#StayAtHome: Social Distancing Policies and Mobility in Latin America and the Caribbean

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Abstract*

This study examines the impact on human mobility of social distancing policies implemented in 18 Latin American and Caribbean countries in March 2020. We use cell phone data and variation across countries regarding the adoption of these policies and their timing to estimate effects on the percentage of people traveling more than 1 kilometer per day. Results indicate that lockdowns reduced mobility by 10 percentage points during the 15 days following its implementation. This accounts for a third of the decline in mobility between the first week in March and the first week in April in countries that implemented lockdowns. The effect during the second week of implementation is 28% lower compared to the effect documented during the first week. Additionally, we find that school closures reduced mobility by 4 percentage points, but no effects were found for bars and restaurants closures and the cancellation of public events.

JEL classifications: C23, H12, I18
Keywords: Coronavirus, Social distancing, Mobility, Lockdowns

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* We would like to recognize the significant support and important comments provided by Ana María Ibañez, Alejandro Izquierdo, and Eric Parrado. We would also like to thank Roberto Araya, Javier Bartoli, Catalina Espinosa, María Frances Gaska, Gabriel Goette, Gastón Líberman, Andrés López, Valeria Lovaisa, Alejandra Mizala, Arturo Muente, Félix Quintero, Jimena Romero, Miguel Soldano, and Rosa Vidarte for their support. We would like to thank Juan Pablo Chauvín, Patricio Domínguez, and Diego Vera for their comments and suggestions, along with the participants of the seminar organized by the Inter-American Development Bank and the seminar on “Coronavirus and Big Data,” organized by the Instituto Interdisciplinario de Economía Polítca of Buenos Aires. The opinions expressed in this document are those of the authors and should not be attributed to the Inter-American Development Bank.

1. Introduction

During the first half of 2020, the coronavirus wreaked havoc on health, the economy, and the overall well-being of the global population. The virus reached Latin America and the Caribbean in early March 2020, by which time its harmful effects were known because of the experiences of countries like China, Italy, and Spain. In turn, the region's governments reacted quickly by implementing social distancing measures to reduce contact between people to slow the spread of the virus. To increase social distancing, governments implemented a series of obligatory measures restricting human mobility, including lockdowns, closing schools, closing bars and restaurants, and canceling public events. At the same time, governments used mass communications campaigns to persuade people to adopt social distancing. For their part, the media and social networks may have played a significant role in promoting social distancing. This collection of actions led to a drastic decline in human mobility in the region between March 13 and 25, 2020 (Aromi et al., 2020; Google, 2020).

Against this background, a key question is: what was the impact of the mentioned social distancing national policies on human mobility? Because these measures are part of the basic arsenal of measures governments can use to quickly promote social distancing at new stages of the fight against the coronavirus, it is important to quantify their impacts. However, there is limited evidence as to the effect of these measures, and it mainly comes from developed countries (Dave et al., 2020a; Dave et al., 2020b; Cronin and Evans, 2020; Maloney and Taskin, 2020; Akim and Ayivodji, 2020). Also, simply analyzing the evolution of mobility in specific countries cannot determine for sure the impact of these measures because, as mentioned previously, changes in people's behavior were also the result of other factors, including communications campaigns by governments and the roles played by the media and by social networks.

This study evaluates the impact on human mobility of the national social distancing policies implemented in 18 Latin American and Caribbean countries during March 2020.[1] Specifically, we study the impact of four social distancing policies implemented by national governments:

[1] The analysis includes all countries of Latin America and the Caribbean with between 1 million and 50 million inhabitants. Brazil and Mexico were not included, as policies and movement within their borders were extremely heterogeneous. Cuba and Haiti were also not included, due to low rates of cellular phone use there. The countries included were: Argentina, Bolivia, Chile, Colombia, Costa Rica, the Dominican Republic, Ecuador, El Salvador, Guatemala, Honduras, Jamaica, Nicaragua, Panama, Paraguay, Peru, Trinidad and Tobago, Uruguay, and Venezuela.

lockdowns, school closures, the closing of bars and restaurants, and the cancellation of public events. To estimate impacts, we used the variation between countries with regard to whether these measures were applied and when. The analysis focuses on March 1 through April 14, a critical period during which the majority of the countries analyzed implemented the measures mentioned above. During this period, the measures imposed to restrict mobility were mostly implemented by national governments, making it possible to analyze their impact at this level.[2] The key outcome analyzed in this study is the percentage of people traveling more than 1 kilometer per day. This outcome is computed using georeferenced data from cellular phones provided by the company Veraset.

In the first part of the analysis, we study the prevalence and implementation order of the social distancing policies under examination. We find clear patterns with regard to countries' adoption of these measures. Specifically, we document that, of the 18 analyzed countries, all of them implemented public event cancellations and closure of schools, with the sole exception of Nicaragua, which did not implement any of the four measures. Additionally, 15 countries ordered the closure of restaurants and bars, while only 11 imposed lockdowns. This preference for implementing certain measures over others is also expressed in the order of implementation. Specifically, we found that the first measures were implemented on Tuesday, March 10, but following a particular sequence. As of Monday, March 16, 15 countries had implemented school closures, 14 had canceled public events, 8 had closed bars and restaurants, and only 2 countries had implemented lockdowns.

In terms of mobility impacts, we found that the introduction of lockdowns produced an average reduction in the percentage of people traveling more than 1 kilometer of 10 percentage points during the 15 days following implementation. This effect, however, diminished over time: while the average effect during the first week was 12 percentage points, the effects during the second week came to only 9 percentage points, a difference that is statistically significant. We also find that closing schools reduced mobility by 4 percentage points. For their part, no significant effects were detected from closing bars and restaurants or from canceling public events. However, it is important to consider that these measures may have a more significant effect on reducing

[2] As described in Section 3, during this period, some local measures were also implemented to restrict human mobility within certain countries, including Argentina and Bolivia. However, considering the percentage of the population affected, it is clear that the national measures played the dominant role.

agglomeration, rather than reducing mobility in general. Therefore, these measures may be effective at slowing the spread of the virus, even without reducing mobility.

The measures analyzed could have different effects in the different countries of the region as a result of the particular characteristics and enforcement efforts, as well as due to differing patterns of pre-coronavirus mobility. Hence, we quantify the effects of the lockdowns in each country using a synthetic control methodology (Abadie et al., 2010). Results indicate that while the lockdowns reduced mobility in Argentina, Bolivia, and Ecuador by between 16 and 19 percentage points, the reduction in Paraguay and Venezuela was only 3 percentage points.

This study complements a growing body of literature seeking to document the impacts of social distancing policies on human mobility during the coronavirus crisis. Analyses performed thus far use as a measurement the percentage of people who stay home (Dave et al., 2020a; Dave et al., 2020b) and visits to certain locations, such as essential and non-essential businesses, entertainment, hotels, restaurants, and workplaces (Akim and Ayivodji, 2020; Bargain and Aminjonov, 2020; Cronin and Evans, 2020; Maloney and Taskin, 2020). For this study, however, the main measurement used is the percentage of people traveling more than one kilometer per day. This indicator makes it possible to capture more general mobility patterns that are not necessarily associated with visits to public places, but that still increase the risk of transmission of the coronavirus, like visits to friends or family members outside the home.

Additionally, the majority of existing studies focus on the effects of social distancing policies in developed countries. Analyses in the United States have found that between 3% and 26% of the total reduction in mobility is the result of the implementation of lockdowns. They have also found that policies like closing schools, restaurants, and non-essential businesses have small but significant effects on mobility (Cronin and Evans, 2020; Maloney and Taskin, 2020). However, these conclusions may be different for lower-income countries, given that poverty rates and informality make it difficult for people to say home. Still, existing studies suggest that lockdowns reduce mobility in medium-income countries and African countries (Akim and Ayivodji, 2020; Maloney and Taskin, 2020).

It is important to recognize that some studies have reported much larger effects of lockdowns on mobility compared to our study. For example, Pullano et al. (2020) found that the national lockdown in France caused a 65% reduction in the number of displacements (from about 57 million to about 20 million trips per day). In contrast, we find that lockdowns in Latin America and the Caribbean reduced the percentage of people traveling more than 1 kilometer per day by 10 percentage points. Beyond the potential differences in results because of the contexts analyzed, some of the differences could be due to the methodology used. In particular, papers such as Pullano et al. (2020) estimated the effects of lockdowns by just comparing the number of trips before and after the onset of the pandemic. These approaches can vastly overestimate the effects of lockdowns because it is well established that lockdowns are responsible for only a fraction of the decrease in mobility after the onset of the pandemic. That is, a substantial fraction of the mobility reduction is due to changes in behavior by individuals who cut back their mobility in the absence of mandates just to protect their health or to contribute to the reduction in virus spread (Cronin and Evans, 2020).

This paper sheds new light on the effects of other policies like school closures, closing restaurants and bars, and canceling public events in developing countries, and it is the first to document the effects of lockdowns on mobility in Latin America and the Caribbean. The paper also takes an in-depth look at the temporal dynamics of lockdowns and finds evidence indicating the effects are reduced over time, in contrast to what has been found for Africa and the United States (Akim and Ayivodji, 2020; Cronin and Evans, 2020). Lastly, this study sheds light on the significant variation in the effects of lockdowns across Latin American and Caribbean countries.

The paper is structured as follows. Section 2 describes the initial worldwide spread of the coronavirus and its arrival in Latin America and the Caribbean. Section 3 analyzes the process of adopting social distancing policies in this region, and Section 4 describes the data and methodology used to construct the mobility series. Finally, Section 5 presents the main findings of the study, and Section 6 concludes.

2. Context[3]

In the early months of 2020, the world was facing the rapid spread and mass infection of the coronavirus. The symptoms of the virus are typically moderate, and 80% of those infected recover without needing to be hospitalized (WHO, 2020a). However, the other 20% experience a range of symptoms—including difficulty breathing—and older patients and patients with preexisting

[3] This section describes the basic characteristics of the coronavirus, its spread until March 2020, and the general policy recommendations issued by the World Health Organization during this initial period to help understand the context in which the governments of Latin America and the Caribbean applied measures during this initial stage.

conditions tend to be more likely to develop a severe illness. In this scenario, patients with moderate symptoms or asymptomatic patients become carriers and potential spreaders of the virus. They can infect the rest of the population, which, after becoming infected, may develop illnesses like pneumonia, acute respiratory distress syndrome, or renal insufficiency, in the worst cases leading to death.

The coronavirus was first reported in Wuhan, China, on December 31, 2019, when the Municipal Health Commission reported a cluster of pneumonia cases. Subsequently, the World Health Organization (WHO) began publishing technical documents on what was known about the virus, offering countries recommendations on how to detect and manage potential cases. Then on January 13, the first case was reported outside of China, in Thailand. From that moment, the coronavirus spread to the rest of the world, reaching the United States on January 20 and then the European continent on January 24, when France reported its first case.

On January 30, the WHO declared the novel coronavirus outbreak a Public Health Emergency of International Concern, with 7,818 cases reported in 19 countries. The next day, Italy reported its first case, with Spain doing likewise on February 1. These two countries were the ones most harshly affected by the pandemic in Europe during this initial stage. Together, as of March 10, Italy and Spain reported 10,376 infections and 492 deaths (European Centre for Disease Prevention and Control, 2020).

The first confirmed case in Latin America and the Caribbean was reported on February 25 in Brazil. Later, on February 28, Mexico reported its first case, followed by Ecuador on February 29 and the Dominican Republic on March 1. As indicated in Table 1, subsequent to March 3, the rest of the countries of the region confirmed the coronavirus was present within their territory, with Belize being the final country to confirm the presence of the virus on March 22. As of that moment, the coronavirus had already spread to the entire region, and the WHO had declared it a pandemic on March 11 due to its rapid spread and severity.

Once the coronavirus reached Latin America and the Caribbean, the region faced new challenges, including a growing number of patients needing hospitalization. In a scenario of an overwhelming surge in the number of people with severe symptoms, health services could be overwhelmed, causing the system to collapse and thus increasing the number of deaths of patients with coronavirus, as well as other patients with treatable illnesses. The situation is even more concerning in this region, where illnesses from developed countries like hypertension and diabetes exist alongside tropical illnesses like chikungunya, dengue, malaria, and zika (Legetic et al., 2016).

