest decline in mobility happened in high-income UPZs most of them localized at the north of the city. In some of these wealthy areas it was notorious for many households fleeing out to their vacation homes, a pattern detected, for instance, in the wealthy neighborhoods of New York City (Kim et al. (2021) ; Coven et al. (2020)). In these locations, the point estimate for the change in mobility beyond the average is around -25pp, which amounts to a total decline of about -80pp with respect to the baseline date. By contrast, the weakest decline in mobility is observed in the southwest and southeast of the city, where there is a high concentration of low-income neighborhoods with high informality levels. In these locations, the point estimate for the UPZ specific mobility change is around 35pp, implying a total change in mobility of around -21pp. Despite the heterogeneity in compliance, all UPZs reacted to the lockdown with an absolute decline in mobility.

We now estimate specifications of the general form of Equation 2 and explore how different socioeconomic characteristics explain these differential responses to lockdown. The socioeconomic characteristics are standardized

[21] Hainmueller et al. (2019) highlight two problems of this type of multiplicative interaction models. First, these models assume a linear interaction effect that changes at a constant rate with the moderator. This is an issue when the treatment variable (lockdown in our analysis) is either binary or continuous and the moderator (UPZ indicator in our analysis) is continuous. When both are binary, as in our case, they suggest using a fully saturated model that dummies out the treatment and the moderator and includes all interaction terms, the approach we follow. Second, estimates of the conditional effects of the independent variable can be misleading if there is a lack of common support of the moderator. This is not an issue, again, because all levels in the interaction terms are parameterized as dummy variables.

to ease comparison. We present results in Figure 5, which shows graphically the main results of regressions in Tables A.2 and A.3 (in Appendix). Each group of coefficients, identified by color and marker, comes from a separate regression.[22]

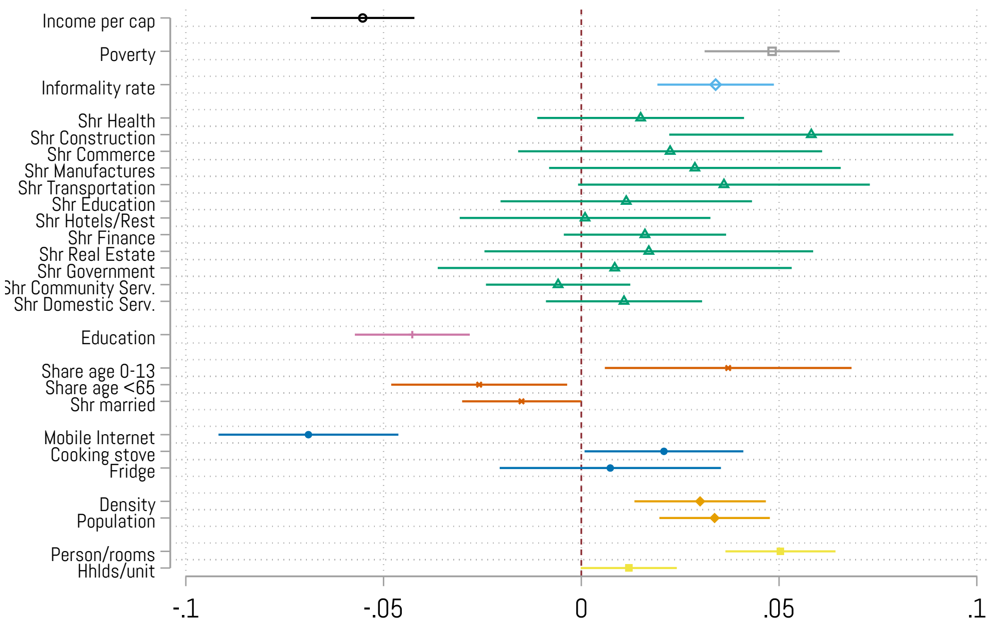


Figure 5: Results from the second stage regressions that explain the heterogeneous reaction to the general lockdown across UPZz. Coefficients shown here are equivalent to the θs from equation 2. Each group of coefficients, identified by color and marker, comes from a separate regression. Details are found in Tables A.2 and A.3 in the appendix.

