WHAT WORKS TO CONTROL COVID-19?

ECONOMETRIC ANALYSIS OF A CROSS-COUNTRY PANEL

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ABSTRACT

We use cross-country panel data to examine the effects of a variety of nonpharmaceutical interventions used by governments to suppress the spread of coronavirus disease (COVID-19). We find that while lockdown measures lead to reductions in disease transmission rates as captured by the reproduction number, R_t, gathering bans appear to be more effective than workplace and school closures, both of which are associated with large declines in gross domestic product. Further, our estimates suggest that stay-at-home orders are less effective in countries with larger family size and in developing economies. We also find that incentives are very important, as efforts at ramping up testing and tracing COVID-19 cases are more effective in controlling the spread of disease in countries with greater coverage of paid sick leave benefits. As future waves of the disease emerge, the use of more targeted and better incentivized measures can help keep the epidemic controlled at lower economic cost.

Keywords: COVID-19, cross-country data, economic impact, nonpharmaceutical interventions

JEL codes: I10, I18, and O40

I. INTRODUCTION

On 23 January 2020, Wuhan in Hubei Province of the People's Republic of China (PRC) became the first city to implement a lockdown featuring strict restrictions on the movement of people as a tool for suppressing the spread of the novel coronavirus disease, COVID-19.[1] Since then lockdowns of varying stringency and duration, together with other types of nonpharmaceutical interventions (NPIs) such as mandates to wear masks and efforts to test, trace, and isolate individuals potentially exposed to COVID-19, have been implemented in many economies.[2] Starting late April, some economies or locations have gradually lifted or eased lockdown measures.[3] Yet, there are also examples of "re-locking" as COVID-19 cases reemerge in various locations.

While lockdowns are likely to have helped restrict COVID-19 transmission, they have taken a big toll on economic activity and people's livelihoods. A key question for policy makers everywhere is: How can economies be reopened while keeping this disease in check? Specifically, what types and combinations of NPIs are effective in containing the spread of COVID-19 and simultaneously entail lower disruption to economic activity?

There are many efforts underway to help address these questions. Broadly, there are two approaches used, one involving the use of mathematical epidemiological models of how infectious diseases spread and the other using empirical statistical approaches such as regression analysis.

Epidemiological models can enable the integration of key assumptions about COVID-19 and its spread into a cohesive framework in which forecasts can be made and simulations can be performed of options for epidemic control. However, such models are very reliant on assumptions, many of which concern matters where evidence is scarce, such as the relative infectivity of asymptomatic individuals. Such models also rely on untested assumptions about how human behavior is altered by policy measures. See Avery et al. (2020) for a review of models of the spread of the novel coronavirus epidemic, including those that have been used for informing policy decisions.

Regression models can reduce this reliance on assumptions by using real world observations and simplified "reduced form" approaches that minimize reliance on prespecification of parameters. In this paper, we use a cross-country regression framework and data from over 70 economies to examine the relationship between a variety of NPIs—such as workplace closures and gathering bans; the extent of testing, tracing, and isolation; and mandates on the use of masks—on both transmission rates of COVID-19 as captured by its reproduction number, R_t, as well as economic activity captured by estimates of quarterly gross domestic product (GDP). In this way, we are able to shed light on the question of how effective different control measures are, and which ones are associated with larger or smaller contractions in economic activity. Our regression analysis uses country fixed effects to control for all time-invariant, country-specific factors that may influence the spread of COVID-19 and GDP growth. Further, we include a linear time trend to capture unobserved temporal features of COVID-19 and the change in the share of time people spend at their residences relative to a pre-COVID-19

[1] The terms lockdown or shutdown are being used by many to describe relatively general and widespread restrictions on movement, work, and travel on people in a city, region, or country. They can be distinguished from quarantines, which involve separating and restricting people who have been exposed to a disease, such as COVID-19.

[2] As noted by the United States Center for Disease Control, NPIs are "actions, apart from getting vaccinated and taking medicine, that people and communities can take to help slow the spread of" infectious diseases like COVID-19.

[3] Lockdown measures were widely adopted in March, during the early phase of worldwide spread.

baseline. Increases in the latter should be associated with reductions in social contacts outside the home and thus in the spread of COVID-19. Only countries with more than 30 observations between January 2020 and June 2020 are included in our regression analysis.

The various COVID-19 control measures we use are guided by recent research, including ongoing work on the Philippines (Raitzer et al. forthcoming). Specifically, this research uses an age-structured susceptible, exposed, infected, and recovered (SEIR) model to examine COVID-19 transmission across scenarios that vary in terms of the nature and duration of lockdowns; extent of tracing, testing, and isolation; and paid sick leave (PSL) as a tool for encouraging self-isolation by workers potentially exposed to COVID-19. It also examines the costs and benefits associated with the alternative scenarios, factoring in health-related costs and benefits as well as the economic losses due to lockdowns.

The findings of Raitzer et al. (forthcoming) motivate crucial aspects of our cross-country regression analysis. A few key findings are worth noting. First, though effective in suppressing disease transmission, lockdowns involving workplace and school closures lead to large reductions in household income, resulting in relatively high costs for the benefits achieved. Second, an extensive system of testing, tracing, and isolation provides a far more economically viable basis for controlling the spread of COVID-19. Third, a PSL policy that encourages workers with COVID-19 or similar symptoms to isolate is not only an effective tool for controlling the disease, it is also a strong complement to tracing and isolation efforts and has a relatively low cost–benefit ratio.

These findings motivate two major ways in which our cross-country regression analysis departs from similar studies. First, in addition to examining the relationship between COVID-19 control measures and disease transmission, we also consider the relationship between the former and economic activity. Second, we consider a broader set of control measures, such as PSL, and also consider how certain country-specific features may affect the efficacy of control measures.

The rest of this paper is organized as follows. Section II goes over recent literature based on cross-country regression analysis and places our contributions in context. Section III describes our data and variable construction. Section IV covers the empirical framework, while section V provides the results of our analysis. Section VI compares our findings with those of other studies and also discusses some limitations of our analysis. Section VII concludes.

II. COVID-19 CONTROL: EVIDENCE FROM CROSS-COUNTRY REGRESSION ANALYSIS

A large and growing literature that examines the socioeconomic consequences of COVID-19, the policies and measures to control its spread, and their effectiveness has emerged since early 2020. It is beyond the scope of this section to describe this literature and readers are referred to a recent survey of the literature provided by Brodeur et al. (2020). Instead, we focus here on studies most closely related to ours—i.e., those using cross-country data to examine the relationship between COVID-19 outcomes and the measures and policies governments have used to control COVID-19.[4] (Later, in section VI, we discuss our findings in the context of these studies.)

An early study is that of Bergman and Fishman (2020), who examine how declines in societal mobility are related to the spread of COVID-19. Mobility is captured using daily data from Google and Apple on travel and location, while COVID-19 transmission is captured using estimates of the effective reproduction number. Bergman and Fishman's reduced form regression estimates, based on panel data from 99 economies covering the period from late February and early May and controlling for country and date fixed effects, suggest that a 10 percentage point reduction in mobility is associated with a 0.04–0.07 reduction in R_t. Bergman and Fishman's focus on mobility leads them to avoid analyzing the effects of specific measures governments have taken to control COVID-19 spread. One reason they note is that lockdowns and reductions in mobility are closely though imperfectly related (for example, mobility can decline even without a lockdown as individuals become cautious about exposure to the virus in public spaces).

Carraro, Ferrone, and Squarcina (2020) seek to estimate how NPIs affect the number of active COVID-19 cases using data on 166 economies spanning January 2020 to 15 May 2020. It regresses log differences of COVID-19 cases on 7- and 14-day lagged measures of NPIs and a variety of controls, such as population density and the share of the population over 65 years of age. The NPI measures are introduced separately. The study finds that measures such as school closures and lockdowns are highly effective in reducing growth of active COVID-19 cases. Brauner et al. (2020) assess NPIs for 41 economies using a Bayesian hierarchal model, and find significant effects of school closure, closure of high risk businesses and gathering bans, but smaller effects of other measures.

Islam et al. (2020) similarly use an interrupted time series model on data for 149 economies, in which log cases are the dependent variable, and a range of 7-day lagged NPIs are independent variables independently regressed, and synthesized via meta-analysis. Of the five control measures (transport closure, school closure, workplace closure, gathering bans, and lockdown) assessed, all but transport closure are found to be significant, with larger effects in high-income economies than low-income ones.

Demirgüç-Kunt, Lokshin, and Torre (2020) focus on the effects of NPIs on economic activity, as captured by high-frequency proxies such as daily electricity consumption and nitrogen dioxide emissions data in addition to mobility data for around 33 economies between January and April. A key finding, drawing on panel regressions that include country fixed effects, is that NPIs implemented in the early stages of the pandemic appear to have less adverse effects on short-term economic outcomes and lower cumulative mortality. To some extent, this is due to earlier implemented NPIs being less stringent.

In this paper, we extend these previous studies in several ways. First, given the large tradeoffs that may exist between the effects of some NPIs, especially lockdowns, on health outcomes versus economic activity, we assess the relationship between NPIs and both COVID-19 outcomes and economic activity. Second, given the various deficiencies in capturing the number of actual COVID-19 cases globally, we use estimates of the reproduction number (as do Bergman and Fishman 2020). Though still imperfect, this measure has several advantages (as noted below). Third, we allow relevant NPIs' effects on COVID-19 transmission to vary by relevant country characteristics. For example, lockdowns are supposed to suppress spread of disease by restricting physical contacts. However, large household sizes can lead lockdowns to have smaller effects on physical contacts. Utilizing appropriate

[4] A number of recent contributions use data from a single country and utilize subnational variations in COVID-19 outcomes and control measures. Brodeur et al. (2020) provide a useful discussion on these.

interaction terms in our regressions of COVID-19 transmission help capture such relationships. Finally, we consider a potentially important measure of COVID-19 control that has so far been missed by the cross-country literature: the use of PSL benefits as a tool for incentivizing and enabling potentially infected workers to self-isolate.

Although widely viewed as a key element of social protection policies, PSL can also play an important role in controlling the spread of infectious diseases. Indeed, the effects of PSL on the spread of diseases such as influenza has been well demonstrated in the scientific literature (Kim 2017). Workers without PSL are more likely to report for work when contagious—a phenomenon often referred to as contagious presenteeism—leading to a spread of disease among coworkers and others. Conversely, providing workers access to PSL has been shown to reduce the spread of contagious diseases (e.g., Pichler, Wen, and Ziebarth 2020; Pichler and Ziebarth 2017).

While the inclusion of country fixed effects means that we cannot assess the independent effect of PSL on COVID-19 spread, we explore its effects indirectly. An important channel through which PSL is expected to influence COVID-19 is through the system of contact tracing, whereby people who have come in recent contact with a COVID-19 positive person are identified and requested to isolate. Especially since a large share of COVID-19 cases involve mild symptoms (or even no symptoms, but still infectious), a call for isolation is unlikely to be followed if doing so leads to a loss of income. Providing PSL can reduce such behavior and the negative externality associated with it by making contact tracing more effective. Appendix 1 describes a model that demonstrates that the mechanics of PSL works as a tool for controlling the spread of infectious diseases such as COVID-19.

III. DATA

A. Data Sources and Variable Construction

The dependent variables used in this study are the daily spread of COVID-19 and quarterly GDP growth rate. The principle explanatory variables are daily values of measures taken to control COVID-19 and the extent to which a population stays at home. All variables are measured at country level.

