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Managing Pandemics: How to Contain COVID-19 through Internal and External Lockdowns and their Release

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Abstract

Containing a pandemic is first and foremost a management problem: one has to find ways to reduce mobility and physical contacts in order to slow down the spread of the virus. We discuss and construct a novel database of internal and external lockdown measures around the world, and analyze whether they helped reduce the spread of infections and the number of deaths. We address the endogeneity of lockdowns by modeling anticipation effects. Our data cover 178 countries in the period from December 2019 to November 2020 and identify lockdown and release periods along with confirmed cases of infections and deaths due to COVID-19. Overall, we find that lockdowns were effective, reduced mobility, and saved about 3.6 million lives in developed countries within 100 days after they were implemented. Measures taken within countries (rather than border closure) and partial lockdowns (instead of more constraining measures) were the most effective. However, in developing countries, where the opportunity cost of staying home might be too high for people to comply, lockdowns were ineffective. Additionally, the release of lockdown measures, which started in mid-May 2020 in most countries, did not lead to a strong resurgence of the virus, except for border closure releases.

Keywords: Healthcare Management, Pandemics, COVID-19, Lockdown/Release Measures

Executive Summary

Problem specification: A key current healthcare management challenge is how to contain the spread of COVID-19 and reduce mortality by sequentially using lockdown and release measures. These measures can be of two kinds: internal-constraining individuals' behaviors within an area-and external-preventing entries into this area.

Core insights: Overall, lockdowns saved about 3.6 million lives in developed countries during the first 100 days, essentially through one key mechanism: reducing people's mobility with internal measures. More specifically, governments implementing measures within countries (rather than border closure) and timely partial lockdowns (instead of stricter ones) were the most effective at mitigating the spread of the virus. Meanwhile, lockdowns were not effective in developing countries, where the opportunity cost of staying home might have been too high for people to comply. Release measures, which started in mid-May 2020 in most countries, did not lead to a strong resurgence of the virus, except for the lifting of border closures.

Practical implications: This study's findings should help policymakers and hospital managers plan for future policies and managerial actions to handle the pandemic. Local and partial measures should be favored. However, other types of measures should be elaborated to fit the case of developing countries.

Length: 188 Words

1 Introduction

On January 11, 2020, China reported the first death due to COVID-19, that of a 61-year-old man who had visited a seafood market in Wuhan, a city in the Hubei province in central China. By the middle of May 2020, a few months later, close to 300,000 deaths had been registered across the world. The health and economic effects of COVID-19 have been unprecedented, and countries implemented (Ru et al., 2021) various forms of lockdown measures at various speeds, designed to reduce mobility and contacts between people.

While lockdowns have been the main measures adopted to manage the dyadic spread of the virus and to reduce mortality rates by restraining the movement of individuals, it is not entirely clear whether these measures have been successful. The announcement of a lockdown could generate higher mobility and fuel infections (Kaplan, 2020), or lockdowns could be ineffective simple because people cannot abide by them. Second, lockdowns have a higher opportunity cost compared to other non-pharmaceutical interventions (NPIs) and could have heterogenous effects across countries.[1]

This paper studies how the responses put in place around the world to manage this crisis have impacted the development of the global pandemic. Our dataset, which covers the January-November 2020 period, allows us to study both how the first wave of the virus was managed through various lockdown measures and whether lifting those measures led to a resurgence of infections. More specifically, we study the overall effects of lockdown policies on infections and death rates as well as differences in their strength and nature across most countries in the world.

Past pandemics have essentially been managed through two organizational mechanisms, which were innovations at the time: (1) quarantines, which were invented in the 14th century to fight against the plague (in particular in Dubrovnik and Venice) and involve temporary isolation

[1] Fenichel et al. (2011) and Eichenbaum et al. (2020b) discuss infection models where agents consider the benefits and costs of mobility and find that, e.g., social distancing, has a greater effect than in models that assume behavior is exogenous.

of one or several individuals to ensure that they are not contaminated and will not spread the disease; (2) cordon sanitaires, which were invented in the 19th century in France (which sent soldiers to the Spanish border to prevent the entry of yellow fever into the country) and are surveillance positions established to block entries and exits into a geographical zone.

These two organizational measures are related and are not mutually exclusive, but they are still conceptually different and rely on different behavioral mechanisms to be effective. In one case (quarantines), one constrains the behaviors and relationships of people within a given geographical zone. In what follows, we call these types of measures "internal measures." In the other (cordon sanitaire), the objective is to maintain a zone safe and protect it from the outside so that people can continue to live freely within that zone. We call these measures "external measures." Table 1 summarizes some of the key differences in these measures, in particular regarding their costs and benefits and the potential constraints on their effectiveness. Internal measures exhibit effects more rapidly (both regarding costs and benefits), but their effectiveness can be limited if anticipation effects are high (individuals anticipate internal measures and go out frequently in advance, increasing the spread of the virus) and as the opportunity costs of staying home increase. External measures suffer less from these issues, but the timing of implementing these measures can be difficult, and, if adopted too late, they might not be effective. For similar reasons, releasing these external measures at the right time might be challenging. As will become clear below, these conceptual distinctions will drive our empirical analysis.

Inspired by this analysis, we empirically explore the underlying mechanisms that can explain why certain types of lockdown measures were more effective than others and why they worked better in some places than in others. Our hypothesis is that the effectiveness of lockdowns depends on individuals' opportunity costs related to staying home. If these opportunity costs are high enough, we expect that people would not adhere to lockdown restrictions, especially as the monitoring cost for authorities would typically be high. This issue is of particular importance for the effectiveness of lockdown policies in developing countries. Indeed, in these

	INTERNAL MEASURES	EXTERNAL MEASURES
Main mechanism	Constrain individual behaviors (mobility, relationships) within a geographical area	Protect a geographical area from the outside
Benefits	Can be calibrated and adapted to individuals' habits and lifestyles in a specific geographical area. This should increase effectiveness	Could be effective in a globalized and connected world
Economic and social costs	High costs for individuals (as their behaviors can be heavily constrained immediately), and fast to appear	Lower and slower to appear (people within the geographical area can keep living a normal life, at least until the lack of imported goods or people become a problem)
Main constraint on effectiveness	Might be less effective if anticipation effects are too high. Might be less effective if opportunity costs of staying home are too high for individuals in the geographical area.	Anticipation effects are probably less important. Timing can be an issue: If implemented too late, measures could be ineffective.
Enforcement costs	High	Lower
Release considerations	Can be adapted and timed based on individuals' behaviors within the geographical area	Difficult to time well as it depends on the situation in many other countries

Table 1: Two main kinds of lockdown measures to fight pandemics.

countries, where many people earn their livings in the informal economy and do not have access to social insurance, we predict that lockdown measures will be less effective than in developed countries.

Endogeneity issues pose major barriers to assessing the causal effects of such lockdowns on the spread of a disease. We address three sources of endogeneity. First, countries differ tremendously around the globe. We model fixed effects in our panel data to absorb these country-specific differences. Second, our focus is on measuring how lockdowns affect the spread of the virus, which is complicated because governments implement lockdowns whenever the virus spreads more rapidly. We devise an empirical specification that allows us to separate the effects of a lockdown before it is implemented from those that occur after the lockdown is in place. Infections that occur before a lockdown is in place are triggered by behavioral changes, in anticipation that a lockdown will be implemented soon, but these infections are not caused by the measures themselves. In contrast, infections that occur after measures have been implemented are likely due to the lockdown that has been put in place. Third, the number of cases reported depends on the rate of testing, and the number of cases might also influence the rate of testing. We address this source of measurement error in cases through the fraction of tests that return a positive result. This positivity rate provides information on the quality of the testing policy, reflecting the relative rate of the outbreak to the rate of testing. The results are robust to the inclusion of this control, which is of primary importance.

The key finding of our analysis is that lockdowns were effective and reduced infections significantly after they were implemented. Lockdowns reduced mobility within a country and saved about 3.6 million lives in developed countries during the first 100 days. We see some evidence of anticipation effects, as the growth rate in cases increases by around 5 to 6 percentage points in the week before a measure is adopted. These anticipation effects are quite small, but our strategy to address anticipation is important. Measures taken within countries (rather than border closure) and partial lockdowns (instead of stricter ones) were effective. However, we do not find significant effects in developing countries, where the opportunity cost of staying home might be too high for people to comply. The release of lockdown measures, which started in mid-May 2020 in most countries, did not lead to a strong resurgence of the virus, except for the release of border closures, which enable new virus variants to circulate in a country, thereby triggering an increase in caseloads.

The outline of this paper is as follows. The next section provides an overview of the existing literature. Section 3 describes how we measure when lockdowns were implemented and released. The section also discusses the information we use to assess whether the lockdown measures were effective, how we assess the robustness of our results, and how we gauge whether the effectiveness of the measures varied around the world. Section 4 presents our main approach for estimating the effects of lockdowns, and Section 5 explains how we address the endogeneity of lockdown adoption. Section 6 presents our main results on lockdowns and their releases, both overall and in sub-samples of countries. The section also includes an attempt to quantify the number of deaths averted due to lockdown measures. Section 7 discusses the results in light of the opportunity costs of following lockdown orders, comments on the effectiveness of external vs. internal measures, and concludes the paper.

2 Existing Literature

Our study relates to three strands in the literature. A first strand empirically studies the effects of NPIs on disease transmission. Hatchett et al. (2007), for instance, looked at how the NPIs adopted by cities in the United States contained the spread of Spanish influenza and sparked interest in how policy measures could be used to manage pandemics. Similar studies have emerged and are looking at the effects of NPIs on the COVID-19 pandemic (Harris, 2020; Hartl et al., 2020; Flaxman et al., 2020a; Askitas et al., 2020). Chinazzi et al. (2020) and Kraemer et al. (2020) explore the extent to which China's lockdowns and cordon sanitaires have reduced the spread of the disease. Maier and Brockmann (2020) find that measures put in place in China before the lockdown contributed to slowing the spread of COVID-19. Hsiang et al. (2020) study the effects of NIPs in China, South Korea, Italy, Iran, France, and the US and find that NPIs reduce the growth of infections. Bendavid et al. (2021) estimate COVID-19 case growth in relation to more and less restrictive NPIs on the subnational regions of 10 countries and find significant reductions in the number of cases, especially for the less restrictive NPIs. Deb et al. (2020) study the effects of lockdowns around the world and find sizable reductions in the number of new infections. Similarly, Blanco et al. (2020), relying on data covering 158 countries, find that containment measures have been effective in reducing contagion and death rates despite showing differences in effectiveness (i.e., restrictions on activities are more effective than restrictions on personal liberties). Their results also indicate that the early adoption of coronavirus containment measures in Western Europe led other countries to accelerate their adoption. Giordano et al. (2020) compare simulation results with real data on the COVID-19 epidemic in Italy and show that restrictive social distancing measures were effective but that their effectiveness could have been further enhanced if combined with widespread testing and contact tracing. Atkeson et al. (2020) study the effects of NPIs on COVID-19 transmission on a sample of 25 countries and derive four stylized facts about COVID-19. First, growth rates of daily deaths fell from a wide range of initially high levels to levels close to zero within 20-30 days after each region experienced 25 cumulative deaths. Second, after this initial period, growth rates of daily deaths hovered around zero or below everywhere in the world. Third, the cross-section standard deviation of growth rates of daily deaths across locations fell very rapidly in the first 10 days of the epidemic and remained at a relatively low level. Fourth, the three above-mentioned facts imply that both the effective reproduction numbers and transmission rates of COVID-19 fell from high initial levels, and the effective reproduction number hovered around one after the first 30 days of the epidemic virtually everywhere in the world. Finally, several groups have collected information on policy responses, most notably Dale et al. (2020) but also Cheng et al. (2020).

A second strand of the literature uses theoretical modeling to better understand the effects of lockdown policies on individual behaviors. Fenichel (2013) shows that policies that limit movement, interpersonal contacts, and impose social distancing help reduce the spread of viruses for healthy individuals and directly impact the often-neglected behavior of recovered and immune individuals. Toxvaerd (2019) model disease propagation where rational and forward-looking individuals attempt to control their exposure to infection by engaging in costly preventive behavior and find that individuals often overexpose themselves to infections, which leads to a suboptimally high disease prevalence. Several studies have already tried to use the ongoing pandemic as a natural experiment to better understand the effect of public policy on the behavior of individuals. Bisin and Moro (2021) introduce a model of diffusion of an epidemic with demographically heterogeneous agents interacting socially to assess the cost of naïve discretionary policies, ignoring agents' and firms' behavioral responses, and find that the adverse effects and costs of policy interventions are potentially first order important. Toxvaerd (2020) present an economic model, suggesting that uncoordinated social distancing acts to flatten the curve of the epidemic by reducing peak disease prevalence. Their results show that the curve becomes flatter the more infectious the disease is and the more severe the health consequences of the disease are for the individuals.

A third strand of the literature explores the impact of lockdowns on economic activity, particularly household spendings. Eichenbaum et al. (2020a) find that older consumers reduce their spending more than younger consumers in a way that mirrors the age dependency in COVID-19 case-fatalities, especially for high-contact goods in periods with high numbers of COVID-19 cases. Baker et al. (2020) find that, in the first half of March 2020, individuals increased their total spending by over 40 percent across a wide range of categories, a trend which was followed by a decrease in overall spending of 25-30 percent during the second half of March, coinciding with the spread of the disease, with only food delivery and grocery spending as major exceptions to the decline. Ajzenman et al. (2020) look at how political leaders' words and actions affect people's behavior. The study finds that when government officials publicly and emphatically dismiss the risks associated with COVID-19 it leads to weakened social distancing measures for the pro-government localities compared to places where political support of the government is less strong, an effect that seems to be more impactful in localities with higher levels of media penetration, active Twitter accounts, and a larger proportion of Evangelic parishioners. While the focus is somewhat different from what we are examining in this paper, this literature is important for assessing the overall implications of lockdowns. We will return to this point in the Discussion section.

We complement the existing literature in four ways. First, our paper is the first to introduce a conceptual difference between internal and external measures and to look at differences in how pandemics can be managed. We also provide a way to capture these differences empirically. Second, while several of the papers we reviewed focus on one or few countries, except for Blanco et al. (2020), our analysis covers 178 countries around the world, which allows us to analyze the heterogeneity in how lockdowns were implemented. Inspired by the history of managing epidemics, we organize our study of heterogeneity in lockdowns around internal vs. external measures, an approach that, to the best of our knowledge, is unique. Third, transmissions might increase before internal measures are implemented, which we refer to as anticipation effects. Anticipation effects need to be taken into consideration when studying the causal effects of lockdowns, and we propose an approach for doing so. Fourth, to the best of our knowledge, we provide the first empirical analysis of what happened when the various lockdown measures were released, something that should be considered as a crucial aspect in evaluating the effectiveness of the management of pandemics. Information on whether or not an epidemic remains contained after the release of a lockdown is crucial when managing the pandemic.

3 Data

Our dataset covers 178 countries, observed over 127 days, from December 31, 2019 to November 24, 2020. We adopt a calendar time definition with December 31, 2019 as the starting date, as it is the first day when a country other than China implemented measures to limit the spread of COVID-19.[2]

3.1 Explanatory variables: Lockdown measures

The goal of this paper is to analyze and understand the effect of the internal and external lockdown measures implemented by most governments around the world on COVID-19 spread and mortality rates. To generate the data regarding the policies implemented by each government, we relied on custom-coded a JAVA web-scraping program that extracted from LexisNexis: i) all news headlines per country from December 31, 2019 to November 24, 2020 and ii) all COVID-19 information from countries' US embassy COVID-19 bulletin.

The data-generation process was conducted in two stages to ensure its validity, enhance its precision, and to provide a cross-source robustness check for the gathered information. In the first stage, our program was linked to LexisNexis, where the algorithm executed an automatic login function, specified the search parameter(s)[3], the dates, pulled specific objects of interest (the headline, date, and the link to the article), and stored them per country in ".csv" files. Because the ".csv" files held a sizable amount of data, we created a library of keywords (lock, lockdown, COVID-19, coronavirus, etc.) to clean the surplus information and generate a sensible number of observations directly connected to COVID-19 headlines per country. A manual re-check was done afterwards to ensure that the date of the headline matches the effective date

[2] Taiwan Centers for Disease Control (CDC) implemented inspection measures for inbound flights from Wuhan, China, in response to reports of an unidentified outbreak on December 31, 2019.

[3] To optimize the search parameter(s), we created a library that pulled all information from LexisNexis using the following search parameters: name of the country only (e.g., Switzerland), name of the country and COVID-19 (e.g., Switzerland & COVID-19), and name of the country and coronavirus (e.g., Switzerland & coronavirus). All the search results were aggregated and stored per country in separate ".csv" files.

for when the measure was implemented by the government.

In the second stage, because we were missing some information for some of the countries involved, and because we wanted to provide additional robustness checks for our data, we performed a second scraping of the information relying on each country's US Embassy COVID-19 bulletin. US embassies across the globe create bulletins that provide a constant flow of information regarding important issues (e.g., COVID-19) within a given country to inform and enhance the safety of their staff and employees[4].

The final dataset contains the dates of implementation for several types of lockdowns designed to stop the spread of COVID-19. Some of the lockdowns are related to measures internal to the country, and some are related to movements between countries (see Figure 1).[5]

The group of internal measures includes the following measures. *State of Emergency* considers the effective date when the country announced state of emergency (e.g., Bosnia declares a nationwide state of emergency due to coronavirus - March 17, 2020), i.e., a situation in which a government is empowered to perform actions or impose policies that it would normally not be permitted to undertake, such as restriction of individuals' movement and closure of non-essential and essential (if necessary) public and private entities. *Curfew* considers the effective date of a country's announcement to limit the movement of individuals within a given period of the day (e.g., President Roch Marc Christian Kabore closed airports and land borders and imposed a nationwide curfew to curb the spread of the pandemic - March 21, 2020). *Partial selective lockdown* considers the earliest effective date when the country announced a partial limitation of movement by implementing, for example, school closures, limiting the number of people permitted to gather in a group (usually less than 100), or closing religious institu-

[4]e.g., https://mk.usembassy.gov/Covid-19-information/ (last accessed: 17.04.20)

[5]Our classification of lockdown measures could be further refined, e.g., regarding which sectors of the country were closed down in a partial lockdown. Our analysis should be interpreted as the average effect over the relatively broad classes of measures. Our classification of measures, while capturing lockdowns in a distinctly granular way, overlaps quite well with the Oxford government response tracker (OGRT) (Hale et al. (2020)). For inside measures, our data indicate a government response four days before the OGRT, while for outside measures the median delay is exactly zero days. Impact estimates that rely on OGRT timing data are similar to those we report. Results are available upon request.

	Measures	Explanation	Example	Severity
INTERNAL MEASURES	***Curfew***	The effective date when a country announced a restriction on the movement of individuals within a given time of the day.	*21st of March 2020:* President Roch Marc Christian Kabore closed airports, land borders and imposed a nationwide curfew to curb the spread of the pandemic.	
	State of emergency	The effective date when a country announced a state of emergency.	*17th of March 2020:* Bosnia declares nationwide state of emergency over coronavirus.	
	Within country regional lockdown	The effective date when a region within a country announced that it will be entering a total lockdown.	*12th of March 2020:* Quebec, Declares State of Emergency to Blunt Pandemic.	
	Partial selective lockdown	The earliest effective date for the partial restriction on the movement of people such as through school closures or through limiting the number of people allowed to gather in a group and/or closure of religious institutions.	*16th of March 2020:* Cambodia Announces Nationwide School Closures as COVID Response Ramps Up.	
EXTERNAL MEASURES	***Selective border closures stage 1***	The earliest effective date when a country closed its borders with a region or country significantly affected by COVID-19 (Wuhan, China, Iran, and Italy - individually or as a group).	*30th of January 2020:* Australia banned the entry of foreign nationals from mainland China.	
	Selective border closures stage 2	The earliest effective date after *Selective border closure stage 1* when a country closed its borders to people from one or multiple other countries in the world significantly affected by COVID-19.	*27th of February 2020:* Fiji extended its travel ban and announced that travelers from Italy, Iran and the South Korean cities of Daegu and Cheongdo would be denied entry.	
	International lockdown	The effective date when a country banned all flights, rail and automotive movements internationally.	*30th of March 2020:* Council of Ministers of Bosnia and Herzegovina issued a decision which bans entrance for all foreigners.	

Figure 1: This figure provides an overview of seven classes of lockdown measures, grouped into internal and external measures, and provides an explanation, an example, and our subjective ex ante assessment of severity.

tions (Cambodia Announces Nationwide School Closures as COVID Response Ramps Up. – 16th of March 2020). *Within country regional lockdown* considers the first effective date when the country or region within a country announced that it would be entering a total lockdown (Quebec, Declares State of Emergency to Blunt Pandemic – March 12, 2020).

The group of external measures includes the following measures. *Selective border close stage 1* considers the first effective date when the country closed borders to any other country in the world, usually heavily infected regions and/or countries, such as Wuhan, China, Iran, and Italy (individually or as a group) (e.g., Australia banned the entry of foreign nationals from mainland China – January 30, 2020). Restrictions apply to both people traveling from and to the banned countries. *Selective border close stage 2* considers the first effective date, after Selective border closure stage 1, when the country closed borders to one or multiple other countries in the world significantly affected by COVID-19 (e.g., Fiji extended its travel ban and announced that travelers from Italy, Iran, and the South Korean cities of Daegu and Cheongdo would be denied entry – February 27, 2020). Again, restrictions apply to both people traveling from and to the banned countries. *International lockdown of the country* considers the effective date when a country totally closed its borders, including all flights, rail, and automotive movement internationally (e.g., The Council of Ministers of Bosnia and Herzegovina issued a decision banning entrance for all foreigners – March 30, 2020). The distribution in time of these variables is summarized in Table S1 in the Appendix.

Additionally, and in an effort to enhance the predictive power of our explanatory variables, we created an additional variable named *Total within country lockdown* that combines the information from both the *State of Emergency* and *Curfew* data. The reasoning behind this variable is that both *State of Emergency* and *Curfew* within a country closed public and private entities and significantly restrained the movements of individuals (limited to bare necessities like food, pharmacy, and hospitals); these measures thus represent a form of total within-country lockdown. The only difference between the two is that the *Curfew* provides an additional level of severity, as it totally forbids the movement of individuals within a given period of the day. Of course, some countries in our sample have implemented both State of Emergency and Curfew. For those cases, we take the earliest effective date between the two as the date for the variable *Total within country lockdown*.

Relying on LexisNexis and using our web-scraping program, we compiled information on each country's release policies by extracting news headlines published between the end of April 2020 and the end of August 2020. To ensure robustness and accuracy, this information was also cross-checked with the country information from COVID-19 bulletins issued by the United States embassies. The final dataset contains the first dates, per country, when each of the implemented COVID-19 lockdown policies were eased.