First, we find that higher income per capita is associated with a stronger decline in mobility following the lockdown: an increase of one standard deviation in this variable is associated with an additional decline of 6pp in mobility. Similarly, an increase of one standard deviation in the multidimensional poverty index (mpi) (UNDP, 2015; Initiative et al., 2018) is associated with 5pp higher mobility.[23] Informality, as expected, is also associated with lower compliance. Together, these results show the decisive role of income in lockdown compliance, in line with (Bargain and Aminjonov, 2020), comparing regions of developed and developing countries, Wright et al. (2020), comparing US counties, and (Ruiz-Euler et al., 2020), comparing cities with different income levels. Results are also in line with the idea of a relative higher cost of staying at home for lower income households (see Wright et al. (2020). In a developing country context, the relative cost of staying at home for lower-income individuals is expected to be even

[22] We estimate several regressions taking into account that there is a high correlation between several of the socioeconomic variables presented in Figure 5.

[23] The mpi is a comprehensize poverty measure, which complements traditional monetary poverty measures with deprivations in health, education, and living standards.

higher.[24]

Second, we analyze the sectoral composition of workers across UPZs. Related work has highlighted that professions associated with teleworking capabilities are concentrated in higher income households (Papanikolaou and Schmidt, 2020), providing another possible mechanism for higher compliance beyond income. Using the sectoral information from the *Multipropósito* survey, we build a measure of the share of workers per sector in each UPZ. We remove any sector that presents less than 1 percent of workers. Only construction resulted to be positively related with mobility which is consistent with the fact that this was one of the first sectors to start operations. Otherwise, we find little significant role of sectoral composition in explaining heterogeneous compliance across UPZs. However, as hinted by Table 1, a possible explanation is the relative dispersion of individuals in different sectors across the areas of the city.

Third, and in terms of demographics, we find that education, measured as the average number of years of education for household members above 12 years of age, is significant and associated with higher compliance. An increase of one standard deviation, corresponding to 1 additional year in UPZ average education, is associated with 4pp lower mobility, in line with (Haug et al., 2020) and Brzezinski et al. (2020). Other demographic characteristics show behavior corresponding to different levels of risk: UPZs with a higher share of younger people comply less, while those with a higher share of older and married people comply more.

Fourth, we look at the role of home infrastructure. The city shows a significant prevalence of precarious home conditions. For example, the share of households without a fridge goes up to 15% in the UPZ with the worst numbers, while the share of households without a cooking stove goes up to 10%. But these factors do not seem to critically influence compliance. Access to home internet, however, is highly associated with compliance: an increase of one standard deviation in the share of households with internet access is associated with a decline of mobility of an additional 7pp, the strongest of all factors studied. The access to home internet variable still shows large variation across households and UPZs, ranging from 36% to 85%. The role of the internet in allowing children to take school remotely and to telework is well known (Vogels et al., 2020). Akim and Ayivodji (2020) report that internet access enhances lockdown compliance at the country level, in a sample of African countries.

Finally, population size and density, as well as overcrowding, are all associated with lower compliance. An increase of one standard deviation in overcrowding, for instance, is associated with 5pp higher mobility in the UPZ. This result is in line with previous evidence showing that the sharing of a smaller space makes COVID19 incidence higher (Center, 2020). The result for overcrowding is a much stronger factor than mere residential density, as for instance in results for the US.

[24] Wright et al. (2020) find that counties with above median income comply with lockdown by reducing movement by an additional 72% relative to the average effect. Our results are significant but less stark, although not directly comparable as we focus on variation in compliance within the same city.

5 Discussion and conclusions

In this paper, we have studied the effect of some NPIs on mobility (in terms of *foot traffic*) in a large city in the developing world, namely Bogotá. The city implemented a wide range of measures, including a city-level lockdown, location-specific restrictions, and the disbursement of cash subsidies. We have analyzed these measures' impact at a detailed spatial level, looking at differences across within-city's locations. To do so, we relied on a unique and novel dataset merging localized data mobility, policies implemented during the pandemic, socioeconomic characteristics, and the evolution of COVID-19 cases. According to our most preferred specification, we have found that the city-level lockdown reduced mobility, on average, by around 41pp. Beyond this effect, localized district-specific restrictions seem to have had small marginal effects on mobility. But we have also found very heterogeneous spatial effects within the city. Our analysis suggests that this unequal response in mobility is partly explained by differences in socioeconomic characteristics across within-city locations.

