Managing Pandemics: How to contain COVID-19 through Lockdowns and Releases

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Abstract

In the absence of a vaccine, containing a pandemic is a management problem: one has to find ways to reduce national and international mobility, as well as physical contacts among people, in order to slow down the spread of the virus. Countries around the world thus introduced lockdown measures to reduce morbidity and mortality rates, and then released these measures. We construct a novel database of these lockdowns measures, and analyze whether they helped reduce the spread of infections and the number of deaths. We also compare their effectiveness in developed versus developing countries. Our data covers 184 countries in the period from 31st December 2019 to November 24th 2020, and identifies lockdown and release periods, along with confirmed cases of infections and deaths due to COVID-19. The panel data structure allows to address major inherent endogeneity issues. The key finding of our analysis is that lockdowns were effective, reduced mobility, and saved about 5,5 million lives in developed countries. Measures taken within countries -rather than border closure- and partial lockdowns -instead of stricter ones- were effective. On the other hand, we do not find significant effects in developing countries, where the opportunity cost of staying home might be too high for people to comply. Releasing lockdown measures, which started mid-May 2020 in most countries, did not lead to a strong resurgence of the virus, except for the release of border closures.

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 the covid-19 and reduce mortality by sequentially using lockdown and release measures.

Core insights: Overall, lockdowns saved about 5,5 million lives in developed countries, essentially through one key mechanism: reducing people's mobility. More specifically, governments undertaking measures within countries -rather than border closure- and timely focusing on partial lockdowns -instead of stricter ones- were the most effective at mitigating the spread of the virus. On the other hand, 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 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: Until vaccines or other pharmaceutical measures become available and accepted, this study's findings should help policy makers and hospital managers to plan for future policies and managerial actions to handle the pandemic. Local and partial measures should be favoured. Other types of measures, however, should be elaborated to fit the case of developing countries.

Length: 188 Words

1 Introduction

On January 11th 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 Hubei province in central China. By the middle of May 2020, a few months later, close to 300,000 deaths have been registered across the world. The health and economic effects of COVID-19 have been unprecedented. 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 wage 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, as well as their differences in strength and nature across most countries in the world, on the increase of new infections and deaths. We focus on lockdowns for two specific reasons. First, lockdowns are the main measures adopted to manage the dyadic spread of the virus and the mortality rates by restraining the movement of individuals. Whether this has been successful or not is something that should be looked at specifically, as it is also plausible that the announcement of a lockdown could generate higher mobility and fuel infections (Kaplan, 2020). Second, lockdowns carry higher opportunity cost compared to other NPIs and could have heterogenous effects across countries.[1]

We 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 of staying home. If these opportunity costs are high enough, we expect that people would not adhere to lockdown restrictions, especially when the monitoring cost for authorities would typically be high. This issue is of particular importance for the effectiveness of lockdown

[1]Fenichel et al. (2011) and Eichenbaum et al. (2020) discuss models of infections 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.

policies in developing countries. Indeed, in these countries where many people earn their living 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. And this is what our empirical analysis shows. We will return to this issue in the Discussion section.

Endogeneity issues pose major barriers to assessing the causal effects of such lockdowns on the spread of a disease. 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. Omitted variable bias, and measurement errors are addressed through country fixed effects and day fixed effects. Furthermore, we also control for the within-country evolution of the disease either by using a lagged outcome or by controlling for the number of days since the first case was reported in the country.

Hatchett et al. (2007) study the NPI adopted by cities in the United States to contain the spread of the Spanish Influenza. Other studies have already emerged that studied 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 to what extent 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 down the spread of COVID-19. Using data collected by their team, Hsiang et al. (2020) study the effects of NIPs in China, South Korea, Italy, Iran, France, and the US and find NPIs reduce the growth of infections. Deb et al. (2020) study the effects of lockdowns around the world, and find sizeable reductions in the number of new infections. 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. Several groups have collected information on policy responses, most notably Dale et al. (2020), but also Cheng et al. (2020).

We complement the existing body of literature in three ways. First, several of the papers we reviewed focus on one country while our analysis covers 184 countries around the world, which allows us to analyze the heterogeneity in how lockdowns were implemented. Closer analysis indicate that the management of pandemics has been quite heterogenous: in some cases, lockdowns were strict and complete, while in others, they were partial. Lockdowns in some countries included a curfew but not all. Some countries closed borders right away, but others did so only as a measure of last resort. As we will see, these differences matter and some measures were more effective than others. Second, transmissions might increase before lockdowns are implemented, a behavior we term anticipation effects. Anticipation effects need to be taken into consideration when studying the causal effects of lockdowns, and we propose an approach to doing so. Third, to 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 the epidemic remains contained after releasing a lockdown, or not, is crucial when managing a pandemic.

2 Data

Our dataset covers 184 countries, of which 108 had implemented at least one of the measures at the time we collected the data, observed over 127 days, from 31st January 2019 to November 24th 2020. We adopt a calendar time definition with 31st December 2019 as the starting date, since it is the first day when a country other than China undertook measures to limit the spread of COVID-19.[2] Figure 2 shows the number of measures taken, and the number of confirmed cases and deaths by the time the first measure had been implemented (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) and then switched to

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

external measures.

2.1 Explanatory variables: Lockdown measures

We compiled information on each country's lockdown policies by extracting news headlines published between end of October 2019 to the end of May 2020 provided by LexisNexis using a web-scraping program. This information was crosschecked with the country information from COVID-19 bulletins issued by the United States Embassy to ensure accuracy. The final dataset contains dates of implementation for several types of lockdowns designed to stop the spread of the 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). Two measures, specifically State of Emergency and Curfew, significantly restrict the movement of individuals within a country, and thus represent a form of total lockdown. We combined these two policies into one measure, which we call Total within country lockdown (see Appendix A for more details on the scraping method and summary statistics).

Additionally, by 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 to the end of August 2020. To ensure robustness and accuracy, this information was also crosschecked with the country information from COVID-19 bulletins issued by the United States Embassy. The final dataset contains the first dates, per country, when each of the implemented COVID-19 lockdown policies were eased.

2.2 Outcome: Covid-19 reported cases and deaths

We use the John Hopkins University data (Dong et al., 2020) as it is, to the best of our knowledge, the most complete and reliable source of data on reported cases and deaths from the Covid-19. We focus our analysis on the number of cases infected by the new Coronavirus for three reasons. First, people who die from the virus got infected first. Hence, controlling the number of contaminated persons inevitably reduces the number of deaths. Second, a major

	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.	*17th of March 2020:* Bosnia declares nationwide state of emergency over coronavirus.	
	State of emergency	The effective date when a country announced a state of emergency.	*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.	
	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: We defined seven different lockdown measures. A state of emergency is a situation where a government is empowered to perform actions or impose policies that it would normally not be permitted to undertake, for example, mandate the restriction of movement of individuals and closure of non-essential and essential (if necessary) public and private entities.

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 for the future burden on the health-care sector than the number of people who have died from the disease. Finally, there is a significant delay in how a taken measure might affect the number of deaths. Indeed, someone has to 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 in percentage rather than in absolute terms. Second, the distribution of the number of reported cases is highly asymmetric due to the exponential growth with 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 suffers from measurement errors. The data contains 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. Some countries have been suspected to under-report or modify their data[3]. Third, this data has to then be recorded by the source monitored by Johns Hopkins University. Hence, our data represents a lower bound on the total number of people ever infected. In our context, we aim to have a measure of the number of people who likely would have needed medical attention. These symptomatic cases should therefore be quite well represented in our data and so, these classical measurement errors should not affect our estimates greatly and if they do so, they create only an attenuation bias.

A more troubling problem would be the presence of non-classical errors-in-variables, that 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. However, we control for such measurement errors, which are caused by time-invariant unobservables, by using country fixed effects in our empirical approach.

[3]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.

2.3 Heterogeneous effects: Developing vs. developed countries

Finally, to study the existence of heterogeneous effects between developed and developing countries, we use the Human Development Index (henceforth HDI) produced by the 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 GNI. Note that the median in our sample is 0.745. We define developing countries as the one with an index up to 0.699, which refers to Low and Medium human development using the United Nation code-book definition while above 0.699 will be defined as developed countries. Table S2 in Appendix B shows the complete list of countries in the two categories.

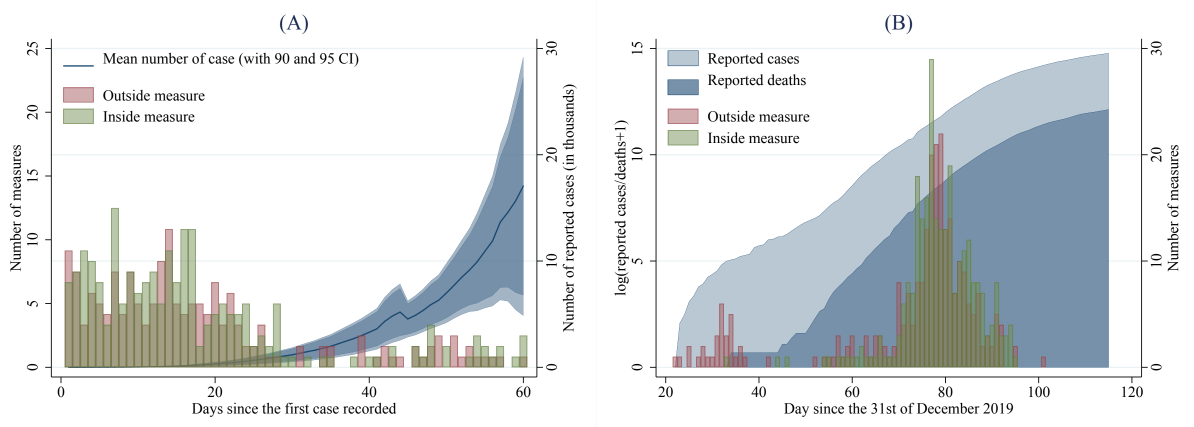

Figure 2: This Figure shows the timing of lockdowns within countries since the beginning of the COVID-19 outbreak in each country (A) and since the end of 2019 (B). We exploit this variation to quantify the effect of each measure on the growth rate of the Covid-19. “External” measures are those that 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 is 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 countries with 90% and 95% confidence intervals. (B) For identification we exploit as well variation through the year as early lockdowns have been taken in February and others only few months after.

3 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 be potentially 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, we see 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 allows us to control for time-invariant unobservables 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 that vary significantly over the time period of interest (a few months). Second, the day fixed effects control for time-varying unobservables affecting the world in the same way (global evolution of the virus (early-stage vs. pandemic), global lockdown, 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 undertaken to contain the spread of the disease comes from reverse causality. The spread of the disease in the country influences the timing and the extent of the lockdown measures implemented by the government. Specifically, the growth rate of infections increases strongly in the 30 days before a lockdown is implemented, consistent with anticipatory behavior or reverse causality (Figure 3). We address this issue in three ways. First, we control for the lagged dependent variable (auto-regressive model of order 1) and hence we control for the state of the virus the day before. Second, 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 contacts preemptively as they understand the risk. To control for this anticipation behavior we include a dummy taking the value one seven days before the lockdown measure.[4] Finally, day fixed effects capture the global evolution of the coronavirus and how it affects the probability of lockdown.

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

Equation 1, describes our baseline model. For the Baseline results we focus on the first wave and hence restrict the sample for hundred days after the implementation of lockdown.

Auto-regressive model of order 1 (AR(1)):

$$
\begin{aligned}
&log(cases_{it}+1) = \\
&\beta_0 + \beta_1 Measure_{it} + \beta_2 DaysAfterMeasure_{it} \\
&+\beta_3 Release_{it} \\
&+\beta_4 log(cases_{i(t-1)}+1) \\
&+\beta_5 Anticipation_{it}^{7days} \\
&+FE_i + FE_t + \epsilon_{ct}
\end{aligned} \tag{1}
$$

with i for country and t for the day. $cases_{it}$ is the total number of people who were infected by the virus in country i on or before calendar day t. $Measure_{it}$ is an indicator variable taking

[4] See Figure 4 justifying the choice of seven days. Robustness tests are available in the Appendix with 5 or 10 days anticipation.

the value 1 from the day the measure was implemented. $DaysAfterMeasure_{it}$ is the number of days since the measure was implemented. Indeed, we do not expect the effect to be revealed and observable on day zero even if not a single new transmission happen as the latest cases are not detected yet. $Release_{it}$ is a dummy taking the value 1 if when country i eases the lockdown measure. $Anticipation_{it}^{7days}$ is a dummy taking the value seven days before the lockdown is enforced to capture anticipation and allow to measure the net effect of the lockdown.[5] FE_i and FE_t are country and day fixed effects. ϵ_{ct} is an error term clustered at the country level.

