Imposing restrictions in the fight against COVID-19: the case of Bogotá

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Imposing restrictions in the fight against COVID-19: The case of Bogotá [*]

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Abstract

Most middle and low-income countries developed their strategies against the COVID-19 spread based on measures designed by high-income countries. The literature shows that costs are higher in the first group, so computing the benefits of the measures is crucial to making decisions by policymakers. I use a difference-in-differences approach to estimate the effect of increasing the restrictive measures in Bogotá (Colombia) on the mortality rate. Specifically by implementing targeted lockdowns by locality. I find that there is no statistically significant effect even in the presence of spillovers. Also, I do not observe evidence of non-compliance drivers in the heterogeneity analysis. Using mobility data, I find that the main mechanism to explain these results is that people reduced mobility in Public Transport, which was guarded by authorities but did not reduce their mobility when they did not perceive that they were being watched. One of the possible interpretations of this result is given that there were other measures at the same time and a potential "wear effect", the implementation of new more restricted measures has not a significant effect on the existing measures.

Keywords: COVID-19; Lockdowns;

1 Introduction

None of the countries were prepared to face a pandemic with the characteristics of the COVID-19 pandemic, but more developed countries led the response. One of the differential factors in this pandemic concerning others like Ebola was where the virus began.

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On that occasion, while Africa faced the consequences of the Ebola spread, the rest of the high-income countries were preparing their protocols. This time, the virus affected first high-income countries. To reduce the propagation of this virus and based on their characteristics, their governments decided to impose different constraints on mobility through lockdowns. The main idea behind these measures was to *flatten the curve* to reduce a likely exceed on hospitals capacity (Miguel and Mobarak, 2021). In this way, they reduce the number of deaths, the primary concern of this pandemic. However, the costs of implementing these measures were very high in terms of different issues such as economic (Padhan and Prabheesh, 2021; Baker et al., 2020) and mental health (Hossain et al., 2020). The cost-benefit analysis supported these decisions in high-income countries (Greenstone and Nigam, 2020). Governments of middle and low-income countries imported these measures and implemented mobility restrictions without considering local conditions that could produce different results. Different social insurance programs, younger age structure, and economic informality can make the costs higher in economic terms (Alfaro et al., 2020) but also the benefits smaller (Ma et al., 2021; Alon et al., 2020).

Given this negative and heterogeneous impact, computing the effects of each restriction is a crucial topic to face this type of crisis. Policymakers must make decisions trying to reduce the mortality of COVID-19 and take social costs into account at the same time. Therefore, the research question I address is the effect of increasing the hardness of the measures through the implementation of targeted lockdowns on the number of deaths in urban contexts with middle-income features. For this proposal, I apply a difference-in-differences approach using the differential lockdown timing implemented in the localities of Bogotá (Colombia) as the treatment.

Results show no significant effect of adding lockdowns to existing measures on deaths per 100.000 habitants. These results are robust to spillover presence, different dependent variable specifications, different treatment of standard error, and Callaway and Sant'Anna (2020) approach. Also, we could think of some socioeconomic variables as possible drivers of noncompliance with lockdowns. Using informality as a proxy of income seek or polling participation as civic culture proxy as (Barrios et al., 2021) propose, I do not find any evidence of non-compliance drivers in the heterogeneity analysis. Even the coefficient of the estimation is similar in all localities. Finally, I find that the main explanation of these results is that there was no reduction in total people movements, just an adjustment in the way the people move. People reduced the use of official public transport, where authorities had controls, but not the total movements.

This paper contributes to the literature that studies the effects of lockdowns on deaths. It has three main contributions: the sample, methodology, and data used to check the mechanisms analyzed. Related to the sample, most of the existing literature focuses on the effect in high-income countries (Chernozhukov et al., 2021; Ferguson et al., 2020) or does not study possible heterogeneous effects due to a pool estimation (Stokes et al., 2020). However, this paper focuses on the largest city in terms of the population of a middle-income country with high levels of informality. Also, the methodologies used are mainly model based on simulations such as SIR and recent developments[1] of its (Acemoglu et al., 2020; Ferguson et al., 2020), Structural Equation Model (Chernozhukov et al., 2021) and event study (Askitas et al., 2020). This paper is included in the last methodology group. However, I keep the country and city constant, providing a stronger counterfactual. Also, I use recent methodologies as Callaway and Sant'Anna (2020) to check the robustness of my estimation. Finally, I innovate in the data used in two ways: the use of Facebook mobility data and the estimation of the dependent variable. While some of the causal studies use Google Mobility Report (Chernozhukov et al., 2021; Askitas et al., 2020) to measure changes in mobility, I use more granular data such as reported

[1] Consult Askitas et al. (2020) to know the developments of SIR in this literature.

by Facebook (Maas, 2019) at locality and UPZ[2] level. This data has already been used in other studies to compute mobility in a Latin American city such as Santiago de Chile (Mena et al., 2021). Regarding the dependent variable, I use a lag of the appearance of the first symptom date that allows me to estimate the contagion date. Furthermore, this paper is the only one that estimates spillover effects to the best of my knowledge.

This paper is structured as follows. Section 2 presents a context of measures developed by the *Alcaldía* in Bogotá. Section 3 describes the data used. Section 4 covers the identification strategy and estimation equations while Section 5 presents the results. Finally, conclusions are exposed in Section 6.