According to our results poorer neighborhoods were less able to comply with the mandatory restrictions and kept relatively higher mobility, even during the generalized lockdown. The lockdown impact was also smaller in areas with with higher population density, informality and overcrowding. We also found that subsidies were not effective in reducing mobility; according to our results, it would have been necessary to give a much higher number of subsidies by UPZ to achieve that goal.

Overall, our results show that the current pandemic was worse for poorer locations of the city. Richer locations were better prepared for such an exogenous negative shock. In developing cities like Bogotá, where inequalities are already high, the unequal impact of the COVID-19 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 response to policies can help better target public spending and government interventions during critical moments, such as new general or localized lockdowns. These results also entail new challenges for policy makers in order to develop effective solutions in situations of emergency. Intrinsic limitations of people given by their income, by the characteristics of their houses, or by the economic sector they are working in must be taken into account to design NPI's such as cash subsidies, that must be granted in the right amounts. Other wise compliance with NPIs will be small representing a risk, not only to these populations but to the entire society.

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A Appendix

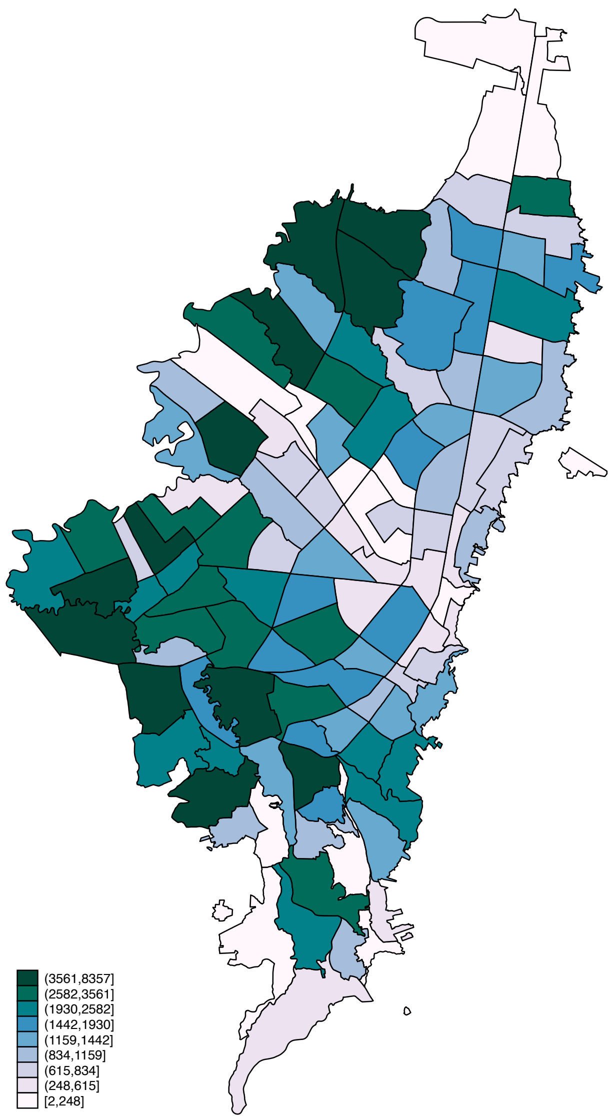

Figure A.1: Aggregate number of cases registered by UPZ for the 30 week period starting in March 2, 2020.

