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Do Coronavirus Containment Measures Work?

Worldwide Evidence

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Abstract

Using a daily data base covering 158 countries during January to August 2020, this paper assesses the effectiveness of coronavirus containment measures in reducing contagion and death rates. To estimate the effectiveness of different containment measures, the paper uses a methodological approach that takes into consideration the persistence in the dynamics between coronavirus containment measures and contagion/death rates, countries' idiosyncratic characteristics, and the endogeneity of the containment measures. To obtain efficient estimates of the effect of coronavirus containment measures on contagion and death rates, a dynamic panel-data technique is used, complemented by efficient instruments for the decision of adopting coronavirus containment measures. The results show that countries with better health systems, higher temperatures, and more democratic regimes tended to delay the adoption of coronavirus containment measures. The results also detect demonstration effects as the early adoption of coronavirus containment measures in Western Europe led other countries to accelerate their adoption. Using predictions from the estimated model, it is possible to benchmark the timing of adoption of coronavirus containment measures and assess whether their adoption was timely or not and if they were lifted prematurely or not. The findings of this exercise show that countries with timely adopted coronavirus containment measures restricted activities, meanwhile they lagged in the adoption of measures restricting individual liberties. The evidence indicates that most countries resisted the urge to lift restrictions in advance, once they have been in place: over 60 percent of the countries have reacted as predicted by our econometric models, maintaining coronavirus containment measures in place until contagion rates receded. Nevertheless, around one-quarter of the countries lifted their restrictions one month or more ahead of what the worldwide evidence would have suggested, in particular by removing lockdowns and re-opening workplaces. Finally, the results show that coronavirus containment measures have been effective in reducing contagion and death rates, but there are differences in the effectiveness among them, and restrictions on activities have been more effective than restrictions on personal liberties.

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1. Introduction

Since the first case reported at the end of December 2019 in China, COVID-19 has quickly spread to 180 countries, sickened more than 50 million people and killed more than 1.2 million. At the end of January, the first confirmed cases outside mainland China occurred in Japan, the Republic of Korea and Thailand. In February, Europe faced its first major outbreak and became the epicenter of the epidemic. The Islamic Republic of Iran emerged as a second focus point at that time. In March and April major outbreaks happened in the United States and Latin America. South Asia viewed the rate of contagion and deaths to have accelerated since July, while the incidence of COVID-19 cases and related deaths in Africa has been limited so far.

Governments worldwide have adopted coronavirus containment measures (hereafter, CCMs) to slow down the rate of contagion and avoid the overwhelming of their health systems. CCMs include a variety of measures that can be classified in two main groups: CCMs that mainly restrict the mobility and contacts among individuals, including stay at home, bans on gatherings and public events, and mobility restrictions; and those that limit activities such as closing schools, lockdowns of workplaces, interruption of public transportation services, and international border closures. The objective of these measures has been to flatten the epidemiological curve to enable health systems to adequately care for patients and reduce the number of deaths.

The effectiveness of CCMs adopted to contain the spread out of COVID-19 worldwide has been mixed so far. Some countries have timely and successfully adopted containment measures and have seen a significant slowdown of contagion rates and limited the number of deaths, which enabled the relaxation of these measures. Other countries took more time to adopt CCMs and faced more difficulties in flattening contagion rates. Moreover, initially successful countries have seen a second spike in contagion rates which forced them to resume more restrictive containment measures.

Assessing the effect of government CCMs on contagion and death rates requires addressing three methodological issues. First is the strong persistence in the relation between containment measures and contagion/death rates which requires the use of models that incorporate dynamic effects. Second, countries have idiosyncratic characteristics which are unobservable which may affect the adoption of CCMs and their effectiveness. The third is that there is a reverse causation and endogeneity, since governments may decide to adopt CCMs as a result of the acceleration of contagion and death rates. Dynamic panel data models can be used to address the persistence and country-specific issues, but their results are hampered by endogeneity problems. Therefore, to obtain efficient estimates of the effect of CCMs on contagion and death rates, the dynamic panel-data techniques need to be complemented by the use of efficient instrumental variables for the choice of adopting CCMs.

To efficiently estimate the effectiveness of the different CCMs adopted worldwide, the paper proposes a methodological approach that addresses these three issues. The proposed methodology consists of three stages. In the first stage, we use maximum likelihood to estimate a Probit model of the determinants of having a CCM in place and compute the predicted probability of adopting CCMs. The predicted value of this model is a valid, yet inefficient, instrument for the CCM. To obtain and efficient instrument, in the second stage, we regress the predicted probability of adopting CCMs on a set of control variables and compute the residual values of the predicted probability of adopting CCMs. This step ensures the conditional independence (orthogonality) assumption that is crucial to identify in a causal manner the role of CCM on contagion and death rates. Finally, in the third stage, we regress the contagion and death rates on the control variables and the residual values of the predicted probability of adopting CCMs.

The proposed methodology enables to address three questions regarding the adoption and effect of CCMs on COVID-19 contagion and death rates:

- What factors influence the governments' decisions to adopt and lift CCMs?
- How timely have governments been in adopting CCMs and how prematurely have they lifted them?
- How effective have CCMs been in reducing contagion and death rates?

The findings of the econometric analysis show that overall governments have been sensitive to the acceleration of contagion and death rates and have adopted CCMs, particularly those that limit the mobility and social contact among individuals. Our econometric results confirm that, on average, higher contagion and death rates tend to increase the probability of adoption of CCMs. In addition, the results suggest that countries with better health systems tend to delay the adoption of CCMs. But the dynamics of the pandemic also plays a role: since the availability of human resources in health systems is somewhat inelastic in the short run, as the cases and casualties mounted, the authorities were forced to adopt CCMs in order to reduce the stress and avoid a collapse of the health system. Results also show that higher temperature and more democratic regimes tend to delay the adoption of CCMs. External pressures reflected in the stringency of CCMs in Western European countries provided for a demonstration effect that led other countries to accelerate the adoption of CCMs.

Findings on the timing of adoption of CCMs show that generally countries have timely adopted CCMs restricting activities, meanwhile they have lagged in the adoption of CCMs restricting individual liberties. Using predictions from the estimated models, it is possible to benchmark the timing of adoption of CCMs and assess if they were adopted timely or not and if they were lifted prematurely or not. Around 70% of countries closed schools and public transportation at the time the models predicted such measures ought to have been implemented. Less timely was the adoption of border closures and banning public events, as between 55 to 60 percent of countries adopted them on time. The benchmarking exercise shows that only 30 percent of the countries adopted measures forcing the population to stay at home and banning meetings in a timely manner.

Results of the estimations suggest that overall CCMs have been effective in reducing the rate of contagion and deaths. Results also show differences in the effectiveness of the different CCMs that have been adopted. Restrictions on activities seem to be more effective than restrictions on personal liberties. Closing schools, workplaces and international borders have a very strong containment effect. The adoption of these CCMS would have reduced the rate of daily cases by around six to eight percentage points 14 days after their implementation, but, interrupting public transport services seems to have had no effect whatsoever on daily cases. Restrictions on personal liberties such as stay at home or banning meetings and public events would have reduced the rate of daily cases by 5 percentage points. Results also show that the CCMs have been effective in reducing daily death rates. However, in this case, the stress of health systems capacity reflected in the rate of daily COVID-19 cases to doctors and nurses also played a critical role in increasing the number of fatalities.

The paper is organized in five sections including this introductory one. Section 2 briefly presents the main global trends of contagion and death rates since the outbreak of the COVID-19 pandemic, highlights regional differences in the evolution of the pandemic, and provides a snapshot of the containment measures adopted by governments to reduce the spread of the pandemic. Section 3 describes the econometric methods used in the identification of the factors influencing the governments' decision to adopt CCMs, their timing and the effectiveness of the different CCMs. Section 4 describes the main results of the estimations. Finally, section 5 summarizes the findings and underlines their policy implications.

2. Global and Regional Trends of COVID-19 and Government Responses

By end of August 2020, COVID-19 had infected almost 25 million people globally and caused nearly one million deaths since it emerged in late 2019.[1] The outbreak was initially centered in Hubei province in China, but it soon shifted to other epicenters, including the Islamic Republic of Iran; northern Italy; Spain; and New York. Cases worldwide leveled off in April after social distancing measures were put in place in many of the areas with early outbreaks (Figure 1). But as countries began to reopen in May and June, the United States, Latin America and the Caribbean (LAC), and the Middle East and North Africa (MENA) have seen a resurgence of COVID-19 cases (Figure 3).

The rapid increase in COVID-19 cases has caused a significant loss of life and overwhelmed many health systems. The daily new cases of COVID-19 deaths peaked globally at 244 per million by the beginning of April, largely driven by Western Europe, LAC and Europe and Central Asia (ECA) (Figure 4). However, as strict lockdowns were adopted, countries managed to contain the mortality rate and, as a result, daily COVID-19 deaths dropped by 50% by the end of August (Figure 3). Most of these deaths could have been caused not by the disease itself, but by the further strain on health care systems. This is particularly true for countries where health systems were unable to cope with the surge in demand due to the lack of health care workers, medical equipment and supplies.

[1] Data on cases and deaths used in our study, which covers the period January 1 to August 31, 2020, were obtained from Hale et al. (2020).