Because of the virus's rapid spread and potential impacts on health services, the WHO identified the main sources of contagion and based on them, produced a series of directives and recommendations for flattening the curve of cases and buying time to find and implement pharmaceutical measures. First, the virus can spread through direct contact with an infected person when that person coughs, sneezes, or speaks, as the droplets expelled can be inhaled by the other person. Also, when these droplets fall on objects and surfaces, people can touch them and then touch their eyes, noses, or mouths, thus infecting themselves with the virus (WHO, 2020b). To prevent infection, the WHO has produced documents recommending distancing measures for individuals, including isolating positive cases and quarantining people who have come in contact with infected individuals. The documents also recommend regular hand washing and maintaining a minimum social distance of 1 meter between people in public spaces, as well as the use of face masks.

The WHO also suggests that, depending on the transmission scenario observed, measures of community distancing can be taken to reduce contact between people. This could include suspending mass gatherings, closing nonessential workplaces and schools, and reducing the use of public transportation. Many countries have also introduced more rigid distancing measures and mobility restrictions, including lockdowns, with the aim of halting transmission by limiting contact between people (WHO, 2020b).

The ideal length of distancing measures and movement restrictions is hard to pin down. According to the WHO (2020), to be prudent, the measures should be extended for 2 to 3 months based on the experience of countries initially hit by the virus. However, a number of factors must be taken into account when the measures are highly restrictive, as restrictions on movement can be structurally more difficult for low-income countries or communities with a high percentage of vulnerable persons. Such is the case for Latin America and the Caribbean, where in 2018, 23% of the population was living on less than $5.5 per day (World Bank, 2020), and in 2016, the informality rate was close to 53% (Salazar-Xirinachs and Chacaltana, 2018).[4] Along with this, low savings rates among the most vulnerable (Cavallo and Serebrisky, 2016) make measures like

[4] In 2011 purchasing power parity (PPP) dollars.

lockdowns more challenging to comply with, as such individuals do not have the resources to stop working and stay home.

3. Social Distancing Policies Implemented in Latin America and the Caribbean

The virus's late arrival to Latin America and the Caribbean meant that governments were able to take advantage of the international experience when making decisions. Thus, when the first cases of coronavirus were detected, a priority was placed on identifying and isolating those infected in order to slow the transmission of the virus. However, doing this was no easy task due to the presence of asymptomatic persons, the number of daily physical interactions, and the difficulty of carrying out generalized testing. Thus, inspired by the steps taken by Asian and European governments, the governments of the region moved to implement other measures to reduce the chances of infected persons coming in contact with the rest of the population. These measures included lockdowns, closing schools, closing bars and restaurants, and canceling public events.

This study focuses on analyzing these four policies. Two criteria were used when selecting these measures. First, the policy would have to be aimed at reducing local transmission by reducing mobility. With this in mind, measures like airport closures were not considered because they are intended to reduce the risk of importing the virus. The second criterion was that implementation of the measure be national in scope. As will be discussed later on in this section, in some countries, measures were implemented at the sub-regional level. However, in this paper, we focus our analysis on national policies that played a decisive role toward the beginning of the pandemic, and that will be relevant in the future should the number of coronavirus cases increase quickly and broadly in a country.

Lockdowns have been one of the most effective measures for guaranteeing physical distancing between persons. According to the United States Center for Disease Control and Prevention (CDC), social distancing means "keeping a safe space between yourself and other people who are not from your household."[5] In most countries in which this measure was implemented, lockdowns meant that everyone had to stay home except for essential workers (medical workers, armed forces and food industry staff). For all other citizens, the lockdowns only allowed them to leave their homes to acquire necessary goods like food and medicine or travel to

[5] See https://www.cdc.gov/coronavirus/2019-ncov/prevent-getting-sick/social-distancing.html.

healthcare centers. These lockdowns frequently included cordon sanitaire—that is, restrictions on mobility between cities or regions.

Of the 18 countries analyzed in this study, 11 implemented national lockdowns, while 7 did not implement these measures during the period under analysis. The first countries to implement lockdowns were Honduras and Peru (March 16), and the last country to do so was Trinidad and Tobago (March 30).[6] Some countries implemented regional lockdowns before implementing their national lockdowns. Such was the case in Bolivia, which implemented a lockdown in Oruro on March 13, subsequently implementing a national lockdown on March 22. Some countries like Chile also implemented local lockdowns at the "*comuna*" level (similar to a county, in the U.S.).

There was also variation in the strictness with which countries implemented the lockdowns. A comparison of news reports from April 5 in each country found varying compliance with the lockdowns and how authorities enforced them. On the one hand, countries like El Salvador, Honduras, and Peru implemented their lockdowns strictly. For example, press reports from around March 25 indicate that in these countries, the police implemented control measures to ensure that the population complied with the rules established in the lockdowns. And the strictest countries fined and imprisoned those who failed to comply with the measures.[7]

The second measure we analyzed was school closings. All the countries we analyzed implemented this measure—with the sole exception of Nicaragua—and did so between March 11 and 20. As with the lockdowns, some schools had decided to suspend classes prior to the national announcement. Such was the case for Chile, where the government extended to schools the option to choose whether to suspend classes if they had positive cases (Ministry of Education of Chile, 2020), and days later ordered all schools closed nationally. As news reports indicated at the time, these early initiatives produced few closings. Our analysis, therefore, focuses on the national decrees suspending classes.

In addition to posing challenges for parents, who were left without childcare, the closures were also pedagogically challenging for teachers, who began teaching classes online. To alleviate

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[6] Table 2 lists the implementation dates by country of each distancing policy analyzed, while Table 3 provides statistics on the number of countries implementing these measures and when they did so.

[7] To reduce the economic impacts of the pandemic and encourage compliance with the lockdowns, some governments launched a series of measures including extraordinary cash transfers to vulnerable homes, distribution of market baskets, advanced distribution of subsidies, and loans to micro-enterprises to enable them to continue paying their workers, among other things (Busso et al., 2020).

the strain on both, governments implemented a series of policies and recommendations. For example, in the Dominican Republic, the announcement that classes would be suspended came along with a request that the private sector make workdays flexible, and offer telework options so parents could take care of their children. This means that school closures can affect mobility directly because students no longer attend schools but also because such closures may impact whether adults go to their workplaces.

Closure of bars and restaurants—the third measure we analyze—was also broad, adopted by all the countries analyzed except Argentina, Nicaragua, and Uruguay. The measure was put in place between March 10 and 21, 2020. Bars and restaurants were restricted because they tended to be frequented by people who were not in each other's family circles, usually in an enclosed space.[8] Additionally, the consumption of alcoholic beverages in those places can reduce people's willingness to comply with the personal protection measures recommended by health authorities (California Department of Public Health, 2020).

Lastly, we looked at the cancellation of public events. All the countries we analyzed implemented this measure, except for Nicaragua, implementing it between March 10 and 21. The strictness with which it was implemented varied. While the first sanitary measure Paraguay took was to cancel all public and private events and performances, El Salvador prevented gatherings of more than 75; Peru did so for events with more than 300 people, and Ecuador did so for events with more than 1,000 people. Despite the differences in the restrictions associated with this measure, the message was the same for all countries: citizens must refrain from attending events that caused crowding. This includes concerts, festivals, weddings, and other events attended by large numbers of people.

In order to analyze the four policies listed here, their date of implementation was collected for each country of the region. Although sub-regional initiatives were documented, we only took into account measures implemented at the national level and by official decree. A search was conducted for presidential decrees with implementation dates and a description of the measures. In the absence of an official decree, we used presidential press conferences, as well as information gathered from local media.

[8] A survey of internet users in Latin American countries found that 41% of respondents ate outside their homes at least once a week (Nielsen, 2017).

4. Georeferenced Data and the Construction of Mobility Series

For this study, we combined human mobility series with information on the social distancing policies implemented in Latin America and the Caribbean. The mobility series were assembled using data collected from cellular phones provided by the company Veraset. The company aggregates data collected by apps installed on smartphones. The unit of observation in the obtained database is a "ping." A ping is a measurement of the latitude and longitude of a cellular phone at a moment in time. In addition to these geographic location variables, an anonymized identifier was also collected for each cellular phone, along with the date and time (including minutes and seconds) of each ping.

We do not have documentation on the process used to determine when a cellular phone records a ping. However, we were able to analyze the data received to document certain general patterns. Specifically, we observed significant variability between users with regard to how many pings were registered in a day. For example, in Ecuador, there were 97,000 users with at least one ping on March 11. The average number of pings per user is 74, with 4 pings in the 25th percentile and 95 in the 75th percentile. The variation among users of the number of pings recorded in a day is due partly to the configuration of the app collecting the information and to the type of operating system used by the device. Also, the analysis of similar databases suggests that the number of pings collected in a day is correlated positively to a person's mobility (Unacast, 2020).

For our analysis, we produced an indicator to represent the percentage of people traveling more than one kilometer per day. This indicator is calculated for each day and for each country between March 1 and April 14. To calculate this measurement of human mobility, we needed to establish criteria to determine which users to include each day. Specifically, we had to define how many pings were needed to include a user on a given day. In making this decision, two objectives must be balanced against each other. On the one hand, it would be good to focus the analysis on users who, on a certain day under analysis, had a high number of pings (and well distributed throughout the day), because the calculation of the distance traveled by that user would be more precise. However, choosing users with a high number of pings in a day could bias the mobility calculation for that day to users with significant mobility, assuming greater mobility produces more pings. For our main analysis, we include users with at least ten pings per day. This way, we prioritize the inclusion of a greater number of users each day. Likewise, we have conducted a robustness analysis to assess whether these design decisions affect the findings presented (see section 5.1), and in general, we have found that the main findings are unchanged.

To calculate the distance traveled by a person over a day, we measure the distance between the first and the second ping of the day, then between the second and third ping of the day, and so forth.[9] We then add up these distances to approximate the total distance traveled over the day.

As our final step to producing the main measurement used for this study, we calculate the percentage of users traveling more than 1 kilometer per day for each country. We chose this variable as a way to identify the fraction of people that stay at home. To be able to measure this statistic without error we should have many "pings" for the same individual and information of the boundaries of the dwelling where the person lives. Though we have access to uniquely rich data, we do not have such detailed and precise geo-referenced information for each user. In principle, we can think that individuals that are registered as traveling a short distance in a day (e.g. 100 meters) should be classified as leaving their homes. However, it can be the case that these individuals did not leave their dwellings and just move around inside their property. Also, GPS have a geolocation measurement error or around 10 to 20 meters that will generate that the registered distance for a person may be hundreds of meters at the end of the day even though the cell phone did not move at all in a day. Considering, these issues we have chosen a threshold of 1 kilometer to classify a person as having left their dwelling in a day. We recognize that this can be an arbitrary distance but it may seem more natural compared to other alternative such as 0.2 km, 0.5 km, 1.5 km or 2 km.[10]

Lastly, adjustments were made to the national mobility series to account for the fact that some regions, within the 18 countries under analysis, implemented lockdowns at the subnational level. For example, on March 27, local lockdowns were implemented in some *comunas* of the Metropolitan Region of Santiago, Chile. These subnational lockdowns must be accounted for in the study's national-level analysis, as for some days, some countries had partial lockdown coverage. To address this issue, national series were generated for the entire period, which do not

[9] The distance is calculated using the haversine formula, which is standard for calculating distances between geographical points.

[10] Note that Zhang et al. (2020) used cell phone data for the U.S. and classified individuals as staying at home if the measured distance in the day did not surpass one mile. Though the threshold used by Zhang et al. (2020) is slightly larger than the one used in our analysis (one mile compared with one kilometer), both studies share the approach of using a unit of the common distance metric used in each context (kilometers for Latin America and the Caribbean, miles for the U.S.).

include the administrative areas at the first level of disaggregation (such as provinces in Argentina) that implemented lockdowns, either in all or part of their territory. For example, in the case of Chile, the series calculated at the national level do not include the mobility of individuals living in the metropolitan region.[11]

Table 4 gives descriptive statistics by country from the sample used for the study. The average number of observations during March 5-11 (pre-coronavirus) ranges between 10,000 for El Salvador, Jamaica, Nicaragua, Panama, Paraguay and 310,000 for Argentina. Dividing the number of observations by the total population of each country gives an approximation of the % coverage of the sample. In this case, the average coverage is 0.42%. Guatemala is the country with the least coverage, with 0.12%, and Trinidad and Tobago is the country with the greatest coverage, with 1.16%. The average of the main mobility indicator is also provided for the pre-coronavirus period—that is, the percentage of people who traveled more than 1 kilometer per day between March 5 and 11. As can be observed, on average for all countries, 66% of people traveled more than 1 kilometer per day during this period. Lastly, the percentage of people older than 15 with access to a cellular phone (not necessarily a smartphone) is shown. The table shows significant coverage of cellular phones in all the countries analyzed, averaging 82%.