(1) Transmission of COVID-19

To measure COVID-19 spread, we use country-level effective reproductive rate, also known as R_t, from Abbott et al. (2020). R_t describes the average number of individuals infected by an infectious individual at time *t*. Using R_t has several advantages when measuring spread. Estimated R_t primarily uses data on confirmed cases from the European Centre for Disease Control and is further adjusted for delays in reporting, right-truncation of notification dates, delays between onset and infection, and the effects of testing procedures. Importantly, R_t provides a unit of measurement that avoids problems with other epidemic control measures. Raw numbers of cases are subject to large lag effects that confound identification of effects of specific control measures, and must be considered in relation to population to be comparable. R_t is inherently comparable and can be quicker to respond to policies. Mortality has both lag effects as well as dependence on treatment capacity, and is subject to inconsistencies in the classification of deaths. This said, it is worth noting that since R_t is estimated from reported cases, it cannot overcome problems shared with other COVID-19 measures, such as those arising from underreporting, changes in surveillance methods over time, differences in case definitions across economies, and conflating imported and local cases. We restrict our sample to countries with more than 30 days of R_t observations.

(2) GDP growth rate

To estimate the relationship between COVID-19 control measures and economic activity, we collect quarterly GDP growth data from 2018 to the second quarter of 2020 and compute the quarter-on-quarter growth rate for our dependent variable.[5] We use the total number of days each measure has been in place each quarter as the independent variables. We assume no measures were in place in before 2020.

(3) COVID-19 control measures

The NPI measures adopted by governments to combat COVID-19 spread can be largely categorized in two groups. The first group involves measures that aim to suppress the disease by restricting mobility through "lockdown" such as school closures, work closures, bans on public gatherings, the closure of public transport, etc. The second group includes mandates for wearing masks, mass testing, contact tracing, and isolation of those potentially infected with COVID-19, and the availability of PSL benefits.

We rely on the *Oxford COVID-19 Government Measure Tracker (*OxCGRT) (Hale et al. 2020) for a number of the control measures.[6] We construct an indicator of PSL using data on short-term paid sick leave from the World Policy Analysis Center.[7] The data contains information on PSL coverage, such as coverage by employment type and duration of PSL. In our baseline model, if an economy offers some duration of PSL and covers some self-employed and part-time workers, we treat it as offering PSL in our empirical model. We also test a specification with a stricter definition of PSL.

We construct the following daily variables from these data sources:

(i) School closure: 1 if closure is required for all school levels; 0 otherwise.
(ii) Workplace closure: 1 if closure is required for all but essential industries (e.g., grocery stores or health sector); 0 otherwise.
(iii) Public transport closure: 1 if public transport is closed or its use is prohibited for most citizens; 0 otherwise.
(iv) Small gathering ban: 1 if gatherings of more than 10 people are restricted; 0 otherwise.
(v) Large gathering ban: 1 if gatherings of more than 100 people are restricted; 0 otherwise.
(vi) Contact tracing: 1 if a government conducts comprehensive contact tracing for all identified cases; 0 otherwise.
(vii) Early contact tracing: number of days of implementation of contact tracing ahead of 100 cumulative cases.
(viii) Large scale testing: 1 if tests are conducted for anyone with COVID-19 symptoms.

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5 Our sources for GDP growth rates include CEIC Data Company, Consensus Economics, Focus Economics, and the Organisation for Economic Co-operation and Development Database.

6 OxCGRT tracks the stringency measures imposed across economies each day. Each measure has corresponding ordinal and binary scales. The ordinal scale starts at 0 which refers to "no measure" having been imposed and it increases by one digit up to 3, 4, or 5 depending on the policy measure. The largest number is considered the most stringent measure imposed. The binary scale provides the geographic coverage of the measure whether it is targeted (0) or a general measure (1). The data was accessed at https://www.bsg.ox.ac.uk/research/research-projects/coronavirus-government-measure-tracker.

7 The data was accessed on 2 July 2020 at WORLD Policy Analysis Center. Short-term Paid Sick Leave Data. https://www.worldpolicycenter.org/maps-data/data-download/short-term-paid-sick-leave-data.

(ix) Mask wearing: 1 if wearing masks is mandatory or widely accepted.[8]
(x) Paid sick leave: 1 if an economy offers some duration of PSL and covers some of self-employed and part-time workers.

The OxCGRT dataset also provides an overall policy stringency index. The index is a weighted sum of various individual policy measures. While the index is not directly involved in our regression analysis, we use it to provide descriptive analysis and proxy mobility trends for countries without mobility data.

(4) Change in time spent at home

To capture the *lack* of mobility or movement by people—something that can be important in reducing social contacts and thus the spread of COVID-19—we use the change in length of time people stay at their residences relative to a baseline as reported by Google COVID-19 Community Mobility Reports.[9] While these reports provide mobility trends for various locations, such as groceries and pharmacies, parks, transit stations, retail and recreational locations, and workplaces, we focus on trends involving the length of time spent at residential locations as this captures simultaneously the stringency of lockdown measures (such as stay-at-home orders) and voluntary reductions in travel by individuals motivated by preventive behavior. We use the term “time at home” to refer to a lack of mobility resulting from either reason.

The Google reports cover 75 countries in our sample. In countries without data from Google, we estimate changes in time at home using the overall stringency index from the OxCGRT dataset.[10] We run a pooled ordinary least squares (pooled-OLS) regression of time at home against the stringency index for countries with information on both variables, and use the estimated coefficients to extrapolate the change in time at home for places without Google data. We also test a specification only including countries with Google data in our econometric exercise.

(5) Other variables and controls

There are a few additional variables used in our analysis. We control for the daily maximum temperature to account for its potential effect on the spread of COVID-19.[11] Temperature has been hypothesized and been associated with COVID-19 transmission (see, for example, Xie and Zhu 2020). Temperature may also condition transmission by affecting the share of contacts that occur under outdoor or indoor conditions. For economies without information on daily temperature, we use temperature from locations with similar latitude as a proxy.

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[8] The data was compiled by #Masks4All team and accessible at https://masks4all.co/what-countries-require-masks-in-public/. The data provides information if the government requires wearing of masks across the country or just some parts of the country. Or, if it is a recommendation only or a universal practice in the country. It also provides the dates of implementation if the mask wearing is required and the links of the source of information. We fill in missing implementation dates by referring to various news articles provided by #Mask4All and other sources.

[9] Google utilizes the location history of Google users to compile a dataset that provides aggregate information on how visits and length of stay at different places change each day compared to a baseline, which is the median value for the corresponding day of the week during the 5-week period from 3 January to 6 February 2020. The data refers to “change in duration” for residential locations, while it refers to “change in visitors” for other categories. Data was accessed through: https://www.google.com/covid19/mobility/.

[10] The stringency index used is the overall policy stringency from OxCGRT. Change in time at home from seven countries are proxied by policy stringency.

[11] We use maximum temperature from Land-Based Station Data of National Centers for Environmental Information. Data was accessed from https://www.ncdc.noaa.gov/data-access/land-based-station-data.

We collect household size from the United Nations Department of Economic and Social Affairs. In addition, the Nextstrain real time tracking database has been used to characterize the presence of genetic variations, or clades, of COVID-19 in particular countries at specific times (Hadfield et al. 2018). In total, our dataset consists of an unbalanced panel of 75 economies from 1 January 2020 to 17 June 2020.[12]

B. Descriptive Statistics

Table 1 provides summary statistics for the variables used in this study. The values taken by the various COVID-19 control measures across the 75 economies are diverse. On average, time at home increased by 15.8% over the baseline period, with a maximum increase of 55% for Singapore in early May. Among all the control measures, contact tracing is widespread. This is because some countries in the sample (especially in developed ones) had contact tracing mechanisms even before the pandemic instead of being introduced only in response to the pandemic. School closures are observed in 75.7% of observations, the second most widely adopted control measure. On average, countries implemented contact tracing 13.09 days after recording 100 cases. One-third of countries have PSL policies in place.

Table 1: Summary Statistics

Variables	N	Mean	Std Dev	Min	Max
R_t and daily control measures					
R_t	6,639	1.082	0.264	0.400	2.100
Change in time at home	6,639	15.770	9.789	–16	55
Small gathering ban	6,639	0.485	0.500	0	1
Large gathering ban	6,639	0.266	0.442	0	1
School closure	6,639	0.757	0.429	0	1
Workplace closure	6,639	0.347	0.476	0	1
Public transport closure	6,639	0.308	0.462	0	1
Mask use	6,639	0.432	0.495	0	1
Mass testing	6,639	0.523	0.500	0	1
Contact tracing	6,639	0.864	0.342	0	1
Time trend	6,639	54.380	31.230	3	170
Max temperature	6,639	22.600	9.399	–5.074	44.980
Household size	75	3.571	1.407	2.070	8.040
Paid sick leave	75	0.333	0.475	0	1
Early tracing	75	13.090	37.650	–107	78
Clade 19A presence	5,102	0.760	0.427	0	1
Clade 19B presence	5,102	0.400	0.490	0	1
Clade 20A presence	5,102	0.752	0.432	0	1
Clade 20B presence	5,102	0.617	0.486	0	1
Clade 20C presence	5,102	0.318	0.466	0	1

continued on next page

[12] From 1 January to 14 February estimates of R_t were available only for the PRC. More economies started reporting COVID-19 cases and show up in our dataset on R_t from the middle of February.

Table 1 *continued*

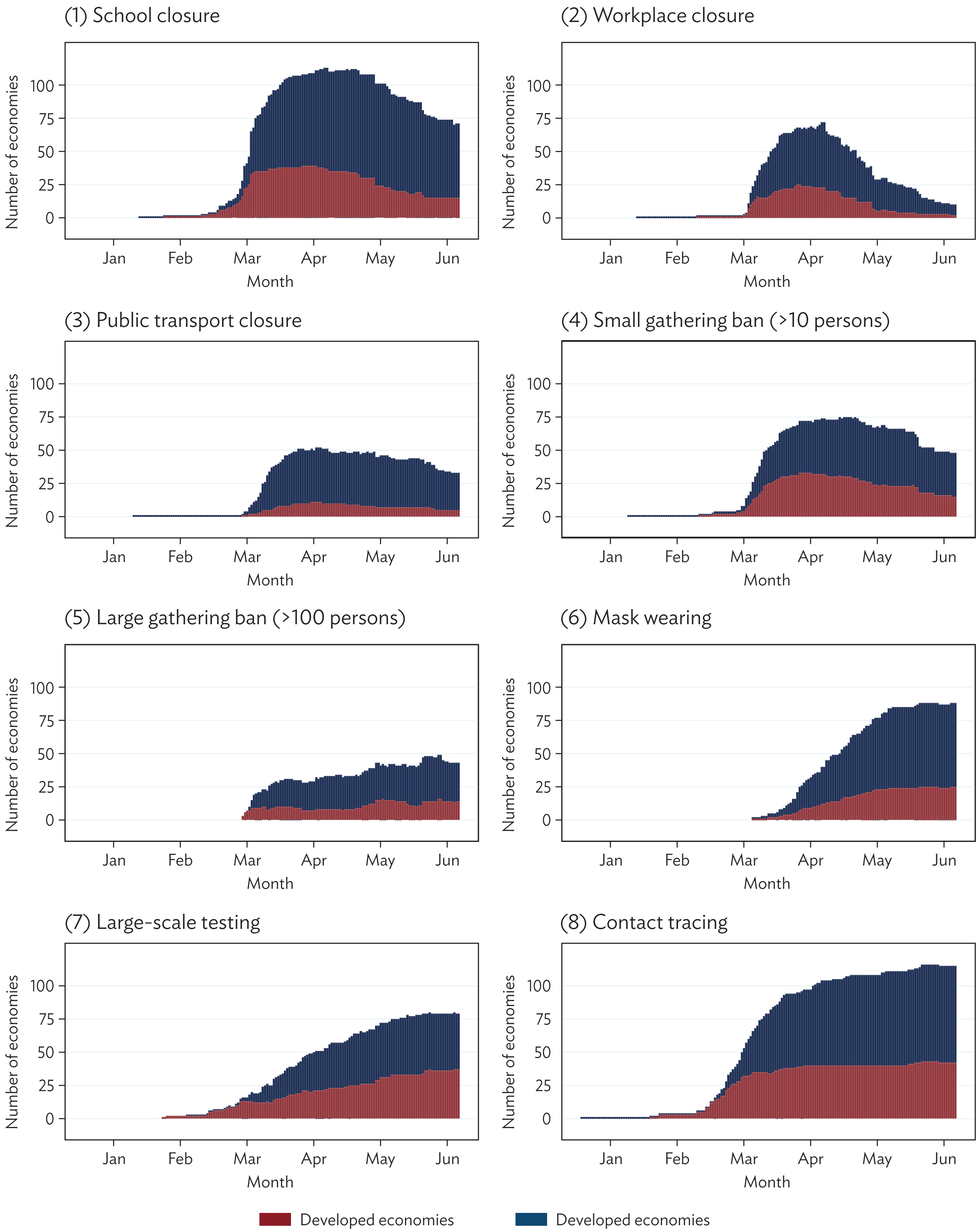
Variables	N	Mean	Std Dev	Min	Max
GDP growth and quarterly control measures					
GDP growth rate	899	1.754	4.719	–30.242	11.981
Workplace closure (ln days)	899	0.257	0.863	0	4.419
School closure (ln days)	899	0.436	1.165	0	4.522
Public transit closed (ln days)	899	0.129	0.631	0	4.522
Index of other measures (ln)	899	0.545	1.457	0	5.613
Days since first case (ln)	899	0.583	1.464	0	5.209
Quarter					
Q1 2018	899	0.108	0.310	0	1
Q2 2018	899	0.108	0.310	0	1
Q3 2018	899	0.108	0.310	0	1
Q4 2018	899	0.108	0.310	0	1
Q1 2019	899	0.108	0.310	0	1
Q2 2019	899	0.107	0.309	0	1
Q3 2019	899	0.107	0.309	0	1
Q4 2019	899	0.106	0.308	0	1
Q1 2020	899	0.083	0.277	0	1
Q2 2020	899	0.058	0.234	0	1