3.2 Parallel with SIR model

Our estimates can also be interpreted in the context of the Susceptible-Infected-Recovered (SIR) epidemiological model Kermack and McKendrick (1927). Individuals are either susceptible to the infection, S_τ, or infected, I_τ, so there can be at most $S_\tau \times I_\tau$ potential contacts between infected and susceptible (the SIR model assumes that recovered individuals play no direct role in new infections). The disease is then transmitted at a rate β_τ from the infected to susceptible individuals, so in every period τ there are $\beta_\tau S_\tau I_\tau$ new cases being reported as infected. The total number of cases until day t is $\sum_{\tau=0}^{t} \beta_\tau S_\tau I_\tau$, and the growth rate of cases is equal to $\beta_{t+1} S_{t+1} I_{t+1}$. Our model provides an estimate of how this growth rate changes as measures are introduced. These changes happen for two main reasons. The transmission rate β_τ can decrease because the number of actual contacts decreases, and the number of infected individuals decreases, thereby creating fewer potential contacts. Our estimates provide the overall effect.

3.3 Heterogeneity exercise: Developed vs. Developing countries

We extend our baseline model to compare the effect between the implementation of lockdowns in developed and developing countries. We used the Human Development Index to define developed and developing countries.

[5] We replicate our results with five and ten days anticipation in Appendix.

Auto-regressive model of order 1 (AR(1)):

$$
\begin{aligned}
&log(cases_{it}+1) = \qquad (2)\\
&\beta_0 + \beta_1 Measure_{it} \times HighHDI_i + \beta_2 DaysAfterMeasure_{it} \times HighHDI_i +\\
&\beta_3 Measure_{it} \times LowHDI_i + \beta_4 DaysAfterMeasure_{it} \times LowHDI_i +\\
&+\beta_5 Release_{it}\\
&\beta_6 log(cases_{i(t-1)}+1) +\\
&+\beta_7 Anticipation_{it}^{7days}\\
&FE_i + FE_t + \epsilon_{ct}
\end{aligned}
$$

$HighHDI_i$ and $LowHDI_i$ are indicator variables taking the value of one or zero for developed and developing countries respectively. Note that we can include both effects simultaneously (Developed and Developing countries) without suffering from perfect multicollinearity, as the baseline are the countries which did not implement lockdown measures. Everything else is defined as in model (1).

4 Results

4.1 Descriptive Analyses: Anticipation Behavior

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 lock-down. After the lockdown is implemented, the growth rate is lower and remains so throughout the 30 days window. Increases in confirmed cases before a lockdown are typical of many countries that implement them to deal with exponential growth in cases. But cases may also increase if people who learn about the lockdown become, temporarily, more mobile. On the other hand, the population might reduce their contacts preemptively as they see neighboring countries locking down or in a difficult situation.

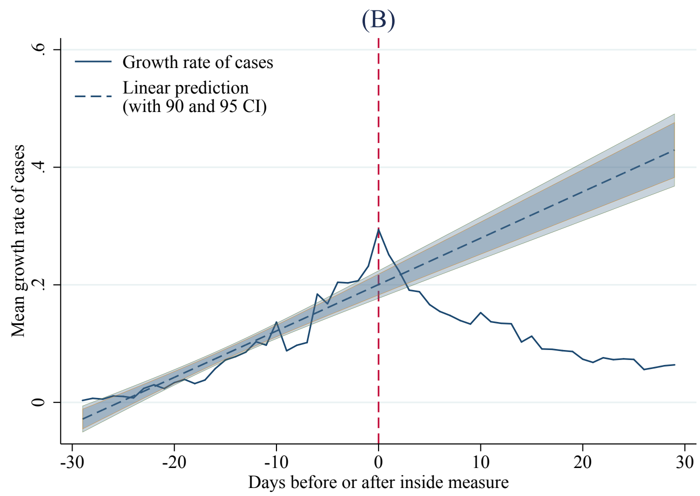

Figure 3: This graph reports the average growth rate of confirmed cases in the interval of 30 days before and after an internal measure was implemented. The graph also shows a prediction of the growth rate based on fitting a linear model to the data before the measure was introduced.

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 sharply falls after the lockdown is implemented. We can see that the population slightly reduced its occupations approximately one week before the implementation in non-necessary places as Retail and Recreation, Parks or Transit stations. On the other hand, for Grocery and Pharmacy, the occupation is flat until the first day of implementation.

4.2 Baseline results: Effectiveness of lockdown measures

We explore here how lockdown measures reduced the growth of infections as a function of the time since the measure was implemented as compared to countries that had not implemented any measure yet. Panel (a) and (b) of Figure 5 show the marginal effects of our baseline model.

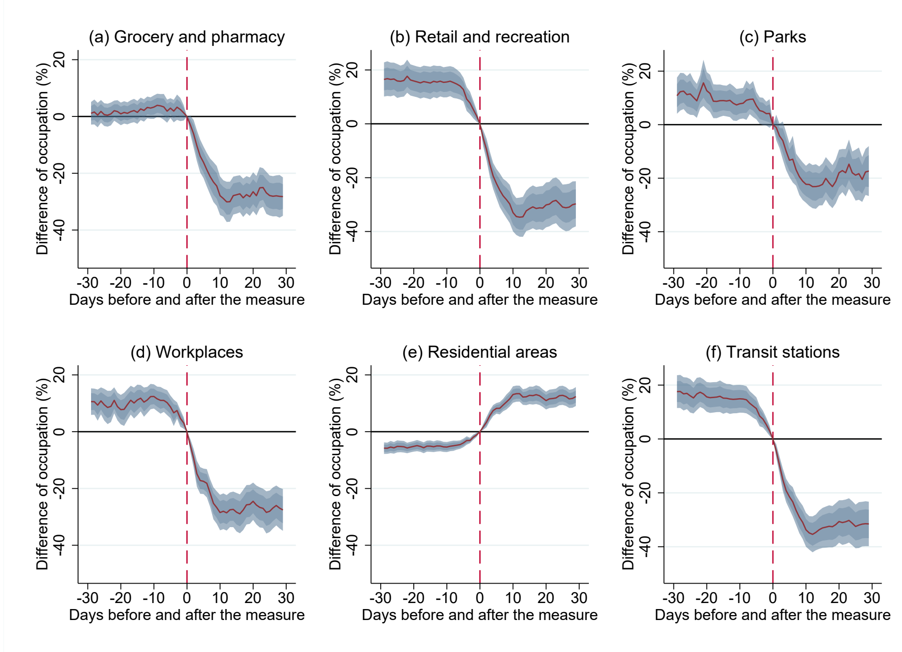

Figure 4: This figure shows the difference in occupation in percent of different area (Google Mobility Trend), as a function of the days before and after the implementation of the first within country lockdown. The y-axis represent percentage variation compared to the reference day (day 0). 90% and 99%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

Those two first panels reflects that restrictions within the country are more effective than measures towards the outside at limiting the spread of the virus. On average, countries who implemented within country restriction of movements experienced a statistically significant reduction of the growth rate of the virus after two weeks. After hundred-days the growth rate was lowered by 10.6% on average.[6] All the within country measure lead to an approximate reduction of 10% of the growth rate after 100 days (see panel c,d and e). On the other hand, blocking the borders (panel (b)) show a statistically significant reduction only after two months. Moreover, after a hundred days, the effect of border closure stage 2 and 1 is either not statistically significant or barely at the 10% threshold while internation lockdown reveal a 8.9% reduction.

[6]Model (1) from Table S5 in Appendix reports the coefficients used for the quantification.

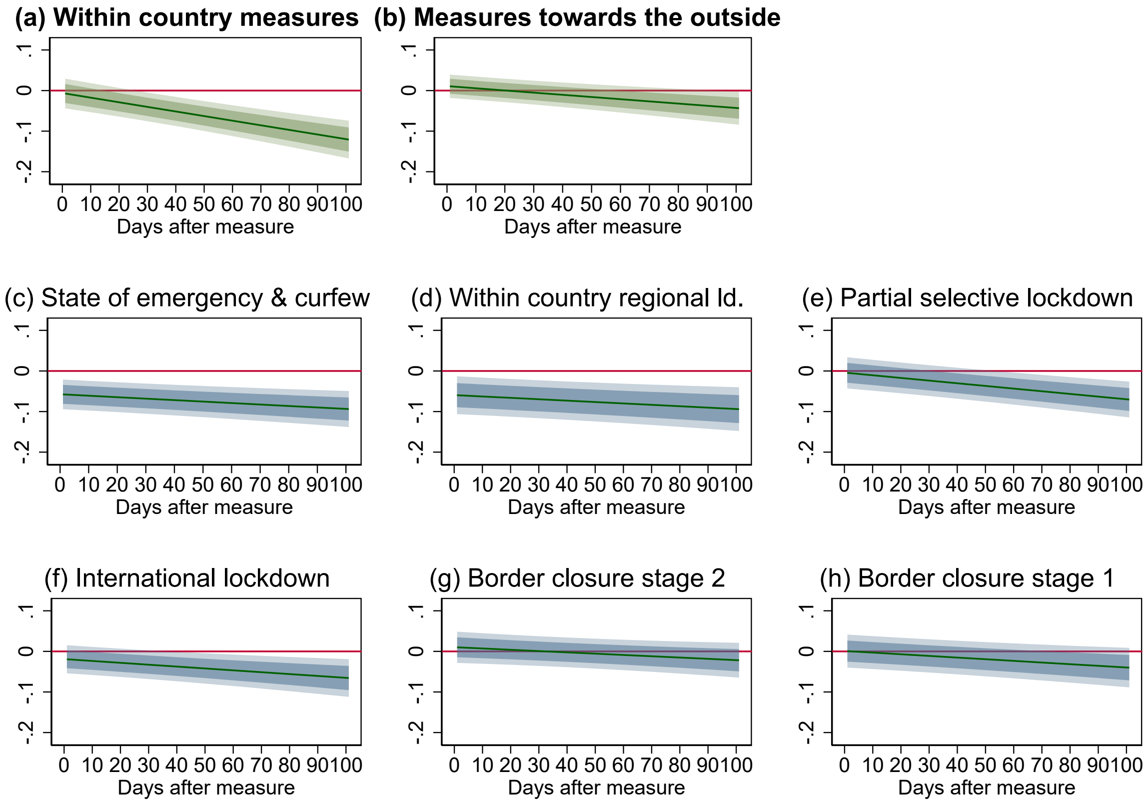

Figure 5: Marginal effect on growth rate of covid19 cases. Within country measures revealed to be more efficient than measures towards the outside with respect to their effect on the spread of the virus. Each sub figure show the impact of a lockdown on the growth rate of infections as a function of time since the measure was implemented. Marginal effects computed with our autoregressive model of order 1. 90% and 99% confidence intervals are shown in different shades of blue or green.

4.3 Quantifying Prevented Deaths

We also estimate model (1) to assess how lockdowns affect deaths. More Covid-19 infections raise the number of admissions into hospital, as more people experience a severe form of Covid-19, and hospitals reach capacity sooner (Wood et al., 2020). Results show that the growth rate in deaths is initially higher, but it declines significantly as the lockdown reduces the spread of the pandemic (Figure 6). Internal measures are more effective than external measures, replicating the result for the growth in the number of cases.

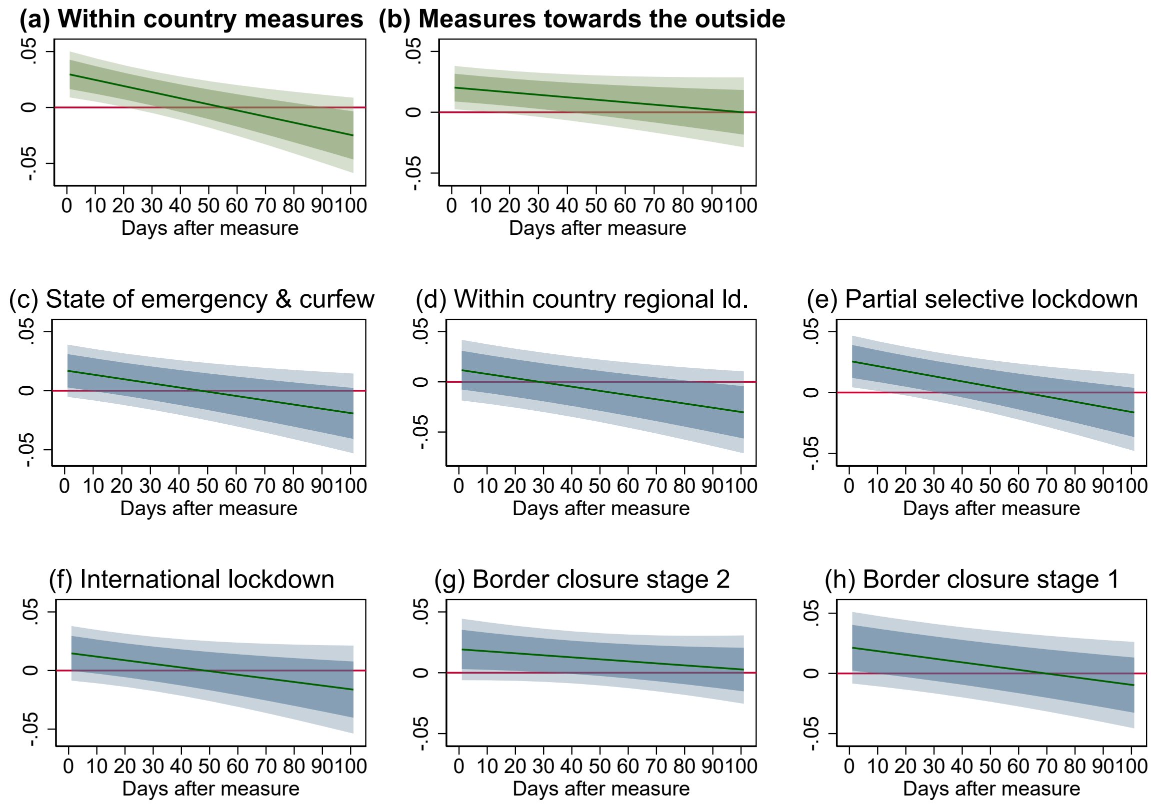

Figure 6: Marginal effect on death rate. Within country measures revealed to be more efficient than measures towards the outside with respect to their effect on the number of deaths. Each sub figure show the impact of a specific lockdown measure on the number of deaths as a function of time since the measure was implemented. Marginal effects computed with our autoregressive model of order 1. 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 by the COVID-19 (statistically significant effect and number of days before the growth rate of the number of deaths is reduced compared to countries which did not implement the measure), ii) the strength of the effect (steepness of the slope). The corresponding results for number of deaths are in the Appendix.