Figure 1: New reported cases by day across the world

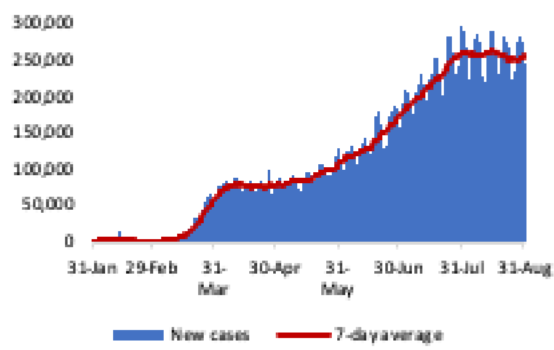


Figure 2: Total confirmed COVID-19 cases across regions

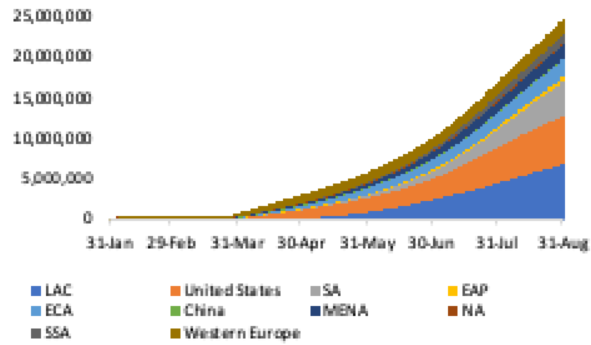


Figure 3: New reported COVID-19 cases across regions
(per million people, 7-day rolling average)

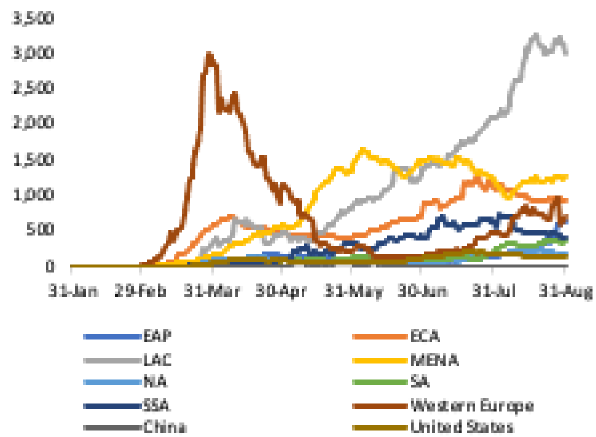
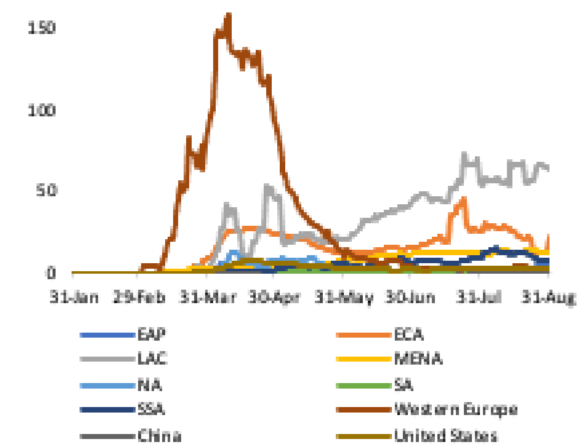


Figure 4: New daily COVID-19 deaths across the world
(per million people, 7-day rolling average)



Source: Authors' calculations using data from Hale et al. (2020)

In order to slow down the rate of contagion and avoid overwhelming their health systems, governments worldwide have adopted coronavirus containment measures. According to the taxonomy defined by the Oxford COVID-19 Government Response Tracker (OxCGRT), CCMs include a variety of measures that can be classified in two main groups: CCMs that mainly restrict individual liberties to prevent social contact include stay at home orders, bans on gatherings and public events and mobility restrictions; and those that limit activities such as closing schools, lockdowns of workplaces, interruption of public transportation services and closures of international borders. Countries varied on the type of CCMs that have been adopted and how quickly they were able to adopt them and also the timing of their lifting.

In general, government responses have become stronger over the course of the outbreak, particularly ramping up over the months of April and May (Table 1). By April 1, among the 186 countries included in our analysis, 168 (90%) required school closing at all levels; 168 (90%) required canceling of public events; 124 (67%) closed their international borders; 124 (67%) put in place internal movement restrictions; 99 (53%) restricted gatherings of

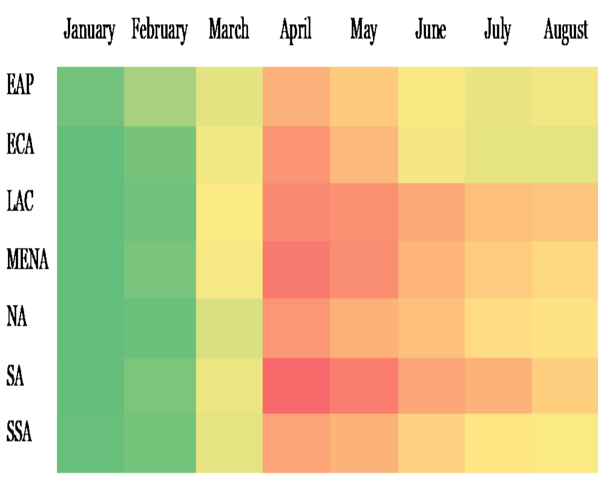
10 people or less; 94 (51%) required closing of workplaces (or work from home) for all-but-essential workplaces (e.g. grocery stores, doctors); 70 (38%) closed or prohibited most citizens from using public transport and 24 (13%) required their citizens no to leave their houses with minimal exceptions (Figure 5).

Since May, stringency levels eased, and governments started rolling back some of the measures particularly in East Asia and Pacific (EAP) and Europe and Central Asia (ECA). Latin America and the Caribbean (LAC) together with South Asia (SA) and Middle East and North Africa (MENA) continued to show higher stringency levels compared to the rest of the regions until the end of August. This can be explained by the fact that these regions continued to show persistently high daily new COVID-19 cases compared to the rest of the world.

The response measures were expected to broadly track the spread of the disease. By June 15, most of the countries had lifted stay at home requirements; public transport, workplace closing and international travel restrictions. But a number of other measures stayed in place until the end of August such as the cancellations of public events (57% of countries); school closings (41%); internal movement restrictions (38%) and restrictions on gatherings (32%) (Figure 5).

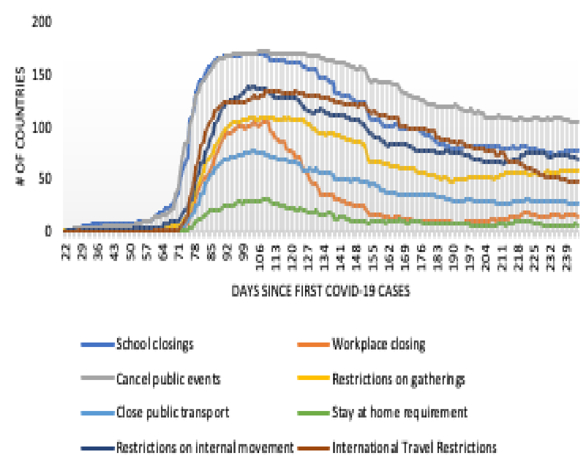
However, the timing at which such measures were adopted has played a critical role in the containment of the contagion and death rates. Some governments immediately ratcheted up measures as the outbreak spread, while in other countries the increase in the stringency of responses lagged the growth in contagion rates. Furthermore, some countries lifted CCMs early and saw a resurgence of cases. As governments continue to respond to COVID-19 it is important not only to look at the timing, but also to the effectiveness of the different types of CCMs that have been adopted. These important dimensions will be studied in the following section of the paper.

Figure 5: The Oxford Covid-19 Government Response Tracker (OxCGRT)



*No measures (Green) to Total Lockdown (Red)

Figure 6: Number of countries implementing (CCMs)



Source: Authors' calculations using data from Hale et al. (2020)

3. Methodology

Assessing the impact of CCMs on the number of cases and casualties requires addressing three relevant challenges: (a) the number of cases and casualties tend to display high persistence, thereby necessitating the use of dynamic models, (b) countries are highly idiosyncratic regarding unobservable features in their health systems and the characteristics of the population, indicating the existence of individual country effects, and (c) reverse causation and endogeneity are very likely, since governments may decide to implement CCM as a result of the evolution of the disease. Dynamic panel data models can be used to address the first two issues, but their results are hampered by the third. Therefore, we complement dynamic panel-data techniques with the use of efficient instruments for the choice of implementing CCMs.[2]

Unveiling the impact of CCMs on the pandemic can be cast as the study of whether a treatment (implementing a CCM) has any discernible effect on pandemic outcomes in country "i" at time "t", which we denote generically by Out_{it}. Outcomes include the number of daily cases and deaths (in logs). A general model is:

(1) $$Out_{it} = f(\alpha_i, x_{it}, CCM_{it}, Out_{it-1})$$

where parameter α_i reflects cross-sectional heterogeneity (i.e., individual effects), x_{it} represents the set of control variables (other than the CCM), and CCM_{it} denotes the implementation of a CCM. The presence of Out_{it-1} indicates the dynamic nature of the model, which captures the inertial component of the disease.

