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A lockdown a day keeps the doctor away: The effectiveness of non-pharmaceutical interventions during the Covid-19 pandemic

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ABSTRACT

A LOCKDOWN A DAY KEEPS THE DOCTOR AWAY: THE EFFECTIVENESS OF NON-PHARMACEUTICAL INTERVENTIONS DURING THE COVID-19 PANDEMIC*

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Countries have employed a variety of non-pharmaceutical interventions (NPIs) in order to curtail the COVID-19 pandemic. However, the success of individual measures in reducing the number of infections remains controversial. This paper exploits a panel data set of 107 countries to estimate the effects of 14 NPIs on the spread of the disease. While almost all measures had a dampening effect on the reproduction rate of the virus, public information campaigns and school closings were most effective, followed by testing policies, contact tracing and international travel restrictions. Public event cancellation and school closings were less effective during the second wave of the pandemic, while public information campaigns and the obligation to wear masks worked better. Several NPIs had a stronger impact on infections in autocratic countries, while others were less effective.

Keywords: COVID-19, non-pharmaceutical interventions, policy analysis, panel data

JEL classification: C1; C5; I1

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1 Introduction

Since the first cases were detected in Wuhan, China, Covid-19 has spread all over the world, having infected more than 520 million individuals and killed more than six million as of May 2022 (Our World in Data, 2022). As the epicentre of the pandemic, Wuhan was the first city to implement a strict lockdown. It proved quite effective to control the spread of the virus and successfully managed to register zero new cases in the region after 76 days of stringent restrictions on the mobility of people (Lau et al. 2020). In the following months, lockdowns have been implemented in many countries, along with other non-pharmaceutical interventions (NPIs) such as opening testing facilities, the obligation to wear face masks in public places and banning large gatherings of people.

However, it remains unclear to what extent individual measures impact the number of new Covid-19 cases. This is an important question, as some of these NPIs come at high economic costs. NPIs probably contributed to the 3.6% fall in global GDP in 2020 (The World Bank 2021). In this regard, policymakers have to consider both an NPI's impact on infections and its social and economic consequences. In addition, the uncertainty surrounding the effectiveness of some measures undermines their acceptability among the public, ultimately reducing their effectiveness as rules are not obeyed. Therefore, a comprehensive approach is needed to ensure that in the face of future Covid waves or new infectious diseases, only effective policies are implemented and that those causing the least distortions for society are implemented first.

This paper estimates the effect of 14 individual NPIs on the reproduction rate of the virus in 2020 by exploiting a panel data set of 182 countries, ranking them by their ability to reduce the spread of the virus.[1] Many studies have estimated the effects of policies at the country level. However, as different NPIs were often introduced simultaneously, it is impossible to disentangle their effect when limiting the investigation to a single country. In contrast, our data structure allows us to exploit variation both across time and countries to estimate treatment effects of individual NPIs.

As with many policy evaluations, estimations are prone to endogeneity, in particular omitted variable bias and reverse causality. Our data structure allows us to control for several potential sources of omitted variable bias (such as the availability of face masks or the willingness of people to wear them) through fixed effects. Reverse causality - i.e. the introduction of NPIs as a response to an increased reproduction rate - is also addressed by fixed effects as well as the use of lagged NPIs. Both strategies might not be sufficient to fully eliminate the downward bias resulting from reverse causality. However, under the assumption that all NPIs are affected equally by such a bias, this should not change the

1. The NPIs investigated are school closings, work place closings, cancellation of public events, restrictions on gatherings, closing of public transport, stay at home requirements, domestic travel restrictions, international travel restrictions, public information campaigns, testing policy, contact tracing, obligations to wear face masks, income support and debt relief.

relative ranking in the effectiveness of individual NPIs - the measuring of which being one of the main objectives of the paper.

We find that over all countries investigated, 11 out of 14 NPIs investigated have had a significantly dampening effect on the reproduction rate in 2020 (reducing it by 0.13 on average). Public information campaign and school closing were most effective, reducing the reproduction rate by 0.352 and 0.242 respectively. They are followed by testing policy (0.225), contact tracing (0.151) and international travel restrictions (0.138). The high impact of information campaigns might be surprising. However, they were often one of the first measures implemented and strongly affected people's behaviour by informing them about the gravity of the situation (Chernozhukov et al. 2021).

We also investigate whether the effectiveness of NPIs varied over time. Perhaps most importantly, the obligation to wear face masks - not in our top five of the most effective overall measures - had a greater impact on the reproduction rate in the second wave. One reason for this finding could be the wider availability of medical masks (as opposed to community masks) and a greater degree of compliance. Public information campaigns were also even more effective during the second half of 2020. In contrast, school closing, public event cancellation, testing and contact tracing were less effective during the second wave of the pandemic. Potentially, this might indicate a less stringent implementation of NPIs by the public. It could also be a sign of the increased infectiousness of later variants of the virus.[2] Finally, we find that some NPIs on average had a stronger effect on infections in autocratic countries, while others proved less effective.

The remainder of the paper is structured as follows. Section 2 summarizes the related literature. Section 3 describes the data used and presents descriptive statistics, while Section 4 outlines the methodology and discusses the main estimation challenges. Section 5 presents the baseline results, followed by robustness checks and extensions in Section 6. Section 7 concludes.

2 Related literature

Several studies investigate factors determining the spread of the disease, without explicit focus on NPIs. Fielding-Miller et al. (2020) investigate the determinants of Covid-19 mortality at the county-level for the US. Using linear regressions and spatial autoregressive models, they establish a positive and significant impact of the percentage of farmworkers, the level of poverty, the population density, and the population over the age of 65. They also provide evidence for the presence of spillover effects to neighbouring counties. Fel-

2. The British variant and the South African variant were both detected as early as October 2020, which might partly explain the surge in cases in late 2020. As of April 2022, the WHO has designated the Delta and Omicron variant as variants of concern due to their increased virulence and transmissibility (WHO 2022).

bermayr et al. (2021) exploit German county-level data to study the spatial distribution of Covid-19 and show that the share of infected population depends on the road distance to the Austrian ski resort of Ischgl (which suffered an outbreak in an early phase of the pandemic), reinforcing the need for early lockdown measures and travel bans.

Roy and Ghosh (2020) use supervised machine learning techniques and principal component analysis to show that population density, testing rate, airport traffic, and high-age groups, are the main features explaining (or at least correlated with) infection and death counts in the most affected US states. Despite increased testing rates, the fraction of individuals who tested positive drop approximately three weeks into the lockdown, suggesting that social distance measures have had an impact on curbing the spread. Finally, the authors find that peaks of infection correlate better with inter-zone mobility than the inter-zone distance, reinforcing the need for movement control.

Extending the analysis to many countries, Valero and Valero-Gil (2020) show that high-income countries exhibit higher death rates than low-income countries. Higher life expectancy is found positively significant only for high-income countries. This result is consistent with Stojkoski et al. (2020) who show that life expectancy is a very precise Covid-19 mortality determinant. In low-income countries, higher health expenditure is associated with more deaths. One explanation might be that the better the health system, the greater the ability to detect Covid-19 cases. The authors conclude that low-income countries underestimate the number of deaths. People in less developed countries are therefore unaware of the magnitude of the pandemic and might not fully adopt social distancing measures.

Eichenbaum et al. (2020) show that traditional models of infectious diseases can be combined with an economic perspective. These hybrid models can help to draw predictions and conclusions on key economic variables that are inevitably affected by a pandemic. Using a revised canonical SIR model, the authors link economic decisions in response to the pandemic with the spread of the virus.[3] Although policy responses help to lower the severity of the pandemic, they inevitably create and exacerbate recessions worldwide. In their work, the authors preclude the implementation of policies that mitigate the economic hardships which affect households and businesses, such as loan facilities, and transfers. There thus exists a trade-off between short-term recessions and public health consequences that governments have to face.

3. The Covid-19 pandemic has raised the need for a proper modelling of the spread of infectious diseases. Epidemiologists and health scientists made extensive use of the so-called "susceptible, infected and removed (SIR)" model. The idea is to partition a given population into these three compartments. The model is then solved by differential equations, but needs a set of parameters. In the most simplistic model, the rate of infection depends on the number of people falling ill and the number of recovered individuals. These two factors are determined respectively by the effective reproduction rate and the rate of recovery. This model has been derived by many in order to take into account other features of the pandemic, such as quarantine or lockdown policies. For instance, Anand et al. (2020) use an augmented SIR model which takes into account the percentage of infected who are tested and quarantined.

M. Liu et al. (2020) allow the rate of growth of Covid-19 to be concave using a SIR model. In other words, the more the disease spreads, the fewer and fewer unexposed individuals are left, which ultimately curbs down the infection rate. Besides, many infectious individuals expose many of the same unexposed individuals (overlapping social connections). The authors find supporting evidence for social distancing policies, while temperature and humidity do not indicate significant effects on new cases.

A large share of the growing Covid-19 literature have investigated the effectiveness of individual policies in a specific country or region. Alipour et al. (2021) conclude that home office is a very effective tool for reducing infection rates, since regions with more workers that can work from home due to the nature of their occupation have experienced lower Covid-19 infection rates and fatalities. Similarly, Pan et al. (2020) study the effects of policy responses to Covid-19 on the outbreak in Wuhan, China. Their study is mainly descriptive, but provides solid preliminary evidence on the effectiveness of policy responses, in particular home quarantines and sanitary cordons.

Using descriptive statistics, Meo et al. (2020) find a negative growth rate per day of both daily cases and deaths 15 days after the end of the lockdown period. However, the growth ratio (daily cases divided by cases on the preceding day) never fell to below one immediately following the lockdown implementation, indicating that the lockdown itself was not sufficient to stop the pandemic. This supports previous claims that imposing individual policies is not sufficient in curbing the spread of Covid-19.

NPIs can be grouped in different categories according to their goals and impacts on the economy. Ferguson et al. (2020) investigate the effect of two distinct categories of policy measures. The mitigation type aims to slow down the epidemic, while the suppression type focuses on reversing epidemic growth. The authors find that both types of policies help to reduce significantly the number of deaths and the amount of healthcare demand. The suppression type is the most sought-after since it prevents overwhelming intensive care units and mitigates the number of deaths. However, it is also considered more costly for the economy as it implies a strict set of policy measures such as closing schools and shops indefinitely, home isolation for symptomatic cases, and full lockdowns. For countries able to achieve it, this leaves suppression as the preferred policy option. The authors show that in the UK and US context, suppression will minimally require a combination of social distancing of the entire population, home isolation of cases, and household quarantine of their family members. This may need to be supplemented by school and university closures, though it should be recognized that such closures may have long-term negative impacts on health systems due to increased absenteeism and chronic depression resulting from a lack of social interaction.

Our paper is not the first to investigate the impact of multiple NPIs on the number of infections. Chen et al. (2020) propose to regress the daily effective reproduction rate on changes in time spent at home, the average household size, the implementation of school closure policies and other NPIs. Their model specification includes a linear time trend, days of the week fixed-effects and country fixed-effects. One limitation of the study is that they do not inform on how widely enforced the policies are. To correct this concern, they use Google mobility data to track the changes of flows in transport hubs such as train stations, but this instrument suffers from some degree of selection bias since only individuals using Google-enabled devices are included. Bergman and Fishman (2020) also take advantage of Google and Apple mobility data to assess the contribution of mobility declines to the control of the Covid-19 spread. Controlling for time trends and country fixed-effects, they estimate that a 10-percentage point decline in mobility is associated with a reduction of up to 0.07 in the value of the effective reproduction rate.

Bendavid et al. (2021) compare the effectiveness of NPIs on case growth rates in sub-national regions of 10 countries. Evidence from their study does not indicate that implementing more restrictive measures (lockdowns) provides additional benefits on reducing the number of daily cases, supporting the argument that less restrictive and less harmful policies can yield similar effects on the spread of the disease.

Carraro et al. (2020) estimate the effect of NPIs on the logarithmic number of active cases using data from 166 economies within the time span of January 2020 and May 2020. NPIs are individually introduced in the regression and lagged 7 and 14 days. 14-days lagged NPIs show stronger negative impacts on active cases, especially for school closure policies and lockdowns. As highlighted by the authors, their econometric specification could suffer from omitted variable bias and reverse causality.

Similarly, Brauner et al. (2020) evaluate NPIs for 41 economies using a Bayesian hierarchical model. They find significant effects of school closure, closure of high-risk businesses, and gathering bans, but smaller effects of other measures. Other policy measures have however not been taken into account, such as testing, tracing, and case isolation, due to a lack of data. Among the 41 countries studied, 33 are located in Europe, which could question external validity of the results. Li et al. (2021) rely on data from 131 countries from January to July 2020 to investigate the impact of eight NPIs on the reproduction rate. They find significant effects of school closures, workplace closures, banning public events, stay at home requirements and domestic travel restrictions. Drawing on data from 182 countries for the entire year of 2020, we aim to draw a more comprehensive picture of the effects of NPIs on the reproduction rate.