How effective were lockdowns in reducing deaths? A key challenge for quantification is how to estimate the counterfactual path of the epidemic, i.e. the path that the epidemic would have taken without the lockdown measures. We use the model (1), for the number of deaths, to compare the the total number of deaths with and without a measure (see Section C). In our context, the ratio prevented deaths to actual deaths is 5.14, somewhat more than five deaths were prevented per every death that unfortunately occurred. A total of 1'314'074 confirmed deaths were observed, so a total of 5'438'857 were prevented through lockdowns.

4.4 Developing versus developed countries

This section explores whether the impact of lockdowns is different in developed countries as opposed to developing countries. Figure 7 shows the marginal effects of all the different types of measures for developed and developing countries.[7] A clear pattern emerges. Lockdown measures didn't reduce the growth rate of the virus in developing economies, while the effects is negative and statistically significant for developed economies. Most of the explanatory variation in our baseline model therefore comes from lockdowns imposed in developed countries.

4.5 Lockdown release

We now turn to the effect of releasing lockdowns. As we are writing this paper, the second wave of COVID-19 is well under way and many countries re-entered a lockdown phase. We aim to understand whether releasing a lockdown triggers a second wave, and estimate (1) for countries which release a lockdown.

Figure 8 presents the marginal effects of the release of different policies.[8] Despite our multiple efforts to tackle reverse causation, counter-factual is more difficult to find for the release as virtually every country ended-up in lockdown over the summer. And countries that released lockdown measures tend to be those that controlled the spread of the COVID-19 better. However, despite seeing that the countries that released are better off compared to the others who are still in lockdown (who potentially started later), they are less and less so. This analysis reveals that, on the day of the release, the growth rate in cases is lower than in the counterfactual. Releasing triggers a very slow increase in the growth rate of COVID-19 cases, of about 0.005

[7]We define developing countries as the ones with an Human Development index up to 0.699, which refers to Low and Medium human development using the United Nation codebook definition while above 0.699 will be defined as developed countries.

[8]We use the same model as for our baseline (equation 1), and "Days after measure" refers to the number of days after releasing a lockdown.

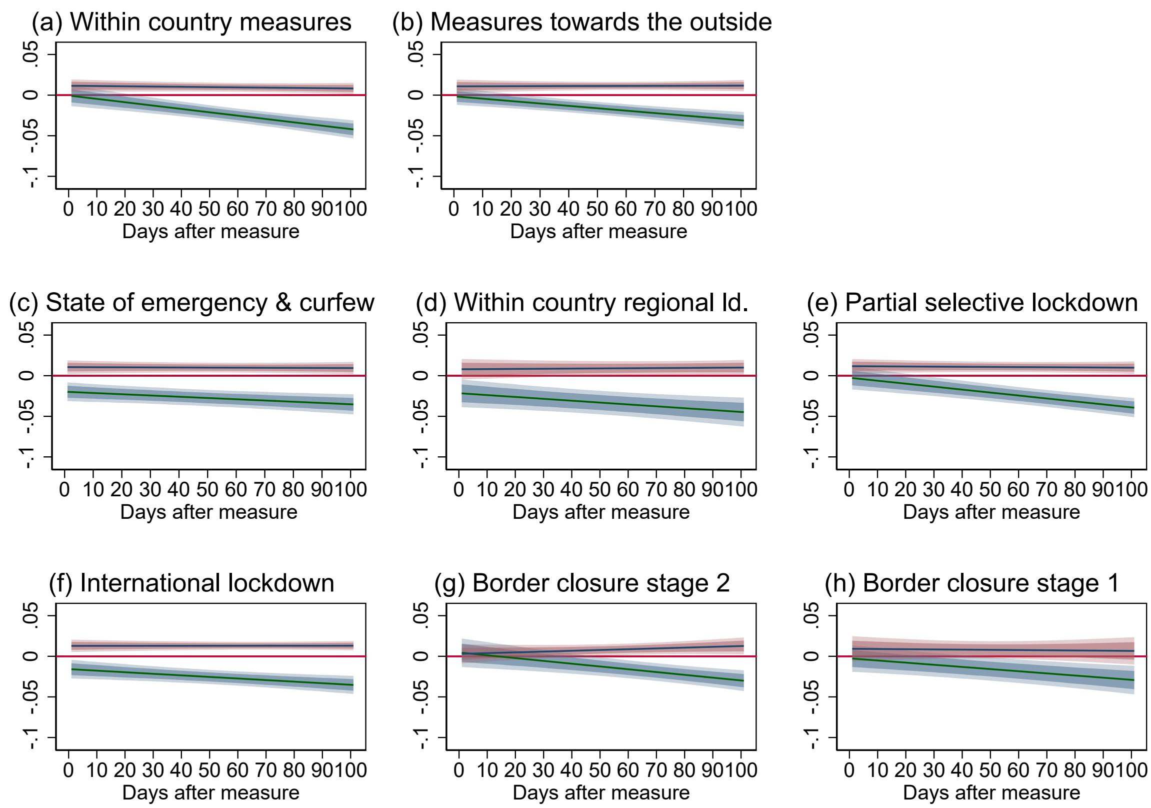

Figure 7: Lockdowns revealed to be efficient solely for developed country. Developing countries are those with Human Development Index values of up to 0.699 (marginal represented in red), which refers to Low and Medium human development using the United Nation codebook definition while those with values above 0.699 will be defined as developed countries (marginal represented in blue). Marginal effects computed with our autoregressive model of order 1. Panel (a) to (f) show the impact of a measure on the growth rate of infections as a function of time since the measure was implemented. 90% and 99% confidence intervals are shown in different shades of red or blue.

after 100 days, which is modest. Releasing the international border closure 2 is associated with a stronger increase in the growth rate of cases suggesting that travel links could be of some importance in the initial phase of a COVID-19 wave.

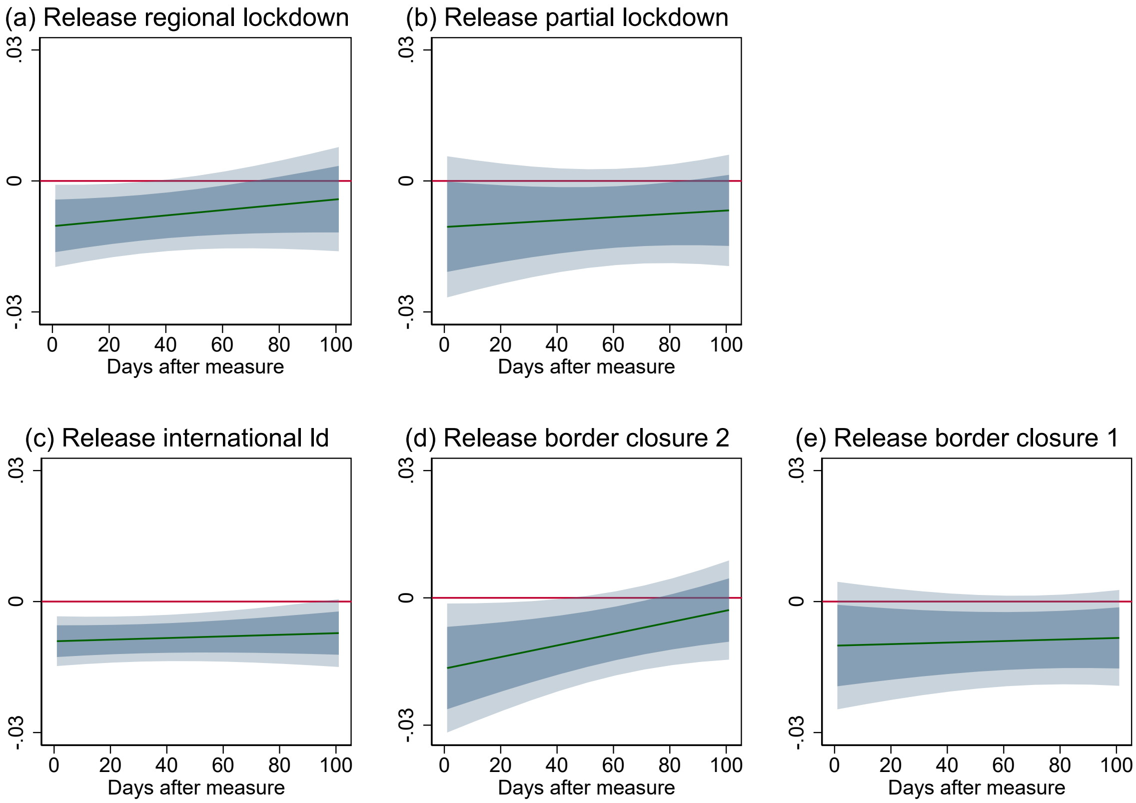

Figure 8: Release of Non-Pharmaceutical Interventions are associated with a low but positive increase rate of the COVID-19. Marginal effects computed with our autoregressive model of order 1. Note that we haven't recorded relesase of state of emergency and curfew lockdown. 90% and 99% confidence intervals 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.

5 Discussion

Our paper studies the COVID-19 lockdown measures adopted in 184 countries and provides several important insights, including about how individuals behave during lockdowns, that are relevant for how pandemics can be managed.

Overall, we find that lockdowns are effective measures to stop both the growth in the number of new cases and in the number of deaths, through a reduction in individuals' mobility for a broad range of daily activities. This result is in line with observations from previous pandemics. In his review of the evidence about 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 thereby led to much lower mortality rates. With the COVID-19 pandemic so far, we estimate that almost 5,5 million deaths had been prevented, or more than three deaths for every single death that occurred.

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, since schools, stores and local businesses are closed, when weighed against the risk of becoming infected. In addition, we speculate that partial lockdowns could send strong enough 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, our results point to the fact that people are adjusting their behaviors quite significantly even when only partial measures have been implemented, which would then be sufficient to decrease the spread of COVID-19 but at lower economic costs. Thus, total lockdowns would then be superfluous. This questions pure epidemiological models, which typically make projections about the spread of COVID-19 without taking into account the adjustments made by rational individuals.

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 at containing the spread of the pandemic, unless if it follows effective internal measures. 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, since 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 ones have been implemented, a result we obtained in a post-hoc analysis, which is 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.

In order to explore our idea that the opportunity costs of staying at home is 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 accordance 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. However, we cannot firmly conclude from our analysis that lockdowns are not effective in developing countries, as the disease in these countries appeared later and we could thus lack sufficient number of observations and statistical power. However, 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 really affect the spread of the disease in developing countries.

Finally, our empirical results suggest that the lifting of lockdowns, which started around the world by May 15, 2020 (Bonardi et al., 2020), did not lead to a resurgence of the virus within 100 days of the release. Releasing border closures could increase infections, but the effect is modest. This should be seen as another indication that, until vaccines are available, lockdowns have indeed been relatively successful ways of managing the pandemic.

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SUPPLEMENTARY MATERIAL

Appendix A Government policy measures data

The goal of this paper is to analyze and understand the effect of the lockdown measures implemented by most governments around the world on the spreading and mortality rate of Covid-19. In doing so, we consider the variance in terms of speed, strength and nature of these lockdown measures across the world observed over 115 days. 171 countries had taken at least one lockdown measure at the time of data collection. To generate the data regarding the policies undertaken by each government, we relied on custom-coded JAVA web scraping program that extracted from LexisNexis: i.) all news headlines per country from 31st of October 2019 to 1st of April 2020 and ii.) all Covid-19 information from country's US embassy Covid-19 bulletin.