GDP = gross domestic product, ln = natural logarithm, Q = quarter.

Source: Authors' estimates.

Figure 1 describes the number of economies adopting each of the measures over time and by development level. There are several interesting features. First, lockdown measures were widely adopted in early March, roughly around the time when the World Health Organization declared COVID-19 to be a global pandemic (March 11), and began to be gradually relaxed starting late April. For example, while schools reopened and workplace closures were relaxed, the former was more common in developed economies. Second, more targeted NPI measures, such as the use of masks and large-scale testing and contact tracing have gained momentum gradually. More economies have allocated resources to enhance contact tracing and mass testing capacity; at the same time, such measures take time and institutional capacity, and the developing world shows up as being slower to put them in place. Compared to lockdown measures, these measures tend not to be phased out once in place.

Figure 1: Number of Economies Adopting Each Measure by Development Level

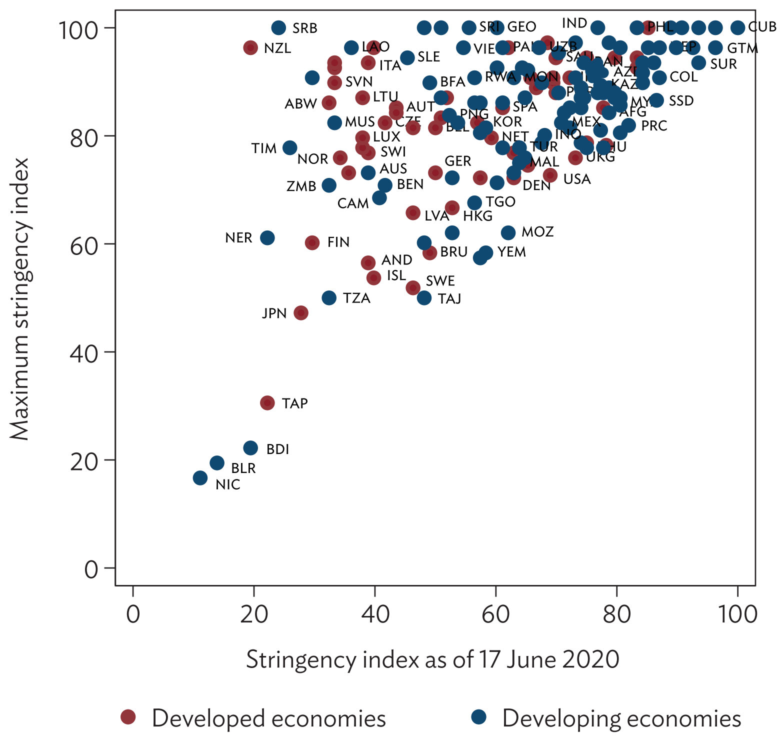


Notes: Developed economies refer to economies that belong to the high-income classification, while developing economies refer to economies that belong to the low-, lower-middle, and upper-middle income classification of the World Bank.

Source: Hale, Thomas, Noam Angrist, Emily Cameron-Blake, Laura Hallas, Beatriz Kira, Saptarshi Majumdar, Anna Petherick, Toby Phillips, Helen Tatlow, and Samuel Webster. 2020. Oxford COVID-19 Government Response Tracker, Blavatnik School of Government. https://www.bsg.ox.ac.uk/research/research-projects/coronavirus-government-response-tracker (accessed 30 June 2020).

Comparing the stringency of lockdown measures across economies reveals more variation in policy adoption. First, many economies have relaxed the overall lockdowns to some degrees since they were first introduced. Figure 2 compares the maximum value of the stringency index with the latest value as of 17 June 2020 using the OxCGRT stringency index. The economies on the 45-degree line maintained stringency index values at their respective maximums, while the economies on the top left half have more or less relaxed some control measures.

Figure 2: Stringency Index: Maximum and Latest Values



Notes: Developed economies refer to economies that belong to the high-income classification, while developing economies refer to economies that belong to the low-, lower-middle, and upper-middle income classification of the World Bank. Please refer to Appendix Table A2.2 for the definition of the three-letter codes. The maximum value of the stringency index is assessed between 1 January and 17 June 2020. The latest value of the stringency index is for 17 June 2020.

Source: Hale, Thomas, Noam Angrist, Emily Cameron-Blake, Laura Hallas, Beatriz Kira, Saptarshi Majumdar, Anna Petherick, Toby Phillips, Helen Tatlow, and Samuel Webster. 2020. Oxford COVID-19 Government Response Tracker, Blavatnik School of Government. https://www.bsg.ox.ac.uk/research/research-projects/coronavirus-government-response-tracker (accessed 30 June 2020).

Second, there is a large difference in stringency values and measures across economies. Figure 3 shows the maximum and latest values of the overall stringency index and selected control measures using the OxCGRT stringency index for various Asian economies. Georgia, India, the Philippines, and Sri Lanka implemented the most stringent measures (100) as of late March. Most economies have stringency index values above 70. Japan is among the most relaxed (less than 50) in Asia during the observation period.

Third, comparing specific measures across economies shows that school closure, prohibitions on public events, and border closures are the three most common restrictions imposed across the region (Figure 3). Workplace and public transport restrictions have been relaxed in most economies over time.

Figure 3: Stringency Index: Maximum and Latest Values

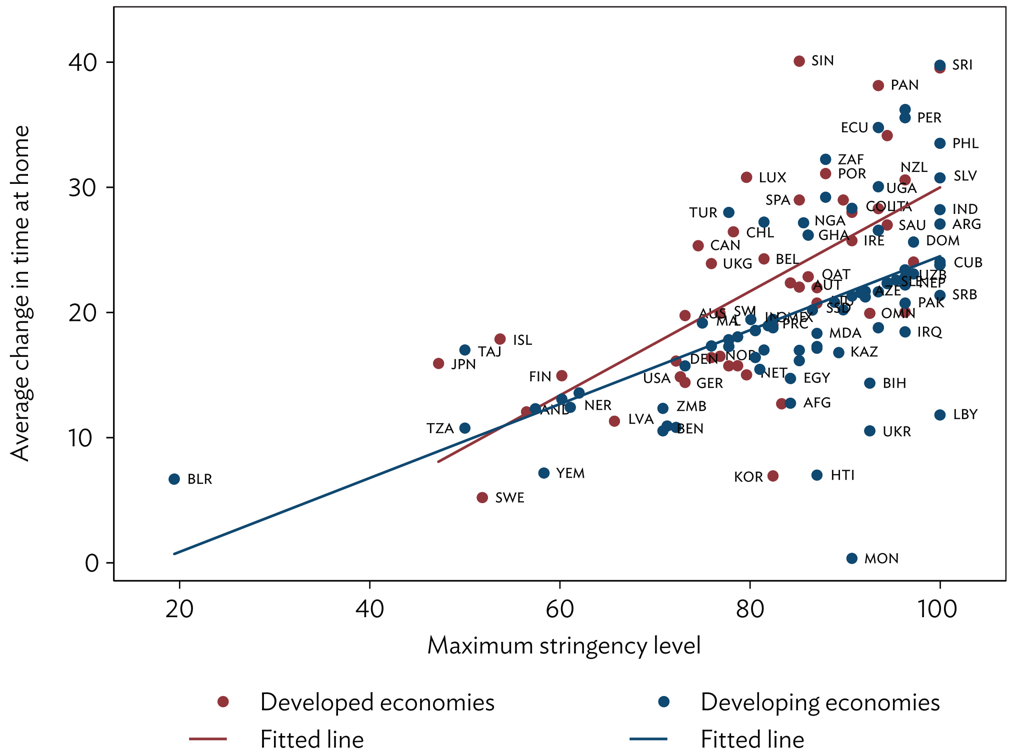
ADB Regional Members	Date when Strigency Index is Highest	Strigency Index (max)	Strigency Index (as of June 17)	School Closure	Workplace Closure	Public Events Cancellation	Gatherings Restriction	Public Transport Closure	Stay at Home	Internal Movement Restriction	Border Control
		0 to 100		0 to 4 (as of June 17)	0 to 4	0 to 3	0 to 5	0 to 3	0 to 4	0 to 3	0 to 4
Philippines	March 22	100	83								
India	March 22	100	77								
Georgia	March 31	100	60								
Sri Lanka	March 27	100	56								
Nepal	March 24	96	87								
Uzbekistan	April 28	96	67								
Pakistan	March 26	96	61								
Viet Nam	April 1	96	55								
Lao People's Democratic Republic	March 30	96	36								
New Zealand	March 26	96	19								
Bangladesh	April 11	94	75								
Kyrgyz Republic	March 25	92	76								
Azerbaijan	April 16	92	78								
Mongolia	May 5	91	63								
Kazakhstan	March 30	89	77								
Fiji	March 30	89	79								
Myanmar	April 17	86	81								
Singapore	April 14	85	78								
Afghanistan	April 12	84	79								
Papua New Guinea	April 16	84	52								
Republic of Korea	April 6	82	57								
Thailand	April 8	82	54								
People's Republic of China	March 26	82	82								
Indonesia	April 24	80	68								
Bhutan	March 27	78	75								
Timor-Leste	April 13	78	26								
Malaysia	May 23	75	64								
Australia	April 2	73	36								
Cambodia	April 9	69	41								
Hong Kong, China	April 6	67	53								
Brunei Darussalam	April 11	58	49								
Tajikistan	May 11	50	48								
Japan	April 16	47	28								
Taipei,China	February 2	31	22								

Notes: The maximum value of the stringency index is assessed between 1 January and 17 June 2020. The latest value of the stringency index is for 17 June 2020.