Islam et al. (2020) take advantage of a larger set of countries and find significant effects of school, workplace and transport closure, gathering bans, and lockdowns. On average, the implementation of these policies was associated with an average reduction in the Covid-19 incidence ratio of 13%. However, they assume independence across countries and do not estimate the effect of international travel restrictions. This is an important concern, as this assumption does not hold in a worldwide pandemic. Our analysis shows that international arrivals, which characterizes the most visited countries, are highly associated with the spread of the virus.

More recently, Xie et al. (2021) have estimated the effect of six different NPIs across US states. Using propensity score matching to control for pre-intervention differences between states and a difference-in-difference estimator where the treatment is the implementation of an NPI, the authors find that lockdowns and stay-at-home orders had significantly reduced the reproduction rate while mask mandates were not significant. Our study builds upon their estimation strategy while focusing instead on worldwide infections and a larger set of NPIs.

Chernozhukov et al. (2021) also use US data and employ a counterfactual experiment to show that making face masks obligatory for employees at the beginning of the pandemic would have substantially reduced the growth rate of infections. The authors also show that without stay-at-home requirements and business closures, the number of cases would have been larger. However, the impact of school closures can only be estimated with high uncertainty because of limited cross-sectional variation. By relying on a sample of 182 countries, we are able to exploit more cross-sectional variation in order to identify a treatment effect.

In line with our analysis, Haug et al. (2020) establish a ranking of NPIs, using neural network analysis. They find the largest impact on the effective reproduction rate of small gatherings' cancellation, closure of educational institutions, border restrictions, movement restrictions, and lockdowns. They stress the importance of compliance and stringency of policies for their effectiveness, but do not directly control for it. We address this by using country-month fixed effects to control for changes in compliance within countries over time. Furthermore, we extend the sample period to the whole of 2020, allowing us to investigate if the effectiveness of NPIs differs across waves and whether autocratic countries are more successful in implementing NPIs.[4]

3 Data and descriptive statistics

We exploit daily data to fit a model assessing the effect of policy responses on the spread of Covid-19, covering 182 countries in the year 2020. Our baseline regression uses the reproduction rate of the virus R_{it} in country i at time t as dependent variable. R_{it} is calculated using daily new cases from Hale et al. (2021), who rely on data from Johns Hopkins University Center for Systems Science and Engineering, which is available for 194 countries since the start of the pandemic. The reproduction rate informs on the

4. By doing so, the paper also relates to Bayerlein et al. (2021), who show that populist governments on average enact less far-reaching policy measures and have higher excess mortality rates than non-populist countries.

average number of people one infected individual will spread the virus to. The assumption underlying this index is that it applies to a population of people who were previously free of infection and have not been vaccinated. The following formula provides the definition of the reproduction rate for a particular country i as defined by Cori et al. (2013):

$$R_{it} = \frac{I_{it}}{\sum_{s=1}^{t} I_{it-s} w_s} \tag{1}$$

where R_{it}, is approximated by the ratio of the number of new infections at time t, to the total of infected at time $t - s$, weighted by their infectiousness w_s, which depends on the serial interval defined as the time duration between a primary infected person having symptoms and a secondary infected person infected by the first person starting to have symptoms (Cori et al. 2013). R_{it} has been estimated using the R package Epiestim (Cori et al. 2019) through a 14-day rolling window, assuming the serial interval to follow a gamma distribution of mean 3.96 days and standard deviation of 4.75 days following Du et al. (2020).

The benefit of using the reproduction rate is that it is directly comparable across countries. In addition, it has a very practical application for public health agencies and policymakers as it allows figuring out how to deal with an outbreak, and better adjust policy interventions in a timely manner. Once the reproduction rate is below one, the spread of Covid-19 will die out and restrictive policy measures can be lifted. However, one needs to be aware that R_{it} is still subject to significant uncertainty as it is calculated on daily new cases, for which precision varies across time and location (although this can partially be addressed with the appropriate fixed effects specification). Overall, there might be an under detection of cases due to low testing capacities and an inability to detect asymptomatic cases, which might bias results to some extent.

Regarding NPIs, we exploit the Oxford COVID-19 Government Response Tracker (OxCGRT, Hale et al. 2021) which provides an extensive data set on existing policy responses worldwide together with the dates of implementation and removal.[5] The database aims to collect, track and compare policy responses in a reliable and consistent manner. Based on publicly available information, the data gather policies under five different types, namely containment measures, economic support policies, health system support policies, vaccination policies and miscellaneous policies. Although such information is not systemically reported or made available by many countries, which could lead to flawed and/or missing data, the OxCGRT remains by far the most complete and up-to-date tool to track policy responses. It allows for direct points of comparison in terms of policy strictness across countries.

5. The OxCGRT database is available at: https://github.com/OxCGRT/covid-policy-tracker/blob/master/documentation/codebook.md

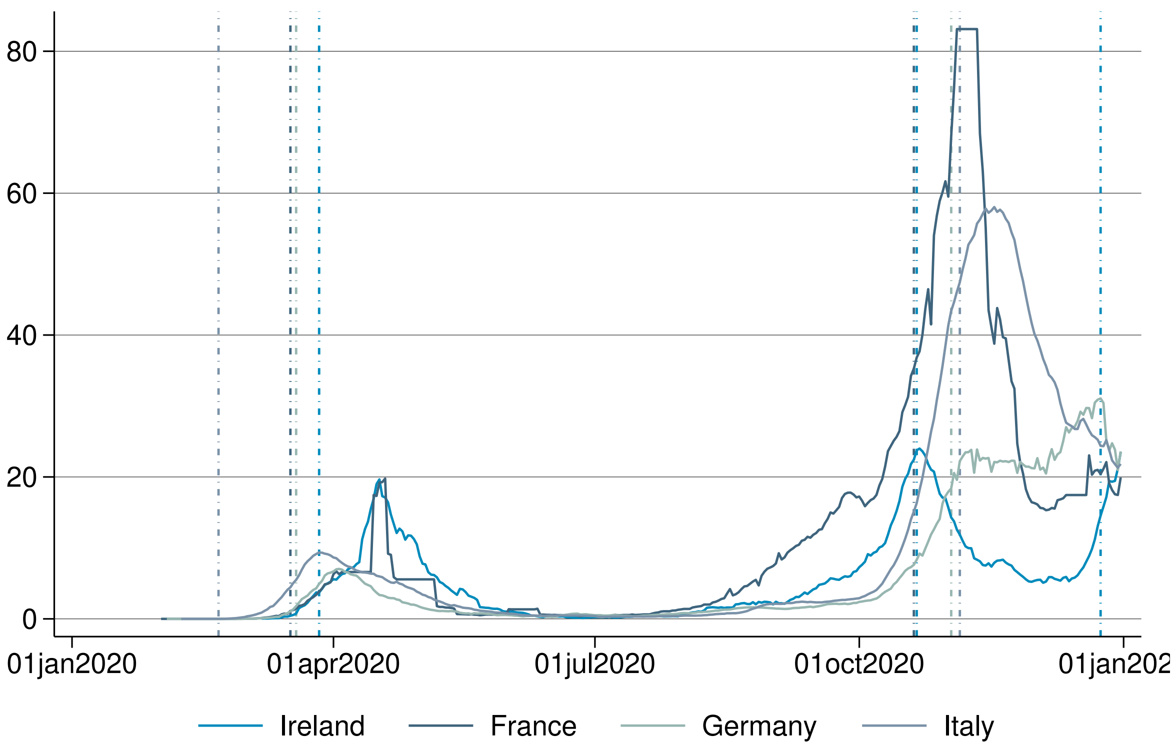
Table 1: Types of non-pharmaceutical interventions

Policy	**Description**	**Ordinal Ranking**
School closing	Record closings of schools and universities.	0-3
Workplace closing	Record closings of workplaces.	0-3
Cancel public events	Record cancelling public events.	0-2
Restrictions on gatherings	Record limits on gatherings.	0-4
Close public transport	Record closing of public transport.	0-2
Stay at home requirements	Record orders to "shelter-in-place" and otherwise confine to the home.	0-3
Domestic travel	Record restrictions on internal movement between cities/regions.	0-2
International travel	Record restrictions on international travel. Note: this records policy for foreign travellers, not citizens.	0-4
Income support	Record if the government is providing direct cash payments to people who lose their jobs or cannot work. Note: only includes payments to firms if explicitly linked to payroll/salaries.	0-2
Debt/contract relief	Record if the government is freezing financial obligations for households (e.g. stopping loan repayments, preventing services like water from stopping, or banning evictions).	0-2
Public info campaign	Record presence of public info campaigns.	0-2
Testing policy	Record government policy on who has access to testing. Note: this records policies about testing for current infection (PCR tests) not testing for immunity (antibody test).	0-3
Contact tracing	Record government policy on contact tracing after a positive diagnosis. Note: we are looking for policies that would identify all people potentially exposed to Covid-19; voluntary Bluetooth apps are unlikely to achieve this.	0-2
Facial coverings	Record policies on the use of facial coverings outside the home.	0-4

Source: Hale et al. (2021)

The data consists of 23 indicators for 182 countries. We restrict our analysis to 14 NPIs for the following reasons. First, miscellaneous policies have been excluded since they record policies that have been implemented in very few countries, making comparison impossible. Second, protection of the elderly policy is also ignored since it might not be of much relevance for the spread of the virus but rather the fatality rate, which is not the purpose of our analysis. Third, we do not include vaccination policies for the simple reason that we focus only on non-pharmaceutical interventions. Moreover, vaccination in 2020 was still at a very early stage, resulting in very scarce data. Finally, we also exclude from the analysis: investment in healthcare, investment in vaccine and fiscal measures, such as economic stimulus spending or tax cuts. Although, some of them could have a negative impact on the spread of the virus, we believe they are more relevant for studying the mortality rate. Furthermore, they are recorded in monetary terms (USD) which render their interpretation relative to ordinally coded NPIs more difficult.

Figure 1: Incidence rate in selected countries



Note: The incidence rate calculated here represents the number of new cases over the last 7 days per 100,000 inhabitants. The vertical dotted lines indicate the date of implementation of lockdowns for each selected country. While France's lockdowns were in force for the entire metropolitan territory (exceptions for overseas territories), Ireland, Germany and Italy had instead regional or local lockdowns due to greater regional autonomy. As lockdown policies are hardly comparable across countries, please read the date of implementation for illustration purposes only. Source: Data from Hale et al. (2021), own calculations.

Each remaining indicator has corresponding ordinal scales, ranging from zero to five depending on the indicator, where zero matches the absence of policy and five indicates a strict implementation of such policy. Table 1 summarizes and briefly describes the NPIs used in our analysis. We also construct a set of dummy variables for each indicator. We assign the value zero if a country does not have any existing measures regarding the policy (e.g. an index of zero for school closure if no school closure policies are in place, regardless of the intensity of the said policy) and one if at least one measure has been implemented (i.e. an index of at least one, e.g. if at least the country recommends the closing of schools or all schools open under significant restrictions compared to non-Covid-19 operations).

The number of daily new cases since the first outbreak has been constantly increasing until governments worldwide decided to implement non-pharmaceutical interventions. Figure 1 illustrates the incidence rate (the number of new cases per 100,000 inhabitants) evolution for Ireland, France, Germany and Italy. We observe that France and Ireland exhibited on average larger values of cases compared to Germany and Italy during the first wave. Overall, the graph indicates that the number of new infections tends to fall in the weeks following lockdowns.

All four countries share a similar trend. Indeed, the spread of the virus in one country impacts neighbouring countries, especially in the Schengen area where individuals have free mobility across borders (Eckardt et al. 2020). Cross-country transmission throughout Europe might be explained by the fact that uncoordinated relaxations of NPIs induce increasing new cases. Ruktanonchai et al. (2020) find that a resurgence of the pandemic could occur as many as five weeks earlier when well-connected countries with stringent NPIs adopt premature exit strategies. Holtz et al. (2020) estimate the impact of uncoordinated policies on mobility in US counties and find that "when only one county implemented a shelter-in-place policy, travel from that county to the non-implementing county increased by 0.55 on average." These geographic spillovers generated by individual regional policies may play a large role in spreading the virus. Consequently, governments should try to reach a higher level of coordination, as individually-taken policies may be detrimental for neighbouring countries.

The majority of policy responses to the pandemic have been implemented with different timing as cases spread. As high-income economies have been taken aback by the pandemic, they only started implementing policies after the first reported cases. For instance, Italy, which has been the first western country to be strongly hit by the Covid-19 disease, implemented a strict lockdown on March 9^{th}, 2020, after reaching 9,172 confirmed cases. On the contrary, low-income economies had additional time to put into place policies.