The data generation process was conducted in two stages to ensure its validity, enhance its precision and to have 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)[9] , the dates, pulled specific objects of interests (the headline, date, and the link to the article) and stored them in per country ".csv" files. Because the ".csv" files held sizable amount of data we created library of keywords (lock, lockdown, covid-19, corona virus, etc.) to clean the surplus of information and to generate 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 for when the measure was implemented by the government.

In the second stage, because we were missing some information for part of the countries involved, and because we wanted to provide additional robustness checks for our data, we initiated a second scrape of information by relying on each country's US Embassy Covid-19 bulletin. US embassies across the globe create bulletins that provides constant flow of information regarding

[9]To optimize the search parameter(s), we created a library that pulled all information from LexisNexis by 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), name of the country and coronavirus (E.g. Switzerland & coronavirus). All the search results were aggregated and stored in per country separate ".csv" files.

important issues (like for example, Covid-19) within a given country to inform and enhance the safety of their staff and employees[10].

The final dataset allowed us to generate the following variables. *State of Emergency* considers the effective date when the country announced state of emergency (E.g: Bosnia declares nationwide state of emergency over coronavirus. – 17th of March 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, that is, restriction of movement of individuals 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, land borders and imposed a nationwide curfew to curb the spread of the pandemic. – 21st of March 2020). *Partial selective lockdown* considers the earliest effective date when the country announced partial limitation of movement by implementing, for example, school closure, limiting the number of people permitted to gather in a group (usually less than 100), closure of religious institutions etc (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 will be entering a total lockdown (Quebec, Declares State of Emergency to Blunt Pandemic. – 12th of March 2020). *Selective border close stage 1* considers the first effective date when the country closed borders towards any other country in the world, usually the countries closed borders to heavily infected regions and/or countries like, Wuhan, China, Iran and Italy (individually or as a group) (E.g: Australia banned the entry of foreign nationals from mainland China. – 30th of January 2020). *Selective border close stage 2* considers the first effective date, after Selective border closure stage 1, when the country closed borders towards one or multiple other countries in the world that are significantly affected by Covid-19 (E.g: Fiji extended its travel ban and announced that travelers from

[10]E.g. (last accessed: 17.04.20), https://mk.usembassy.gov/covid-19-information/

	Mean	Min.	First Quartile	Median	Third Quartile	Max
Country international lockdown	79.8	31	77	79	83	91
Curfew	79.8	32	76	80	85	93
Partial selective lockdown	75	45	73	75	79	91
Selective border closing stage 1	49.1	21	31	38.5	70	79
Selective border closing stage 2	69.3	27	64	72	76	83
State of emergency total lockdown	79.6	43	76	79	85	94
Within country regional lockdown	43.8	0	24	53	62	85
State of emergency and curfew lockdown	77.5	53	73	78	83	92
Inside measures	75	32	72.5	76	80	93
Outside measures	67.3	21	63	75.5	79	94

Table S1: When the measures have been taken in number of days since the 31st of December 2019?

Italy, Iran and the South Korean cities of Daegu and Cheongdo would be denied entry. – 27th of February 2020). *International Lockdown of the Country* considers the effective date when a country totally closed its borders regarding all flights, rail and automotive movement internationally (E.g: Council of Ministers of Bosnia and Herzegovina issued a decision which bans entrance for all foreigners. – 30th of March 2020). The distribution in time of these variables is summarized in Table S1.

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 the *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 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 date effective between the two as a date for the variable *Total within country lockdown*.

Appendix B 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 S2: Developing and developed countries list

Appendix C Quantifying Prevented Deaths

A key challenge for quantification is how to estimate the counterfactual path of the epidemic, i.e. the path that the epidemic would have taken without the lockdown measures. We use the model (1), 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 which help assess this, β_1 which indicates by how much more the number of deaths grows in a country that has implemented a measure when the lockdown is implemented (intercept in Figure 6), and β_2 which describes the gradual slowing down of the growth rate in deaths due to the measure (slope in Figure 6, results in section D.1.2).[11]

We base our simulation on countries that have implemented inside measures, as those are shown to be effective. We consider the average time, T, from the day when a measure has been implemented, 0, until the average date of release during our analysis period. With a lockdown, the day to day ratio in 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 they implemented the measure until 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 the lockdown, it would not benefit 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 5.14, somewhat more than five deaths were prevented per every death that unfortunately occurred. We then use the total number of deaths in countries that implemented the measure, which is $D = 1'314'074$, to calculate the

[11] Our models assume that lockdowns potentially reduce deaths from the date they are implemented. An alternative model that allows for 35 days after the lockdown is implemented yields similar results (available upon request from the authors). Another approach to estimate the counterfactual path are 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 that people adapt behavior to lower reproduction numbers (Eichenbaum et al., 2020).

total number of prevented deaths, which is $D * (g_0 - g_1)/g_1 = 5'438'857$. A total of almost 5,5 million deaths were prevented, or a bit more than five prevented deaths for each actual death.

Appendix D Regression tables

The regression tables are presented in this section. Appendix D.1.1 reports the coefficient for the baseline model for the growth rate of reported cases while D.1.2 reports the coefficients for the growth rate of deaths. More importantly, Tables S5 and S6 reports the coefficients for used to produce the main Figure 5 and Tables S23 and S24 for Figure 6.

Then, Appendix D.2.1 and D.2.2 report the results respectively for the growth rate of cases and deaths for the heterogeneity exercise between developed and developing countries. In particular, Tables S15 and S16 reports the coefficients for Figure 7 in the main text.

Throughout this Appendix section we report the results allowing for different lag after the NPI to capture either the incubation time either the time before the person contaminated might lose her/his life. The results are robust to those wide range of lags (from 5 to 28 days). However, it is reasuring to see that the effects tend to weaken as we use less realistic lags (e.g: 21 days for the incubation time). The corresponding figures are available in Appendix E.

D.1 Baseline model: Effectiveness of lockdown measures

D.1.1 Number of reported cases

	log(cases+1)			
	(1)	(2)	(3)	(4)
LagLogConfirmed	0.993***	0.994***	0.994***	0.994***
	(0.001)	(0.000)	(0.000)	(0.000)
Within country lockdown				
DaysAfterMeasure	-0.001***			
	(0.000)			
Measure	-0.019			
	(0.015)			
Anticipation 5 days	0.102***			
	(0.015)			
MeasureRelease	-0.012***			
	(0.004)			
State of emergency lockdown				
DaysAfterMeasure		-0.000***		
		(0.000)		
Measure		-0.057***		
		(0.015)		
Anticipation 5 days		0.084***		
		(0.016)		
MeasureRelease		0.000		
		(.)		
Within countrytial lockdown				
DaysAfterMeasure			-0.000***	
			(0.000)	
Measure			-0.070***	
			(0.019)	
Anticipation 5 days			0.084***	
			(0.020)	
MeasureRelease			-0.005	
			(0.003)	
Partial lockdown				
DaysAfterMeasure				-0.001***
				(0.000)
Measure				-0.015
				(0.016)
Anticipation 5 days				0.060***
				(0.016)
MeasureRelease				-0.010*
				(0.005)
Constant	0.057***	0.064***	0.064***	0.064***
	(0.004)	(0.003)	(0.002)	(0.002)
Observations	38475	45157	52819	45386
Adjusted R^2	0.999	0.999	0.999	0.999

AR(1) 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 S3: Baseline: Within country measures (anticipation 5 days)

	log(cases+1)			
	(1)	(2)	(3)	(4)
LagLogConfirmed	0.994***	0.994***	0.994***	0.994***
	(0.001)	(0.001)	(0.000)	(0.000)
Measures toward the outside				
DaysAfterMeasure	-0.001***			
	(0.000)			
Measure	0.002			
	(0.012)			
Anticipation 5 days	0.045***			
	(0.013)			
MeasureRelease	-0.013***			
	(0.003)			
International lockdown				
DaysAfterMeasure		-0.000***		
		(0.000)		
Measure		-0.021		
		(0.014)		
Anticipation 5 days		0.048***		
		(0.015)		
MeasureRelease		-0.014***		
		(0.004)		
Selective border closure 2				
DaysAfterMeasure			-0.000**	
			(0.000)	
Measure			0.002	
			(0.018)	
Anticipation 5 days			0.030*	
			(0.018)	
MeasureRelease			-0.008*	
			(0.005)	
Selective border closure 1				
DaysAfterMeasure				-0.000***
				(0.000)
Measure				-0.008
				(0.018)
Anticipation 5 days				0.040**
				(0.018)
MeasureRelease				-0.011**
				(0.005)
Constant	0.056***	0.064***	0.062***	0.063***
	(0.004)	(0.004)	(0.002)	(0.002)
Observations	37016	40564	51438	52240
Adjusted R^2	0.999	0.999	0.999	0.999

AR(1) 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 S4: Baseline: Measures towards the outside (anticipation 5 days)

	log(cases+1)			
	(1)	(2)	(3)	(4)
LagLogConfirmed	0.993***	0.994***	0.994***	0.994***
	(0.001)	(0.000)	(0.000)	(0.000)
Within country lockdown				
DaysAfterMeasure	-0.001***			
	(0.000)			
Measure	-0.006			
	(0.014)			
Anticipation 7 days	0.093***			
	(0.014)			
MeasureRelease	-0.012***			
	(0.004)			
State of emergency lockdown				
DaysAfterMeasure		-0.000***		
		(0.000)		
Measure		-0.057***		
		(0.014)		
Anticipation 7 days		0.090***		
		(0.015)		
MeasureRelease		0.000		
		(.)		
Within countrytial lockdown				
DaysAfterMeasure			-0.000***	
			(0.000)	
Measure			-0.059***	
			(0.018)	
Anticipation 7 days			0.076***	
			(0.019)	
MeasureRelease			-0.005	
			(0.003)	
Partial lockdown				
DaysAfterMeasure				-0.001***
				(0.000)
Measure				-0.004
				(0.015)
Anticipation 7 days				0.049***
				(0.015)
MeasureRelease				-0.010*
				(0.005)
Constant	0.055***	0.062***	0.064***	0.064***
	(0.004)	(0.003)	(0.002)	(0.002)
Observations	38405	45005	52559	45224
Adjusted R^2	0.999	0.999	0.999	0.999

AR(1) 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 S5: Baseline: Within country measures (anticipation 7 days)

	log(cases+1)			
	(1)	(2)	(3)	(4)
LagLogConfirmed	0.994***	0.994***	0.994***	0.994***
	(0.001)	(0.001)	(0.000)	(0.000)
Measures toward the outside				
DaysAfterMeasure	-0.001***			
	(0.000)			
Measure	0.011			
	(0.011)			
Anticipation 7 days	0.036***			
	(0.011)			
MeasureRelease	-0.013***			
	(0.003)			
International lockdown				
DaysAfterMeasure		-0.000***		
		(0.000)		
Measure		-0.019		
		(0.013)		
Anticipation 7 days		0.049***		
		(0.014)		
MeasureRelease		-0.014***		
		(0.004)		
Selective border closure 2				
DaysAfterMeasure			-0.000**	
			(0.000)	
Measure			0.010	
			(0.015)	
Anticipation 7 days			0.021	
			(0.015)	
MeasureRelease			-0.008*	
			(0.005)	
Selective border closure 1				
DaysAfterMeasure				-0.000***
				(0.000)
Measure				0.001
				(0.016)
Anticipation 7 days				0.031**
				(0.015)
MeasureRelease				-0.011**
				(0.005)
Constant	0.056***	0.063***	0.062***	0.063***
	(0.004)	(0.004)	(0.002)	(0.002)
Observations	36950	40476	51190	51968
Adjusted R^2	0.999	0.999	0.999	0.999

AR(1) 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: Measures towards the outside (anticipation 7 days)

	log(cases+1)			
	(1)	(2)	(3)	(4)
LagLogConfirmed	0.993***	0.994***	0.994***	0.994***
	(0.001)	(0.000)	(0.000)	(0.000)
Within country lockdown				
DaysAfterMeasure	-0.001***			
	(0.000)			
Measure	0.012			
	(0.014)			
Anticipation 10 days	0.075***			
	(0.016)			
MeasureRelease	-0.012***			
	(0.004)			
State of emergency lockdown				
DaysAfterMeasure		-0.000***		
		(0.000)		
Measure		-0.047***		
		(0.015)		
Anticipation 10 days		0.083***		
		(0.017)		
MeasureRelease		0.000		
		(.)		
Within countrytial lockdown				
DaysAfterMeasure			-0.000***	
			(0.000)	
Measure			-0.053**	
			(0.021)	
Anticipation 10 days			0.073***	
			(0.023)	
MeasureRelease			-0.005	
			(0.003)	
Partial lockdown				
DaysAfterMeasure				-0.001***
				(0.000)
Measure				0.005
				(0.014)
Anticipation 10 days				0.041***
				(0.014)
MeasureRelease				-0.010*
				(0.005)
Constant	0.054***	0.061***	0.063***	0.063***
	(0.004)	(0.003)	(0.002)	(0.002)
Observations	38300	44777	52169	44981
Adjusted R^2	0.999	0.999	0.999	0.999