Source: Hale, Thomas, Noam Angrist, Emily Cameron-Blake, Laura Hallas, Beatriz Kira, Saptarshi Majumdar, Anna Petherick, Toby Phillips, Helen Tatlow, and Samuel Webster. 2020. Oxford COVID-19 Government Response Tracker, Blavatnik School of Government. https://www.bsg.ox.ac.uk/research/research-projects/coronavirus-government-response-tracker (accessed 30 June 2020).

Fourth, compared to developed economies, developing economies show relatively smaller increases in time spent at home even as more stringent lockdown measures were imposed. Figure 4 plots the maximum value of the stringency index imposed in each economy and the average changes in time spent at home during this period relative to the pre-COVID-19 baseline. There is no clear difference between changes in time at home by development level when the stringency index is moderate (less than 70). When the overall stringency index is high, developing economies show relatively smaller changes in time at home. A potential explanation for this is that people in developing economies simply cannot afford to stay at home for too long. For example, Dingel and Neiman (2020) show that emerging economies have a lower share of their labor force that can work from home.

Figure 4: Average Change in Time at Home during Period of Maximum Stringency



Notes: Developed economies refer to economies that belong to the high-income classification, while developing economies refer to economies that belong to the low-, lower-middle, and upper-middle income classification of the World Bank. Please refer to Appendix Table A2.2 for the definition of the three-letter codes. Average change in time at home indicates the average percentage change in time spent at home relative to a pre-COVID-19 baseline point of comparison during the period that an economy's stringency index is at its maximum value. Lines indicate linear fitted trends.

Source: Author's estimates.

IV. EMPIRICAL FRAMEWORK

We use panel regressions to estimate the relationship between R_t and COVID-19 control measures. Country fixed effects are included to account for time-invariant, or slow to change economywide features that may affect R_t, such as climate and geography, the nature and efficacy of the public health system, demographic characteristics, and prevalence of relevant comorbidities. A few time-invariant features are, however, introduced as interaction terms. We also include a linear time trend for days from outbreak in each country to absorb time-varying factors that affect R_t similarly across countries and day of week dummies to absorb cyclical patterns related to case reporting, as well as transmission risk contacts.

In principle, our approach is similar to using a difference-in-difference estimator and yields estimates of causal relationships, as long as the "parallel trends" assumption of similar changes over time in R_t in the absence of control measures of interest holds. Further, our use of a time trend that has a unique starting point per country based on when the pandemic emerged allows for control of R_t

reductions that occur naturally as the epidemic progresses and is an improvement over controls for time that are based solely on calendar dates.

We smooth our COVID-19 control measures and the time at home variable by using their corresponding 3-day moving average values. We then use 1-day lagged values of moving average as regressors to cover the periods up to that of the dependent variable.[13] R_t, as the dependent variable, is intended to be the instantaneous measure of how many individuals are being infected by the infectious on the given date, so that long lag effects are not needed, but there is also some imprecision in both the R_t measure and the policy implementation dates that the moving averages help to resolve.

Formally, we estimate the following model for R_t:

$$\begin{aligned} R_{t\,ct} = {} & \beta_M M_{c,t-1}^{ma(3)} + \beta_{MH} M_{c,t-1}^{ma(3)} \times HH_c \\ & + \beta_M Measure_{c,\,t-1}^{ma(3)} \\ & + \beta_{Tracing} Tracing_{c,\,t-1}^{ma(3)} \\ & + \beta_{EarlyT}\, Tracing_{c,\,t-1}^{ma(3)} \times EarlyT_c \\ & + \beta_{PSLT}\, Tracing_{c,\,t-1}^{ma(3)} \times PSL_c \\ & + \beta_{temp} Temp_{c,t-1}^{ma(3)} \\ & + \beta_t T \\ & + \beta_{wk} WK_t \\ & + \alpha_c + \epsilon_{ct} \end{aligned} \tag{1}$$

where Rt_{ct} is the reproduction number in country c on date t; $M_{c,t-1}^{ma(3)}$ is the 3-day moving average of changes in time at home on date $t-1$; HH_c is average household size and is interacted with time at home; $Measure_{c,t-1}^{ma(3)}$ is a vector of a series of 3-day moving average of country-specific control measures on date $t-1$ in country c, including school closure, workplace closure, public transport closure, small and large gathering ban, and large scale testing. $Tracing_{c,\,t-1}^{ma(3)}$ is the 3-day moving average of contact tracing measures on date $t-1$ in country c. $EarlyT_c$ is the number of days that contact tracing has been implemented prior to a country having 100 cumulative COVID-19 cases. It takes on negative values if tracing is implemented after 100 cumulative cases; PSL_c denotes the presence or absence of paid sick leave in country c; $Temp_{c,t-1}$ is the maximum temperature for country c on date $t-1$; T is linear time trend; WK_t is day of the week dummies; α_c is a country fixed effect; and ϵ_{ct} is the idiosyncratic error term for country c on date t.

To this regression we add a set of variables controlling for the timing of the appearance of genetic strains or clades of COVID-19 in selected runs. There has been speculation within the scientific community that new mutations have made COVID-19 more easily transmitted, and the inclusion of the variables helps to test this hypothesis.

To estimate the effects of COVID-19 control measures on GDP growth, we also use panel regression with country fixed effects to account for country-specific variations that could affect GDP growth. We also include quarter fixed effects in the specification, as well as the lagged effect of growth

[13] A range of lag structures and smoothing periods was tested, and the 3-day moving average with 1-day lag performed best in the regressions.

in the same quarter in the previous year. Days since the first identified case in the country are also included to control for demand-side responses to the presence of the pandemic that may occur absent any control measures. The main independent variables are the natural log of the number of days that each control measure has been in place over each quarter. The control measures that can be included are constrained by correlations when summed to the quarterly level; thus those not expected to affect GDP (i.e., mask mandates, testing, and tracing) are summed to an index, whereas those expected to affect GDP are included separately.

Formally, we estimate the following model for GDP growth:

$$g_{cq} = \gamma_P lnDMeasure_{cq} + lnF_{cq} + \rho_q + g_{cq-4} + \delta_c + \varepsilon_{cq} \quad (2)$$

In equation (2), g_{cq} is the GDP growth rate of country c in quarter q; $DMeasure_{cq}$ is a vector of the total number of days various control measures have been implemented in country c in quarter q; F_{cq} is the number of days since the first COVID-19 case in the country; ρ_q is the quarter fixed effect; δ_c is a country fixed effect; ε_{cq} is the idiosyncratic error term for country c in quarter q.

Multicollinearity may be a concern that arises from the possible correlation of independent variables in the regression, as many countries have adopted a number of the control measures of interest. However, the data sources used indicate that the changes in these measures have not been simultaneous over time, so that it is possible to disentangle their effects with a two-way fixed effects model that focuses causal identification on differences in changes over time. Pairwise correlations in these differences are presented in Appendix Table A2.1.

V. RESULTS

A. Baseline Results of R_t and Measures

Table 2 presents our baseline results from equation (1). All specifications include day of the week fixed effects and country fixed effects.[14] Column (1) only includes change in time at home and its interaction with household size. Column (2) includes all COVID-19 control measures but does not control for time at home or PSL. Column (3) adds to Column (2) changes in time at home and Column (4) further adds an interaction of contact tracing and PSL. Column (4) is our preferred specification. There are several findings worth noting.

First, as expected, the coefficient on change in time at home is negative and significant. On average, a 1% increase in time at home leads to a 0.02 unit reduction in R_t. However, given the positive and significant coefficient on the change in time at home and household size interaction term, the effect is smaller if household size is larger. Compared to another country with one-unit smaller household size (i.e., on average, one fewer person per household), the effect of change in time at home and R_t reduction is 0.003 smaller (or 15% smaller on average). This implies that asking people to stay at home may be less

[14] We tested the specifications using pooled-OLS method. The large discrepancies of coefficients and level of significance of many independent variables (such as change in time at home, school closure, etc.) between pooled-OLS estimates and baseline results indicate missing variable bias when excluding country fixed effects. The pooled-OLS model also yields a much smaller explanatory power.

effective in reducing COVID-19 spread when household size is larger.[15] Including the mobility measure increases the explanatory power of the model substantially, indicating that it captures behavioral responses in addition to those dictated by the various control measures.

Second, the coefficients on lockdown measures included in the model are all negative and significant, except for closure of public transport, which is negative but not significant. Interestingly, the various lockdown measures lead to varying degrees of reduction in R_t. Small and large gathering bans lead to a 0.10 unit reduction in R_t, similar to the effect of school closures, which leads to a 0.09 unit reduction in R_t, followed by workplace closures (0.05 unit reduction). We do not find closures of public transport to have a significant effect on R_t.

Table 2: Baseline Results: R_t and Control Measures

Variables	(1)	(2)	(3)	(4)
Change in time at home	−.0176***		−.0204***	−.0211***
	(.0043)		(.0038)	(.0039)
Change in time at home x Household size	5.9e-04		.003***	.0031***
	(.0011)		(9.4e-04)	(9.9e-04)
Small gathering ban		−.175***	−.0975**	−.099***
		(.0377)	(.0372)	(.0372)
Large gathering ban		−.143***	−.0987***	−.0976***
		(.0363)	(.0335)	(.0337)
School closure		−.177***	−.0942***	−.092***
		(.0253)	(.0257)	(.0252)
Workplace closure		−.105***	−.0474*	−.0471*
		(.0261)	(.0256)	(.0254)
Public transport closure		−.0197	−.0105	−.0079
		(.0318)	(.0312)	(.0309)
Mask use		−.0416	−.0535	−.0603*
		(.0347)	(.034)	(.0342)
Mass testing		−.0542*	−.0551**	−.0542**
		(.0297)	(.0267)	(.0261)
Contact tracing		−.146**	−.156***	−.0472
		(.0649)	(.0562)	(.0636)
Early tracing		−.0032**	−.0037***	−.0029***
		(.0015)	(.0013)	(.001)
Tracing x PSL				−.207***
				(.0697)
Time trend		−.0029***	−.0028***	−.0028***
		(5.5e-04)	(5.6e-04)	(5.6e-04)
Max temperature		−.0036*	−.0059**	−.0058**
		(.0021)	(.0024)	(.0024)
Day of the week FE	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes

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[15] For context, average household size is 2.73 in developed countries in our sample, compared to 4.26 in developing economies.

Table 2 *continued*

Variables	**(1)**	**(2)**	**(3)**	**(4)**
Observations	6,639	6,639	6,639	6,639
No. of countries	75	75	75	75
R-squared	0.204	0.522	0.566	0.572
F statistic	13.500	37.341	33.242	34.866

FE = fixed effects, PSL = paid sick leave.

Notes: Robust standard errors clustered by country in parentheses. *** = p<0.01, ** = p<0.05, * = p<0.1.

Source: Authors' estimates.

Third, we find most coefficients on the remaining NPIs to be negative and significant, and that the interaction term on contact tracing and PSL is the largest among all control measures considered. Specifically, when not controlling for PSL, tracing leads to a 0.16 unit of reduction in R_t, and the coefficient is significant. But when tracing is interacted with PSL, the coefficient on tracing is no longer significant and its level becomes much smaller. On the other hand, the coefficient of the interaction term between tracing and PSL is negative and statistically significant, suggesting that tracing is effective in reducing R_t in countries that provide PSL benefits. In other words, the effect of tracing on R_t arises from the combined effect of contact tracing and providing PSL benefits. On average, economies with PSL and tracing experience a 0.21 unit of reduction in R_t compared to economies only implementing tracing, meaning that one infected individual on average infects 0.21 fewer other people. We also find the coefficient on early tracing to be negative and significant.