Table 2: Summary statistics

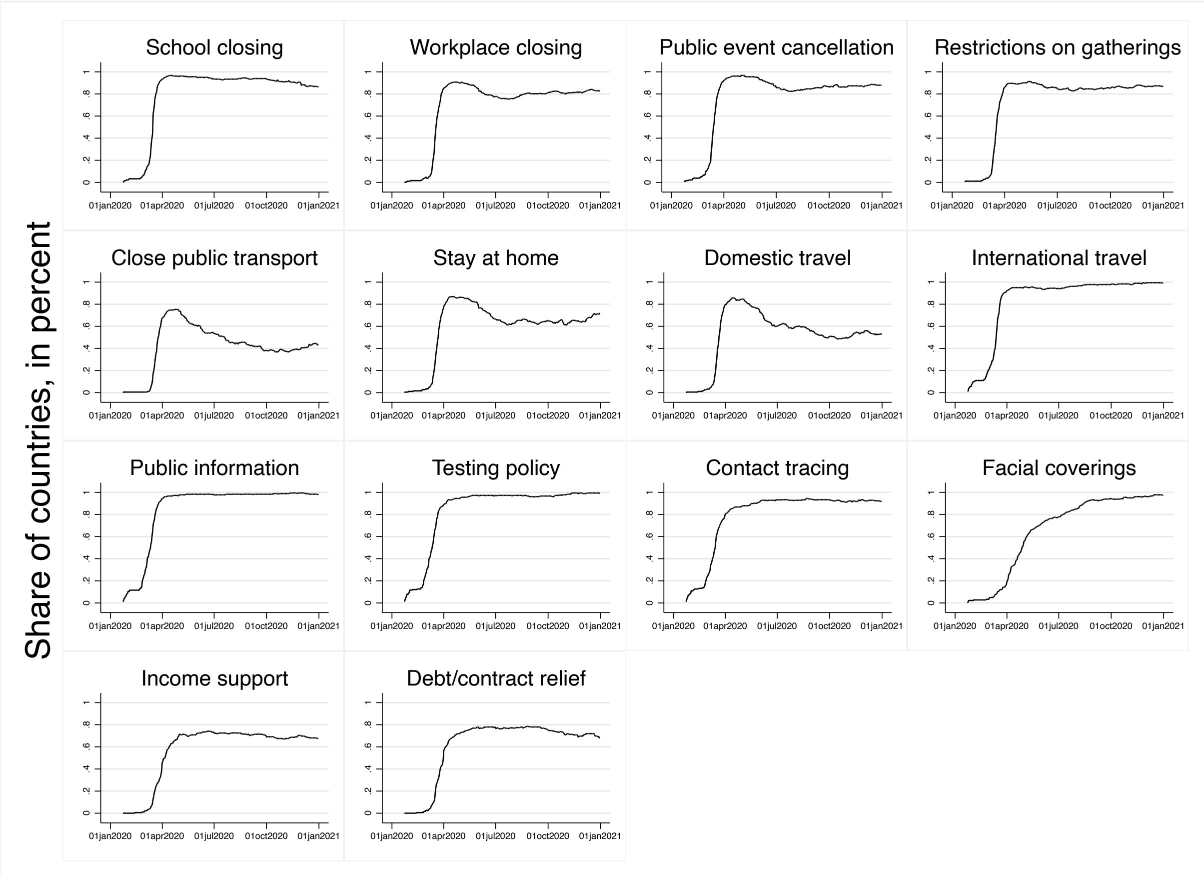
Variable	Mean	Std. Dev.	Min.	Max.	N
Log of daily new cases	3.766	2.927	0	13.621	54557
Reproduction rate (14 days rolling window)	1.274	0.893	0.015	14.872	54625
Log of GDP per capita	8.81	1.514	5.351	12.185	52243
Log of population density	4.415	1.624	-1.991	9.942	53426
Log of international arrivals	14.983	1.746	9.547	18.308	42198
School closing	2.04	1.067	0	3	54617
Workplace closing	1.506	1.001	0	3	54617
Cancel public events	1.501	0.751	0	2	54617
Restrictions on gatherings	2.637	1.476	0	4	54617
Close public transport	0.637	0.754	0	2	54617
Stay at home requirements	1.073	0.928	0	3	54617
Domestic travel	1.002	0.913	0	2	54617
International travel	2.719	1.233	0	4	54617
Public info campaign	1.849	0.479	0	2	54617
Testing policy	1.739	0.874	0	3	54617
Contact tracing	1.431	0.696	0	2	54617
Facial coverings	1.991	1.446	0	4	54617
Income support	0.879	0.777	0	2	54617
Debt/contract relief	1.063	0.838	0	2	54617
School closing dummy	0.883	0.322	0	1	54617
Workplace closing dummy	0.767	0.423	0	1	54617
Cancel public events dummy	0.843	0.364	0	1	54617
Restrictions on gatherings dummy	0.809	0.393	0	1	54617
Close public transport dummy	0.469	0.499	0	1	54617
Stay at home requirements dummy	0.653	0.476	0	1	54617
Domestic travel dummy	0.584	0.493	0	1	54617
International travel dummy	0.93	0.256	0	1	54617
Public info campaign dummy	0.950	0.219	0	1	54617
Testing policy dummy	0.936	0.245	0	1	54617
Contact tracing dummy	0.881	0.324	0	1	54617
Facial coverings dummy	0.726	0.446	0	1	54617
Income support dummy	0.631	0.483	0	1	54617
Debt/contract relief dummy	0.678	0.467	0	1	54617

Note: NPIs are encoded using an ordinal scale ranging from 0 to either 2, 3, 4 or 5, where 0 matches the absence of the policy at a given day and the maximum value indicating its strictest implementation. Summary statistics for NPIs are generated using lagged NPIs. Source: Hale et al. (2021), World Tourism Organization (2022) and The World Bank (2021).

Countries also decided to implement lockdowns with different intensities and went very different ways in fighting the pandemic. Indeed, the data indicate that a few countries focused on lockdown policies, while others responded with economic relief policies. For instance, Sweden, Andorra, the Benelux countries and Canada appear to be providing relatively strong economic support to households. Sweden adopted a different strategy than recommended by the WHO, allowing community transmission to occur relatively unchecked (Claeson and Hanson 2021).

Table 2 provides summary statistics for the variables used in our analysis. Looking at the mean values of the dummy variables shows that school closing, public event cancellation, restrictions on gatherings, international travel restrictions, information campaigns, testing and contact tracing were the most implemented policies in 2020. On the contrary, domestic travel restrictions and public transportation closing were implemented less often.

Figure 2: NPI rate of implementation in 2020



Note: Share of countries having implemented individual NPIs. Total number of countries in the sample: 182. Source: Data from Hale et al. (2021), own calculations.

Figure 2 illustrates the share of countries that have at least partially implemented a particular policy (i.e. the index being at least one) at a particular point in time.[6] Most countries implemented most policies in March 2020. However, NPIs were not implemented on the same day, as Figure B.1 in the Appendix illustrates. Consequently, cross-country variation in policy implementation can be exploited to identify treatment effects. Figure B.1 also reveals that public information campaigns, testing and contact tracing were often one of the first measures in place, with around 50 percent of countries having implemented them to some extent by March 11^{th}, 2020.

To better understand the spread of Covid-19, it is necessary to assess its link with key economic variables informing on country specific factors. Table A.1 reported in the appendix provides insightful relationships between the logarithm of daily new cases and key variables. Column 1 reports positive correlations between daily new cases and GDP per capita as well as the number of tests (Column 1). GDP per capita proxies the wealth status and indicates the capacity of the health system to some extent, so that richer countries might simply detect more cases. In poorer countries, unreported cases due to low testing capabilities are therefore leading to a substantial underestimation of total cases, as indicated by Gupta and Shankar (2020) and Valero and Valero-Gil (2020).

Column 2 of Table A.1 reports a positive correlation between cases and population density, indicating that large and highly populated cities are more inclined to be affected by Covid-19 cases. Finally, Column 3 shows a positive correlation of infections with international arrivals. The work of Russell et al. (2020) indicates that international travel restrictions would have a large impact on the spread of the virus for countries having strong travel links with highly infected countries. We control for these variables by applying country-month fixed effects. The exception is the number of tests, which we control explicitly for in a robustness check.

4 Methodology

We assess the effect of NPIs on the spread of Covid-19, measured by the reproduction rate, with the following estimation equation:

$$R_{it} = \beta_0 + \beta^{'}(OxCGRT_{it-10}) + \nu_{im} + \nu_{dow} + \epsilon_{it} \tag{2}$$

where R_{it} is the reproduction rate in country i at time t (measured in days). $OxCGRT_{it-10}$ is the set of 14 NPIs imposed in country i at time $t-10$ to fight the pandemic. It is either measured by the OxCGRT indicator or a dummy that equals one if the respective indicator is greater or equal to one and zero otherwise. All NPIs are lagged by 10 days

6. We borrow from Chernozhukov et al. (2021), who provide a similar graph to illustrate variation in NPIs across US states.

in order to reflect the delay with which policies start to show some effects (Carraro et al. 2020; Islam et al. 2020; Pedersen and Meneghini 2021).

ν_{im} are country-month fixed effects that control for unobserved time varying country characteristics that may simultaneously impact the spread of the virus as well as the imposition of NPIs, resulting in omitted variable bias. For example, the behaviour of people towards social distancing measures might vary across countries but also over time. People in Asian countries might be more used to wearing face masks, making the obligation to wear them easier to implement. Over time, people might start disobeying rules as a certain fatigue sets in. Previous studies have tried to deal with this by including linear time trends (Chen et al. 2020; Bergman and Fishman 2020; Islam et al. 2020). This approach might be appropriate for the first wave of Covid-19, but not for the entire period of 2020 which shows up to three waves depending on geographical location. In contrast to this earlier work, the country-month fixed effects employed in our specification better capture the non-linearities inherent in the different waves.

The dynamics in both the pandemic and the implementation of NPIs might justify the use of even more disaggregated fixed effects (e.g. country-week fixed effects). However, this would eliminate too much variation, as only the within country-week variation could be used to estimate treatment effects. If NPIs need more than the postulated 10 days to unveil their full effect, country-week fixed effects would severely hinder correct inference. For the same reason, country-month fixed effects might already absorb too much variation, especially if NPIs are implemented towards the end of the calendar month. We therefore also repeat the baseline regressions with quarter-fixed effects, which absorb less variation but increase the risk of omitted variable bias. Day-of-the-week fixed effects ν_{dow} control for global differences in testing patterns on different days of the week (e.g. testing centres might be closed during the weekend). ϵ_{it} is an error term.

Another estimation challenge is endogeneity resulting from reverse causality. Specifically, if the reproduction rate reaches a certain level, this might trigger the implementation of NPIs, resulting in an underestimation of the (expectedly negative) treatment effect (bias towards zero). The problem is alleviated by the use of country-month fixed effects as well as lagged NPIs. Regarding the lagged NPIs, the reproduction rate today should not impact the implementation of NPIs ten days ago, in particular as the decision by policymakers to implement them was in turn made even earlier. Even if the use of lagged NPIs does not fully eliminate reverse causality (for example if certain components of the reproduction rate such as the infectivity of the virus are correlated over time), the resulting downward bias should be the same for all NPIs and should thus not affect the relative ranking of individual NPIs.

5 Baseline results

Table 3 provides the results of our baseline specification using indices of NPIs or dummy NPIs as explanatory variables (both lagged by 10 days). Column 1 presents estimated coefficients of the econometric model specified in Equation 2, which includes country-month fixed effects and day of the week fixed effects. The results indicate significantly negative effects of 10 NPIs on the reproduction rate. Only income support exhibits a positive and significant coefficient (although this disappears once we control for lagged values of the reproduction rate, see Table 7).[7] Estimated coefficients for public transportation closing, stay at home requirements and domestic travel restrictions are not statistically significantly different from zero. Public information campaigns have the strongest marginal impact on infections. Specifically, a one unit increase in the public information campaign indicator is associated with a reduction in R_{it} by 0.248. It is followed by contact tracing policies and public event cancellation, which indicate a marginal effect of -0.105 and -0.09 respectively.

Using country-month fixed effects implies that treatment effects are estimated by exploiting variation within country-month clusters. On the one hand, this ensures that unobserved country specific and time varying factors are controlled for. On the other hand, this strategy might only imperfectly capture the effect of NPIs as they may take several weeks to unfold their full effect. Specifically, if an NPI is implemented towards the end of January, one would expect its impact on infections to show up in the data in February. If, however, the NPI remains in force throughout February, it will be absorbed by the country-month fixed effects.[8]

In order to increase variation, Column 2 includes country-quarter fixed effects instead of country-month fixed effects. Estimated coefficients are broadly similar to those from Column 1, although some of them increase in magnitude. Estimated coefficients for stay at home requirements, domestic travel restrictions and debt/contract relief turn positive and significant, indicating that country-quarter fixed effects might only insufficiently capture country specific trends and give rise to reverse causality (i.e. an increase in R_{it} inducing the imposition of further NPIs).