2 Context

Bogotá is the city of Colombia where the first COVID-19 case occurred and the city most affected by the virus in Colombia. The first case related to COVID-19 in Bogotá was notified on March 6th, 2020. Just two weeks later, on March 20th, the *Alcaldía* announced the implementation of a *lockdown simulacrum*. The main reason behind this was to be prepared given the high spread of this virus in European countries. Based on these guidelines, the National Government also declared a national lockdown to start on 25th March. However, the costs of these measures were high. In June, due to the economic and social crisis provoked by these measures, the *Alcaldía* decided to reduce the level of restrictions by implementing a rotatory system called *Pico y cédula*[3].

At the beginning of July, the epidemiologic situation gets worse. There were more than 43.000 infected people, and 1.200 people died. Also, the hospital occupation was

[2] UPZ is a more disaggregated than localities urban division of Bogotá that agglutinates some neighborhoods.

[3] This measure restringed purchases to people whose identification number ends in even or odd. Sectors such as health care were excluded. (Alcaldía Mayor de Bogotá, 2020a)

above 84% (Observatorio de Salud, 2020). In this context, the Mayor of the City, Claudia Lopez, requested the central government a general lockdown that was declined[4] due to economics and social costs. Therefore, she decided to implement focalized lockdowns covering the whole city at four different timings in addition to the measures that were already being implemented, such as mask mandate, *Pico y cédula*, school closures, and national preventive isolation. These lockdowns consist of constraints on the "free movement of vehicles and people, except for essential activities" (Alcaldía Mayor de Bogotá, 2020b). The Mayor's office divided localities into four groups and assigned 14 days of lockdowns for each locality[5]. The localities assigned for the first round of lockdown were those with the highest number of cases and positive, transmission, and mortality rates (Alcaldía Mayor de Bogotá, 2020b). A concern is that these localities had different trends than the others, but I will show in section 5 that they had more cases but were moving in parallel.

Concerning this research, I take just the first lockdown group. I made this decision to solve problems associated with the activation-deactivation of the treatment and have *pure* control and treatment groups. This group starts mobility restrictions on July 13th and finishes on July 26th. But I take until July 22nd to avoid heterogeneity caused by different treatment timings due to the overlap of groups. Also, I take ten days before treatment as pre-treatment period. Figure 1 shows which localities belong to this group and the temporal framework used. Redline highlights the limit of time used in main specifications, and the whole sample is used in robustness specifications. Also, I use the 19 urban localities of Bogotá, excluding Sumapaz from the sample due to the rural condition of this locality [6]. Figure 2 shows trends in treated and non-treated localities before and during the application of lockdowns. Table A.1 presents summary stats at pre-treatment

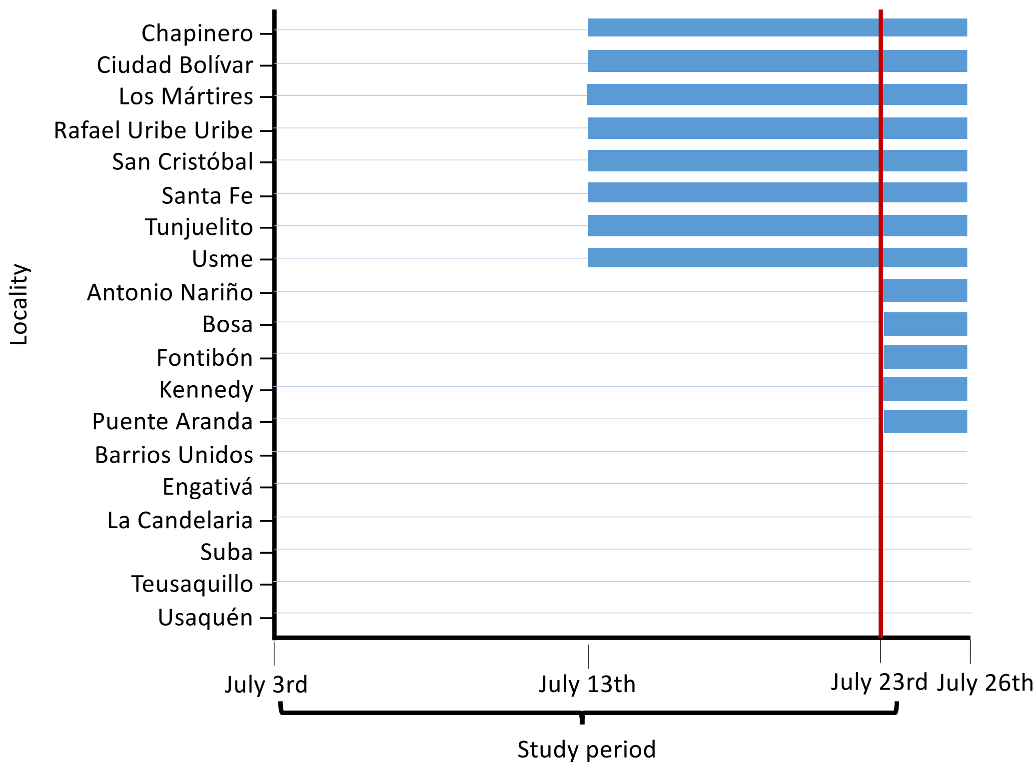
[4]https://www.semana.com/semana-tv/semana-noticias/articulo/coronavirus-hoy-duque\
-evaluara-peticion-medica-pero-rechaza-cuarentena-total/686880/

[5]Some localities belonged to two groups (Santa Fe, Puente Aranda, Chapinero, and Antonio Nariño).

