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A Lockdown a Day Keeps the Doctor Away: The Global Effectiveness of Non-Pharmaceutical Interventions in Mitigating the Covid-19 Pandemic

Abstract

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 181 countries to estimate the effects of twelve NPIs on the spread of the disease in 2020. The employed fixed effects estimation greatly reduces endogeneity concerns. While almost all measures had a dampening effect on the reproduction rate of the virus, school closings and restrictions on gatherings were most effective, followed by international travel restrictions and contact tracing. The obligation to wear face masks was more effective during the second wave. Measures requiring significant resources, such as testing, were more effective in developed countries.

JEL-Codes: C130, C230, D040, I180.

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

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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 682 million individuals and killed more than six million as of March 2023 (Our World in Data, 2023). As the epicentre of the pandemic, Wuhan was the first city to implement a strict lockdown. After 76 days of stringent restrictions on the mobility of people, no new cases were registered (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 social and 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 twelve individual NPIs on the reproduction rate of the virus in 2020 by exploiting a panel data set of 181 countries, ranking them by their ability to reduce the spread of the virus.[1] Many studies have estimated the effects of policies within specific countries. 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 over time and across 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 partially addressed by fixed effects as well as the use of lagged NPIs. Both strategies might not be sufficient to fully eliminate the attenuation bias resulting from reverse causality. Our estimates should thus be seen as lower bounds of the real treatment effect.

We find that over all countries in the sample, nine out of twelve NPIs investigated

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 and obligations to wear face masks.

had a significantly dampening effect on the reproduction rate in 2020 (reducing it by 0.08 on average). School closing and restrictions on gatherings were most effective, reducing the reproduction rate by 0.21 and 0.10 respectively. They are followed by international travel restrictions (-0.09), contact tracing (-0.09), and workplace closing (-0.08).

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 and workplace closings were also more effective during the second half of 2020. In contrast, almost all other NPIs were less effective during the second wave of the pandemic. Potentially, this might indicate a less stringent implementation of NPIs by the public. As argued by Boldea et al. (2023), it could also be a sign of the increased infectiousness of later variants of the virus.

Comparing effects across developed and developing countries, we show that testing policies, the requirement to wear face masks and contact tracing were particularly effective in developed countries. In fact, testing was by far the most effective instrument in developed countries. All three policies require resources such as test kits and masks, which are more readily available in richer countries. Public information campaigns were also highly effective in developed countries. They were often one of the first measures implemented and strongly affected people's behaviour by informing them about the gravity of the situation and providing general guidance, such as the requirement to keep minimum distances of 1.5m (Chernozhukov et al. 2021).

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

Since the start of the Covid-19 pandemic, an impressive body of literate studying the determinants of infection rates and mortality has emerged. These include population characteristics such as population density (Gerritse 2022), age structure (Fielding-Miller et al. 2020), life expectancy (Stojkoski et al. 2020), testing rate and airport traffic (Roy and Ghosh 2020), income (Valero and Valero-Gil 2021) as well as temperature and humidity (M. Liu et al. 2020). Spillover effects across regions also play a role in spreading the disease (Fielding-Miller et al. 2020; Eckardt et al. 2020; Ruktanonchai et al. 2020; Holtz et al. 2020). For example, Felbermayr et al. 2021 exploit German county-level data to 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.[2] Breidenbach and Mitze (2022) find that the number of infections in German districts increased in the weeks following first league football matches.

Our paper relates to the strand of literature investigating the effectiveness of non-pharmaceutical interventions in reducing the number of infections. Many studies have investigated the effectiveness of individual policies in a specific country or region. Alipour et al. (2021) use German data to show 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. Russell et al. (2020) conclude 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. Isphording et al. (2021) do not find any impact of school re-openings in Germany on the number of infections, whereas Amodio et al. (2022) show that earlier school openings in Sicily led to a rising number of cases. Similarly, evidence provided by Goldhaber et al. (2022) indicates that in person schooling contributed to an increase in infections in Michigan and Washington.

Pan et al. (2020) study the effects of policy responses to Covid-19 on the outbreak in Wuhan, China. They provide preliminary evidence on the effectiveness of policy responses, in particular home quarantines and sanitary cordons. Fang et al. (2020) show that the lockdown in Wuhan reduced mobility both within the city, as well as across cities, thus reducing the spread of Covid-19. Bilgel (2022) provides similar evidence for Turkey. 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. Cerqueti et al. (2021) conclude that the lockdown and other NPIs imposed in Italy in early 2020 saved more than 21,000 lives. Friedson et al. (2021) show that shelter in place orders significantly reduced infections and deaths in California. Cho (2020) finds that stricter lockdown measures in Sweden would have significantly reduced both the number of infections and excess mortality.

We are not the first to investigate the impact of multiple NPIs on the number of infections. Chen et al. (2020) 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

2. 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 (Anand et al. 2020) which can be combined with an economic perspective (Eichenbaum et al. 2020).

week fixed effects and country fixed effects. Bergman and Fishman (2020) 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. Our paper, in contrast, uses country-month fixed effects instead of a combination of linear time trends and country fixed effects, which allows to better capture time varying country-characteristics.

Bendavid et al. (2021) compare the effectiveness of NPIs on case growth rates in sub-national regions of ten 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. Ferguson et al. (2020) find that a combination of different NPIs is best suited to reduce transmission. Carraro et al. (2020) use data from 166 economies from January 2020 to May 2020, showing that school closures and lockdowns have a stronger impact on the number of active cases than other NPIs.

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 NPIs 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 181 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%. Xie et al. (2022) 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. We show that the requirement to wear face masks became highly effective only in the second wave of the pandemic.

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 181 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 entire year 2020, allowing us to investigate if the effectiveness of NPIs differs across waves and whether developed countries are more successful in implementing NPIs than developing ones.

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 181 countries in the year 2020.[3] 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. The reproduction rate informs on the 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 in country i at time t, to total infections, measured by the sum of past infections at any 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

3. A full list of countries is provided in Table A.2 in the appendix.

infected person infected by the first person starting to have symptoms (Cori et al. 2013).[4]

The benefit of using the reproduction rate is that it is directly comparable across countries, as it is not affected by a country's general testing capacity. Changes in R should have the same meaning independent of whether a country detects 100 percent or 50 percent of cases, as long as testing capacity remains constant within countries. The increase in testing capacity over time is captured by country-month fixed effects. Once the reproduction rate is below one, the spread of Covid-19 will die out and restrictive policy measures can be lifted. However, 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.

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 such as government press releases and reports from international organisations (Hale et al. 2021), 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 a direct comparison in terms of policy strictness across countries.

The dataset covers 23 indicators. We restrict our analysis to twelve 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

4. 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). 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.

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

economic stimulus spending or tax cuts, income support as well as debt or contract relief.

Table 1: Summary statistics

Variable	Mean	Std. Dev.	Min.	Max.	N
Reproduction rate (14 days rolling window)	1.212	0.734	0.015	14.872	52349
Log of daily number of tests	8.436	1.978	0.693	14.585	25990
School closing	2.121	1.008	0	3	52349
Workplace closing	1.567	0.974	0	3	52349
Public event cancellation	1.561	0.704	0	2	52349
Restrictions on gatherings	2.739	1.409	0	4	52349
Close public transport	0.663	0.758	0	2	52349
Stay at home requirements	1.114	0.922	0	3	52349
Domestic travel restrictions	1.042	0.909	0	2	52349
International travel restrictions	2.827	1.133	0	4	52349
Public information campaign	1.92	0.319	0	2	52349
Testing policy	1.807	0.819	0	3	52349
Contact tracing	1.489	0.646	0	2	52349
Facial coverings	2.06	1.422	0	4	52349
School closing (0/1)	0.917	0.276	0	1	52349
Workplace closing (0/1)	0.797	0.402	0	1	52349
Public event cancellation (0/1)	0.875	0.33	0	1	52349
Restrictions on gatherings (0/1)	0.84	0.366	0	1	52349
Close public transport (0/1)	0.488	0.5	0	1	52349
Stay at home requirements (0/1)	0.678	0.467	0	1	52349
Domestic travel restrictions (0/1)	0.607	0.488	0	1	52349
International travel restrictions (0/1)	0.965	0.183	0	1	52349
Public information campaign (0/1)	0.986	0.117	0	1	52349
Testing policy (0/1)	0.972	0.164	0	1	52349
Contact tracing (0/1)	0.916	0.277	0	1	52349
Facial coverings (0/1)	0.751	0.433	0	1	52349