Identifying causal effects from the observed data depends on the validity of the identification assumptions used in the empirical approach. In our context, this would indicate the need of properly specifying the determinants of the outcomes, as well as controlling for potential endogeneity of the CCM (Jordá and Taylor, 2016). This, in turn, requires separating the determinants of the outcome from those that led to the adoption of such CCM. In what follows we first address the issue of the modeling strategy for the treatments (i.e., the implementation of the CCM) and later the issue of potential endogeneity of the CCM and other controls that co-determine the outcomes.

a. CCMs as Treatments

In principle, the analysis of the effects of policy variables on the outcomes of interest should consider the intensity of such policies and would suggest the use of continuous variables. The adoption of a CCM, on the contrary, can be viewed as a discrete, once-and-for-all event (under the assumption that such measure does not change in time). It seems therefore appropriate to use a dummy variable (D_{it}) taking value 1 whenever the CCM is in

[2] Data on CCMs only indicate whether containment measures have been enacted or not, but they do not inform on the enforcement of such measures by the government.

place and zero otherwise. We assume that such policy is determined by a set of control variables (denoted by w_{it}), that would include historical data on the outcomes and other variables that may influence the adoption of the CCM. Modeling the adoption of the CCM takes the form $D_{it} = D(w_{it}, \psi_i, \varepsilon_{it})$, where ψ_i refers to the parameters of the implied policy function and ε_{it} is an idiosyncratic source of random variation. The potential impact of the CCM can be measured by the value that the observed outcome would take when the CCM is not adopted ($D_{it} = 0$) and when it is ($D_{it} = 1$). Considering that the impact of a CCM on the evolution of the pandemic might take time to yield its results, in the empirical section we look for the effects on daily cases and casualties 14 days after the adoption of each CCMs (two weeks is the average incubation period of coronavirus).

Consider now expressing equation (1) in linear form:

$$(2) \qquad Out_{it} = \alpha_i + \beta_i x_{it} + \theta D_{it} + \gamma Out_{it-1} + u_{it}$$

Standard panel data estimators, such as pooled or fixed-effects models, yield inconsistent estimates because there would be correlation between Out_{it-1} and the error term u_{it} via the unobservable individual effect, α_i (Nickell, 1981). One solution to this problem involves taking first differences (Δ) of the original model.

$$(3) \qquad \Delta Out_{it} = \beta_i \Delta x_{it} + \theta \Delta D_{it} + \gamma \Delta Out_{it-1} + \Delta u_{it}$$

First differencing removes the individual effect (and any other country specific, time invariant variable) at the cost of inducing correlation between the differenced lagged dependent variable ΔOut_{it-1} and the disturbance process Δu_{it} (the former contains Out_{it-1} and the error term contains u_{it-1}). Nonetheless, as the individual fixed effect is removed, instrumental variables estimators can be used. As shown by Anderson and Hsiao (1981) and Arellano and Bond (1991), second and third lags of Out_{it}, either in the form of differences or levels can be used as instruments.

The methodology described above enables an unbiased estimation of the parameters of the model. However, appropriate estimation of θ requires the effect of the CCM –that is $Out_{it}(D_{it} = 1) - Out_{it}(D_{it} = 0)$ –to be orthogonal to the determinants of the containment measure $D_{it}|w_{it}$. This conditional independence assumption plays an important role and allows us to identify the average causal effect of a policy intervention relative to a baseline value of the outcome variable (Jordá and Taylor, 2016).

b. Endogeneity of Containment Measures

When assessing the effects of CCMs on the pandemic outcome, a legitimate concern is that estimates may be biased because policy instruments are not actually exogenous. While one should expect that imposing CCMs would induce lower contagion rates and casualties of the pandemic, it is quite apparent that CCMs are implemented with an eye on the evolution of the pandemic. If there is reverse causality, the conditional independence assumption fails, and estimates of the model will deliver a biased and inconsistent estimate of θ and of the effects of the CCMs. This is a case known as the endogenous dummy variable problem (Heckman, 1978), which can be applied to the adoption of CCMs since they are imposed precisely as the result of the perceived need of adopting policy measures to achieve or secure policy outcomes.

We address the possible endogeneity of the CCM by using instrumental variables, following Schmidt-Hebbel and Soto (2018). Assuming that we have a set of valid instruments w_{it} for adopting CCM (not including the elements that determine the pandemic outcomes in x_{it}), we can consistently estimate our models by the following a three-stage procedure:

(1) In the first stage, we use maximum likelihood to estimate a Probit model of the determinants of having a the CCM in place and compute the predicted probability $\widehat{CCM}_{it}$. The dependent variable is binary, taking value 1 if the CCM is in place and value 0 otherwise. The predicted value of this model is a valid, yet inefficient, instrument for the CCM.

(2) In the second stage, we regress the $\widehat{\mathrm{CCM}}_{\mathrm{it}}$ on x_{it} using OLS and compute the residual values $\overline{\overline{\mathrm{CCM}}}_{\mathrm{it}}$. This step ensures the conditional independence (orthogonality) assumption that is crucial to identify in a causal manner the role of CCM on the outcomes (Wooldridge, 2002, p. 623).

(3) In the third stage, we regress the different outcome variables, Out_{it}, on x_{it} and the residuals of the second stage, $\overline{\overline{\mathrm{CCM}}}_{\mathrm{it}}$. In this stage we control for a number of independent variables in order to isolate the true contribution of CCM to the different outcomes of the pandemic.[3]

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[3] This procedure is different from the "pseudo-IV" procedure of running an OLS regression of $\mathrm{CCM}_{\mathrm{it}}$ on $\widehat{\mathrm{CCM}}_{\mathrm{it}}$ and x_{it}. In the latter case, consistency is not guaranteed unless the first stage is correctly specified, and the standard errors need to be adjusted. There are many advantages of our approach. First, it takes the binary nature of the endogenous variable into account. Although the two-stage least squares consistency of the second stage does not hinge on getting the functional form right in the first stage (see Angrist and Krueger, 2001), two-stage least squares leads to biased estimates in finite samples and it is not known how misspecification in the first stage may affect this bias. Second, unlike some of the alternative procedures, it does not require the binary response model of the first stage to be correctly specified. Third, although some

Probit panel-data models are used to generate a suitable instrument for each of the eight CCMs, separately. The general specification for the models is:

$$\text{(4)} \quad \Pr(y_{it} = 1) = \alpha_i + \beta_1 Cases_{it} + \beta_2 Deaths_{it} + \beta_3 DSO_{it} + \beta_4 DSO_{it}^2 + \beta_5 HCI_{it} + \beta_6 CperPh_{it} + \beta_7 CperNr_{it} + \beta_8 Temp_{it} + \beta_9 Democracy_{it} + \beta_{10} DemEffect_{it} + \varepsilon_{it}$$

where $y_{it} = 1$ indicates that at time *t* the country implemented the CCM. Parameter α_i indicates the existence of idiosyncratic characteristics at the country level, that prompts the use of the random effects models to avoid biasing the estimation.

We include the same set of control variables when modeling the probability of a country having implemented a CCM. The first two controls are the number of daily cases and daily deaths, for which we naturally expect $\beta_1, \beta_2 > 0$. By nature, pandemics tend to spread in the population with an "S" shape which, in turn, depends on the time elapsed since the beginning of the contagion period (see Gatto et al, 2020; Scally 2020). We use the time in days elapsed since the outbreak (i.e., the date when the first case was officially reported in each country), which we label as *DSO*, and its squared value to capture the non-linear diffusion of the disease. Our prior is that $\beta_3 > 0$ and $\beta_4 < 0$.

Response measures to the pandemics reveal, to a large extent, the stance of the health system in each country. Kandel et al (2020) evaluate health security capacities in 182 countries, using 18 indicators that reflect the ability of each country to prevent, detect, and respond to the pandemic, as well as its operational readiness. Their results show that countries vary widely in terms of their capacity to prevent, detect, and respond to outbreaks. Half of all countries analyzed have strong operational readiness capacities in place, which suggests that an effective response to potential health emergencies could be enabled, including to COVID-19. Therefore, we expect that stronger health capacities would allow authorities to deal with the pandemic without necessarily resorting to harsh restrictions on the activities and liberties of the population $\beta_5 < 0$. We proxy health capacities with a *Health Capacity Index* (HCI) which, as described in the appendix, comprises of a standardized measure of the health personnel, infrastructure and financial resources available in each country at the start of the pandemic.

In addition to the general state of the health system, we also control the pressure on health systems caused by the increase in cases. Indeed, we include time-varying stress levels of health workers by including the number of daily infections per physician and per nurses, which we label as *CperPh* and *CperNr*, respectively. As noted by Ma et al. (2020) and others, health care professionals caring for COVID-19 patients have been contaminated or experienced substantial psychological distress. Authorities ought to take into consideration the stress levels of health workers when assessing the implementation of a CCM and we expect that more stressed systems tend to increase the probability of adoption of CCMs ($\beta_6, \beta_7 > 0$).

Temperature has also been identified as a potential accelerant of the spread of the disease. Both epidemiological and laboratory studies have shown that ambient temperature could affect the transmission and survival of coronaviruses. Xie and Zhu (2020) find that

regressors are generated in the first stage, the standard IV standard errors are still asymptotically valid (Wooldridge, 2002).

temperature played a significant role for the spread of COVID-19 in 122 cities in China. Holtmann et al. (2020) also find that weather conditions affect the initial stages of the spreading of Coronavirus in 47 countries, with higher temperatures leading to slower spreading. While ambient temperatures may affect the COVID-19 survival in the environment, it is also possible that a population confined to indoor activities is more susceptible to the infection. We thus control for the minimum temperature (*Temp*) recorded each day in each country and expect that higher temperatures may induce governments to delay the adoption of CCMs ($\beta_8 < 0$).