Intuitively, offering PSL incentivizes workers who may be infected to report their symptoms and self-isolate. In the absence of PSL benefits, workers may choose to hide their symptoms or illness and continue to report for work and get paid. This is particularly relevant for COVID-19 where a large share of cases have mild symptoms or are asymptomatic, but are still capable of spreading the disease. When a worker with a mild case has to choose between staying at home and losing income or reporting for work and getting paid, the absence of PSL can nudge the worker to choose the latter even it means that they might infect coworkers. Providing PSL can not only reduce such "contagious presenteeism," it is also very likely to make tracing of COVID-19 cases easier and more accurate.

Fourth, comparing the results in Columns (2) and (4) shows that the coefficients on lockdown measures become smaller when we control for changes in time at home, with their magnitude smaller by about a half. For example, the coefficient on workplace closure changes from −0.105 to −0.047. On the other hand, there is little difference in the coefficients of nonlockdown measures, such as a mandate on masks, mass testing, and tracing. This indicates that reduced mobility is an important channel linking lockdown measures to reductions in R_t. The coefficients on control measures in Column (2) can be interpreted as an upper bound of their effects on R_t, while the coefficients on control measures in Column (4) can be interpreted as a lower bound.

Fifth, we have performed the same regression with additional control variables for the presence of major COVID-19 clades, and this reveals that more recent clade 20B appears to increase transmission rates (Table 3). In this specification, most of the other coefficients remain similar, although masks, gathering bans, and mobility reductions have larger effects, whereas testing loses significance. Because clades are not characterized for some countries, the sample is slightly smaller, and we use the specification without this variable in the other analyses presented subsequently. However, we include the result here, as the implication of this result is that newer mutations may be making COVID-19 more infectious and difficult to control. When this is considered along with our significant negative coefficients on temperature, this may imply that large second waves are likely when temperatures cool in countries with many infections later in 2020.

Table 3: R_t and Control Measures when Genetic Strains are Controlled

Variables	Baseline	Clade
Change in time at home	−.0211***	−.0278***
	(.0039)	(.0032)
Change in time at home x Household size	.0031***	.0052***
	(9.9e-04)	(9.3e-04)
Small gathering ban	−.099***	−.134***
	(.0372)	(.0421)
Large gathering ban	−.0976***	−.117***
	(.0337)	(.0363)
School closure	−.092***	−.0888***
	(.0252)	(.0284)
Workplace closure	−.0471*	.0158
	(.0254)	(.0222)
Public transport closure	−.0079	−.0185
	(.0309)	(.0331)
Mask use	−.0603*	−.0896**
	(.0342)	(.0339)
Mass testing	−.0542**	−.0155
	(.0261)	(.0264)
Contact tracing	−.0472	.0297
	(.0636)	(.0606)
Early tracing	−.0029***	−.0018*
	(.001)	(.001)
Tracing x PSL	−.207***	−.226***
	(.0697)	(.0667)
Time trend	−.0028***	−.0024***
	(5.6e-04)	(5.8e-04)
Max temperature	−.0058**	−.0083***
	(.0024)	(.002)
Clade 19A presence		−.0506
		(.0523)
Clade 19B presence		−.0271
		(.0536)
Clade 20A presence		−.0712
		(.0508)
Clade 20B presence		.0845**
		(.0393)
Clade 20C presence		−.054
		(.0411)
Day of the week dummy	Yes	Yes
Country FE	Yes	Yes
Observations	6,639	5,102
No. of countries	75	56
R-squared	0.572	0.649
F statistic	34.866	58.414

FE = fixed effects, PSL = paid sick leave.

Notes: Robust standard errors clustered by country in parentheses. *** = p<0.01, ** = p<0.05, * = p<0.1.

Source: Authors' estimates.

B. Robustness Tests

We test the robustness of our baseline results in two ways. We use an alternative and stricter definition of a PSL benefit that is relevant as a COVID-19 control measure. We also restrict our samples to countries with direct Google mobility time at home data. Our results are maintained under both cases.

First, to see if our highly significant result on the interaction of PSL and tracing is spurious due to the construction of the PSL dummy, we test the same specification using a much stricter PSL dummy. In the baseline specification, we constructed our PSL dummy by distinguishing whether a country offers *some* duration of PSL and the program covers *some* self-employed and part-time workers. In this setup, 25 out of 75 countries are considered to offer PSL. As an alternative, we consider a country to offer a COVID-19 relevant PSL only if the scheme offers at least 2 weeks of well-paid sick leave; it starts from the first day of absence from work; and guarantees coverage for both part-time and self-employed workers. In this strict setup, the number of countries offering PSL is down to 9 out of 75. The results, shown in Column (1) of Table 4, are only slightly different in terms of the coefficient compared to the baseline specification, with the significance levels of tracing, early tracing, and interaction term involving tracing and PSL the same as those in the baseline.

Second, we restrict our sample to only those countries with direct time at home data from Google. In our baseline specification, we use predicted time at home for countries without Google data to increase sample size. There are seven countries in our sample using the stringency-proxied time at home.[16] To see if our result is sensitive to the inclusion of projected time at home due to multicollinearity, we restrict our sample to the 68 countries with direct Google data in Column (2) of Table 4. Results are largely similar compared to the baseline results. The signs and significances of coefficients on the independent variables that are prone to the issue of multicollinearity largely stay the same, including change in time at home, household and change in time at home interaction, gathering bans, school closure, public transport closure, contact tracing, early tracing, and tracing and PSL interaction.

Table 4: Robustness Test of R_t and Control Measures

	Strict PSL Definition	Google Mobility Only
Variables	**(1)**	**(2)**
Change in time at home	−.0197***	−.0239***
	(.0037)	(.004)
Change in time at home x Household size	.0027***	.0036***
	(9.3e-04)	(.0011)
Small gathering ban	−.1***	−.0929***
	(.0374)	(.0302)
Large gathering ban	−.1***	−.0958***
	(.0346)	(.0307)
School closure	−.0979***	−.0761***
	(.0256)	(.0223)
Workplace closure	−.0449*	−.0214
	(.0253)	(.0254)
Public transport closure	−.0092	−.0088
	(.031)	(.0336)

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[16] These seven countries are: Azerbaijan, Cuba, Guinea, Iran, Palestine, the PRC, and Uzbekistan.

Table 4 *continued*

Variables	Strict PSL Definition (1)	Google Mobility Only (2)
Mask use	−.0603*	−.0346
	(.0341)	(.0297)
Mass testing	−.0511**	−.0229
	(.0256)	(.025)
Contact tracing	−.0813	−.0456
	(.0551)	(.0598)
Early tracing	−.0035***	−.0032***
	(9.9e-04)	(.0012)
Tracing x PSL	−.220***	−.196***
	(.0729)	(.0709)
Time trend	−.0028***	−.0032***
	(5.6e-04)	(4.7e-04)
Max temperature	−.0057**	−.009***
	(.0024)	(.0024)
Day of the week FE	Yes	Yes
Country FE	Yes	Yes
Observations	6,639	5,932
No. of countries	75	68
R-squared	0.572	0.618
F statistic	33.615	36.297

FE = fixed effects, PSL = paid sick leave.

Notes: Robust standard errors clustered by country in parentheses. *** = p<0.01, ** = p<0.05, * = p<0.1.

Source: Authors' estimates.

C. Heterogeneity in Results across Developed and Developing Economies

To see whether there exists heterogeneity in the effects of control measures on R_t across developed and developing economies and phases of the pandemic, we split the sample by development level as defined by the World Bank and by prepeak and postpeak phases as defined by active cases.

Columns (1) and (2) of Table 5 show the results when samples are split by economic development level of countries implementing the measures.[17] There are two differences worth noting. First, the effect of change in time at home, and its interaction with household size are significant in developed countries, but not significant in developing economies. One reason for this is suggested by Figure 4: people in developing economies do not stay at home as much during lockdown. Second, the coefficient of the PSL and contact tracing interaction term in developing economies is a lot larger than that in developed countries. A reason that may underpin both findings could be that workers in developing economies have less ability to cope with income loss, so that contagious presenteeism may be more frequent.

We also split the sample in each country by the first wave peak of the pandemic in each country, as captured within the time frame of our sample. The peak of the pandemic is defined as the date with the largest number of active cases before 17 June 2020. The results (Columns 3 and 4 of Table 4) show

[17] We categorize high-income countries classified by the World Bank as developed, and the rest as developing.

that the coefficients on time at home and control measures in the prepeak sample have similar significance levels to those in the baseline, while coefficients in the postpeak sample are not significant. This indicates that the baseline results are largely driven by the prepeak phase of the pandemic. In other words, the association between R_t and control measures are much weaker in the postpeak phase.

Table 5: Split Sample Heterogeneity of R_t and Control Measures

	Developed	Developing	Prepeak	Postpeak
Variables	**(1)**	**(2)**	**(3)**	**(4)**
Change in time at home	−.0331***	−.0024	−.0216***	.0037
	(.0053)	(.0063)	(.0045)	(.0059)
Change in time at home x	.0064**	−9.0e-04	.0035***	−6.5e-04
Household size	(.0024)	(.0013)	(.001)	(.0019)
Small gathering ban	−.0985**	−.0929	−.0769*	−.1**
	(.0382)	(.0662)	(.0408)	(.0477)
Large gathering ban	−.0888**	−.0936*	−.0963**	−.0681
	(.0393)	(.0543)	(.0438)	(.0495)
School closure	−.0712**	−.142***	−.101***	−.04
	(.0334)	(.048)	(.0301)	(.0307)
Workplace closure	−.0192	−.0434	−.0653**	−.0038
	(.0322)	(.0337)	(.03)	(.0264)
Public transport closure	.0371	−.0472	−.021	.0167
	(.0528)	(.0349)	(.0405)	(.0394)
Mask use	−.0402	−.0876	−.0045	−.0461*
	(.0386)	(.0528)	(.0343)	(.026)
Mass testing	−.035	−.0834*	−.0686*	.011
	(.0299)	(.0433)	(.0347)	(.0262)
Contact tracing	−.0782	−.0634	−.0068	−.0283
	(.0669)	(.0731)	(.0662)	(.0975)
Early tracing	−.0026**	−.0028	−.0015	−9.4e-04
	(.0012)	(.0017)	(.0012)	(.0018)
Tracing x PSL	−.15*	−.258**	−.229***	0
	(.0764)	(.104)	(.0839)	(.)
Time trend	−.003***	−.0021**	−.0033***	.0034***
	(6.3e-04)	(9.5e-04)	(6.8e-04)	(4.6e-04)
Max temperature	−.0115***	−.0013	−.004	−.0024
	(.0021)	(.0031)	(.0031)	(.002)
Day of the week FE	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes
Observations	3,157	3,482	3,875	2,764
No. of countries	34	41	75	58
R-squared	0.680	0.507	0.591	0.316
F statistic	107.936	57.032	26.761	17.078

FE = fixed effects, PSL = paid sick leave.

Notes: Robust standard errors clustered by country in parentheses. *** = p<0.01, ** = p<0.05, * = p<0.1. Column 1 is restricted to the sample of developed economies (i.e., high-income economies), and Column 2 is the sample of developing economies. Column 3 is restricted to the sample before the date with the highest active cases, and Column 4 is the sample after the date with the highest active cases.

Source: Authors' estimates.

The findings for the samples split by prepeak and postpeak periods are further confirmed by the results of the quantile regressions. Table 6 shows the regression results at 10th/30th/50th/70th/90th percentile of R_t. Several control measures, such as gathering bans, a mandate on masks, and the combination of testing and tracing are associated with larger reductions in R_t when R_t is high. Similar results are found for change in time at home.