5. The Impact of Social Distancing Policies on Mobility

This section evaluates the impact that distancing policies had on human mobility in Latin America and the Caribbean at the start of the pandemic. The first subsection uses a difference in differences model to analyze the average impact of lockdowns, closing schools, closing bars and restaurants, and canceling public events. The second subsection goes into depth in analyzing lockdowns, showing the temporal dynamic of the impacts of this policy using an event study design. The third subsection presents further disaggregated results by analyzing the individual impact of lockdowns on each country using synthetic control methods (Abadie et al., 2010).

[11] The following geographical areas were removed for each country: Argentina (Chaco, Jujuy, Mendoza, Misiones, Salta, Santa Fe, and Tierra del Fuego), Bolivia (Oruro), Chile (Araucanía, Aysen, Bio-Bio, Los Lagos, Magallanes and the Chilean Antarctic, Ñuble, Valparaiso, and the Santiago Metropolitan Region), and Colombia (Boyaca, Cundinamarca, Meta, and Santander).

5.1. The Average Impact of Social Distancing Policies

To assess the average impact of the social distancing policies, we construct a balanced panel with one observation per country and day for the period of March 1 through April 14. In this subsection, we utilize the following two-ways fixed effects difference in differences model:

$$Mobility_{it} = \; country_i + day_t + \beta_1 Lockdown_{it} + \varepsilon_{it} \qquad (1)$$

where $Mobility_{it}$ represents the percentage of people traveling more than 1 kilometer in country i and day *t*. $Lockdown_{it}$ is an indicator equal to 1 if this policy is in place in a particular country on a certain day (and zero if not). In turn, $country_i$ and day_t are fixed effects per country and per day, respectively. The parameter of interest, β_1, represents the average impact of implementing a lockdown in the sample of countries and period under analysis.

Recent literature demonstrates that fixed effects models like the one presented in equation (1) can produce estimates that are biased when the units are treated at different times, even in the event of parallel trends between the treatment group and the comparison group in the absence of treatment (de Chaisemartin and D'Haultfoeuille, 2019; Goodman-Bacon, 2018; Sun and Abraham, 2020). This is because two-way fixed effects models assume that the treatment effect is constant across units and over time. Chaisemartin and D'Haultfoeuille (2019) show why this assumption imposes a problem. First, they show that when different units are treated at different points in time, the treatment effect is a weighted average of the effects from numerous difference-in-differences models, which compare the evolution between consecutive time periods across pairs of groups. Second, the weights of this computation may be negative because some units that serve as controls in certain difference-in-difference comparisons, may be treated in both periods in some other comparisons. In turn, these negative weights can bias the estimator so that the general Average Treatment Effect can become negative when all individual Average Treatment Effects are positive.

However, de Chaisemartin and D'Haultfoeuille (2019) present a new estimator that produces unbiased estimates, and that can be applied in cases in which the units entering the treatment group remain treated through the period under analysis. The estimator computes an average treatment effect at each pair of group-time cells whose treatment status changes from t-1 to t. Given that this condition is met in our analysis, we estimate equation (1) following the methodology described in de Chaisemartin and D'Haultfoeuille (2019).

To estimate the impact of school closures, closing bars and restaurants, and canceling public events, we used equations similar to (1) but replaced the lockdown indicator with the indicator of the policy analyzed. For school closings, we introduced two variations. First, we only included observations from weekdays in the sample (given that school closures should have no effect on weekends).[12] Additionally, the policy indicator has a value of 1 for school closures only in countries where the school year had already begun by the time the closures were ordered.[13]

Tables 5 and 6 presents the results of estimating equation (1) for each of the individual social distancing policies (columns (1) and (4)). The results indicate that lockdowns had a negative statistically significant impact on mobility. Specifically, the percentage of people traveling more than one kilometer declined by an average of 10 percentage points after the implementation of this policy. To benchmark this effect, we calculated the decline in mobility between the first week in March and the first week in April in the 11 countries that implemented lockdowns (34 percentage points). Therefore, the average impact of lockdowns accounts for close to a third of the average decline in mobility. Additionally, compared to pre-coronavirus levels (March 5-11), we found that lockdowns reduced the percentage of people traveling more than 1 kilometer by 15% (online appendix Table A.2). This finding was obtained by including the percentage change in mobility compared to the pre-coronavirus period in equation (1) as a dependent variable. Additionally, we estimate that school closures reduced mobility by 4 percentage points. The impact of lockdowns and school closures are significant at the 5% level. In contrast, the impact of closing bars and restaurants and canceling public events is close to zero and not statistically significant.[14]

We conducted five complementary analyses to check the validity of the methodology applied. First, we used a model similar to the one presented in equation (1), but simultaneously controlling for the other three policies studied herein. Note that the methodology described in de Chaisemartin and D'Haultfoeuille (2019) does not permit using all four policies in a single equation. Rather, a separate model must be used for each coefficient of interest, adding the other policies as controls. Columns (2) and (5) of tables 5 and 6 present the estimated coefficients for

[12] One alternative would be to include weekends and set the "Schools closed" indicator to 0 on those days. However, this would make it infeasible to use the estimator described in de Chaisemartin and D'Haultfoeuille (2019), which requires any unit entering treatment to remain in that state for the duration of the period under analysis.

[13] Closing schools in countries where the school year had not yet begun (Ecuador and Peru) should have no impact on mobility.

[14] The findings presented in Table 5 are similar to those obtained by using the traditional difference in differences estimator, with the exception of the effect of school closings, for which the effect was found to be close to 0 and not significant (see online appendix Table A.1)

each policy when the other policies are controlled for. The findings indicate that the estimated effects are similar to the baseline specification, with the exception of the coefficient for the impact of school closures, which increases slightly to 5 percentage points.

Second, we explored whether there is evidence of parallel trends between treatment and comparison groups during the period prior to the implementation of each policy. For the four policies under analysis, we find consistent evidence of the existence of parallel trends, providing support for the identification strategy used in this study.

Third, it is possible that countries that implemented social distancing measures may have been reacting to certain bad news "shocks" (for example, reports of sharp increases in the number of cases), which may have directly reduced mobility aside from any policies implemented by the government. To tackle this issue, we have estimated additional specifications that included the number of new cases per million inhabitants as a control in the regressions.[15] As shown in columns (3) and (6) in tables 5 and 6, the coefficients remain virtually unchanged when adding this additional control.[16]

Fourth, we explored whether results were sensitive to using a more restrictive filter to select users included in the analysis. As mentioned in the data section, in our baseline specification we included in the sample users who had at least 10 pings per day. To explore the robustness of the results to alternative specifications, we estimated effects including only users with at least 10 pings during the day, at least 4 pings at night (10 pm to 6 am), and who were present in our sample for at least 30 days. Results in this more restrictive dataset, presented in Table A.3, are similar to those in the baseline specification. In particular, lockdowns reduce our measure of mobility by 11 percentage points, school closures by 4 percentage points, and there are no statistically significant effects for bars and restaurants closures and the cancellation of public events.

Fifth, we produced alternative estimates using Google Mobility Reports data. The results are reported in Table A.4. We focus our analysis on two data series that we consider most relevant for our analysis. The first is the percent change in visits to retail and recreation locations, and the second is the percent change in visits to workplaces. Note that this alternative analysis involves

[15] Statistics on number of cases were obtained from "Our World in Data" (https://ourworldindata.org/coronavirus).

[16] It may be the case that countries decided to implement a package of measures (in addition to the ones studied in this paper), which may have separately impacted mobility. In this case, the estimate presented for a policy would be overestimating the real impacts. In contrast, if governments tend to space out the measures implemented over time (for example, if when a country closes schools, it becomes less likely to implement other actions), then the findings presented could be underestimating the real impacts of the policies implemented.

using a different data source (Google instead of Veraset) and also a different concept of mobility (visits to places instead of the fraction of users traveling more than 1 kilometer). Moreover, the Google series present percent changes with respect to the period of January 3 to February 6. Consequently, our percent change results, presented in Table A.2, are more directly comparable to those generated using Google data. In spite of all these differences, we arrive at similar qualitative results. Using Google data, we find that: lockdowns reduced the visits to retail and recreation places by 23 percent[17] (22 percent for work places), school closings reduced visits to retail and recreation places by 9 percent (12 percent for work places), and bars and restaurants closings, as well as the cancellation of public events, did not affect visits to these commercial and work-related locations.[18] In turn, Table A.2, which uses our baseline specification but presenting results in percent changes, indicate that lockdowns reduced the fraction of individuals traveling more than one kilometer by 15 percent, school closings reduced this mobility measure by 7 percent, and no effects were found for bars and restaurants closings, and the cancellation of public events. The slightly smaller effects found with our mobility measure could potentially indicate that lockdowns and school closings reduced more visits to commercial and work-related locations compared to more general visits to all places (including social visits to family members, friends, and visits to hospitals and pharmacies).

5.2. Dynamic Impacts of the Lockdowns

The results from the previous subsection indicate that the lockdowns significantly reduced mobility. In this section, we delve further into this analysis, given the key role this policy can play in the fight against the coronavirus.[19]

[17] Note that the decrease in mobility caused by lockdown explains a third of the total decrease in mobility from the first week of March (pre) to the first of April (post). In other words, on average the pre-post mobility difference is about 70%-75% and lockdowns corresponds to a 30% of that decrease over the first month of the pandemic.

[18] Note that the effects estimated using Google Mobility Reports data are not as robust to controlling for other policies as the baseline results presented in the paper using data from the firm Veraset. In particular, Table A.4 shows that the effects of school closings on the mobility measures obtained from Google are statistically significant when controlling for other policies but are not statistically significant when these additional policies are not controlled for. Also, results indicate statistically significant effects at the 10 percent confidence level for bars and restaurants closings on the number of visits to retain and recreation when not controlling for the other policies analyzed here.

[19] In principle, we can empirically analyze the dynamic impacts of school closures. However, because school closures have an immediate impact that is directly verifiable, it is difficult to believe they could have effects that change over time. Also, given that the vast majority of countries closed schools between Friday, March 13, and Monday, March 16, there is not enough variation to estimate impacts beyond the first day of school closures.

We begin this analysis by comparing the average characteristics of the 11 countries that implemented lockdowns with those of the 7 countries that did not implement lockdowns.[20] This analysis, presented in Table 7, suggests that both groups are balanced in terms of important indicators like the percentage of the population older than 65, the percentage of rural population, years of education, and per capita GDP. Likewise, the last two columns of this table show average mobility during the week of March 5-11 (when mobility still had not been affected by the coronavirus crisis), as well as for the day before the first lockdown declaration (March 15). Relevant to this analysis, the two groups are balanced in both pre-lockdown mobility indicators. The variable with significant differences across the two groups is total population, which averages 19 million for the countries that implemented lockdowns and 9 million for the countries that did not.

Next, we analyzed the temporal dynamic of the impact of the lockdowns. For this, we used the balanced panel with day-country observations described in the previous subsection. In particular, we estimate a two-way fixed effects model with 16 leads and lags. More specifically, we conducted an event study estimating the following equation:

$$Mobility_{it} = country_i + day_t + \sum_{l=-15}^{l=15} \delta_l \, Lockdown_{i\,t-l} + \eta_{it} \qquad (2)$$

in which $Mobility_{it}$ represents the percentage of people traveling more than 1 kilometer in country i and day t; $country_i$ and day_t are fixed effects per country and per day, respectively; $Lockdown_{i\,t-l}$ is a dummy variable that takes the value of 1 if two conditions are met: (i) the country i implemented a lockdown at some point; (ii) the country i had the lockdown in place in the day t-l.[21] The coefficients of interest, δ_l, capture the increase in mobility compared to the reference period (16 or more days before the introduction of the lockdown). For example, for the case of Argentina that implemented a lockdown on March 20, the observation that corresponds to March 5 has only one indicator (in addition to the fixed effects for country and day) for δ_{-15} because that day corresponds to a 15-day lead with respect to when treatment started.