Given that most of the CCMs entail the curtailing of individual liberties and the pandemic has a global nature, political regimes and external pressures or demonstration effects from outside may also influence the adoption of CCMs. More democratic regimes may find difficulties in restricting individual liberties affecting mobility and social contact, while autocratic regimes tend to be more able to apply tighter restrictions to contain the pandemic. We control for a measure of democracy levels obtained from The Economist (2020) database and expect $\beta_9 < 0$. In addition to internal pressures to implement or delay the adoption of CCMs, authorities have faced international pressure and learned from the experience of other countries in dealing with the pandemic. In particular, the adoption of stringency measures in Western European countries, which were among the first to suffer from massive contagion, influenced the speed at which other countries implemented CCMs. We use a measure of the stringency of CCMs in 26 European economies as a demonstration effect for the adoption of CCMs in the world and expect $\beta_{10} > 0$.[4]

4. Econometric Results

a. Adoption of CCMs

The econometric results of our estimations for the adoption of CCMs are presented in Table 1. We have grouped the results according to the two categories described above (those that mainly restrict individual liberties reducing mobility and social contacts and those that limit activities). Tests indicate that there is evidence of country heterogeneity (individual effects are not zero as shown in the high proportion of total variance due to panel-level variance) and that Panel-Probit techniques are required to ensure an adequate specification. The models present a reasonable fit to the observed data, as shown in McKelvey & Zavoina's pseudo R^2 indicators, ensuring that our instruments are highly –but not perfectly—correlated to the CCM.

The results match the theoretical priors and most right-hand-side variables are statistically significant. The evidence supports the above discussion on the determinants of having pandemic control measures in place. As expected, as the number of cases and casualties increases there is a higher probability of countries adopting CCMs, particularly those that limit the mobility and contact of individuals. In the same vein, we found that the number of days

[4] Included countries are Andorra, Austria, Belgium, Cyprus, Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Iceland, Ireland, Italy, Latvia, Lithuania, Luxembourg, the Netherlands, Norway, Portugal, the Slovak Republic, Spain, Sweden, Switzerland and Great Britain.

elapsed since the outbreak of the pandemic in each country is an important determinant of the adoption of all CCMs and that the relationship is nonlinear as theorized.

Results regarding the influence of health systems capabilities on the decision of adopting CCMs are also consistent with our expectations. We found that in general countries with better health systems tend to delay the adoption of CCMs, as expressed in the negative estimated parameters in all cases, reflecting their larger capacity to cope with the demands of medical attention of those in need. But the dynamics of the pandemic also play a role: since the availability of human resources in health systems is somewhat inelastic in the short run, as the cases and casualties mounted, the authorities were forced to adopt CCMs in order to avoid a collapse of health systems and reduce the stress over physicians and nurses. As shown in Table 1, in many of the CCM models our stress variables are statistically significant and positively correlated with the adoption of CCMs (such as lockdowns, banning public events and closing of schools and workplaces). Some estimated parameters are not significant or display a negative sign, attesting to the crudeness of our stress measures.

Finally, we obtained the expected results for the three additional exogenous variables. On one hand, we found that higher temperatures reduce the likelihood of adopting any CCM, a result which is in line with previous evidence as discussed above. On the other hand, we also found that the stringency of the CCMs in Western European provided for a demonstration effect in the rest of the world, leading other countries to accelerate the adoption of containment policies. Finally, we found that adoption of most of the CCMs has been negatively correlated with the Democracy Index, suggesting that restricting individual liberties and activities may be easier in countries where governments concentrate power and do not have to be concerned with the political costs of adopting CCMs.

Table 1. Instrumenting Coronavirus Measures

	Restrictions on Personal Liberties			
	Stay at Home (lockdowns)	Cancelling Public Events	Ban on Private Gatherings	Restrictions on Movements
Daily cases (thousands)	0.137***	0.364***	0.129***	0.160***
	(0.0187)	(0.0528)	(0.0139)	(0.0197)
Daily deaths	0.00304***	-0.000911	0.00247***	-0.000172
	(0.0003)	(0.0005)	(0.0003)	(0.0002)
Days elapsed since outbreak	0.0166***	0.0146***	0.0136***	0.0201***
	(0.0010)	(0.0011)	(0.0009)	(0.0009)
Days elapsed since outbreak squared	-0.0000313***	-0.0000513***	-0.0000155***	-0.0000495***
	(0.00000352)	(0.00000397)	(0.00000344)	(0.00000330)
Health Capacity Index	-0.627***	-2.552***	-5.037**	-3.440***
	(0.144)	(0.194)	(0.143)	(0.152)
Daily cases/doctors	0.0441***	0.618***	-0.129***	0.0143
	(0.0216)	(0.0690)	(0.0109)	(0.0172)
Daily cases/nurses	0.0155	0.173	-0.0462**	0.116***
	(0.0217)	(0.158)	(0.0187)	(0.0217)
Temperature (min)	-0.0607***	-0.0665***	-0.0510***	-0.0599***
	(0.0022)	(0.00286)	(0.0022)	(0.0021)
Democracy Index	-0.227***	-0.214***	0.108***	0.00477
	(0.008)	(0.0132)	(0.0086)	(0.0073)
Demonstration Effect	0.0661***	0.0774***	0.0621***	0.0579***
	(0.0012)	(0.00127)	(0.0011)	(0.0009)
Constant	-2.710***	-1.323***	-3.186***	-2.792***
	(0.113)	(0.0866)	(0.0878)	(0.0821)
Observations	*31,065*	*31,065*	*31,065*	*31,065*
Number of Countries	*158*	*158*	*158*	*158*
Proportion of total variance due to panel-level variance	*0.570*	*0.588*	*0.610*	*0.554*
Pseudo R^2	*0.652*	*0.875*	*0.561*	*0.604*

Note: Standard errors in parentheses, * p<0.1, ** p<0.05, *** p<0.01

Table 1. Instrumenting Coronavirus Measures (contd.)

Closing of Activities

	Schools	Workplaces	Public Transportation	International Borders
Daily cases (thousands)	-0.4790***	0.1000***	0.0989***	-0.00556***
	(0.0564)	(0.0216)	(0.0164)	(0.00102)
Daily deaths	0.0410***	0.0003	0.0016***	0.0013***
	(0.003)	(0.0003)	(0.0003)	(0.0002)
Days elapsed since outbreak	0.0102***	0.0223***	0.0128***	0.0071***
	(0.0013)	(0.0010)	(0.0012)	(0.0009)
Days elapsed since outbreak squared	-0.000022***	-0.000031***	-0.000036***	-0.000035***
	(0.00000475)	(0.00000351)	(0.00000430)	(0.00000328)
Health Capacity Index	-1.674***	-1.219***	-5.035***	0.299*
	(0.171)	(0.173)	(0.196)	(0.161)
Daily cases/doctors	0.371***	-0.0098	0.0038	0.087***
	(0.120)	(0.0175)	(0.0136)	(0.0232)
Daily cases/nurses	2.343***	0.409*	*0.263***	0.136***
	(0.348)	(0.0217)	(0.0252)	(0.0230)
Temperature (min)	-0.0655***	-0.0636***	-0.0228***	-0.0041***
	(0.0033)	(0.0024)	(0.0023)	(0.0019)
Democracy Index	-0.130***	-0.202***	-0.348***	-0.0730***
	(0.0125)	(0.0085)	(0.0088)	(0.0088)
Demonstration Effect	0.0840***	0.0867***	0.0582***	0.0508***
	(0.0014)	(0.0015)	(0.0013)	(0.0009)
Constant	-1.238***	-3.302***	-2.381***	-0.545***
	(0.0943)	(0.1150)	(0.1090)	(0.0617)
Observations	*31,065*	*31,065*	*31,065*	*31,065*
Number of Countries	*158*	*158*	*158*	*158*
Proportion of total variance due to panel-level variance	*0.623*	*0.503*	*0.588*	*0.532*
Pseudo R^2	*0.956*	*0.746*	*0.646*	*0.434*

Note: Standard errors in parentheses, * p<0.1, ** p<0.05, *** p<0.01

b. Timing of Adoption and Lifting of CCMs

We use the Probit models to create benchmarks that allow us to investigate if CCMs were put in place at the right time and/or whether they were lifted ahead of time. Using the estimated models, we predict the day when countries should have adopted or lifted each CCM. If the model-predicted probability is above 50%, we conclude that the country ought to have implemented the CCM.[5] If the probability is less than 50%, we conclude that the CCM should have been lifted, conditional on it being in place in the first place. We then compare whether, according to our models, the country was late in adopting such CCM or early in removing it. The results are presented in Figures 7 and 8 at the global level.

Before discussing the results, it is worth mentioning that countries reacted relatively fast to the pandemic and started implementing CCMs in early March of 2020. By March, the number of cases in the world had not reached 100,000 and the number of deaths did not exceed 10,000 (the majority of them in China). Only one country has not imposed any CCM at the time of writing (Nicaragua). And only two countries –Sweden and Japan—have only implemented Border Closures but not restrictions on mobility or activities for its inhabitants. Among those economies that have implemented CCMs, the most popular are School and Work Closures, enacted in virtually all countries in the world by April 1, 2020.

As can be seen in Figure 7 there are wide disparities in the timing of adoption of the different types of CCMs. It seems that CCMs affecting activities have been timelier adopted than CCMs affecting individual liberties. Around 70% of countries closed Schools and Public Transportation at the time the models predicted such measures ought to have been implemented. Figures increase significantly if we consider those countries adopting the CCM within one week from the predicted data to be "roughly in time" (to 91% and 78% respectively). Less timely was the adoption of Border Closures and Banning Public Events, but still with a high rate of "In time or roughly in time" decisions (over 75%). On the contrary, countries have lagged significantly behind in the adoption of restrictions to civil liberties in the form of lockdowns (stay at home), banning meetings, and restricting internal mobility. Around one-half of the countries were late by more than one week in adopting lockdown measures and banning meetings. While seven days may not seem a long period of time, consider that during the first two weeks of March 2020 – when CCMs were absent in most countries—the ratio of new daily cases to total cases in the world was around 30%. By the last week of March, when CCMs were being rapidly implemented, it has reduced to around 11%.

[5] The 50% mark is, of course, arbitrary. Nevertheless, qualitative results are not affected if the benchmark is made slightly stricter or more lax.