Table 6: Quantile Regression of R_t and Control Measures

Variables	(1) R_t=0.8 (10th percentile)	(2) R_t=1.0 (30th percentile)	(3) R_t=1.1 (50th percentile)	(4) R_t=1.2 (70th percentile)	(5) R_t=1.5 (90th percentile)
Change in time at home	−.0063*	−.0111***	−.0111***	−.0206***	−.0395***
	(.0036)	(.0035)	(.0035)	(.0062)	(.0125)
Change in time at home x Household size	.0023**	.0023***	.0023***	.0034*	−.0015
	(9.3e-04)	(8.4e-04)	(8.4e-04)	(.0018)	(.0033)
Small gathering ban	−.0584	−.0816**	−.0816**	−.111**	−.114
	(.0373)	(.0335)	(.0335)	(.0473)	(.0998)
Large gathering ban	−.0574	−.0509*	−.0509*	−.0844**	−.142
	(.0418)	(.0277)	(.0277)	(.0384)	(.0955)
School closure	−.105***	−.038	−.038	.0074	−.0939
	(.0295)	(.0256)	(.0256)	(.0279)	(.0784)
Workplace closure	−.0332	−.025	−.025	−.0494	−.0365
	(.0269)	(.0259)	(.0259)	(.0389)	(.0648)
Public transport closure	−.0249	−.0013	−.0013	−2.0e-04	−.0494
	(.0297)	(.0239)	(.0239)	(.0548)	(.0946)
Mask use	−.0416	−.051*	−.051*	−.0769*	−.142*
	(.0296)	(.0266)	(.0266)	(.0459)	(.0755)
Mass testing	−.0129	.004	.004	−.0257	−.159**
	(.0301)	(.0259)	(.0259)	(.0312)	(.0781)
Contact tracing	−.005	.0557	.0557	.0577	−.208
	(.0375)	(.0445)	(.0445)	(.0488)	(.162)
Early tracing	2.6e-04	−5.1e-04	−5.1e-04	−.0021	−.0095***
	(5.5e-04)	(7.8e-04)	(7.8e-04)	(.0013)	(.0028)
Tracing x PSL	−.0511	−.169***	−.169***	−.275***	−.399
	(.0455)	(.0607)	(.0607)	(.0678)	(.248)
Time trend	8.2e-04*	1.2e-05	1.2e-05	−.0042***	−.0104***
	(4.8e-04)	(4.8e-04)	(4.8e-04)	(6.7e-04)	(.0015)
Max temperature	−.0033*	−.0042**	−.0042**	−.0037	−.0068
	(.0018)	(.0019)	(.0019)	(.0038)	(.0063)
Day of the week FE	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes
Observations	6,639	6,639	6,639	6,639	6,639
No. of countries	75	75	75	75	75
R-squared	0.227	0.387	0.387	0.512	0.557
F statistic	2.512	8.280	8.280	36.169	29.619

FE = fixed effects, PSL = paid sick leave.

Notes: Robust standard errors clustered by country in parentheses. *** = p<0.01, ** = p<0.05, * = p<0.1.

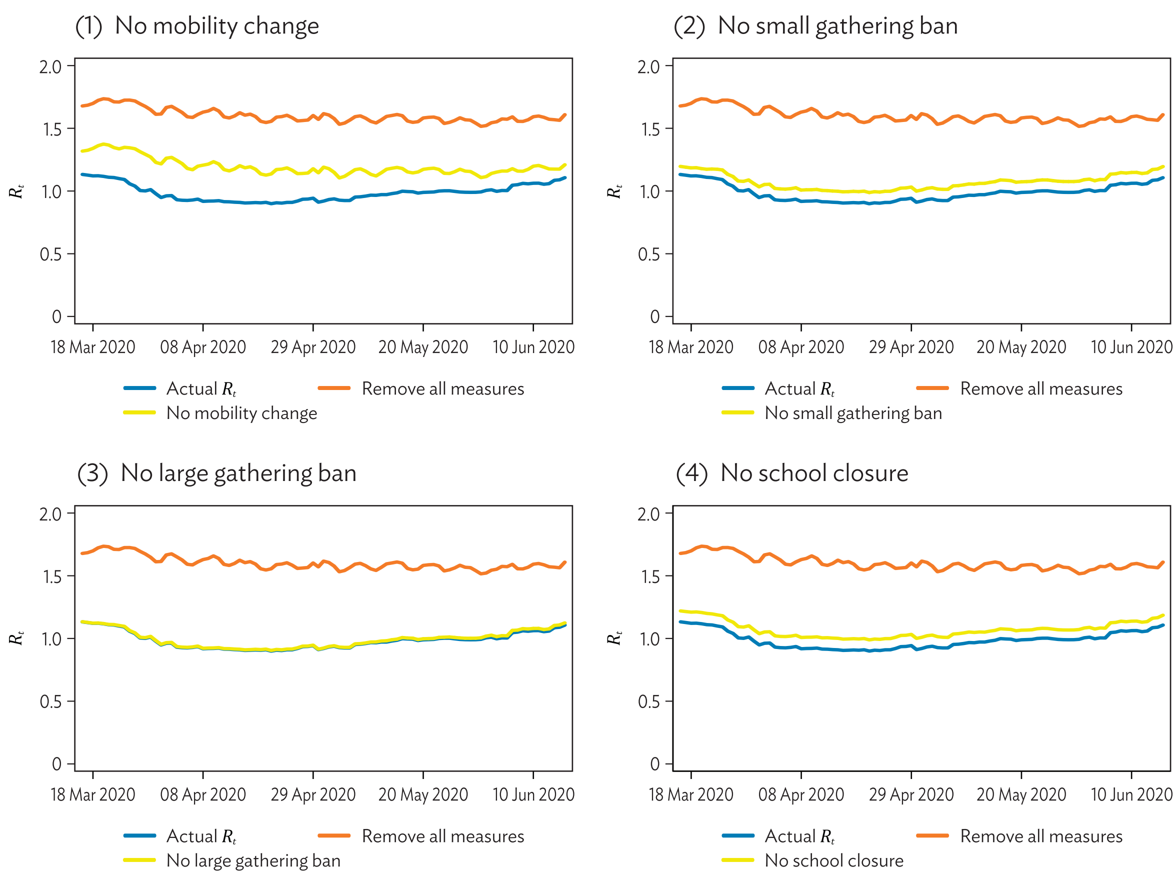
Source: Authors' estimates.

D. Evaluating Counterfactuals of COVID-19 Transmission

We conduct an exercise involving the counterfactual of how R_t would evolve if certain measures were not implemented. Using the baseline regression results, we predict the counterfactual R_t by removing each control measure for a given country at each date. We also predict the R_t in a country if it were to not implement the control measures it did. We then aggregate both sets of counterfactual R_t and actual R_t across countries at each given date and weight these by cases in each country.

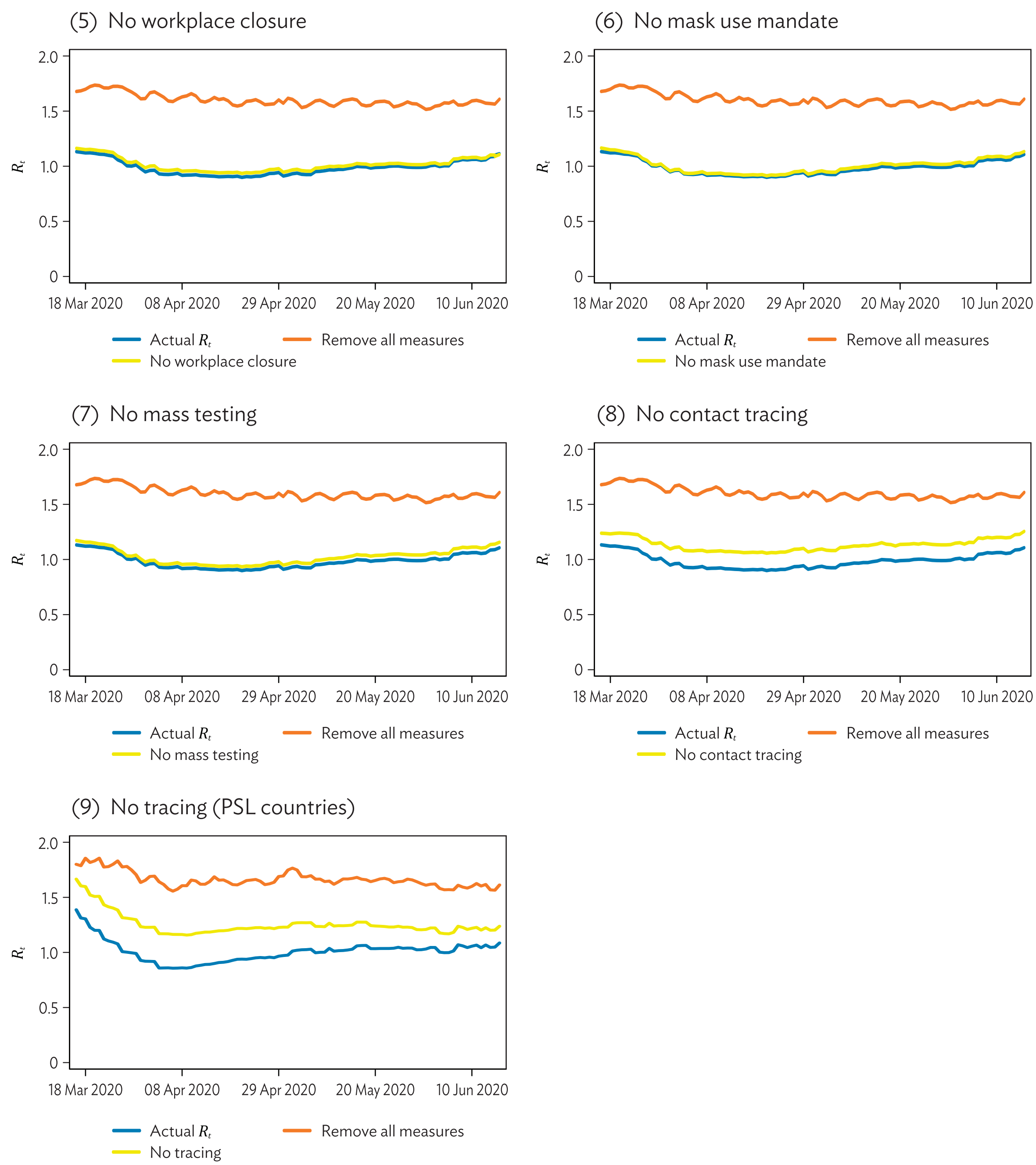
Figure 5 shows the aggregated actual R_t and counterfactual R_t for sample countries when removing all control and time at home measures, and the counterfactual R_t when removing one specific measure. A key finding here is that absent explicit control measures, the time-varying reproductive rate is substantially lower than typical initial R_0 estimates of 2 or more. A lower reproductive rate has many important implications, including a lower herd immunity threshold and lower expected share of the population that will be eventually infected absent control measures. The contribution of adopted measures to keeping R_t reduced generally follows the coefficients estimated, but the figures also imply that relaxation of measures will be likely to lead to second waves in many countries, as the R_t will substantially exceed 1.

Figure 5: Actual versus Counterfactual R_ts



continued on next page

Figure 5 *continued*



PSL = paid sick leave.

Notes: (i) "Removing all measures" indicates the counterfactual R_t resulting from an absence of all COVID-19 control measures and no changes in the time spent at home, while a "No" preceding a specific control measure indicates the counterfactual R_t resulting from an absence of that measure while keeping other measures as they actually are. (ii) Removed measures include small and large size gathering bans, school closure, workplace closure, mass testing, mask mandates, contact tracing, and PSL. For the counterfactual involving the changes in time spent at home, we set the change in time at home to 0. (iii) For contact tracing, we additionally perform a counterfactual exercise for the subsample of countries with PSL. (iv) R_t values are weighted by the cumulative case counts in each country.