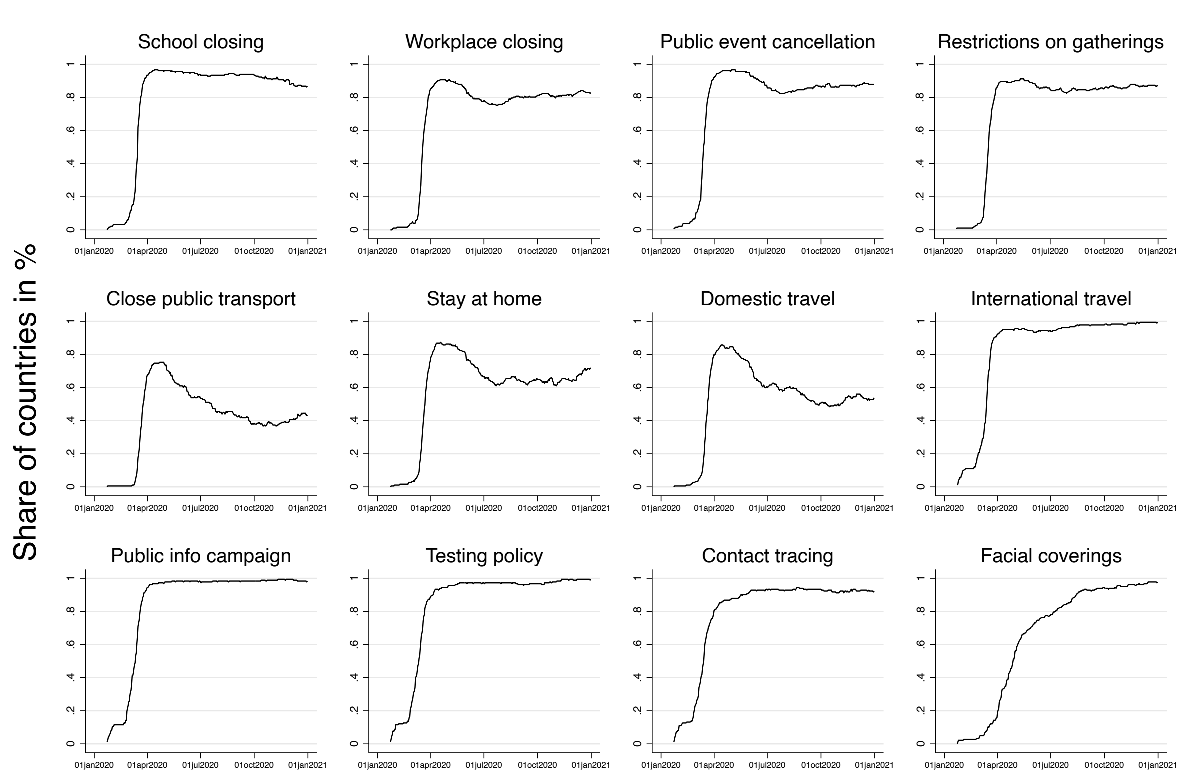
Note: NPIs are encoded using an ordinal scale ranging from 0 to either 2, 3, or 4. 0 matches the absence of the policy at a given day and the maximum value indicates its strictest implementation. The bottom panel summarises dummies that equal 1 if the indicator is greater or equal to 1 and 0 otherwise. Source: Data from Hale et al. (2021).

Each remaining indicator has corresponding ordinal scales, ranging from zero to four depending on the indicator, where zero matches the absence of policy and four indicates a strict implementation of such policy.[6] Table A.1 in the appendix summarises and briefly describes the NPIs used in our analysis. We also construct a set of dummy variables for

6. More detailed information on how the indicators are constructed is provided by Hale et al. 2022.

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) and one if at least one measure has been implemented (i.e. an index of at least one regardless of the intensity of the policy).

Figure 1: NPI rate of implementation in 2020



Note: Share of countries having implemented individual NPIs over time. Total number of countries in the sample: 181. Source: Data from Hale et al. (2021), own calculations.

Table 1 provides summary statistics for the variables used in our analysis. Looking at the mean values of the dummy variables shows that public information campaigns, testing policy and international travel restrictions were the most implemented policies in 2020. On the contrary, domestic travel restrictions and public transportation closing were implemented less often. Figure 1 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.[7] Most countries have implemented most of the 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

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

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.

4 Methodology

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

$$R_{it} = \boldsymbol{NPI}_{it-10}\boldsymbol{\beta}^{'} + R_{it-10} + \nu_{im} + \nu_{dow} + \epsilon_{it} \tag{2}$$

where R_{it} is the reproduction rate in country i at time t (measured in days). $\boldsymbol{NPI}_{it-10}$ is a vector of twelve NPIs imposed in country i at time $t-10$. 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 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).

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 include R_{it-10}, i.e. 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, and prevents dynamic feedback effects correlated with interventions from biasing results.

ν_{im} are country-month fixed effects (i.e. country fixed effects interacted with month fixed effects). They control for various unobserved characteristics that may simultaneously impact the spread of the virus as well as the imposition of NPIs, resulting in omitted variable bias. First, ν_{im} capture unobserved time invariant country characteristics, such as cross-country differences in population density, annual GDP, health systems,[8] region or pre-existing cultures of wearing face masks, making the obligation to wear them easier to implement.[9]

In addition, ν_{im} also control for unobserved country specific factors that vary over the months (but not within months). This includes many characteristics that were built in

8. In poorer countries, low testing capabilities may substantially underestimate total cases (Gupta and Shankar 2020; Valero and Valero-Gil 2021).

9. Note that Nickell bias is asymptotically eliminated in long panels (Nickell 1989).

response to the outbreak, such as increased testing capacities, but also changing behaviour of people towards social distancing as well as seasonality effects of the disease. 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. Our approach also captures global time trends common to all countries.

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.[10] This leads to an underestimation of the true treatment effect.[11] 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. 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 of reverse causality is alleviated by the use of country-month fixed effects, the lagged reproduction rate 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 to implement them was made even earlier. In fact, our event study (Figure 3) does not indicate significant pre-treatment effects. 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 (towards zero) means that our estimates should be seen as lower bounds of the true treatment effect. The bias should not affect the relative ranking of individual NPIs under the assumption that it is of similar magnitude for all NPIs.

10. 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.

11. 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.

5 Baseline results

Table 2 provides the results of our baseline specification using indices of NPIs or dummy NPIs as explanatory variables (both lagged by ten days). Column 1 presents estimated coefficients of the econometric model specified in Equation 2, including country-month fixed effects and day of the week fixed effects but excluding the lagged dependent variable as additional regressor. Column 3 reports results from the dynamic model.