Figure 7
Timing of Adoption of CCMs

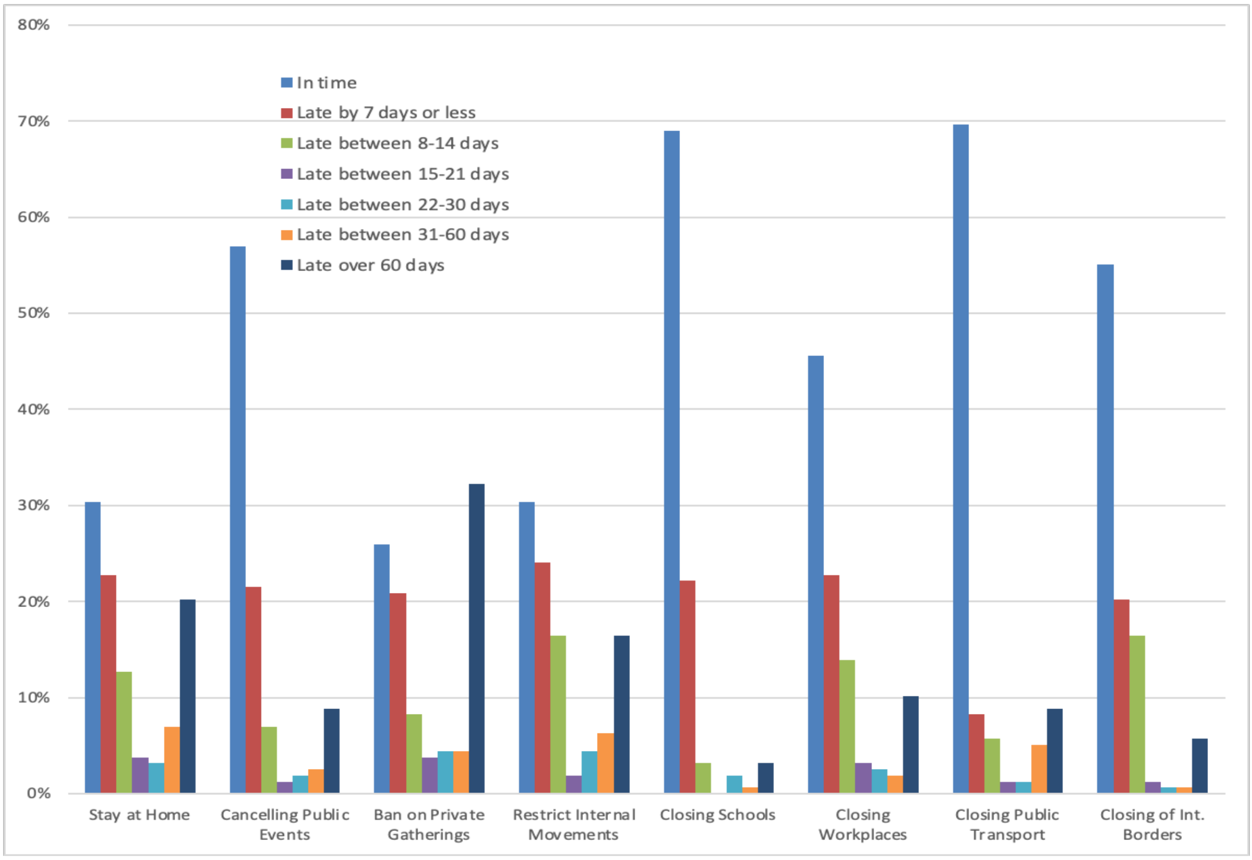
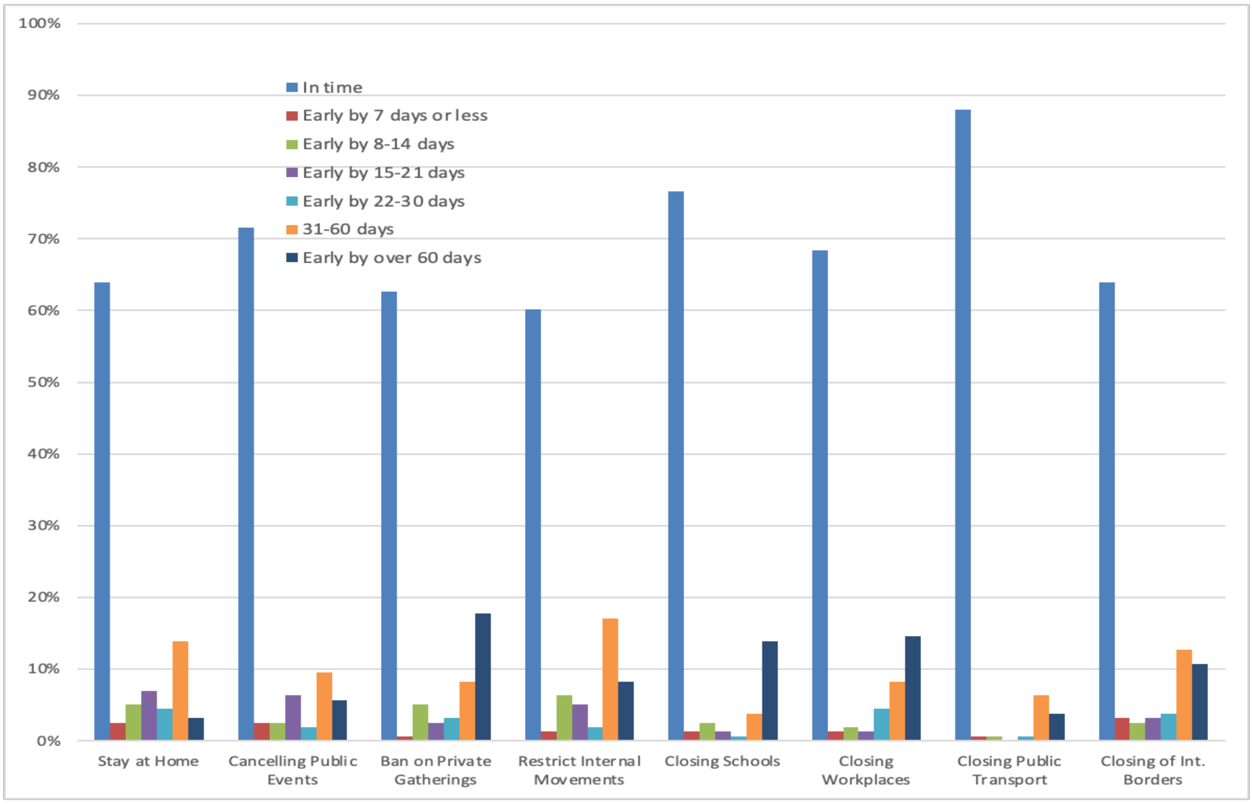


Figure 8 presents the evidence on the timing of lifting CCMs. Since CCMs impose a heavy cost on the economy and the families, pressures to lift restrictions mount over time and governments tend to become increasingly sensitive to these pressures. Nevertheless, it can be seen that most countries have resisted the urge to lift restrictions in advance, once they have been in place: over 60% of the countries have reacted as predicted by our econometric models, maintaining CCMs in place until recommended. Nevertheless, around one-quarter of the countries lifted their restrictions one month or more ahead of what the worldwide evidence would have suggested. This effect is more pronounced in the case of lockdowns, restrictions on internal movements, and closing workplaces.

Figure 8
Timing of Lifting CCMs



c. *Effectiveness of CCMs*

In what follows we assess the effectiveness of CCMs in reducing the number of daily cases and deaths. Given the mechanics of a pandemic, we focus on the effects of the different CCMs on both outcomes 14 days after the containment measures are implemented, in accordance with the average incubation period of the disease (our results, nevertheless, remain qualitatively unaffected if we reduce the incubation period to 10 days).

A second consideration is the persistence of the pandemic: given that the contagion spreads as a function of the number of infected individuals, one should expect significant persistence in both contagion and death rates. Indeed, the primary objective of CCMs is precisely to induce a downward shift in contagion rates and, indirectly, lethality rates. This would call for the use of dynamic panel-data models. Standard estimators (such as Pooled Mean Groups (PMG) by Pesaran et al (1999) and Dynamic Panel Data (DPD) models Arellano and Bond (1991)) are ill-suited for our problem, as the number of countries and time periods is too high for conventional or GMM estimators. Non-stationarity issues, as well as missing data, are difficult to handle in such context. Therefore, we model daily changes in cases and deaths as our variables of interest (ΔOut_{it}) and control for the past level of cases and casualties, in the manner of error-correction models (as shown in equation 5). We also include the diffusion process of the pandemic (represented by the spread variable and its square) as well as our indicators of stress on the health system.

(5) $$\Delta Out_{it} = \alpha_i + \gamma_1 Cases_{it-1} + \gamma_2 DSO_{it} + \gamma_3 DSO_{it}^2 + \gamma_4 CperPh_{\,it} + \gamma_5 CperNr_{\,it} + \gamma_6 Temp_{it} + \gamma_7 \overline{\overline{CCM}}_{it} + \varepsilon_{it}$$

where $\overline{\overline{CCM}}_{it}$ correspond to the efficient instruments obtained using the above procedure.

In Table 2 we present the main econometric results of modeling the rate of daily cases using both the naïve dummy variable model (that is, the case where we ignore the endogeneity of CCMs) as well as our efficient-instrumental variable approach. We focus on the impact of CCMs and omit those of other controls, but full results are in the appendix.[6] Given the high collinearity of CCMs (see Appendix Table 3), we analyze their individual effects and not their collective impact.

The estimated impacts of CCMs are in general very significant in statistical as well as in epidemiological terms, i.e., in their impact on containing contagion and lethality rates. Note, importantly, that the estimated effects using the efficient instrumental variable approach are much larger than those obtained using the naïve dummy variable model, reflecting the bias in the latter. In fact, the estimated parameters of the efficient instruments are between two and six times larger than those of the naïve estimator.