AR(1) 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: Within country measures (anticipation 10 days)

	log(cases+1)			
	(1)	(2)	(3)	(4)
LagLogConfirmed	0.994***	0.994***	0.994***	0.994***
	(0.001)	(0.001)	(0.000)	(0.000)
Measures toward the outside				
DaysAfterMeasure	-0.001***			
	(0.000)			
Measure	0.015			
	(0.012)			
Anticipation 10 days	0.035***			
	(0.013)			
MeasureRelease	-0.013***			
	(0.003)			
International lockdown				
DaysAfterMeasure		-0.000***		
		(0.000)		
Measure		-0.017		
		(0.015)		
Anticipation 10 days		0.051***		
		(0.018)		
MeasureRelease		-0.014***		
		(0.004)		
Selective border closure 2				
DaysAfterMeasure			-0.000**	
			(0.000)	
Measure			0.016	
			(0.014)	
Anticipation 10 days			0.016	
			(0.013)	
MeasureRelease			-0.008*	
			(0.005)	
Selective border closure 1				
DaysAfterMeasure				-0.000***
				(0.000)
Measure				0.006
				(0.015)
Anticipation 10 days				0.027*
				(0.014)
MeasureRelease				-0.011**
				(0.005)
Constant	0.054***	0.061***	0.062***	0.062***
	(0.003)	(0.003)	(0.002)	(0.002)
Observations	36851	40344	50818	51560
Adjusted R^2	0.999	0.999	0.999	0.999

AR(1) 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: Measures towards the outside (anticipation 10 days)

D.1.2 Number of reported deaths

	log(deaths+1)			
	(1)	(2)	(3)	(4)
LagLogDeath	0.997***	0.996***	0.997***	0.996***
	(0.000)	(0.000)	(0.000)	(0.000)
Within country lockdown				
DaysAfterMeasure	-0.001***			
	(0.000)			
Measure	0.030***			
	(0.008)			
Anticipation 7 days	0.014*			
	(0.008)			
MeasureRelease	-0.008**			
	(0.003)			
State of emergency lockdown				
DaysAfterMeasure		-0.000***		
		(0.000)		
Measure		0.017**		
		(0.009)		
Anticipation 7 days		0.014		
		(0.009)		
MeasureRelease		0.000		
		(.)		
Within countrytial lockdown				
DaysAfterMeasure			-0.000***	
			(0.000)	
Measure			0.012	
			(0.012)	
Anticipation 7 days			0.019	
			(0.012)	
MeasureRelease			-0.002	
			(0.004)	
Partial lockdown				
DaysAfterMeasure				-0.000***
				(0.000)
Measure				0.026***
				(0.008)
Anticipation 7 days				0.006
				(0.009)
MeasureRelease				-0.010**
				(0.004)
Constant	0.021***	0.026***	0.028***	0.027***
	(0.002)	(0.001)	(0.001)	(0.001)
Observations	38405	45005	52559	45224
Adjusted R^2	0.999	0.999	0.999	0.999

AR(1) 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 (deaths): Within country measures (anticipation 7 days)

	log(deaths+1)			
	(1)	(2)	(3)	(4)
LagLogDeath	0.997***	0.997***	0.996***	0.997***
	(0.001)	(0.000)	(0.000)	(0.000)
Measures toward the outside				
DaysAfterMeasure	-0.000**			
	(0.000)			
Measure	0.020***			
	(0.007)			
Anticipation 7 days	0.003			
	(0.007)			
MeasureRelease	-0.012***			
	(0.003)			
International lockdown				
DaysAfterMeasure		-0.000**		
		(0.000)		
Measure		0.015		
		(0.009)		
Anticipation 7 days		0.014		
		(0.010)		
MeasureRelease		-0.011**		
		(0.004)		
Selective border closure 2				
DaysAfterMeasure			-0.000	
			(0.000)	
Measure			0.019*	
			(0.010)	
Anticipation 7 days			-0.002	
			(0.008)	
MeasureRelease			-0.010**	
			(0.004)	
Selective border closure 1				
DaysAfterMeasure				-0.000***
				(0.000)
Measure				0.022*
				(0.012)
Anticipation 7 days				0.009
				(0.012)
MeasureRelease				-0.011**
				(0.005)
Constant	0.022***	0.024***	0.029***	0.028***
	(0.002)	(0.002)	(0.001)	(0.001)
Observations	36950	40476	51190	51968
Adjusted R^2	0.999	0.999	0.999	0.999

AR(1) 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 (deaths): Measures towards the outside (anticipation 7 days)

	log(deaths+1)			
	(1)	(2)	(3)	(4)
LagLogDeath	0.997***	0.996***	0.997***	0.996***
	(0.000)	(0.000)	(0.000)	(0.000)
Within country lockdown				
DaysAfterMeasure	-0.001***			
	(0.000)			
Measure	0.032***			
	(0.008)			
Anticipation 10 days	0.013			
	(0.009)			
MeasureRelease	-0.008**			
	(0.003)			
State of emergency lockdown				
DaysAfterMeasure		-0.000***		
		(0.000)		
Measure		0.020**		
		(0.009)		
Anticipation 10 days		0.012		
		(0.011)		
MeasureRelease		0.000		
		(.)		
Within countrytial lockdown				
DaysAfterMeasure			-0.000***	
			(0.000)	
Measure			0.013	
			(0.013)	
Anticipation 10 days			0.019	
			(0.014)	
MeasureRelease			-0.002	
			(0.004)	
Partial lockdown				
DaysAfterMeasure				-0.000***
				(0.000)
Measure				0.025***
				(0.008)
Anticipation 10 days				0.008
				(0.009)
MeasureRelease				-0.010**
				(0.004)
Constant	0.021***	0.026***	0.028***	0.027***
	(0.002)	(0.001)	(0.001)	(0.001)
Observations	38300	44777	52169	44981
Adjusted R^2	0.999	0.999	0.999	0.999

AR(1) 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 (deaths): Within country measures (anticipation 10 days)

	log(deaths+1)			
	(1)	(2)	(3)	(4)
LagLogDeath	0.997***	0.997***	0.996***	0.997***
	(0.001)	(0.000)	(0.000)	(0.000)
Measures toward the outside				
DaysAfterMeasure	-0.000**			
	(0.000)			
Measure	0.024***			
	(0.007)			
Anticipation 10 days	-0.002			
	(0.007)			
MeasureRelease	-0.012***			
	(0.003)			
International lockdown				
DaysAfterMeasure		-0.000**		
		(0.000)		
Measure		0.020**		
		(0.009)		
Anticipation 10 days		0.008		
		(0.011)		
MeasureRelease		-0.011**		
		(0.004)		
Selective border closure 2				
DaysAfterMeasure			-0.000	
			(0.000)	
Measure			0.018*	
			(0.010)	
Anticipation 10 days			-0.000	
			(0.007)	
MeasureRelease			-0.010**	
			(0.004)	
Selective border closure 1				
DaysAfterMeasure				-0.000***
				(0.000)
Measure				0.026***
				(0.009)
Anticipation 10 days				0.004
				(0.008)
MeasureRelease				-0.011**
				(0.005)
Constant	0.023***	0.025***	0.029***	0.028***
	(0.002)	(0.002)	(0.001)	(0.001)
Observations	36851	40344	50818	51560
Adjusted R^2	0.999	0.999	0.999	0.999

AR(1) 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 (deaths): Measures towards the outside (anticipation 10 days)

D.2 Extension: Developed vs. Developing

D.2.1 Number of reported cases

log(confirmed+1)	(1)	(2)	(3)	(4)
LagLogConfirmed	0.994***	0.994***	0.995***	0.994***
	(0.001)	(0.000)	(0.000)	(0.000)
Within country lockdown				
DaysAfterMeasure× LowHDI	-0.001***			
	(0.000)			
Measure× LowHDI	0.012			
	(0.015)			
DaysAfterMeasure× HighHDI	-0.001***			
	(0.000)			
Measure× HighHDI	-0.007			
	(0.015)			
Anticipation 5 days	0.077***			
	(0.015)			
MeasureRelease	-0.013***			
	(0.004)			
State of emergency lockdown				
DaysAfterMeasure× LowHDI		-0.000		
		(0.000)		
Measure× LowHDI		-0.009		
		(0.017)		
DaysAfterMeasure× HighHDI		-0.000***		
		(0.000)		
Measure× HighHDI		-0.043***		
		(0.015)		
Anticipation 5 days		0.058***		
		(0.016)		
MeasureRelease		0.000		
		(.)		
Within countrytial lockdown				
DaysAfterMeasure× LowHDI			-0.000	
			(0.000)	
Measure× LowHDI			-0.041**	
			(0.020)	
DaysAfterMeasure× HighHDI			-0.000***	
			(0.000)	
Measure× HighHDI			-0.065***	
			(0.017)	
Anticipation 5 days			0.068***	
			(0.017)	
MeasureRelease			-0.008**	
			(0.003)	
Partial lockdown				
DaysAfterMeasure× LowHDI				-0.000***
				(0.000)
Measure× LowHDI				0.008
				(0.017)
DaysAfterMeasure× HighHDI				-0.001***
				(0.000)
Measure× HighHDI				-0.010
				(0.016)
Anticipation 5 days				0.046***
				(0.015)
MeasureRelease				-0.010**
				(0.005)
Constant	0.053***	0.061***	0.061***	0.062***
	(0.004)	(0.003)	(0.002)	(0.002)
Observations	38475	45157	52819	45386
Adjusted R^2	0.999	0.999	0.999	0.999

AR(1) 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: Extension: Within country measures (anticipation 5 days)

log(confirmed+1)	(1)	(2)	(3)	(4)
LagLogConfirmed	0.995***	0.995***	0.994***	0.995***
	(0.001)	(0.001)	(0.000)	(0.000)
Measures toward the outside				
DaysAfterMeasure× LowHDI	-0.000*			
	(0.000)			
Measure× LowHDI	0.018			
	(0.015)			
DaysAfterMeasure× HighHDI	-0.001***			
	(0.000)			
Measure× HighHDI	-0.001			
	(0.013)			
Anticipation 5 days	0.039***			
	(0.013)			
MeasureRelease	-0.009***			
	(0.003)			
International lockdown				
DaysAfterMeasure× LowHDI		-0.000**		
		(0.000)		
Measure× LowHDI		0.009		
		(0.016)		
DaysAfterMeasure× HighHDI		-0.000***		
		(0.000)		
Measure× HighHDI		-0.028*		
		(0.015)		
Anticipation 5 days		0.040***		
		(0.015)		
MeasureRelease		-0.012***		
		(0.004)		
Selective border closure 2				
DaysAfterMeasure× LowHDI			0.000	
			(0.000)	
Measure× LowHDI			-0.007	
			(0.020)	
DaysAfterMeasure× HighHDI			-0.001***	
			(0.000)	
Measure× HighHDI			0.006	
			(0.019)	
Anticipation 5 days			0.030*	
			(0.018)	
MeasureRelease			-0.007	
			(0.005)	
Selective border closure 1				
DaysAfterMeasure× LowHDI				-0.000
				(0.000)
Measure× LowHDI				-0.003
				(0.022)
DaysAfterMeasure× HighHDI				-0.000***
				(0.000)
Measure× HighHDI				-0.014
				(0.016)
Anticipation 5 days				0.042***
				(0.016)
MeasureRelease				-0.010*
				(0.005)
Constant	0.053***	0.060***	0.061***	0.062***
	(0.004)	(0.003)	(0.002)	(0.002)
Observations	37016	40564	51438	52240
Adjusted R^2	0.999	0.999	0.999	0.999