[20] The countries that implemented lockdowns are Argentina, Bolivia, Colombia, Ecuador, El Salvador, Honduras, Panama, Paraguay, Peru, Trinidad and Tobago, and Venezuela. The countries that did not implement lockdowns are Chile, Costa Rica, the Dominican Republic, Guatemala, Jamaica, Nicaragua, and Uruguay.

[21] We also include two additional variables that account for the days before our 15-day window and for the days after our 15-day window. We use the former variable as our reference category for the analysis.

This specification flexibly captures the dynamic of the lockdown's daily effects. Specifically, the coefficients δ_0 to δ_{15} make it possible to estimate the impacts of the lockdown for every day subsequent to the introduction of the lockdown. Additionally, analysis of the coefficients δ_{-15} to δ_{-1} enables exploring whether parallel trends were present prior to the introduction of the lockdown for countries that implemented it and countries that did not. As in Subsection 5.1, these effects are estimated using the methodology presented in de Chaisemartin and D'Haultfoeuille (2019).[22]

Figure 1 presents the findings of this event study. The coefficients for the days prior to the lockdown are close to 0 and never statistically significant. These findings indicate the existence of parallel trends prior to the introduction of a lockdown and provide evidence in favor of the identification strategy used. Analyzing the day-by-day impacts of the lockdowns, we note that mobility falls drastically by 10 percentage points on day 0 (when the lockdowns are introduced). The impact is even greater on days 1 through 3, reaching close to 13 percentage points. But over subsequent days, there is a distinct diminishment of these impacts, and by day 15 of the lockdown, the impact on mobility is only 7 percentage points. These findings contrast with existing evidence for Africa and the United States, which has generally revealed effects that are relatively stable over time (Akim and Ayivodji, 2020; Cronin and Evans, 2020; Dave et al., 2020a).

To more systematically document the drop in the impact of lockdowns, we use the following event study, which has the same structure as the one presented in equation (2), with the difference that effects are estimated for periods of around one week, rather than one day:

$$Mobility_{it} = country_i + day_t + \sum_{\tau} \delta_\tau \, L_{i\tau} + \eta_{it} \qquad (3)$$

where the variables $Mobility_{it}$, day_t and $country_i$ correspond to the same variables included in equation (2). $L_{i\tau}$ is a set of four variables. The first indicator takes the value of 1 for the 7 days prior to the introduction in country *i* of the lockdown, the second indicator is equal to 1 for the day of the introduction of the lockdown, and the third indicator takes the value of 1 for the 7 days after. Likewise, the fourth indicator has a value of 1 for days 8 to 15 following the introduction of the lockdown, and the final indicator is equal to 1 for the 16 or more days after the introduction of the

[22] The coefficients and standard errors associated with the equation (3) employed using the methodology described in de Chaisemartin and D'Haultfoeuille (2019) are very similar to those obtained using the traditional event study method. The coefficients and standard errors of both estimates are reported in online appendix Table A.5.

lockdown. The coefficients δ associated with the indicators described reflect the increase in mobility compared to the period of 9 or more days before introduction of the lockdown.[23]

Results presented in Table 8 indicate the existence of parallel trends prior to the introduction of the lockdowns, as the coefficient for the period of -8 to -1 is not significant and close to zero. The table also shows an effect of about 11 percentage points for day 0, which increases in the first week following the introduction of the lockdown (days 1 to 7) but declines over the following week (days 8 to 15). This decline in impact between the first week and the second week is 28% (8.92/12.40-1) and statistically significant.

Why would the impacts of lockdowns decline over time? There are two possible explanations: people from the treatment group increased their mobility over time (or did so more than the comparison group), or the people in the comparison group reduced their mobility over time (or did so more than the treatment group). With regard to the first explanation, the people in the treatment group may have increased mobility during the second week compared to the first week post-lockdown because they were initially afraid of becoming infected, and this caused a significant and immediate reduction in mobility. However, with the passage of time, upon receiving more information on how to prevent contagion, people may have gained more confidence and begun to increase their mobility (Dave et al., 2020a). The increase in mobility for people subjected to the lockdown may also be the result of the levels of poverty and informality in the Latin American context that force people to go out after several days of lockdown because they need to generate income to cover essential living expenses. Concerning the latter explanation, those in the comparison group may have reduced their mobility during the second week because the process of disseminating information on the virus was slower, meaning that their reduction in mobility was not immediate. In that case, the lockdown not only would lead to a greater reduction in mobility but would also make people to reduce their mobility more quickly.

To explore these potential explanations, Figure 2 presents the difference in mobility between the first and second weeks following the implementation of the lockdown for each treatment country and its comparison group. Specifically, the countries are ordered according to

[23] Because the de Chaisemartin and D'Haultfoeuille (2019) methodology does not make it possible to directly calculate effects by period, we employed the traditional event study estimator to estimate equation (3). These findings should be robust to the estimation method used, given that the results generated when analyzing effects by day estimating a traditional event study are very similar to those generated using the methodology described in de Chaisemartin and D'Haultfoeuille (2019).

when they implemented a lockdown and placed into two groups: countries that introduced this policy early (between March 16 and 17) and countries that implemented it later (between March 20 and 30). The figure shows that the countries that implemented a lockdown early saw mobility decline in the second week post lockdown compared to the first by around 6 percentage points. However, during that period, mobility was reduced by close to 12 percentage points in the countries in the comparison group. These results suggest that the lockdown initially accelerated the decline in mobility in countries where it was implemented, but that the decline is followed by a process of convergence. Meanwhile, different patterns are observed for countries that implemented a lockdown later. In this case, while mobility remains stable in the comparison countries, it increases slightly in the majority of countries that implemented a lockdown. Thus, for this group of countries that implemented lockdowns later, the findings suggest that the decline in impacts is the result of an increase in mobility among those subject to a lockdown. However, of the total effect of the lockdown on mobility, the increase in mobility in the treatment countries seems to be less important compared to the convergence of the comparison countries.

An important question is whether the effects of lockdowns vary across different types of countries. Indeed, Maire (2020) used cell phone data and found that lockdowns generated much larger reductions in mobility in high-income countries compared to low-income countries. Performing this type of analysis is severely limited in our case because there are only 11 countries that experienced a lockdown in our sample, making it difficult to detect heterogeneous effects. Still, we explored whether the effects have differed by countries with different levels of GDP per capita. To do so, we interacted the lockdown variable in our main regression (presented in equation 1) with a dummy variable that equals one for countries whose GDP per capita is below the median level for countries that implemented a lockdown in our sample. These results suggest that there is no evidence of heterogeneous effects regarding GDP per capita in our sample (results available upon request).

5.3. Dynamic Impacts of Lockdowns per Country

How did the effects of the lockdowns vary by country? To answer this question, we analyze the mobility trend of each country that implemented a lockdown and compare it against the average mobility of the 7 countries that did not establish a lockdown. For each country that implemented a lockdown, we analyze the period covering the 15 days prior to and 15 days after the introduction of this measure.

Figure 3 shows the mobility trend of each country that introduced a lockdown (black line) versus the comparison group (gray line). The horizontal axis marks days relative to the introduction of the lockdown (day 0 is when it was implemented), while the vertical axis charts the percentage of people traveling more than 1 kilometer per day. For the case of Argentina, which implemented a lockdown on March 20, mobility is observed to decline during the days prior to the introduction of the lockdown, then decrease sharply during the days subsequent to the introduction of this measure. Also, we note that average mobility in the comparison countries followed a very similar trend in the days prior to the introduction of the lockdown in Argentina, but that the series diverges drastically when Argentina imposes its lockdown. Lastly, we observed that the mobility series of Argentina and the comparison countries tend to converge with the passage of days subsequent to the introduction of the lockdown, replicating the general finding that the effects of the lockdown lessen over time. These patterns documented for Argentina tend to be replicated in the majority of countries analyzed.

To build the comparison series presented in Figure 3, a simple mobility average was calculated for the 7 countries that did not introduce lockdowns. To refine this analysis, we used a synthetic control methodology (Abadie et al., 2010) that involves producing comparison series by calculating a weighted average for the countries that did not implement the lockdown. The weights used for each comparison country are selected to minimize the root mean square error in the period prior to the intervention. Table A.6 in the online appendix shows the weights used for the comparison countries to generate the synthetic control for each country that implemented a lockdown.

Table 9 shows the mobility difference for each country that introduced a lockdown compared to its synthetic control per day relative to the introduction of this measure. The lower row also presents the average effects estimated by country. The findings indicate significant country-by-country heterogeneity in the effects of the lockdowns. Countries with the greatest impact include the cases of Bolivia, Ecuador, and Argentina, with drops in mobility of 19, 17, and 16 percentage points, respectively, as a result of the lockdown. On the other hand, there are countries where the impacts were noticeably less, such as Paraguay and Venezuela, where mobility declined by only 3 percentage points. There are a variety of possible explanations for this heterogeneity of effects among countries, including different ways of communicating the lockdowns, different punishments for people violating them, varying enforcement efforts made by governments to ensure lockdowns were followed, and the socioeconomic characteristics of the population as far as the opportunity to telework and having sufficient financial resources to cover expenses during the lockdown period. Likewise, other policies could be interacting with the effects of the lockdowns, including monetary transfers from governments to reduce the impact on the population of remaining at home without work.[24]

Then, we examine whether the effects observed from the lockdowns are statistically significant, or if they may have arisen simply from variability in the sample. In the case of the synthetic control methodology, the inferences are based on permutation tests called "placebo tests" (Abadie and Gardeazabal, 2003). These tests are performed by assigning each country from the comparison group to "treatment" and generating a distribution of placebo effects. The effect estimated using the synthetic control methodology is then compared with the placebo effect distribution (see the results in online appendix Table A.7). Generally, the p-values are relatively low and close to zero, except for countries where a lesser effect was documented, like Paraguay and Venezuela.

Synthetic control methods, though useful to estimate effects when individual units are treated, can generate biased results when there is not a good fit for the pre-treatment outcomes. To solve this problem, Ben-Michael, Feller, and Rothstein (2020) propose the augmented synthetic control method, which, through a ridge regression model, allows the described bias to be corrected. We implement this procedure and generate alternative estimates that are presented in Table A.8. In general results are similar to those presented in Table 9 for the baseline estimation. In fact, for the 11 countries analyzed, only in the case of Colombia the results diverge by more than 3 percentage points (the baseline synthetic control method estimates the effects of lockdowns at 3 percentage points compared with an effect of 8 percentage point for the augmented synthetic control method).

[24] When comparing impacts among countries, it is important to recognize that the representativeness of the sample used in this study can fluctuate significantly among countries. In all countries, smartphone coverage is biased toward higher-income populations. However, this bias should be expected to be higher in countries with lower income levels. This is because the percentage of people of lower socioeconomic status with smartphones will vary substantially between countries with different income levels. For example, it should be expected that smartphone coverage among individuals in the lowest income quintile in Chile will be notably higher than such coverage in countries like Honduras or Nicaragua.

On the other hand, the reduction in people's mobility in each country may also be linked to characteristics such as the region in which they live, place of residence, or age. For example, working-aged people living farther away from economic centers may be expected to have reduced their mobility to a greater extent, or older adults may not have significantly changed their mobility. However, given the information we have available, it is not possible to identify these characteristics for each user, and, therefore, we cannot estimate the heterogeneous effects of lockdowns for different groups. Still, a recent paper by Aromi et al. (2021) shed light on this issue. The study explored the differential change in mobility by socioeconomic status for eight large Latin American cities during the beginning of the pandemic.[25] The authors show that before the pandemic, there was a positive association between socioeconomic status and mobility in all cities analyzed. People in the top socioeconomic decile, measured by fraction of individuals with secondary education, had higher mobility than people in the bottom decile. After the onset of the pandemic, the relationship changed as the reduction in mobility was 75% higher for top decile. The authors argue that this change may be due to a higher capacity of high-income individuals of working remotely and the difficulty of low-income people to stop working to reduce mobility during the pandemic.