Table 2 shows the effectiveness of each of the eight CCMs. Panel A of Table 2 indicates that Restrictions on Personal Liberties would have reduced the rate of daily cases by around five percentage points 14 days after implementation. Naturally, the effects in each economy depend on the compliance of the population to CCMs, as well as those CCMs being appropriately enforced by the authorities. The estimated effects are an average of the response in the 158 countries in our sample. Panel B of Table 2 shows more heterogeneous effects: while closing schools and workplaces has a very strong containment effect, closing public transport seems to have had no effect whatsoever on daily cases.

[6] Results show that cases and casualties display strong persistence and a slowly declining growth rate that depends in non-linear form on the time elapsed since the outbreak of the pandemic in each country. As expected, a lower number of daily cases per physician and/or nurse also tends to reduce contagions and deaths. We do not find strong evidence that temperatures have any systematic effect of COVID-19 casualties and/or deaths.

Table 2. Daily Cases
Panel A: Restrictions on Personal Liberties

	Dummy Variable	Efficient Instrument	Dummy Variable	Efficient Instrument	Dummy Variable	Efficient Instrument	Dummy Variable	Efficient Instrument
				Additional Controls Omitted				
Stay at Home	-0.0147***	-0.0445***						
	(0.00387)	(0.00941)						
Ban Meetings			-0.0133**	-0.0478***				
			(0.00406)	(0.0104)				
Ban on Public Events					-0.0219***	-0.0511***		
					(0.00472)	(0.00934)		
Restrictions on Movements							-0.0121***	-0.0515***
							(0.00337)	(0.0115)
Observations	26,973	25,359	26,973	25,359	26,973	25,359	26,973	25,359
Countries	158	158	158	158	158	158	158	158
Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Panel B: Restrictions on Activities

	Dummy Variable	Efficient Instrument	Dummy Variable	Efficient Instrument	Dummy Variable	Efficient Instrument	Dummy Variable	Efficient Instrument
				Additional Controls Omitted				
Close Schools	-0.0290***	-0.0791***						
	(0.00543)	(0.0131)						
Close Workplaces			-0.0206***	-0.0543***				
			(0.0038)	(0.0102)				
Close Public Transport					-0.00887	-0.00997		
					(0.00516)	(0.0122)		
Close Borders							-0.0137**	-0.0810***
							(0.00473)	(0.0224)
Observations	26973	25359	26973	25359	26973	25359	26973	25359
Countries	158	158	158	158	158	158	158	158
Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	158

Note: Standard errors in parentheses *p<0.05; ** p<0.01, *** p<0.001

Table 3 replicates these exercises for the case of the daily death rate. Again, we report only the estimated parameters of the CCMs. Contrary to the case of daily cases, the results for daily casualties are notoriously different: when using the naïve dummy variable approach, all parameters are statistically insignificant and of negligible magnitude. On the contrary, estimates using the efficient instrumental variable approach indicate that all but one of the CCMs are effective in reducing the daily number of deaths.

Table 3: Daily Casualties
Panel A: Restrictions on Personal Liberties

	Dummy Variable	Efficient Instrument	Dummy Variable	Efficient Instrument	Dummy Variable	Efficient Instrument	Dummy Variable	Efficient Instrument
				Additional Controls Omitted				
Stay at Home	-0.00481	-0.0556***						
	(0.00316)	(0.0102)						
Ban Meetings			-0.00227	-0.0641***				
			(0.00338)	(0.0117)				
Ban on Public Events					-0.000789	-0.0253**		
					(0.00523)	(0.00849)		
Restrictions on Movements							-0.00416	-0.0644***
							(0.00329)	(0.0126)
Observations	23217	22311	23217	22311	23217	22311	23217	22311
Countries	152	152	152	152	152	152	152	152
Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Panel B: Restrictions on Activities

	Dummy Variable	Efficient Instrument	Dummy Variable	Efficient Instrument	Dummy Variable	Efficient Instrument	Dummy Variable	Efficient Instrument
				Additional Controls Omitted				
Close Schools	-0.0036	-0.0398**						
	(0.00544)	(0.0151)						
Close Workplace			-0.00494	-0.0532***				
			(0.00427)	(0.0107)				
Close Public Transport					-0.00599	-0.0693***		
					(0.00463)	(0.0108)		
Close Borders							-0.00543	-0.0432
							(0.00488)	(0.037)
Observations	23217	22311	23217	22311	23217	22311	23217	22311
Countries	152	152	152	152	152	152	152	152
Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	158

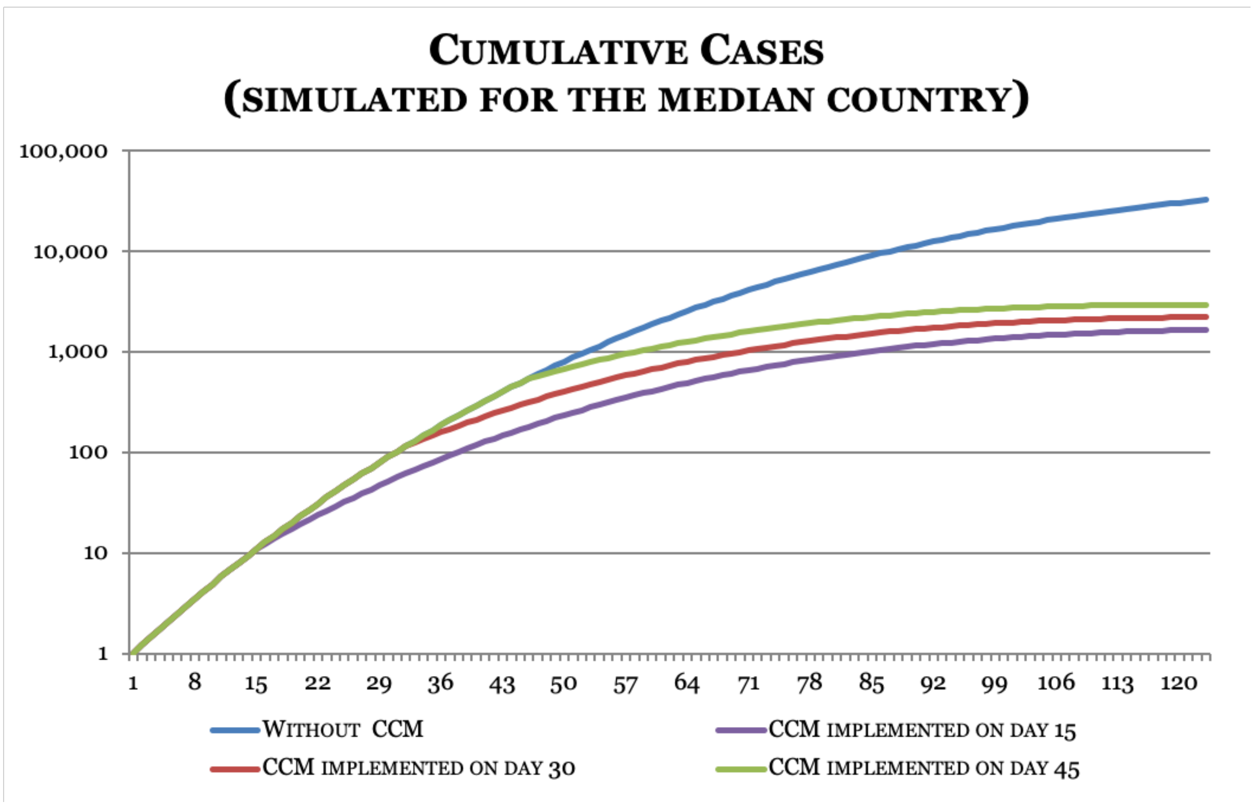
Note: Standard errors in parentheses *p<0.05; ** p<0.01, *** p<0.001

In order to show the epidemiological implications of our results we undertake the following counterfactual exercise. Note first that the parameters for the efficient instrumental variable models are very similar among the different CCMs. The counterfactual exercise uses the estimated model for Lockdowns, but the results do not change when using the other models in Panel A of Table 2. We simulate the evolution of the rate of daily cases and the cumulative number of cases in four scenarios:

(a) The base case where CCMs are not implemented (a laissez-faire policy, as is the case of Japan or Sweden)
(b) The case when the CCM is implemented very early on, that is 15 days after the first case is reported.
(c) The median case where CCMs were implemented around 30 days after the first case was reported.
(d) The late adoption of CCMs 45 days after the outbreak.

The simulations are presented in Figure 9, where it can be grasped the value of enacting the containment measure as well as the importance of the timing of adoption. Without any containment policy, the number of cases reaches over 32,000 120 days after the outbreak. If CCMs are implemented very early on, the number of cases barely reaches 1,600. The median delay in the adoption of CCMs was around one month after the outbreak, in which case countries would have suffered from around 2,200 cases after four months, while the late adopter would see around 3,000 cases. Two forces are at play. On one hand, the CCM lowers the rate of growth of cases. On the other hand, the lower the cases, the smaller is the base for spreading of the disease and the weaker is the dynamic effect embedded in the model. Both mechanisms reinforce each other and explain the significant differences in the number of cases when CCMs are implemented vis-à-vis the laissez-faire case.

Figure 9
Counterfactual Exercise



5. Summary and Conclusions

By August 31, 2020, COVID-19 infected almost 25 million people globally and caused nearly one million deaths since it emerged in late 2019. The rapid increase in COVID-19 cases has caused a significant loss of life and overwhelmed many health systems. The daily new cases of COVID-19 deaths peaked globally at 244 per million by the beginning of April, largely driven by Western Europe, LAC and Europe and Central Asia. However, as authorities started to impose strict containment measures, countries managed to first stabilize and later contain mortality rates and, as a result, daily new COVID-19 deaths dropped by 50% by end of August.