3.2 Outcome: COVID-19 reported cases and deaths

We use data from John Hopkins University (Dong et al., 2020) because it is, to the best of our knowledge, the most complete and reliable source of data on reported COVID-19 cases and deaths. We focus our analysis on the number of cases of infection for three reasons. First, people who die from the virus were infected first. Hence, controlling the number of contaminated persons inevitably reduces the number of deaths. Second, a major objective in the management of the pandemic, which is reflected by the "flatten the curve" argument, is to avoid the overcrowding of the medical sector (and in particular intensive care units). From this angle, the number of people who are infected by the virus is a better indicator of the future burden on the healthcare sector than the number of people who have died from the disease. Finally, there is a significant delay in how a measure might affect the number of deaths. Indeed, someone must contract the virus, pass the incubation time, experience complications, and then eventually pass away. This process is potentially long and variable from one individual to another, which makes it more difficult to assess the impact of the measure.

We transform the outcome using the natural logarithm for two reasons. First, we are interested in the variation of the outcome as a percentage rather than in absolute terms. Second, the distribution of the number of reported cases is highly asymmetric due to the exponential growth, with a mean of 1112.61, a median of 0, and a skewness of 19.54. To fit our linear regression model with an outcome with exponential growth and highly positively skewed data, we use the logarithm and add one to the number of reported cases ($ln(ConfirmedCases_{it} + 1)$. In doing so, we reduce the skewness to 1.77. We proceed similarly for the number of deaths (skewness of 18.12).

It is important to note that the data on COVID-19 infections and deaths suffer from measurement errors. The data contain reported cases only, which are not equivalent to the total number of actual infections in the country due to testing limitations. In most countries, testing is limited to those who show symptoms and are part of an at-risk group or those who experience severe symptoms and need to be hospitalized. In countries with no systematic testing, which is the overwhelming majority, asymptomatic cases or those with mild symptoms who did not get tested are not observed. Second, new cases have to be recorded and transmitted to the public institute or authority that publishes the data. It is suspected that some countries under-report or modify their data[6]. Third, these data must then be recorded by the source monitored by Johns Hopkins University. Hence, our data represent a lower bound on the total number of people ever infected. Arguably, systematic under-reporting, measurement error in the dependent variable, is not a major concern in our context (e.g., if countries only report a fixed proportion of true cases, the case growth rate would not be affected).

A more troubling problem would be the presence of non-classical errors-in-variables, which may result, for example, if countries that under-report the number of cases systematically are also those with a lower-quality health sector or are autocracies. This type of measurement error might be present, as countries with a well-developed response to COVID-19 might also have better testing facilities. We discuss below how we address this important concern.

Figure 2 shows the number of measures implemented and the number of confirmed cases and deaths by time since the first case was detected (panel (A)) and by day of the year (panel (B)). Governments initially adopted internal measures during the period from the end of January to early February 2020 (20 to 40 days after Taiwan) before implementing external measures as well.

3.3 Robustness: Positivity rate

The number of cases reported depends on the rate of testing, and the number of cases might also influence the rate of testing. We address this source of measurement error in cases through the fraction of tests that return a positive result, or the positivity rate. The positivity rate informs

[6]Can China's Covid-19 Statistics Be Trusted? (last accessed: 14.04.20) https://thediplomat.com/2020/03/can-chinas-Covid-19-statistics-be-trusted/. China's data, in fact, reveal a puzzling link between COVID-19 cases and political events (last accessed: 14.04.20) https://www.economist.com/graphic-detail/2020/04/07/chinas-data-reveal-a-puzzling-link-between-Covid-19-cases-and-political-events.

the quality of the testing policy, reflecting the relative rate of the outbreak to the rate of testing.

We use the data on 121 countries from Hasell et al. (2020), who provide a time series for the daily number of tests performed, or people tested, together with metadata describing the data quality and comparability issues that must be considered when interpreting the time series. We augment our baseline model with the positivity rate as a control variable in a robustness exercise. This is a central test to convey, as the number of cases reported depends on the testing rate. The positivity rate is a good indicator of the relative testing rate to the spread of the virus. We keep this control as a robustness test for two reasons. First, the data set is only available for a subset of countries (121 compared to our 178 full sample). Second, the results are highly robust to the inclusion of this control.

3.4 Heterogeneous effects: Developing vs. developed countries

To study the existence of heterogeneous effects between developed and developing countries, we use the Human Development Index (henceforth HDI) produced by the United Nations (UN) (Programme (2020)). The HDI is a composite index defined as the geometric mean of normalized indices ($\in [0;1]$) for life expectancy, education and gross national income (GNI). Note that the median in our sample is 0.745. We define developing countries as those with an index up to 0.699, indicating low and medium human development using the UN code-book definition, while an index above 0.699 will be defined as developed countries. Table S4 in the Appendix C shows the complete list of countries in the two categories.

We have explored models that allow for different impacts of the measures for each country. We find that, on average, the models with country heterogeneity are similar to the analysis that does not allow for country-specific heterogeneity. The results are available upon request from the authors.

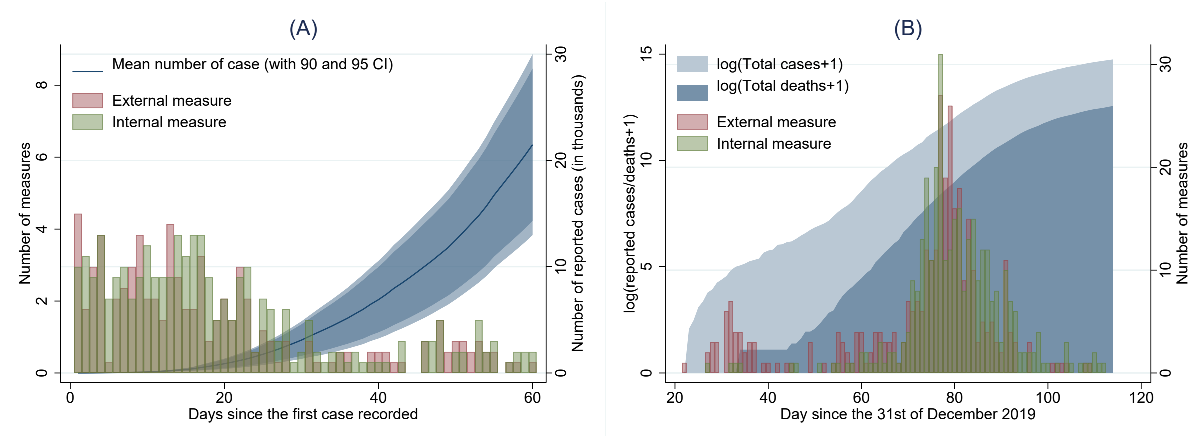

Figure 2: Figure shows the timing of lockdowns within countries since the beginning of the COVID-19 outbreak in each country (A) and since the end of 2019 (B). We exploit this variation to quantify the effect of each measure on the growth rate of COVID-19. "External" measures are those that restrict movements into or out of the country, while "Internal" measures are those restricting movements within a country. Both graphs exclude China. (A) Most lockdowns restricting movements within countries or movements between countries were implemented during the first 30 days after the first case was reported in the country, while some measures were implemented up to 60 days after the first case. The blue line represents the mean number of reported cases by country with 90% and 95% confidence intervals. (B) For identification, we also exploit variation through the year, as early lockdowns were implemented in February and others only a few months later.

4 Empirical model

Our main analyses are based on models of the growth rate in the total number of confirmed cases in a country. The growth rate in the number of cases, or new infections, captures the impact of the lockdown measures on the spread of the disease (Avery et al., 2020). The underlying mechanism to contain the pandemic should be the reduction in the number of contacts between people who could potentially be infected and those who are actually infected. Successful lockdown measures are expected to restrict the movements of both the susceptible people and the infected people (Kermack and McKendrick, 1927; Maier and Brockmann, 2020; Tian et al., 2020). As we will see later (c.f. Figure 4), using Google Mobility Reports, there is a stark reduction of occupation rates around the globe in most sensitive areas (grocery and pharmacy, retail and recreation, parks, workplace and transit stations).

The panel structure of our data allows us to control quite extensively for the risk of omitted variable bias. First, the country fixed effects allow us to control for time-invariant unobservable factors at the country level (quality of the healthcare system, age distribution of the population, population density, geographical location, number of neighboring countries, climate conditions, etc.). Some of these factors could vary over time, but we do not expect them to vary significantly over the time period of interest (a few months). Second, the day fixed effects control for time-varying unobservable factors affecting the world in the same way (global evolution of the virus (early-stage vs. pandemic), global lockdowns, etc.). Finally, the fixed effects also address the measurement errors by controlling for numerous factors that could correlate with the quality of the reporting and the spread of the coronavirus. The country fixed effects allow us to exploit within-country variation: if some policies or unobserved country characteristics affect the rate of case reporting (constant bias over time), this does not affect the within-country variation that we exploit.

The second main difficulty in measuring the effect of governmental measures implemented to contain the spread of the disease comes from reverse causality. The spread of the disease in a country influences the timing and extent of the lockdown measures implemented by the government. For instance, governments may implement lockdown measures when the effective reproduction number reaches a value larger than 1 or in the event of any other statistic that signals a deterioration of the pandemic situation. In this case, the growth rate of infections will increase before a measure is implemented. We find in our own data that case numbers grow strongly several days before a lockdown is implemented, consistent with reverse causality (Figure 3). We address this issue as follows: Due to the wide access to information on cases and the news reporting the situation in the world, people might anticipate a lockdown and either increase contact before the restriction or reduce contact preemptively because they understand the risk. To control for this anticipation behavior, we include a dummy that takes the value of one seven days before the lockdown measure. This dummy variable captures growth in the number of cases at a time when governments decided to introduce the lockdown measure, and we control for this directly in our baseline specification (Section 5 provides details).[7] Day fixed effects capture the global evolution of the coronavirus and how it affects the probability of a lockdown.

5 Addressing endogeneity

Next, we describe how our main specification addresses endogeneity. Let $lc_{it} = log(cases_{it}+1)$ be the log of cases in country i at time t. Then, $dlc_{it} = lc_{it} - lc_{it-1}$ is the daily change in log cases, or the daily growth rate in cases. Our empirical strategy models the growth rate of cases, as it has a direct relationship with the evolution of the pandemic and, in some cases, an indirect relationship with its reproduction number (Aguiar et al., 2020).

The central challenge in estimating the effects of lockdowns on the growth rate is the presence of endogeneity of lockdown adoption. Countries implemented lockdown measures to protect their health systems. This means that a lockdown is implemented when the growth rate of cases is high or if it is accelerating. Failure to model endogeneity in policy adoption leads to biases in estimates. A strategy that compares a country after a lockdown has been implemented to countries that have not (yet) implemented a lockdown will fail since countries with a lockdown are in a situation of high, and possibly accelerating, growth, whereas countries that have not yet implemented a lockdown are in a situation that can still be controlled.

Our strategy leverages the fact that lockdowns are very seldom implemented instantaneously or overnight. Countries announce a lockdown but allow for a planning horizon p. This planning horizon is short, ranging from a few days to perhaps about a week, as governments need to react quickly to the exploding case numbers but still need to allow people to adjust to the measure. Specifically, suppose a country adopts a lockdown if the cumulative number of cases exceeds a

[7] Technically, we introduce a control variable that absorbs the reverse causality in lockdowns. See Figure 4 justifying the choice of seven days. Robustness tests are available in the Appendix with 5 or 10 days of anticipation.

country-specific threshold γ_i.[8] The government announces the lockdown in t, to take place in $t+p$.

$$Measure_{it+p} = I(lc_{it} > \gamma_i)$$

where $I()$ is a function that takes the value one if its argument is true and zero otherwise. The country decides to introduce the lockdown at time t because the number of cases exceeds the capacity of its health system. This situation is reached if a country had high growth in cases in the past.

5.1 Baseline model: Number of days after the measure was taken

We address the endogeneity problem related to lockdown measures as follows. We fix a specific value for the planning horizon, e.g., one week ($p = 7$).[9] We then construct a binary variable $Anticipation_{it}^{7days}$, which is equal to zero until one week before the lockdown is implemented and takes the value of one from one week before the lockdown is implemented until the end of the observation period. We add this variable, $Anticipation_{it}^{7days}$, to our main estimation equation in our baseline model:

$$\begin{aligned} dlc_{it} = & \\ & \beta_1 Measure_{it} + \beta_2 DaysAfterMeasure_{it} \\ & + \beta_3 Release_{it} \\ & + \beta_4 Anticipation_{it}^{7days} \\ & + FE_i + FE_t + \epsilon_{it} \end{aligned} \tag{1}$$

[8] The parameter γ_i is unknown to us and set by each country i in ways that depend on the capacity of its health sector.

[9] We replicate our results with p equal to 5 and 10 days anticipation in Appendix. See Section 6.1 for more details on our methodology to estimate the potential anticipation effect.

dlc_{it} the daily change in log cases, or the daily growth rate in cases. $Measure_{it}$ is an indicator variable taking the value of one from the day the measure was implemented. $DaysAfterMeasure_{it}$ is zero before a measure has been introduced and is equal to the number of days since the measure was implemented after the measure was introduced. Indeed, we do not expect the effect to be revealed and observable on day zero even if no new transmission occurs, as the latest cases are not yet detected. $Release_{it}$ is a dummy taking the value of one when country i eases the lockdown measure. FE_i and FE_t are country and day fixed effects, which capture country-specific and calendar time effects.[10] ϵ_{it} is an error term clustered at the country level.[11]

The variables $Measure_{it}$ and $DaysAfterMeasure_{it}$ both capture the effects of the measure, and their effects are identified through a comparison of the growth in cases after the measure has been introduced to the situation before introducing a measure. $Anticipation_{it}^{7days}$ captures the growth in cases *just before* the lockdown is put in place, and adding this dummy variable to the main estimation equation results in re-adjusting the level of counterfactual growth to the level that already existed just before the lockdown is implemented. Since the potentially fast growth in cases that triggered the lockdown is not caused by the lockdown, this excess growth needs to be removed and not captured in the estimate of the lockdown's success. Indeed, for internal meausures, there is excess growth in the number of cases before the measure is introduced, and adding $Anticipation_{it}^{7days}$ to the model neutralizes its impact on the effects of internal measures (Appendix D).[12]

[10] Our baseline specification does not model the fact that the growth rate in total cases tends to decline as the epidemic in a country ages (Komarova et al., 2020). We have explored whether estimates of the impact of lockdowns are sensitive to whether countries implement them in a high- vs. low-growth environment. The initial impact of lockdowns on growth is larger for countries implementing measures in a high-growth environment, but long-run estimates of the impact of measures 100 days after implementing a measure are not sensitive to when countries implement lockdowns. Results are available upon request from the authors.

[11] Our baseline specification models the effects of the first type of measure implemented by a country, even though most countries implement at least two types of measures, and the overlap in implementation is substantial. We probe the sensitivity of our results by introducing treatment effects for both inside and outside measures. The results, available upon request from the authors, are not sensitive to modeling two types of measures.

[12] While lockdown implementation could be anticipated easily, e.g., you can stop going to work or the grocery store before the lockdown, it seems unlikely that the population could change its behavior in anticipation of a release (e.g., traveling when there is still a ban or going to the gym when they are closed). We have experimented with models allowing for anticipation of release, which leave our main results unaffected (available upon request).

The key challenge in identifying the effects of $Measure_{it}$ and $DaysAfterMeasure_{it}$ is a shift in the average of the growth residuals, ϵ_{it}, which coincides with the introduction of the measure. The anticipation variable $Anticipation_{it}^{7days}$ shifts from zero to one in the period just *before* the measure is introduced. This variable therefore absorbs a shift in the mean of growth residuals, ϵ_{it}, between the period before the anticipation variable shifts to one and just before the measure was introduced. Models that include lagged dependent variables are prone to Nickell (1981) bias. In our context, the lagged growth rate of cases does not enter the model directly, so the standard argument due to lagged dependent variables does not apply.

Equation (5) describes our baseline model. For the baseline results, we focus on the first wave and hence restrict the sample for one hundred days after the implementation of a lockdown. When interpreting the release effect, it is important to bear in mind that countries might release from a strict lockdown to a less strict lockdown (e.g., from total to partial lockdown). This may attenuate the estimated acceleration of the pandemic after releasing the measures. The partial effects may be better interpreted as an upper bound on the effect of moving down to the next-most severe form of restrictions.

5.2 Relation with SIR model

Here we briefly discuss the relationship between our approach and Susceptible-Infected-Recovered (SIR) models. Giannitsarou et al. (2021) set up a (SIR)-type model of COVID-19 to capture the (numbers of shares of) individuals who are currently exposed, infected, recovered, or susceptible. Exposed individuals are asymptomatic or have not yet tested positive but could potentially develop the illness, while recovered individuals return to becoming susceptible. The main interesting output from their analysis is the number of new infections that occur between two days (their model is in continuous time, we adopt discrete time owing to the nature of our data):

$$nI(t) = [1 - d(t)]\beta(t)M(t)$$

Hence, we do not include an anticipation effect for release.

where $nI(t)$ is the number of new cases on day t, $d(t)$ is a measure of lockdown strength, $\beta(t)$ is the probability of transmission for one meeting, and $M(t)$ is the total number of meetings. The total number of meetings is the total number of possible contacts between those who are currently infected, $I(t)$, and those exposed, becoming infected at rate ϵ, $\epsilon E(t)$, with those who are susceptible and recovered individuals who become susceptible again at rate α, so $M(t) = [I(t) + E(t)][S(t) + R(t)]$.

We estimate the effects of lockdowns on the (changes in the log) total number of people ever infected, which is the ratio of new infections to total people ever infected:

$$\frac{nI(t)}{tI(t)} = \frac{nI(t)}{\sum_0^t nI(t)} = \frac{[1 - d(t)]\beta(t)M(t)}{\sum_0^t(1 - d(t))(t)M(t)}$$

Our estimates therefore provide information on the combined effects of the path of policy, $d(t)$, the changes in the virus transmission probability, $\beta(t)$, and meetings. In a short period around the lockdown, $\beta(t)$ and $M(t)$ could be considered as almost constant, so our approach can uncover the policy effect on transmissions, $1 - d(t)$.

5.3 Heterogeneity: Developed vs. Developing countries

We extend our baseline model to compare the effect between the implementation of lockdowns in developed and developing countries.[13] We used the HDI to define developed and developing countries.

$$\begin{aligned} &dlc_{it} = \qquad (2)\\ &\beta_1 Measure_{it} \times HighHDI_i + \beta_2 DaysAfterMeasure_{it} \times HighHDI_i +\\ &\beta_3 Measure_{it} \times LowHDI_i + \beta_4 DaysAfterMeasure_{it} \times LowHDI_i +\\ &+\beta_5 Release_{it} \end{aligned}$$

[13]The parameters capturing the effects of measures, β_1 and β_2, vary across countries, but, on average, the findings from a model with country heterogeneity are rather similar to the baseline analysis. Results are available upon request from the authors.

$$+\beta_6 Anticipation_{it}^{7days}$$

$$+FE_i + FE_t + \epsilon_{ct}$$

the variables $HighHDI_i$ and $LowHDI_i$ are indicator variables taking the value of one or zero for developed (HDI >=0.7) and developing countries (HDI<0.7), respectively. Note that we can include both effects simultaneously (Developed and Developing countries) without suffering from perfect multicollinearity, as the baseline includes countries that did not implement lockdown measures. Everything else is defined as in model (5).

6 Results

6.1 Descriptive Analyses: Anticipation Behavior

Here we start by presenting descriptive evidence on the rate of growth in confirmed cases and mobility as a function of the days before and after the implementation of the first within-lockdown measures. Figure 3 shows the residual variation in infections (top) conditional on the infections that occurred until the previous day – the growth rate in confirmed cases. Confirmed cases increase very rapidly in the period before a lockdown is implemented, especially in the period two weeks before implementing the lockdown. After the lockdown is implemented, the growth rate is lower and remains so throughout the 30-day window. Increases in the number of confirmed cases before a lockdown are typical of many countries that implement them to deal with exponential growth in cases. However, cases may also increase if people who learn about the lockdown become, temporarily, more mobile. Alternately, people might reduce their contacts preemptively if they see neighboring countries locking down or in a difficult situation.