6. Conclusion

This study evaluates the impact on mobility of national policies seeking to encourage social distancing. The sample includes mobility series from 18 Latin American and Caribbean countries for the period March 1 to April 14, constructed using georeferenced data from cellular telephones. The findings indicate that the lockdowns reduced the percentage of people traveling more than 1 kilometer per day by 10 percentage points. The effects are found to vary over time and among countries. Particularly, the effects on mobility are 28% less during the second week following the implementation of a lockdown, compared to the first week. Also, while lockdowns reduced mobility by between 16 and 19 percentage points in Argentina, Bolivia, and Ecuador, in Paraguay and Venezuela, the reduction was only 3 percentage points. We also find that school closures have a negative impact on mobility of 4 percentage points. Additionally, closing of bars and restaurants

[25] The study analyzed mobility in Bogota, Buenos Aires, Guadalajara, Guayaquil, Mexico DF, Rio de Janeiro, Santiago de Chile, and Sao Paulo.

and cancellation of public events were found to have no impact on the mobility measurement analyzed.

This analysis has its limitations. Given that the variation used in the study is not experimental, the estimates presented may have certain biases. With regard to external validity, because the coverage of smartphones is greater in populations with higher incomes, estimated effects are more representative for this population than for the general population. With regard to this, the average effects found may hide important heterogeneous effects between high-income and low-income populations. Lastly, this study presents the results of a particular mobility measure, and it will be important to analyze the results when other alternative measures are used.

Aside from these limitations, the results presented have important policy implications. Specifically, they suggest that lockdowns are a tool that can produce reductions in mobility quickly. This is important given the expectation that reduced mobility slows the spread of the coronavirus. This expected link between mobility and spread, based on the mechanisms by which the virus spreads, has been confirmed by recent empirical studies (Glaeser et al., 2020). However, it is important to consider the evidence presented with regard to variation in effects over time and among countries. These considerations suggest that the impacts of lockdowns on mobility cannot be assumed to be automatic and free from uncertainty. The study also indicates that closing schools also reduced mobility to a certain degree.

Different research questions could be addressed by future studies. First, studies could analyze the causes of the changes in the effects of the lockdowns over time and among countries. Second, studies could explore how monetary transfer programs affect mobility and how they can interact with the social distancing measures presented herein (Akim and Ayivodji, 2020, analyze this phenomenon in Africa). Third, studies could analyze the impacts of policies implemented at different levels of geographic aggregation, such as country level, an initial subnational level (like state or province), or further subnational level (like a municipality or *comuna*). Fourth, studies could analyze the different effects of introducing and lifting lockdowns. Finally, it is crucial to delve further into the impacts of lockdowns on the spread of coronavirus and economic activity and how human mobility moderates these effects.

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Table 1. Date of First Coronavirus Case

Country	Date
Brazil	25-feb
Mexico	28-feb
Ecuador	29-feb
Dominican Republic	1-mar
Argentina	3-mar
Chile	3-mar
Costa Rica	6-mar
Peru	6-mar
Paraguay	7-mar
Panama	9-mar
Bolivia	10-mar
Jamaica	10-mar
Guyana	11-mar
Honduras	11-mar
Trinidad and Tobago	12-mar
Guatemala	13-mar
Uruguay	13-mar
Venezuela	13-mar
El Salvador	18-mar
Nicaragua	18-mar
Belize	22-mar

Notes: This table shows the dates on which the first cases of coronavirus were reported in each country.

Table 2. Implementation Date of Social Distancing Measures

Country	Lockdowns	School closings	Bars and restaurants closings	Cancellations of public events
	(1)	(2)	(3)	(4)
Argentina	20-Mar	16-Mar		12-Mar
Bolivia	22-Mar	13-Mar	16-Mar	12-Mar
Chile		16-Mar	21-Mar	21-Mar
Colombia	24-Mar	16-Mar	19-Mar	12-Mar
Costa Rica		17-Mar	15-Mar	10-Mar
Dominican Republic		18-Mar	18-Mar	18-Mar
Ecuador	17-Mar	13-Mar	17-Mar	13-Mar
El Salvador	22-Mar	12-Mar	14-Mar	14-Mar
Guatemala		16-Mar	17-Mar	15-Mar
Honduras	16-Mar	13-Mar	15-Mar	15-Mar
Jamaica		13-Mar	18-Mar	13-Mar
Nicaragua				
Panama	25-Mar	11-Mar	15-Mar	10-Mar
Paraguay	21-Mar	10-Mar	10-Mar	10-Mar
Peru	16-Mar	16-Mar	16-Mar	12-Mar
Trinidad and Tobago	30-Mar	13-Mar	20-Mar	20-Mar
Uruguay		16-Mar		13-Mar
Venezuela	17-Mar	16-Mar	13-Mar	13-Mar

Notes: This table shows the implementation date by country of the four social distancing measures analyzed.

Table 3. Statistics on Social Distancing Policies Implemented

Event	Number of countries (1)	Implementation day of policies in March 2020				
		Mean (2)	Minimum (3)	25th percentile (4)	75th percentile (5)	Maximum (6)
Lockdowns	11	21	16	17	25	30
School closings	17	15	11	13	16	18
Bars and restaurants closings	15	16	10	15	18	21
Cancellations of public events	17	16	10	12	15	21

Notes: This table shows statistics on the implementation of the social distancing policies analyzed. The sample includes 18 Latin American and Caribbean countries. Note that all measures were implemented during March 2020. Column (1) indicates the number of countries that adopted the measure as of March 30, 2020. Columns (2) to (6) present statistics regarding when the measures were implemented. The dates are standardized, so that 1 corresponds to March 1, 2020.

Table 4. Sample Coverage and Mobility by Country

Country	Observations (millions)	Population (millions)	Coverage (%)	Traveled more than 1 km, March 5-11 (%)	Mobile phone access (% age 15+)
	(1)	(2)	(3)=(1)/(2)	(4)	(5)
Argentina	0.31	44.49	0.69	65.03	81.60
Bolivia	0.04	11.35	0.39	63.73	87.91
Chile	0.03	18.73	0.18	67.57	90.22
Colombia	0.19	49.65	0.38	55.79	83.51
Costa Rica	0.05	5.00	1.01	70.16	91.55
Dominican Republic	0.05	10.63	0.48	63.61	81.38
Ecuador	0.06	17.08	0.34	65.54	76.63
El Salvador	0.01	6.42	0.22	66.71	74.05
Guatemala	0.02	17.25	0.12	68.51	75.77
Honduras	0.02	9.59	0.22	64.12	80.06
Jamaica	0.01	2.93	0.51	60.96	-
Nicaragua	0.01	6.47	0.14	60.01	79.94
Panama	0.01	4.18	0.33	69.52	77.31
Paraguay	0.01	6.96	0.21	70.55	81.90
Peru	0.13	31.99	0.40	73.42	78.75
Trinidad and Tobago	0.02	1.39	1.16	68.81	90.96
Uruguay	0.02	3.45	0.63	74.71	91.49
Venezuela	0.04	28.87	0.14	67.35	73.70
Average	**0.06**	**15.36**	**0.42**	**66.45**	**82.16**

Notes: This table presents the descriptive statistics of the sample coverage and mobility by country. Column (1) reports the average observations between March 5 and 11. Column (2) reports the total population. Column (3) presents the coverage of the sample, which is calculated by dividing the number of observations (column 1) by the total population (column 2). Column (4) shows the average percentage of people who travel more than 1 kilometer between March 5 and 11. Column (5) shows the percentage of people over the age of 15 who has access to a mobile phone. The last row of the table presents the average of each of the columns for the 18 countries analyzed.

Table 5. The Effect of Lockdowns and School Closings on Mobility

	% of people who travel more than 1 km					
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Lockdowns	-10.26**	-10.09**	-10.11**			
	(3.12)	(3.09)	(2.98)			
School closings				-3.74*	-4.85*	-4.89*
				(1.64)	(1.91)	(2.20)
Controls for other policies	No	Yes	Yes	No	Yes	Yes
Control for new cases (per million inhabitants)	No	No	Yes	No	No	Yes
Dependent variable average (March 5-11)	66.45	66.45	66.45	68.04	68.04	68.04
N	810	810	810	594	594	594

Notes: This table shows the average effects of social distancing policies on human mobility. The dependent variable is the percentage of people who travel more than one kilometer per day. The results are generated from a balanced panel of 18 Latin American and Caribbean countries covering the period from March 1 to April 14, 2020. Each column corresponds to a regression. The rows indicate the policy analyzed in each regression. The sample used to evaluate the impact of school closings, the results of which are presented in columns (4), (5), and (6), do not include weekdays. In columns (1) and (4), the calculation is made without controls. In the following columns, controls for the other three distancing policies and control for new cases are included in the regression. Standard errors, presented in parentheses, are calculated by bootstrapping with 400 repetitions and clusters at the country level. Significance at one and five percent indicated by **, and *, respectively.

Table 6. The Effect of Bar and Restaurants Closings and Cancellations of Public Events on Mobility

	% of people who travel more than 1 km					
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Bars and restaurants closings	-2.53	-0.53	-0.54			
	(1.39)	(1.68)	(1.78)			
Cancellations of public events				0.08	0.01	0.11
				(0.75)	(0.78)	(0.82)
Controls for other policies	No	Yes	Yes	No	Yes	Yes
Control for new cases (per million inhabitants)	No	No	Yes	No	No	Yes
Dependent variable average (March 5-11)	66.45	66.45	66.45	66.45	66.45	66.45
N	810	810	810	810	810	810

Notes: This table shows the average effects of social distancing policies on human mobility. The dependent variable is the percentage of people who travel more than one kilometer per day. The results are generated from a balanced panel of 18 Latin American and Caribbean countries covering the period from March 1 to April 14, 2020. Each column corresponds to a regression. The rows indicate the policy analyzed in each regression. In columns (7) and (10), the calculation is made without controls. In the following columns, controls for the other three distancing policies and control for new cases are included in the regression. Standard errors, presented in parentheses, are calculated by bootstrapping with 400 repetitions and clusters at the country level. Significance at one and five percent indicated by **, and *, respectively.

Table 7. Descriptive Statistics of Countries with and without Lockdowns

	With lockdown (1)	Without lockdown (2)	Difference (3)	P-value (4)
Population (millions)	19.27	9.21	10.06	0.04
Population over the age of 65 (%)	7.96	8.83	-0.87	0.32
Rural population (%)	28.76	27.35	1.41	0.77
Average years of education (older than 25)	8.94	8.82	0.12	0.84
Life expectancy at birth	74.94	76.36	-1.42	0.10
GDP per capita, PPP (thousands of current dollars)	15.56	15.36	0.19	0.94
Poverty rate at US$5.50 per day (2011 PPP) (%)	24.68	17.22	7.46	0.14
Share of income of the highest decile (%)	34.00	34.98	-0.98	0.48
Unemployment (%)	5.45	7.26	-1.81	0.19
Self-employed (% of employed)	43.76	35.68	8.07	0.17
Mobile phone access (% age 15+)	80.58	85.06	-4.48	0.16
Internet access (% age 15+)	57.00	62.18	-5.18	0.42
Travels more than 1 km, March 5-11 average (%)	66.42	66.50	-0.09	0.93
Travels more than 1 km, March 15 (%)	60.19	61.16	-0.97	0.75

Notes: This table shows descriptive statistics of sociodemographic and mobility variables. Column (1) reports the average of the variables for the 11 countries that implemented the quarantine. Column (2) reports the average of the variables for the 7 comparison countries. Column (3) presents the difference in the averages between both groups. Column (4) shows the p-value of the difference from the average for each of the variables. Mobility is reported for March 15 because this is the day before the quarantine takes effect for the first countries that implemented it (Honduras and Peru).