7. Y. Liu et al. (2021) indicate that variables with positive effects on R_{it} are likely to capture residual non-random errors for other NPIs in the same cluster, biasing the estimated coefficients.

8. For this reason, estimations using the index are more reliable than the dummy regression, as the index varies more within country over time than the dummy. Using a moving average also increases variation.

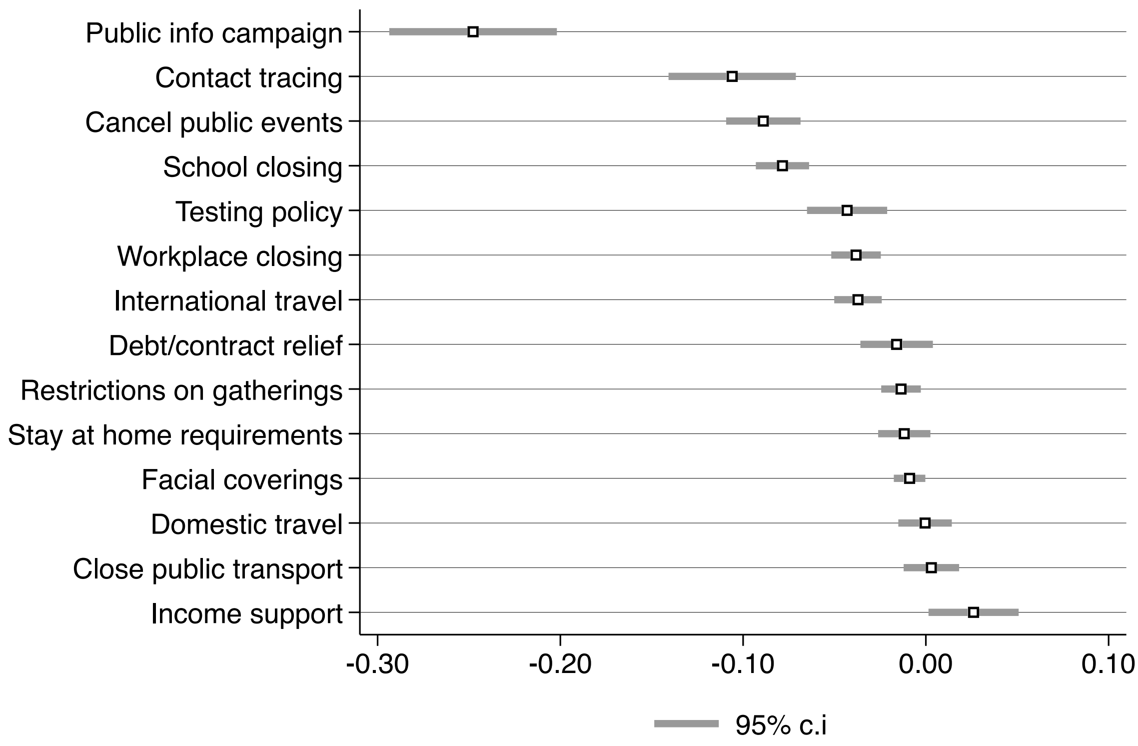
Table 3: The impact of NPIs on the reproduction rate

Dependent variable: R_{it}	(1)	(2)	(3)	(4)
NPIs coding:	Index	Index	Dummy	Dummy
School closing	-0.079***	-0.104***	-0.242***	-0.194***
	(0.007)	(0.007)	(0.025)	(0.025)
Workplace closing	-0.037***	-0.069***	-0.080***	-0.177***
	(0.007)	(0.006)	(0.017)	(0.015)
Cancel public events	-0.090***	-0.083***	-0.127***	-0.086***
	(0.010)	(0.010)	(0.022)	(0.020)
Restrictions on gatherings	-0.014**	-0.014***	-0.078***	-0.092***
	(0.006)	(0.005)	(0.023)	(0.021)
Close public transport	0.002	-0.046***	-0.027**	-0.084***
	(0.008)	(0.007)	(0.011)	(0.010)
Stay at home requirements	-0.011	0.014**	-0.041***	-0.025**
	(0.007)	(0.006)	(0.014)	(0.012)
Domestic travel	0.000	0.014**	-0.010	0.031***
	(0.007)	(0.006)	(0.013)	(0.012)
International travel	-0.037***	-0.011*	-0.138***	-0.152***
	(0.007)	(0.006)	(0.035)	(0.035)
Public info campaign	-0.248***	-0.313***	-0.352***	-0.551***
	(0.023)	(0.024)	(0.059)	(0.061)
Testing policy	-0.041***	-0.028***	-0.225***	-0.213***
	(0.011)	(0.008)	(0.052)	(0.043)
Contact tracing	-0.105***	-0.084***	-0.151***	-0.083***
	(0.018)	(0.014)	(0.034)	(0.029)
Facial coverings	-0.009**	-0.020***	-0.022	-0.010
	(0.004)	(0.003)	(0.016)	(0.012)
Income support	0.026**	0.035***	0.024	0.050***
	(0.013)	(0.011)	(0.018)	(0.015)
Debt/contract relief	-0.019**	0.027***	-0.034**	0.032**
	(0.010)	(0.009)	(0.016)	(0.014)
Observations	54,617	54,623	54,617	54,623
R-squared	0.615	0.474	0.616	0.474
Country-month FE	YES	NO	YES	NO
Country-quarter FE	NO	YES	NO	YES
Day of the week FE	YES	YES	YES	YES

Note: NPIs lagged by 10 days. Robust standard errors in parentheses. * p-value < 0.1, ** p-value < 0.05, *** p-value < 0.01.

Figure 3 illustrates the marginal effects of each NPI (coefficients extracted from Table 3 Column 1), ranked by their relative effectiveness. It illustrates that imposing stricter public information campaigns, contact tracing schemes and public event cancellations has the strongest impact on the reproduction rate. Compared to these measures, a stricter implementation of domestic travel restrictions as well as public transport closing have a negligible impact on R_{it}, while the estimated coefficient for income support policies is even significantly positive.

Figure 3: Ranking of NPIs



Note: Coefficients extracted from Table 3 Column 1. The figure shows point estimates and 95 percent confidence intervals.

The estimated coefficients presented in Columns 1 and 2 cannot be compared directly with each other, because the underlying indicators do not always have the same range (see Tables 1 and 2 for the varying maximum values of the indicators). Columns 3 and 4 therefore present regression results using dummy variables for the NPIs instead. This enables a direct comparison of coefficients. Using dummies allows us to investigate the overall effect a particular NPI had on the reproduction rate in 2020, taking into account both the frequency of implementation and the average severity. In particular, Column 3 indicates that having implemented any public information policy is associated with an average reduction of 0.352 of the reproduction rate. Public information campaigns have thus been the most effective way to reduce the infection rate.[9] Strong negative coefficients are also found for school closing and testing policy. Having implemented these measures implied an average reduction of R_{it} by 0.242 and 0.225 respectively. These three policies also remain the most effective ones when controlling for country-quarter fixed effects instead of country-month fixed effects (Column 4).

Contact tracing also records strong negative effects across different specifications. Systematic tracing of contact cases, that is, individuals that were in contact with infected, proves to be effective in reducing the reproduction rate. Of course this policy requires great resources and the cooperation of the public as, for instance, wide use of Covid tracing apps. In line with experiences in Australia and New Zealand, that closed their borders to almost all travellers as early as March 20^{th}, 2020 and registered very few cases since then, the estimated coefficient of international travel restrictions is also significantly negative. Estimated coefficients of the dummy regressors are also significantly negative for the cancellation of public events, workplace closings, restrictions on gatherings, stay at home requirements, debt/contract relief policies as well as closing of public transport.

Figure 4 ranks estimated coefficients of NPIs using the dummy specification (Table 3 Column 3). It thus gives an indication of the overall impact of specific NPIs. On average, public information campaign, school closing and testing policy were most effective in curbing the infection rate, while domestic travel restrictions and income support policies were least effective.

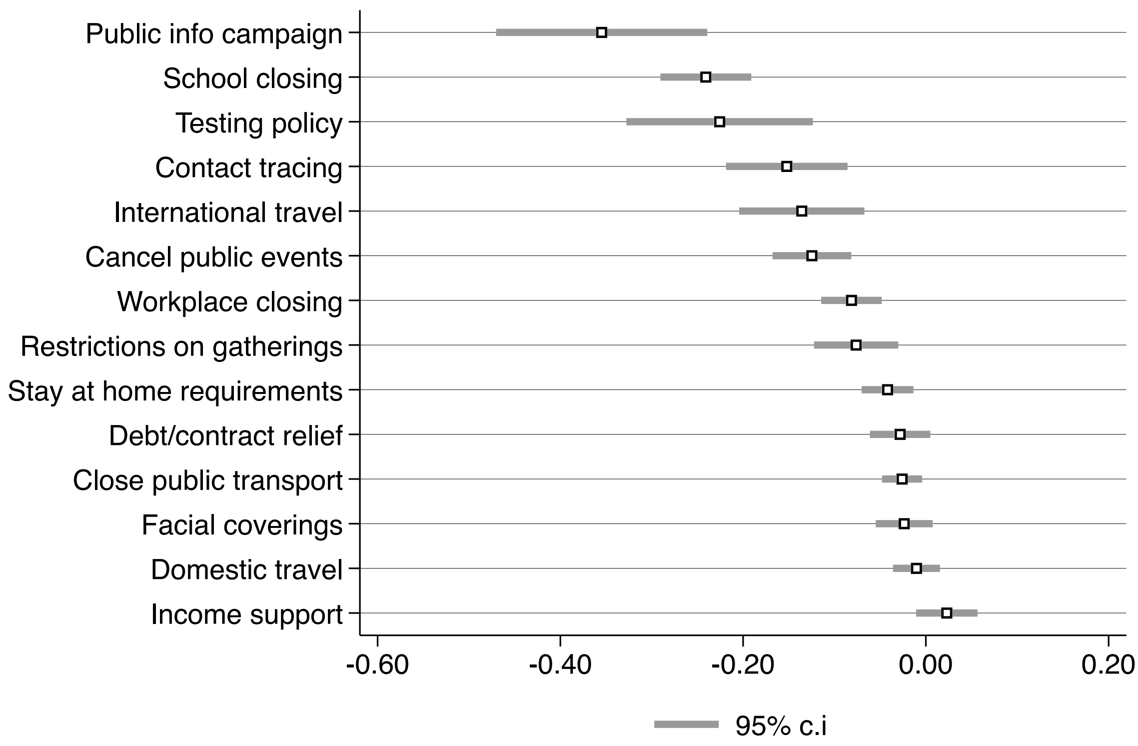
This does not mean, however, that the NPIs ranked on top should necessarily be the instruments of choice when it comes to reducing the reproduction rate. Instead, the benefits of imposing specific NPIs need to be weighed up against their costs. Public information campaigns do seem to be the first instrument of choice, as they are both highly effective and can be expected to come at relatively low costs. While school closing is generally deemed to have high costs for society, testing policy - the third most effective instrument - can clearly be implemented more easily and should thus be one of the first measures implemented during a pandemic (and one of the last measures to be dropped when the number of infections fades).

The heterogeneity in the effectiveness of the different NPIs can have various reasons. First, the effectiveness of a measure depends on the strictness of its implementation (recall that the dummy equals one if any measures were implemented) and its level of enforcement. The dummy regressions do not take into account the strictness of the measures. As shown in Table 2, the individual NPIs were imposed to varying degrees. For example, school closing policies seem to have been implemented more strictly (mean of 2.04) than

9. It is possible that public information campaigns might be correlated with a general effort of the government to curb the pandemic, which would lead to an overestimation of the estimated effect of public information campaigns on the reproduction rate. However, given the elaborate fixed effects strategy as well as the granular information on different NPIs, such omitted variable bias should be minimal.

workplace closings (mean of 1.50, both indicators ranging from 0 to 3). It could thus be the case that workplace closings would have had a stronger impact on the reproduction rate had they been implemented more strictly. Controlling for the proper implementation of policies is also difficult and can be costly for the government, i.e. deploying law enforcement officers to control passers-by during lockdowns (Carraro et al. 2020). The dummies do not capture this.

Figure 4: Ranking of dummy NPIs



Note: Coefficients extracted from Table 3 Column 3. The figure shows point estimates and 95 percent confidence intervals.

Second, as argued by Chernozhukov et al. (2021), NPIs have both a direct effect on the number of infections and an indirect effect as they affect people's behaviour. Specifically, the implementation of specific NPIs informs people about the severity of the situation so that they adjust their behaviour, for example by going out less often, wearing masks properly or by strictly keeping a minimum distance to others in public. This impact on people's behaviour may be particularly strong at the beginning of the pandemic, so that NPIs implemented first may have a stronger indirect impact on infections. This could be one reason for the strong impact of public information campaigns that were typically one of the first measures implemented (see Figure B.1 in the appendix).