Table 2: The impact of NPIs on the reproduction rate

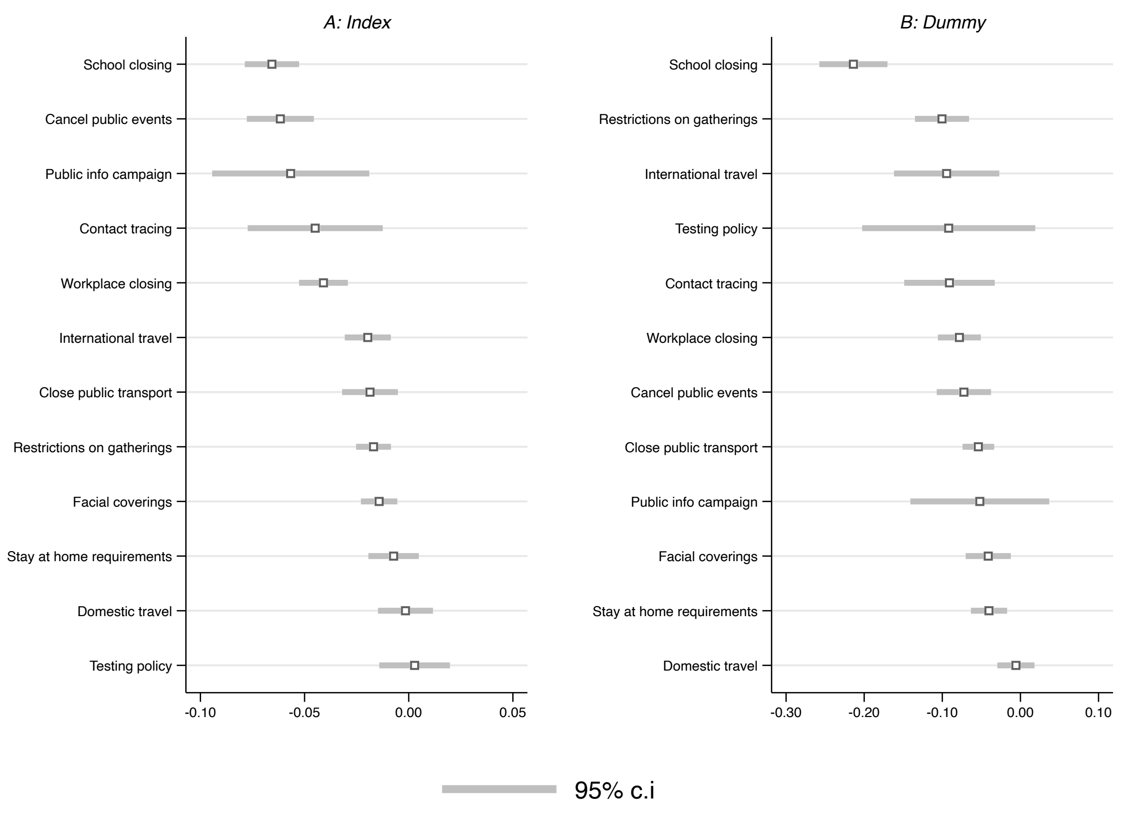
Dependent variable: R_{it}	(1)	(2)	(3)	(4)
NPIs coding:	Index	Dummy	Index	Dummy
School closing	-0.070***	-0.228***	-0.066***	-0.214***
	(0.007)	(0.022)	(0.007)	(0.022)
Workplace closing	-0.043***	-0.086***	-0.041***	-0.078***
	(0.006)	(0.014)	(0.006)	(0.014)
Cancel public events	-0.064***	-0.075***	-0.062***	-0.072***
	(0.008)	(0.018)	(0.008)	(0.018)
Restrictions on gatherings	-0.018***	-0.104***	-0.017***	-0.100***
	(0.004)	(0.018)	(0.004)	(0.018)
Close public transport	-0.021***	-0.058***	-0.019***	-0.054***
	(0.007)	(0.010)	(0.007)	(0.010)
Stay at home requirements	-0.009	-0.043***	-0.007	-0.040***
	(0.006)	(0.012)	(0.006)	(0.012)
Domestic travel	-0.003	-0.009	-0.002	-0.006
	(0.007)	(0.012)	(0.007)	(0.012)
International travel	-0.023***	-0.106***	-0.020***	-0.094***
	(0.006)	(0.034)	(0.006)	(0.034)
Public info campaign	-0.067***	-0.071	-0.057***	-0.052
	(0.019)	(0.045)	(0.019)	(0.045)
Testing policy	0.000	-0.103*	0.003	-0.092
	(0.009)	(0.056)	(0.009)	(0.057)
Contact tracing	-0.051***	-0.102***	-0.045***	-0.091***
	(0.016)	(0.029)	(0.017)	(0.030)
Facial coverings	-0.015***	-0.044***	-0.014***	-0.041***
	(0.004)	(0.015)	(0.004)	(0.015)
R_{it-10}			0.035***	0.034***
			(0.007)	(0.007)
R^2	0.691	0.691	0.691	0.691

Note: OLS regressions with country-month and day of the week fixed effects. Robust standard errors in parentheses. 52,349 observations. * p-value < 0.1, ** p-value < 0.05, *** p-value < 0.01.

The estimated coefficient of the lagged reproduction rate is positive and statistically significant, indicating persistence. Estimated NPI coefficients from both models are qualitatively similar. Results from our preferred specification (Column 3) indicate significantly negative effects of nine NPIs on the reproduction rate. Estimated coefficients for stay at home requirements, domestic travel restrictions and testing policy are not significantly different from zero. School closings have the strongest marginal impact on infections. Specifically, a one unit increase in the school closing indicator is associated with a reduction in R_{it} by 0.066. It is followed by public event cancellations and public information campaigns, which indicate marginal effects of -0.062 and -0.057 respectively.

Panel A of Figure 2 illustrates the marginal effects of each NPI (coefficients extracted from Table 2 Column 3), ranked by their relative efficiency. It illustrates that imposing stricter school closing measures, public event cancellations, public information campaigns, contact tracing schemes and workplace closings have the strongest marginal impact on the reproduction rate. Compared to these measures, a stricter implementation of domestic travel restrictions as well as testing have a negligible impact on R_{it}.

Figure 2: Ranking of NPIs



Note: Coefficients extracted from Table 2 Columns 3 (Panel A) and 4 (Panel B). The figure shows point estimates and 95 percent confidence intervals.

The estimated coefficients presented in Columns 1 and 3 cannot be compared directly with each other, because the underlying indicators do not always have the same range (see Tables 1 and A.1 for the varying maximum values of the indicators). Columns 2 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 marginal effects and average severity.

Column 4 indicates that school closings are associated with an average reduction of 0.21 of the reproduction rate. School closings have thus been the most effective way to reduce the infection rate.[12] Strong negative coefficients are also found for restrictions on gatherings (-0.1), international travel restrictions (-0.094) and contact tracing (-0.091). The ranking is slightly altered when excluding the lagged dependent variable (Column 2) but all point estimates remain similar in magnitude.

Estimated coefficients of the dummy regressors are also significantly negative for workplace closings, public event cancellations, public transport closures, the obligation to wear face masks and stay at home requirements. Panel B of Figure 2 ranks estimated coefficients of NPIs using the dummy specification (Table 2 Column 4). It thus gives an indication of the overall impact of specific NPIs. On average, school closing, restrictions on gatherings, international travel restrictions and contact tracing were most effective in curbing the infection rate, while domestic travel restrictions 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. In addition to their macroeconomic effects (Famiglietti and Leibovici 2022; Bairoliya and İmrohoroğlu 2023), lockdowns are associated with an increase in domestic violence (Berniell and Facchini 2021). School closing is also deemed to have high costs for society, particularly for pupils (J. Liu et al. 2021; Felfe et al. 2022). Compared to these measures, contact tracing can 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 1, the individual NPIs were imposed to varying degrees. For example, school closing policies seem to have been implemented more strictly (mean of 2.1) than

12. It is possible that school closings might be correlated with a general effort of the government to curb the pandemic, which would lead to an overestimation of the estimated effect 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 1.56, 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.

Second, as argued by Chernozhukov et al. (2021) and Funke et al. (2022), 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.

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 infections 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 was still in service throughout 2020 and social distancing is difficult to implement in such confined spaces (Data Europa 2020).