Source: Authors' estimates based on baseline regression results.

E. Quarterly Gross Domestic Product Growth Rate and Control Measures

We now turn our focus to the economic costs of the various control measures. Table 7 shows the results of regressing quarterly GDP growth rates on key control measures of workplace, school, and transport closures, as well as other interventions. Countries implementing workplace and school closures experienced significant growth contractions as a result. For 1% increase in the duration of workplace and school closures, growth contracts by approximately 0.005 percentage points. On the other hand, the results suggest that other types of control measures, such as contact tracing and testing do not lead to contraction of the economy.

Table 7: Regression Results of Quarterly Gross Domestic Product and Control Measures

Variables	Quarterly GDP Growth
Workplace closure	−0.491**
	(0.204)
School closure	−0.464*
	(0.266)
Public transport closure	−0.194
	(0.390)
Index of other control measures	−0.252
	(0.220)
Days since first case	−1.166**
	(0.532)
GDP in quarter in previous year	−0.481***
	(0.112)
Constant	4.322***
	(0.388)
Observations	511
R-squared	0.816
F statistic	50.991

GDP = gross domestic product.

Notes: Quarter dummies omitted. Standard errors in parentheses. *** = p<0.01, ** = p<0.05, * = p<0.1.

Source: Authors' estimates.

VI. DISCUSSION

A. Limitations

Our empirical analysis is subject to two main data limitations. The first concerns our dependent variable, R_t, for the regressions of COVID-19 control measure effectiveness. The procedure used to estimate R_t depends on the quality of case reporting, even if it attempts to correct for reporting delays and underreporting. The procedure relies on global corrections and may not be fully able to account for differences among countries, although this is a limitation shared by almost all studies of COVID-19 outcomes. Estimates of R_t are also unstable when cases are low, so that some truncation is needed to cover periods during which the variable is stable.

The second data limitation concerns how widely enforced or applicable the various COVID-19 control measures are across countries and over time. In particular, unlike our measure of mobility (as captured by time at home) which is continuous, the degree to which control measures such as workplace closures or a mandate to use masks are adhered to is an unknown. To the extent that enforcement is not captured by the inclusion of country fixed effects, our coefficients may be estimated with some bias. For example, some measures may be enforced more intensely or more effectively in certain countries and at different phases of the pandemic. Mobility has been measured based on Google, which may have issues of selection bias, in that the data are only captured from populations with smart devices and location tracking enabled. Thus, the variable may only reflect the patterns of part of the population, and the representativeness of that part of the population may differ across countries. Unfortunately, we are not aware of a similar mobility data source without this problem that could substitute for all our sample countries.

Although our approach is able to control for time-invariant factors that differ among countries, it is dependent on the parallel trends assumption that the countries that did not institute a particular measure at a particular time would have had similar trends to those that did absent the measure. This assumption appears to be reasonable, given the similarity of initial reproductive rates across countries, as well as that the regressions are operating off the specific timing of when measures were adopted within the outbreak. The specific timing variations appear to largely be driven by exogenous specificities of decision-making within individual countries.

In terms of isolating the economic effects of containment measures, the analysis is constrained by the infrequency of GDP estimates. This infrequency limits observation sizes and renders multicollinearity a constraint that limits the variables that can be included simultaneously in the regression.

B. Consistency with Other Literature

Despite these limitations, our findings contribute to the body of work that is trying to understand the effectiveness of different measures to control the spread of COVID-19 and their associated costs on the economy. As future waves of the disease emerge, control measures proven to be effective and with lower economic costs should be implemented early and fast. Such measures should also be central features of the "new normal" until herd immunity is achieved.

In many ways, the results of our work are consistent with other recent analyses of COVID-19 control measures and policies to control similar respiratory communicable diseases. Islam et al. (2020)

reached somewhat similar conclusions, with limited effects of transport closure detected, but effects on other measures found. Our analysis adds to this by including control measures omitted from that analysis, such as testing, contact tracing, and PSL, and by using a specification that accounts for interaction and individual measure effects.

Flaxman et al. (2020) find a large effect of lockdown on R_t, although the paper is unable to distinguish this from other interventions, due to timing similarities, which this paper overcomes through the use of data from more countries. The Brauner et al. (2020) paper is similarly able to overcome this limitation by analyzing a larger observation set (41 countries), and finds large effects from closing most nonessential businesses, closing universities and schools, and smaller, but significant effects of mandating wearing masks.

Carraro, Ferrone, and Squarcina (2020) similarly conclude that fewer measures are effective in low-income economies than higher-income ones, and find many of the same measures effective in high-income economies, but find workplace closure as an effective measure in low-income economies. Our paper finds a much smaller effect of business closing in both high- and low-income economies. Part of the latter result is due to the inclusion of a mobility variable that captures an additional behavioral response, but even in the specification lacking the variable, we still find a smaller effect of business closing, due to additional controls included in our regression, such as temperature. Islam et al. (2020) also share our finding of lower effectiveness of measures in low-income economies.

The result that larger household sizes tend to diminish the effectiveness of mobility reductions is a new contribution to the literature from an empirical perspective. At the same time, it is well understood from the perspective of social contact networks that larger household sizes mean that a larger share of total contacts that can contribute to disease spread is within the household, and that reduction of outside home contacts and intensification of within home contacts as mobility is reduced will lower contact rates less than in a smaller household contact setting (Nande et al. 2020).

Our novel finding of the importance of PSL to contact tracing effectiveness, while new for COVID-19, is also not without precedent in the broader literature. The importance of PSL to reduce disease transmission in workplaces and overall disease reproductive rates has been demonstrated for influenza like illnesses (Pichler, Wen, and Ziebarth 2020; Pichler and Ziebarth 2017). Given the particular characteristics of COVID-19—that most workers with mild symptoms face minimal risk from engaging in contagious presenteeism, and that the benefits of accurately disclosing information on exposure and symptoms accrue principally as an externality to other parties—it is logical to expect that payment to help correct incentives will make tracing more effective. The theoretical model in Appendix 1 provides further details.

Our results on additional controls are also consistent with prior literature. Wu et al. (2020) find that higher temperature is associated with lower transmission of COVID-19. There is also suggestive evidence that recent mutations are increasing COVID-19 transmission, in line with the significant coefficient on the presence of one of the newer clades (Korber et al. 2020). Unlike several other papers, our analysis finds a lower effective reproductive rate absent control measures of approximately 1.6, rather than the initial reproductive rate of around 2.5 typically generated from early observations (such as by Wu, Leung, and Leung 2020). At the same time, there are unobserved behavioral responses that are likely conditioning this difference, such as more frequent handwashing and maintenance of physical distance when in public settings. In addition, recent papers suggest that heterogeneity in social contacts and susceptibility may make transmission over longer time periods behave as though the reproductive rate is lower than observed in the initial phases of the pandemic (Gomes et al. 2020).

In terms of economic effects, our results confirm the findings of Demirgüç-Kunt, Lokshin, and Torre (2020) that there are substantial effects on economic activity of lockdown measures, especially, business closure, as shown in our results. Unlike their analysis, however we find significant effects of school closure.

Our findings of large consequences of school closure however are consistent with literature that demonstrates how parental labor force participation declines when schools are closed and parents need to devote additional time to childcare, affecting both household income and broader macroeconomic output (e.g., Sadique, Adams, and Edmunds 2008). In essence, suspension of school or remote education requires parents to stay at home, crowds out labor supply and reduces productivity when working from home. For example, Fuchs-Schündeln, Kuhn, and Tertilt (2020) estimate that school and childcare center closure will affect 11% of workers and 8% of working hours. Dingel, Patterson, and Vavra (2020) estimate that 14% of workers under the age of 55 would likely face childcare obstacles to returning to work with schools closed. A second mechanism may be that, school closure, which is often implemented as a very early control measure, draws attention to epidemic risks and prompt a large share of the population to take COVID-19 seriously, thus reducing certain types of consumption, such as going to restaurants or travelling, as part of precautionary behavior.

VII. CONCLUSION

We have examined how the transmission of COVID-19 as captured by the reproduction number, R_t, is associated with various measures undertaken to control its spread by analyzing daily data from 75 economies for the first half of 2020. There are a number of important findings from a policy perspective.

First, while the reduction of COVID-19 spread is strongly driven by increases in time at home, this relationship is weaker when household size is large and especially so in developing economies. This suggests that lockdown orders that aim to suppress the spread of COVID-19 by restraining the mobility of people are less likely to be effective in communities with large households or where compliance is not compatible with the economic pressures that the population faces.

Second, the largest reductions in R_t are driven by gathering bans and school closures, followed by the use of masks, mass testing, and workplace closure. These effects are largely driven when the measures are put in place in the early phase of the pandemic. More generally, this demonstrates the importance of considering behavioral incentives set by policies to ensure that they have desired effects.

Third, we find that contact tracing, when implemented early and in contexts where PSL benefits tend to cover all types of workers (i.e., including self-employed and temporary workers), is strongly associated with reductions in R_t, especially in developing economies.

Fourth, countries implementing workplace and school closures experienced larger contractions in GDP growth in the first half of 2020, while countries implementing other measures do not show significant contractions in economic growth. This highlights the importance of moving beyond these measures to more targeted strategies, such as gathering bans, testing, and contact tracing supported by appropriate incentives.

Overall, our results suggest that tools such as workplace closures may be too blunt to deal with the spread of COVID-19, as they also take a huge toll on the economy. Countries would be better off expanding not only their capacity to test, trace, and isolate potential carriers of COVID-19 but also their PSL benefits to discourage the negative externality that potentially sick and infectious workers impose when they report for work and make tracing efforts more effective and accurate. In particular, efforts should be made to cover the self-employed and temporary workers under PSL for the entire duration of the pandemic. Our results also suggest that school closures have high costs and do not contribute much to epidemic control postpeak and when R_t levels are low. They should not be used for protracted periods.

APPENDIX 1: PAID SICK LEAVE, THE DECISION TO ISOLATE WHEN SICK, AND DISEASE TRANSMISSION

A. Model Setup

The absence of paid sick leave (PSL) can lead to faster transmission of coronavirus disease (COVID-19). To see why, consider the following simple model of a single firm with $N+1$ workers living in a two-period horizon, period 0 and 1. The time it takes for any worker from being infected to fully recovered is one period. In the case of COVID-19, this period can be interpreted as around 14 days. During the window of infection, the worker can infect other workers if she goes to work and thus interact with coworkers.

In each period, workers choose the number of days working (l) and consume a uniform consumption good (c). Wage and price of consumption goods are normalized to be 1. Assuming there are no initial endowments or intertemporal financing, each worker consumes whatever she earns in each period. Unhealthy workers gain disutility from working, while healthy workers do not. The quasi-linear utility function of worker i can be written as

$$U_i = \sum_{t=0}^{1} \beta^t \{u(c_{it}) - l_{it} \times \mathrm{I}_{it}\} \text{ for } i \in [0, N],$$

where $c_{it} \geq 0$ is consumption and $l_{it} \in [0,1]$ is the fraction of time at work in period t; function u is standard well-behaved utility function with the following properties: $u' > 0, u'' < 0, \lim_{c \to 0} u' = +\infty, and \lim_{c \to \infty} u' = 0$; I_{it} is a health indicator which equals to 1 if the worker is unhealthy and 0 otherwise.

At the beginning of the first period, all $N+1$ workers are healthy and have not gained immunity of COVID-19 yet. In the first period, worker 0 gets infected from external sources. She then chooses the l_{00} duration at work in period 0 and recovers in period 1. For the other N workers, they have an equal $p(l_{00})$ chance of being infected and become unhealthy, which is an increasing function of l_{00}, or $p' > 0$.