AR(1) 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: Extension: Measures towards the outside (anticipation 5 days)

log(confirmed+1)	(1)	(2)	(3)	(4)
LagLogConfirmed	0.994***	0.994***	0.995***	0.994***
	(0.001)	(0.000)	(0.000)	(0.000)
Within country lockdown				
DaysAfterMeasure× LowHDI	-0.001***			
	(0.000)			
Measure× LowHDI	0.012			
	(0.015)			
DaysAfterMeasure× HighHDI	-0.001***			
	(0.000)			
Measure× HighHDI	-0.007			
	(0.015)			
Anticipation 5 days	0.077***			
	(0.015)			
MeasureRelease	-0.013***			
	(0.004)			
State of emergency lockdown				
DaysAfterMeasure× LowHDI		-0.000		
		(0.000)		
Measure× LowHDI		-0.009		
		(0.017)		
DaysAfterMeasure× HighHDI		-0.000***		
		(0.000)		
Measure× HighHDI		-0.043***		
		(0.015)		
Anticipation 5 days		0.058***		
		(0.016)		
MeasureRelease		0.000		
		(.)		
Within countrytial lockdown				
DaysAfterMeasure× LowHDI			-0.000	
			(0.000)	
Measure× LowHDI			-0.041**	
			(0.020)	
DaysAfterMeasure× HighHDI			-0.000***	
			(0.000)	
Measure× HighHDI			-0.065***	
			(0.017)	
Anticipation 5 days			0.068***	
			(0.017)	
MeasureRelease			-0.008**	
			(0.003)	
Partial lockdown				
DaysAfterMeasure× LowHDI				-0.000***
				(0.000)
Measure× LowHDI				0.008
				(0.017)
DaysAfterMeasure× HighHDI				-0.001***
				(0.000)
Measure× HighHDI				-0.010
				(0.016)
Anticipation 5 days				0.046***
				(0.015)
MeasureRelease				-0.010**
				(0.005)
Constant	0.053***	0.061***	0.061***	0.062***
	(0.004)	(0.003)	(0.002)	(0.002)
Observations	38475	45157	52819	45386
Adjusted R^2	0.999	0.999	0.999	0.999

AR(1) 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: Extension: Within country measures (anticipation 7 days)

log(confirmed+1)	(1)	(2)	(3)	(4)
LagLogConfirmed	0.995***	0.995***	0.994***	0.995***
	(0.001)	(0.001)	(0.000)	(0.000)
Measures toward the outside				
DaysAfterMeasure× LowHDI	-0.000*			
	(0.000)			
Measure× LowHDI	0.018			
	(0.015)			
DaysAfterMeasure× HighHDI	-0.001***			
	(0.000)			
Measure× HighHDI	-0.001			
	(0.013)			
Anticipation 5 days	0.039***			
	(0.013)			
MeasureRelease	-0.009***			
	(0.003)			
International lockdown				
DaysAfterMeasure× LowHDI		-0.000**		
		(0.000)		
Measure× LowHDI		0.009		
		(0.016)		
DaysAfterMeasure× HighHDI		-0.000***		
		(0.000)		
Measure× HighHDI		-0.028*		
		(0.015)		
Anticipation 5 days		0.040***		
		(0.015)		
MeasureRelease		-0.012***		
		(0.004)		
Selective border closure 2				
DaysAfterMeasure× LowHDI			0.000	
			(0.000)	
Measure× LowHDI			-0.007	
			(0.020)	
DaysAfterMeasure× HighHDI			-0.001***	
			(0.000)	
Measure× HighHDI			0.006	
			(0.019)	
Anticipation 5 days			0.030*	
			(0.018)	
MeasureRelease			-0.007	
			(0.005)	
Selective border closure 1				
DaysAfterMeasure× LowHDI				-0.000
				(0.000)
Measure× LowHDI				-0.003
				(0.022)
DaysAfterMeasure× HighHDI				-0.000***
				(0.000)
Measure× HighHDI				-0.014
				(0.016)
Anticipation 5 days				0.042***
				(0.016)
MeasureRelease				-0.010*
				(0.005)
Constant	0.053***	0.060***	0.061***	0.062***
	(0.004)	(0.003)	(0.002)	(0.002)
Observations	37016	40564	51438	52240
Adjusted R^2	0.999	0.999	0.999	0.999

AR(1) 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: Extension: Measures towards the outside (anticipation 7 days)

log(confirmed+1)	(1)	(2)	(3)	(4)
LagLogConfirmed	0.994***	0.994***	0.995***	0.994***
	(0.001)	(0.000)	(0.000)	(0.000)
Within country lockdown				
DaysAfterMeasure× LowHDI	-0.001***			
	(0.000)			
Measure× LowHDI	0.030**			
	(0.014)			
DaysAfterMeasure× HighHDI	-0.001***			
	(0.000)			
Measure× HighHDI	0.011			
	(0.014)			
Anticipation 10 days	0.064***			
	(0.014)			
MeasureRelease	-0.013***			
	(0.004)			
State of emergency lockdown				
DaysAfterMeasure× LowHDI		-0.000*		
		(0.000)		
Measure× LowHDI		-0.011		
		(0.016)		
DaysAfterMeasure× HighHDI		-0.000***		
		(0.000)		
Measure× HighHDI		-0.044***		
		(0.014)		
Anticipation 10 days		0.068***		
		(0.016)		
MeasureRelease		0.000		
		(.)		
Within countrytial lockdown				
DaysAfterMeasure× LowHDI			-0.000	
			(0.000)	
Measure× LowHDI			-0.033	
			(0.022)	
DaysAfterMeasure× HighHDI			-0.000***	
			(0.000)	
Measure× HighHDI			-0.057***	
			(0.020)	
Anticipation 10 days			0.065***	
			(0.021)	
MeasureRelease			-0.007**	
			(0.003)	
Partial lockdown				
DaysAfterMeasure× LowHDI				-0.000***
				(0.000)
Measure× LowHDI				0.020
				(0.014)
DaysAfterMeasure× HighHDI				-0.001***
				(0.000)
Measure× HighHDI				0.002
				(0.014)
Anticipation 10 days				0.036***
				(0.013)
MeasureRelease				-0.010*
				(0.005)
Constant	0.050***	0.058***	0.061***	0.061***
	(0.004)	(0.003)	(0.002)	(0.002)
Observations	38300	44777	52169	44981
Adjusted R^2	0.999	0.999	0.999	0.999

AR(1) 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: Extension: Within country measures (anticipation 10 days)

log(confirmed+1)	(1)	(2)	(3)	(4)
LagLogConfirmed	0.995***	0.995***	0.994***	0.995***
	(0.001)	(0.001)	(0.000)	(0.000)
Measures toward the outside				
DaysAfterMeasure× LowHDI	-0.000*			
	(0.000)			
Measure× LowHDI	0.028**			
	(0.013)			
DaysAfterMeasure× HighHDI	-0.001***			
	(0.000)			
Measure× HighHDI	0.009			
	(0.012)			
Anticipation 10 days	0.032**			
	(0.012)			
MeasureRelease	-0.009***			
	(0.003)			
International lockdown				
DaysAfterMeasure× LowHDI		-0.000**		
		(0.000)		
Measure× LowHDI		0.010		
		(0.015)		
DaysAfterMeasure× HighHDI		-0.000***		
		(0.000)		
Measure× HighHDI		-0.027*		
		(0.015)		
Anticipation 10 days		0.045***		
		(0.017)		
MeasureRelease		-0.012***		
		(0.004)		
Selective border closure 2				
DaysAfterMeasure× LowHDI			0.000	
			(0.000)	
Measure× LowHDI			0.007	
			(0.017)	
DaysAfterMeasure× HighHDI			-0.001***	
			(0.000)	
Measure× HighHDI			0.020	
			(0.016)	
Anticipation 10 days			0.016	
			(0.013)	
MeasureRelease			-0.007	
			(0.005)	
Selective border closure 1				
DaysAfterMeasure× LowHDI				-0.000
				(0.000)
Measure× LowHDI				0.012
				(0.019)
DaysAfterMeasure× HighHDI				-0.000***
				(0.000)
Measure× HighHDI				0.001
				(0.014)
Anticipation 10 days				0.028**
				(0.013)
MeasureRelease				-0.010**
				(0.005)
Constant	0.051***	0.057***	0.061***	0.062***
	(0.003)	(0.003)	(0.002)	(0.002)
Observations	36851	40344	50818	51560
Adjusted R^2	0.999	0.999	0.999	0.999

AR(1) 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: Extension: Measures towards the outside (anticipation 10 days)

D.2.2 Number of reported deaths

	log(deaths+1)			
	(1)	(2)	(3)	(4)
LagLogDeath	0.995***	0.993***	0.992***	0.993***
	(0.001)	(0.000)	(0.000)	(0.000)
Within country lockdown				
DaysAfterMeasure× LowHDI	0.000			
	(0.000)			
Measure× LowHDI	0.010			
	(0.010)			
DaysAfterMeasure× HighHDI	-0.001***			
	(0.000)			
Measure× HighHDI	0.057***			
	(0.010)			
State of emergency lockdown				
DaysAfterMeasure× LowHDI		0.000		
		(0.000)		
Measure× LowHDI		0.001		
		(0.010)		
DaysAfterMeasure× HighHDI		-0.001***		
		(0.000)		
Measure× HighHDI		0.044***		
		(0.009)		
Within countrytial lockdown				
DaysAfterMeasure× LowHDI			0.000	
			(0.000)	
Measure× LowHDI			-0.007	
			(0.013)	
DaysAfterMeasure× HighHDI			-0.001***	
			(0.000)	
Measure× HighHDI			0.050***	
			(0.012)	
Partial lockdown				
DaysAfterMeasure× LowHDI				0.000
				(0.000)
Measure× LowHDI				-0.005
				(0.011)
DaysAfterMeasure× HighHDI				-0.001***
				(0.000)
Measure× HighHDI				0.050***
				(0.010)
Constant	0.023***	0.027***	0.028***	0.027***
	(0.002)	(0.002)	(0.001)	(0.001)
Observations	38650	45537	53469	45791
Adjusted R^2	0.998	0.997	0.997	0.997

AR(1) 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: Extension (deaths): Within country measures (lag before effect expected to kick in 5 days)

	log(deaths+1)			
	(1)	(2)	(3)	(4)
LagLogDeath	0.995***	0.994***	0.992***	0.992***
	(0.001)	(0.001)	(0.000)	(0.000)
Measures toward the outside				
DaysAfterMeasure× LowHDI	0.000***			
	(0.000)			
Measure× LowHDI	-0.012			
	(0.008)			
DaysAfterMeasure× HighHDI	-0.000***			
	(0.000)			
Measure× HighHDI	0.038***			
	(0.007)			
International lockdown				
DaysAfterMeasure× LowHDI		0.000**		
		(0.000)		
Measure× LowHDI		-0.006		
		(0.009)		
DaysAfterMeasure× HighHDI		-0.001***		
		(0.000)		
Measure× HighHDI		0.041***		
		(0.010)		
Selective border closure 2				
DaysAfterMeasure× LowHDI			0.000**	
			(0.000)	
Measure× LowHDI			-0.016	
			(0.013)	
DaysAfterMeasure× HighHDI			-0.000***	
			(0.000)	
Measure× HighHDI			0.036***	
			(0.012)	
Selective border closure 1				
DaysAfterMeasure× LowHDI				0.000
				(0.000)
Measure× LowHDI				0.001
				(0.015)
DaysAfterMeasure× HighHDI				-0.000***
				(0.000)
Measure× HighHDI				0.039***
				(0.010)
Constant	0.023***	0.025***	0.028***	0.027***
	(0.002)	(0.002)	(0.001)	(0.001)
Observations	37181	40784	52058	52920
Adjusted R^2	0.998	0.998	0.997	0.997

AR(1) 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: Extension (deaths): Measures towards the outside (anticipation 5 days)

	log(deaths+1)			
	(1)	(2)	(3)	(4)
LagLogDeath	0.995***	0.993***	0.992***	0.993***
	(0.001)	(0.000)	(0.000)	(0.000)
Within country lockdown				
DaysAfterMeasure× LowHDI	0.000			
	(0.000)			
Measure× LowHDI	0.010			
	(0.010)			
DaysAfterMeasure× HighHDI	-0.001***			
	(0.000)			
Measure× HighHDI	0.057***			
	(0.010)			
State of emergency lockdown				
DaysAfterMeasure× LowHDI		0.000		
		(0.000)		
Measure× LowHDI		0.001		
		(0.010)		
DaysAfterMeasure× HighHDI		-0.001***		
		(0.000)		
Measure× HighHDI		0.044***		
		(0.009)		
Within countrytial lockdown				
DaysAfterMeasure× LowHDI			0.000	
			(0.000)	
Measure× LowHDI			-0.007	
			(0.013)	
DaysAfterMeasure× HighHDI			-0.001***	
			(0.000)	
Measure× HighHDI			0.050***	
			(0.012)	
Partial lockdown				
DaysAfterMeasure× LowHDI				0.000
				(0.000)
Measure× LowHDI				-0.005
				(0.011)
DaysAfterMeasure× HighHDI				-0.001***
				(0.000)
Measure× HighHDI				0.050***
				(0.010)
Constant	0.023***	0.027***	0.028***	0.027***
	(0.002)	(0.002)	(0.001)	(0.001)
Observations	38650	45537	53469	45791
Adjusted R^2	0.998	0.997	0.997	0.997

