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The Effect of Distancing Policies on the Reproduction Number of COVID-19*

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Abstract. Distancing policies became the primary preventive intervention during the COVID-19 pandemic. This paper estimates the effect of such interventions on the effective reproduction number (R_t) of this virus on a daily panel of 109 countries. Distancing interventions affect COVID infections indirectly through the regulation of social behaviors, which are also a function of voluntary decisions. The main contribution of this paper is the separation of policy-compliant and voluntary distancing effects. I identify the policy-compliant component of distancing behavior as rapid changes in social activity immediately after an intervention. This allows me to isolate the voluntary component as residual changes in activity. I use the isolated voluntary component as a control in the main estimation of distancing policy effects on R_t. I distinguish between (i) place restrictions: restricting destinations and (ii) mobility restrictions: regulations on inland movements. I find strong and permanent effects for both types of restrictions. Place restrictions that target specific destinations are found to be less effective than general mobility restrictions. The effect of voluntary distancing is also significantly negative but weaker than that of policy restrictions. These results suggest that governments can use distancing restrictions effectively in pushing the effective reproduction number below the containment threshold: $R_t = 1$.

JEL: C3, C33, C43, C54, E65, H1, H12, H39, H84, I1, I12, I18

Keywords: COVID-19, non-pharmaceutical interventions, causal identification, reproduction number, regression-discontinuity-in-time

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1 Introduction

Distancing policies, such as school closures, gathering limits, or stay-at-home orders were the primary preventive interventions in essentially all countries in the COVID-19 pandemic of 2020–2021. The logic behind these policies is to reduce the chances of already infected people infecting others. The number of new infections an infected person is expected to cause during her illness is the effective reproduction number, R_t.

The main objective of this paper is to quantify the effect of distancing policies on the effective reproduction number of COVID-19.[1] The main contribution of this paper is the separation of policy-induced and voluntary distancing effects. I identify the policy-induced component of distancing behavior as rapid changes in social activity immediately after an intervention. This allows me to isolate the voluntary component as residual changes in activity. I use this isolated voluntary component as a control in the main estimation of distancing policy effects on R_t. Because holding voluntary distancing effects fixed allows for the identification of unbiased policy effects in a comparison of countries with different policy interventions.

In Section 2 I start with the description of the data. I use four datasets: (i) daily preventive policy interventions from Hale et al. (2020), (ii) reported COVID cases, deaths, recoveries, and (iii) Google's publicly available mobility reports from Wahltinez et al. (2020), and (iv) Google's COVID-19 Aggregated Mobility Research Dataset, which is available with permission from Google. I build a daily frequency cross-country panel database covering 109 countries and spanning calendar days between February 2020 and April 2021. The population of the countries involved in the sample is 5.4 billion, representing 70 percent of the world's population in 2020.

After the data description, I define the most important variables in this paper: distancing policies, reproduction numbers, social activity, and imported cases. This study focuses on the effects of two different distancing policy types: *place* and *mobility* restrictions. A place restriction targets specific destinations or events where people are not allowed to go. These are school and workplace closures; cancellations of public events; and gathering limits. A mobility restriction controls how and when people are allowed to move around within their countries, regardless of their destination. These are restrictions on public transportation, stay-at-home orders, and within-country travel restrictions.

Because of its policy relevance, I chose the effective reproduction number R_t as the outcome variable of this study. All preventive measures aim to achieve $R_t \leq 1$, which defines the containment of an epidemic. Knowing the effects of distancing interventions in terms of R_t is therefore useful information for decision-makers. I proxy R_t by the instantaneous reproduction number R_t^I. The advantage of using R_t^I is that it is much easier to calculate and proportional to R_t. Therefore, any proportional effects measured on R_t^I can be interpreted as effects on R_t.

Social activity proxies distancing behaviors. It is an indicator derived from Google mobility indicators, which measure the frequency of Google users in public spaces relative to pre-COVID levels. I use this indicator to isolate its voluntary component, which is the most important control in the main estimation.Finally, imported cases are proxied by an indicator that I created using the proprietary Google COVID-19 Aggregated Mobility Research Dataset[2].

In Section 3, I present my empirical strategy. I carry out my estimation in a two-stage design. The first stage is the separation of the voluntary and policy-compliant components of social activity. The second stage is the main estimation of distancing policy effects on the effective reproduction number. In the first stage, I identify the policy-compliant component of distancing behavior as rapid changes in social activity immediately after an intervention. I isolate the voluntary component as residual changes

[1] COVID-19, officially known as SARS-CoV-2, is a virus spread by human droplets like the regular flu. It has a higher basic reproduction number and mortality rate than the regular flu, according to Petersen et al. (2020). Neither vaccines nor designated medical treatments were available until the end of 2020.

[2] This dataset is only available with permission from Google LLC.

in activity. This allows me to identify policy-compliant and voluntary distancing effects separately in the second stage by using this isolated voluntary activity component as a control variable. In the second stage, the effects of distancing policies are identified from a comparison of countries that have introduced a particular restriction to those that have not, holding voluntary activity, other preventive policies, and covariates fixed.

At the end of this Section, I discuss possible threats to identification. A policy intervention can work as a signal, inducing voluntary distancing. This kind of voluntary distancing does not harm identification because it is a direct consequence of the interventions.[3] Countries differ in demographics, population density, and the quality of political and healthcare institutions, which are likely to correlate with interventions, social activity, and reproduction numbers. I address these differences by including country-fixed effects in both stages, assuming the invariability of these factors on daily frequencies. Countries also differ in the timing of their interventions, which is addressed by the inclusion of time-fixed effects.