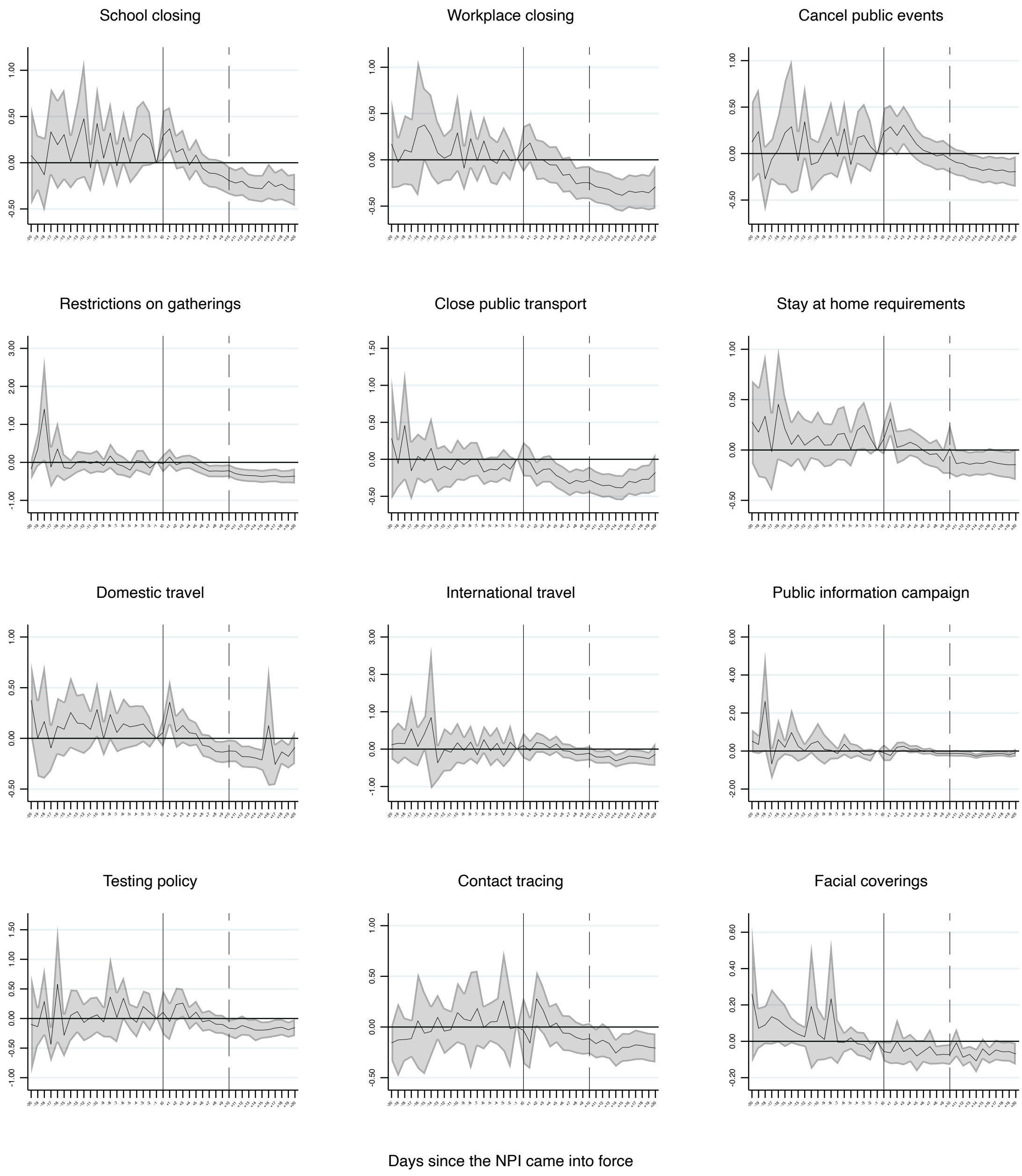
Effects over time Figure 3 illustrates the impact of individual NPIs over time (20 days before until 20 days after implementation). The corresponding regressions are estimated using NPI dummies.[13] This event study serves two principal goals: First, it shows that NPIs did not have a significant impact on the reproduction rate before their implementation (i.e. when $-20 \leq T < -1$). We hence do not observe differences in pre-treatment trends.

Second, the figure shows that our results are robust to different lag-structures, although certain NPIs take longer to show an impact than others. Following implementation, significant effects can be observed for almost all NPIs that were identified to be effective in our baseline regression in Table 2. Specifically, effects over time are clearly

13. We estimate the following equation separately for each NPI: $R_{it} = \sum_{T=-20,T\neq-1}^{20} \delta_T(NPI_{it}day_T) + \boldsymbol{NPI}_{it}^{others}\boldsymbol{\beta}' + R_{it-10} + \nu_{im} + \nu_{dow} + \epsilon_{it}$. day_T is a dummy identifying a certain period before or after the implementation of the NPI. We omit the first lead ($T = -1$, one day before implementation) to interpret the coefficient relative to a baseline, a common practice in panel event studies. We restrict ourselves to the period January to June 2020 as we are only interested in the impact of NPIs in force. We hence want to avoid too many switches in a dummy for a specific NPI.

visible for school closing, workplace closing, public event cancellation, restrictions on gatherings, public transport closing and contact tracing. Evidence is slightly weaker for stay at home requirements, international travel restrictions and facial coverings.

Figure 3: The impact of NPIs over time



Note: Event study of individual NPIs, controlling for the implementation of all others. Estimated coefficients on vertical axis, days before and after implementation on horizontal axis. The solid vertical line marks the day the policy entered into force, the dashed vertical line indicates 10 days after implementation (our baseline lag structure). The plots show point estimates with 95% confidence intervals, indicating significant effects of severeal NPIs following their implementation.

6 Extensions and robustness

6.1 Difference in NPI effectiveness across waves

One reason for the severity of the second wave of Covid-19 cases might be reduced compliance with restrictions. Closing of venues, prohibition of gatherings and curfews as early as 6pm 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 (Boldea et al. 2023).[14] Many European countries experienced two waves of infections in 2020 (see Figure B.2 in the appendix). To examine whether the effect of NPIs on the reproduction rate was different in the second wave, we estimate the following regression equation:

$$\begin{aligned} R_{it} &= (\boldsymbol{NPI}_{it-10} firstwave_t)\boldsymbol{\beta}' + (\boldsymbol{NPI}_{it-10} secondwave_t)\boldsymbol{\theta}' \\ &\quad + R_{it-10} + \nu_{im} + \nu_{dow} + \epsilon_{it} \end{aligned} \tag{3}$$

where $firstwave_t$ is a dummy variable taking the value one for every observation between January 1^{st}, 2020 and June 30^{th}, 2020 (which broadly corresponds to the period in which the first wave struck most countries) and zero otherwise. Similarly, $secondwave_t$ 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. By comparing the estimated β and θ for each NPI, we can test whether an NPI was more effective in the first or the second wave.

The regression results are reported in Table 3. Column (1) reports estimated coefficients of NPI indices interacted with $firstwave_t$, while Column (2) reports estimated coefficients for the interactions of NPI indices with $secondwave_t$ (both from the same regression). Column (3) reports the F-statistics, testing for equality of coefficients. Columns (4) and (5) report estimated coefficients from the regression on dummy NPIs while Column (6) reports the F-statistic from the test for equality of coefficients.

Looking at the dummy regression, estimated coefficients of the interaction of the first wave dummy with the individual NPIs are larger in magnitude for school closing, public event cancellation, restrictions on gatherings, public transport closing, stay at home requirements, international travel restrictions, testing policy and contact tracing. This suggests that these NPIs were less effective during the second wave.[15]

14. 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).

15. Note that the estimated coefficient for testing policy in Column (2) is positive and statistically significant. 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.