B. Regime without Paid Sick Leave

We first consider the regime without PSL. Since each worker consumers their labor income, the individual utility maximization problem for worker 0 can be written as:

$$\max_{\{c_{0t}, l_{0t}\}} U_0 = \sum_{t=0}^{1} \beta^t \{u(c_{0t}) - l_{0t} \times \mathrm{I}_{0t}\}$$

$$s.t.: c_{0t} = l_{0t};$$

$$\mathrm{I}_{00} = 1, and\ \mathrm{I}_{01} = 0.$$

We are most interested in the labor supply of worker 0 in period 0: l_{00}^*. It can be shown that:

$$u'(l_{00}^*) = 1, \tag{A.1}$$

where l_{00}^* is the individual optimal labor supply of worker 0 at period 0. Obviously, the only condition governs l_{00}^* is the marginal utility from consumption goods in period 0 of worker 0. The effect of increased infection probability $p(l_{00})$ is not the concern of worker 0.

When considering the socially optimal case, the choices of each worker need to maximize the sum of all workers' utility:

$$\max_{\{c_{it}, l_{it}\}} U_s = \sum_{i=0}^{N} \sum_{t=0}^{1} \beta^t \{u(c_{it}) - l_{it} \times \mathrm{I}_{it}\}$$

$$s.t.: c_{it} = l_{it};$$

$$\mathrm{I}_{00} = 1, \mathrm{I}_{01} = 0;$$

$$\mathrm{I}_{j0} = 0, \mathrm{I}_{j1} = p(l_{00}), \qquad for\ \forall j \neq 0$$

Under optimization conditions, the socially optimal l_{00}^s satisfies:

$$u'(l_{00}^s) = 1 + \beta N p'(l_{00}^s) u'^{-1}\big(p(l_{00}^s)\big). \tag{A.2}$$

Combine equation (A.1) and (A.2) we have

$$u'(l_{00}^s) = u'(l_{00}^*) + \beta N p'(l_{00}^s) u'^{-1}\big(p(l_{00}^s)\big). \tag{A.3}$$

The left-hand side of equation (A.3) is the marginal social benefit of one unit of extra labor supply of worker 0 in period 0. The right-hand side of equation (A.1) is the marginal social cost of one unit of extra labor supply of worker 0 in period 0, which includes the marginal disutility incurred to worker 0 working when contagious in period 0, and marginal disutility incurred to all other N workers working when contagious in period 1.

There are two observations that can be drawn from equation (A.3). First, the individually optimal labor supply l_{00}^* exceeds the socially optimal labor supply l_{00}^s. This is because the likelihood of being infected for the N workers increases as the labor supply of worker 0 in period 0 increases, $p'(l_{00}^s) > 0$, and the properties of quasi-linear utility function make sure that $u'^{-1}\big(p(l_{00}^s)\big) > 0$. Therefore, $u'(l_{00}^s) > u'(l_{00}^*)$, which means $l_{00}^* > l_{00}^s$.

Second, the discrepancy between l_{00}^* and l_{00}^s increases with the number of exposed workers, N. When $N = 0, l_{00}^* = l_{00}^s$.

C. Regime with Paid Sick Leave

Suppose unhealthy workers could claim wage replacement ratio $s \in (0,1]$ from the PSL program for every unit of time not going to work, the individual and social planner's utility maximization problems are the same as the case without PSL, except the budget constraint for worker i in period t is now

$$c_{it} = (1 - s) l_{it} + s.$$

We first consider the case where s must be less than 1. The first-order condition of worker 0's individual utility maximization means

$$u'\big((1-s)l_{00}^{**}+s\big)=\frac{1}{1-s}. \tag{A.4}$$

where l_{00}^{**} is the optimal individual labor supply of worker 0 in period 0 when PSL is available. And the first-order conditions of social utility maximization mean

$$u'\big((1-s)l_{00}^{s*}+s\big)=\frac{1}{1-s}+\frac{\beta N p'(l_{00}^{s*})u'^{-1}\left(\frac{p(l_{00}^{s*})}{1-s}-s\right)}{(1-s)^2}, \tag{A.5}$$

where l_{00}^{s*} is the optimal social labor supply of worker 0 in period 0 when PSL is available.

It is easy to show that the two observations in the no PSL case still hold. That is, $l_{00}^{**}>l_{00}^{s*}$ and the difference increases with N.

More importantly, it can be shown that $l_{00}^{**}<l_{00}^{*}$ when $s\neq 1$. Equation (A.1) and (A.4) mean

$$u'\big((1-s)l_{00}^{**}+s\big)>u'(l_{00}^{*}).$$

Since $u'<0$, it follows that

$$l_{00}^{**}<l_{00}^{*}+s(l_{00}^{**}-1)<l_{00}^{*},$$

which means the individually optimal labor supply of worker 0 in period 0 under the PSL regime is less than her labor supply under the no PSL regime. Further, the reduced labor supply $l_{00}^{*}-l_{00}^{**}$ increases with PSL replacement ratio s.

It then follows that the likelihood for the other N workers to get infected is less than the no PSL regime, i.e., $p(l_{00}^{**})<p(l_{00}^{*})$. The reduced likelihood increases with PLS replacement ratio. In other words, a regime with positive PSL replacement ratio is predicted to experience slower transmission of COVID-19 than a regime not implementing any PSL schemes.

In the extreme case where $s=1$, worker 0 does not go to work at period 0, suppressing the case in this period, and zero case happens in period 1.

D. Discussion

To summarize, under the assumptions of usual properties of utility function and contact-duration-dependent infection rate, this model demonstrates that the individually optimal labor supply of a COVID-19 infected individual exceeds her socially optimal labor supply and brings excess likelihood of infection to coworkers. Introducing PSL could reduce or eliminate the discrepancy between individually and socially optimal labor supply of infected workers.

The model is deliberately simple in scope to illustrate the negative externality from the income-transmission trade-off of unhealthy workers. The following assumptions of the model could be generalized to study dynamic and more generalized issues, such as the design of optimal PSL scheme. First, the current model focuses on comparing the labor supply of worker 0 under individually and socially optimal case. It does not discuss the labor supply of the other N workers, nor does it solve for welfare loss due to socially suboptimal choices. Second, the model only considers two periods and is not concerned with future transmissions. To expand the framework into multiple time periods, standard SEIR assumptions could be introduced to track the immune, infected, and exposed workers. Third, the replacement ratio s is not necessarily constant over time. In an optimal design, it should be contingent on the share of infected and exposed workers. It could also introduce new cases from external shocks. Forth, the model assumes perfect information. In implementation, a PSL scheme design should introduce incentive compatibility constraint to curb moral hazard from both healthy and unhealthy workers. Lastly, the model is not concerned with the cost and financing of PSL.

In general, the framework could be extended toward a principal–agent model with infinite time horizon, tracking immunity profile using SEIR assumptions, time-variant replacement ratio, incentive compatibility constraint, and nonzero external infection likelihood. It can then be used to study the dynamics of optimal PSL replacement ratio and welfare gains of such PSL schemes.

APPENDIX 2: OTHER SUPPLEMENTAL INFORMATION

Table A2.1: Pairwise Correlations of the First Differences of 3-Day Moving Averages of Nonpharmaceutical Intervention

Variables	Change in Time at Home	Small Gathering Ban	Large Gathering Ban	School Closure	Workplace Closure	Public Transport Closure	Mask Use	Mass Testing	Contact Tracing	Maximum Temperature
Change in time at home	1.000									
Small gathering ban	0.121	1.000								
Large gathering ban	−0.004	−0.538	1.000							
School closure	0.100	0.134	−0.020	1.000						
Workplace closure	0.138	0.230	−0.097	0.124	1.000					
Public transport closure	0.114	0.160	−0.052	0.068	0.237	1.000				
Mask use	−0.001	−0.024	0.032	−0.009	−0.065	−0.025	1.000			
Mass testing	0.020	−0.026	0.020	−0.050	−0.040	0.018	0.032	1.000		
Contact tracing	0.035	−0.003	0.049	0.011	0.029	0.017	−0.011	0.059	1.000	
Maximum temperature	−0.094	0.000	−0.003	0.030	0.015	−0.014	−0.002	−0.031	−0.015	1.000

Source: Authors' estimates.

Table A2.2: List of Economies and Their Corresponding Three-Letter Codes

Economy	Code	Economy	Code
Aruba	ABW	Mongolia	MON
Afghanistan	AFG	Mozambique	MOZ
Andorra	AND	Mauritius	MUS
Argentina	ARG	Myanmar	MYA
Australia	AUS	Nepal	NEP
Austria	AUT	Niger	NER
Azerbaijan	AZE	The Netherlands	NET
Bangladesh	BAN	Nigeria	NGA
Burundi	BDI	Nicaragua	NIC
Belgium	BEL	Norway	NOR
Benin	BEN	New Zealand	NZL
Burkina Faso	BFA	Oman	OMN
Bhutan	BHU	Pakistan	PAK
Bosnia and Herzegovina	BIH	Panama	PAN
Belarus	BLR	Peru	PER
Brunei Darussalam	BRU	Philippines	PHL
Cambodia	CAM	Papua New Guinea	PNG
Canada	CAN	Portugal	POR
Chile	CHL	People's Republic of China	PRC
Colombia	COL	Qatar	QAT
Cuba	CUB	Republic of Korea	ROK
Czechia	CZE	Rwanda	RWA
Denmark	DEN	Saudi Arabia	SAU
Dominican Republic	DOM	Singapore	SIN
Ecuador	ECU	Sierra Leone	SLE
Egypt	EGY	El Salvador	SLV
Finland	FIN	Spain	SPA
Georgia	GEO	Serbia	SRB
Germany	GER	Sri Lanka	SRI
Ghana	GHA	South Sudan	SSD
Guatemala	GTM	Suriname	SUR
Hong Kong, China	HKG	Slovenia	SVN
Haiti	HTI	Sweden	SWE
India	IND	Switzerland	SWI
Indonesia	INO	Tajikistan	TAJ
Ireland	IRE	Taipei,China	TAP
Iraq	IRQ	Togo	TGO
Iceland	ISL	Timor-Leste	TIM
Italy	ITA	Turkey	TUR
Japan	JPN	Tanzania	TZA
Kazakhstan	KAZ	Uganda	UGA
Lao People's Democratic Republic	LAO	United Kingdom	UKG
Libya	LBY	Ukraine	UKR
Lithuania	LTU	United States	USA
Luxembourg	LUX	Uzbekistan	UZB
Latvia	LVA	Viet Nam	VIE
Malaysia	MAL	Yemen	YEM
Moldova	MDA	South Africa	ZAF
Mexico	MEX	Zambia	ZMB

Note: For ADB member economies, the three-letter codes follow the codes prescribed in the ADB Handbook of Style and Usage 2017 edition. The rest are represented based on the three-letter codes defined in the International Organization for Standardization 3166-1 (ISO Alpha-3).

Source: Authors' compilation.

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What Works to Control COVID-19?

Econometric Analysis of a Cross-Country Panel

The paper examines the effects of nonpharmaceutical interventions on transmission of the novel coronavirus disease (COVID-19) as captured by its reproduction rate R_t. Using cross-country panel data, the paper finds that while lockdown measures have strong effects on R_t, gathering bans appear to be more effective than workplace and school closures. Ramping up the testing and tracing of COVID-19 cases is found to be especially effective in controlling the spread of the disease where there is greater coverage of paid sick leave benefits. Workplace and school closures are found to have large negative effects on gross domestic product compared with other measures, suggesting that a more targeted approach can be taken to keep the epidemic controlled at lower cost.

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