In order to slow down the rate of contagion and avoid the collapse of their health systems, governments worldwide have adopted CCMs. Government responses have become stronger over the course of the outbreak, particularly ramping up over the month of April and May. With the slowdown of contagion rates since May in the northern hemisphere, stringency levels eased, and some countries started rolling back some of the CCMs. Other countries, however, were unable to quickly contain infection rates and maintained CCMs until the end of August. This heterogeneity in the timing of the adoption and the choice of CCM has certainly been motivated by different factors, in turn leading to disparate effects on contagion and mortality rates.

The paper addressed three questions concerning the adoption and effect of CCMs on contagion and death rates:

- What factors influence the governments' decision to adopt and lift CCMs?
- How timely have governments been in adopting CCMs?
- How effective have CCMs been in reducing contagion and death rates?

The findings of the econometric analysis show that in general governments have been responsive to the acceleration of contagion rates and number casualties by adopting CCMs. Indeed, the increases in the number of cases and deaths increase the probability of governments adopting CCMs. Conversely, as the number of cases and deaths declined by the end of the boreal summer, the probability of governments lifting CCMs increased significantly. Moreover, the probability of adopting CCMs increases with the number of days elapsed since the outbreak of the pandemic in each country but the relationship is nonlinear, which means that as time passes there was an increasing pressure to impose CCMs. In addition, the results suggest that, reflecting their larger capacity to cope with the demands of medical attention of those in need, countries with better health systems tended to delay the adoption of CCMs. But since the availability of human resources in health systems is somewhat inelastic in the short run, as the cases and casualties grow and health systems are overwhelmed, the probability of adoption of CCMs increases. The findings indicate that restricting individual liberties and activities may be easier in countries where governments do not have to worry about the political costs of the pandemic control. The quick adoption of CCMs in Western European countries provided for a strong demonstration effect that led other countries to accelerate the adoption of CCMs. Finally, the results show that kinder weather conditions (higher temperatures from January to August) have led to delayed the adoption of CCMs.

Findings on the timing of adoption of CCMs show that generally countries have timely adopted CCMs restricting activities, meanwhile they have lagged in the adoption of CCMs restricting individual liberties. Around 70% of countries timely closed schools and public transportation (i.e., at the time the models predicted such measures ought to have been implemented). Less timely was the adoption of border closures and banning public events as between 55 and 60 percent of countries adopted them on time. The benchmarking exercise shows that only 30 percent of the countries adopted stay at home and banning private meetings in a timely manner. Evidence indicates also that most countries have resisted the urge to lift restrictions in advance, once they have been in place: over 60% of the countries have reacted as predicted by our econometric models, maintaining CCMs in place until contagion rates have receded. Nevertheless, around one-quarter of the countries lifted their restrictions one month or more ahead of what the worldwide evidence would have suggested. This effect is more pronounced in the case of lockdowns, restrictions on internal movements, and closing workplaces.

The effectiveness of the CCMs worldwide has been mixed. Some countries have been able to quickly curb the curve of infection while others are still struggling in slowing down infection rates. The effectiveness of CCMs depends on how timely they were introduced, the type of CCMs that were adopted, and other factors. Naturally, the effects in each country depend on the compliance of the population to CCMs, as well as those CCMs being appropriately enforced by the authorities.

Results of the estimations suggest that CCMs have been effective in reducing the rate of contagion and deaths. Results also show differences in the effectiveness across the variety of CCMs that have been adopted. Restrictions on activities seem to be more effective than restrictions on personal liberties. Closing schools, workplaces and international borders have a very strong containment effect. The adoption of these CCMs would have reduced the rate of daily cases by around six to eight percentage points 14 days after their implementation but interrupting public transport services seems to have had no effect whatsoever on daily cases. The reduction in daily contagion rates had a significant cumulative effect since the spreading of the disease directly depends on the prevalence of disease in the population; counterfactual simulations of our statistical models suggest that timely introduction of CCMs could lower the number of those sick by one order of magnitude. Restrictions on personal liberties such as stay at home or banning meetings and public events would have reduced the rate of daily cases by five percentage points. Results also show that the CCMs have been effective in reducing daily death rates. However, in this case, health system capacity, in particular the rate of daily COVID-19 cases to doctors and nurses also plays a critical role in reducing fatalities cases.

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Appendix

APPENDIX TABLE 1: DAILY CASES

PANEL A: RESTRICTIONS ON PERSONAL LIBERTIES

	STAY AT HOME		BAN ON MEETINGS		BAN ON PUBLIC EVENTS		MOBILITY RESTRICTIONS	
TOTAL CASES	-0.0136***	-0.00899***	-0.0136***	-0.00848***	-0.0124***	-0.00701**	-0.0138***	-0.00856***
(LAGGED)	(0.00216)	(0.00224)	(0.00222)	(0.00228)	(0.00223)	(0.00233)	(0.00215)	(0.00228)
DAILY CASES	-0.00675	-0.00642*	-0.00696*	-0.00644*	-0.00693*	-0.00589	-0.00693*	-0.00631*
/HOSPITAL BEDS	(0.00348)	(0.00310)	(0.00333)	(0.00302)	(0.00329)	(0.00327)	(0.00330)	(0.00316)
DAILY	0.00931**	0.00750**	0.00932**	0.00755**	0.00914**	0.00712*	0.00915**	0.00746**
CASES/DOCTORS	(0.00309)	(0.00274)	(0.00296)	(0.00287)	(0.00297)	(0.00285)	(0.00295)	(0.00281)
DAILY	0.000449	0.00225	0.000544	0.00202	0.00102	0.00134	0.00109	0.00195
CASES/NURSES	(0.0041)	(0.00442)	(0.00403)	(0.00419)	(0.00401)	(0.00472)	(0.00405)	(0.00443)
TEMPERATURE	-0.000698	-0.000681	-0.000636	-0.000615	-0.000675	-0.000654	-0.000673	-0.000654
LAGGED 14 DAYS	(0.000487)	(0.000479)	(0.000494)	(0.000481)	(0.000491)	(0.000462)	(0.000490)	(0.000486)
DAYS ELAPSED	-0.00083***	-0.00113***	-0.00084***	-0.00119***	-0.00079***	-0.00133***	-0.00081***	-0.00117***
SINCE OUTBREAK	(0.000161)	(0.000176)	(0.000163)	(0.000196)	(0.000165)	(0.000209)	(0.000162)	(0.000187)
DAYS ELAPSED	0.00235***	0.00313***	0.00241***	0.00328***	0.00208***	0.00361***	0.00233***	0.00323***
SINCE OUTBREAK	-4.76E-04	-4.86E-04	-4.79E-04	-5.24E-04	-4.82E-04	-5.54E-04	-4.85E-04	-5.,05E-04
SQUARED (10^{-3})								
STAY AT HOME	-0.0147***							
(LAGGED 14 DAYS)	(0.00387)							
INSTRUMENT		-0.0445***						
STAY HOME		(0.00941)						
(LAGGED 14 DAYS)								
BAN MEETINGS			-0.0133**					
(LAGGED 14 DAYS)			(0.00406)					
INSTRUMENT BAN				-0.0478***				
MEETINGS				(0.0104)				
(LAGGED 14 DAYS)								
BAN ON PUBLIC					-0.0219***			
EVENTS (LAGGED					(0.00472)			
14 DAYS)								
INSTRUMENT BAN						-0.0511***		
ON PUBLIC						(0.00934)		
EVENTS (LAGGED								
14 DAYS)								
RESTRICTIONS ON							-0.0121***	
MOVEMENTS							(0.00337)	
(LAGGED 14 DAYS)								
INSTRUMENT								-0.0515***
RESTRICTIONS ON								(0.0115)
MOVEMENTS								
(LAGGED 14 DAYS)								
CONSTANT	0.227***	0.206***	0.225***	0.206***	0.227***	0.207***	0.226***	0.206***
	(0.0133)	(0.0139)	(0.0135)	(0.0140)	(0.0133)	(0.0135)	(0.0133)	(0.0141)
OBSERVATIONS	26,973	25,359	26,973	25,359	26,973	25,359	26,973	25,359
COUNTRIES	158	158	158	158	158	158	158	158
FIXED EFFECTS	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Panel B: Restrictions on Activities