Figure 4 shows the percentage difference of occupation captured by the Google Mobility Reports as a function of the days before and after the implementation of the first within-country lockdown. We observe that mobility falls sharply after the lockdown is implemented. We can see that the population slightly reduced its occupations approximately one week before

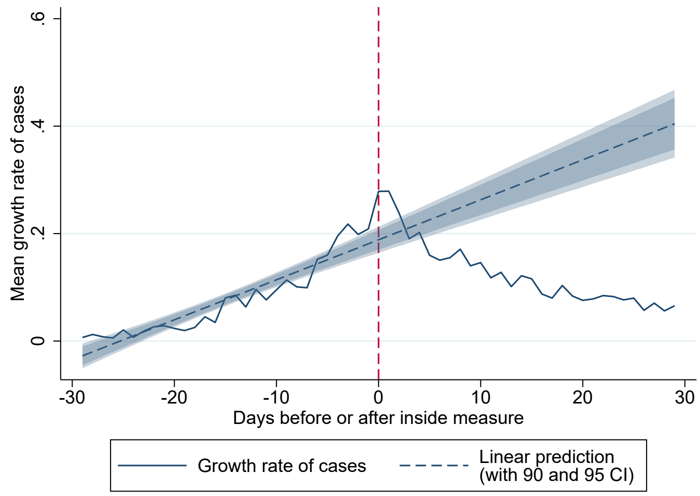

Figure 3: This graph reports the average growth rate of confirmed cases in the period 30 days before and after an internal measure was implemented. The graph also presents a prediction of the growth rate based on fitting a linear model to the data before the measure was introduced.

the implementation in non-necessary places, including retail and recreation, parks, or transit stations. Conversely, for grocery and pharmacy, the occupation is flat until the first day of implementation.[14]

We complement this qualitative analysis with a data-driven anticipation window. Using Google Mobility reports, we track mobility at "Transit stations," and we believe this provides information about anticipatory behavior for several reasons. First, people use transit for many reasons (e.g. work, shopping). Mobility at transit stations provides information on mobility overall. In contrast to mobility in cars, social distancing in transit stations is challenging, as many people need to use the same means of transit. Anticipatory behavior should therefore be detected in transit stations. To identify the anticipation window, we proceed as follows. First,

[14] Berry et al. (2021) and Goolsbee and Syverson (2021) claim that shelter-in-place measures in the U.S. had no additional effects on infections or deaths, beyond voluntary behavioral adjustments. Figure 4 also shows, *for all countries in our sample*, voluntary adjustments , but a further and stronger reduction in mobility after measures are introduced, results which are consistent with findings in Yan et al. (2021) for the U.S.. Quantitatively, the anticipatory reduction in mobility in anticipation of the measures is smaller – around 15 percent for transit stations and retail and recreation, and even less for parks, grocery shopping, and workplaces – than the drop in mobility triggered by the measures – 25 percent for transit stations and retail and recreation and around 20 percent for parks, grocery shopping, and workplaces. Measures contribute as much, or more, to containing the pandemic as voluntary behavioral adjustments.

we compute the change in mobility relative to the day of the lockdown from 30 days before to 30 days after for each measure. Then, we identify the first day when average mobility is statistically different from the 30 days prior (t-test with an alpha of 5%). This difference was 6.75 days before the lockdown, on average across all measures, ranging from 3 to 13 days. Based on this data-driven approach, we adopt a seven-day anticipation window in the baseline results (robustness checks in the Appendix report estimates with 5- and 10-day anticipation effect; see Appendix F).[15]

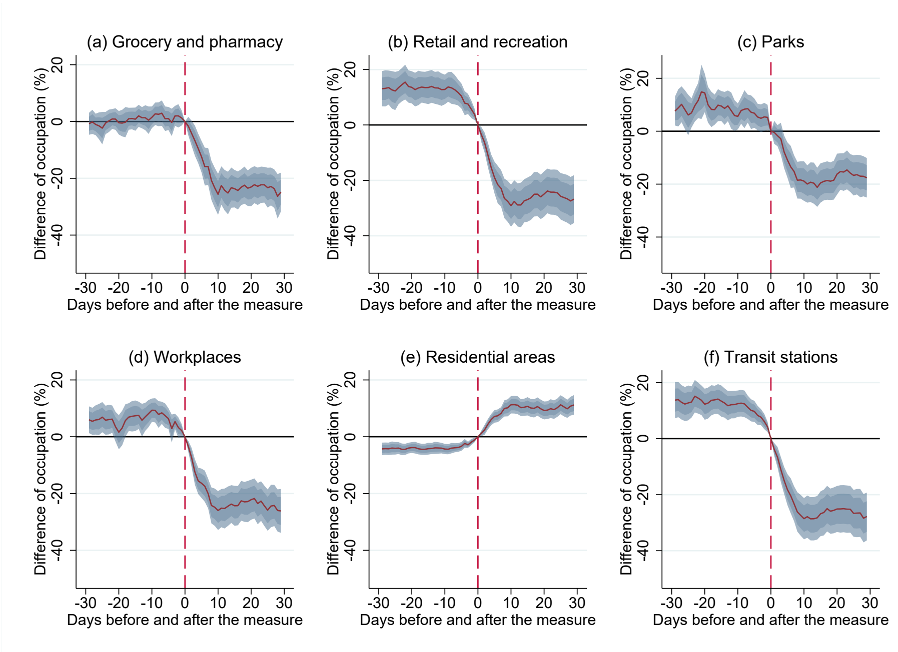

Figure 4: The figure shows the percentage difference in occupation of different areas (Google Mobility Trend) as a function of the days before and after the implementation of the first within-country lockdown. The y-axis represents percentage variation compared to the reference day (day 0). 90% and 99% confidence intervals are plotted in different shades of blue, while the line represents the mean value. The figure shows a very clear drop of occupations everywhere but in residential areas.

[15]Additionally, we also tried a ”calibrated” approach, where each measure has a different anticipation effect based on the estimation from the Google Mobility data. The results were virtually identical (no statistical differences with an alpha of 5%).

6.2 Baseline results: Effectiveness of lockdown measures

We explore here how internal and external lockdown measures reduced the growth of infections as a function of the time since the measure was implemented in comparison to countries that had not implemented any measure yet. Panels (a) and (b) of Figure 5 show the marginal effects of our baseline model. These two panels show that restrictions within the country are more effective than external measures at limiting the spread of the virus. On average, countries that implemented within-country movement restrictions experienced a statistically significant reduction in the growth rate of the virus after two weeks. After 100 days, the growth rate was reduced by more than 15.1% on average.[16] All the within-country measures lead to an approximate reduction of 10% of the growth rate after 100 days (see panels c, d, and e). Meanwhile, blocking the borders (panel (b)) shows a statistically significant reduction only after two months and a 4.2% reduction after 100 days.[17] Moreover, after one hundred days, the effects of international lockdowns and border closure stages 1 and 2 are barely statistically significant and about half the magnitude of within-country measures (after 100 days, the effects are, respectively: -3.9%, -5.9% and -4.3%.[18]

The difference between within-country and external measures could be affected by the timing of the decision. For example, if one type of measure systematically succeeded the other, the second might seem more effective because it benefits from the effect of the first one, or if the decisions take place in different phases of the epidemic, it might also affect their efficiency. First, 47 countries implemented an inside measure first, 97 implemented an outside measure first, and 20 countries implemented both measures on the same day. Additionally, six countries implemented only outside measures and eight only within-country measures. The median calendar day when inside measures were implemented is 76 (16th of March), while it is 75.5 for outside measures, so the two classes of measures have a very similar distribution with respect

[16]Model (1) from Table S9 in the Appendix reports the coefficients used for the quantification.
[17]Model (1) from Table S10 in the Appendix reports the coefficients used for the quantification.
[18]Models (2) to (4) from Table S10 in the Appendix report the coefficients used for the quantification.

to the timing of the implementation. Second, to completely address this worry we conduct a model including both our variable for within-country and external measures at the same time. This model allows us to compute the effect of one type of measure while capturing the effect of the other. The estimates are virtually unaffected by this alternative specification (See Appendix E).

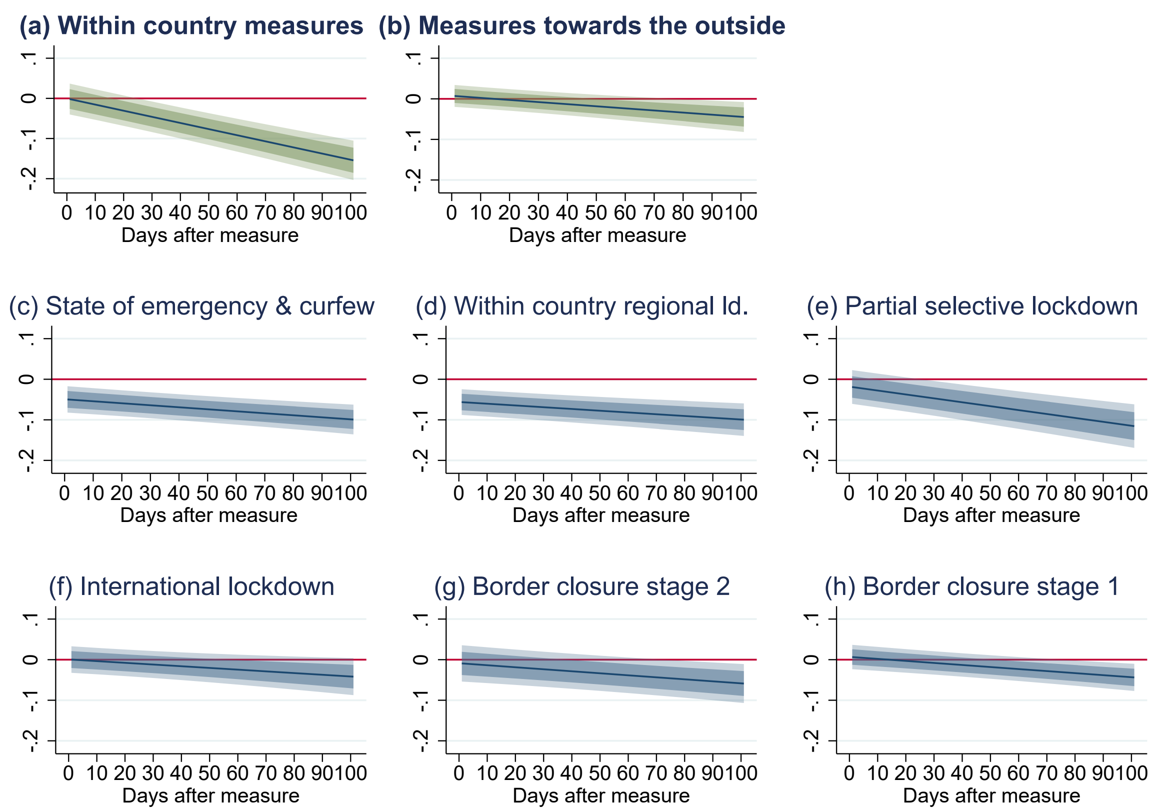

Figure 5: Marginal effect on the growth rate of COVID-19 cases. Internal measures were shown to be more efficient than external measures with respect to their effect on the spread of the virus. Each sub-figure shows the impact of a lockdown on the growth rate of infections as a function of the time since the measure was implemented. 90% and 99% confidence intervals are shown in different shades of blue or green.

6.3 Robustness: Controlling for the positivity rate

In this section, we show that our model is robust to the inclusion of the positivity rate as a control. Figure 7 represents the marginal effect of our baseline, with the positivity rate as a control.

The small differences could be due to the fact that the sample of countries with the positivity rate is smaller. In order to assess the differences due to the sample, Figure 8 shows the marginal effects of our baseline model when the sample is restricted to the same countries available with the positivity rate. Hence, by comparing our baseline (Figure 5) with the baseline model with the sample restricted to the countries with data on the positivity rate (Figure 8), we can observe that the effects are almost identical but somewhat slightly smaller with slightly larger confidence intervals (potentially due to the reduction of the sample size). Additionally, when comparing the baseline model with the model augmented with the positivity rate, the results are virtually identical.

Next, to assess the robustness of our model to the inclusion of the positivity rate more precisely, we compare the estimates (reduction after 100 days) of the two main models (Internal measures and External measures). The reduction in the growth rate after 100 days after an internal measure is 15.1%[19] in our baseline, while it is 20.3%[20] for the model with the positivity rate included as a control and 16.22% when the baseline model has the restricted sample [21].

Despite the average reduction being 5 percentage points larger while we control for positivity rate, the difference is not statistically significant. Hence, our main model will not include the positivity rate for two reasons. First, it allows keeping the full sample of 184 countries (instead of 115 with data on positivity rate). Second, if anything we are more conservative with our estimates.

[19] Model (1) from Table S9 in Appendix reports the coefficients used for the quantification.
[20] Model (1) from Table S17 in Appendix H.2 reports the coefficients used for the quantification.
[21] Model (1) from Table S19 in Appendix H.2 reports the coefficients used for the quantification.

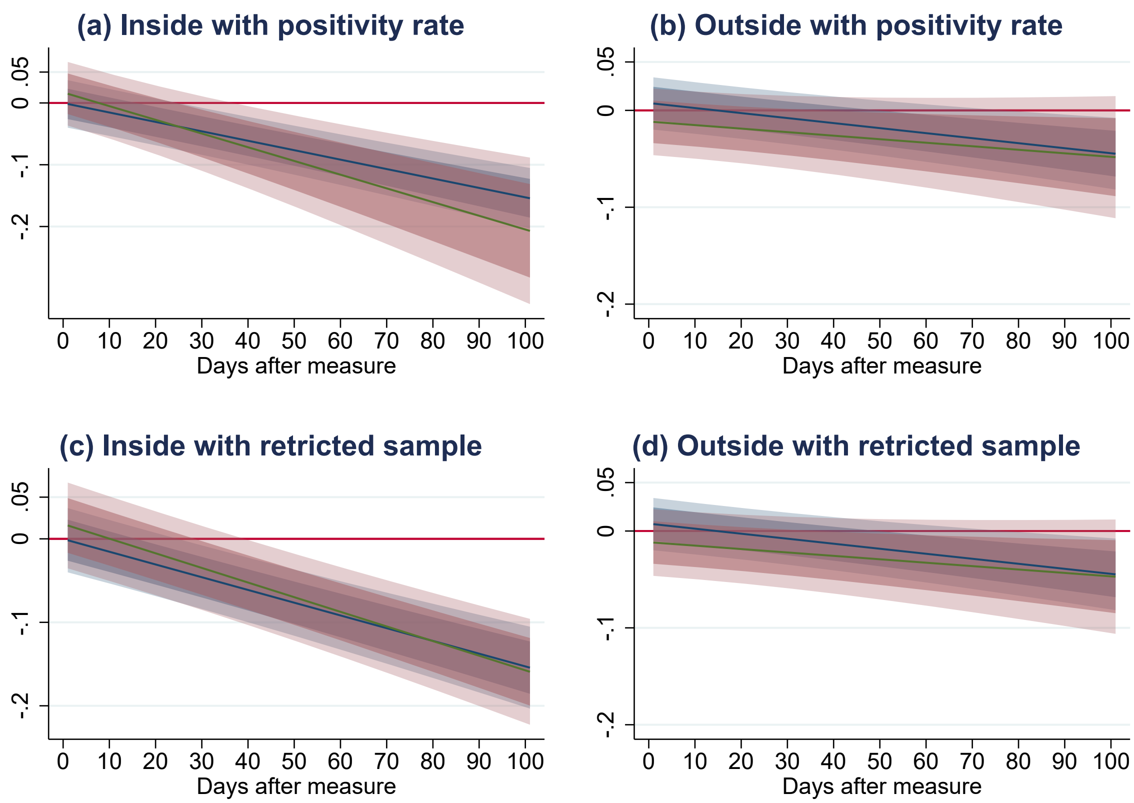

Figure 6: Comparison of the marginal effects of lockdowns on the growth rate of COVID-19 cases between our baseline, the model where we control for the positivity rate and the one where we restrict the sample to the countries with positivity rate data. Each sub-figure shows the impact of a lockdown on the growth rate of infections as a function of the time since the measure was implemented. 90% and 99% confidence intervals are shown in different shades of blue or red. The blue line with blue confidence intervals represent our baseline estimates while the green line with red confidence intervals in panel (a) and (b) reprent the estimates while controling for positivity rate. Finally, green line with red confidence intervals in panel (c) and (d) reprent the marginal effect for the estimate wi the sample restricted to countries with data on positivity rate.

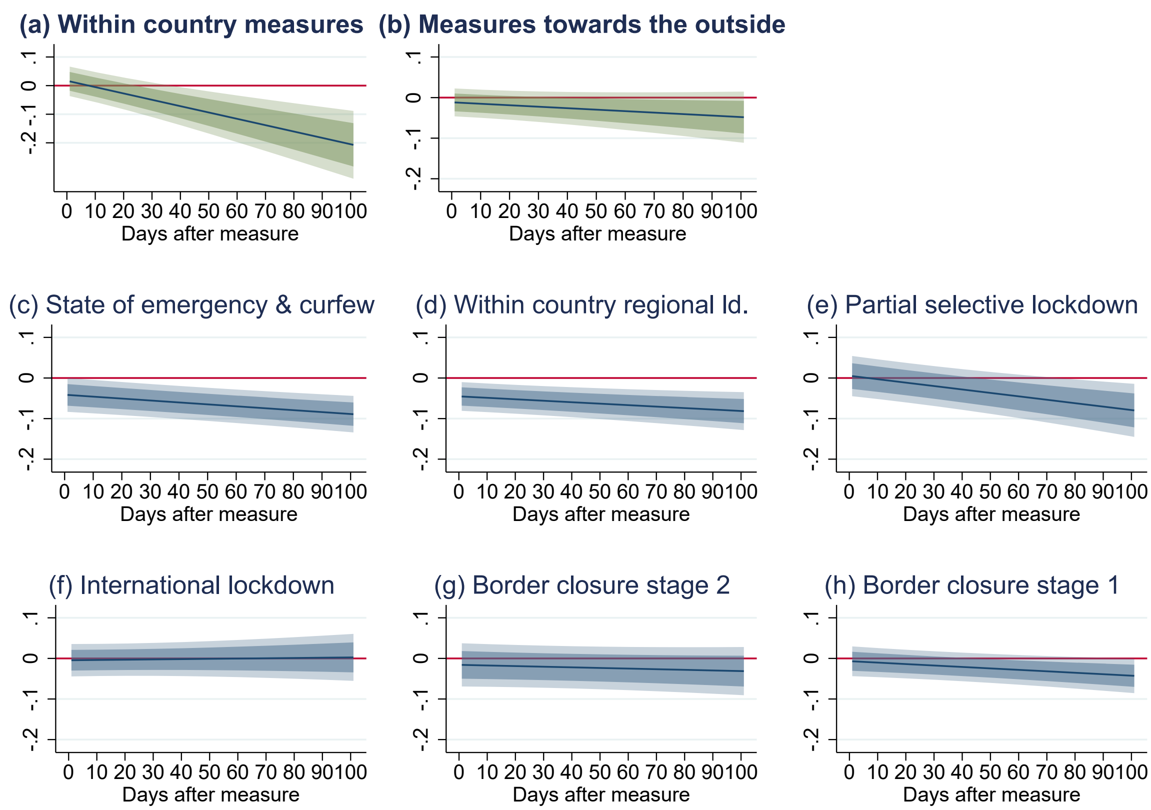

Figure 7: Marginal effect on the growth rate of COVID-19 cases controlling for the positivity rate. Internal measures were found to be more efficient than external measures with respect to their effect on the spread of the virus. Each sub-figure shows the impact of a lockdown on the growth rate of infections as a function of the time since the measure was implemented. 90% and 99% confidence intervals are shown in different shades of blue or green.

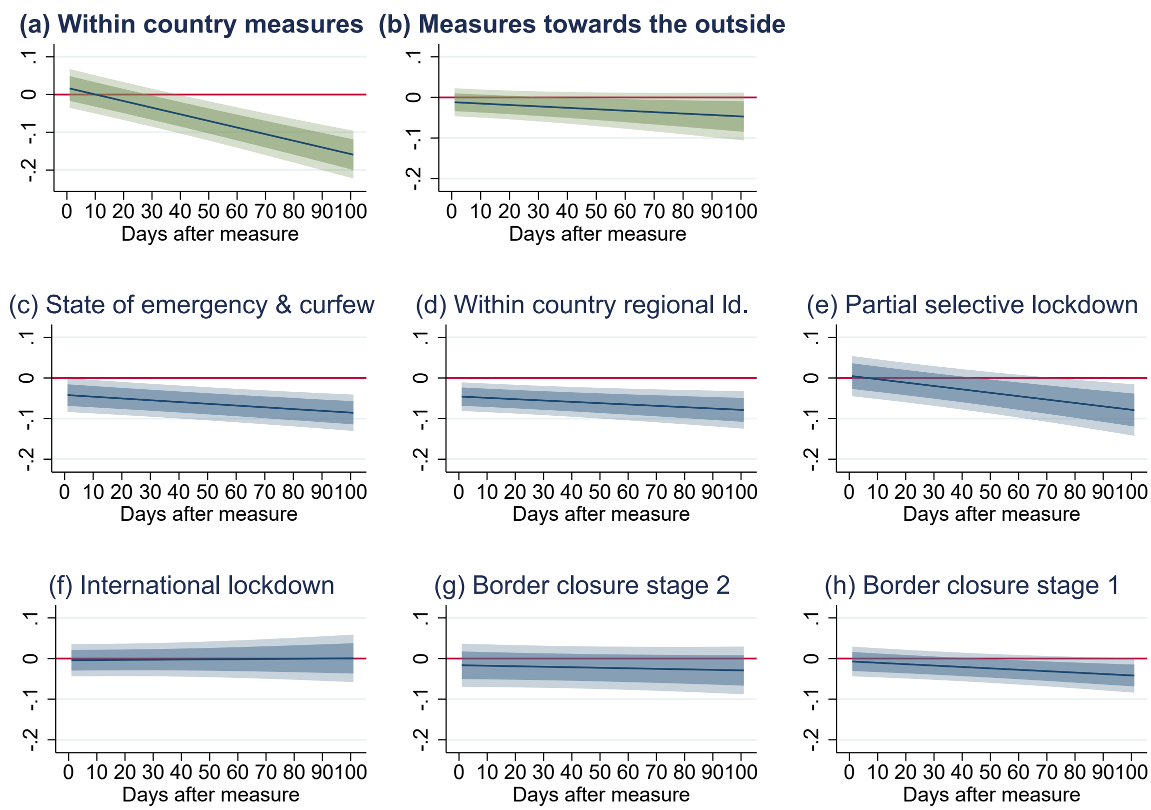

Figure 8: Marginal effect on the growth rate of COVID-19 cases when restricting the sample to countries with data on the positivity rate. Internal measures were found to be more efficient than external measures with respect to their effect on the spread of the virus. Each sub-figure shows the impact of a lockdown on the growth rate of infections as a function of the time since the measure was implemented. 90% and 99% confidence intervals are shown in different shades of blue or green.

6.4 Quantifying Prevented Deaths

We also estimate model (5) to assess how lockdowns affect death rates. More COVID-19 infections increase the number of admissions to hospitals, as more people experience a severe form of COVID-19, and hospitals reach capacity sooner (Wood et al., 2020). The results show that the growth rate in deaths is initially higher, but it declines significantly as the lockdown reduces the spread of the virus (Figure 9). Internal measures are more effective than external measures, replicating the result for the growth in the number of cases.

How effective were lockdowns in reducing deaths? A key challenge in quantification is how to estimate the counterfactual path of the epidemic, that is, the path that the epidemic would have taken without the lockdown measures. We use model (5) with the baseline anticipation window of 7 days, for the number of deaths, to compare the evolution of the total number of deaths with and without a measure. The model has two parameters that aid in this assessement: β_1, which indicates how much more the number of deaths grows in a country that has implemented a measure when the lockdown is implemented (intercept in Figure 9), and β_2, which describes the gradual slowing down of the growth rate in deaths due to the measure (slope in Figure 9, results shown in section H.1.2). Overall, we find that almost 3.6 million deaths were prevented during the first 100 days, which is our analysis period. Lockdowns prevent around five deaths for each actual death (Appendix G).