[6]Sumapaz has the 0.39% of the density of the locality with the lower density of Bogotá (Usme)

and socioeconomic variables by treatment status.

Figure 1: Timeline of treatment application



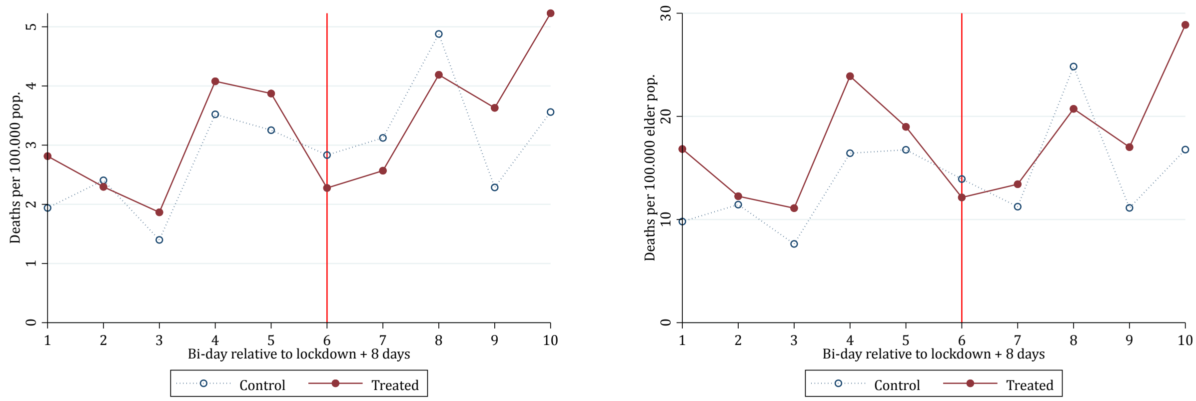
Notes: Color blue refers to lockdown period.

Additionally to these targeted lockdowns, other measures such as *Pico y cédula* or the virtuality of the education sector were still active. Nevertheless, these measures affected both control and treatment groups, so I estimate the differential impact of the lockdowns.

3 Data

Disease data. The number of deaths and cases are provided by Observatorio de Salud (2020) database. The level of disaggregation is locality and day level. I aggregate by bi-days to reduce the noise associated with the reported day. One of the concerns about the data is the difference between reported and infection dates. I use the first symptom date

Figure 2: Evolution of mortality rates by treatment status



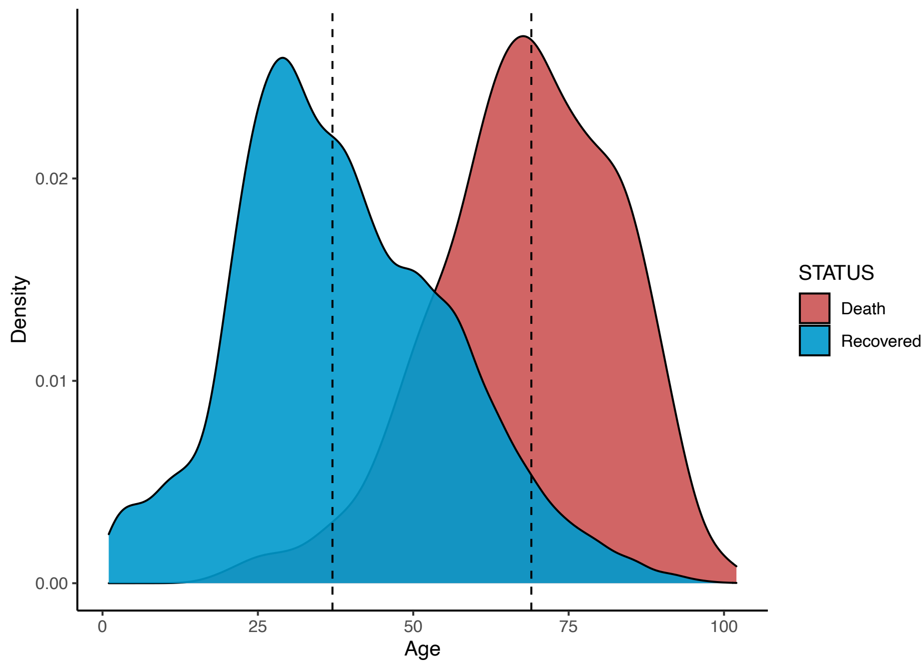
(A) Whole population

(B) Elder subsample

and different lags to estimate the contagion day to solve this problem. Using information provided by WHO (2020), the mean of the incubation period is 5-6 days. However, several research establishes heterogeneity by age. Tan et al. (2020) set 8 days to people older to 70 years. Dai et al. (2020) raises to 7.7 for people elder to 60 years. If we consult the distribution of deaths using the sample data in Figure 3, we note that in the sample, it is centered near 70 years. So, following the literature, I include a lag of 8 days concerning the contagion date in my main specification. This allows me to approximate deaths to the date of contagion, being able to analyze the effect of lockdowns on the death rate immediately after the implementation. I take different lags to study the robustness of this parameter. Finally, I use the number of deaths per 100.000 inhabitants as the outcome variable. I discard the number of cases because asymptomatic people do not report the first day of symptoms which allows approximating the contagion day. The amount of these asymptomatic people oscillates between 30% and 50% depending on localities.