Relatedly, the impact of certain NPIs might depend on whether other NPIs have been implemented before. For example, conditional on the obligation to wear FFP2 masks in public transport, closing down public transport is likely to have a smaller impact on infection than if mandatory mask wearing wasn't in place. Chen et al. (2020) actually report insignificant effects of public transport closure on new cases.

Finally, the lack of adequate infrastructure might also prevent social distancing to be put into practice, for example, in public transportation. In many countries, a minimum of public transportation is still in service and social distancing is difficult to implement in such confined spaces (Data Europa 2020).

6 Extensions and robustness

6.1 First vs second wave: Are NPIs still effective?

One reason for the severity of the second wave of Covid-19 cases might be reduced compliance with restrictions. Closing of venues, prohibition of large and small gatherings, along with curfews as early as 6pm in some places have put social order and trust in government responses to the test. In addition, the emergence of mutations of the virus might exacerbate and spread the virus faster (Liu et al. 2021), ultimately reducing the effectiveness of NPIs.

Figures B.2 and B.3 in the Appendix track the incidence rate in European countries and in the ASEAN region (plus China and Japan). As indicated by the graphs, European countries seem to exhibit two waves of infections in 2020 whereas Asian countries, particularly ASEAN members, have less correlated rates of infection across countries. To examine whether the effect of NPIs on the reproduction rate was different in the second wave, we estimate the following regression equation:

$$
\begin{aligned}
R_{it} = & \beta_0 + \beta^{'}(OxCGRTpol_{it-10}) + \theta^{'}(OxCGRTpol_{it-10} * secondwave_t) + \\
& + \nu_{im} + \nu_{dow} + \epsilon_{it}
\end{aligned}
\tag{3}
$$

where $secondwave_t$ is a dummy variable taking the value one for every observation between July 1^{st}, 2020 and December 31^{st}, 2020 (which broadly corresponds to the period in which the second wave struck most countries) and zero otherwise. The coefficient θ of the interaction between NPIs and this dummy allows capturing differential effects in the second wave. It tests the hypothesis that the impact of the NPIs in the first wave is equal to the one in the second wave.

Table 4: First and second wave effects

Dependent variable: R_{it} NPIs coding:	(1.1) Index	(1.2) Index * 2nd wave	(2.1) Dummy	(2.2) / Dummy * 2nd wave
School closing	-0.102***	0.077***	-0.289***	0.213***
	(0.012)	(0.014)	(0.040)	(0.047)
Workplace closing	-0.027**	-0.017	-0.044	-0.051
	(0.012)	(0.013)	(0.029)	(0.032)
Cancel public events	-0.140***	0.107***	-0.188***	0.144***
	(0.020)	(0.021)	(0.039)	(0.042)
Restrictions on gatherings	0.00632	-0.028***	-0.059	-0.012
	(0.010)	(0.010)	(0.037)	(0.043)
Close public transport	-0.002	0.002	-0.024	0.002
	(0.013)	(0.015)	(0.022)	(0.023)
Stay at home requirements	-0.033**	0.037**	-0.060**	0.044
	(0.014)	(0.014)	(0.028)	(0.030)
Domestic travel	0.015	-0.026*	-0.015	0.016
	(0.014)	(0.015)	(0.025)	(0.027)
International travel	-0.055***	0.043***	-0.140***	0.075
	(0.012)	(0.013)	(0.046)	(0.053)
Public info campaign	-0.172***	-0.198***	-0.253***	-0.595***
	(0.028)	(0.035)	(0.068)	(0.108)
Testing policy	-0.063***	0.049**	-0.254***	0.178**
	(0.016)	(0.019)	(0.063)	(0.082)
Contact tracing	-0.114***	0.037	-0.165***	0.095*
	(0.024)	(0.026)	(0.045)	(0.049)
Facial coverings	0.018***	-0.061***	0.024	-0.17***
	(0.005)	(0.009)	(0.018)	(0.035)
Income support	0.001	0.094***	-0.012	0.131***
	(0.016)	(0.024)	(0.022)	(0.035)
Debt/contract relief	-0.019	0.012	-0.053**	0.050*
	(0.014)	(0.017)	(0.023)	(0.028)
Observations	/	54,617	/	54,617
R-squared	/	0.617	/	0.617
Country-month FE	/	YES	/	YES
Day of the week FE	/	YES	/	YES

Note: NPIs lagged by 10 days. Robust standard errors in parentheses. * p-value < 0.1, ** p-value < 0.05, *** p-value < 0.01.

The regression results are reported in Table 4. Column 1.1 reports estimated coefficients of NPIs using indices, while Column 1.2 reports estimated coefficients for the interactions of NPI indices with the second wave dummy (both from the same regression). Columns 2.1 and 2.2 report estimated coefficients from the regression on dummy NPIs. Estimated coefficients of the interaction terms of the second wave dummy with school closing, public event cancellation, testing policy and contact tracing are significantly positive in both regressions and slightly smaller but similar in magnitude to the (negative) coefficients without interaction. This suggests that these NPIs were less effective in the second wave compared to the first one.

Coefficients for the interaction terms of the second wave dummy with workplace closings, restrictions on gatherings, transportation closing, stay-at-home requirements, domestic and international travel restrictions are not statistically significant. This indicates that their overall negative impact (or its absence) on the reproduction rate persisted throughout the second wave. More interestingly, it seems that public information campaign and facial coverings are the only NPIs to report a stronger negative effect for the second wave. The first could be explained by the improved dissemination of information to the public, growing acceptance in health authorities guidance, as well as change in habits regarding public health measures. The last observation could be explained by the increased use of medical masks relative to community masks, as well as improved compliance.

6.2 Controlling for adherence to the rule of law and the ability of countries to implement NPIs effectively

As highlighted by previous studies, the effectiveness of NPIs depends to a large extent on the way they are implemented. Consequently, countries that manage to implement and enforce regulations should be able to reduce the spread of the virus more effectively. We exploit the World Justice Project Rule of Law Index, which provides a good overview of how the rule of law is observed and respected within each country (World Justice Project 2021). The index is built upon nine factors, namely constraints on government powers, absence of corruption, open government, fundamental rights, order and security, regulatory enforcement, civil justice, criminal justice and informal justice.

To check whether differences in effectiveness may occur between countries with high and low compliance to Covid-19 restrictions, we focus on 3 specific factors on which the rule of law index is built upon: Constraints on government powers, fundamental rights, and regulatory enforcement. We hypothesize that relatively autocratic countries with higher regulatory enforcement and/or a lower level of constraints on government powers might be able to apply NPIs more effectively. Similarly, (autocratic) countries that grant relatively lower fundamental rights to their citizens might find it easier to implement more stringent, freedom-depriving measures.

We then create two sets of dummy variables for each of the indices. The first dummy is equal to one if the country is considered to have a high index (which corresponds to a country with an index above the sample mean), and zero otherwise. Conversely, the second dummy is equal to one if the country exhibits an index below the sample mean, and zero otherwise. Finally, each NPI is interacted with these dummies. The estimation equation is as follows:

$$\begin{aligned} R_{it} = &\beta_0 + \lambda'(OxCGRTpol_{it-10} * RoL_i^h) + \theta'(OxCGRTpol_{it-10} * RoL_i^l) + \\ &+ \nu_{im} + \nu_{dow} + \epsilon_{it} \end{aligned} \tag{4}$$

where RoL_i is a dummy variable that refers to one of the three indices constraints on government power, fundamental rights and regulatory enforcement. We compare estimated coefficients for countries with indices above (RoL_i^h) and below (RoL_i^l) the average by performing significance tests. Results with NPI indices are presented in Table 5 below.

Estimated coefficients for the variables school closing as well as international travel restrictions are significantly larger in magnitude in countries with a low index of constraints on governments power, fundamental rights, and regulatory enforcement, respectively. In other words, increasing the stringency of these two policies is relatively more effective in countries with low level of government constraints, fundamental rights and regulatory enforcement. One could argue that this result stems from the fact that governments having higher enforcement power and more severe repression in case of non-respect of Covid-19 restrictions are more effective in implementing NPIs, with China being the most prominent example. Indeed, populations within countries that face harsh repression have no choice but to respect the measures.

For other NPIs, the evidence is less straight forward. Increasing the stringency of public event cancellation seems to have been more effective in countries with lower fundamental rights. However, this is not true with respect to the other two indicators investigated. In contrast, estimated coefficients for stay at home requirements, restrictions on gatherings and public information campaigns are higher for countries having higher level of fundamental rights. However, public information campaigns seem to have been more effective in countries low regulatory enforcement. On the other hand, income support policies and debt contract relief worked better in countries with high levels of regulatory enforcement.

Regressing R on NPI dummies instead of indices yields similar results (Table A.3 in the appendix). Taking into account both frequency and average degree of implementation, school closings and international travel restrictions have been more effective in countries with low level of government constraints, fundamental rights and regulatory enforcement.

In contrast, stay at home requirements and testing were more effective in countries with high fundamental rights.

6.3 Robustness

Weighted moving averages To validate the robustness of our previous results, we use weighted moving averages with a span of 10 days of each NPI instead of 10-day lags in order to reflect the delay in which policies start to show some effects (Carraro et al. 2020; Islam et al. 2020; Pedersen and Meneghini 2021). Each observation is a weighted average of NPI_t and the nine preceding observations. The largest weight is applied to the observation that lies furthest in the past [10] Using moving averages allows giving less weight to NPIs at the beginning of their implementation, while progressively adding weight until policies reach their full effect after 10 days.

Regression results are reported in Column 1 of Table 6. Estimated coefficients broadly remain qualitatively similar to the baseline results, although public transport closure and debt/contract relief turn significantly negative in our preferred specification with country-month fixed effects. School closing is now the most effective policy, closely followed by contact tracing, public information campaign and public events cancellation. Although the ranking has been somewhat affected, they are still featured among the five most effective policies.

Controlling for the number of tests Testing capacity continuously increased throughout the pandemic. Intuitively, the more a country is testing, the more cases are detected. In addition, the testing capacity reflects on the quality of the health system and the means made available by governments. In another robustness check, we control for the number of tests per day. Columns 2 and 3 of Table 6 report the results when adding the logarithm of the number of tests per day as a regressor. Overall, estimated coefficients are qualitatively similar to the baseline results. Most notably, estimated coefficients for public transport closing and income support become negative when regressing on the NPI index (Column 2). The same is true for facial coverings and income support when looking at the dummy regressions (Column 3). Increasing the intensity of the public information campaign and contact tracing continue to have the highest marginal effect (Column 2), whereas public information campaign and testing policy remain the most effective policies overall (Column 3). The results are, however, not fully comparable to the baseline results because the number of tests was not systematically reported by countries during the early period of the pandemic. This drawback almost halves the number of observations, thus reducing variation needed to identify treatment effects.