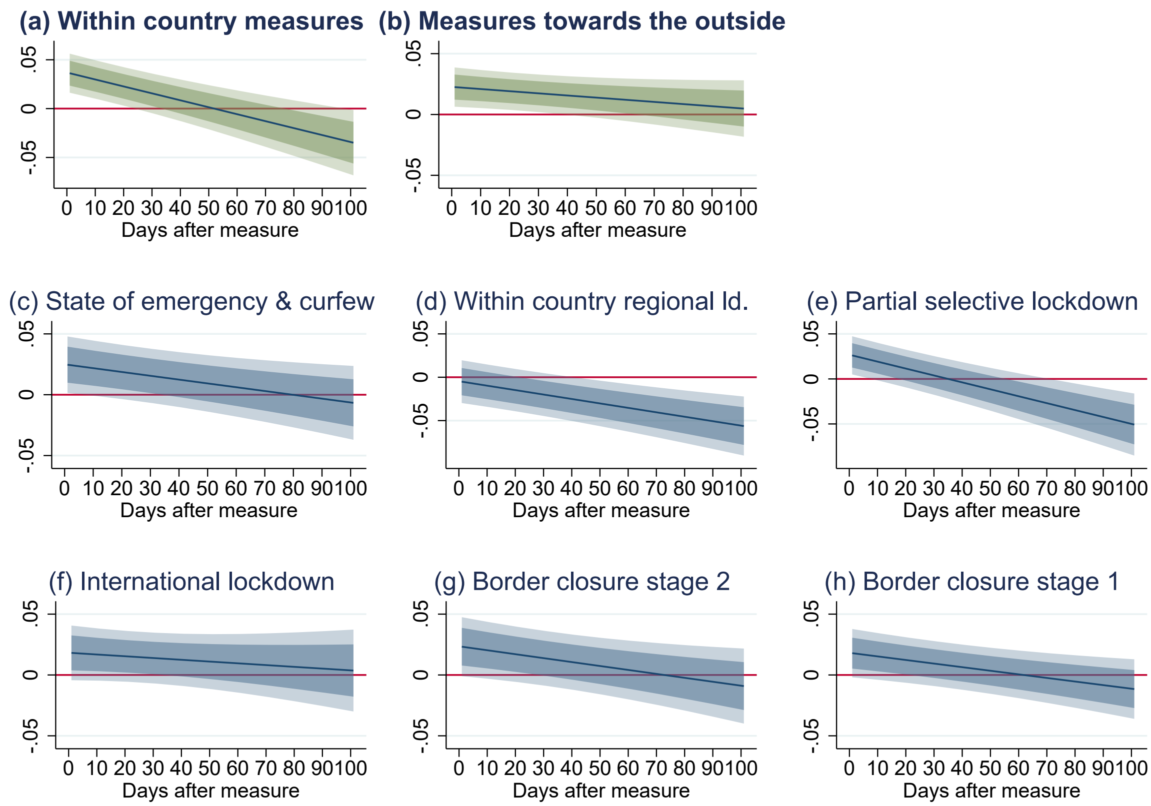

Figure 9: Marginal effect on the death growth rate. Internal measures were found to be more efficient than external measures with respect to their effect on the number of deaths. Each subfigure shows the impact of a specific lockdown measure on the number of deaths as a function of the time since the measure was implemented. 90% and 99% confidence intervals are shown in different shades of blue or green. The model shows: i) the effectiveness of numerous lockdown measures that governments implemented across countries to mitigate the number of deaths from COVID-19 (statistically significant effects and the number of days before the growth rate of the number of deaths is reduced compared to countries that did not implement the measure), ii) the strength of the effect (steepness of the slope). The corresponding results for the number of deaths are reported in the Appendix.

6.5 Developing versus developed countries

This section explores whether the impact of lockdowns is different in developed and developing countries. Figure 10 shows the marginal effects of all the different types of measures for developed and developing countries.[22] [23] A clear pattern emerges. Lockdown measures did not reduce the growth rate of the virus in developing economies, while the effects are negative and statistically significant for developed economies. Most of the explanatory variation in our baseline model thus comes from lockdowns imposed in developed countries. We discuss these results in Section 7, suggesting that the difference in opportunity cost could be the main driver.

6.6 Lockdown release

We now turn to the effect of releasing lockdowns. As we are writing this paper, the third wave of COVID-19 is well under way, and many countries might re-enter a lockdown phase. It is thus important to understand whether releasing a lockdown triggers another wave and to estimate (5) for countries that release a lockdown.

Figure 11 presents the marginal effects of the release of the different internal and external measures.[24] Despite multiple efforts to address reverse causation, a counter-factual is more difficult to find for the release, as virtually every country was experiencing a lockdown over the summer, and countries that released lockdown measures tended to be those that controlled the spread of COVID-19 better. However, while the countries that released the lockdowns are better off compared to the others who are still in a lockdown (who potentially started later), the improvement is diminishing. This analysis reveals that, on the day of the release, the growth rate in cases is lower than in the counterfactual state of not releasing the measure. Releasing triggers a very slow increase in the growth rate of COVID-19 cases of about 0.008 after 100

[22] We define developing countries as those with an HDI up to 0.699, indicating low and medium human development using the UN codebook definition, while those with an HDI above 0.699 are defined as developed countries.

[23] The results with a split into three groups (high, medium, and low) are available in the Appendix (See Appendix I.2.2).

[24] We use the same model as for our baseline (equation 5), and the ”Days after measure” refers to the number of days after releasing a lockdown.

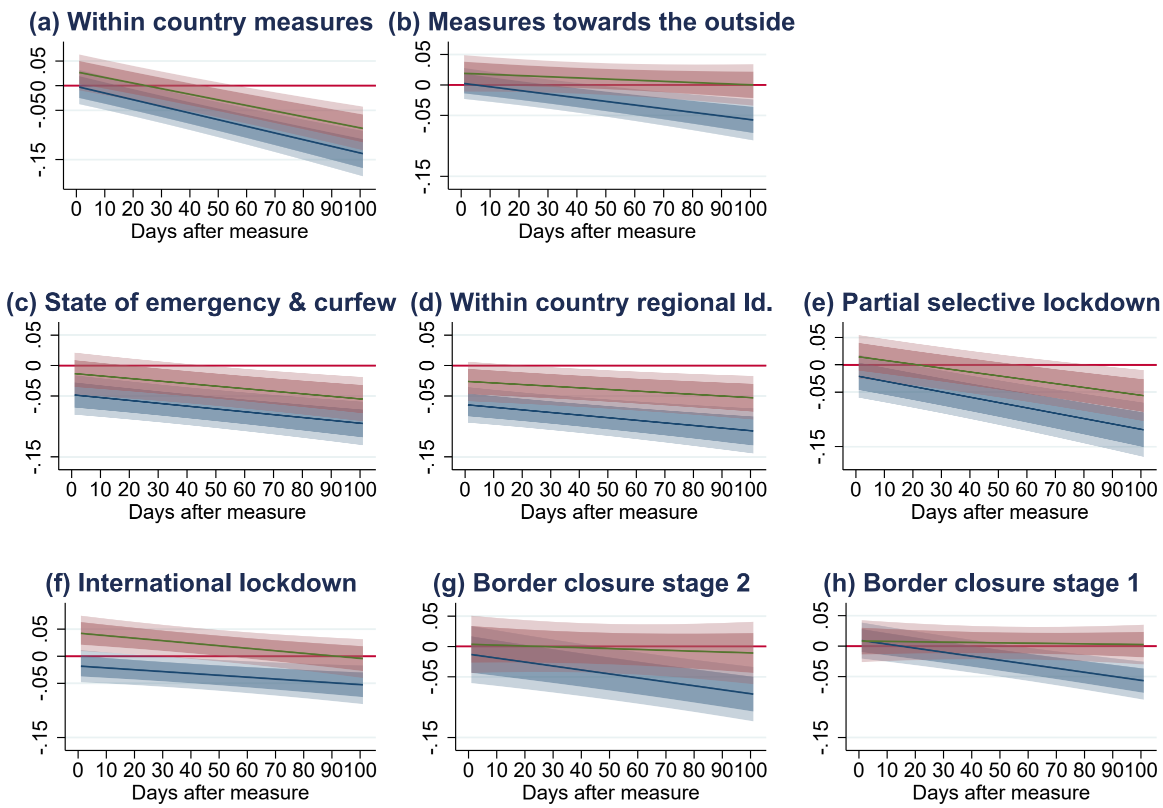

Figure 10: Lockdowns are found to be efficient only for developed countries. Developing countries are those with HDI values up to 0.699 (marginal represented in red), indicating low and medium human development using the UN codebook definition, while those with values above 0.699 are defined as developed countries (marginal represented in blue). Panels (a) to (f) show the impact of a measure on the growth rate of infections as a function of the time since the measure was implemented. 90% and 99% confidence intervals are shown in different shades of red or blue.

days. Releasing international border closure 2 is associated with a stronger increase in the growth rate of cases, suggesting that travel links could be relevant in the initial phase of a COVID-19 wave. As suggested early in the paper, this might also suggest that the timing of the release of external measures might be more difficult to manage than the release of internal measures.

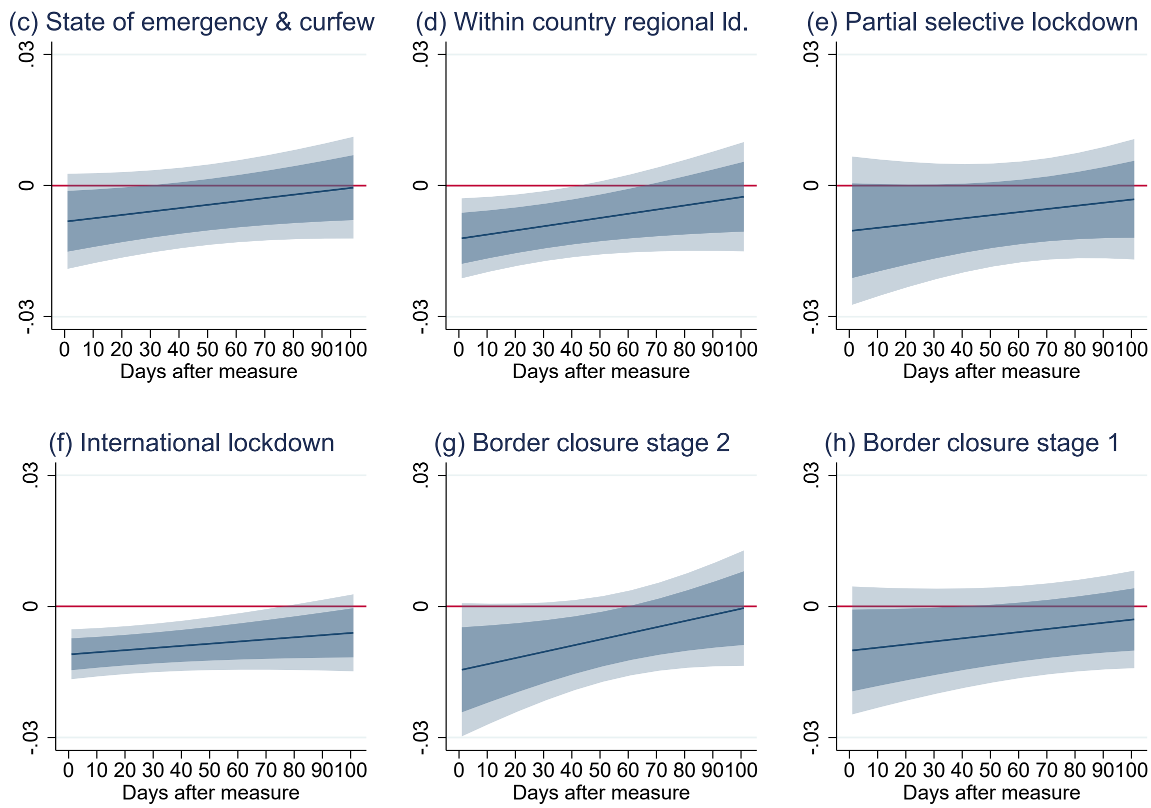

Figure 11: THe release of NPIs is associated with a low but positive increase in the rate of COVID-19. 90% and 99% confidence intervals are shown in different shades of green or blue. The vertical dashed line shows the average day when the measure was implemented in the sample.

7 Discussion and Conclusions

Our paper studies the COVID-19 lockdown measures, both internal and external, adopted in 178 countries and provides several important insights that are relevant for effectively managing pandemics. Note first that these results remain relevant even when vaccines become available, which has been the case for COVID-19 since late 2020. In part, this is because getting vaccination rates to a high enough level to reach collective immunity has proven to be harder than planned. Moreover, vaccines might not be effective for new variants of viruses. For similar reasons, we believe our results might also be relevant for future pandemics.

Overall, we find that lockdowns are effective measures to stop the growth in the number of new cases and in the number of deaths due to the reduction of individuals' mobility related to a broad range of daily activities. This result is in line with observations from previous pandemics. In his review of evidence regarding the Spanish influenza, Garrett (2008) compares the city of Philadelphia, where public officials allowed a large parade to take place, with that of St. Louis, a comparable city, where public officials responded by closing nearly all public places as soon as the influenza had reached the city, which resulted in much lower mortality rates. We estimate that almost 3.6 million deaths were prevented within 100 days, our analysis period, or more than five deaths for every single death that occurred.

Another striking result of our analysis is that internal measures matter much more than external ones. In particular, closing borders is the least effective policy for containing the spread of the pandemic, something that might be due to the difficulty of timing such measures correctly. Even in a globalized world, local policies are the name of the game. This result is in sharp contrast to current political discussions in the US and elsewhere, which often focus on border closures instead of emphasizing within-country lockdowns. We believe that this is due to the key effect of internal measures, as even a partial lockdown reduces the opportunity costs for people of staying at home, whereas external measures do not have this effect. In addition, the success of lockdown measures could also be due to their ability to trigger a strong adjustment in individuals' behaviors. This would again explain why external measures matter only after internal measures have been implemented, a result we obtained in a post-hoc analysis (available from the authors upon request). External measures could deliver some added benefit in terms of limiting the magnitude of social interactions by reducing the number of new people that enter the country who might or might not abide by the internally implemented lockdowns.

Also in favor of internal measures, we did not find that these measures were plagued by anticipation effects. For most human activities, the announcement of internal measures did not lead to a surge of activity that could have strongly increased the number of infections.

Contrary to popular belief, however, our analysis suggests that the most extreme measures, such as those related to declaring a state of emergency or implementing curfews and immediate border closures, are not necessarily the most effective policies, even without considering their economic costs. First, our empirical results show that partial or regional lockdowns are as effective as stricter measures. Since partial measures are likely to be less damaging to the economy than stricter lockdowns, they could be considered to be better. This analysis should of course be confirmed by a joint study of both the economic and health impacts of COVID-19, but the fact that partial internal measures are effective at reducing the spread of the disease and decreasing mortality rates is an important result by itself.

Why are less strict measures as effective? One possible explanation is that partial and selective lockdowns are enough to decrease the opportunity costs for people of staying at home, as schools, stores, and local businesses are closed, when weighed against the risk of becoming infected. Given that uncoordinated social distancing flattens the curve of the pandemic by reducing peak disease prevalence (Toxvaerd, 2020), we speculate that partial lockdowns could send even stronger signals to people not only to stay at home but also to quickly adopt sanitary measures or avoid group activities that could increase the spread of the disease. In other words, similarly to the way in which the pandemic altered the spending habits of individuals in general (Baker et al., 2020; Eichenbaum et al., 2020a) and in accordance with their vulnerability to the virus (Eichenbaum et al., 2020a), our results show that people adjust their behaviors significantly even when only partial measures have been implemented, making the implementation of partial measures sufficient to decrease the spread of COVID-19 at a lower economic cost. Thus, total lockdowns would then be superfluous. This challenges purely epidemiological models, which typically make projections about the spread of COVID-19 without taking into account the adjustments made by rational individuals.

Extrapolating our results, one can infer that, at some level of strength of internal measures, there are decreasing health benefits for making internal measures stricter. This could aid in

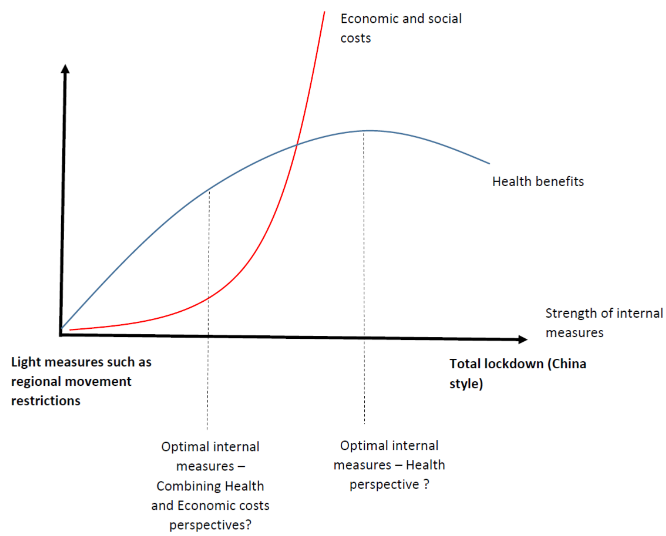

Figure 12: How to determine optimal internal measures

determining an optimal solution from a health perspective. However, while such a measurement is beyond the scope of this paper, it is also clear that internal measures generate economic and social costs that increase rapidly as the measures become stronger. This leads to the idea that optimal internal measures could be determined by integrating the two perspectives (Figure 11).

In order to explore our idea that the opportunity costs of staying at home are driving the results, we split our sample between developed and developing countries. The opportunity costs of adhering to lockdown rules and staying at home are much higher in developing economies, where many people work in the informal sector and do not have access to an adequate safety net. In line with our hypothesis, we find that internal lockdown policies had a significant effect on reducing both the number of cases and the number of deaths in developed economies, but we do not find such statistically significant effects in developing countries. We cannot firmly conclude from our analysis that lockdowns are not effective in developing countries, as the disease in these countries appeared later, and thus we lack a sufficient number of observations and statistical power. Nonetheless, our results so far indicate that lockdowns would have to be coupled with other measures that reduce the opportunity costs of staying at home to significantly affect the spread of the disease in developing countries.

Finally, our empirical results suggest that the lifting of lockdowns, which started around the world in May 15, 2020 (Bonardi et al., 2020), did not lead to a resurgence of the virus within 100 days of their release. We do find that releasing border closures could increase infections. This could be another indication that timing the release of external measures is more difficult than timing the release of internal ones. But again, beyond this point, our results support the idea that lockdowns have been relatively successful ways of managing the pandemic.

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SUPPLEMENTARY MATERIAL
Managing Pandemics: How to contain COVID-19 through Internal and External Lockdowns and their Releases

Appendix A Government policy measures data

	Mean	SD	Median	Min.	Max.	Count
International lockdown	83.56	9.30	81.00	73.00	151.00	162
State of emergency and curfew	85.83	17.90	83.00	32.00	205.00	123
Partial selective lockdown	74.89	9.19	76.00	27.00	104.00	134
Within-country regional lockdown	86.00	17.84	83.00	33.00	143.00	109
Selective border closing stage 2	71.71	13.11	72.50	31.00	140.00	78
Selective border closing stage 1	56.81	20.10	60.00	22.00	96.00	111
Within-country measures	76.33	11.70	76.00	27.00	141.00	172
Measures towards the outside	65.60	21.58	74.50	22.00	151.00	170

Table S1: When the measures were implemented in number of days since December 31, 2019 and how many countries implemented them

Appendix B Comparison between our data set and Oxford government response tracker data

Overall, our database provides somewhat different information compared to the OGRT. While both use actual implementation dates, we do not cover all the measures in the OGRT, that is, OGRT's start date may refer to different measures than in our database. For example, the OGRT separately considers the cancellation of public events, restrictions on gathering size, and school closures with their respective dates of implementation, while we repsent all of these measures under "partial selective lockdowns," and the date of implementation is the first date when any of these measures was implemented. In short, we aimed to capture significant shocks or major policy changes able to considerably change the trajectory of the pandemic, while the Oxford data contain every marginal change in policy. Hence, in the context of our study, we aimed to focus on major changes rather than capturing every potential small adjustment.

To explore these differences further, we conducted two comparative exercises. First, we compared the date of implementation of lockdowns in our dataset with the OGRT. Second, we replicated our main results with data from the OGRT. The details of those two exercises are provided below. Considering the difference in the nature of the data, the overlap between the two databases remains substantial, and any differences in timing information are most likely due to differences in the scope of tracking rather than measurement error.

We then compared the inside and outside lockdown measure dates with measures contained in the OGRT (Hale et al. (2020)). The Oxford project collects data on 23 government measures, which are then aggregated in an ordinal scale of stringency. The agreement is quite high. Oxford also groups measures into inside and outside measures (restriction on internal movements, restriction on international travel). Then, both variables have different levels of stringency (0-2 for internal movement restriction, 0-4 for international movement restriction). Hence, we coded different variables for each of those levels in order to compare them with our own data. Tables S2 and S3 present quartiles of the difference in implementation dates between the measures in our database compared to the OGRT (Table 2 provides the same in absolute values). Our measure of international travel restriction is the closest to the level 3 defined in Oxford, with a median difference of 0 (with a difference between -4.5 and +1 for 50% of the countries). Median absolute differences in implementation times are lowest for outside 3, three days, but also quite low for outside 2, four days (Table S3). Our measure of internal restrictions is the closest to the level 1 defined in Oxford. The median difference is four days earlier for our data (first quartile eleven and third quartile zero). Based on absolute differences in implementation times, inside measures of level 1 from the Oxford data are the closest to our data, with a median difference of six days.

	p25	p50	p75	sd	count
Outside level 1	0.0	5.0	28.0	32.0	151
Outside level 2	-2.0	0.0	6.0	27.3	151
Outside level 3	-4.5	0.0	1.0	26.4	148
Outside level 4	-43.5	-12.0	-1.5	33.4	124
Inside level 1	-11.0	-4.0	0.0	13.9	143
Inside level 2	-14.0	-7.0	-1.0	23.4	132

Table S2: Difference in days between our measure and Oxford government response tracker

	p25	p50	p75	sd	count
Outside level 1	3.0	12.0	36.0	25.8	151
Outside level 2	1.0	4.0	18.0	23.8	151
Outside level 3	0.0	3.0	12.0	24.0	148
Outside level 4	4.0	16.5	46.0	29.9	124
Inside level 1	2.0	6.0	11.0	12.2	143
Inside level 2	3.0	8.0	16.0	22.2	132

Table S3: Difference (absolute value) in days between our measure and Oxford government response tracker

Appendix C List of countries: Developing vs. developed

Developing countries	Developed countries
Afghanistan, Angola, Bangladesh, Benin, Bhutan, Burkina Faso, Burma, Burundi, Cabo Verde, Cambodia, Cameroon, Central African Republic, Chad, Comoros, Congo (Brazzaville), Congo (Kinshasa), Djibouti, Egypt, El Salvador, Eritrea, Eswatini, Ethiopia, Gambia, Ghana, Guatemala, Guinea, Guinea-Bissau, Guyana, Haiti, Honduras, India, Iraq, Ivory Coast, Kenya, Kyrgyzstan, Liberia, Madagascar, Malawi, Mali, Mauritania, Morocco, Mozambique, Namibia, Nepal, Nicaragua, Niger, Nigeria, Pakistan, Papua New Guinea, Rwanda, Sao Tome and Principe, Senegal, Sierra Leone, South Sudan, Sudan, Syria, Tajikistan, Tanzania, Timor-Leste, Togo, Uganda, Vietnam, Yemen, Zambia, Zimbabwe	Albania, Algeria, Andorra, Antigua and Barbuda, Argentina, Armenia, Australia, Austria, Azerbaijan, Bahamas, Bahrain, Barbados, Belarus, Belgium, Belize, Bolivia, Bosnia and Herzegovina, Botswana, Brazil, Brunei, Bulgaria, Canada, Chile, China, Colombia, Costa Rica, Croatia, Cuba, Cyprus, Czech Republic, Denmark, Dominica, Dominican Republic, Ecuador, Egypt, Estonia, Fiji, Finland, France, Gabon, Georgia, Germany, Greece, Grenada, Hungary, Iceland, Indonesia, Iran, Ireland, Israel, Italy, Jamaica, Japan, Jordan, Kazakhstan, Kuwait, Latvia, Lebanon, Libya, Liechtenstein, Lithuania, Luxembourg, Malaysia, Maldives, Malta, Mauritius, Mexico, Moldova, Monaco, Mongolia, Montenegro, Netherlands, New Zealand, North Macedonia, Norway, Oman, Panama, Paraguay, Peru, Philippines, Poland, Portugal, Qatar, Romania, Russia, Saint Kitts and Nevis, Saint Lucia, Saint Vincent and the Grenadines, San Marino, Saudi Arabia, Serbia, Seychelles, Singapore, Slovakia, Slovenia, South Africa, South Korea, Spain, Sri Lanka, Suriname, Sweden, Switzerland, Taiwan, Thailand, Trinidad and Tobago, Tunisia, Turkey, US, Ukraine, United Arab Emirates, United Kingdom, Uruguay, Uzbekistan, Venezuela

Table S4: Developing and developed countries list

Appendix D Effects of Measures vs Anticipation Effects

This section provides further details on the strategy for identifying the causal effects of measures on the growth rate of cases by modeling anticipation. We contrast two models. The first model, "With Anticipation," is the model we describe in the paper, and we reproduce it here for convenience

$$\begin{aligned} &dlc_{it} = \\ &\beta_1 Measure_{it} + \beta_2 DaysAfterMeasure_{it} \\ &+\beta_3 Release_{it} \\ &+\beta_4 Anticipation_{it}^{7days} \\ &+FE_i + FE_t + \epsilon_{it} \end{aligned} \tag{3}$$

This model controls for a binary variable, $Anticipation_{it}^{7days}$, which leads the introduction of the measure by seven days (e.g., the variable shifts from zero to one seven days before the policy is in place and remains one thereafter).