Civic culture. As suggested by Barrios et al. (2021), one of the variables to measure social capital is the participation share in elections; this is due to the private cost and the social benefit that the democratic process entails. For this reason, I use the average of the

Figure 3: Density of age according to disease type



participation data by locality in the 2018 presidential elections[7] (including the first and second rounds) to calculate social capital. This data is provided by the Bogotá Spatial Data Infrastructure (IDECA).

Sociodemographic variables. The *Encuesta Multipropósito* developed by Secretaría Distrital de Planeación provides data representative at locality and UPZ level in 2017. I use sociodemographic and socioeconomic data to understand better the mechanisms that could affect the effectiveness of the treatment. The level of disaggregation in inquiry is by the individual, so I aggregate by percentages for each locality to compute the proportion. I compute the informality rate to check rent-seeking as a potential mechanism that could reduce the lockdown effectiveness. Also, I use the median of the *estrato* to approximate the wealth composition. The economic literature is very critical of this wealth measure (Sepulveda, 2014). Still, most of these critics are related to the power to predict at the household level but not most aggregated levels. I use the inverse of the

[7] I chose this election because I do not have municipality elections by locality.

estrato, which implies that a higher level means lower wealth.

Public Transport movements. I acquire data on the card usage of the Bus Rapid Transport (BRT) and other buses[8] on stations to measure mobility. This data has anonymized time, card type, and station in which the card was used. I aggregate by station and bi-day data. Card type allows me to make a proxy of the user's age which is very useful to subset the sample. There exists a specific card type – *Tu llave 62*– for people older than 62 years. It allows me to make a particular measure for people's age that were more affected by the virus, as we can see in Figure 3. So, I compute the percentage of validation divided by the whole population of the locality but also validations of people older than 62 years old by the number of the people who belong to this age range.

One particularity of BRT data is the location of the stations. Most of them are located within the boundary of two localities. To solve that, I create a 500 meters buffer. Then, I impute the people of every station to the localities in function to the area of each locality in this buffer. The main assumption is that localities with more area have more people using that station. Also, I compute 250 and 750 meters buffers to check the robustness of this estimation. This computing is explained in Appendix Figure A.1 and A.2. In the case of other buses, it is not necessary to do because of the distribution of the stops within the localities. Also, these data have a significant limitation: validations do not allow travel tracking.

Facebook movements. Facebook Data for Good Program[9] provides datasets with mobility of their users to manage crisis response (Maas, 2019). I use the Movement Tile dataset to check mobility as a compliance proxy and a mechanism to spread the virus. This dataset has the number of Facebook users with locations activated on their cell phones

[8]Bogotá has two public transport services: Transmilenio (BRT) and SITP (other buses) that connects the rest of the city.

[9]https://dataforgood.fb.com/

who travel from one tile[10] to another or within the same tile. I can distinguish between total, internal, and net movements between localities. Total refers to the aggregations of movements without taking into account locality provenance. Internal movements are those whose start and endpoint are situated in the same locality. I use internal and net movements to differentiate between long and short distances. Then, I build Voronoi diagrams to compute the tile polygon area. In the case of a tile belonging to more than one locality, I compute the number of movements based on the area of each locality in the tile. This process is shown in Appendix Figure A.3. Finally, I disaggregate it into three-time intervals. The Facebook dataset comes in intervals (0-8h, 8-16h, and 16-0h), and I compute the same intervals to official public transport validations to make them comparable.

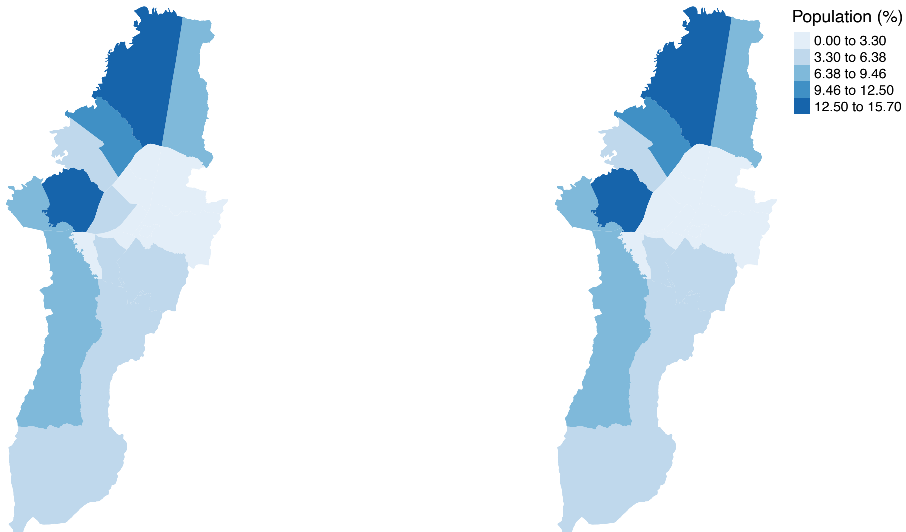
The median number of Facebook users in the pretreatment period is 2.786.268 people, which is greater than other mobility surveys. One of the concerns of this dataset could be the lack of a representative sample due to the distribution of Facebook users. To check this, I use the Facebook Population dataset to compute the relative number of Facebook users by locality and compare the same data calculated with 2018 Census statistics. We can see in Figure 4 that both distributions are very similar. Considering a possible affectation of the population by the treatment, I use the percentage movements divided by the median users in the pretreatment period by locality.