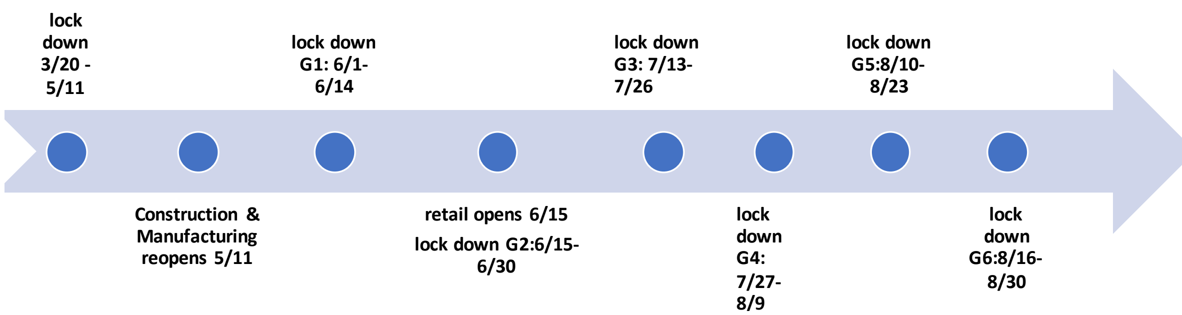

Figure A.2: After the first general lockdown, 6 localized stay at home orders were implemented by districts, shown in the timeline as groups G1 to G6. The districts included in each were the following: **G1:**Kennedy; **G2:**Ciudad Bolívar, Suba Engativa y Bosa; **G3:**Ciudad Bolívar, San Cristóbal, 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 lockdown.

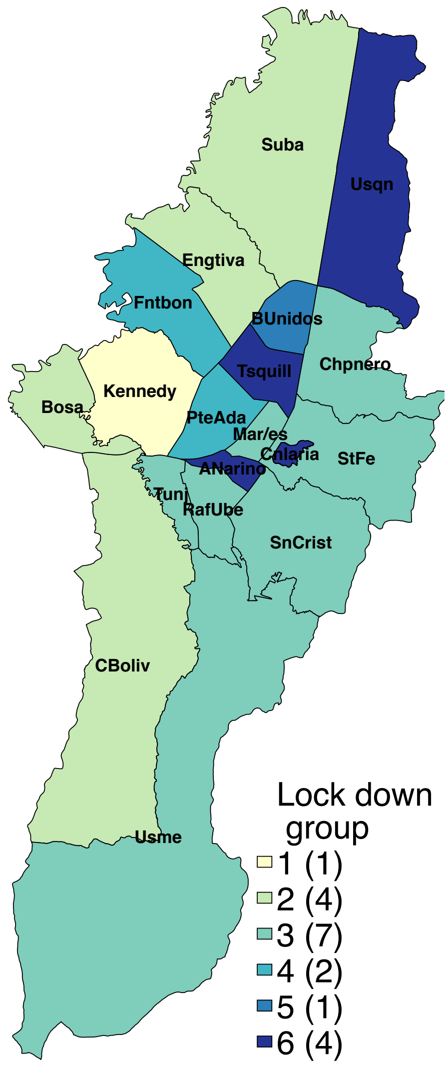

Figure A.3: After the first general lockdown from March 20 to April 12, 6 localized stay at home orders were implemented by districts. Figure A.2 show specific dates and districts in each group G1 to G6. This map shows districts included in each group. The number in the bracket indicates how many districts are in each group. Some districts went through more than one lockdown. They are associated with the group with which the experienced their earlier lockdown.