10. The smoothing technique applied was: $(1/55)[10 * x_{t-9} + 9 * x_{t-8} + 8 * x_{t-7} ... +]$.

Table 5: Rule of law - NPI indices

Dependent variable: R_{it} NPI:	(1) High CoG Index	/ Low CoG Index	/ Wald test Index	(2) High FR Index	/ Low FR Index	/ Wald test Index	(3) High RE Index	/ Low RE Index	/ Wald test Index
School closing	-0.071***	-0.107***	**5.65**	-0.063***	-0.117***	**12.32**	-0.049***	-0.106***	**12.81**
	(0.011)	(0.011)	0.017	(0.011)	(0.011)	0.000	(0.013)	(0.010)	0.000
Workplace closing	-0.027**	-0.041***	0.67	-0.036***	-0.031***	0.07	-0.047***	-0.031***	0.02
	(0.013)	(0.011)	0.412	(0.012)	(0.012)	0.791	(0.016)	(0.010)	0.409
Cancel public events	-0.117***	-0.102***	0.43	-0.080***	-0.140***	**6.74**	-0.104***	-0.100***	0.02
	(0.016)	(0.016)	0.514	(0.015)	(0.017)	0.009	(0.019)	(0.015)	0.875
Restrictions on gatherings	-0.025**	-0.011	1.17	-0.029***	-0.008	**2.74**	-0.013	-0.018**	0.11
	(0.010)	(0.008)	0.279	(0.010)	(0.009)	0.097	(0.011)	(0.008)	0.737
Close public transport	-0.004	0.023*	1.18	0.001	0.006	0.05	-0.024	0.023*	**3.04**
	(0.021)	(0.014)	0.277	(0.017)	(0.015)	0.821	(0.024)	(0.013)	0.081
Stay at home requirements	-0.020	-0.012	0.16	-0.043***	0.015	**9.18**	-0.014	-0.014	0.00
	(0.015)	(0.012)	0.687	(0.013)	(0.014)	0.003	(0.018)	(0.011)	0.976
Domestic travel	-0.008	0.010	0.90	-0.003	0.001	0.05	-0.010	0.004	0.45
	(0.014)	(0.012)	0.343	(0.013)	(0.013)	0.815	(0.017)	(0.011)	0.502
International travel	0.013	-0.046***	**19.60**	-0.001	-0.049***	**13.93**	-0.002	-0.030***	**3.04**
	(0.010)	(0.008)	0.000	(0.009)	(0.009)	0.000	(0.013)	(0.007)	0.081
Public info campaign	-0.190***	-0.192***	0.01	-0.239***	-0.145***	**10.17**	-0.119***	-0.229***	**12.75**
	(0.023)	(0.019)	0.941	(0.021)	(0.020)	0.001	(0.025)	(0.018)	0.000
Testing policy	-0.092***	-0.056***	2.02	-0.074***	-0.067***	0.08	-0.079***	-0.070***	0.10
	(0.019)	(0.016)	0.155	(0.018)	(0.017)	0.778	(0.023)	(0.014)	0.754
Contact tracing	-0.146***	-0.103***	2.46	-0.117***	-0.108***	0.12	-0.122***	-0.124***	0.01
	(0.021)	(0.017)	0.116	(0.019)	(0.018)	0.731	(0.023)	(0.016)	0.932
Facial coverings	0.006	0.010	0.12	0.007	0.016*	0.54	0.013	0.009	0.07
	(0.011)	(0.008)	0.734	(0.010)	(0.008)	0.464	(0.014)	(0.00706)	0.792
Income support	-0.0657***	-0.020	2.51	-0.026	-0.039	0.18	-0.130***	0.013	**22.08**
	(0.021)	(0.020)	0.113	(0.017)	(0.025)	0.671	(0.024)	(0.018)	0.000
Debt/contract relief	-0.032	-0.043***	0.20	-0.008	-0.063***	**5.84**	-0.086***	-0.031**	**3.58**
	(0.019)	(0.014)	0.658	(0.016)	(0.017)	0.016	(0.026)	(0.012)	0.059
Observations	/	/	37,410	/	/	37410	/	/	37410
R-squared	/	/	0.572	/	/	0.572	/	/	0.572
Country-month FE	/	/	YES	/	/	YES	/	/	YES
Day of the week FE	/	/	YES	/	/	YES	/	/	YES

Note: NPI Indices lagged by 10 days. Robust standard errors in parentheses. * p-value < 0.1, ** p-value < 0.05, *** p-value < 0.01. F statistic and P-value of tests for coefficient differences are reported in Column 'Wald Test'.

Table 6: Robustness specifications

Dependent variable: R_{it}	(1)	(2)	(3)	(4)	(5)
NPIs coding:	Index	Index	Dummy	Index	Dummy
Robustness specification:	WMA	Tests	Tests	Omit NPIs	Omit NPIs
School closing	-0.225***	-0.040***	-0.160***	-0.105***	-0.281***
	(0.016)	(0.009)	(0.030)	(0.007)	(0.025)
Workplace closing	-0.048***	-0.031***	-0.069***	-0.035***	-0.086***
	(0.012)	(0.007)	(0.016)	(0.007)	(0.017)
Cancel public events	-0.091***	-0.042***	-0.053**	-0.115***	-0.147***
	(0.018)	(0.010)	(0.022)	(0.010)	(0.022)
Restrictions on gatherings	-0.034***	-0.042***	-0.180***	-0.018***	-0.075***
	(0.009)	(0.006)	(0.026)	(0.006)	(0.024)
Close public transport	-0.045***	-0.023***	-0.060***	-0.000	-0.027**
	(0.014)	(0.009)	(0.012)	(0.008)	(0.011)
Stay at home requirements	-0.002	-0.011	-0.066***	-0.011	-0.048***
	(0.012)	(0.008)	(0.016)	(0.007)	(0.014)
Domestic travel	-0.012	-0.001	-0.008		
	(0.012)	(0.009)	(0.017)		
International travel	-0.062***	-0.045***	-0.163***	-0.062***	-0.217***
	(0.010)	(0.006)	(0.056)	(0.007)	(0.035)
Public info campaign	-0.126***	-0.262***	-0.194*		
	(0.047)	(0.040)	(0.109)		
Testing policy	-0.041***	-.0311***	-0.323***	-.0840***	-0.377***
	(0.015)	(0.011)	(0.068)	(0.012)	(0.046)
Contact tracing	-0.160***	-0.080***	-0.135***	-0.173***	-0.200***
	(0.029)	(0.023)	(0.050)	(0.018)	(0.033)
Facial coverings	-0.012**	-0.011***	-0.021*	-0.007	-0.022
	(0.006)	(0.003)	(0.011)	(0.004)	(0.016)
Income support	0.047***	-0.045***	-0.063***	0.020	0.013
	(0.018)	(0.014)	(0.016)	(0.013)	(0.017)
Debt/contract relief	-0.073***	-0.008	-0.015		
	(0.016)	(0.007)	(0.015)		
Tests (ln)		-0.014*	-0.012		
		(0.008)	(0.008)		
Observations	54,293	26,381	26,381	54,617	54,617
R-squared	0.618	0.581	0.584	0.613	0.616
Country-month FE	YES	YES	YES	YES	YES
Day of the week FE	YES	YES	YES	YES	YES

Note: NPIs lagged by 10 days except for Column 1 which uses a weighted moving average over 10 days. Robust standard errors in parentheses. * p-value < 0.1, ** p-value < 0.05, *** p-value < 0.01.

Multicollinearity of NPIs We suspect a strong correlation across policy responses, as one policy is rarely implemented individually and separately, but rather encompassed in a broader public health strategy. Table A.2 in the appendix presents the correlation matrix between policy variables (Index ordinal coding). It indicates a relatively moderate correlation of NPIs. A stronger coefficient is found for public event cancellation and gatherings restrictions. However, our model benefits from a long time span, capturing variation both over time and across countries.[11]

Following Y. Liu et al. (2021), we perform a hierarchical clustering analysis, which allows identifying potential confounding, both in the temporal and sectoral dimensions. In order to avoid misinterpretation of regression results, we investigate both temporal clustering patterns and clustering patterns across countries. Countries are likely to mimic each other's interventions, as the spread of the virus is similar across territories. First, to characterize the temporal dimensions, we average every value of each NPI by country. What is resulting is a set of time series which presents the worldwide average value of each NPI for each day. Similarly, we average every value of each NPI in the time dimension, resulting in a cross-section representing the average value of NPIs by country.

As explained by Zheng and Li (2014), reducing the dimensions offered by the panel data structure would result in a significant loss of information, either across time or across countries. To address this, we produce results for both dimensions and indicate which NPIs are susceptible to be correlated. We conduct hierarchical cluster analysis using Ward's method with Euclidean distances.[12] First, each observation is treated as its own cluster. Then, the distance is calculated between each observation, and they are merged as a new cluster if the merging leads to a minimum increase in the total within-cluster variance. The process is iteratively performed until all observations are clustered. Figures B.4 and B.5 report the dendrograms from the hierarchical cluster analysis of NPIs.

The height of the node connecting two policies on the dendrogram represents the degree of similarity between their cross-section (Figure B.4) or their time-series (Figure B.5). Hence, we can observe that "restrictions on gatherings" and "international travel" are quite similar in their implementation timing and across countries. Similarly, "domestic travel restrictions, stay-at-home requirements, and public transport closing" are also clustered together. Indeed, it is likely that these variables are implemented after reaching a certain peak of infections and therefore considered altogether to reduce the spread, as they complement each other. Public information campaigns and school closing policies are also clustered together in both dimensions. It is therefore important to interpret the results of regressions with caution, as NPIs that are closely correlated should be regarded within the context of the respective clusters rather than as individual measures (Zheng and Li 2014).

Following the clustering analysis, we omit domestic travel restrictions, as they may

11. Additionally, the estimation has been tested for multicollinearity. Using the variance inflation factor (VIF), it appears that only public information campaign and public event cancellation suffer from high multicollinearity, as their VIF statistic exceeds the threshold of 10.

12. Ward's method seeks to minimize the Euclidean distance between two clusters and iterate until all data has been clustered (at the beginning, each point is treated as its own cluster). The following equation describes the "merging cost" which to minimize: $\triangle(A,B) = \sum_i (x_i - \overline{x})^2 - \sum_{i \in a} (x_i - \overline{a})^2 - \sum_{i \in b} (x_i - \overline{b})^2$

capture the effect of stay at home requirements. Similarly, we exclude the variable information campaign as it is clustered with school closing. Finally, we also drop debt contract relief, one of the two economic relief policies, as it correlates with income support. We are then left with a total of 11 NPIs. Estimated coefficients, reported in Columns 4 and 5 of Table 6, have to be interpreted with caution. Since we dropped public information campaign, its effect is now captured by the school closing variable. The same reasoning holds for the effect of income support and stay at home requirements, which partly capture debt/contract relief policies and domestic travel restrictions, respectively. Overall, results are once again qualitatively similar to the baseline results.

Lagged values of the reproduction rate Chernozhukov et al. 2021 argue that information on the current state of the pandemic affects people's behaviour. Following high infection rates, people may reduce their mobility or increase social distancing, e.g. by better adhering to the 1.5m distance rule. Hence, if the current state of the pandemic affects both people's behaviour and the implementation of NPIs, this would result in biased estimates of the treatment effect. Following Chernozhukov et al. 2021, we therefore run our baseline specification with the reproduction rate lagged by 10 days as an additional regressor. This also addresses persistence of R_{it}, controlling for the current state of the pandemic.

Regression results are reported in Columns 1 and 3 of Table 7. Most coefficients remain robust. The testing policy coefficient turns insignificant, while the coefficient for facial coverings is now also significantly negative in the dummy specification. The coefficient for public information campaign becomes insignificant in the dummy specification. While the 10-day lag should capture adjustments in behaviour, 1-day lags might be better in addressing persistence of R. In the same table, we therefore also report regression results using R_{t-1} instead of R_{t-10} as additional regressor (Columns 2 and 4). Coefficients are generally smaller in magnitude, which is not unexpected given a high degree of multicollinearity between NPIs at $t-10$ and the reproduction rate at $t-1$. The estimated coefficients should thus be interpreted with care.

Standardised (beta) coefficients Using NPI indices as regressors is problematic because they do not all have the same range. For example, the index for facial coverings ranges from zero to four, while the index for domestic travel restrictions only ranges from zero to two. An increase in the index from, say, one to two, therefore does not indicate the same increase in strictness for the requirements to wear facial coverings as it does for domestic travel restrictions. In another robustness test, we therefore estimate standardised regression coefficients that relate a change in one standard deviation of the independent variable to the change in standard deviations of the dependent variable. Regression results are reported in Column 5 of Table 7. While the size and interpretation of the coefficients changes, the ranking of the individual NPIs remains relatively constant. Public information campaigns remain by far the most effective instrument, with school closing, contact tracing and the cancellation of public events remaining in the top four.

Further robustness checks In order to make sure our own calculation of the reproduction rate was consistent with other studies, we also report results using the reproduction rate calculated by Hale et al. (2021). Two differences arise between their calculation and ours. First, the authors use a 10-day sliding window over which to estimate R while we use 14 days. Second, Hale et al. (2021) base their calculation on the work of Arroyo-Marioli et al. (2021) which estimates the reproduction rate using the Kalman filter. Additionally, computing R at the beginning of the pandemic leads to high values of the reproduction rate, which may impact estimation. We have dropped values above 15 while Hale et al. (2021) dropped even more outliers. Overall, using their data allows verifying that public information campaign, public event cancellation as well as school closing are among the five most effective policies (Column 6 of Table 7). Surprisingly, we find a negative coefficient for income support as well as debt cancellation, indicating their effectiveness at reducing the reproduction rate.

Results have been replicated with Driskoll and Kraay standard errors in order to take into account cross-sectional dependencies.[13] Coefficients and significance remain stable, indicating that cross-sectional dependencies are not a problem in our estimation, as we exploit a very large set of countries. The estimation did not indicate much difference in coefficients and confidence intervals. We can therefore rule out cross-section dependencies to some extent. Indeed, it could be that policy responses to the pandemic have not been decided fully independently within each country, especially for those belonging to free trade areas, or benefiting from a strong regional integration. For instance, the European Commission strived to adopt a European common response to tackle the crisis by issuing guidelines and recommendations for health related measures as well as border management.[14]

13. Driskoll and Kraay standard errors are obtained by correcting the covariance matrix to take into account serial correlation, heteroscedasticity, and cross-sectional dependence, see Hoechle (2007). Results available on request.