The second model, "No Anticipation," does not include the variable $Anticipation_{it}^{7days}$, but it is otherwise identical to the first model (3). The model is defined as follows:

$$\begin{aligned} &dlc_{it} = \\ &\beta_1 Measure_{it} + \beta_2 DaysAfterMeasure_{it} \\ &+\beta_3 Release_{it} \\ &+FE_i + FE_t + \epsilon_{it} \end{aligned} \tag{4}$$

We estimate both models on the set of internal measures (Table S5). The model "With Anticipation" predicts that the growth rate of cases decreases by about one-tenth of a log point

	With Anticipation	No Anticipation
	(1)	(2)
Days after measure	-0.001***	-0.001***
	(0.000)	(0.000)
Inside measures	-0.016	0.046***
	(0.014)	(0.010)
Anticipation, 7 days	0.091***	
	(0.013)	
Release internal measures	-0.013***	-0.012***
	(0.004)	(0.004)
Constant	0.031***	0.042***
	(0.004)	(0.004)
Observations	38405	38650
Adjusted R^2	0.146	0.138

Notes: Models absorb fixed effects for countries and calendar day. ”With Anticipation” is the main model we use to identify the causal effects of measures (equation 5). ”No Anticipation” does not include the binary variable $Anticipation_{i,t+7}$, which leads the binary variable $Measure_{it}$ by seven days, but it is otherwise identical to the ”With Anticipation” model.

Table S5: Parameter Estimates of the Anticipation and No Anticipation Models

each day after internal measures are implemented (”Days after measure,” -0.001). On the day that the measure is introduced, the growth rate of cases is not statistically different from the period just before enacting the policy (”Inside measures,” -0.016). However, in the week before the policy is introduced, the growth rate of cases is 9.1 log points higher than in the period before that (”Anticipation, 7 days,” 0.091). The release of measures reduces the growth rate by 1.3 log points.

Estimates of the ”No Anticipation” model align well with the model that allows for anticipation effects, except for the coefficient $Measure_{it}$, which captures the effects of lockdowns on the day of their introduction. The ”No Anticipation” model suggests that the growth rate of cases is 4.6 log points higher than it would be without the measure, and this effect is statistically significantly different from zero. The model with anticipation suggests that the growth rate is 1.6 log points lower but not statistically different from the situation without the measure. The ”No Anticipation” estimate suggests that lockdowns increase the growth in the number of cases, while internal measures reduce mobility and should therefore reduce the growth in the number of cases.

To better understand why the two models differ, we compare the predictions of the two models with the raw data (Figure D). Both models predict well in the period from 30 to 10 days before the measure is introduced and also after the measure has been introduced, but the predictions diverge substantially in the period just before introducing the measure. The growth rate of COVID-19 cases increases strongly, from about 10 log points to around 25 log points, around one week before the measure is introduced (”Data,” Figure D). The ”No Anticipation” model fails to capture this increase and predicts a gradual and slow increase in the growth rate of cases. The model therefore predicts that the growth rate of cases increases substantially from the day before the measure is introduced until the measure starts. In contrast, the ”With Anticipation” model captures the dynamics of the growth rate fairly well, predicting a sharp increase in the growth rate during the week before enacting the measure. Additionally, introducing the measure has no effect on the growth rate of cases in the ”With Anticipation” model, which is consistent with the data.

The estimated residuals provide information about the differences in fit (Figure D). The ”No Anticipation” model shows a bad fit to the data in the week before the measure is implemented, whereas the ”With Anticipation” model improves substantially on the model without anticipation effects.

Models that do not include a correction for anticipatory behavior tend to underestimate the growth in cases *before* a measure is introduced. This tends to lead to an erroneous conclusion that introducing lockdowns increases the growth rate of cases. The opposite is true: measures reduce the growth in cases, as our analysis in the main text illustrates.

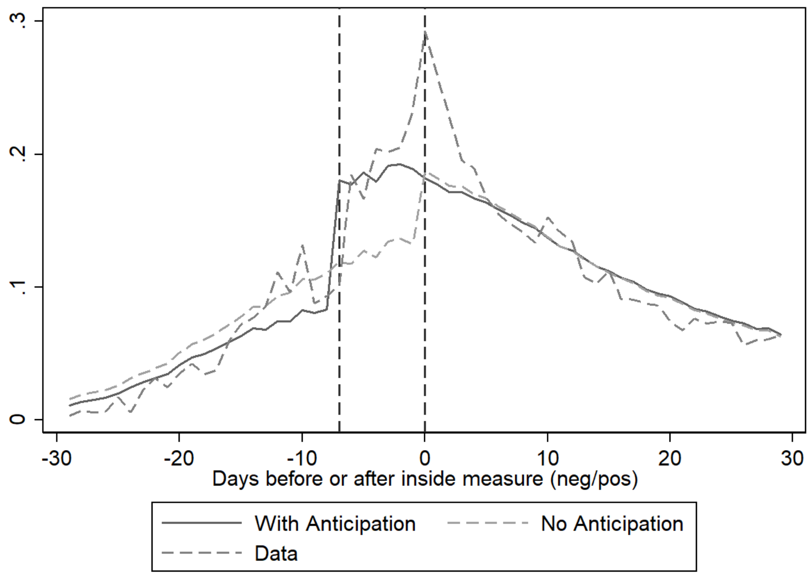

Figure S1: This graph reports the average growth rate of confirmed cases in the interval of 30 days before and after an internal measure was implemented (data) along with the prediction of the two models. ”With Anticipation” is the main model we use to identify the causal effects of measures (equation 5). ”No Anticipation” does not include the binary variable $Anticipation_{i,t+7}$, which leads the binary variable $Measure_{it}$ by seven days, but it is otherwise identical to the ”With Anticipation” model.

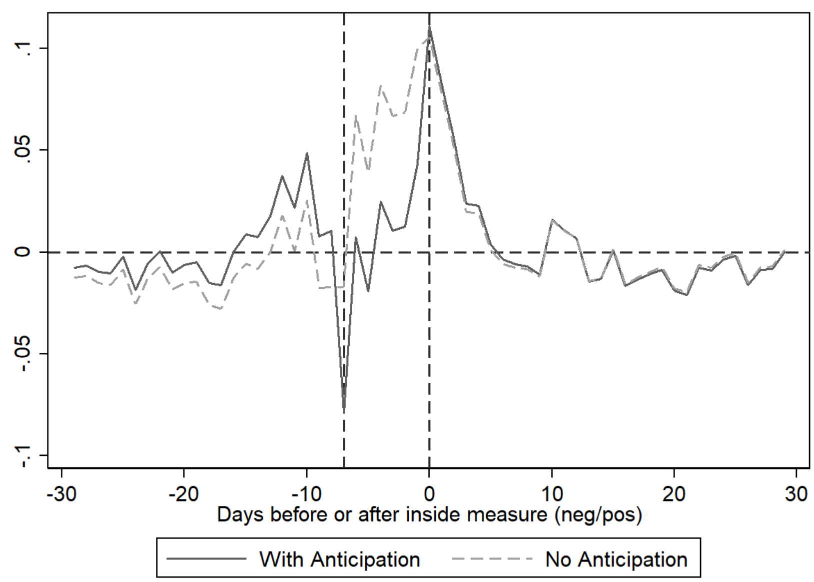

Figure S2: This graph reports the average residual growth rate of confirmed cases in the interval of 30 days before and after an internal measure was implemented (data) based on the two models. "With Anticipation" is the main model we use to identify the causal effects of measures (equation 5). "No Anticipation" does not include the binary variable $Anticipation_{i,t+7}$, which leads the binary variable $Measure_{it}$ by seven days, but it is otherwise identical to the "With Anticipation" model.

Appendix E Timing and overlap

In this section, we describe and present the results of our augmented model capturing the effect of within-country measures and external measures in one model.

$$
\begin{aligned}
& dlc_{it} = \\
& \beta_1^I Measure_{it}^{Inside} + \beta_2^I DaysAfterMeasure_{it}^{Inside} \\
& + \beta_3^I Release_{it}^{Inside} \\
& + \beta_4^I Anticipation_{it}^{Inside;7days} \\
& + \beta_1^O Measure_{it}^{Outside} + \beta_2^O DaysAfterMeasure_{it}^{Outside} \\
& + \beta_3^O Release_{it}^{Outside} \\
& + \beta_4^O Anticipation_{it}^{Outside;7days} \\
& + FE_i + FE_t + \epsilon_{it}
\end{aligned}
$$

Note the superscript ”Inside” or ”Outside,” which specifies the type of measure. The rest is defined as in our baseline model. The superscripts ”I” or ”O” for β parameters refer to ”Inside” or ”Outside” measures. $Measure_{it}$ is an indicator variable that takes the value of one from the day the measure was implemented. $DaysAfterMeasure_{it}$ is zero before a measure has been introduced and equals the number of days since the measure was implemented after the measure was introduced. Indeed, we do not expect the effect to be revealed and observable on day zero, even if no new transmission occurs, as the latest cases have not yet been detected. $Release_{it}$ is a dummy that takes the value of when when country i eases the lockdown measure. FE_i and FE_t are country and day fixed effects. ϵ_{it} is an error term clustered at the country level.

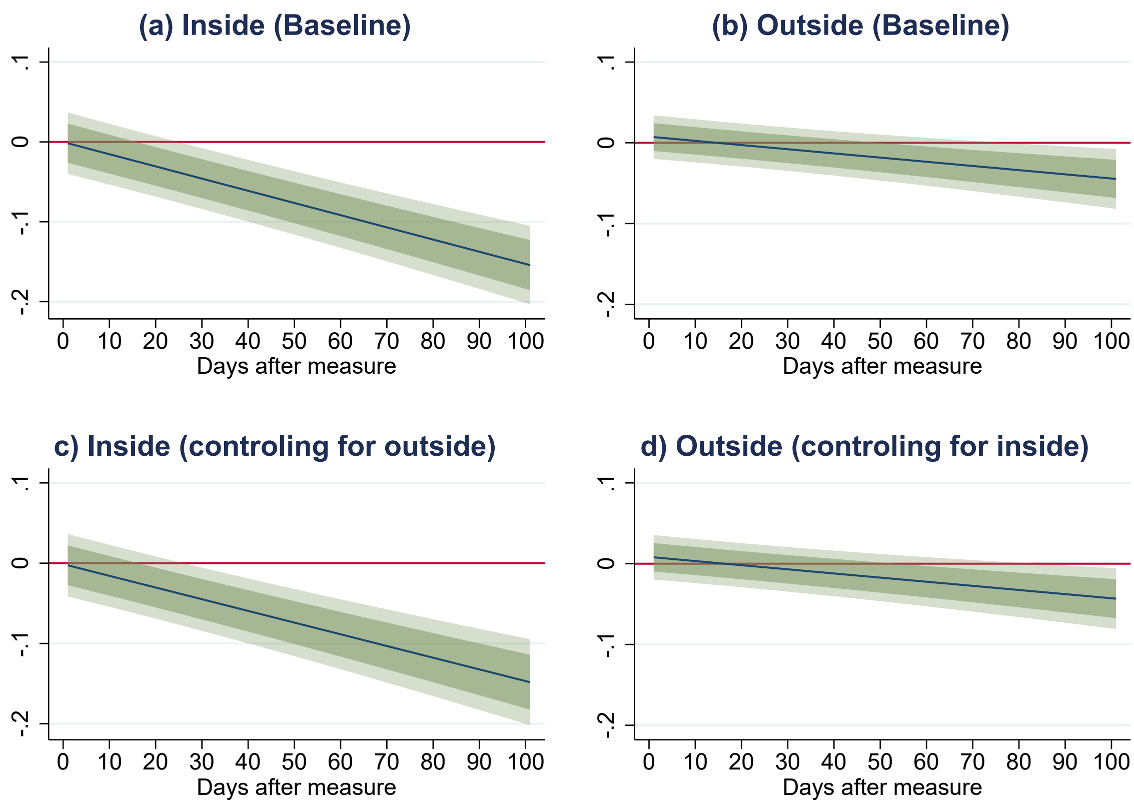

Figure S3: Marginal effect on growth rate of COVID-19 cases with seven-day anticipation effect. Panels a) and b) report our baseline effect, while panels c) and d) report the effects for our augmented model (capturing the effect of internal and external measures in the same model). Each sub-figure shows the impact of a lockdown on the growth rate of infections as a function of the time since the measure was implemented. 90% and 99% confidence intervals are shown in different shades of green.

Appendix F Anticipation

Figure S4 shows the occupation change relative to the first day of the lockdown implementation for transit stations.

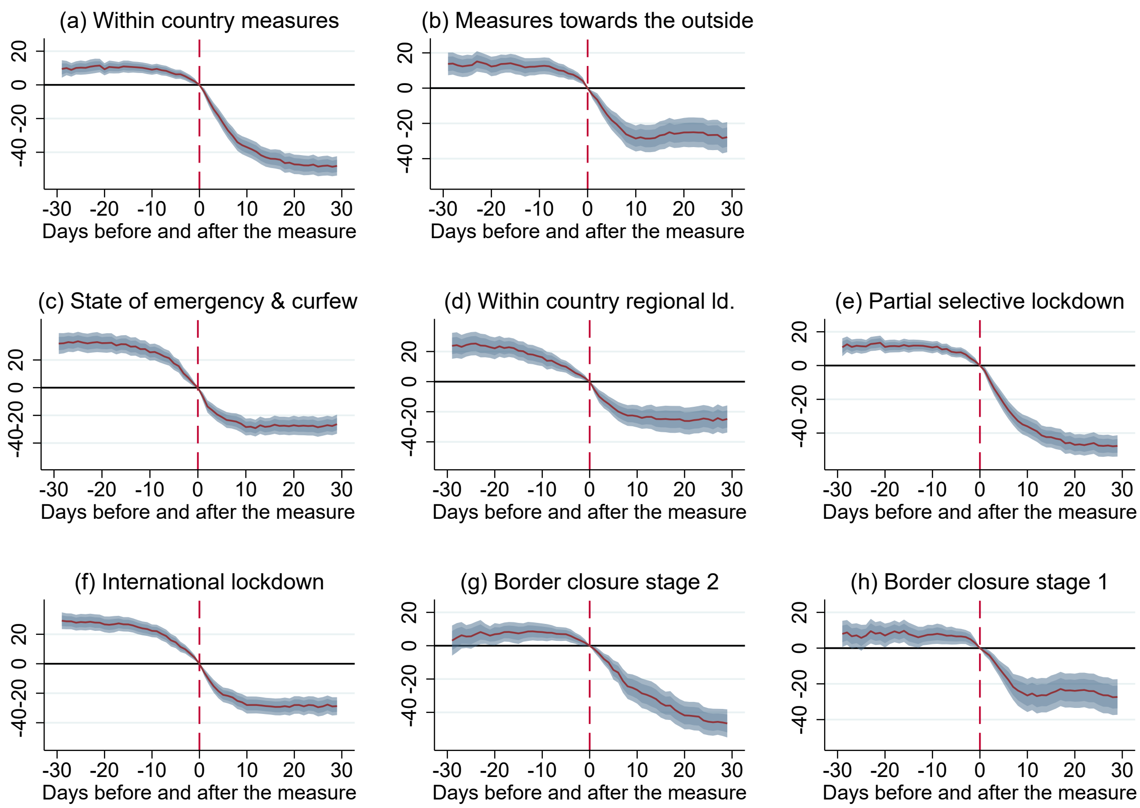

Figure S4: This figure shows the difference in occupation in percent of transit stations (Google Mobility Trend) as a function of the number of days before and after the implementation of the different types of lockdowns. The y-axis represents the percentage variation compared to the reference day (day 0). 90% and 99% confidence intervals are plotted in different shades of blue, while the line represents the mean value. The figure shows a very clear reduction in occupation everywhere but in residential areas.

Appendix G Prevented Deaths

Our models assume that lockdowns potentially reduce deaths from the date they are implemented. An alternative model that examines 35 days after the lockdown is implemented yields similar results (available upon request from the authors). Another approach to estimate the counterfactual path is based on R_0, the basic reproduction number (Flaxman et al., 2020b). Assuming that the reproduction number remains unchanged, this approach does not take into account the fact that people adapt their behavior to lower reproduction numbers (Eichenbaum et al., 2020b).

We base our simulation on countries that have implemented internal measures, as they have been shown to be effective (Table S6). We consider a window of 100 days from the day when a measure has been implemented, day 0, until the average date of release during our analysis period. With a lockdown, the day-to-day ratio in the number of cases is $exp(\hat{\beta}_1+\hat{\beta}_2\times t)$, where t is the number of days since the lockdown was implemented. The overall increase in the number of deaths between the day the measure was implemented and the end of the observation period is the product of all day-to-day ratios of cases, or $g_1 = \prod_{t=0}^{T} exp(\hat{\beta}_1 + \hat{\beta}_2 \times t)$, where $\prod$ is the product of its arguments. If the country had not implemented a lockdown, it would not benefit from the change in the growth rate, so $\beta_2 = 0$. The counterfactual increase in the number of deaths over the same period is $g_0 = \prod_{t=0}^{T} exp(\hat{\beta}_1) = exp(\hat{\beta}_1 \times T)$.

The ratio of $(g_0 - g_1)/g_1$ provides information on how many deaths were prevented per actual death that occurred. In our context, this ratio is 5.278, that is, somewhat more than five deaths were prevented per every death that occurred. We then use the total number of deaths in countries that implemented the measure in a window of 100 days after implementing the lockdown, which is around $D = 682$ thousand, to calculate the total number of prevented deaths, which is $D * (g_0 - g_1)/g_1 = 3.6$ million. A total of almost 3.6 million deaths were prevented during the first 100 days of a lockdown, or a little more than five prevented deaths for each actual death.

	log(deaths+1)			
	(1)	(2)	(3)	(4)
Within country lockdown				
DaysAfterMeasure	-0.0007***			
	(0.0001)			
Measure	0.0370***			
	(0.0078)			
Anticipation 7 days	0.0232***			
	(0.0081)			
MeasureRelease	-0.0090***			
	(0.0031)			
State of emergency lockdown				
DaysAfterMeasure		-0.0003***		
		(0.0001)		
Measure		0.0250***		
		(0.0090)		
Anticipation 7 days		0.0089		
		(0.0087)		
MeasureRelease		-0.0006		
		(0.0044)		
Within countrytial lockdown				
DaysAfterMeasure			-0.0005***	
			(0.0001)	
Measure			-0.0046	
			(0.0096)	
Anticipation 7 days			0.0428***	
			(0.0100)	
MeasureRelease			0.0011	
			(0.0043)	
Partial lockdown				
DaysAfterMeasure				-0.0008***
				(0.0001)
Measure				0.0269***
				(0.0083)
Anticipation 7 days				0.0284***
				(0.0095)
MeasureRelease				-0.0118**
				(0.0056)
Constant	0.0110***	0.0154***	0.0164***	0.0162***
	(0.0025)	(0.0011)	(0.0010)	(0.0013)
Observations	36074	44478	46431	41492
Adjusted R^2	0.113	0.110	0.116	0.117

First difference model estimatated with OLS with country and day fixed effects.
Standard errors in parenthesis clustered at the country level.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.001$.

Table S6: Baseline (deaths): Internal measures (anticipation 7 days)

Appendix H Regression tables

The regression tables are presented in this section. Appendix H.1.1 reports the coefficient for the baseline model for the growth rate of reported cases, while H.1.2 reports the coefficients for the growth rate of deaths. More importantly, Tables S9 and S10 report the coefficients used to produce the main Figure 5 and Tables S31 and S32 for Figure 9.

Then, Appendix H.3.1 and H.3.2 report the results for the growth rate of cases and deaths, respectively, for the heterogeneity exercise between developed and developing countries. In particular, Tables S23 and S24 report the coefficients for Figure 10 in the main text.

H.1 Baseline model: Effectiveness of lockdown measures

H.1.1 Number of reported cases

	log(cases+1)			
	(1)	(2)	(3)	(4)
Within country lockdown				
DaysAfterMeasure	-0.0015***			
	(0.0001)			
Measure	-0.0165			
	(0.0169)			
Anticipation 5 days	0.1091***			
	(0.0169)			
MeasureRelease	-0.0109***			
	(0.0040)			
State of emergency lockdown				
DaysAfterMeasure		-0.0005***		
		(0.0001)		
Measure		-0.0576***		
		(0.0147)		
Anticipation 5 days		0.1005***		
		(0.0152)		
MeasureRelease		-0.0015		
		(0.0045)		
Within countrytial lockdown				
DaysAfterMeasure			-0.0004***	
			(0.0001)	
Measure			-0.0501***	
			(0.0126)	
Anticipation 5 days			0.0642***	
			(0.0133)	
MeasureRelease			-0.0017	
			(0.0037)	
Partial lockdown				
DaysAfterMeasure				-0.0010***
				(0.0001)
Measure				-0.0318*
				(0.0190)
Anticipation 5 days				0.0799***
				(0.0203)
MeasureRelease				-0.0120*
				(0.0065)
Constant	0.0317***	0.0300***	0.0368***	0.0378***
	(0.0043)	(0.0018)	(0.0014)	(0.0021)
Observations	36112	44614	46595	41606
Adjusted R^2	0.152	0.144	0.141	0.144

First difference model estimatated with OLS with country and day fixed effects.
Standard errors in parenthesis clustered at the country level.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.001$.