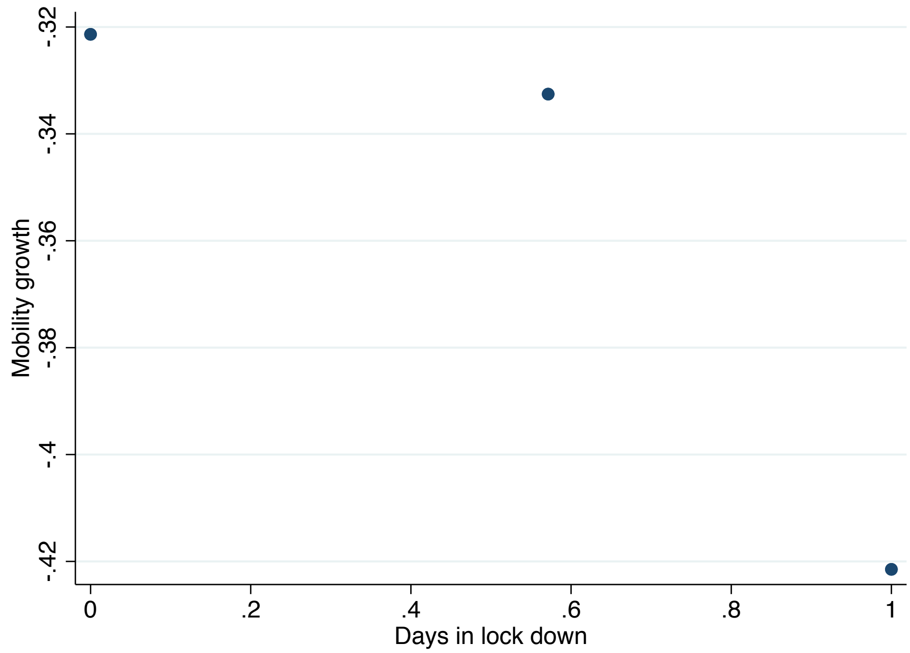

Figure A.4: Binned scatterplot showing change in mobility during different levels of lockdown. Negative numbers in the vertical axis refer to mobility drops with respect to the baseline date of March 2, 2020.