14. For an overview of the European Commission's response, see European Commission (2022).

Table 7: Further robustness checks

Dependent variable: R_{it}	(1)	(2)	(3)	(4)	(5)	(6)
NPIs coding:	Index	Index	Dummy	Dummy	Index	Index
Robustness specification:	R_{it-10}	R_{it-1}	R_{it-10}	R_{it-1}	Beta	Oxford
R_{it-10}	0.034***		0.033***			
	(0.007)		(0.007)			
R_{it-1}		0.394***		0.394***		
		(0.015)		(0.015)		
School closing	-0.065***	-0.043***	-0.217***	-0.140***	-0.095***	-0.070***
	(0.006)	(0.005)	(0.022)	(0.019)	(0.007)	(0.005)
Workplace closing	-0.037***	-0.023***	-0.065***	-0.045***	-0.042***	-0.0402***
	(0.006)	(0.005)	(0.013)	(0.012)	(0.006)	(0.005)
Cancel public events	-0.062***	-0.051***	-0.078***	-0.073***	-0.076***	-0.056***
	(0.008)	(0.007)	(0.017)	(0.016)	(0.010)	(0.007)
Restrictions on gatherings	-0.017***	-0.006	-0.099***	-0.040**	-0.024*	-0.018***
	(0.004)	(0.004)	(0.017)	(0.016)	(0.005)	(0.004)
Close public transport	-0.005	-0.000	-0.040***	-0.018**	0.001	-0.004
	(0.006)	(0.005)	(0.009)	(0.008)	(0.007)	(0.005)
Stay at home requirements	-0.010	-0.010**	-0.043***	-0.032***	-0.012	-0.030**
	(0.006)	(0.005)	(0.011)	(0.010)	(0.007)	(0.004)
Domestic travel	-0.003	0.003	-0.008	-0.001	0.000*	-0.004
	(0.006)	(0.005)	(0.010)	(0.009)	(0.007)	(0.005)
International travel	-0.015***	-0.011**	-0.065**	-0.043*	-0.052***	-0.040***
	(0.005)	(0.005)	(0.030)	(0.024)	(0.006)	(0.003)
Public info campaign	-0.051***	-0.037**	-0.040	-0.028	-0.134***	-0.121***
	(0.019)	(0.016)	(0.044)	(0.040)	(0.023)	(0.020)
Testing policy	-0.001	-0.003	-0.064	-0.019	-0.040***	-0.006
	(0.008)	(0.007)	(0.047)	(0.033)	(0.011)	(0.007)
Contact tracing	-0.042***	-0.026**	-0.078***	-0.045**	-0.083***	-0.026***
	(0.014)	(0.012)	(0.027)	(0.022)	(0.017)	(0.008)
Facial coverings	-0.013***	-0.008**	-0.032**	-0.017	-0.014*	-0.031***
	(0.004)	(0.003)	(0.013)	(0.011)	(0.004)	(0.003)
Income support	0.017	0.005	0.020	0.004	0.023*	-0.082***
	(0.012)	(0.010)	(0.016)	(0.013)	(0.012)	(0.008)
Debt/contract relief	-0.023***	-0.011	-0.044***	-0.024*	-0.018*	-0.057***
	(0.009)	(0.008)	(0.013)	(0.014)	(0.009)	(0.006)
Observations	52,790	54,420	52,790	54,420	54,617	44,591
R-squared	0.691	0.749	0.690	0.748	0.616	0.815
Country-month FE	YES	YES	YES	YES	YES	YES
Day of the week FE	YES	YES	YES	YES	YES	YES

Note: NPIs are lagged by 10 days. Columns 1-4 reports results controlling for lagged values of the dependent variable. Column 5 reports the standardized beta coefficients for the specification in Table 3 Column 1 (Index specification of NPIs). Column 6 reports results using the reproduction rate from Hale et al. (2021). Robust standard errors in parentheses. * p-value < 0.1, ** p-value < 0.05, *** p-value < 0.01

7 Conclusion

This paper analyses the effectiveness of NPIs in reducing the reproduction rate of SARS-CoV-2. We rank NPIs by their relative effectiveness in reducing the spread of the virus. Our results suggest that public information campaigns have been the most efficient policy, with a marginal effect of tightening restrictions of -0.248 on the reproduction rate. They are followed closely by contact tracing policies (-0.105), public event cancellation (-0.09) and school closing (-0.079). A more stringent testing policy, workplace closing, international travel restrictions, restrictions on gatherings, the mandatory wearing of face masks and debt relief are also associated with a reduced reproduction rate, albeit to a lesser extent.

As indices of the various NPIs have different ranges, using them as regressors makes it difficult to effectively compare estimated coefficients. Using dummies allows us to compare the overall impact of individual NPIs on the reproduction rate. The dummy regression reveals that public information campaigns and school closings were the most effective instruments, reducing the reproduction rate by 0.352 and 0.242 respectively. They are followed by testing policy, contact tracing, international travel restrictions, cancelling public events, workplace closings and restrictions on gatherings. This does not mean, however, that NPIs should generally be introduced in this order. Instead, the benefits of each NPI should be weighed carefully against their costs to society. We hope that our results can assist policymakers in better understanding the benefits of individual NPIs in terms of their impact on the reproduction rate.

Comparing effects of NPIs across the first and second wave, we find that public information campaign and the mandatory wearing of face masks report a stronger negative impact on the spread of the virus during the second wave. This improved effectiveness of facial coverings is likely driven by the increased use of medical masks in European countries from mid 2020 as well as a greater degree of compliance. In contrast, effects of other NPIs have slightly dissipated over time, as school closing and public event cancellation were less effective during the second wave. The same is true - albeit to a lesser extent - for testing and contact tracing.

Using the rule of law index of the World Justice Project, we show that countries that do not limit power attributed to the government and countries with low fundamental rights for their citizens benefit more from increasing the stringency of school closings and international travel restrictions. This suggests that, perhaps, a lower degree of freedom for individuals enables governments to increase compliance with certain NPIs. In contrast, increasing the stringency of restrictions on gatherings, stay at home requirements and public information campaigns proved more effective in countries with stronger fundamental rights. As these are generally policies that rely on the cooperation of the population, our findings suggest that such policies are more effective in democracies that rely on public consensus.

As the vaccination rate amongst the global population increases continuously, NPIs may play a smaller role in controlling the pandemic. However, many people in developing countries are still far from being fully vaccinated so that NPIs remain relevant in these countries in the foreseeable future. In addition, Covid-19 may sadly not be the last pandemic that humankind has to face, so that a better understanding of the effectiveness of NPIs can contribute to a better preparation for when a similar disease or new variant of Covid-19 strikes again.

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Appendix

A Additional Tables

Table A.1: Correlations between daily new cases and selected indicators

	(1)	(2)	(3)
Dependent variable:	Log of daily new cases	Log of daily new cases	Log of daily new cases
Log of daily number of tests	0.0665***	0.0721***	0.102***
	(0.0151)	(0.0152)	(0.0149)
Log of GDP per capita	0.231***		
	(0.0106)		
Log of population density		0.0536***	
		(0.0105)	
Log of international arrivals			0.833***
			(0.0118)
Constant	2.648***	4.486***	-8.565***
	(0.171)	(0.148)	(0.228)
Observations	27,873	27,796	24,251
R-squared	0.017	0.002	0.173

Note: OLS regressions controlling for cumulative number of tests performed. Robust standard errors in parentheses. * p-value < 0.1, ** p-value < 0.05, *** p-value < 0.01. Data on population density, GDP per capita and international arrivals are extracted from the World Development Indicators (World Bank) database.

Table A.2: Cross-correlation of policy measures

Var	c1	c2	c3	c4	c5	c6	c7	c8	h1	h2	h3	h6	h7	e1	e2
c1	1.0000														
c2	0.6575	1.0000													
	(0.0000)														
c3	0.7071	0.6966	1.0000												
	(0.0000)	(0.0000)													
c4	0.6290	0.6789	0.7608	1.0000											
	(0.0000)	(0.0000)	(0.0000)												
c5	0.5245	0.5580	0.4778	0.4855	1.0000										
	(0.0000)	(0.0000)	(0.0000)	(0.0000)											
c6	0.6066	0.6511	0.5853	0.6055	0.5891	1.0000									
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)										
c7	0.5931	0.6103	0.5865	0.5343	0.6130	0.6634	1.0000								
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)									
c8	0.5274	0.4448	0.5282	0.4453	0.3730	0.4037	0.4373	1.0000							
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)								
h1	0.5167	0.4504	0.5502	0.5328	0.2684	0.3790	0.3400	0.5343	1.0000						
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)							
h2	0.3114	0.3118	0.4006	0.4208	0.1393	0.2213	0.1607	0.3387	0.5142	1.0000					
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)						
h3	0.3273	0.2806	0.3859	0.4047	0.1316	0.2239	0.1489	0.3257	0.5312	0.5626	1.0000				
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)					
h6	0.3163	0.3295	0.3998	0.4601	0.1763	0.3109	0.2629	0.1897	0.4234	0.4413	0.3903	1.0000			
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)				
h7	0.0200	0.0360	0.0492	0.0550	0.0004	0.0166	0.0193	0.0100	0.0243	0.0626	0.0246	0.0501	1.0000		
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.9257)	(0.0000)	(0.0000)	(0.0112)	(0.0000)	(0.0000)	(0.0000)	(0.0000)			
e1	0.2541	0.3192	0.3259	0.3684	0.0884	0.1880	0.1353	0.2683	0.3660	0.4680	0.4161	0.2527	0.0678	1.0000	
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)		
e2	0.3607	0.3843	0.4028	0.3836	0.2338	0.3251	0.2611	0.3315	0.4074	0.4493	0.3981	0.3756	0.0378	0.4453	1.0000
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	

Note: c1: School closing, c2: Workplace closing, c3: Cancel public events, c4: Restrictions on gatherings, c5: Close public transport, c6: Stay at home requirements, c7: Domestic travel, c8: International travel, h1: Public info campaign, h2: Testing policy, h3: Contact tracing, h6: Facial coverings, h7: Vaccination policy, e1: Income support, e2: Debt contract relief