Table 8. Dynamic Effects of Lockdowns on Mobility

	% of people who travel more than 1 km		
	(1)	(2)	(3)
Trend from days -8 to -1 (pre-lockdown)	0.03	0.66	0.62
	(1.17)	(1.12)	(1.08)
Effect of day 0 (post-lockdown)	-10.85**	-10.04**	-10.09**
	(2.61)	(2.67)	(2.68)
Effects of days 1 to 7 (post-lockdown)	-12.40**	-11.85**	-11.89**
	(2.23)	(2.17)	(2.15)
Effects of days 8 to 15 (post-lockdown)	-8.92**	-8.50**	-8.51**
	(2.24)	(2.19)	(2.16)
Effects of days 16 and beyond (post-lockdown)	-7.60**	-7.25**	-7.20**
	(2.28)	(2.19)	(2.19)
Controls for other policies	No	Yes	Yes
Control for new cases (per million inhabitants)	No	No	Yes
N	810	810	810

Notes: This table shows the average effect of distancing policies on human mobility for five time periods: pre-lockdown (days -8 to -1), post-lockdown effect for day 0, postlockdown effect for days 1 to 7, postlockdown effect for days 8 to 15, and postlockdown effect beyond 15 days. The dependent variable is the percentage of people who travel more than one kilometer per day. The sample includes the 18 Latin American and Caribbean countries analyzed in this study during the period from March 1 to April 14, 2020. Each column corresponds to a regression. In column (1), the estimate is made without controls that vary over time, while in the following columns controls for the other three distancing policies (closing schools, closing bars and restaurants, and cancellations of public events) and control for new cases are included in the regression. Standard errors, presented in parentheses, are calculated by bootstrapping with 400 repetitions and clusters at the country level. Significance at one and five percent indicated by **, and *, respectively.

Table 9. The Dynamic Effects of Lockdowns on Mobility by Country

Post-lockdown days	Argentina	Bolivia	Colombia	Ecuador	El Salvador	Honduras
0	-19.02	-13.00	-6.15	-17.62	-13.04	-7.48
1	-18.02	-21.35	-12.15	-25.37	-15.39	-18.08
2	-15.49	-16.53	-11.66	-23.15	-13.86	-19.60
3	-23.21	-18.78	-14.17	-22.16	-11.65	-15.19
4	-20.28	-20.58	-4.95	-18.30	-12.19	-19.22
5	-17.58	-21.72	-0.35	-12.07	-10.10	-13.86
6	-16.78	-21.78	-12.44	-20.05	-8.91	-8.74
7	-16.58	-15.54	-10.30	-16.51	-6.80	-14.52
8	-14.19	-21.55	-7.43	-16.74	-9.59	-14.81
9	-12.48	-20.05	-7.98	-17.66	-9.24	-6.51
10	-17.25	-19.20	-9.66	-16.08	-8.79	-6.37
11	-17.52	-19.51	-2.09	-11.85	-9.24	-4.78
12	-13.68	-19.72	-1.02	-8.65	-10.27	-3.76
13	-13.07	-21.18	-10.28	-14.94	-7.65	-0.46
14	-13.95	-18.11	-3.32	-15.21	-8.22	-7.24
15	-9.50	-17.58	-9.40	-14.93	-8.51	-12.51
Average	-16.16	-19.14	-7.71	-16.96	-10.22	-10.82

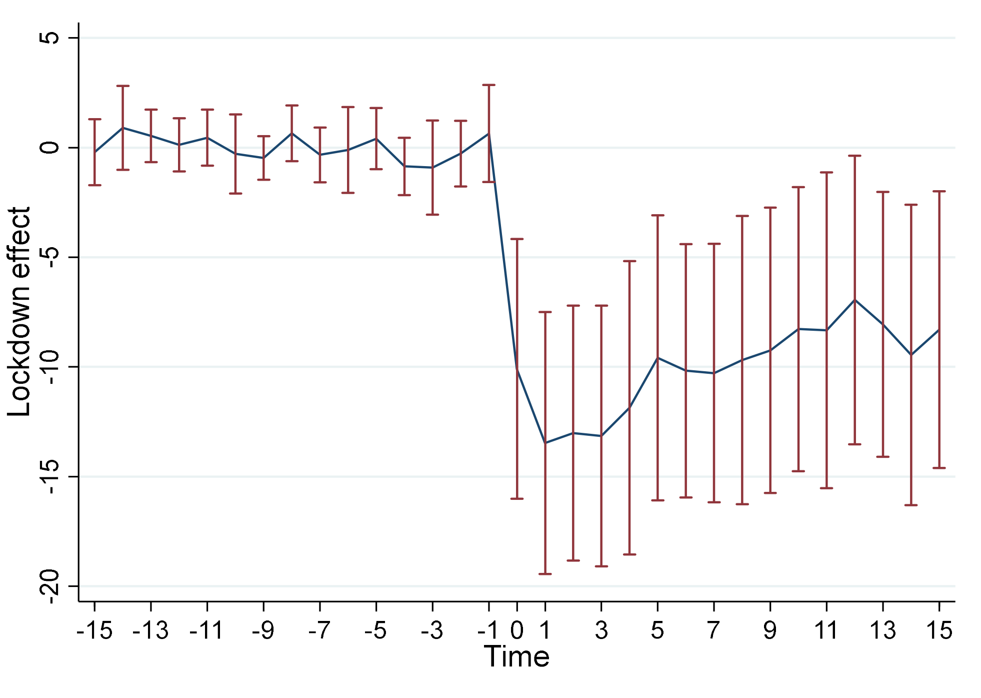
Notes: This table shows the daily effects of lockdowns on human mobility. The sample consists of each country analyzed that implemented a lockdown and countries included in the corresponding synthetic control.

Table 9. The Dynamic Effects of Lockdowns on Mobility by Country (continued)

Post-lockdown days	Panama	Paraguay	Peru	Trinidad and Tobago	Venezuela
0	-9.56	-3.99	-1.54	-19.00	-11.85
1	-9.29	-7.58	-13.23	-9.82	-11.58
2	-11.60	-8.01	-9.84	-8.43	-10.07
3	-8.29	-5.74	-13.66	-8.96	-9.23
4	-6.62	-4.21	-16.08	-6.65	-5.36
5	-11.66	-4.43	-10.94	-7.70	-4.00
6	-9.90	-2.62	-5.00	-6.72	-7.09
7	-13.21	-0.36	-11.15	-5.48	-6.74
8	-10.21	2.08	-10.79	-7.32	0.27
9	-14.26	1.13	-11.64	-6.58	1.60
10	-7.40	3.32	-9.51	-6.08	2.15
11	-15.40	-0.44	-9.86	-5.59	4.69
12	-12.66	-2.88	-6.47	-2.05	4.95
13	-9.16	-3.11	-5.10	-5.12	-0.72
14	-11.31	-0.71	-10.02	-15.23	0.89
15	-5.49	-3.24	-9.06	-4.91	0.07
Average	-10.38	-2.55	-9.62	-7.85	-3.25

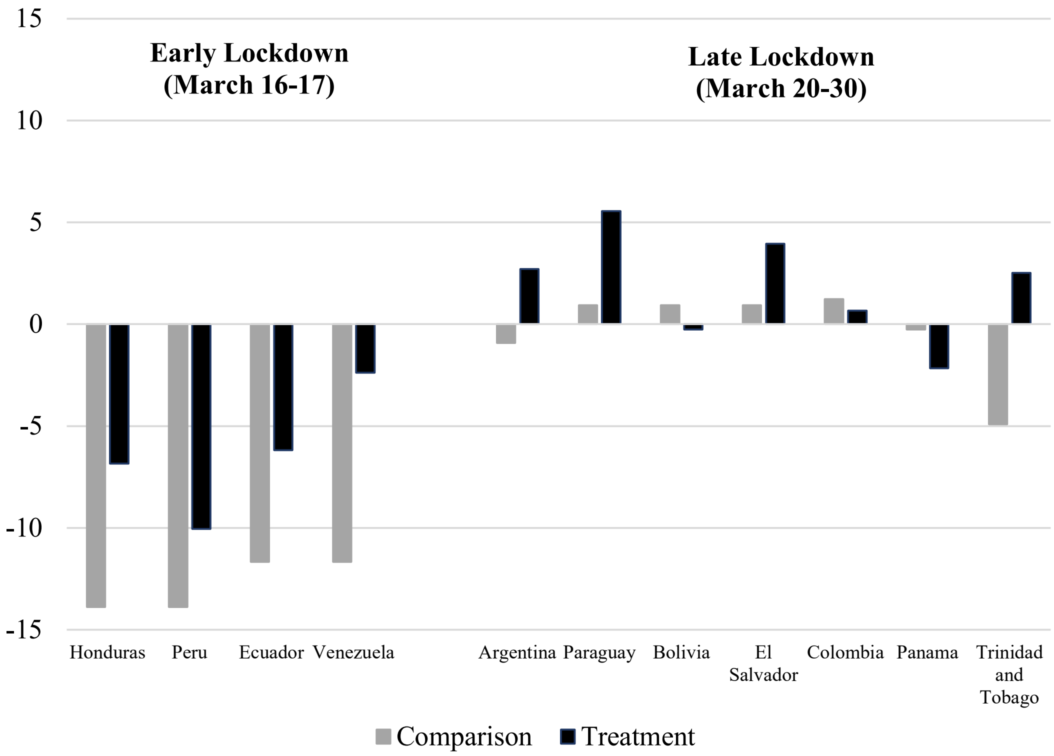
Notes: This table shows the daily effects of lockdowns on human mobility. The sample consists of each country analyzed that implemented a lockdown and countries included in the corresponding synthetic control.

Figure 1. Event Study of the Effects of Lockdowns on Mobility



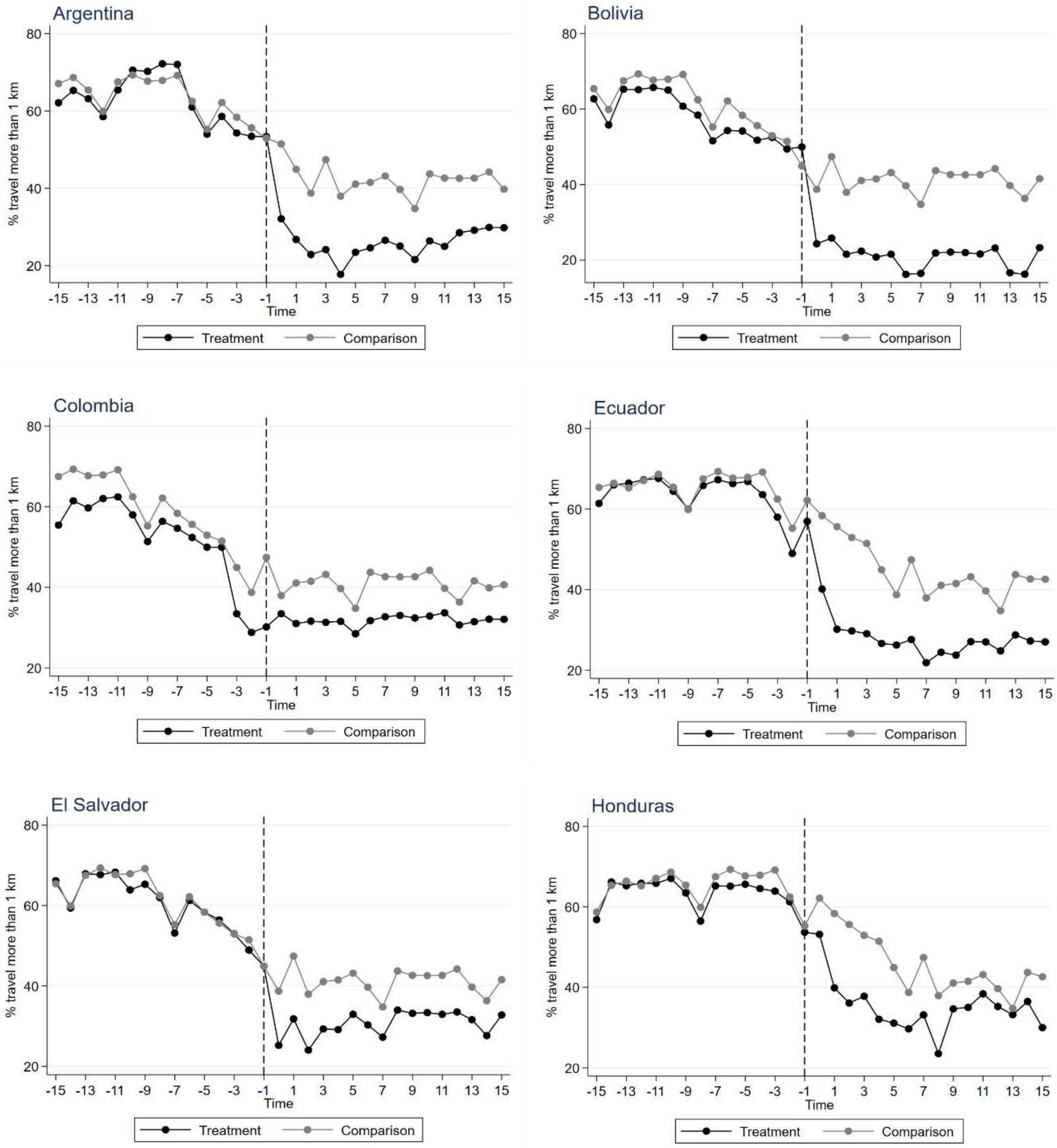
Notes: This figure shows the average daily effects of lockdowns on human mobility. The results are generated following the methodology described in de Chaisemartin and D'haultfoeuille (2019). For each coefficient, a bar represents its respective 95% confidence interval. The horizontal axis represents days before and after the start of the lockdown in each country. Positive numbers represent days post-lockdown implementation and negative numbers pre-lockdown, with 0 being the first day of the lockdown. The vertical axis shows the effect on the % of people who travel more than 1 km.