	Close Schools		Close Workplaces		Close Public Transportation		Close International Borders	
Total Cases (lagged)	-0.0114***	-0.00573*	-0.0126***	-0.00761**	-0.0146***	-0.0123***	-0.0139***	-0.00780***
	(0.00220)	(0.00224)	(0.00221)	(0.00232)	(0.00210)	(0.00199)	(0.00208)	(0.00217)
Daily cases /Hospital beds	-0.00656*	-0.00539	-0.00674*	-0.00601*	-0.00699*	-0.00716*	-0.00711*	-0.00583*
	(0.00322)	(0.00295)	(0.00326)	(0.00293)	(0.00334)	(0.00316)	(0.00333)	(0.00293)
Daily cases/doctors	0.00882**	0.00663*	0.00904**	0.00712**	0.00941**	0.00815**	0.00927**	0.00695**
	(0.00293)	(0.00262)	(0.00290)	(0.00263)	(0.00301)	(0.00287)	(0.002939)	(0.00257)
Daily cases/nurses	0.000564	0.000978	0.00071	0.00179	0.000581	0.00296	0.00133	0.00163
	-0.00395	-0.00454	-0.00422	-0.00428	-0.00401	-0.00423	-0.004	-0.00442
Temperature lagged 14 days	-0.000665	-0.000584	-0.000666	-0.00063	-0.0006	-0.000711	-0.000598	-0.000564
	(0.000496)	(0.000444)	(0.000488)	(0.000477)	(0.000473)	(0.000436)	(0.000473)	(0.000470)
Days elapsed since outbreak	-0.00084***	-0.00148***	-0.00078***	-0.00128***	-0.00082***	-0.00089***	-0.0008***	-0.00134***
	(0.000174)	(0.000229)	(0.000167)	(0.000204)	(0.000159)	(0.000151)	(0.000174)	(0.000174)
Days elapsed since outbreak squared (10^{-3})	0.00222***	0.00396***	0.00213***	0.00349***	0.00243***	0.00276***	0.00227***	0.00372***
	(4.93E-07)	(6,08E-07)	(4.93E-07)	(5.41E-07)	(4.68E-07)	(4.53E-07)	(4.67E-07)	(6.80E-07)
Close Schools (lagged 14 days)	-0.0290***							
	(0.00543)							
Instrument Close Schools (lagged 14 days)		-0.0791***						
		(0.00131)						
Close Workplace (lagged 14 days)			-0.0206***					
			(0.0038)					
Instrument Close Workplaces (lagged 14 days)				-0.0543***				
				(0.0102)				
Close Public Transport (lagged 14 days)					-0.00887			
					(0.00156)			
Instrument Close Public Transport (lagged 14 days)						-0.00997		
						(0.0112)		
Close Borders (lagged 14 days)							-0.0137**	
							(0.00473)	
Instrument Close Borders (lagged 14 days)								-0.0810***
								(0.0224)
Constant	0.231***	0.209***	0.224***	0.207***	0.225***	0.208***	0.229***	0.210***
	(0.0133)	(0.0130)	(0.0131)	(0.0137)	(0.0132)	(0.0136)	(0.0134)	(0.0136)
Observations	26973	25359	26973	25359	26973	25359	26973	25359
Countries	158	158	158	158	158	158	158	158
Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	158

Appendix Table 2: Rate of Growth in Daily Casualties

Panel A: Restrictions on Personal Liberties

	Stay at Home		**Ban on Meetings**		**Ban on Public Events**		**Mobility Restrictions**	
Total Cases	-0.0291***	-0.0223***	-0.0294***	-0.0214***	-0.0296***	-0.0244***	-0.0291***	-0.0219***
(lagged)	(0.00245)	(0.00288)	(0.00238)	(0.00279)	(0.00238)	(0.00280)	(0.00254)	(0.00286)
Daily cases	-0.0101**	-0.00813**	-0.0102**	-0.00827**	-0.0102**	-0.00866**	-0.0102**	-0.00810*
/Hospital beds	(0.00315)	(0.00301)	(0.00310)	(0.00282)	(0.00310)	(0.00318)	(0.00310)	(0.00313)
Stress1:	0.00944***	0.00757**	0.00942***	0.00776**	0.00941***	0.00811**	0.00937***	0.00767**
cases/doctors	(0.00255)	(0.00238)	(0.00250)	(0.00247)	(0.00250)	(0.00252)	(0.00249)	(0.00248)
Stress2:	0.00736	0.00579	0.00752	0.00547	0.00761*	0.00600	0.00762*	0.00533
cases/nurses	(0.00386)	(0.00396)	(0.00382)	(0.00347)	(0.00384)	(0.00413)	(0.00384)	(0.00397)
Temperature	-0.00132**	-0.00140**	-0.00129**	-0.00124*	-0.00128*	-0.00125*	-0.00131**	-0.00135**
lagged 14 days	(0.000493)	(0.000510)	(0.000488)	(0.000502)	(0.000491)	(0.000513)	(0.000489)	(0.000509)
Days elapsed	-0.00072***	-0.00124***	-0.00073***	-0.00140***	-0.00072***	-0.00111***	-0.00072***	-0.00131***
since outbreak	(0.000493)	(0.000215)	(0.000189)	(0.00025)	(0.000187)	(0.000255)	(0.000186)	(0.000237)
Days elapsed	0.00299***	0.00410***	0.00304***	0.00448***	0.00304***	0.00392***	0.00299***	0.00426***
since outbreak squared (10^{-3})	(5.76E-04)	(6.12E-04)	(5.80E-04)	(6,96E-04)	(5.74E-04)	(7.19E-04)	(5.76E-04)	(6.61E-04)
Stay at Home	-0.00481							
(lagged 14 days)	(0.00316)							
Instrument Stay Home (lagged 14 days)		-0.0556***						
		(0.0102)						
Ban Meetings			-0.00227					
(lagged 14 days)			(0.00338)					
Instrument Ban Meetings (lagged 14 days)				-0.0641***				
				(0.0117)				
Ban on Public Events (lagged 14 days)					-0.000789			
					(0.00523)			
Instrument Ban on Public Events (lagged 14 days)						-0.0253**		
						(0.00849)		
Restrictions on Movements (lagged 14 days)							-0.00416	
							(0.00329)	
Instrument Restrictions on Movements (lagged 14 days)								-0.0644***
								(0.0126)
Constant	0.233***	0.250***	0.231***	0.256***	0.231***	0.242***	0.232***	0.253***
	(0.0118)	(0.0144)	(0.0118)	(0.0156)	(0.0126)	(0.0150)	(0.0115)	(0.0152)
Observations	23,217	22,311	23,217	22,311	23,217	22,311	23,217	22,311
Countries	158	158	158	158	158	158	158	158
Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Panel B: Restrictions on Activities

	Close Schools		Close Workplaces		Close Public Transportation		Close International Borders	
Total Cases	-0.0292***	-0.0240***	-0.0288***	-0.0219***	-0.0293***	-0.0279***	-0.0292***	-0.0257***
(lagged)	(0.00236)	(0.00256)	(0.00258)	(0.00280)	(0.00244)	(0.00270)	(0.00241)	(0.00244)
Daily cases	-0.0102**	-0.00858**	-0.0101**	-0.00813**	-0.0103**	-0.00936**	-0.0103**	-0.00890**
/Hospital beds	(0.00309)	(0.00304)	(0.00309)	(0.00288)	(0.00311)	(0.00285)	(0.00313)	(0.00300)
Stress1:	0.00938***	0.00806**	0.00936***	0.00770**	0.00952***	0.00846**	0.00942***	0.00825***
cases/doctors	(0.00250)	(0.00243)	(0.00249)	(0.00232)	(0.00250)	(0.002566)	(0.00251)	(0.00239)
Stress2:	0.00753	0.00591	0.00746	0.00543	0.00739	0.00725*	0.00777*	0.00644
cases/nurses	(0.00383)	(0.00397)	(0.00387)	(0.00375)	(0.00385)	(0.00343)	(0.00388)	(0.00393)
Temperature	-0.00129**	-0.00114*	-0.00129**	-0.00120*	-0.00129**	-0.00121*	-0.00128*	-0.00113
lagged 14 days	(0.00490)	(0.00524)	(0.00494)	(0.00513)	(0.00487)	(0.00471)	(0.00491)	(0.00576)
Days elapsed	-	-0.0013***	-	-0.00139***	-	-0.00086***	-0.00072***	-0.00114**
since outbreak	0.00073***	(0.000309)	0.000726***	(0.000253)	0.000722***	(0.000177)	(0.000186)	(0.000423)
	(0.000294)		(0.000189)		(0.000186)			
Days elapsed	0.00304***	0.00430**	0.00299***	0.00453***	0.00300***	0.00332***	0.00298***	0.00411***
since outbreak	(0.000578)	*	(0.000576)	(0.000708)	(0.000568)	(0.000550)	(0.000578)	(0. 000119)
squared (10^{-3})		(0.000867)						
Close Schools	-0.0036							
(lagged 14 days)	(0.00544)							
Instrument		-0.0398**						
Close Schools		(0.0151)						
(lagged 14 days)								
Close			-0.00494					
Workplace			(0.00427)					
(lagged 14 days)								
Instrument				-0.0532***				
Close				(0.0107)				
Workplaces								
(lagged 14 days)								
Close Public					-0.00599			
Transp. (lagged					(0.00463)			
14 days)								
Instrument						-0.0693***		
Close Public						(0.0108)		
Transp. (lagged								
14 days)								
Close Borders							-0.00543	
(lagged 14 days)							(0.00448)	
Instrument								-0.0432
Close Borders								(0.0370)
(lagged 14 days)								
Constant	0.233***	0.249***	0.233***	0.255***	0.232***	0.235***	0.234***	0.246***
	(0.0134)	(0.0178)	(0.0119)	(0.0158)	(0.0118)	(0.0122)	(0.0118)	(0.0242)
Observations	23,217	22,311	23,217	22,311	23,217	22,311	23,217	22,311
Countries	158	158	158	158	158	158	158	158
Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Appendix Table 3: Correlation Matrix of Instrumental Variables for CCMs

	Stay at Home	Ban Public Events	Ban Gatherings	Restrict Mobility	Closing Schools	Closing Workplaces	Close Public Transport	Close Borders
Stay at Home	1.0000							
Ban Public Events	0.8447	1.0000						
Ban Gatherings	0.8011	0.8149	1.0000					
Restrict Mobility	0.8849	0.8692	0.9748	1.0000				
Closing Schools	0.6235	0.8448	0.6728	0.6882	1.0000			
Closing Workplaces	0.8872	0.9078	0.8471	0.8970	0.8355	1.0000		
Close Public Transport	0.7425	0.5649	0.5989	0.6487	0.3442	0.5656	1.0000	
Close Borders	0.4930	0.6802	0.5119	0.5212	0.9025	0.7069	0.2258	1.0000