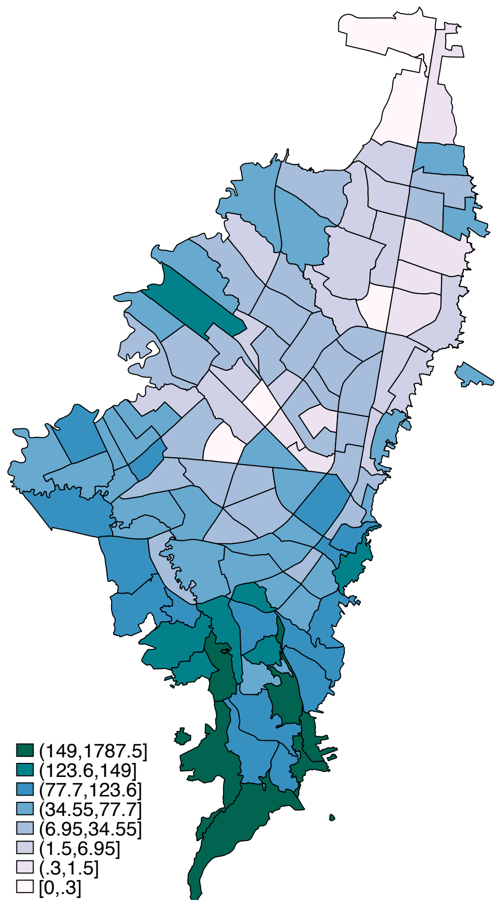

Figure A.5: Number of Subsidies (per 100 inhabitants) by UPZ

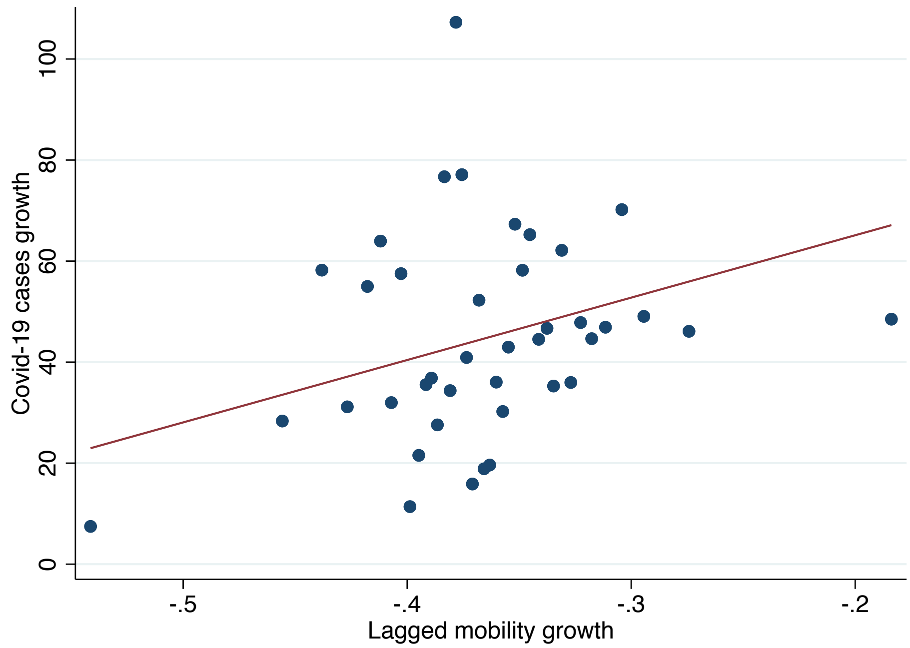

Figure A.6: Binned scatterplot showing the relationship between COVID-19 cases and fall in mobility. Binscatter groups all observations in 40 quantiles for simplicity of presentation. The scatter controls for week and UPZ fixed effects. Values in the horizontal axis refer to mobility fall with respect to the baseline date of March 2, 2020, and are lagged one week with respect to cases.

	Percentage change in mobility					
	(1)	(2)	(3)	(4)	(5)	(6)
Lockdown (continuous)	-0.41***					
	(0.03)					
Lockdown		-0.41***	-0.41***	-0.66***	-0.56***	
		(0.03)	(0.03)	(0.02)	(0.02)	
Placebo						-0.01
						(0.01)
R-squared	0.605	0.605	0.605	0.752	0.722	0.752
Observations	1456	1456	1456	1456	1456	1456
UPZ FEs	✓	✓	✓	✓	✓	✓
Week FEs	✓	✓	✓	✓	✓	✓
trend			✓			
UPZ specific trend				✓		✓
UPZ specific lock down effect					✓	

Robust standard errors reported in parenthesis. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.1: Impact of lockdowns on mobility

	UPZ mobility premium				
	(1)	(2)	(3)	(4)	(5)
Income per cap	-0.06***				
	(0.01)				
Poverty		0.05***			
		(0.01)			
Informality rate			0.03***		
			(0.01)		
Shr Health				0.02	
				(0.02)	
Shr Construction				0.06***	
				(0.02)	
Shr Commerce				0.02	
				(0.02)	
Shr Manufactures				0.03	
				(0.02)	
Shr Transportation				0.04	
				(0.02)	
Shr Education				0.01	
				(0.02)	
Shr Hotels/Rest				0.00	
				(0.02)	
Shr Finance				0.02	
				(0.01)	
Shr Real Estate				0.02	
				(0.02)	
Shr Government				0.01	
				(0.03)	
Shr Community Serv.				-0.01	
				(0.01)	
Shr Domestic Serv.				0.01	
				(0.01)	
Education					-0.04***
					(0.01)
R-squared	0.386	0.294	0.146	0.589	0.231
Observations	73	73	73	73	73

Robust standard errors reported in parenthesis.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.2: Impact of socioeconomic characteristics on UPZ mobility premium captured by interaction coefficients, the β_i from equation 1 (continued in table A.3)

	UPZ mobility premium			
	(1)	(2)	(3)	(4)
Share age 0-13	0.04*			
	(0.02)			
Share age >65	-0.03*			
	(0.01)			
Shr married	-0.02*			
	(0.01)			
Mobile Internet		-0.07***		
		(0.01)		
Cooking stove		0.02*		
		(0.01)		
Fridge		0.01		
		(0.02)		
Density			0.03***	
			(0.01)	
Population			0.03***	
			(0.01)	
Person/rooms				0.05***
				(0.01)
Hhlds/unit				0.01
				(0.01)
R-squared	0.639	0.420	0.333	0.369
Observations	73	73	73	73

Robust standard errors reported in parenthesis.

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

Table A.3: Impact of socioeconomic characteristics on UPZ mobility premium captured by interaction coefficients, the β_i from equation 1 (continued from table A.2)