Figure 2. Change in Mobility between the First and Second Week Post-Lockdown



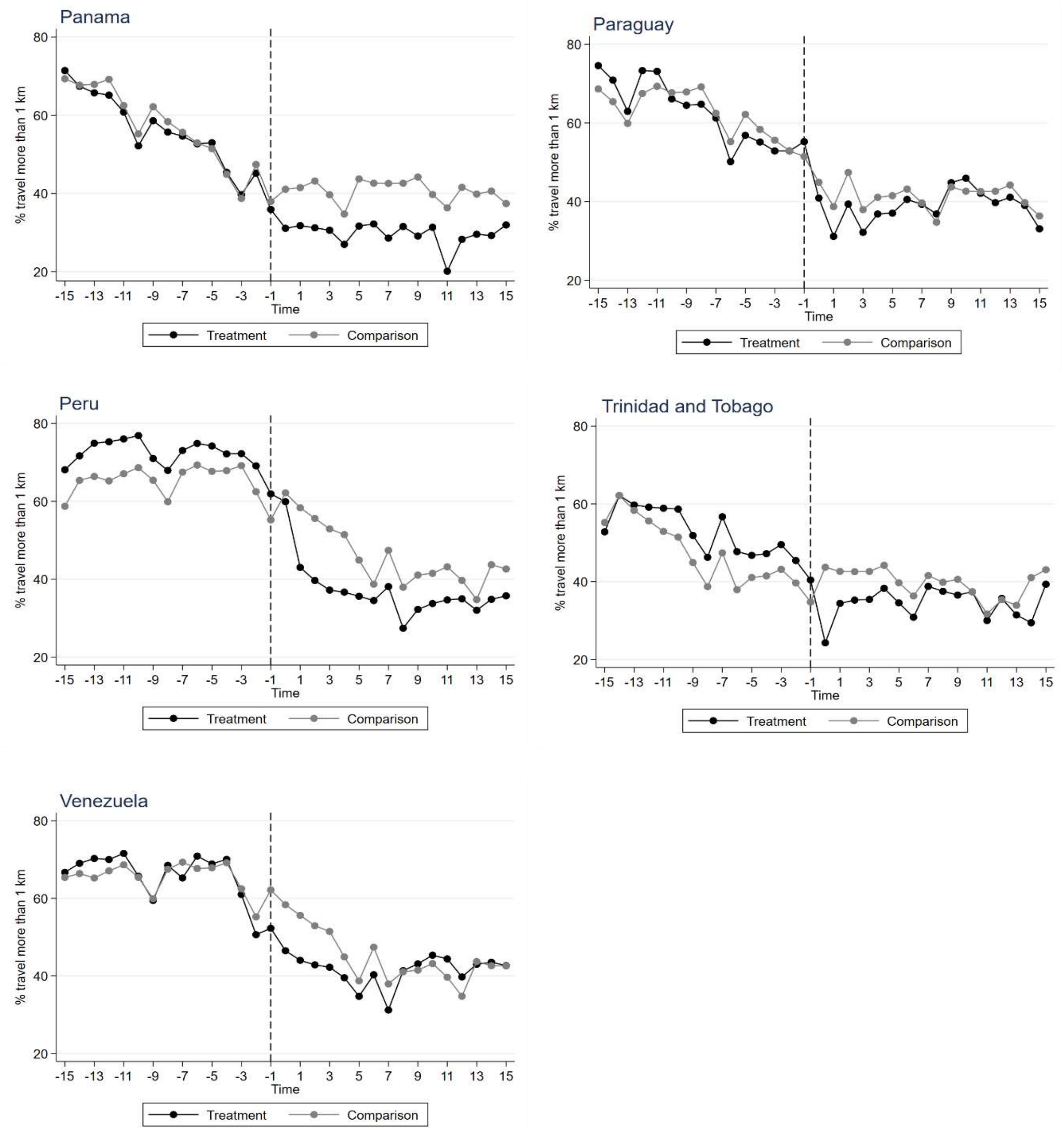
Notes: This figure shows the change in mobility between the first and second week after a lockdown was implemented for the countries that implemented lockdowns and the average of this change for the group of comparison countries (that did not apply lockdowns). The countries are divided into two groups. The first is made up of the countries that implemented the lockdown early, that is, between March 16 and 17 (Ecuador, Honduras, Peru, and Venezuela). The second includes countries with late implementation, between March 20 and 30 (Argentina, Bolivia, Colombia, El Salvador, Panama, Paraguay, and Trinidad and Tobago). The dates of lockdown implementation by country are presented in Table 2.

Figure 3. Mobility Trends in Countries with Lockdowns and in Comparison Countries



Notes: These figures show pre-lockdown days (negative) and post-lockdown days on the horizontal axis. The 0 represents the first day of lockdown. The black line represents the percentage of people that travel more than 1 kilometer in a day for each country. The gray line represents the percentage of people that travel more than 1 kilometer in a day for the group of comparison countries.

Figure 3. Mobility Trends in Countries with Lockdowns and in Comparison Countries (continued)



Notes: These figures show pre-lockdown days (negative) and post-lockdown days on the horizontal axis. The 0 represents the first day of lockdown. The black line represents the percentage of people that travel more than 1 kilometer in a day for each country. The gray line represents the percentage of people that travel more than 1 kilometer in a day for the group of comparison countries.

ONLINE APPENDIX
(not for publication)

Table A.1. The Effects of Social Distancing Policies on Mobility

	% of people who travel more than 1 km				
	(1)	**(2)**	**(3)**	**(4)**	**(5)**
Lockdowns	-10.24**				-10.12**
	(1.98)				(1.97)
Schools closings		0.17			-0.23
		(4.28)			(2.08)
Bars and restaurants closings			-3.43		-1.07
			(2.94)		(2.35)
Cancellations of public events				-3.90	-2.87
				(2.58)	(2.09)
N	810	594	810	810	810

Notes: This table shows the average effect of social distancing policies on human mobility. The dependent variable is the percentage of people who travel more than one kilometer in a day. The sample includes the 18 Latin American and Caribbean countries during the period from March 1 to April 14, 2020. The regressions include fixed effects by day and country. Each column corresponds to a regression. The rows indicate the explanatory variables included in each regression. Bootstrap standard errors are estimated with 400 repetitions and with clusters at the country level. Significance at one and five percent indicated by **, and *, respectively.

Table A.2. The Effects of Social Distancing Policies on the Percentage Change in Mobility

	Percentage change in the % of people who travel more than 1 km compared to the pre-coronavirus average (March 5 -11)							
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
Lockdowns	-15.33**	-15.10**						
	(4.86)	(4.79)						
Schools closings			-5.62*	-7.25**				
			(2.26)	(2.51)				
Bars and restaurants closings					-3.79	-0.78		
					(2.12)	(2.58)		
Cancellations of public events							0.23	0.11
							(1.15)	(1.19)
Controls for other policies	No	Yes	No	Yes	No	Yes	No	Yes
N	810	810	594	594	810	810	810	810

Notes: This table shows the average effects of social distancing policies on the percentage change observed in human mobility. This change is calculated as the percentage difference from the pre-coronavirus average (March 5-11). The results are generated from a balanced panel of 18 Latin American and Caribbean countries covering the period from March 1 to April 14, 2020. Each column corresponds to a regression. The rows indicate the policy analyzed in each regression. The sample used to evaluate the impact of school closings, the results of which are presented in columns (3) and (4), do not include weekdays. In the odd columns, the calculation is made without controls, while in even columns controls for the other three social distancing policies are included. Standard errors, presented in parentheses, are calculated by bootstrapping with 400 repetitions and clusters at the country level. Significance at one and five percent indicated by **, and *, respectively.

Table A.3. The Effects of Social Distancing Policies on Mobility - Restricted Sample

	% of people who travel more than 1 km							
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
Lockdowns	-11.40**	-11.38**						
	(3.59)	(3.55)						
School closings			-2.98	-4.35*				
			(1.84)	(2.05)				
Bars and restaurants closings					-2.28	-0.66		
					(1.68)	(1.80)		
Cancellations of public events							-0.25	-0.29
							(0.60)	(0.71)
Controls for other policies	No	Yes	No	Yes	No	Yes	No	Yes
N	810	810	594	594	810	810	810	810

Notes: This table shows the average effects of social distancing policies on human mobility. The dependent variable is the percentage of people who travel more than one kilometer per day. The results are generated from a balanced panel of 18 Latin American and Caribbean countries covering the period from March 1 to April 14, 2020. The sample used contains users not only with 10 pings during the day, but also, at least 4 pings during the night and observed in the dataset for more than 30 days. Each column corresponds to a regression. The rows indicate the policy analyzed in each regression. The sample used to evaluate the impact of school closings, the results of which are presented in columns (3) and (4), do not include weekdays. In the odd columns, the calculation is made without controls, while in even columns controls for the other three distancing policies are included in the regression. Standard errors, presented in parentheses, are calculated by bootstrapping with 400 repetitions and clusters at the country level. Significance at one and five percent indicated by **, and *, respectively.

Table A.4. The Effects of Social Distancing Policies on Mobility - Google Mobility Reports

	Percentage change in mobility compared to the period between January 3 and February 6							
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
Panel A: Retail and Recreation								
Lockdowns	-23.23**	-22.95**						
	(7.11)	(6.91)						
School closings			-5.74	-9.34**				
			(4.03)	(2.85)				
Bars and restaurants closings					-7.72*	-3.14		
					(3.64)	(2.75)		
Cancellations of public events							-1.89	-2.07
							(1.54)	(1.47)
Panel B: Workplaces								
Lockdowns	-22.05**	-22.28**						
	(6.65)	(6.58)						
School closings			-8.61	-11.73**				
			(4.33)	(3.52)				
Bars and restaurants closings					-4.85	-0.51		
					(3.71)	(3.23)		
Cancellations of public events							-0.13	-0.45
							(1.29)	(1.31)
Controls for other policies	No	Yes	No	Yes	No	Yes	No	Yes
N	810	810	594	594	810	810	810	810

Notes: This table shows the average effects of social distancing policies on the percentage change observed in human mobility. This measure is obtained from google mobility reports. The results are generated from a balanced panel of 18 Latin American and Caribbean countries covering the period from March 1 to April 14, 2020. Each column corresponds to a regression. The rows indicate the policy analyzed in each regression. Panel A corresponds to the recreation and retail measure, which includes visits to restaurants, cafes, shopping centers, theme parks, museums, libraries, and movie theaters. Panel B corresponds to the workplace measure. The sample used to evaluate the impact of school closings, the results of which are presented in columns (3) and (4), do not include weekdays. In the odd columns, the calculation is made without controls, while in even columns controls for the other three distancing policies are included in the regression. Standard errors, presented in parentheses, are calculated by bootstrapping with 400 repetitions and clusters at the country level. Significance at one and five percent indicated by **, and *, respectively.