Table 3: The impact of NPIs on the reproduction rate: First and second wave

Dependent variable: R_{it}	(1)	(2)	(3)	(4)	(5)	(6)
NPIs coding:		Index			Dummy	
Wave:	First	Second	*F-stat*	First	Second	*F-stat*
School closing	-0.098***	-0.009	**51.85**	-0.307***	-0.022	**48.10**
	(0.010)	(0.008)		(0.035)	(0.021)	
Workplace closing	-0.031***	-0.043***	1.09	-0.027	-0.082***	**3.96**
	(0.009)	(0.007)		(0.021)	(0.018)	
Cancel public events	-0.092***	-0.028***	**15.22**	-0.092***	-0.025	**3.93**
	(0.015)	(0.008)		(0.029)	(0.018)	
Restrictions on gatherings	-0.012*	-0.010**	0.05	-0.118***	-0.044*	**4.80**
	(0.007)	(0.005)		(0.025)	(0.023)	
Close public transport	-0.021*	-0.013**	0.37	-0.067***	-0.032***	**2.84**
	(0.011)	(0.006)		(0.018)	(0.008)	
Stay at home requirements	-0.026**	0.002	**5.35**	-0.074***	-0.011	**6.61**
	(0.011)	(0.005)		(0.022)	(0.011)	
Domestic travel	0.014	-0.008	**2.84**	-0.002	0.001	0.01
	(0.012)	(0.005)		(0.023)	(0.011)	
International travel	-0.034***	0.002	**11.14**	-0.100**	0.025	**6.48**
	(0.009)	(0.006)		(0.045)	(0.029)	
Public info campaign	0.021	-0.186***	**50.33**	0.075	-0.589***	**35.65**
	(0.023)	(0.025)		(0.050)	(0.101)	
Testing policy	-0.016	0.025**	**6.30**	-0.109*	0.058	**3.20**
	(0.012)	(0.011)		(0.061)	(0.086)	
Contact tracing	-0.046**	-0.029**	0.54	-0.099***	-0.016	**3.83**
	(0.022)	(0.013)		(0.038)	(0.027)	
Facial coverings	0.002	-0.047***	**24.84**	-0.002	-0.161***	**15.60**
	(0.005)	(0.009)		(0.014)	(0.039)	
Control: R_{it-10}		✓			✓	
R^2		0.693			0.692	

Note: OLS regressions with country-month and day of the week fixed effects. Robust standard errors in parentheses. 52,349 observations. *F-stat* in bold indicates significant difference between the coefficients of the NPI for the first wave and the second wave. * p-value < 0.1, ** p-value < 0.05, *** p-value < 0.01.

Public information campaigns, workplace closings and facial coverings report a stronger negative effect in the dummy regression for the second wave, suggesting high effectiveness despite the presence of more infectious variants in the second half of 2020. The first could be explained by the improved dissemination of information to the public, growing acceptance in health authorities' guidance, as well as a change in habits regarding public health measures. The last observation could be explained by the increased use of medical masks, which have a higher protective efficacy than community masks (Ueki et al. 2020), as well as improved compliance.[16]

6.2 Effectiveness of NPIs in developed and developing countries

Different countries may vary in their ability to effectively implement NPIs. For example, testing and facial coverings require significant resources. In another extension, we therefore compare the effectiveness of NPIs across developing and developed countries.[17] To do so, we create two dummies, identifying developed and developing countries respectively. Each NPI is interacted with these dummies. The estimation equation is as follows:

$$\begin{aligned} R_{it} = {} & (\boldsymbol{NPI}_{it-10} developed_i)\boldsymbol{\beta}' + (\boldsymbol{NPI}_{it-10} developing_i)\boldsymbol{\theta}' \\ & + R_{it-10} + \nu_{im} + \nu_{dow} + \epsilon_{it} \end{aligned} \tag{4}$$

where $developed_i$ is a dummy variable that equals one if country i is a developed country (and zero otherwise) and $developing_i$ is a dummy that equals one if country i is a developing country (and zero otherwise). We compare estimated coefficients for developed and developing countries by performing significance tests. Results are presented in Table 4 below.

Considering the dummy regression (Columns 4 to 6), estimated coefficients for testing policy and facial coverings are larger in magnitude for developed than for developing countries, indicating a higher degree of overall effectiveness. In fact, testing seems to have been the most effective NPI in developed countries. These policies require resources such as test kits and masks, which are more readily available in richer countries. Contact tracing also records stronger negative effects for developed countries. Systematic tracing of contact cases, that is, individuals that were in contact with infected individuals, proves to be effective in reducing the reproduction rate. This policy requires great resources and the cooperation of the public, through, for instance, wide use of Covid tracing apps. Public information campaigns, stay at home requirements and public transport closures were also more effective in developed countries. School closing and workplace closing, on the other hand, were more effective in developing countries.

16. Unfortunately, the OxCGRT database does not differentiate between community face- and FFP2 masks. It merely captures the extent to which masks were recommended or required in public places.

17. A list of developed and developing countries is provided by Table A.2 in the appendix.

Table 4: The impact of NPIs on the reproduction rate by country group

Dependent variable: R_{it}	(1)	(2)	(3)	(4)	(5)	(6)
NPIs coding:		Index			Dummy	
Interaction:	Developed	Developing	*F-stat*	Developed	Developing	*F-stat*
School closing	-0.048***	-0.077***	**5.80**	-0.118***	-0.250***	**9.19**
	(0.007)	(0.010)		(0.031)	(0.031)	
Workplace closing	-0.002	-0.056***	**19.91**	-0.047**	-0.097***	**3.19**
	(0.009)	(0.008)		(0.021)	(0.019)	
Cancel public events	-0.088***	-0.040***	**9.29**	-0.088***	-0.042	1.86
	(0.010)	(0.012)		(0.019)	(0.028)	
Restrictions on gatherings	-0.023***	-0.014**	1.28	-0.093***	-0.109***	0.20
	(0.006)	(0.006)		(0.027)	(0.023)	
Close public transport	-0.056***	-0.011	**10.35**	-0.124***	-0.026**	**20.37**
	(0.011)	(0.008)		(0.017)	(0.013)	
Stay at home requirements	-0.028***	-0.002	**4.57**	-0.072***	-0.027*	**3.71**
	(0.009)	(0.008)		(0.018)	(0.015)	
Domestic travel	-0.010	0.004	1.31	-0.004	-0.004	0.00
	(0.009)	(0.009)		(0.014)	(0.017)	
International travel	-0.043***	-0.011*	**6.29**	-0.115**	-0.068*	0.47
	(0.011)	(0.006)		(0.056)	(0.038)	
Public info campaign	-0.125***	-0.027	**5.17**	-0.256***	0.056	**10.99**
	(0.037)	(0.021)		(0.079)	(0.052)	
Testing policy	0.024	-0.010	**3.52**	-0.543***	0.051	**13.90**
	(0.015)	(0.010)		(0.151)	(0.052)	
Contact tracing	-0.121***	-0.007	**7.53**	-0.221***	-0.049*	**4.23**
	(0.039)	(0.015)		(0.080)	(0.026)	
Facial coverings	-0.065***	-0.000	**43.56**	-0.156***	0.005	**25.13**
	(0.008)	(0.005)		(0.027)	(0.017)	
Control: R_{it-10}		✓			✓	
R^2		0.693			0.692	

Note: OLS regressions with country-month and day of the week fixed effects. Robust standard errors in parentheses. 52,349 observations. *F-stat* in bold indicates significant difference between the coefficients of the NPI for developed and developing countries. * p-value < 0.1, ** p-value < 0.05, *** p-value < 0.01.

6.3 Further extensions and robustness

We employ a wide range of checks to ensure robustness of our baseline results. To sum up, school closing, public event cancellations and restrictions on gatherings remain highly significant throughout. Workplace closing, international travel restrictions, contact tracing and public transport closures are also extremely robust, followed (to a lesser extent) by the obligation to wear face masks. Stay at home requirements are mostly significant when considering the dummy specification, whereas public information campaigns mainly show significant effects in the index specification. Evidence for the effectiveness of testing is extremely weak. Domestic travel restrictions are completely ineffective in almost all specifications.