Table S7: Baseline: Internal measures (anticipation 5 days)

	log(cases+1)			
	(1)	(2)	(3)	(4)
Measures toward the outside				
DaysAfterMeasure	-0.0005***			
	(0.0001)			
Measure	-0.0052			
	(0.0117)			
Anticipation 5 days	0.0488***			
	(0.0112)			
MeasureRelease	-0.0186***			
	(0.0037)			
International lockdown				
DaysAfterMeasure		-0.0004***		
		(0.0001)		
Measure		-0.0088		
		(0.0141)		
Anticipation 5 days		0.0412***		
		(0.0148)		
MeasureRelease		-0.0189***		
		(0.0052)		
Selective border closure 2				
DaysAfterMeasure			-0.0005***	
			(0.0001)	
Measure			-0.0106	
			(0.0200)	
Anticipation 5 days			0.0454**	
			(0.0189)	
MeasureRelease			-0.0081*	
			(0.0046)	
Selective border closure 1				
DaysAfterMeasure				-0.0005***
				(0.0001)
Measure				0.0001
				(0.0130)
Anticipation 5 days				0.0322***
				(0.0116)
MeasureRelease				-0.0125**
				(0.0063)
Constant	0.0332***	0.0355***	0.0326***	0.0351***
	(0.0039)	(0.0041)	(0.0010)	(0.0015)
Observations	34587	38779	49820	43075
Adjusted R^2	0.135	0.132	0.141	0.139

First difference model estimatated with OLS with country and day fixed effects.
Standard errors in parenthesis clustered at the country level.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.001$.

Table S8: Baseline: External measures (anticipation 5 days)

	log(cases+1)			
	(1)	(2)	(3)	(4)
Within country lockdown				
DaysAfterMeasure	-0.0015***			
	(0.0001)			
Measure	-0.0001			
	(0.0150)			
Anticipation 7 days	0.0974***			
	(0.0141)			
MeasureRelease	-0.0108***			
	(0.0040)			
State of emergency lockdown				
DaysAfterMeasure		-0.0005***		
		(0.0001)		
Measure		-0.0492***		
		(0.0126)		
Anticipation 7 days		0.0960***		
		(0.0127)		
MeasureRelease		-0.0016		
		(0.0045)		
Within countrytial lockdown				
DaysAfterMeasure			-0.0004***	
			(0.0001)	
Measure			-0.0559***	
			(0.0123)	
Anticipation 7 days			0.0745***	
			(0.0129)	
MeasureRelease			-0.0017	
			(0.0037)	
Partial lockdown				
DaysAfterMeasure				-0.0010***
				(0.0001)
Measure				-0.0181
				(0.0161)
Anticipation 7 days				0.0676***
				(0.0170)
MeasureRelease				-0.0119*
				(0.0065)
Constant	0.0290***	0.0287***	0.0355***	0.0372***
	(0.0043)	(0.0018)	(0.0014)	(0.0021)
Observations	36074	44478	46431	41492
Adjusted R^2	0.152	0.146	0.143	0.144

First difference model estimatated with OLS with country and day fixed effects.
Standard errors in parenthesis clustered at the country level.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.001$.

Table S9: Baseline: Internal measures (anticipation 7 days)

	log(cases+1)			
	(1)	(2)	(3)	(4)
Measures toward the outside				
DaysAfterMeasure	-0.0005***			
	(0.0001)			
Measure	0.0076			
	(0.0105)			
Anticipation 7 days	0.0358***			
	(0.0095)			
MeasureRelease	-0.0186***			
	(0.0037)			
International lockdown				
DaysAfterMeasure		-0.0004***		
		(0.0001)		
Measure		0.0007		
		(0.0127)		
Anticipation 7 days		0.0313**		
		(0.0131)		
MeasureRelease		-0.0190***		
		(0.0052)		
Selective border closure 2				
DaysAfterMeasure			-0.0005***	
			(0.0001)	
Measure			-0.0087	
			(0.0174)	
Anticipation 7 days			0.0453***	
			(0.0165)	
MeasureRelease			-0.0083*	
			(0.0046)	
Selective border closure 1				
DaysAfterMeasure				-0.0005***
				(0.0001)
Measure				0.0070
				(0.0117)
Anticipation 7 days				0.0257**
				(0.0099)
MeasureRelease				-0.0126**
				(0.0064)
Constant	0.0333***	0.0355***	0.0322***	0.0350***
	(0.0039)	(0.0042)	(0.0010)	(0.0015)
Observations	34545	38721	49594	42915
Adjusted R^2	0.134	0.131	0.141	0.139

First difference model estimatated with OLS with country and day fixed effects.
Standard errors in parenthesis clustered at the country level.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.001$.

Table S10: Baseline: External measures (anticipation 7 days)

	log(cases+1)			
	(1)	(2)	(3)	(4)
Within country lockdown				
DaysAfterMeasure	-0.0015***			
	(0.0001)			
Measure	0.0168			
	(0.0136)			
Anticipation 10 days	0.0839***			
	(0.0126)			
MeasureRelease	-0.0119***			
	(0.0042)			
State of emergency lockdown				
DaysAfterMeasure		-0.0005***		
		(0.0001)		
Measure		-0.0324***		
		(0.0113)		
Anticipation 10 days		0.0813***		
		(0.0115)		
MeasureRelease		-0.0017		
		(0.0045)		
Within countrytial lockdown				
DaysAfterMeasure			-0.0004***	
			(0.0001)	
Measure			-0.0537***	
			(0.0140)	
Anticipation 10 days			0.0773***	
			(0.0151)	
MeasureRelease			-0.0017	
			(0.0037)	
Partial lockdown				
DaysAfterMeasure				-0.0010***
				(0.0001)
Measure				-0.0149
				(0.0144)
Anticipation 10 days				0.0696***
				(0.0148)
MeasureRelease				-0.0117*
				(0.0065)
Constant	0.0266***	0.0278***	0.0340***	0.0351***
	(0.0044)	(0.0019)	(0.0014)	(0.0020)
Observations	36017	44274	46185	41321
Adjusted R^2	0.151	0.145	0.146	0.145

First difference model estimatated with OLS with country and day fixed effects.
Standard errors in parenthesis clustered at the country level.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.001$.

Table S11: Baseline: Internal measures (anticipation 10 days)

	log(cases+1) (1)	(2)	(3)	(4)
Measures toward the outside				
DaysAfterMeasure	-0.0005***			
	(0.0001)			
Measure	0.0165*			
	(0.0099)			
Anticipation 10 days	0.0271***			
	(0.0088)			
MeasureRelease	-0.0186***			
	(0.0037)			
International lockdown				
DaysAfterMeasure		-0.0004***		
		(0.0001)		
Measure		0.0060		
		(0.0123)		
Anticipation 10 days		0.0264**		
		(0.0129)		
MeasureRelease		-0.0191***		
		(0.0052)		
Selective border closure 2				
DaysAfterMeasure			-0.0005***	
			(0.0001)	
Measure			0.0044	
			(0.0147)	
Anticipation 10 days			0.0318**	
			(0.0130)	
MeasureRelease			-0.0083*	
			(0.0047)	
Selective border closure 1				
DaysAfterMeasure				-0.0005***
				(0.0001)
Measure				0.0110
				(0.0112)
Anticipation 10 days				0.0228**
				(0.0095)
MeasureRelease				-0.0126*
				(0.0065)
Constant	0.0331***	0.0352***	0.0324***	0.0347***
	(0.0039)	(0.0043)	(0.0010)	(0.0014)
Observations	34482	38634	49255	42675
Adjusted R^2	0.133	0.131	0.140	0.139

First difference model estimatated with OLS with country and day fixed effects.
Standard errors in parenthesis clustered at the country level.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.001$.

Table S12: Baseline: External measures (anticipation 10 days)

H.1.2 Number of reported deaths

	log(deaths+1)			
	(1)	(2)	(3)	(4)
Within country lockdown				
DaysAfterMeasure	-0.0007***			
	(0.0001)			
Measure	0.0370***			
	(0.0078)			
Anticipation 7 days	0.0232***			
	(0.0081)			
MeasureRelease	-0.0090***			
	(0.0031)			
State of emergency lockdown				
DaysAfterMeasure		-0.0003***		
		(0.0001)		
Measure		0.0250***		
		(0.0090)		
Anticipation 7 days		0.0089		
		(0.0087)		
MeasureRelease		-0.0006		
		(0.0044)		
Within countrytial lockdown				
DaysAfterMeasure			-0.0005***	
			(0.0001)	
Measure			-0.0046	
			(0.0096)	
Anticipation 7 days			0.0428***	
			(0.0100)	
MeasureRelease			0.0011	
			(0.0043)	
Partial lockdown				
DaysAfterMeasure				-0.0008***
				(0.0001)
Measure				0.0269***
				(0.0083)
Anticipation 7 days				0.0284***
				(0.0095)
MeasureRelease				-0.0118**
				(0.0056)
Constant	0.0110***	0.0154***	0.0164***	0.0162***
	(0.0025)	(0.0011)	(0.0010)	(0.0013)
Observations	36074	44478	46431	41492
Adjusted R^2	0.113	0.110	0.116	0.117

First difference model estimatated with OLS with country and day fixed effects.
Standard errors in parenthesis clustered at the country level.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.001$.

Table S13: Baseline (deaths): Internal measures (anticipation 7 days)

	log(deaths+1)			
	(1)	(2)	(3)	(4)
Measures toward the outside				
DaysAfterMeasure	-0.0002**			
	(0.0001)			
Measure	0.0227***			
	(0.0063)			
Anticipation 7 days	-0.0005			
	(0.0053)			
MeasureRelease	-0.0183***			
	(0.0042)			
International lockdown				
DaysAfterMeasure		-0.0001		
		(0.0001)		
Measure		0.0183**		
		(0.0088)		
Anticipation 7 days		0.0030		
		(0.0079)		
MeasureRelease		-0.0192***		
		(0.0058)		
Selective border closure 2				
DaysAfterMeasure			-0.0003***	
			(0.0001)	
Measure			0.0236**	
			(0.0095)	
Anticipation 7 days			0.0091	
			(0.0087)	
MeasureRelease			-0.0103**	
			(0.0041)	
Selective border closure 1				
DaysAfterMeasure				-0.0003***
				(0.0001)
Measure				0.0182**
				(0.0077)
Anticipation 7 days				0.0063
				(0.0070)
MeasureRelease				-0.0113*
				(0.0067)
Constant	0.0171***	0.0169***	0.0171***	0.0183***
	(0.0021)	(0.0029)	(0.0006)	(0.0010)
Observations	34545	38721	49594	42915
Adjusted R^2	0.107	0.107	0.109	0.109

First difference model estimatated with OLS with country and day fixed effects.
Standard errors in parenthesis clustered at the country level.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.001$.

Table S14: Baseline (deaths): External measures (anticipation 7 days)

	log(deaths+1)			
	(1)	(2)	(3)	(4)
Within country lockdown				
DaysAfterMeasure	-0.0007***			
	(0.0001)			
Measure	0.0393***			
	(0.0074)			
Anticipation 10 days	0.0232***			
	(0.0075)			
MeasureRelease	-0.0093***			
	(0.0031)			
State of emergency lockdown				
DaysAfterMeasure		-0.0003***		
		(0.0001)		
Measure		0.0301***		
		(0.0081)		
Anticipation 10 days		0.0029		
		(0.0078)		
MeasureRelease		-0.0006		
		(0.0044)		
Within countrytial lockdown				
DaysAfterMeasure			-0.0005***	
			(0.0001)	
Measure			-0.0067	
			(0.0110)	
Anticipation 10 days			0.0489***	
			(0.0122)	
MeasureRelease			0.0011	
			(0.0043)	
Partial lockdown				
DaysAfterMeasure				-0.0008***
				(0.0001)
Measure				0.0297***
				(0.0075)
Anticipation 10 days				0.0271***
				(0.0083)
MeasureRelease				-0.0117**
				(0.0056)
Constant	0.0097***	0.0157***	0.0152***	0.0156***
	(0.0025)	(0.0011)	(0.0011)	(0.0013)
Observations	36017	44274	46185	41321
Adjusted R^2	0.113	0.110	0.119	0.117

First difference model estimatated with OLS with country and day fixed effects.
Standard errors in parenthesis clustered at the country level.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.001$.

Table S15: Baseline (deaths): Internal measures (anticipation 10 days)

	log(deaths+1)			
	(1)	(2)	(3)	(4)
Measures toward the outside				
DaysAfterMeasure	-0.0002**			
	(0.0001)			
Measure	0.0246***			
	(0.0058)			
Anticipation 10 days	-0.0034			
	(0.0042)			
MeasureRelease	-0.0182***			
	(0.0042)			
International lockdown				
DaysAfterMeasure		-0.0001		
		(0.0001)		
Measure		0.0187**		
		(0.0087)		
Anticipation 10 days		0.0028		
		(0.0078)		
MeasureRelease		-0.0194***		
		(0.0058)		
Selective border closure 2				
DaysAfterMeasure			-0.0003***	
			(0.0001)	
Measure			0.0235**	
			(0.0092)	
Anticipation 10 days			0.0099	
			(0.0087)	
MeasureRelease			-0.0105**	
			(0.0042)	
Selective border closure 1				
DaysAfterMeasure				-0.0003***
				(0.0001)
Measure				0.0204***
				(0.0068)
Anticipation 10 days				0.0040
				(0.0051)
MeasureRelease				-0.0115*
				(0.0067)
Constant	0.0179***	0.0169***	0.0170***	0.0184***
	(0.0021)	(0.0030)	(0.0006)	(0.0010)
Observations	34482	38634	49255	42675
Adjusted R^2	0.107	0.107	0.109	0.109

First difference model estimatated with OLS with country and day fixed effects.
Standard errors in parenthesis clustered at the country level.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.001$.

Table S16: Baseline (deaths): External measures (anticipation 10 days)

H.2 Robustness:Positivity rate

H.2.1 Number of reported cases (controlling for the positivity rate)

	log(cases+1)			
	(1)	(2)	(3)	(4)
Short-term positive rate	0.0439**	0.0589***	0.0726***	0.0510***
	(0.0170)	(0.0149)	(0.0139)	(0.0194)
Within country lockdown				
DaysAfterMeasure	-0.0022***			
	(0.0004)			
Measure	0.0171			
	(0.0200)			
Anticipation 7 days	0.0714***			
	(0.0161)			
MeasureRelease	-0.0112**			
	(0.0046)			
State of emergency lockdown				
DaysAfterMeasure		-0.0005***		
		(0.0001)		
Measure		-0.0412**		
		(0.0162)		
Anticipation 7 days		0.0889***		
		(0.0162)		
MeasureRelease		0.0012		
		(0.0058)		
Within countrytial lockdown				
DaysAfterMeasure			-0.0004***	
			(0.0001)	
Measure			-0.0452***	
			(0.0138)	
Anticipation 7 days			0.0561***	
			(0.0152)	
MeasureRelease			0.0054	
			(0.0045)	
Partial lockdown				
DaysAfterMeasure				-0.0008***
				(0.0002)
Measure				0.0056
				(0.0193)
Anticipation 7 days				0.0393**
				(0.0181)
MeasureRelease				-0.0136
				(0.0089)
Constant	0.0607***	0.0328***	0.0417***	0.0455***
	(0.0175)	(0.0024)	(0.0023)	(0.0048)
Observations	19615	25568	25944	21995
Adjusted R^2	0.208	0.211	0.205	0.197

First difference model estimatated with OLS with country and day fixed effects.
Standard errors in parenthesis clustered at the country level.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.001$.

Table S17: Baseline: Internal measures with positivity rate (anticipation 7 days)

	log(cases+1)			
	(1)	(2)	(3)	(4)
Short-term positive rate	0.0456*	0.0360**	0.0655***	0.0558***
	(0.0266)	(0.0150)	(0.0134)	(0.0194)
Measures toward the outside				
DaysAfterMeasure	-0.0004*			
	(0.0002)			
Measure	-0.0115			
	(0.0133)			
Anticipation 7 days	0.0438***			
	(0.0132)			
MeasureRelease	-0.0108**			
	(0.0048)			
International lockdown				
DaysAfterMeasure		0.0001		
		(0.0002)		
Measure		-0.0045		
		(0.0155)		
Anticipation 7 days		0.0355*		
		(0.0183)		
MeasureRelease		-0.0121**		
		(0.0048)		
Selective border closure 2				
DaysAfterMeasure			-0.0002	
			(0.0002)	
Measure			-0.0158	
			(0.0207)	
Anticipation 7 days			0.0361*	
			(0.0203)	
MeasureRelease			0.0003	
			(0.0052)	
Selective border closure 1				
DaysAfterMeasure				-0.0004***
				(0.0001)
Measure				-0.0067
				(0.0143)
Anticipation 7 days				0.0249**
				(0.0124)
MeasureRelease				-0.0025
				(0.0072)
Constant	0.0427***	0.0308***	0.0365***	0.0445***
	(0.0092)	(0.0077)	(0.0019)	(0.0024)
Observations	18684	21690	27275	22823
Adjusted R^2	0.189	0.194	0.205	0.199

First difference model estimatated with OLS with country and day fixed effects.
Standard errors in parenthesis clustered at the country level.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.001$.

Table S18: Baseline: External measures with positivity rate (anticipation 7 days)

H.2.2 Number of reported cases (baseline model restricted to the sample with positivity rate data)

	log(cases+1)			
	(1)	(2)	(3)	(4)
Within country lockdown				
DaysAfterMeasure	-0.0018***			
	(0.0002)			
Measure	0.0178			
	(0.0200)			
Anticipation 7 days	0.0767***			
	(0.0157)			
MeasureRelease	-0.0105**			
	(0.0046)			
State of emergency lockdown				
DaysAfterMeasure		-0.0004***		
		(0.0001)		
Measure		-0.0417**		
		(0.0162)		
Anticipation 7 days		0.0891***		
		(0.0162)		
MeasureRelease		-0.0019		
		(0.0056)		
Within countrytial lockdown				
DaysAfterMeasure			-0.0003***	
			(0.0001)	
Measure			-0.0456***	
			(0.0137)	
Anticipation 7 days			0.0562***	
			(0.0152)	
MeasureRelease			0.0052	
			(0.0044)	
Partial lockdown				
DaysAfterMeasure				-0.0008***
				(0.0002)
Measure				0.0054
				(0.0193)
Anticipation 7 days				0.0392**
				(0.0181)
MeasureRelease				-0.0139
				(0.0088)
Constant	0.0447***	0.0331***	0.0427***	0.0462***
	(0.0107)	(0.0023)	(0.0023)	(0.0049)
Observations	20012	26416	26706	22441
Adjusted R^2	0.207	0.212	0.205	0.198

First difference model estimatated with OLS with country and day fixed effects.
Standard errors in parenthesis clustered at the country level.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.001$.

Table S19: Baseline: Internal measures with positivity rate (anticipation 7 days)

	log(cases+1)			
	(1)	(2)	(3)	(4)
Measures toward the outside				
DaysAfterMeasure	-0.0004*			
	(0.0002)			
Measure	-0.0116			
	(0.0134)			
Anticipation 7 days	0.0440***			
	(0.0132)			
MeasureRelease	-0.0123***			
	(0.0044)			
International lockdown				
DaysAfterMeasure		0.0000		
		(0.0002)		
Measure		-0.0042		
		(0.0155)		
Anticipation 7 days		0.0357*		
		(0.0183)		
MeasureRelease		-0.0154***		
		(0.0047)		
Selective border closure 2				
DaysAfterMeasure			-0.0001	
			(0.0002)	
Measure			-0.0163	
			(0.0207)	
Anticipation 7 days			0.0360*	
			(0.0203)	
MeasureRelease			-0.0016	
			(0.0053)	
Selective border closure 1				
DaysAfterMeasure				-0.0003**
				(0.0001)
Measure				-0.0069
				(0.0143)
Anticipation 7 days				0.0250**
				(0.0124)
MeasureRelease				-0.0059
				(0.0077)
Constant	0.0422***	0.0310***	0.0377***	0.0448***
	(0.0087)	(0.0079)	(0.0019)	(0.0024)
Observations	19000	22127	27969	23459
Adjusted R^2	0.190	0.195	0.205	0.200

First difference model estimatated with OLS with country and day fixed effects.
Standard errors in parenthesis clustered at the country level.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.001$.

Table S20: Baseline: External measures with positivity rate (anticipation 7 days)

H.3 Extension: Developed vs. Developing

H.3.1 Number of reported cases

	log(confirmed+1) (1)	(2)	(3)	(4)
Within country lockdown				
DaysAfterMeasure× LowHDI	-0.0011***			
	(0.0001)			
Measure× LowHDI	0.0192			
	(0.0154)			
DaysAfterMeasure× HighHDI	-0.0013***			
	(0.0002)			
Measure× HighHDI	-0.0110			
	(0.0147)			
Anticipation 5 days	0.0882***			
	(0.0147)			
MeasureRelease	-0.0104***			
	(0.0039)			
State of emergency lockdown				
DaysAfterMeasure× LowHDI		-0.0004***		
		(0.0001)		
Measure× LowHDI		-0.0144		
		(0.0151)		
DaysAfterMeasure× HighHDI		-0.0004***		
		(0.0001)		
Measure× HighHDI		-0.0506***		
		(0.0142)		
Anticipation 5 days		0.0780***		
		(0.0145)		
MeasureRelease		-0.0041		
		(0.0041)		
Within countrytial lockdown				
DaysAfterMeasure× LowHDI			-0.0003**	
			(0.0001)	
Measure× LowHDI			-0.0181	
			(0.0120)	
DaysAfterMeasure× HighHDI			-0.0004***	
			(0.0001)	
Measure× HighHDI			-0.0573***	
			(0.0110)	
Anticipation 5 days			0.0528***	
			(0.0106)	
MeasureRelease			-0.0040	
			(0.0034)	
Partial lockdown				
DaysAfterMeasure× LowHDI				-0.0007***
				(0.0001)
Measure× LowHDI				0.0074
				(0.0176)
DaysAfterMeasure× HighHDI				-0.0010***
				(0.0001)
Measure× HighHDI				-0.0283
				(0.0174)
Anticipation 5 days				0.0623***
				(0.0181)
MeasureRelease				-0.0123**
				(0.0061)
Constant	0.0272***	0.0299***	0.0370***	0.0374***
	(0.0045)	(0.0018)	(0.0014)	(0.0020)
Observations	36112	44614	46595	41606
Adjusted R^2	0.153	0.146	0.145	0.147

First difference model estimatated with OLS with country and day fixed effects.
Standard errors in parenthesis clustered at the country level.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.001$.