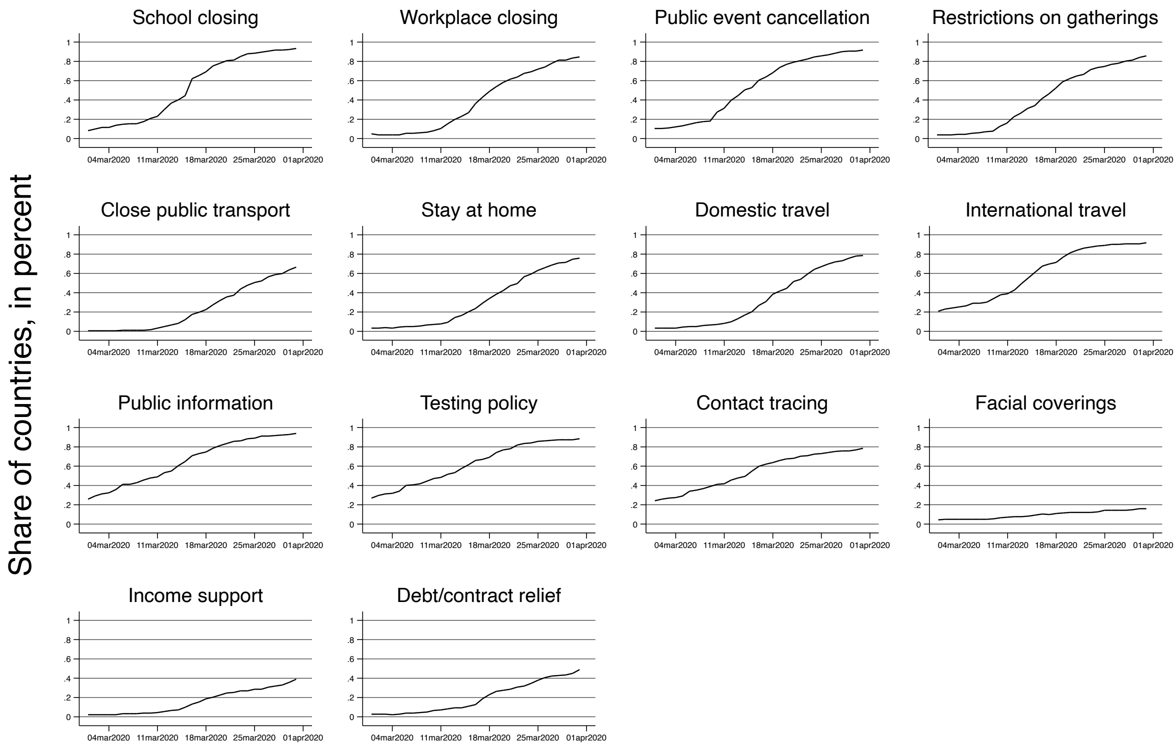
Table A.3: Rule of law - NPI dummies

Dependent variable: R_{it} NPI:	(1) High CoG Dummy	/ Low CoG Dummy	/ Wald test Dummy	(2) High FR Dummy	/ Low FR Dummy	/ Wald test Dummy	(3) High RE Dummy	/ Low RE Dummy	/ Wald test Dummy
School closing	-0.181***	-0.428***	**22.40**	-0.187***	-0.386***	**14.66**	-0.105**	-0.378***	**25.14**
	(0.035)	(0.038)	0.000	(0.038)	(0.035)	0.000	(0.044)	(0.033)	0.000
Workplace closing	-0.079**	-0.119***	0.88	-0.103***	-0.109***	0.02	-0.100***	-0.104***	0.01
	(0.031)	(0.029)	0.349	(0.030)	(0.030)	0.886	(0.036)	(0.027)	0.921
Cancel public events	-0.234***	-0.111***	**6.58**	-0.172***	-0.212***	0.69	-0.240***	-0.124***	**5.58**
	(0.033)	(0.035)	0.010	(0.033)	(0.035)	0.4054	(0.039)	(0.030)	0.018
Restrictions on gatherings	-0.085**	-0.063**	0.23	-0.056	-0.090***	0.54	-0.071*	-0.078***	0.02
	(0.036)	(0.031)	0.631	(0.034)	(0.032)	0.4641	(0.039)	(0.029)	0.891
Close public transport	-0.007	0.014	0.35	-0.024	0.015	1.30	-0.006	0.015	0.33
	(0.028)	(0.022)	0.554	(0.024)	(0.025)	0.255	(0.031)	(0.021)	0.566
Stay at home requirements	-0.059**	-0.003	2.28	-0.092***	0.051*	**14.66**	-0.048	-0.019	0.55
	(0.027)	(0.026)	0.131	(0.025)	(0.028)	0.000	(0.031)	(0.023)	0.460
Domestic travel	-0.031	-0.012	0.31	-0.023	-0.027	0.02	-0.028	-0.023	0.02
	(0.026)	(0.022)	0.580	(0.023)	(0.025)	0.893	(0.029)	(0.021)	0.8865
International travel	0.046	-0.214***	**22.77**	-0.003	-0.228***	**17.90**	-0.033	-0.136***	**3.22**
	(0.043)	(0.034)	0.000	(0.039)	(0.036)	0.000	(0.048)	(0.032)	0.073
Public info campaign	-0.140***	-0.203***	0.87	-0.218***	-0.111**	2.54	-0.042	-0.242***	**8.59**
	(0.050)	(0.045)	0.350	(0.048)	(0.047)	0.111	(0.053)	(0.043)	0.003
Testing policy	-0.484***	-0.166***	**20.59**	-0.403***	-0.220***	**7.40**	-0.367***	-0.266***	1.97
	(0.056)	(0.042)	0.000	(0.050)	(0.045)	0.006	(0.060)	(0.039)	0.160
Contact tracing	-0.207***	-0.170***	0.40	-0.227***	-0.157***	1.51	-0.192***	-0.201***	0.03
	(0.051)	(0.031)	0.528	(0.046)	(0.032)	0.220	(0.052)	(0.031)	0.873
Facial coverings	0.025	0.012	0.11	0.023	0.024	0.00	0.056	0.005	1.43
	(0.031)	(0.025)	0.735	(0.027)	(0.028)	0.970	(0.037)	(0.023)	0.232
Income support	-0.069**	-0.019	1.47	-0.023	-0.048*	0.39	-0.162***	0.002	**13.01**
	(0.033)	(0.024)	0.226	(0.027)	(0.028)	0.535	(0.040)	(0.022)	0.000
Debt/contract relief	-0.059*	-0.063***	0.01	0.014	-0.119***	**11.90**	-0.157***	-0.038*	**6.58**
	(0.033)	(0.023)	0.925	(0.027)	(0.027)	0.000	(0.041)	(0.022)	0.010
Observations	/	/	37,410	/	/	37,410	/	/	37,410
R-squared	/	/	0.575	/	/	0.575	/	/	0.575
Country-month FE	/	/	YES	/	/	YES	/	/	YES
Day of the week FE	/	/	YES	/	/	YES	/	/	YES

Note: NPI dummies lagged by 10 days. Robust standard errors in parentheses. * p-value < 0.1, ** p-value < 0.05, *** p-value < 0.01. F statistic and P-value of tests for coefficient differences are reported in Column 'Wald Test'.

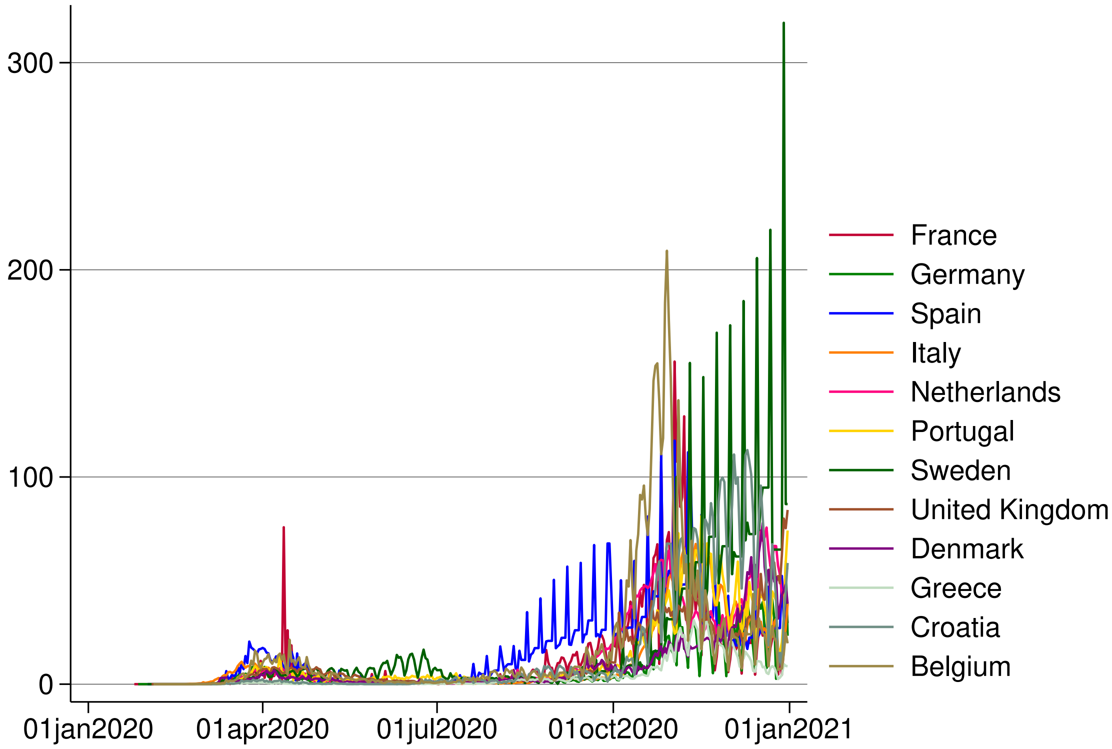
B Additional Figures

Figure B.1: NPI rate of implementation in March 2020



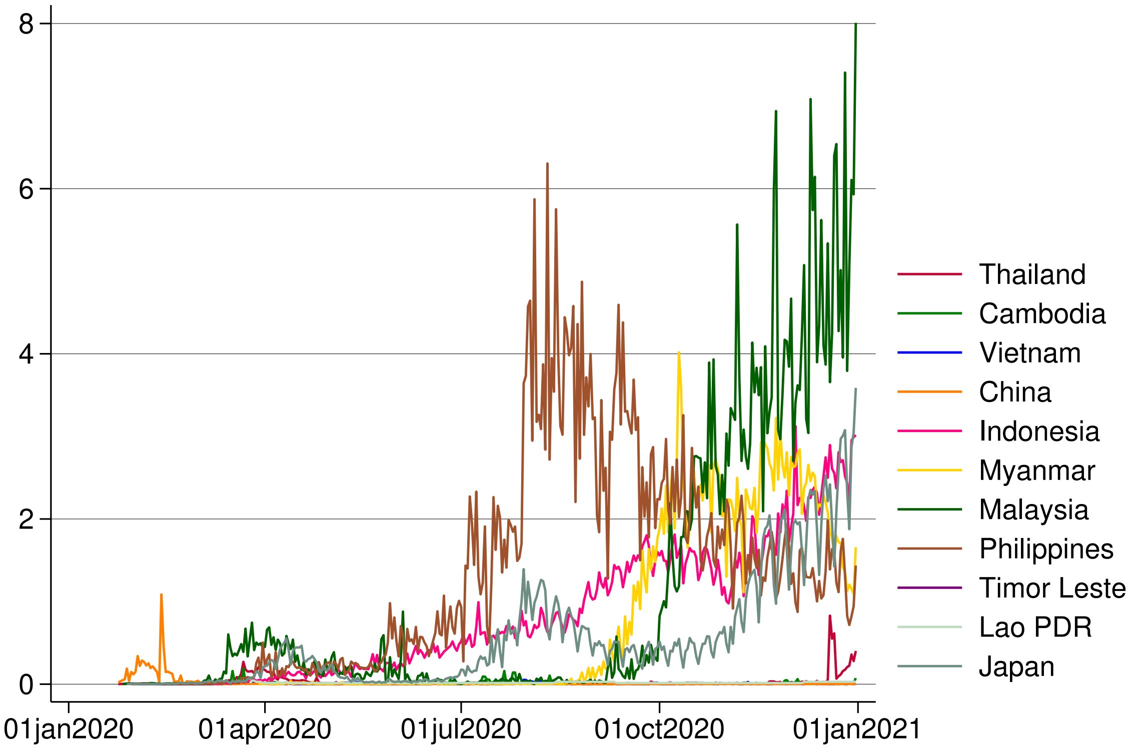
Note: Share of countries having implemented individual NPIs. Total number of countries in the sample: 182. Source: Data from Hale et al. (2021), own calculations.

Figure B.2: Incidence rate in selected European economies



Source: Data from Hale et al. (2021).

Figure B.3: Incidence rate in ASEAN (Brunei excluded, China and Japan included)



Source: Data from Hale et al. (2021).

Figure B.4: Hierarchical sectional clustering of NPIs

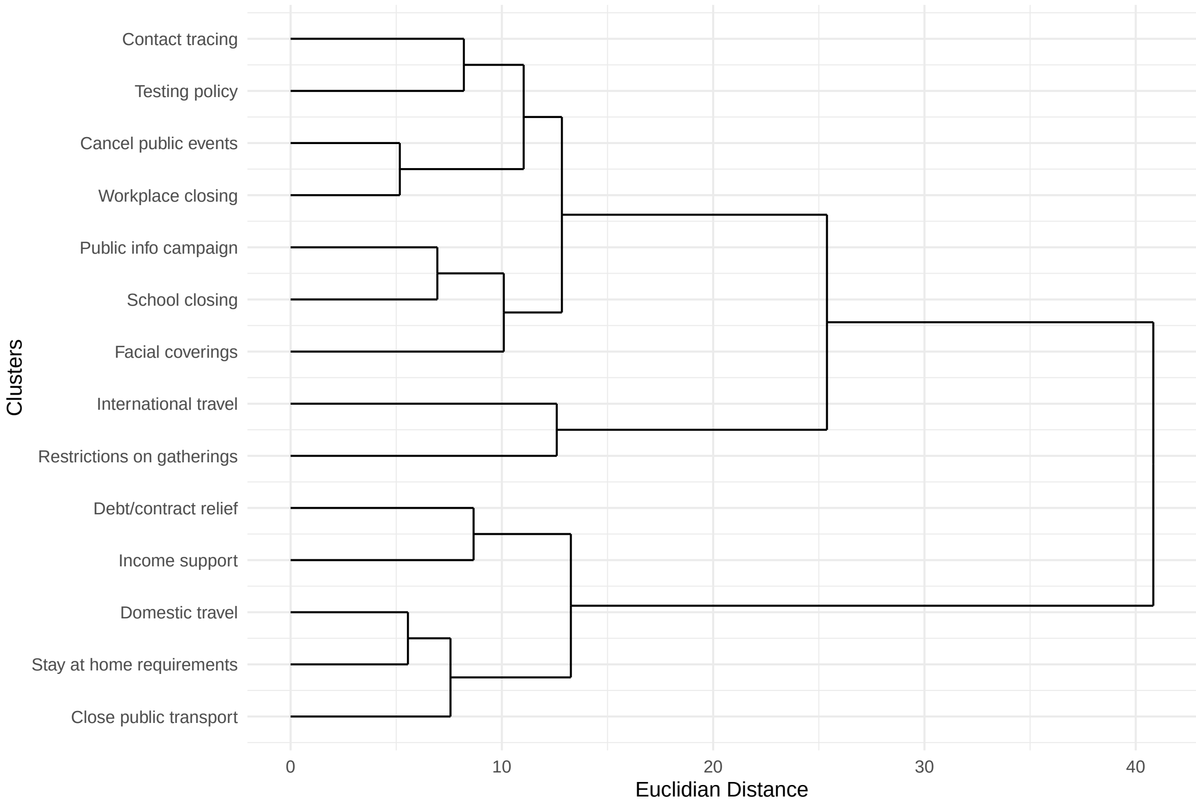


Figure B.5: Hierarchical temporal clustering of NPIs