Table 5: The impact of NPIs on the reproduction rate: Extensions and robustness 1

Dependent variable: R_{it}	(1)	(2)	(3)	(4)	(5)	(6)
NPIs coding:	Index	Index	Dummy	Index	Dummy	Index
Robustness specification:	WMA	Tests	Tests	Omit	Omit	Beta
School closing	-0.089***	-0.034***	-0.132***	-0.068***	-0.217***	-0.066***
	(0.009)	(0.009)	(0.028)	(0.007)	(0.022)	(0.007)
Workplace closing	-0.055***	-0.035***	-0.095***	-0.041***	-0.078***	-0.040***
	(0.008)	(0.007)	(0.015)	(0.006)	(0.014)	(0.006)
Cancel public events	-0.043***	-0.057***	-0.089***	-0.066***	-0.075***	-0.043***
	(0.010)	(0.009)	(0.020)	(0.008)	(0.018)	(0.006)
Restrictions on gatherings	-0.026***	-0.036***	-0.160***	-0.017***	-0.101***	-0.024***
	(0.005)	(0.005)	(0.022)	(0.004)	(0.018)	(0.006)
Close public transport	-0.039***	-0.024***	-0.071***	-0.019***	-0.055***	-0.014***
	(0.009)	(0.008)	(0.011)	(0.007)	(0.010)	(0.005)
Stay at home requirements	0.003	-0.009	-0.050***	-0.008	-0.042***	-0.007
	(0.008)	(0.007)	(0.013)	(0.006)	(0.011)	(0.006)
Domestic travel	-0.018**	-0.004	-0.010			-0.001
	(0.008)	(0.008)	(0.016)			(0.006)
International travel	-0.032***	-0.033***	-0.127*	-0.021***	-0.098***	-0.022***
	(0.007)	(0.006)	(0.066)	(0.006)	(0.034)	(0.006)
Public info campaign	-0.098***	-0.070*	0.163			-0.018***
	(0.029)	(0.041)	(0.104)			(0.006)
Testing policy	-0.003	-0.019*	-0.300***	0.001	-0.099*	0.002
	(0.011)	(0.010)	(0.087)	(0.009)	(0.055)	(0.007)
Contact tracing	-0.068***	-0.064**	-0.129**	-0.047***	-0.092***	-0.029***
	(0.021)	(0.028)	(0.056)	(0.017)	(0.029)	(0.011)
Facial coverings	-0.021***	-0.020***	-0.061***	-0.014***	-0.041***	-0.020***
	(0.005)	(0.003)	(0.010)	(0.004)	(0.015)	(0.006)
Tests (ln)		0.007	0.009			
		(0.007)	(0.007)			
Control: R_{it-10}	✓	✓	✓	✓	✓	✓
Observations	52,341	25,979	25,979	52,349	52,349	52,349
R^2	0.694	0.574	0.577	0.691	0.691	0.691

Note: OLS regressions with country-month and day of the week fixed effects. Robust standard errors in parentheses. * p-value < 0.1, ** p-value < 0.05, *** p-value < 0.01.

Weighted moving averages To validate the robustness of our previous results, we use weighted moving averages with a span of ten days of each NPI instead of 10-day lags 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). Each observation is a weighted average of NPI_{it} and the nine preceding observations. The largest weight is applied to the observation that lies furthest in the past.[18] 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 ten days.

Regression results are reported in Column 1 of Table 5. Estimated coefficients broadly remain qualitatively similar to the baseline results, although domestic travel restrictions turn significantly negative. Public information campaigns now have the strongest marginal effects, followed by school closure, contact tracing, workplace closing and public event cancellation. Although the ranking has been somewhat altered, they are still featured among the top five 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. Although our fixed effects specification takes into account increases in testing capacity over the months, it does not control for variation in testing within month. In another robustness check, we control for the number of tests per day. Columns 2 and 3 of Table 5 report the results.

Overall, estimated coefficients are qualitatively similar to the baseline results. Most notably, the estimated coefficient for testing policy becomes significantly negative (Columns 2 and 3). School closing, restrictions on gatherings and contact tracing remain highly effective (Column 3). The results are, however, not fully comparable to the baseline results because the number of tests is not systematically reported by all countries. This drawback almost halves the sample size, thus reducing variation needed to identify treatment effects. The results imply that testing was highly effective in the countries that report the number of tests every day. Since the sample contains a greater share of developed countries (41 developed and 66 developing countries, compared to 53 developed and 128 developing countries in the baseline sample), the findings are in line with our previous results that testing was the most effective instrument in developed countries.

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.3 in the appendix presents the correlation

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

matrix between policy variables (index ordinal coding). It indicates a relatively moderate correlation of NPIs. In addition, our model benefits from a long time span, capturing variation both over time and across countries.[19]

Following Y. Liu et al. (2021), we perform a hierarchical clustering analysis, which allows identifying potential confounding, both in the temporal and sectoral dimensions.[20] We omit domestic travel restrictions, as they may capture the effect of stay at home requirements. Similarly, we exclude the variable information campaign as it is clustered with school closing. We are then left with a total of ten NPIs. Estimated coefficients, reported in Columns 4 and 5 of Table 5, have to be interpreted with caution. NPIs that are closely correlated should be regarded within the context of the respective clusters rather than as individual measures (Zheng and Li 2014). Since we dropped public information campaign, its effect is now captured by the school closing variable. The same reasoning holds for the effect of stay at home requirements, which partly capture domestic travel restrictions. Overall, results are once again qualitatively similar to the baseline results. The only exception is testing policy, which becomes statistically significant in the dummy specification (Column 5).

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. 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 6 of Table 5. While the size and interpretation of the coefficients changes, school closing keeps having the strongest marginal impact.

Different lag structure of the reproduction rate While the 10-day lag should capture adjustments in behaviour, 1-day lags might be better in addressing persistence of R. We therefore also report regression results using R_{it-1} instead of R_{it-10} as additional regressor (Columns 1 and 2 of Table 6). Most coefficients remain qualitatively similar, but are generally smaller in magnitude. This 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.

19. 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.

20. A detailed description of the clustering analysis is provided in Section C of the appendix.

Table 6: The impact of NPIs on the reproduction rate: Extensions and robustness 2

Dependent variable: R_{it}	(1)	(2)	(3)	(4)	(5)	(6)
Timing:	Daily		Daily		Weekly	
NPIs coding:	Index	Dummy	Index	Dummy	Index	Dummy
School closing	-0.032***	-0.104***	-0.066***	-0.214***	-0.085***	-0.331***
	(0.005)	(0.019)	(0.016)	(0.049)	(0.019)	(0.069)
Workplace closing	-0.018***	-0.032***	-0.041***	-0.078**	-0.023	-0.046
	(0.005)	(0.011)	(0.013)	(0.031)	(0.015)	(0.037)
Cancel public events	-0.030***	-0.031**	-0.062***	-0.072*	-0.082***	-0.092**
	(0.007)	(0.015)	(0.020)	(0.038)	(0.020)	(0.044)
Restrictions on gatherings	-0.009***	-0.053***	-0.017*	-0.100**	-0.021*	-0.112**
	(0.003)	(0.014)	(0.010)	(0.039)	(0.011)	(0.048)
Close public transport	-0.008	-0.024***	-0.019	-0.054**	-0.019	-0.045*
	(0.005)	(0.008)	(0.019)	(0.027)	(0.016)	(0.023)
Stay at home requirements	-0.007	-0.023**	-0.007	-0.040	0.006	-0.030
	(0.005)	(0.009)	(0.014)	(0.030)	(0.015)	(0.032)
Domestic travel	0.002	0.000	-0.002	-0.006	-0.002	-0.006
	(0.005)	(0.009)	(0.013)	(0.026)	(0.015)	(0.026)
International travel	-0.009*	-0.050*	-0.020*	-0.094	-0.037***	-0.159*
	(0.005)	(0.029)	(0.012)	(0.074)	(0.014)	(0.083)
Public info campaign	-0.022	-0.021	-0.057	-0.052	-0.138**	-0.042
	(0.016)	(0.036)	(0.043)	(0.100)	(0.066)	(0.194)
Testing policy	0.001	-0.042	0.003	-0.092	0.006	-0.269*
	(0.007)	(0.048)	(0.020)	(0.126)	(0.020)	(0.158)
Contact tracing	-0.025*	-0.051**	-0.045	-0.091	-0.086**	-0.150**
	(0.014)	(0.025)	(0.037)	(0.064)	(0.044)	(0.068)
Facial coverings	-0.006*	-0.014	-0.014	-0.041	-0.008	-0.026
	(0.003)	(0.010)	(0.014)	(0.044)	(0.010)	(0.035)
Control: R_{it-1d}	✓	✓				
Control: R_{it-1w}					✓	✓
Control: R_{it-10d}			✓	✓		
Country-month FE	✓	✓	✓	✓	✓	✓
Day of the week FE	✓	✓	✓	✓		
Clustered s.e.			Country	Country		
Observations	52,338	52,338	52,349	52,349	7,295	7,304
R-squared	0.782	0.782	0.691	0.691	0.854	0.854

Note: Robust standard errors in parentheses, unless otherwise specified. * p-value < 0.1, ** p-value < 0.05, *** p-value < 0.01.