4 Identification Strategy

Given the focalized structure of the lockdowns, I can estimate the effect of lockdowns on deaths per 100.000 habitants by applying a difference-in-differences approach that explores variation before/after a lockdown in localities affected/not affected. However, to explore potential different effects compared to high-income countries, it is crucial to compute possible heterogeneous effects that allow us to understand better which could be the

[10]The tile size is 5.9 km2.

Figure 4: Comparison of population distribution



(A) Population distribution according to Facebook

(B) Population distribution according to 2018 Census

compliance drivers. So, then I prove various heterogeneities by interacting socioeconomic variables with treatment. Finally, I compute the presence of externalities to check internal validation.

The difference-in-differences equation I estimate is the following:

$$y_{it} = \alpha + \beta PostTreatment_{it} + \delta_t + \gamma_i + \epsilon_{it} \tag{1}$$

Where y_{it} refers to number of deaths per 100.000 inhabitants in locality i on bi-day t. I use this variable because it is the most important in the making decision of policymakers and the goal why they implemented the *flatten the curve* strategy. I use bi-days instead of days because the last is noisier. δ_t and γ_i absorb time and locality fixed effects, which allow me to control by inherent locality features like density and city shocks like the weather. β is the coefficient of interest that shows the effect of lockdowns on the outcome variable. It is not recommended to use clustered standard errors because of the small number of localities (19), so I use wild cluster bootstrap to solve it (Cameron et al., 2008) with 999 replications and cluster by locality and bi-day. Also, I apply this model to a restricted sample from 3rd July to 22nd July. I restrict the sample in the main specification to 22nd July instead of 26th July to have just one timing of the treatment. On 23rd July, two groups are receiving treatment, so by reducing the sample date, I avoid a possible bias in the estimator due to different timings in the treatment applications (Goodman-Bacon, 2018). To solve this issue, I would have to apply Callaway and Sant'Anna (2020) estimation, which complicates heterogeneity computing. However, I also check for the whole period in my robustness analysis using this approach. In Appendix, I include regressions without time fixed effects (Table A.2).

The main assumption of these models to establish a causal relationship is the existence of parallel trends. So, I disaggregate the treatment into periods by applying an event study design to check this assumption in the pre-period and to have a better approximation of the estimator behavior by day. The estimated equation is the following:

$$y_{it} = \alpha + \sum_{j=2}^{-10} \beta_j (Lag_j)_{it} + \sum_{k=0}^{10} \beta_k (Lead_k)_{it} + \delta_t + \gamma_i + \epsilon_{it} \tag{2}$$

Where β_k captures the effect of each kth bi-day post-treatment and β_j the impact of jth bi-days previous to lockdown.

Also, to study the mechanism that can determine the effectiveness, I use a difference-in-differences with some socioeconomics variables measured in the pre-treatment period, such as informality, wealth, education, poverty, informality, and internet access interacted with post-treatment variable. Moreover, I use the participation share in presidential elections in the year 2018 as a proxy variable to civic capital in the way of Barrios et al. (2021) does.

Finally, I check the internal validity of the results by computing the possible presence of externalities. Targeted policies can have the presence of spillovers. Applying these mobility restriction measures can provoke an immediate effect on its neighbors. This can be affected by reducing the number of people in the locality, minimizing the probability of contagion, and hence the mortality rate. For testing this, I estimate Equation (3) based on Butts (2021) research.

$$y_{it} = \alpha + \delta_t + \delta_i + \beta PostTreatment_{it} + \tau_1 Within_{it} * (1 - Treat_{it}) + \tau_2 Within_{it} * Treat_{it} + \epsilon_{it} \tag{3}$$

Besides the variables of Equation (1) I include τ_1 and τ_2 for estimating the effect of having a treated locality near and a potential change on β based on the treatment of neighbors, respectively. Also, $Within_{it}$ is an indicator that takes the value of one if the exposure to treatment is larger than the percentile 75th. Exposure is measured as the percentage of neighbors that are treated. Based on Butts (2021) this measure needs to have a value of one if the locality has treated localities in a predetermined radius. However, given the reduced sample, I try to capture this effect by considering the localities most exposed to treatment.