AR(1) 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 (deaths): Within country measures (lag before effect expected to kick in 7 days)

	log(deaths+1)			
	(1)	(2)	(3)	(4)
LagLogDeath	0.995***	0.994***	0.992***	0.992***
	(0.001)	(0.001)	(0.000)	(0.000)
Measures toward the outside				
DaysAfterMeasure× LowHDI	0.000***			
	(0.000)			
Measure× LowHDI	-0.012			
	(0.008)			
DaysAfterMeasure× HighHDI	-0.000***			
	(0.000)			
Measure× HighHDI	0.038***			
	(0.007)			
International lockdown				
DaysAfterMeasure× LowHDI		0.000**		
		(0.000)		
Measure× LowHDI		-0.006		
		(0.009)		
DaysAfterMeasure× HighHDI		-0.001***		
		(0.000)		
Measure× HighHDI		0.041***		
		(0.010)		
Selective border closure 2				
DaysAfterMeasure× LowHDI			0.000**	
			(0.000)	
Measure× LowHDI			-0.016	
			(0.013)	
DaysAfterMeasure× HighHDI			-0.000***	
			(0.000)	
Measure× HighHDI			0.036***	
			(0.012)	
Selective border closure 1				
DaysAfterMeasure× LowHDI				0.000
				(0.000)
Measure× LowHDI				0.001
				(0.015)
DaysAfterMeasure× HighHDI				-0.000***
				(0.000)
Measure× HighHDI				0.039***
				(0.010)
Constant	0.023***	0.025***	0.028***	0.027***
	(0.002)	(0.002)	(0.001)	(0.001)
Observations	37181	40784	52058	52920
Adjusted R^2	0.998	0.998	0.997	0.997

AR(1) 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 (deaths): Measures towards the outside (anticipation 7 days)

	log(deaths+1)			
	(1)	(2)	(3)	(4)
LagLogDeath	0.995***	0.993***	0.992***	0.993***
	(0.001)	(0.000)	(0.000)	(0.000)
Within country lockdown				
DaysAfterMeasure× LowHDI	0.000			
	(0.000)			
Measure× LowHDI	0.010			
	(0.010)			
DaysAfterMeasure× HighHDI	-0.001***			
	(0.000)			
Measure× HighHDI	0.057***			
	(0.010)			
State of emergency lockdown				
DaysAfterMeasure× LowHDI		0.000		
		(0.000)		
Measure× LowHDI		0.001		
		(0.010)		
DaysAfterMeasure× HighHDI		-0.001***		
		(0.000)		
Measure× HighHDI		0.044***		
		(0.009)		
Within countrytial lockdown				
DaysAfterMeasure× LowHDI			0.000	
			(0.000)	
Measure× LowHDI			-0.007	
			(0.013)	
DaysAfterMeasure× HighHDI			-0.001***	
			(0.000)	
Measure× HighHDI			0.050***	
			(0.012)	
Partial lockdown				
DaysAfterMeasure× LowHDI				0.000
				(0.000)
Measure× LowHDI				-0.005
				(0.011)
DaysAfterMeasure× HighHDI				-0.001***
				(0.000)
Measure× HighHDI				0.050***
				(0.010)
Constant	0.023***	0.027***	0.028***	0.027***
	(0.002)	(0.002)	(0.001)	(0.001)
Observations	38650	45537	53469	45791
Adjusted R^2	0.998	0.997	0.997	0.997

AR(1) 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 (deaths): Within country measures (anticipation 10 days)

	log(deaths+1)			
	(1)	(2)	(3)	(4)
LagLogDeath	0.995***	0.994***	0.992***	0.992***
	(0.001)	(0.001)	(0.000)	(0.000)
Measures toward the outside				
DaysAfterMeasure× LowHDI	0.000***			
	(0.000)			
Measure× LowHDI	-0.012			
	(0.008)			
DaysAfterMeasure× HighHDI	-0.000***			
	(0.000)			
Measure× HighHDI	0.038***			
	(0.007)			
International lockdown				
DaysAfterMeasure× LowHDI		0.000**		
		(0.000)		
Measure× LowHDI		-0.006		
		(0.009)		
DaysAfterMeasure× HighHDI		-0.001***		
		(0.000)		
Measure× HighHDI		0.041***		
		(0.010)		
Selective border closure 2				
DaysAfterMeasure× LowHDI			0.000**	
			(0.000)	
Measure× LowHDI			-0.016	
			(0.013)	
DaysAfterMeasure× HighHDI			-0.000***	
			(0.000)	
Measure× HighHDI			0.036***	
			(0.012)	
Selective border closure 1				
DaysAfterMeasure× LowHDI				0.000
				(0.000)
Measure× LowHDI				0.001
				(0.015)
DaysAfterMeasure× HighHDI				-0.000***
				(0.000)
Measure× HighHDI				0.039***
				(0.010)
Constant	0.023***	0.025***	0.028***	0.027***
	(0.002)	(0.002)	(0.001)	(0.001)
Observations	37181	40784	52058	52920
Adjusted R^2	0.998	0.998	0.997	0.997

AR(1) 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 (deaths): Measures towards the outside (anticipation 10 days)

Appendix E Additional figures

Throughout this Appendix section we report the marginal effects allowing for different 5, 7 and 10 days of anticipation effect. The results are robust to those wide range of lags (from 5 to 28 days). However, it is reasuring to see that the effects tend to weaken as we use less realistic lags (e.g: 21 days for the incubation time). The corresponding Tables are available in Appendix D.

E.1 Baseline model: Effectiveness of lockdown measures

E.1.1 Number of reported cases

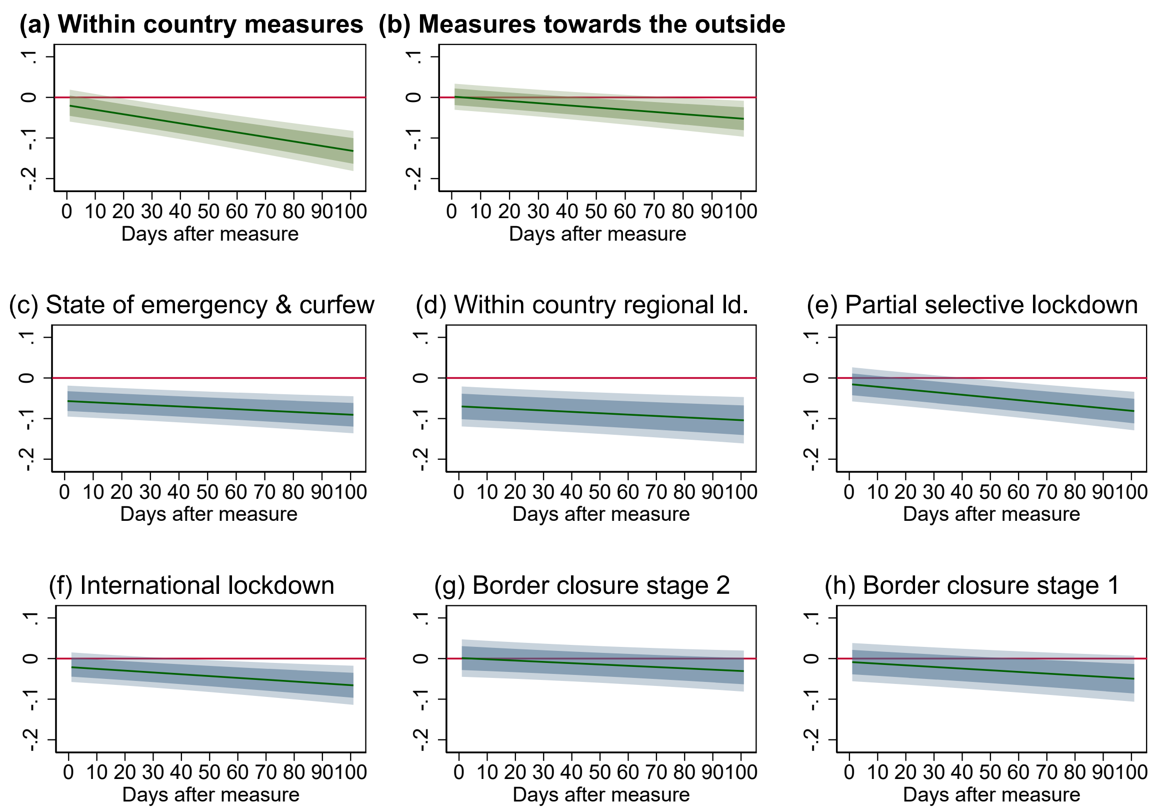

Figure S1: Marginal effect on growth rate of covid19 cases. Within country measures revealed to be more efficient than measures towards the outside with respect to their effect on the spread of the virus. Each sub figure show the impact of a lockdown on the growth rate of infections as a function of time since the measure was implemented. Marginal effects computed with our autoregressive model of order 1. 90% and 99% confidence intervals are shown in different shades of blue or green.

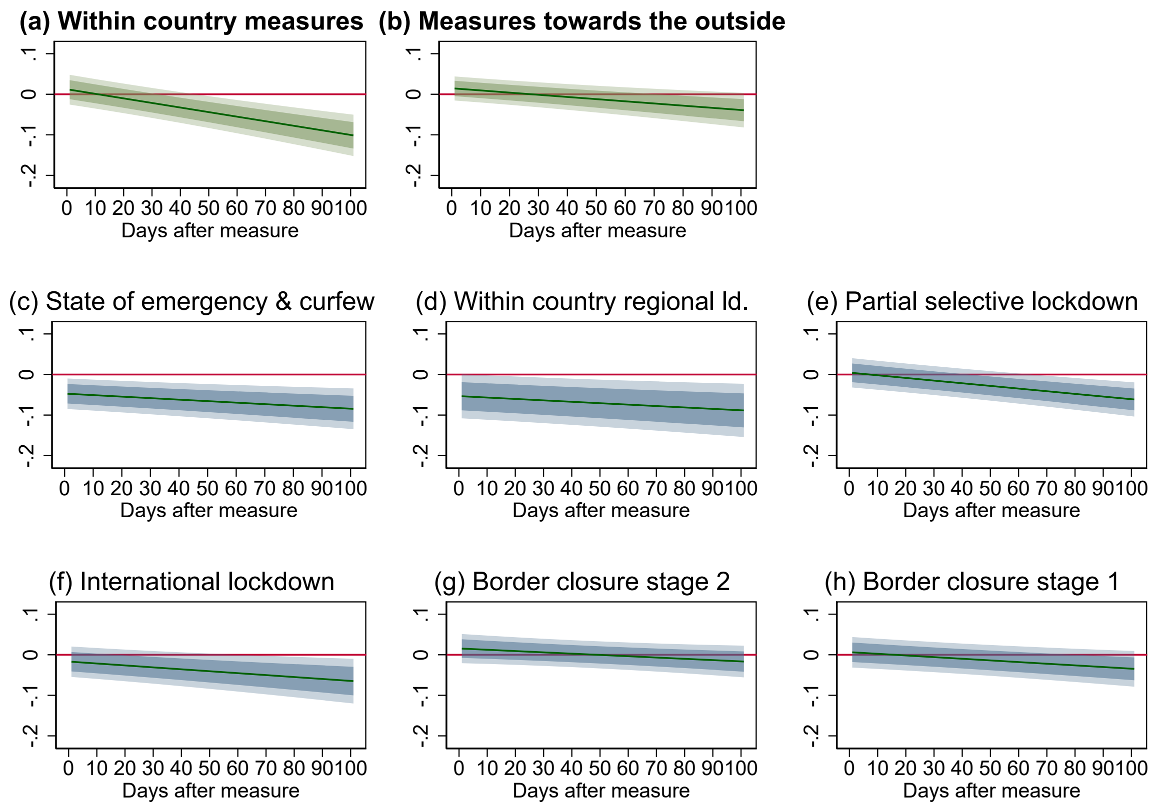

Figure S2: Marginal effect on growth rate of covid19 cases. Within country measures revealed to be more efficient than measures towards the outside with respect to their effect on the spread of the virus. Each sub figure show the impact of a lockdown on the growth rate of infections as a function of time since the measure was implemented. Marginal effects computed with our autoregressive model of order 1. 90% and 99% confidence intervals are shown in different shades of blue or green.