Standard errors clustered by country Clustering standard errors by country results in several coefficients becoming statistically insignificant (Columns 3 and 4 of Table 6).

The two most effective instruments, school closing and restrictions on gatherings, remain, however, highly statistically significant (Column 4).

Weekly data Instead of using daily data, we compute weekly averages of the reproduction rate. We then regress the new R_{it} on past values of NPIs and the reproduction rate (both lagged by one week). Weekly NPI indices are computed as simple averages. The NPI dummy is defined to equal one if the index in a given week was greater than zero for at least four days. Since we continue using country-month fixed effects, this strategy significantly reduces the within country-month variation needed to identify treatment effects. Nevertheless, school closings, restrictions on gatherings, contact tracing, international travel restrictions as well as public event cancellations remain highly significant.

Further extensions As illustrated by Figures 1 and B.1, most countries implemented many NPIs in March 2020. In another robustness check, we therefore remove this month from our sample. The regression results, reported in Columns 1 and 2 of Table A.4, reveal that most estimated coefficients remain qualitatively similar to the baseline. International travel restrictions constitute a notable exception, as they turn statistically insignificant.

Results have been replicated with Driskoll and Kraay standard errors in order to take into account cross-sectional dependencies (Columns 3 and 4 of Table A.4 in the appendix).[21] Significance of most estimated coefficients remains stable, indicating that cross-sectional dependencies are not a problem in our estimation, as we exploit a very large set of countries.[22]

7 Conclusion

This paper analyses the effectiveness of NPIs in reducing the reproduction rate of SARS-CoV-2. Exploiting variation over time and across 181 countries enables us to employ an extensive fixed effects strategy that greatly reduces endogeneity concerns that typically plague policy evaluation. We rank NPIs by their relative effectiveness in reducing the spread of the virus. Our results suggest that school closings have been the most efficient policy, in the sense that increasing their stringency had the strongest dampening effects on the reproduction rate (-0.066). They are followed by the cancellation of public events (marginal effect of tightening restrictions of -0.062), public information campaigns

21. 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).

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

(-0.057), contact tracing (-0.045) and workplace closing (-0.041). More stringent international travel restrictions, public transport closing, restrictions on gatherings and the mandatory wearing of face masks are also associated with a reduced reproduction rate, albeit to a lesser extent. Results are particularly robust for school closing, restrictions of gatherings and public event cancellations. Estimated coefficients for domestic travel restrictions are not statistically different from zero in most specifications.

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 school closings and restrictions on gatherings were the most effective instruments, reducing the reproduction rate by 0.214 and 0.1 respectively. They are followed by international travel restrictions, contact tracing, workplace closing, public event cancellations, public transport closures, facial coverings and stay at home requirements. 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 campaigns, workplace closings and the mandatory wearing of face masks report a stronger negative impact on the spread of the virus during the second wave. The improved effectiveness of facial coverings is likely driven by the increased use of medical masks from mid 2020 as well as a greater degree of compliance. In contrast, effects of other NPIs such as school closing and public event cancellation have slightly dissipated over time.

Looking at the impacts of NPIs across developed and developing countries, we find that policies that require large resources and benefit from an advanced public health service were more effective in developed counties. These are testing policy, the obligation to wear face masks and contact tracing. In fact, testing policy, which was insignificant in our baseline regression, turns out to be the most effective NPI in developed countries. The findings suggest that better health systems may actually enable the more effective implementation of certain NPIs.

As the vaccination rate amongst the global population increases continuously, NPIs 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: 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 restrictions	Record restrictions on internal movement between cities/regions.	0-2
International travel res.	Record restrictions on international travel. This records policy for foreign travellers, not citizens.	0-4
Public info campaign	Record presence of public info campaigns.	0-2
Testing policy	Record government policy on who has access to testing. 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. 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)

Table A.2: Country classification

Developed countries (53)		Developing countries (128)				
Albania	Japan	Afghanistan	Congo	Iraq	Nicaragua	Syrian Arab Republic
Andorra	Latvia	Algeria	Congo, Dem. Rep.	Jamaica	Niger	Tajikistan
Australia	Lithuania	Angola	Costa Rica	Jordan	Nigeria	Tanzania
Austria	Luxembourg	Argentina	Côte d'Ivoire	Kazakhstan	Oman	Thailand
Belarus	Macao China	Aruba	Cuba	Kenya	Pakistan	Timor-Leste
Belgium	Malta	Azerbaijan	Djibouti	Korea, Rep.	Palestine	Togo
Bermuda	Moldova	Bahamas	Dominica	Kosovo	Panama	Trinidad and Tobago
Bosnia and Herzegovina	Monaco	Bahrain	Dominican Republic	Kuwait	Papua New Guinea	Tunisia
Bulgaria	Netherlands	Bangladesh	Ecuador	Kyrgyz Republic	Paraguay	Turkey
Canada	New Zealand	Barbados	Egypt Arab Rep.	Lao PDR	Peru	Uganda
Croatia	Norway	Belize	El Salvador	Lebanon	Philippines	United Arab Emirates
Cyprus	Poland	Benin	Eritrea	Lesotho	Puerto Rico	Uruguay
Czech Republic	Portugal	Bhutan	Ethiopia	Liberia	Qatar	Uzbekistan
Denmark	Romania	Bolivia	Fiji	Libya	Rwanda	Vanuatu
Estonia	Russian Federation	Botswana	Gabon	Madagascar	Saudi Arabia	Venezuela, RB
Faroe Islands	San Marino	Brazil	Gambia, The	Malawi	Senegal	Vietnam
Finland	Serbia	Brunei	Georgia	Malaysia	Seychelles	Virgin Islands (U.S.)
France	Slovak Republic	Burkina Faso	Ghana	Mali	Sierra Leone	Yemen
Germany	Slovenia	Burundi	Guam	Mauritania	Singapore	Zambia
Greece	Spain	Cambodia	Guatemala	Mauritius	Solomon Islands	Zimbabwe
Greenland	Sweden	Cameroon	Guinea	Mexico	Somalia	
Hong Kong China	Switzerland	Cape Verde	Guyana	Mongolia	South Africa	
Hungary	Taiwan	Central African Republic	Haiti	Morocco	South Sudan	
Iceland	Ukraine	Chad	Honduras	Mozambique	Sri Lanka	
Ireland	United Kingdom	Chile	India	Myanmar	Sudan	
Israel	United States	China	Indonesia	Namibia	Suriname	
Italy		Colombia	Iran, Islamic Rep.	Nepal	Swaziland	

Note: Country classification based on WHO classification

Table A.3: Cross-correlation of policy measures

Var	c1	c2	c3	c4	c5	c6	c7	c8	h1	h2	h3	h6
c1	1.000											
c2	0.522	1.000										
c3	0.536	0.563	1.000									
c4	0.434	0.563	0.631	1.000								
c5	0.451	0.487	0.382	0.397	1.000							
c6	0.505	0.582	0.472	0.486	0.542	1.000						
c7	0.500	0.519	0.484	0.431	0.564	0.622	1.000					
c8	0.343	0.258	0.313	0.219	0.287	0.266	0.322	1.000				
h1	0.224	0.208	0.271	0.300	0.106	0.195	0.143	0.179	1.000			
h2	-0.070	0.033	0.065	0.120	-0.055	-0.031	-0.082	0.042	0.185	1.000		
h3	-0.056	-0.020	0.031	0.079	-0.074	-0.040	-0.102	0.006	0.219	0.317	1.000	
h6	0.039	0.116	0.159	0.266	0.031	0.152	0.103	-0.087	0.216	0.234	0.153	1.000

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 restrictions, c8: International travel restrictions, h1: Public information campaign, h2: Testing policy, h3: Contact tracing, h6: Facial coverings. All pairwise correlation coefficients are statistically significant at the 1% level.