Table A.5. Dynamic Effects of Lockdowns on Mobility

Time	(1)	(2)	(3)	(4)
-15	0.76	-0.55	0.64	-0.58
	(1.15)	(0.90)	(1.13)	(0.83)
-14	-0.12	0.25	-0.27	0.21
	(0.81)	(1.27)	(0.87)	(1.06)
-13	-1.04	0.84	-0.91	0.75
	(1.02)	(1.45)	(1.10)	(1.21)
-12	-0.53	1.33	-0.86	1.27
	(0.56)	(1.77)	(0.66)	(1.76)
-11	0.28	1.46	0.41	1.62
	(0.69)	(1.59)	(0.77)	(1.62)
-10	-0.38	0.78	-0.11	1.49
	(1.12)	(1.94)	(1.02)	(1.84)
-9	-0.12	0.25	-0.33	0.73
	(0.73)	(2.08)	(0.64)	(1.95)
-8	0.83	1.09	0.65	2.02
	(0.74)	(2.00)	(0.75)	(1.92)
-7	-0.57	1.41	-0.47	2.02
	(0.56)	(2.18)	(0.57)	(2.17)
-6	-0.81	0.79	-0.29	1.28
	(0.84)	(2.10)	(1.03)	(1.94)
-5	0.32	1.10	0.45	1.50
	(0.74)	(1.87)	(0.71)	(1.66)
-4	0.24	0.69	0.13	1.65
	(0.61)	(2.02)	(0.62)	(1.92)
-3	0.60	-0.62	0.54	0.14
	(0.58)	(1.59)	(0.61)	(1.47)
-2	0.78	-0.55	0.90	-0.02
	(0.94)	(1.77)	(0.99)	(1.64)
-1	-0.07	0.00	-0.21	0.00
	(0.74)		(0.81)	

Notes: This table shows in columns (1) and (3) the estimates for 15 placebos and 15 dynamic effects using the estimator described in de Chaisemartin and D'Haultfoeuille (2019), and in columns (2) and (4), the estimates that arise from the traditional event study method. Columns (3) and (4) control for the implementation of other social distancing measures (school closings, bar and restaurants closings, and cancellation of public events). All times less than zero represent the pre-lockdown differences and times from 0 to 15 represent the daily impact of lockdown on mobility. Bootstrap standard errors are estimated with 400 repetitions and clusters at the country level. Significance at one and five percent indicated by **, and *, respectively.

Table A.5. Dynamic Effects of Lockdowns on Mobility (continued)

Time	(1)	(2)	(3)	(4)
0	-10.26**	-10.47**	-10.10**	-9.67**
	(2.92)	(3.18)	(3.11)	(3.16)
1	-13.43**	-13.56**	-13.47**	-12.84**
	(3.13)	(2.71)	(3.07)	(2.60)
2	-12.82**	-13.09**	-13.02**	-12.45**
	(3.00)	(2.62)	(2.95)	(2.51)
3	-12.86**	-13.12**	-13.15**	-12.55**
	(2.98)	(2.46)	(3.04)	(2.38)
4	-11.72**	-12.42**	-11.86**	-11.92**
	(3.44)	(2.67)	(3.43)	(2.60)
5	-9.66**	-10.77**	-9.59**	-10.28**
	(3.27)	(2.82)	(3.26)	(2.73)
6	-9.74**	-10.55**	-10.18**	-10.09**
	(2.84)	(2.72)	(2.93)	(2.65)
7	-9.41**	-10.36**	-10.29**	-9.94**
	(2.77)	(2.68)	(2.94)	(2.64)
8	-8.94**	-9.67**	-9.69**	-9.25**
	(3.23)	(2.73)	(3.26)	(2.67)
9	-8.37**	-9.14**	-9.25**	-8.72**
	(3.16)	(3.01)	(3.09)	(2.96)
10	-7.37*	-7.93**	-8.28*	-7.51**
	(3.18)	(2.78)	(3.16)	(2.73)
11	-7.58*	-8.38*	-8.33*	-7.96*
	(3.50)	(3.26)	(3.40)	(3.18)
12	-6.43*	-7.38*	-6.95*	-6.96*
	(3.33)	(2.99)	(3.19)	(2.89)
13	-7.14*	-7.80**	-8.10**	-7.41**
	(2.96)	(2.81)	(3.03)	(2.72)
14	-8.26*	-8.75**	-9.45**	-8.37**
	(3.21)	(2.89)	(3.28)	(2.83)
15	-7.17*	-7.83**	-8.30*	-7.45**
	(3.04)	(2.50)	(3.18)	(2.46)
Controls for other measures	No	No	Yes	Yes
N	810	810	810	810

Notes: This table shows in columns (1) and (3) the estimates for 15 placebos and 15 dynamic effects using the estimator described in de Chaisemartin and D'Haultfoeuille (2019), and in columns (2) and (4), the estimates that arise from the traditional event study method. Columns (3) and (4) control for the implementation of other social distancing measures (school closings, bar and restaurants closings, and cancellation of public events). All times less than zero represent the pre-lockdown differences and times from 0 to 15 represent the daily impact of lockdown on mobility. Bootstrap standard errors are estimated with 400 repetitions and clusters at the country level. Significance at one and five percent indicated by **, and *, respectively.

Table A.6. Weight of Comparable Units when Constructing Synthetic Controls for Lockdowns

	Argentina	**Bolivia**	**Colombia**	**Ecuador**	**El Salvador**	**Honduras**
Chile	0.11	0.04	0.00	0.11	0.11	0.11
Costa Rica	0.11	0.05	0.00	0.08	0.11	0.09
Dominican Republic	0.15	0.16	0.00	0.15	0.16	0.15
Guatemala	0.13	0.09	0.00	0.10	0.14	0.11
Jamaica	0.22	0.47	1.00	0.30	0.22	0.27
Nicaragua	0.16	0.13	0.00	0.20	0.15	0.20
Uruguay	0.11	0.06	0.00	0.07	0.12	0.08

Notes: This table shows the weight of each comparable country in the construction of the synthetic control for the treated country analyzed.

Table A.6. Weight of Comparable Units when Calculating Synthetic Controls for Lockdowns (continued)

	Panama	Paraguay	Peru	Trinidad and Tobago:	Venezuela
Chile	0.08	0.15	0.00	1.00	0.14
Costa Rica	0.10	0.15	0.00	0.00	0.15
Dominican Republic	0.19	0.14	0.00	0.00	0.14
Guatemala	0.14	0.14	0.00	0.00	0.14
Jamaica	0.25	0.14	0.00	0.00	0.14
Nicaragua	0.13	0.14	0.00	0.00	0.14
Uruguay	0.11	0.15	1.00	0.00	0.15

Notes: This table shows the weight of each comparable country in the construction of the synthetic control for the treated country analyzed.

Table A.7. P-values of the Effects of Lockdowns on Mobility by Countries

Time	Argentina	Bolivia	Colombia	Ecuador	El Salvador	Honduras
0	0.00	0.00	0.57	0.00	0.00	0.14
1	0.00	0.00	0.00	0.00	0.00	0.00
2	0.00	0.00	0.00	0.00	0.00	0.00
3	0.00	0.00	0.00	0.00	0.00	0.00
4	0.00	0.00	0.00	0.00	0.00	0.00
5	0.00	0.00	0.71	0.00	0.14	0.00
6	0.00	0.00	0.00	0.00	0.00	0.00
7	0.00	0.00	0.00	0.00	0.00	0.00
8	0.00	0.00	0.00	0.00	0.00	0.00
9	0.00	0.00	0.00	0.00	0.00	0.14
10	0.00	0.00	0.00	0.00	0.00	0.14
11	0.00	0.00	1.00	0.00	0.00	0.14
12	0.00	0.00	0.71	0.00	0.00	0.43
13	0.00	0.00	0.00	0.00	0.29	0.86
14	0.00	0.00	0.86	0.00	0.00	0.00
15	0.29	0.00	0.29	0.00	0.29	0.00

Notes: This table shows the p-values of the placebo tests for the synthetic control effect by country. In each column, the sample is made up of the treated country and the corresponding comparables. The p-value shows the proportion of countries where the effect is greater, in absolute value, than that of the treated country. Each column shows the p-value of the placebo test associated with the effect for each post-lockdown day.

Table A.7. P-values of the Effects of Lockdowns on Mobility by Countries (continued)

Time	Panama	Paraguay	Peru	Trinidad and Tobago	Venezuela
0	0.14	0.71	0.71	0.00	0.00
1	0.29	0.00	0.00	0.00	0.00
2	0.00	0.29	0.29	0.00	0.00
3	0.00	0.57	0.00	0.00	0.14
4	0.14	0.29	0.00	0.00	0.14
5	0.00	0.29	0.00	0.14	0.71
6	0.00	0.57	0.29	0.14	0.14
7	0.00	1.00	0.00	0.57	0.14
8	0.00	0.43	0.00	0.14	0.57
9	0.00	0.71	0.00	0.14	0.29
10	0.29	0.43	0.00	0.29	0.29
11	0.00	1.00	0.00	0.29	0.29
12	0.00	0.57	0.00	0.71	0.57
13	0.29	0.57	0.57	0.29	0.71
14	0.00	1.00	0.00	0.00	1.00
15	0.29	0.57	0.14	0.14	1.00

Notes: This table shows the p-values of the placebo tests for the synthetic control effect by country. In each column, the sample is made up of the treated country and the corresponding comparables. The p-value shows the proportion of countries where the effect is greater, in absolute value, than that of the treated country. Each column shows the p-value of the placebo test associated with the effect for each post-lockdown day.

Table A.8. The Dynamic Effects of Lockdowns on Mobility by Country - Augmented Synthetic Control Method

Time	Argentina	Bolivia	Colombia	Ecuador	El Salvador	Honduras
0	-19.56	-12.98	0.67	-16.44	-13.17	-7.71
1	-18.53	-21.79	-4.61	-22.21	-15.42	-16.71
2	-16.01	-17.87	-4.43	-20.03	-12.60	-18.49
3	-23.98	-19.66	-6.48	-19.37	-12.79	-14.46
4	-20.16	-22.02	-2.70	-16.18	-12.81	-18.17
5	-19.46	-23.22	0.38	-10.31	-11.09	-13.07
6	-18.85	-23.42	-7.50	-18.37	-8.56	-7.32
7	-19.01	-17.61	-3.95	-14.54	-5.42	-12.43
8	-14.67	-22.80	-3.76	-16.01	-10.02	-14.42
9	-12.07	-22.06	-3.87	-16.71	-8.27	-5.28
10	-18.32	-20.81	-4.35	-15.16	-8.59	-5.98
11	-18.02	-21.21	1.11	-10.04	-8.52	-4.42
12	-14.57	-21.67	-0.96	-6.10	-9.37	-4.92
13	-13.55	-23.57	-3.17	-13.70	-4.07	-2.40
14	-14.20	-19.99	-0.71	-13.57	-6.04	-7.33
15	-6.94	-20.09	-6.04	-12.96	-5.92	-13.02
Average	-16.75	-20.67	-3.15	-15.11	-9.54	-10.38

Notes: This table shows the daily effects of lockdowns on human mobility. The sample consists of each country analyzed that implemented a lockdown and countries included in the corresponding augmented synthetic control (Ben-Michael, Feller and Rothstein, 2020).

Table A.8. The Dynamic Effects of Lockdowns on Mobility by Country - Augmented Synthetic Control Method (continued)

Time	Panama	Paraguay	Peru	Trinidad and Tobago	Venezuela
0	-11.65	-5.73	-4.70	-24.23	-7.61
1	-10.99	-7.86	-8.48	-13.86	-6.39
2	-13.63	-10.22	-6.53	-11.76	-7.64
3	-8.11	-6.98	-8.47	-12.26	-8.59
4	-5.31	-6.86	-8.88	-12.23	-5.75
5	-12.57	-6.10	-4.79	-13.16	-2.42
6	-10.08	-4.23	1.78	-9.92	-6.77
7	-13.42	-0.74	0.09	-8.34	-7.41
8	-10.17	2.10	-6.85	-9.20	-0.74
9	-14.27	-0.11	-4.46	-7.51	0.03
10	-4.92	1.60	-8.26	-1.17	0.48
11	-13.36	-0.65	-9.10	-7.46	4.21
12	-12.00	-3.80	-8.55	-4.68	4.74
13	-6.69	-5.40	-8.85	-5.21	-1.50
14	-9.11	-3.63	-8.24	-16.98	-0.84
15	-3.44	-3.11	-8.58	-5.64	-0.34
Average	-9.98	-3.86	-6.43	-10.23	-2.91

Notes: This table shows the daily effects of lockdowns on human mobility. The sample consists of each country analyzed that implemented a lockdown and countries included in the corresponding augmented synthetic control (Ben-Michael, Feller and Rothstein, 2020).