E.1.2 Number of deaths

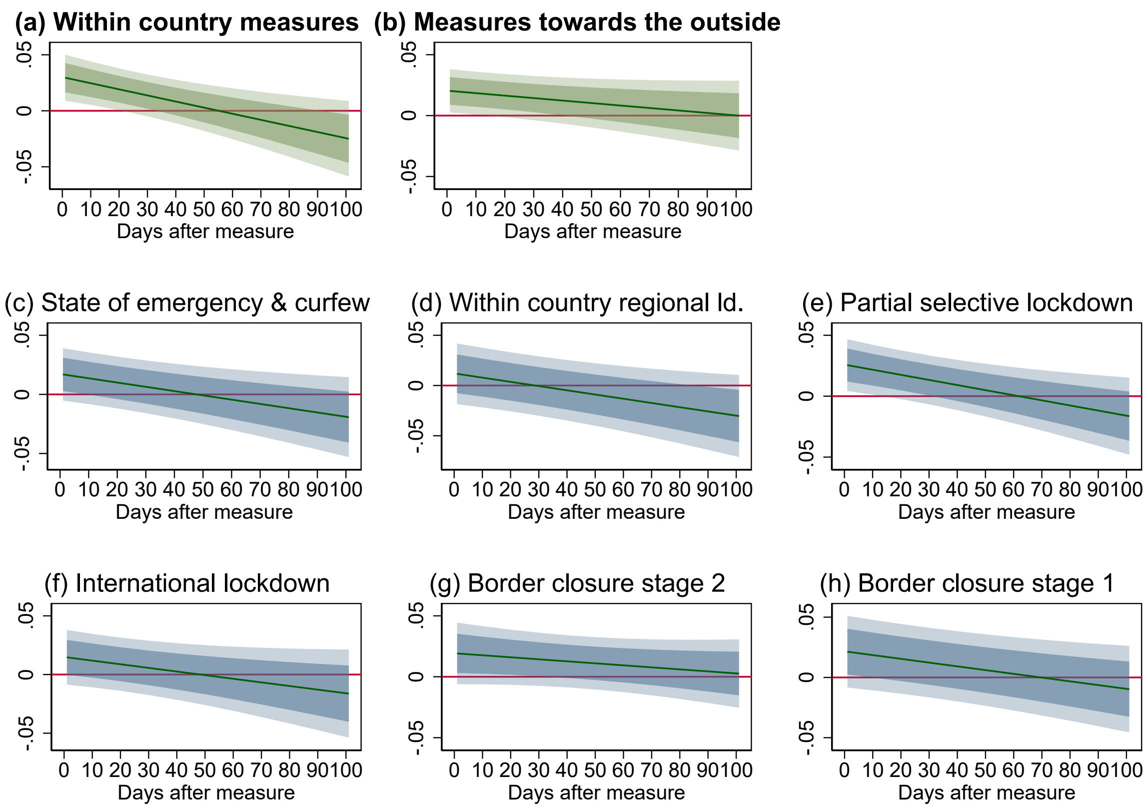

Figure S3: Marginal effect on growth rate of covid19 cases. Within country measures revealed to be more efficient than measures towards the outside with respect to their effect on the spread of the virus. Each sub figure show the impact of a lockdown on the growth rate of infections as a function of time since the measure was implemented. Marginal effects computed with our autoregressive model of order 1. 90% and 99% confidence intervals are shown in different shades of blue or green.

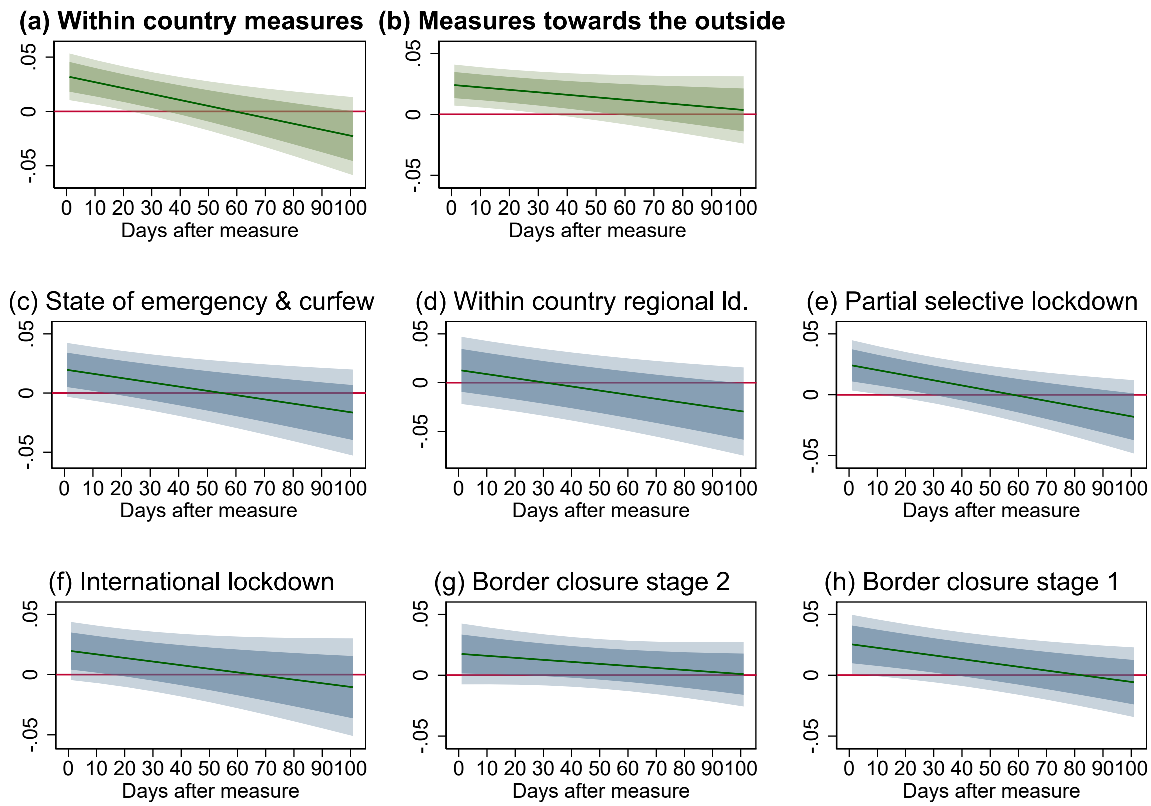

Figure S4: Marginal effect on growth rate of covid19 cases. Within country measures revealed to be more efficient than measures towards the outside with respect to their effect on the spread of the virus. Each sub figure show the impact of a lockdown on the growth rate of infections as a function of time since the measure was implemented. Marginal effects computed with our autoregressive model of order 1. 90% and 99% confidence intervals are shown in different shades of blue or green.

E.2 Extension: Developed vs. Developing

E.2.1 Number of reported cases

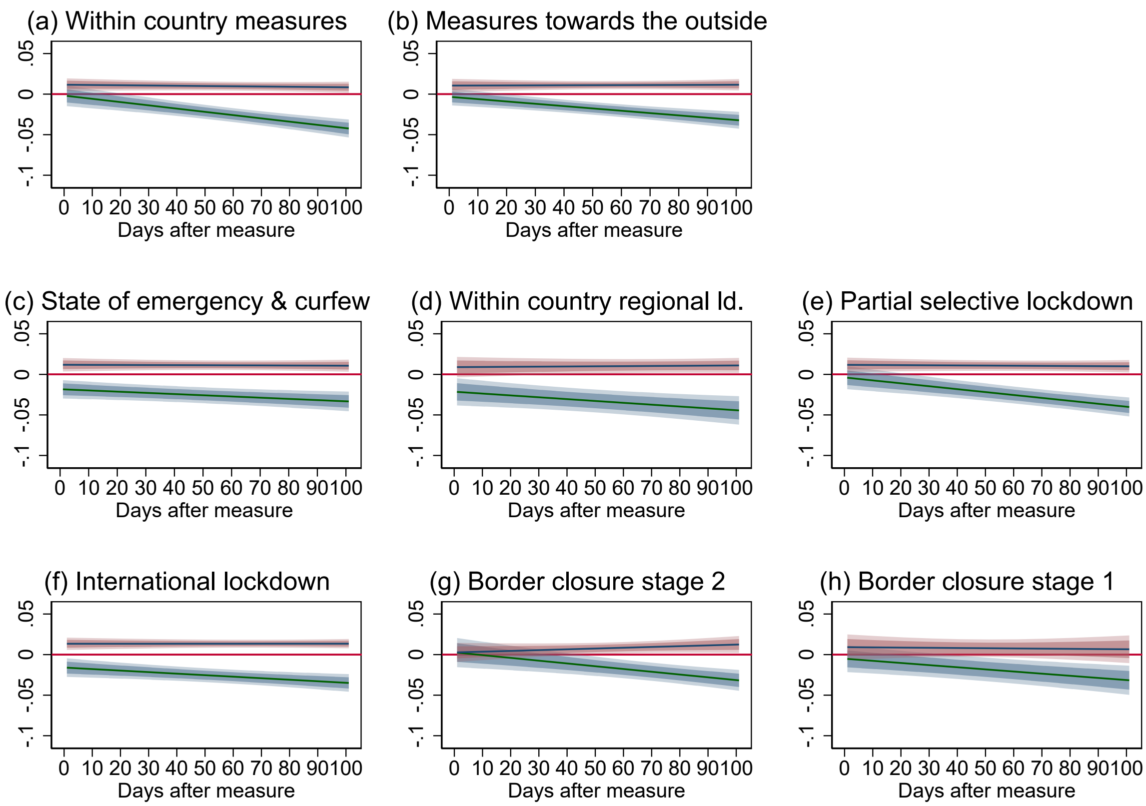

Figure S5: Lockdowns revealed to be efficient solely for developed country. Developing countries are those with Human Development Index values of up to 0.699 (marginal represented in red), which refers to Low and Medium human development using the United Nation codebook definition while those with values above 0.699 will be defined as developed countries (marginal represented in blue). Marginal effects computed with our autoregressive model of order 1. Panel (a) to (f) show the impact of a measure on the growth rate of infections as a function of time since the measure was implemented. 90% and 99% confidence intervals are shown in different shades of red or blue.

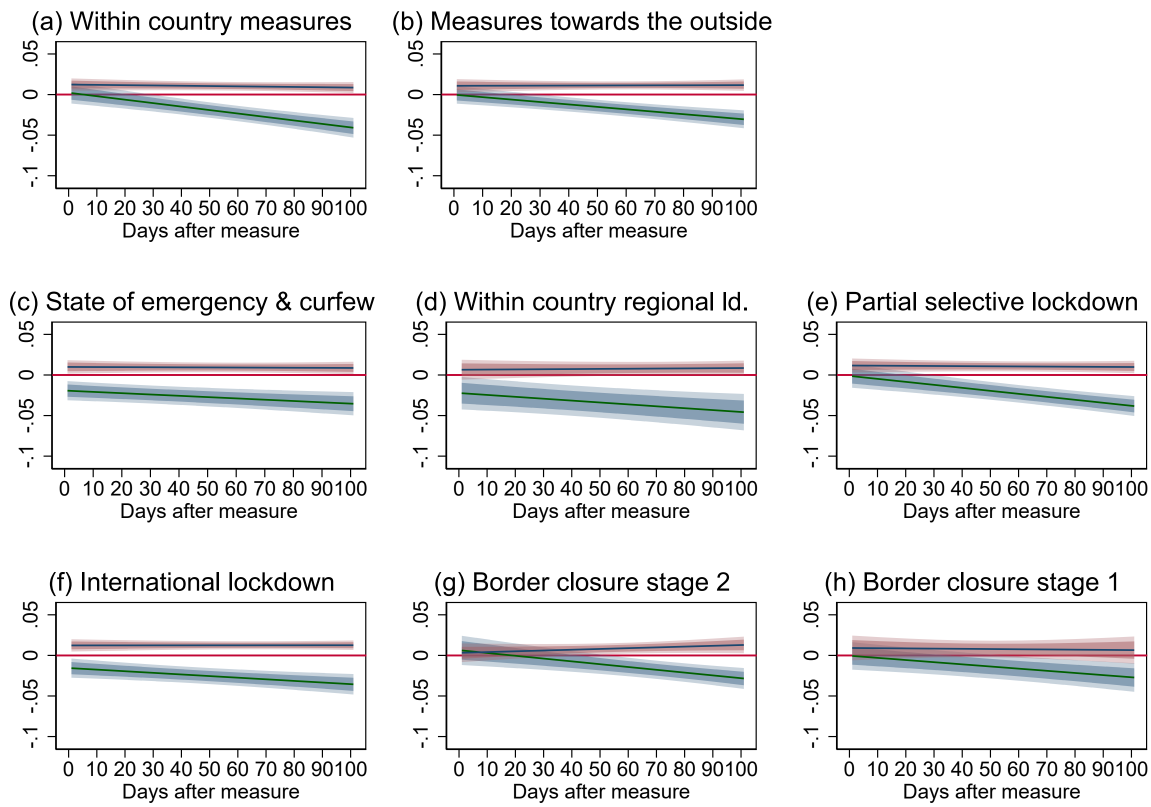

Figure S6: Lockdowns revealed to be efficient solely for developed country. Developing countries are those with Human Development Index values of up to 0.699 (marginal represented in red), which refers to Low and Medium human development using the United Nation codebook definition while those with values above 0.699 will be defined as developed countries (marginal represented in blue). Marginal effects computed with our autoregressive model of order 1. Panel (a) to (f) show the impact of a measure on the growth rate of infections as a function of time since the measure was implemented. 90% and 99% confidence intervals are shown in different shades of red or blue.