5 Results

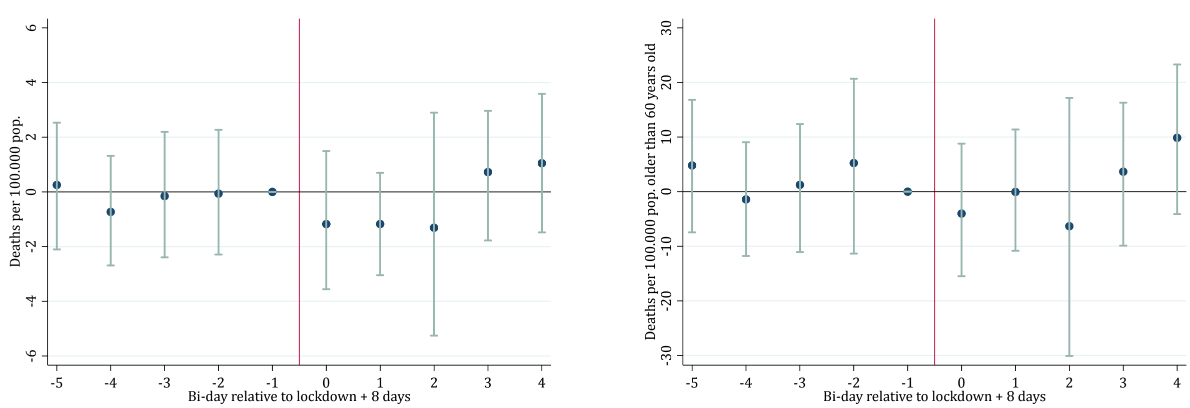
This section is divided into five subsections. First, I present the results estimated with the main specifications. Then, I check the presence of spillovers. In the third part, I make additional robustness checks to evaluate the consistency of the results. In the fourth part, I analyze possible heterogeneities. Finally, I propose and check the mechanisms to understand the results.

5.1 Main results

Figure 5 shows the dynamic coefficients of the estimation of Equation (2). Figure 5A shows results for the entire population and Figure 5B reduces the sample to people older than 60 years. First, we can see that the parallel trends assumption holds in the pre-period of both cases. But also that there are no statistically significant differences in the number of deaths per 100.000 population after the localities enter lockdown. Even if the study shows a reduction in the coefficients that turn negative, this difference is not statistically significant.

The results of the estimation of Equation 1 are presented in Table 1. Columns (1) and (2) present results for estimation with the number of deaths per 100.000 population as the dependent variable. Columns (3) and (4) use the number of deaths of people older than 60 years per 100.000 population older than 60 years. Since I use wild cluster bootstrap to estimate error, the table reports p-value in square brackets and coefficient interval in parenthesis, and there are no standard errors reported.

Figure 5: Dynamic coefficients of difference-in-differences



(A) Effect on whole population

(B) Effect on elder subsample

Table 1: Main results with spillovers

Dependent variable:	Deaths per 100.000 population		Deaths per 100.000 population elder	
Days lag	8	7	8	7
	(1)	(2)	(3)	(4)
Lockdown	-0.24	0.22	-1.35	2.24
	[0.70]	[0.74]	[0.73]	[0.57]
	(-1.34, 0.94)	(-1.07, 1.41)	(-8.12, 5.75)	(-5.73, 9.52)
Mean Dep. Variable	2.72	2.85	14.16	14.31
Adjusted R^2	0.31	0.27	0.15	0.14
Observations	190	190	190	190

Notes: P-value is reported in square brackets and confidence intervals at 95% in brackets. *** p<0.01, ** p<0.05, * p<0.1.

5.2 Spillovers

Table 2 presents results estimating the presence of spillover effects. We can see how the direct effect of treatment is kept as not statistically significant. However, there exists a reduction of the effect at the expense of controlled groups. It could be given the presence of an anticipation effect. Given that other localities will be treated in the following periods, the people who live in these places increase mobility patterns spreading the virus (see Section 5.5).

5.3 Robustness

Figure 6 shows that results are robust when I apply other lag to estimate contagion date. Results are robust to different samples. Figure 6A takes into account the whole sample, and Figure 6B refers to the deaths of people older than 60 years old. However, the effect is not statistically significant in either of them. Also, these results are consistent when I apply a logarithmic transformation of the dependent variable and to different error specifications, as is shown in Table A.3 and Figure A.4 respectively. Finally, I extend the interval time to July 26th. The use of this date gives two different timing of the treatment –two groups of lockdowns are active– so I use Callaway and Sant'Anna (2020),