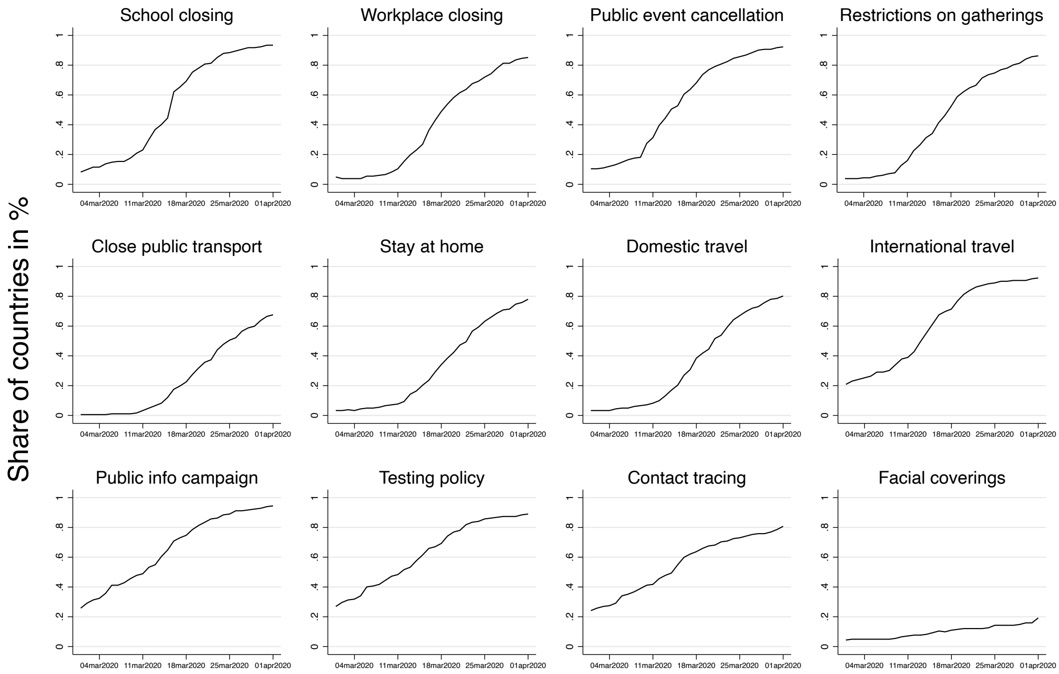
Table A.4: The impact of NPIs on the reproduction rate: Extensions and robustness 3

	(1)	(2)	(3)	(4)
Dependent variable:	R_{it}		R_{it}	
NPIs coding:	Index	Dummy	Index	Dummy
School closing	-0.038***	-0.099***	-0.066***	-0.066***
	(0.007)	(0.023)	(0.010)	(0.010)
Workplace closing	-0.038***	-0.051***	-0.041***	-0.041***
	(0.006)	(0.014)	(0.008)	(0.008)
Cancel public events	-0.037***	-0.037**	-0.062***	-0.062***
	(0.008)	(0.016)	(0.013)	(0.013)
Restrictions on gatherings	-0.008*	-0.052***	-0.017**	-0.017**
	(0.004)	(0.018)	(0.007)	(0.007)
Close public transport	-0.027***	-0.062***	-0.019*	-0.019*
	(0.007)	(0.010)	(0.011)	(0.011)
Stay at home requirements	-0.006	-0.035***	-0.007	-0.007
	(0.006)	(0.012)	(0.007)	(0.007)
Domestic travel	0.011*	0.016	-0.002	-0.002
	(0.006)	(0.011)	(0.009)	(0.009)
International travel	-0.006	0.016	-0.020**	-0.020**
	(0.006)	(0.022)	(0.009)	(0.009)
Public info campaign	-0.107***	-0.330***	-0.057**	-0.057**
	(0.023)	(0.068)	(0.024)	(0.024)
Testing policy	0.017**	0.041	0.003	0.003
	(0.008)	(0.052)	(0.013)	(0.013)
Contact tracing	-0.021**	-0.049**	-0.045**	-0.045**
	(0.009)	(0.019)	(0.022)	(0.022)
Facial coverings	-0.013***	-0.035**	-0.014	-0.014
	(0.004)	(0.015)	(0.009)	(0.009)
R_{it-10}	0.097***	0.098***	0.035***	0.035***
	(0.015)	(0.015)	(0.013)	(0.013)
March is dropped	✓	✓		
Driskool & Kraay s.e.			✓	✓
Observations	48750	48750	52,349	52,349
R^2	0.724	0.724	0.691	0.691

Note: OLS regressions with country-month and day of the week fixed effects. Robust standard errors in parentheses, unless otherwise specified. * p-value < 0.1, ** p-value $<$ 0.05, *** p-value < 0.01.

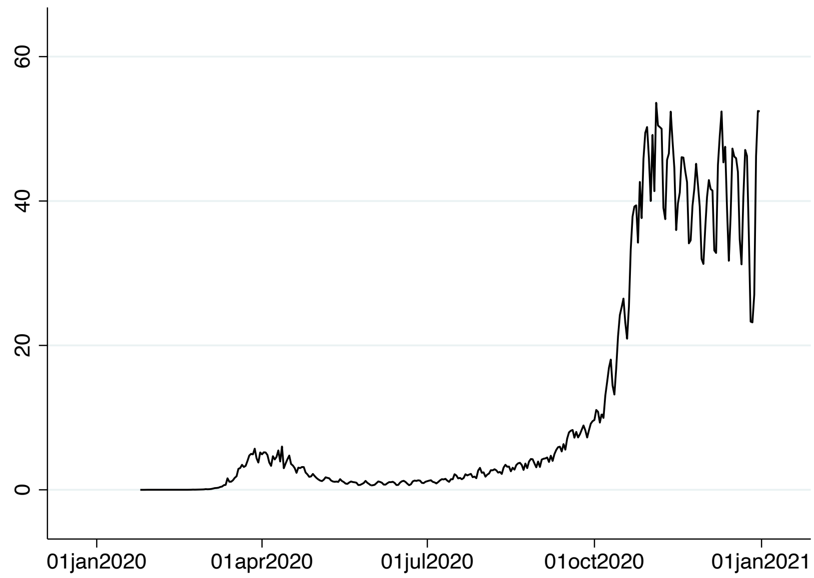
B Additional Figures

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



Note: Share of countries having implemented individual NPIs over time. Total number of countries in the sample: 181. Source: Data from Hale et al. (2021), own calculations.

Figure B.2: Average incidence rate across EU 27



Note: The incidence rate measures the daily total number of COVID-19 cases reported per 100,000 people (i.e. $Cases/population \times 100,000$). Source: Data from Hale et al. (2021).

C Multicollinearity of NPIs

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. 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: $\triangle(A, B) = \sum_i (x_i - \overline{x})^2 - \sum_{i \in a} (x_i - \overline{a})^2 - \sum_{i \in b} (x_i - \overline{b})^2$ 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.

Domestic travel restrictions, stay-at-home requirements, and public transport closing are quite similar in their implementation timing and across countries. 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).