Table S21: Extension: Internal measures (anticipation 5 days)

	log(confirmed+1)			
	(1)	(2)	(3)	(4)
Measures toward the outside				
DaysAfterMeasure× LowHDI	-0.0002			
	(0.0001)			
Measure× LowHDI	0.0096			
	(0.0123)			
DaysAfterMeasure× HighHDI	-0.0006***			
	(0.0001)			
Measure× HighHDI	-0.0068			
	(0.0107)			
Anticipation 5 days	0.0425***			
	(0.0099)			
MeasureRelease	-0.0134***			
	(0.0037)			
International lockdown				
DaysAfterMeasure× LowHDI		-0.0005***		
		(0.0001)		
Measure× LowHDI		0.0364***		
		(0.0133)		
DaysAfterMeasure× HighHDI		-0.0003***		
		(0.0001)		
Measure× HighHDI		-0.0243**		
		(0.0122)		
Anticipation 5 days		0.0337***		
		(0.0122)		
MeasureRelease		-0.0151***		
		(0.0051)		
Selective border closure 2				
DaysAfterMeasure× LowHDI			-0.0001	
			(0.0002)	
Measure× LowHDI			0.0027	
			(0.0203)	
DaysAfterMeasure× HighHDI			-0.0006***	
			(0.0001)	
Measure× HighHDI			-0.0137	
			(0.0205)	
Anticipation 5 days			0.0427**	
			(0.0180)	
MeasureRelease			-0.0072	
			(0.0046)	
Selective border closure 1				
DaysAfterMeasure× LowHDI				-0.0001
				(0.0002)
Measure× LowHDI				0.0036
				(0.0143)
DaysAfterMeasure× HighHDI				-0.0007***
				(0.0001)
Measure× HighHDI				0.0051
				(0.0122)
Anticipation 5 days				0.0265**
				(0.0103)
MeasureRelease				-0.0105*
				(0.0056)
Constant	0.0323***	0.0348***	0.0326***	0.0351***
	(0.0038)	(0.0040)	(0.0010)	(0.0014)
Observations	34587	38779	49820	43075
Adjusted R^2	0.138	0.139	0.143	0.141

First difference model estimatated with OLS with country and day fixed effects.
Standard errors in parenthesis clustered at the country level.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.001$.

Table S22: Extension: External measures (anticipation 5 days)

	log(confirmed+1)			
	(1)	(2)	(3)	(4)
Within country lockdown				
DaysAfterMeasure× LowHDI	-0.0011***			
	(0.0001)			
Measure× LowHDI	0.0192			
	(0.0154)			
DaysAfterMeasure× HighHDI	-0.0013***			
	(0.0002)			
Measure× HighHDI	-0.0110			
	(0.0147)			
Anticipation 5 days	0.0882***			
	(0.0147)			
MeasureRelease	-0.0104***			
	(0.0039)			
State of emergency lockdown				
DaysAfterMeasure× LowHDI		-0.0004***		
		(0.0001)		
Measure× LowHDI		-0.0144		
		(0.0151)		
DaysAfterMeasure× HighHDI		-0.0004***		
		(0.0001)		
Measure× HighHDI		-0.0506***		
		(0.0142)		
Anticipation 5 days		0.0780***		
		(0.0145)		
MeasureRelease		-0.0041		
		(0.0041)		
Within countrytial lockdown				
DaysAfterMeasure× LowHDI			-0.0003**	
			(0.0001)	
Measure× LowHDI			-0.0181	
			(0.0120)	
DaysAfterMeasure× HighHDI			-0.0004***	
			(0.0001)	
Measure× HighHDI			-0.0573***	
			(0.0110)	
Anticipation 5 days			0.0528***	
			(0.0106)	
MeasureRelease			-0.0040	
			(0.0034)	
Partial lockdown				
DaysAfterMeasure× LowHDI				-0.0007***
				(0.0001)
Measure× LowHDI				0.0074
				(0.0176)
DaysAfterMeasure× HighHDI				-0.0010***
				(0.0001)
Measure× HighHDI				-0.0283
				(0.0174)
Anticipation 5 days				0.0623***
				(0.0181)
MeasureRelease				-0.0123**
				(0.0061)
Constant	0.0272***	0.0299***	0.0370***	0.0374***
	(0.0045)	(0.0018)	(0.0014)	(0.0020)
Observations	36112	44614	46595	41606
Adjusted R^2	0.153	0.146	0.145	0.147

First difference model estimatated with OLS with country and day fixed effects.
Standard errors in parenthesis clustered at the country level.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.001$.

Table S23: Extension: Internal measures (anticipation 7 days)

	log(confirmed+1)			
	(1)	(2)	(3)	(4)
Measures toward the outside				
DaysAfterMeasure× LowHDI	-0.0002			
	(0.0001)			
Measure× LowHDI	0.0096			
	(0.0123)			
DaysAfterMeasure× HighHDI	-0.0006***			
	(0.0001)			
Measure× HighHDI	-0.0068			
	(0.0107)			
Anticipation 5 days	0.0425***			
	(0.0099)			
MeasureRelease	-0.0134***			
	(0.0037)			
International lockdown				
DaysAfterMeasure× LowHDI		-0.0005***		
		(0.0001)		
Measure× LowHDI		0.0364***		
		(0.0133)		
DaysAfterMeasure× HighHDI		-0.0003***		
		(0.0001)		
Measure× HighHDI		-0.0243**		
		(0.0122)		
Anticipation 5 days		0.0337***		
		(0.0122)		
MeasureRelease		-0.0151***		
		(0.0051)		
Selective border closure 2				
DaysAfterMeasure× LowHDI			-0.0001	
			(0.0002)	
Measure× LowHDI			0.0027	
			(0.0203)	
DaysAfterMeasure× HighHDI			-0.0006***	
			(0.0001)	
Measure× HighHDI			-0.0137	
			(0.0205)	
Anticipation 5 days			0.0427**	
			(0.0180)	
MeasureRelease			-0.0072	
			(0.0046)	
Selective border closure 1				
DaysAfterMeasure× LowHDI				-0.0001
				(0.0002)
Measure× LowHDI				0.0036
				(0.0143)
DaysAfterMeasure× HighHDI				-0.0007***
				(0.0001)
Measure× HighHDI				0.0051
				(0.0122)
Anticipation 5 days				0.0265**
				(0.0103)
MeasureRelease				-0.0105*
				(0.0056)
Constant	0.0323***	0.0348***	0.0326***	0.0351***
	(0.0038)	(0.0040)	(0.0010)	(0.0014)
Observations	34587	38779	49820	43075
Adjusted R^2	0.138	0.139	0.143	0.141

First difference model estimatated with OLS with country and day fixed effects.
Standard errors in parenthesis clustered at the country level.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.001$.

Table S24: Extension: External measures (anticipation 7 days)

	log(confirmed+1)			
	(1)	(2)	(3)	(4)
Within country lockdown				
DaysAfterMeasure× LowHDI	-0.0012***			
	(0.0001)			
Measure× LowHDI	0.0392***			
	(0.0132)			
DaysAfterMeasure× HighHDI	-0.0014***			
	(0.0002)			
Measure× HighHDI	0.0103			
	(0.0126)			
Anticipation 10 days	0.0747***			
	(0.0117)			
MeasureRelease	-0.0111***			
	(0.0041)			
State of emergency lockdown				
DaysAfterMeasure× LowHDI		-0.0004***		
		(0.0001)		
Measure× LowHDI		-0.0024		
		(0.0120)		
DaysAfterMeasure× HighHDI		-0.0005***		
		(0.0001)		
Measure× HighHDI		-0.0370***		
		(0.0110)		
Anticipation 10 days		0.0709***		
		(0.0106)		
MeasureRelease		-0.0041		
		(0.0041)		
Within countrytial lockdown				
DaysAfterMeasure× LowHDI			-0.0003***	
			(0.0001)	
Measure× LowHDI			-0.0266*	
			(0.0140)	
DaysAfterMeasure× HighHDI			-0.0004***	
			(0.0001)	
Measure× HighHDI			-0.0640***	
			(0.0135)	
Anticipation 10 days			0.0694***	
			(0.0136)	
MeasureRelease			-0.0041	
			(0.0034)	
Partial lockdown				
DaysAfterMeasure× LowHDI				-0.0007***
				(0.0001)
Measure× LowHDI				0.0156
				(0.0137)
DaysAfterMeasure× HighHDI				-0.0010***
				(0.0001)
Measure× HighHDI				-0.0194
				(0.0139)
Anticipation 10 days				0.0603***
				(0.0134)
MeasureRelease				-0.0119*
				(0.0061)
Constant	0.0236***	0.0279***	0.0343***	0.0349***
	(0.0045)	(0.0019)	(0.0014)	(0.0020)
Observations	36017	44274	46185	41321
Adjusted R^2	0.153	0.147	0.149	0.149

First difference model estimatated with OLS with country and day fixed effects.
Standard errors in parenthesis clustered at the country level.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.001$.

Table S25: Extension: Internal measures (anticipation 10 days)

	log(confirmed+1)			
	(1)	(2)	(3)	(4)
Measures toward the outside				
DaysAfterMeasure× LowHDI	-0.0002			
	(0.0001)			
Measure× LowHDI	0.0265**			
	(0.0113)			
DaysAfterMeasure× HighHDI	-0.0006***			
	(0.0001)			
Measure× HighHDI	0.0104			
	(0.0097)			
Anticipation 10 days	0.0251***			
	(0.0082)			
MeasureRelease	-0.0132***			
	(0.0037)			
International lockdown				
DaysAfterMeasure× LowHDI		-0.0005***		
		(0.0001)		
Measure× LowHDI		0.0464***		
		(0.0125)		
DaysAfterMeasure× HighHDI		-0.0003***		
		(0.0001)		
Measure× HighHDI		-0.0142		
		(0.0114)		
Anticipation 10 days		0.0235**		
		(0.0112)		
MeasureRelease		-0.0152***		
		(0.0051)		
Selective border closure 2				
DaysAfterMeasure× LowHDI			-0.0001	
			(0.0002)	
Measure× LowHDI			0.0160	
			(0.0163)	
DaysAfterMeasure× HighHDI			-0.0006***	
			(0.0001)	
Measure× HighHDI			-0.0004	
			(0.0160)	
Anticipation 10 days			0.0310**	
			(0.0127)	
MeasureRelease			-0.0074	
			(0.0047)	
Selective border closure 1				
DaysAfterMeasure× LowHDI				-0.0001
				(0.0002)
Measure× LowHDI				0.0111
				(0.0130)
DaysAfterMeasure× HighHDI				-0.0007***
				(0.0001)
Measure× HighHDI				0.0127
				(0.0114)
Anticipation 10 days				0.0205**
				(0.0090)
MeasureRelease				-0.0107*
				(0.0057)
Constant	0.0329***	0.0350***	0.0324***	0.0348***
	(0.0038)	(0.0041)	(0.0010)	(0.0014)
Observations	34482	38634	49255	42675
Adjusted R^2	0.137	0.139	0.143	0.141

First difference model estimatated with OLS with country and day fixed effects.
Standard errors in parenthesis clustered at the country level.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.001$.

Table S26: Extension: External measures (anticipation 10 days)

H.3.2 Number of reported deaths

	log(deaths+1)			
	(1)	(2)	(3)	(4)
Within country lockdown				
DaysAfterMeasure× LowHDI	-0.0002			
	(0.0001)			
Measure× LowHDI	0.0221***			
	(0.0078)			
DaysAfterMeasure× HighHDI	-0.0010***			
	(0.0001)			
Measure× HighHDI	0.0660***			
	(0.0079)			
State of emergency lockdown				
DaysAfterMeasure× LowHDI		0.0000		
		(0.0001)		
Measure× LowHDI		0.0200**		
		(0.0080)		
DaysAfterMeasure× HighHDI		-0.0005***		
		(0.0001)		
Measure× HighHDI		0.0413***		
		(0.0079)		
Within countrytial lockdown				
DaysAfterMeasure× LowHDI			0.0000	
			(0.0001)	
Measure× LowHDI			0.0114	
			(0.0075)	
DaysAfterMeasure× HighHDI			-0.0008***	
			(0.0001)	
Measure× HighHDI			0.0404***	
			(0.0089)	
Partial lockdown				
DaysAfterMeasure× LowHDI				-0.0001
				(0.0001)
Measure× LowHDI				0.0169*
				(0.0091)
DaysAfterMeasure× HighHDI				-0.0010***
				(0.0001)
Measure× HighHDI				0.0617***
				(0.0082)
Constant	0.0153***	0.0079***	0.0110***	0.0123***
	(0.0022)	(0.0010)	(0.0009)	(0.0012)
Observations	36207	44954	47005	41891
Adjusted R^2	0.248	0.649	0.618	0.555

First difference model estimatated with OLS with country and day fixed effects.
Standard errors in parenthesis clustered at the country level.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.001$.

Table S27: Extension (deaths): Internal measures (anticipation 5 days)

	log(deaths+1)			
	(1)	(2)	(3)	(4)
Measures toward the outside				
DaysAfterMeasure× LowHDI	0.0003***			
	(0.0001)			
Measure× LowHDI	-0.0043			
	(0.0063)			
DaysAfterMeasure× HighHDI	-0.0004***			
	(0.0001)			
Measure× HighHDI	0.0352***			
	(0.0068)			
International lockdown				
DaysAfterMeasure× LowHDI		0.0003*		
		(0.0001)		
Measure× LowHDI		0.0054		
		(0.0092)		
DaysAfterMeasure× HighHDI		-0.0005***		
		(0.0001)		
Measure× HighHDI		0.0308***		
		(0.0096)		
Selective border closure 2				
DaysAfterMeasure× LowHDI			0.0003	
			(0.0002)	
Measure× LowHDI			0.0015	
			(0.0114)	
DaysAfterMeasure× HighHDI			-0.0006***	
			(0.0001)	
Measure× HighHDI			0.0464***	
			(0.0088)	
Selective border closure 1				
DaysAfterMeasure× LowHDI				0.0002**
				(0.0001)
Measure× LowHDI				-0.0113
				(0.0077)
DaysAfterMeasure× HighHDI				-0.0005***
				(0.0001)
Measure× HighHDI				0.0384***
				(0.0078)
Constant	0.0163***	0.0145***	0.0057***	0.0096***
	(0.0020)	(0.0024)	(0.0006)	(0.0009)
Observations	34692	38924	50385	43475
Adjusted R^2	0.312	0.430	0.685	0.667

First difference model estimatated with OLS with country and day fixed effects.
Standard errors in parenthesis clustered at the country level.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.001$.

Table S28: Extension (deaths): External measures (anticipation 5 days)

	log(deaths+1)			
	(1)	(2)	(3)	(4)
Within country lockdown				
DaysAfterMeasure× LowHDI	-0.0002			
	(0.0001)			
Measure× LowHDI	0.0221***			
	(0.0078)			
DaysAfterMeasure× HighHDI	-0.0010***			
	(0.0001)			
Measure× HighHDI	0.0660***			
	(0.0079)			
State of emergency lockdown				
DaysAfterMeasure× LowHDI		0.0000		
		(0.0001)		
Measure× LowHDI		0.0200**		
		(0.0080)		
DaysAfterMeasure× HighHDI		-0.0005***		
		(0.0001)		
Measure× HighHDI		0.0413***		
		(0.0079)		
Within countrytial lockdown				
DaysAfterMeasure× LowHDI			0.0000	
			(0.0001)	
Measure× LowHDI			0.0114	
			(0.0075)	
DaysAfterMeasure× HighHDI			-0.0008***	
			(0.0001)	
Measure× HighHDI			0.0404***	
			(0.0089)	
Partial lockdown				
DaysAfterMeasure× LowHDI				-0.0001
				(0.0001)
Measure× LowHDI				0.0169*
				(0.0091)
DaysAfterMeasure× HighHDI				-0.0010***
				(0.0001)
Measure× HighHDI				0.0617***
				(0.0082)
Constant	0.0153***	0.0079***	0.0110***	0.0123***
	(0.0022)	(0.0010)	(0.0009)	(0.0012)
Observations	36207	44954	47005	41891
Adjusted R^2	0.248	0.649	0.618	0.555

First difference model estimatated with OLS with country and day fixed effects.
Standard errors in parenthesis clustered at the country level.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.001$.

Table S29: Extension (deaths): Internal measures (anticipation 7 days)

	log(deaths+1)			
	(1)	(2)	(3)	(4)
Measures toward the outside				
DaysAfterMeasure× LowHDI	0.0003***			
	(0.0001)			
Measure× LowHDI	-0.0043			
	(0.0063)			
DaysAfterMeasure× HighHDI	-0.0004***			
	(0.0001)			
Measure× HighHDI	0.0352***			
	(0.0068)			
International lockdown				
DaysAfterMeasure× LowHDI		0.0003*		
		(0.0001)		
Measure× LowHDI		0.0054		
		(0.0092)		
DaysAfterMeasure× HighHDI		-0.0005***		
		(0.0001)		
Measure× HighHDI		0.0308***		
		(0.0096)		
Selective border closure 2				
DaysAfterMeasure× LowHDI			0.0003	
			(0.0002)	
Measure× LowHDI			0.0015	
			(0.0114)	
DaysAfterMeasure× HighHDI			-0.0006***	
			(0.0001)	
Measure× HighHDI			0.0464***	
			(0.0088)	
Selective border closure 1				
DaysAfterMeasure× LowHDI				0.0002**
				(0.0001)
Measure× LowHDI				-0.0113
				(0.0077)
DaysAfterMeasure× HighHDI				-0.0005***
				(0.0001)
Measure× HighHDI				0.0384***
				(0.0078)
Constant	0.0163***	0.0145***	0.0057***	0.0096***
	(0.0020)	(0.0024)	(0.0006)	(0.0009)
Observations	34692	38924	50385	43475
Adjusted R^2	0.312	0.430	0.685	0.667

First difference model estimatated with OLS with country and day fixed effects.
Standard errors in parenthesis clustered at the country level.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.001$.

Table S30: Extension (deaths): External measures (anticipation 7 days)

	log(deaths+1)			
	(1)	(2)	(3)	(4)
Within country lockdown				
DaysAfterMeasure× LowHDI	-0.0002			
	(0.0001)			
Measure× LowHDI	0.0221***			
	(0.0078)			
DaysAfterMeasure× HighHDI	-0.0010***			
	(0.0001)			
Measure× HighHDI	0.0660***			
	(0.0079)			
State of emergency lockdown				
DaysAfterMeasure× LowHDI		0.0000		
		(0.0001)		
Measure× LowHDI		0.0200**		
		(0.0080)		
DaysAfterMeasure× HighHDI		-0.0005***		
		(0.0001)		
Measure× HighHDI		0.0413***		
		(0.0079)		
Within countrytial lockdown				
DaysAfterMeasure× LowHDI			0.0000	
			(0.0001)	
Measure× LowHDI			0.0114	
			(0.0075)	
DaysAfterMeasure× HighHDI			-0.0008***	
			(0.0001)	
Measure× HighHDI			0.0404***	
			(0.0089)	
Partial lockdown				
DaysAfterMeasure× LowHDI				-0.0001
				(0.0001)
Measure× LowHDI				0.0169*
				(0.0091)
DaysAfterMeasure× HighHDI				-0.0010***
				(0.0001)
Measure× HighHDI				0.0617***
				(0.0082)
Constant	0.0153***	0.0079***	0.0110***	0.0123***
	(0.0022)	(0.0010)	(0.0009)	(0.0012)
Observations	36207	44954	47005	41891
Adjusted R^2	0.248	0.649	0.618	0.555

First difference model estimatated with OLS with country and day fixed effects.
Standard errors in parenthesis clustered at the country level.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.001$.

Table S31: Extension (deaths): Internal measures (anticipation 10 days)

	log(deaths+1)			
	(1)	(2)	(3)	(4)
Measures toward the outside				
DaysAfterMeasure× LowHDI	0.0003***			
	(0.0001)			
Measure× LowHDI	-0.0043			
	(0.0063)			
DaysAfterMeasure× HighHDI	-0.0004***			
	(0.0001)			
Measure× HighHDI	0.0352***			
	(0.0068)			
International lockdown				
DaysAfterMeasure× LowHDI		0.0003*		
		(0.0001)		
Measure× LowHDI		0.0054		
		(0.0092)		
DaysAfterMeasure× HighHDI		-0.0005***		
		(0.0001)		
Measure× HighHDI		0.0308***		
		(0.0096)		
Selective border closure 2				
DaysAfterMeasure× LowHDI			0.0003	
			(0.0002)	
Measure× LowHDI			0.0015	
			(0.0114)	
DaysAfterMeasure× HighHDI			-0.0006***	
			(0.0001)	
Measure× HighHDI			0.0464***	
			(0.0088)	
Selective border closure 1				
DaysAfterMeasure× LowHDI				0.0002**
				(0.0001)
Measure× LowHDI				-0.0113
				(0.0077)
DaysAfterMeasure× HighHDI				-0.0005***
				(0.0001)
Measure× HighHDI				0.0384***
				(0.0078)
Constant	0.0163***	0.0145***	0.0057***	0.0096***
	(0.0020)	(0.0024)	(0.0006)	(0.0009)
Observations	34692	38924	50385	43475
Adjusted R^2	0.312	0.430	0.685	0.667

First difference model estimatated with OLS with country and day fixed effects.
Standard errors in parenthesis clustered at the country level.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.001$.

Table S32: Extension (deaths): External measures (anticipation 10 days)

Appendix I Additional figures

Throughout this Appendix section, we report the marginal effects, allowing for an anticipation effect of 5 or 10 days for the baseline model. The results are robust to this wide range of lags. We also report the marginal effects for splitting the countries into three groups based on the HDI (high, medium, and low). The corresponding Tables are available in Appendix H.