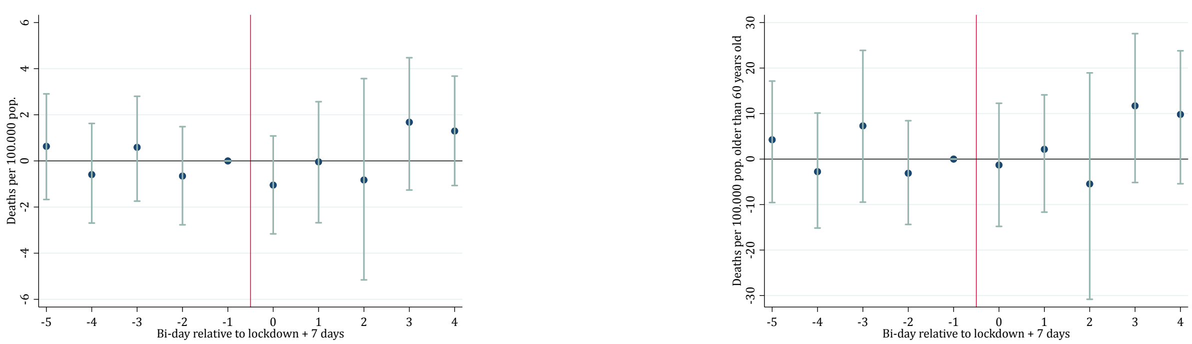
Table 2: Main results

Dependent variable:	Deaths per 100.000 population		Deaths per 100.000 population elder	
Days lag	8	7	8	7
	(1)	(2)	(3)	(4)
Lockdown	-0.21	0.34	-1.46	3.26
	[0.79]	[0.66]	[0.75]	[0.50]
	(-1.60, 1.30)	(-1.24, 1.79)	(-9.90, 7.31)	(-6.44, 12.20)
Spillovers onto control	1.10**	1.18**	6.32**	7.22**
	[0.03]	[0.02]	[0.03]	[0.03]
	(0.13, 2.16)	(0.21, 2.25)	(0.92, 12.24)	(0.98, 13.90)
Spillovers onto treated	1.02	0.85	6.63	4.52
	[0.19]	[0.28]	[0.18]	[0.36]
	(-0.64, 2.45)	(-0.84, 2.29)	(-3.62, 15.29)	(-5.67, 13.45)
Dep. Variable Mean	2.72	2.85	14.16	14.31
Adjusted R^2	0.30	0.27	0.15	0.14
Observations	190	190	190	190

Notes: P-value is reported in square brackets and confidence intervals at 95% in brackets. *** p<0.01, ** p<0.05, * p<0.1.

Sun and Abraham (2021) and De Chaisemartin and d'Haultfoeuille (2020) estimators to avoid possible bias estimation due to heterogeneous treatment effects (Goodman-Bacon, 2018). Results are displayed in Figure A.5.

Figure 6: Robustness to Difference in Difference estimator (Lag 7 days)



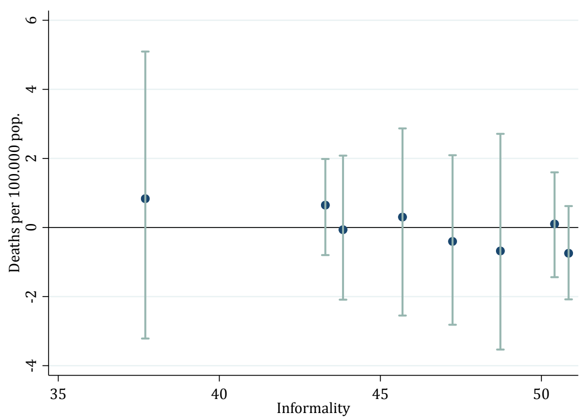
(A) Effect on whole population

(B) Effect on elder subsample

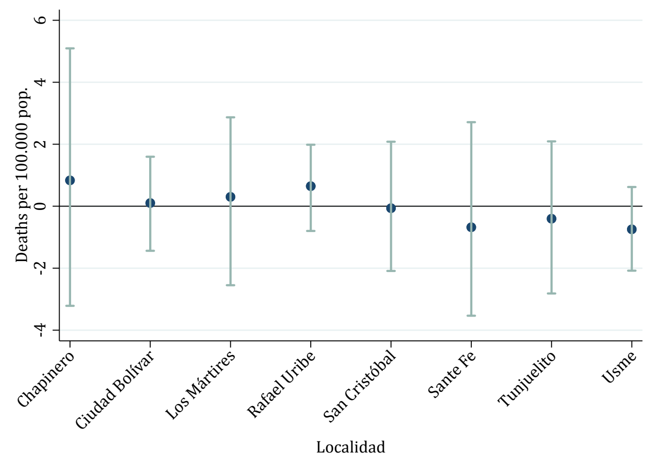
5.4 Heterogeneity

Figure 7 shows that there are no heterogeneous results by informality or locality. Figure 7B displays that the effect is similar and not statistically significant in all the localities. Also, 7A indicates that informality is not a driver of possible heterogeneities due to income-seeking. There also no statistically significant effects are kept by other socioeconomics variables such as Internet deprivation, poverty, or health system deprivation (consult Table A.4 in Appendix). Also, in civic culture proxy like absenteeism in voting.

Figure 7: Heterogeneity results



(A) Effect by Informality



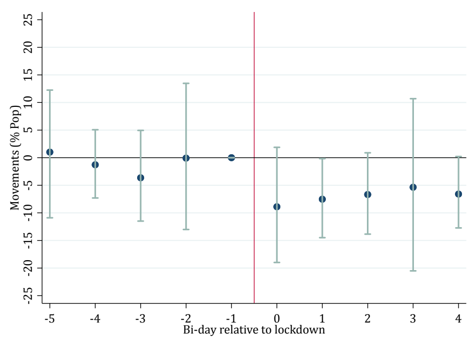
(B) Effect by Locality

5.5 Mechanisms

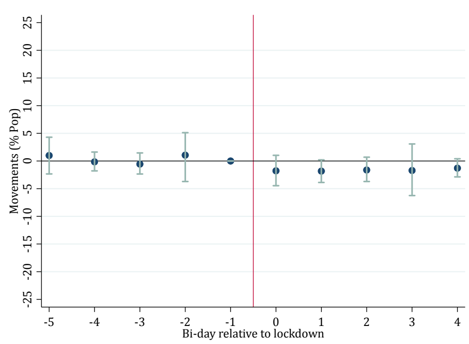
The implementation of lockdown measures aims to reduce mortality by reducing contact between people. By reducing close contact between infected and uninfected people, the spread of the virus is contained, and therefore the number of deaths is diminished. Given that there was no effect of this measure on mortality, one possibility to understand the lack of the effect on the number of deaths could be that people did not reduce their movements.

Results in Figure 8 show a reduction in the use of official public transport. Two possible reasons explain these results. The first is that people did not have to move to other localities to work, so they do not have to use this transport. The other reason is that BRT had controls to check if people met the requirements to mobilize, and there were sanctions on people that did not follow these measures. These results are robust to different buffer specifications (see Figure A.6). Results disaggregated by hour are shown in Table A.5.

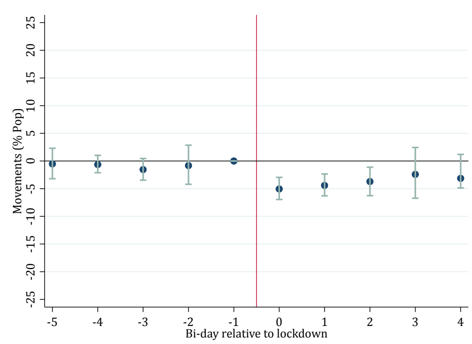
Figure 8: Public Transport mobility results



(A) BRT all validations



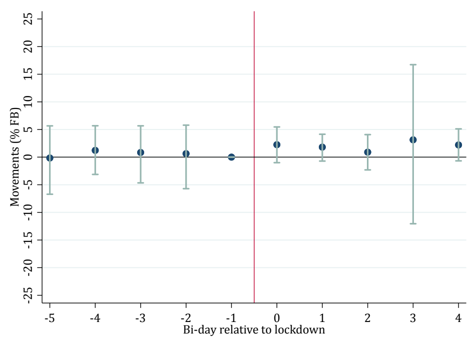
(B) BRT elder



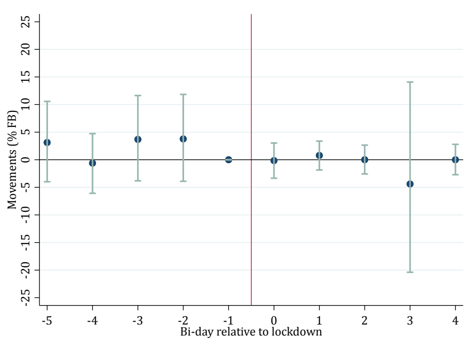
(C) Other Buses

Figure 9 shows the effect on mobility measured with Facebook data. It is a more interesting dataset because it considers people's movement beyond official public transport and authorities' control. Also, it allows knowing about the direction of the movements. We can see no statistically significant effect in the total mobility in net entrances, neither in net departures nor internal movements. However, despite not being significant, there is a change in the coefficient from movements between localities (entrances and departures) and within localities (internal). Table A.6 shows results of estimating Equation (1) disaggregated by hour, where we see a reduction in the number of entrances from other localities in the 8 hours to 16 hours time interval and in the number of departures from 4 pm to 0 am. These results enable us to see a reduction in movements between localities during work hours. We can conclude that people reduced mobility to other localities during working hours but kept movement within localities and the rest of the day. Table A.7 presents results when I use data disaggregated at the UPZ level and Table A.8 the estimation including spillover effects.

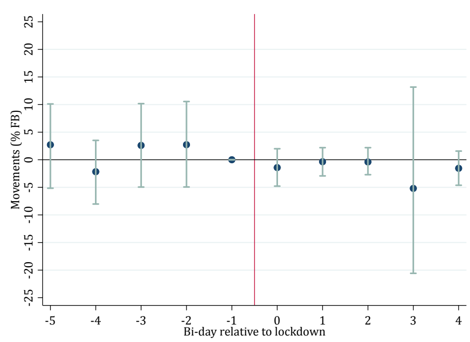
Figure 9: Facebook mobility results



(A) Internal mobility



(B) Entrances



(C) Departures

6 Conclusions

Taking into account the socioeconomic costs of each health measure is very important when policymakers develop public policy. The literature shows how the costs of lockdowns relative to benefits differ in high-income countries compared to middle and low-income countries. Exploiting the structure of lockdowns in Bogotá, I estimate the effect of increasing the strictness of restrictions on the number of deaths. I do not find statistically significant effects on mortality rates by applying more restrictive mobility measures. Finally, I estimate mobility as the main mechanism for reducing the number of deaths. I find a reduction in the use of public transport that can be caused by the presence of authorities at the stations and the prohibition to going to work of most of the jobs. However, I do not find any effect when I analyze the Facebook movement data, which allows me to estimate what people do in other places less monitored by authorities.

Finally, there are some limitations to be taken into account: (1) the estimation of the number of deaths and mobility can generate some noise –but it affects both control and treatment groups–, (2) this lockdown was established after an extended national lockdown and at the same time as other measures (mask mandates, school closures, ...) so that it could exist a "wear effect". The potential existence of this effect could impede the isolation of the pure lockdown effect. At last, (3) the sample (N = 19) is small. Notwithstanding, some learnings can be established from these results: (1) importing policies from countries with structural differences can produce different results in terms of benefits and costs, (2) it is essential to establish mechanisms to ensure that people comply with them, specifically when a "wear effect." can be present. Following that, I propose more focused mobility restrictions, for example, at the UPZ level in the case of Bogotá. Targeted restrictions allow dedicating resources, such as agents, to ensure that measures are being complied with. In addition, they reduce the economic reduce costs of closing the whole locality.

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