I.1 Baseline model: Effectiveness of lockdown measures

I.1.1 Number of reported cases

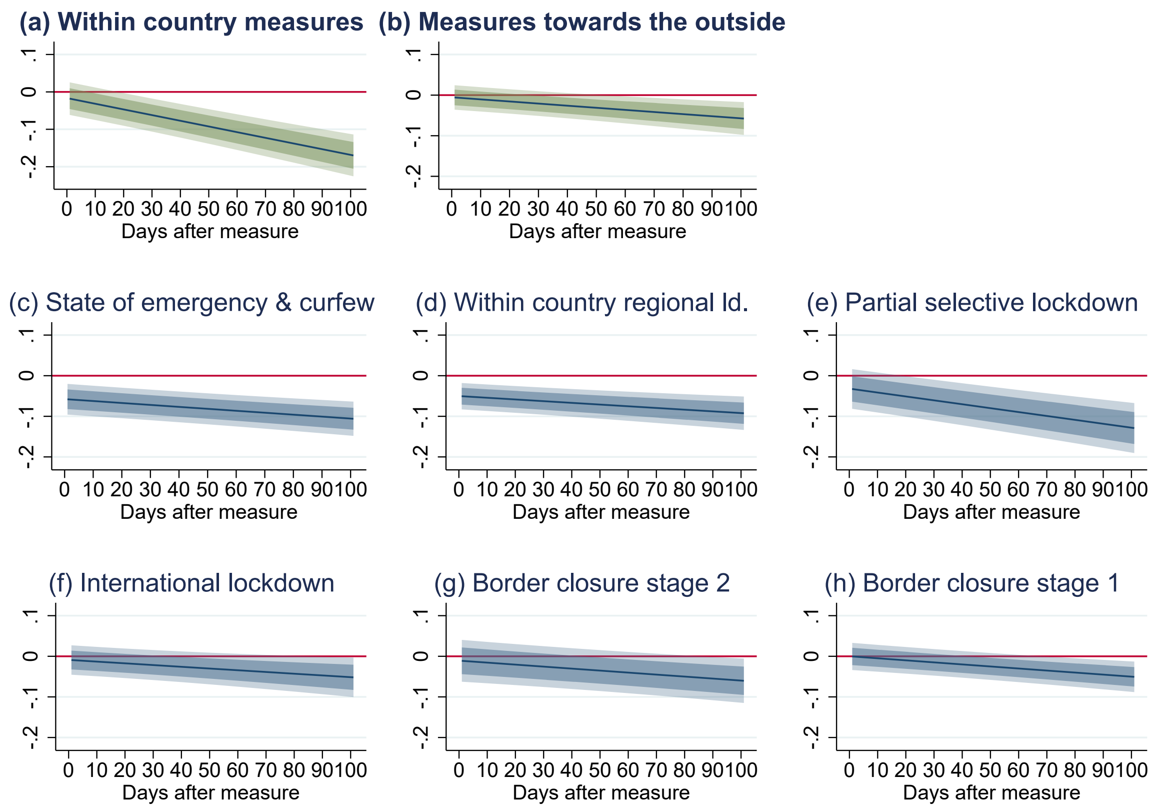

Figure S5: Marginal effect on the growth rate of COVID-19 cases with a 5-day anticipation effect. Internal measures were found to be more efficient than external measures with respect to their effect on the spread of the virus. Each sub-figure shows the impact of a lockdown on the growth rate of infections as a function of the time since the measure was implemented. 90% and 99% confidence intervals are shown in different shades of blue or green.

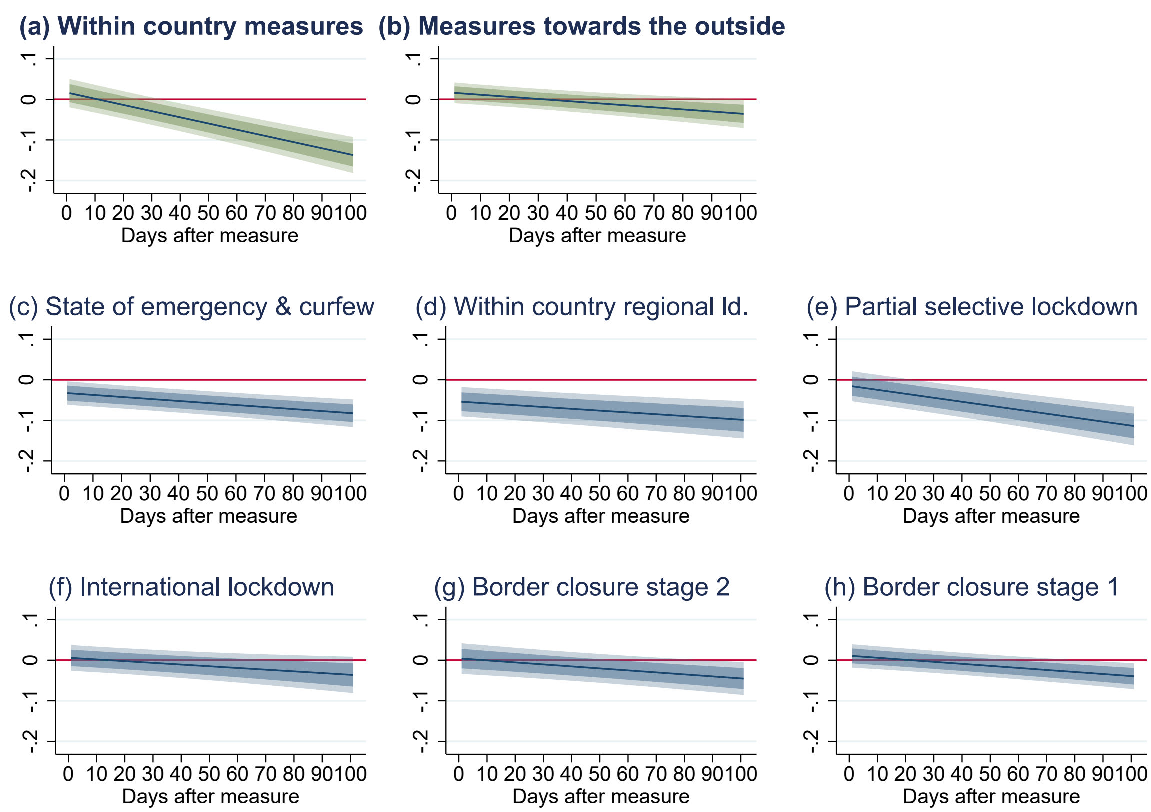

Figure S6: Marginal effect on the growth rate of COVID-19 cases with a 10-day anticipation effect. Internal measures were found to be more efficient than external measures with respect to their effect on the spread of the virus. Each sub-figure shows the impact of a lockdown on the growth rate of infections as a function of the time since the measure was implemented. 90% and 99% confidence intervals are shown in different shades of blue or green.

I.1.2 Number of deaths

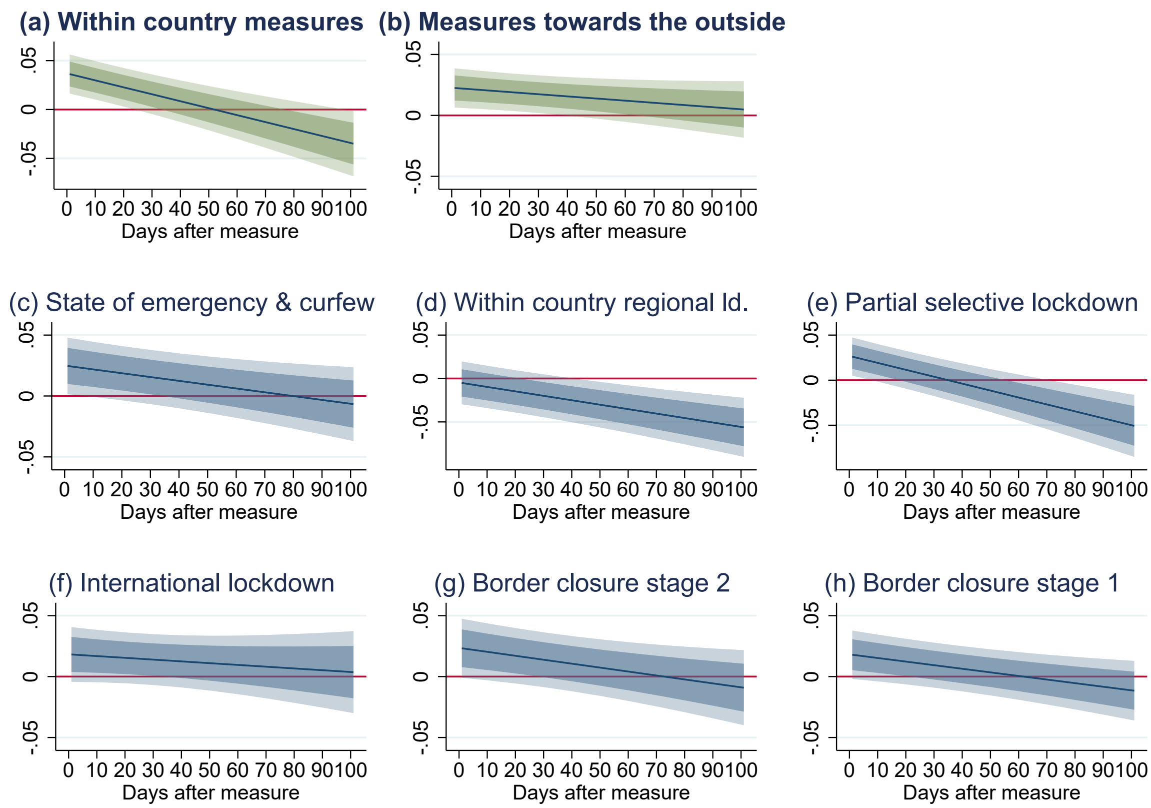

Figure S7: Marginal effect on the growth rate of COVID-19 deaths with a 7-day anticipation effect. Internal measures revealed to be more efficient than external measures with respect to their effect on the spread of the virus. Each sub-figure shows the impact of a lockdown on the growth rate of deaths as a function of the time since the measure was implemented. 90% and 99% confidence intervals are shown in different shades of blue or green.

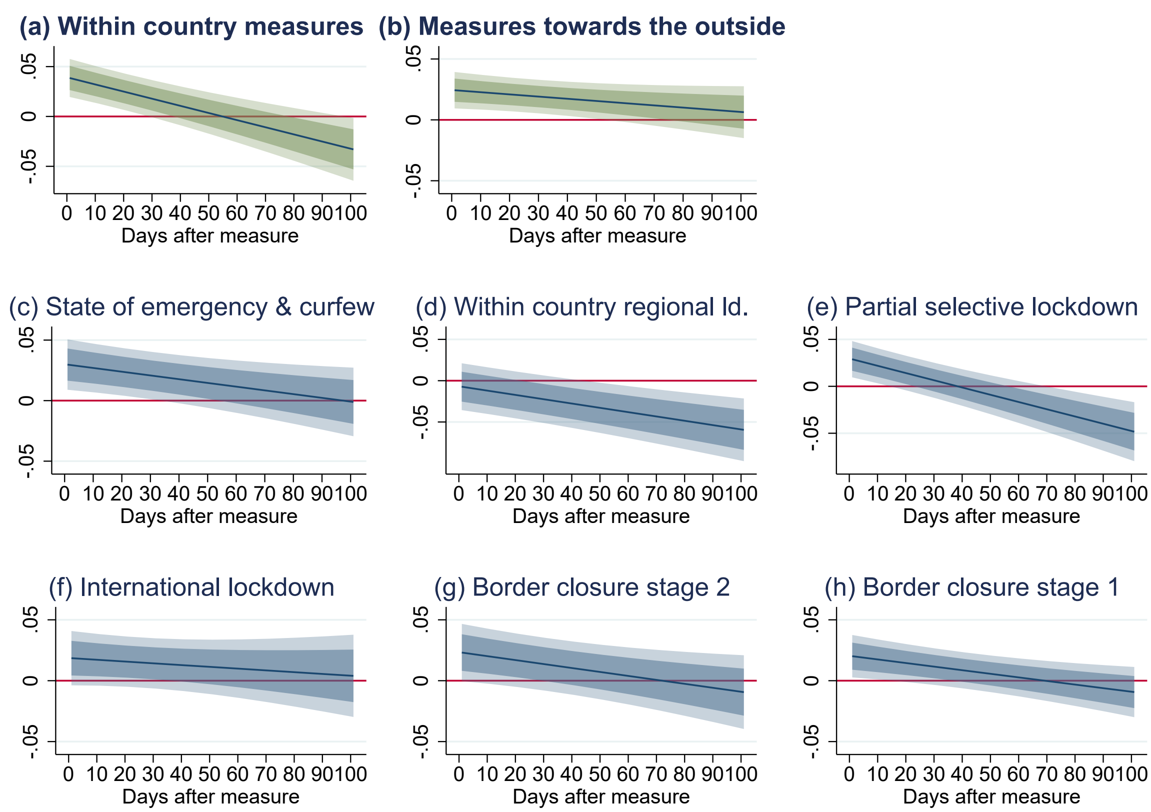

Figure S8: Marginal effect on the growth rate of COVID-19 deaths with a 10-day anticipation effect. Internal measures revealed to be more efficient than external measures with respect to their effect on the spread of the virus. Each sub-figure show the impact of a lockdown on the growth rate of deaths as a function of the time since the measure was implemented. 90% and 99% confidence intervals are shown in different shades of blue or green.

I.2 Extension: Developed vs. Developing

I.2.1 Number of reported cases

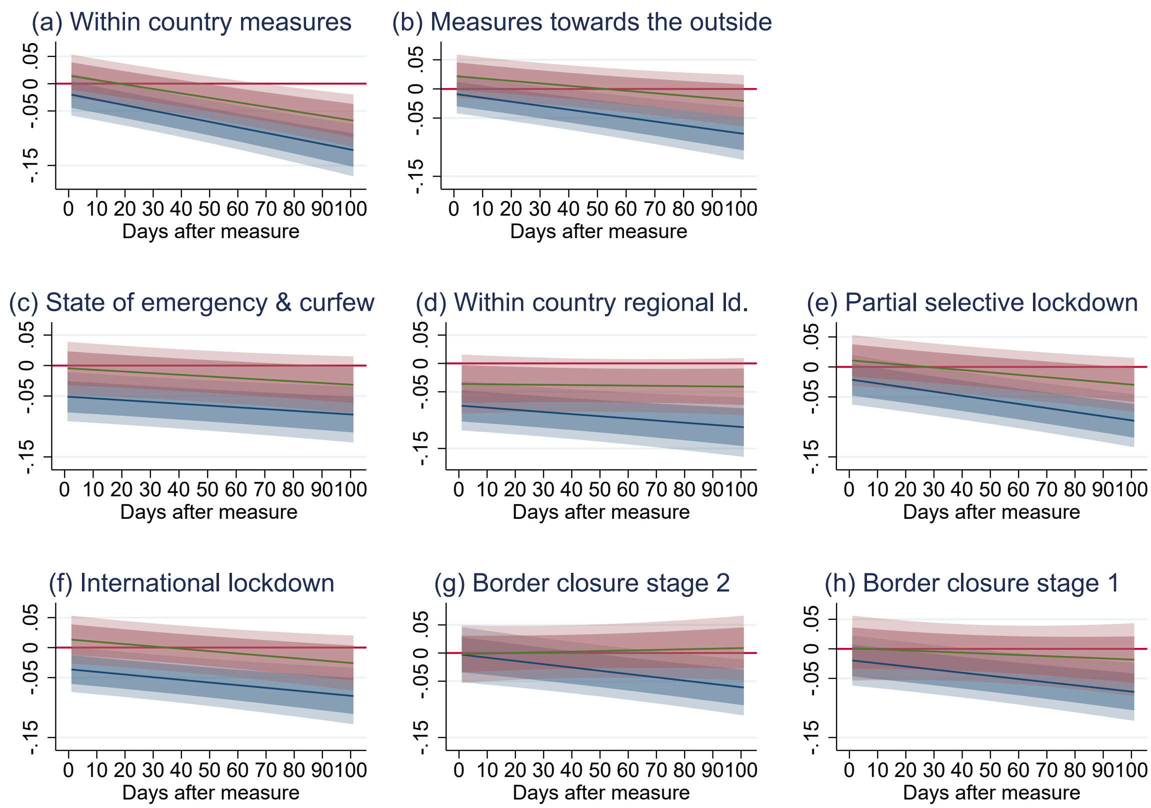

Figure S9: Marginal effect on the growth rate of COVID-19 cases with a 5-day anticipation effect. Developing countries are those with HDI values of up to 0.699 (marginal represented in red), indicating low and medium human development using the UN codebook definition, while those with values above 0.699 are defined as developed countries (marginal represented in blue). Panels (a) to (f) show the impact of a measure on the growth rate of infections as a function of the time since the measure was implemented. 90% and 99% confidence intervals are shown in different shades of red or blue.

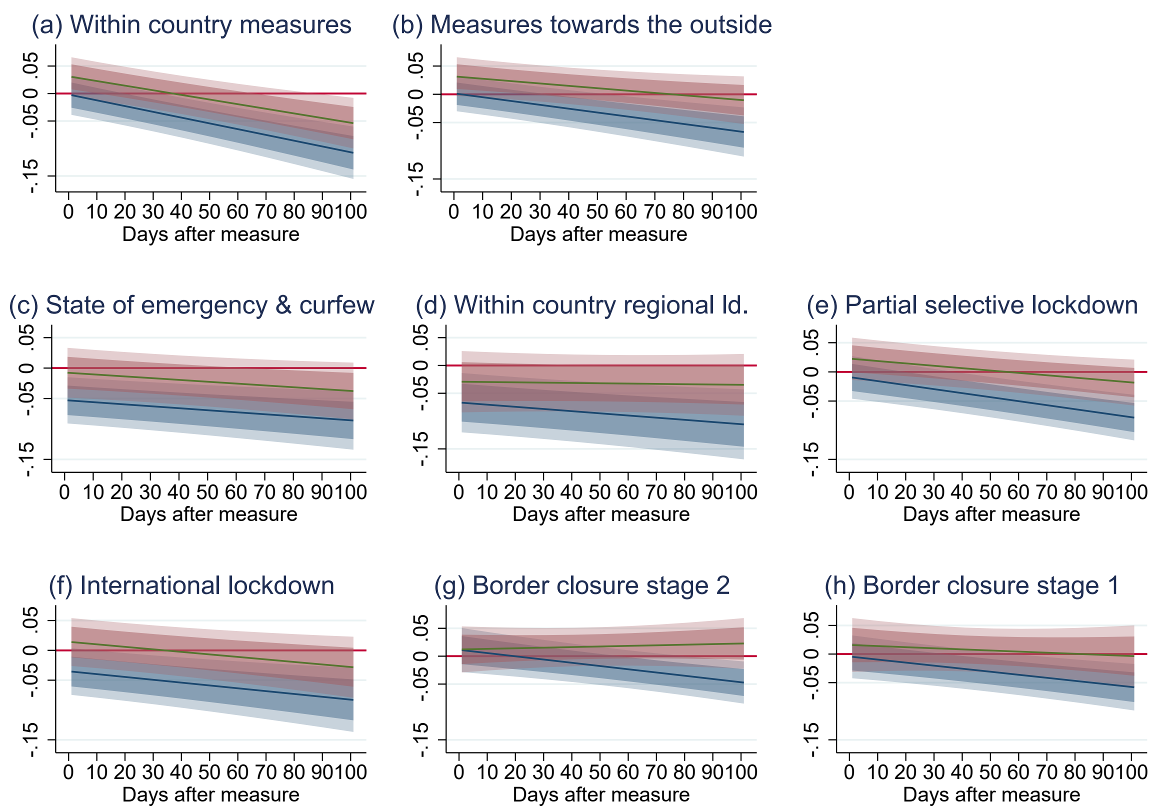

Figure S10: Marginal effect on the growth rate of COVID-19 cases with a 10-day anticipation effect. Developing countries are those with HDI values of up to 0.699 (marginal represented in red), indicating low and medium human development using the UN codebook definition, while those with values above 0.699 are defined as developed countries (marginal represented in blue). Panels (a) to (f) show the impact of a measure on the growth rate of infections as a function of the time since the measure was implemented. 90% and 99% confidence intervals are shown in different shades of red or blue.

I.2.2 Low, medium, and high development

In this section, we presents the results for a split into three groups based on the HDI. The three groups are defined as follows: high (HDI$\geq$0.799), medium (0.699 $\geq$HDI$<$ 0.799), and low (HDI$<$ 0.699). The marginal effects reveal the same pattern as the split in the two categories reported in the main paper. This additional result indicates that the lockdowns were only beneficial for countries with high or medium HDIs.

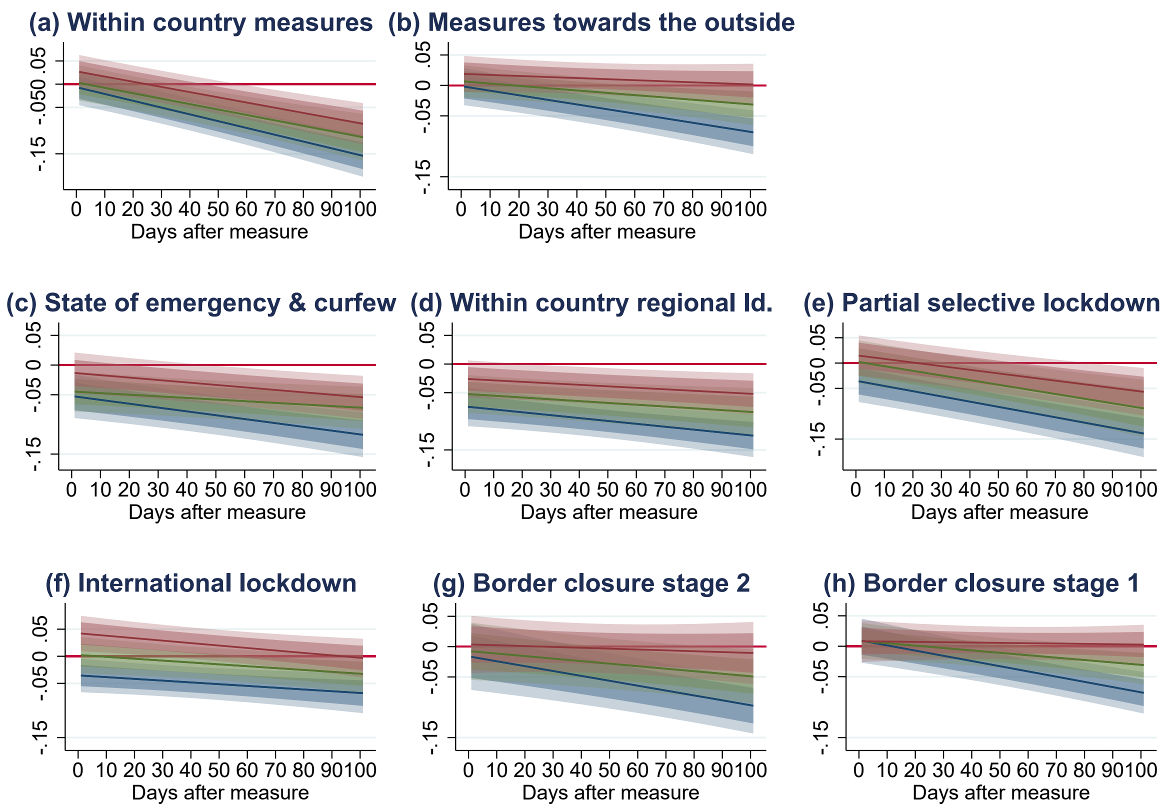

Figure S11: Marginal effect on the growth rate of COVID-19 cases with a 7-day anticipation effect. The three groups are defined as follows: high in blue (HDI$\geq$0.799), medium in green (0.699 $\geq$HDI$<$ 0.799), and low in red (HDI$<$ 0.699). Panels (a) to (f) show the impact of a measure on the growth rate of infections as a function of the time since the measure was implemented. 90% and 99% confidence intervals are shown in different shades of red, green, or blue.