Different countries provided different levels of economic support, which might have worked as incentives to leave workplaces for sick people. I address these differences by controlling for all available information on economic support. I control for daily weather conditions to address the effects of the climate on the reproduction numbers of the virus. Finally, I control for weekly seasonality in both stages of my design.

I present all results in Section 4. I find that place restrictions reduce R_t by 29 percent and mobility restrictions by 61 percent on average. These are strong effects on the reduction of the effective reproduction number, suggesting that distancing policies were an effective tool for reducing the impact of the pandemic. Place restrictions that target specific destinations are found to be less effective than general mobility restrictions. A one standard deviation drop in voluntary social activity is found to decrease R_t by 17 percent. The effect of voluntary distancing is also significantly negative but weaker than that of policy restrictions. Based on these results, I calculate the contribution of distancing policies and voluntary distancing to the average decline of R_t observed in the first wave. I find that distancing policies contributed 6.5 times more than voluntary distancing to the decline in reproduction numbers.

These findings suggest that although voluntary distancing behaviors help to slow down the reproduction of the virus, any kind of distancing policy measures are much more effective in stopping a pandemic. In the second part of Section 4, I investigate heterogeneous policy effects. The first of these exercises analyses the strength of the policy effects on different time horizons. I am interested in how long the effects identified in the main design last. I do that because it is useful to know how long a government can rely on a place or a mobility restriction. To do that, I modified my second stage design into an event study design, allowing for heterogeneous effects on different time horizons. I find similarly strong effects on shorter and longer horizons for both restriction types. These results suggest that governments can rely on these distancing restrictions on longer horizons when fighting longer waves of infections.

In the second exercise, I break down the larger restriction categories into their components: place and mobility restrictions. I also allow for heterogeneity in the different stringency levels of these policies. I do this to provide comparative results for more delicate policy interventions. I found that school and workplace closures, gathering limits, and stay-at-home orders were effective restrictions in the reduction of reproduction numbers. I cannot find supporting evidence, however, for the effectiveness of the cancellation of public events, restrictions on public transportation, and inland travel restrictions.

School closures are found to be effective only if they are mandated. Workplace closures are found to be effective already when they were only a recommendation. Their efficiency only marginally increases with stringency. Gathering limits become effective at the 100+ limit and gain effectiveness at more restrictive limits. Stay-home orders are found to be effective when they are just recommended. They also gain effectiveness as they become more stringent. Overall, these findings suggest that there was heterogeneity between the effectiveness of different policies, implying that different policy mixes could have led to very

[3] It has to be noted, though, that this kind of induced voluntary distancing is also accounted for in policy effects in this study.

different outcomes.

Conclusions are discussed in the final section of this study. Based on my results, I conclude that governments can use distancing restrictions effectively to push the effective reproduction number below the containment threshold of $R_t \leq 1$. They can rely on these effects for as long as these measures are in place. Considering the heterogeneous effects of particular distancing policies suggests that a careful selection of these policies and their stringency levels is recommended before their implementation.

Literature

This paper belongs to the empirical evaluation of non-pharmaceutical interventions (NPI) during the COVID-19 pandemic, surveyed exhaustively by Perra (2021). This literature already provides strong qualitative evidence for the effectiveness of NPIs. The quantitative comparison of these papers is difficult, however, because of the high variety in the chosen outcomes and treatments.

Within this literature, this paper is a contribution to cross-regional studies. These studies encompass a set of countries or states within a federation such as the US or Germany. Islam et al. (2020) study the effect of five physical distancing interventions on a sample of 149 countries and regions on estimated incidence rate ratios. They found that any physical distancing intervention reduced COVID-19 incidence by 13%. This finding is qualitatively in line with the findings of this study, as I also find significantly negative effects of distancing policies on case reproduction. It is much more difficult to contrast these results quantitatively because the outcome variable chosen for this study is new incidence per total number of active infections. Askitas et al. (2021) estimates the effect of different NPIs non-parametrically in an event study design controlling for overlapping interventions. They found that closing schools and workplaces had significant effects on reducing COVID-19 infections, while later installed restrictions on inland travel and public transport had no effects. When comparing different NPIs I find that school and workplace closures were much more effective in the reduction of the reproduction number than restrictions on inland travel and public transportation. As lower reproduction implies lower incidence, these findings are in line. This paper considers other NPIs as well, finding that stay-at-home orders and gathering limits set at 100+ people are found to be similarly effective to school and workplace closures. Ullah and Ajala (2020) contrasts the effects of distancing measures to testing policies on a very similar sample. They find that a unit change in their lockdown index decreases the total number of confirmed cases by 0.19 percent, which becomes significant after 7 days of its implementation and stays intact even after 21 days. This study takes into account testing policies, but the outcome variable is so different I dispense comparison.

There are papers which choose the effective reproduction number as their outcome variable, similarly to this paper. Haug et al. (2020) rank 46 different NPIs by their impact on R_t on a sample of 79 territories. Overall they find that less stringent NPIs are just as effective as more drastic ones. They find that the most effective NPI is a small gathering limit, which reduces R_t by about 9 % on average.[4] They found the impact of a school closure on R_t at about 7.5%. These results are about 1/3 of the effects found in this study. They find weaker, but significantly negative effects for individual movement restrictions, lockdowns. These findings are qualitatively comparable to stay-at-home orders of this study. They evaluate many other NPIs that are not directly comparable NPIs studied in this paper.

Koh et al. (2020) confirms that all forms of lockdown interventions effectively reduce average R_t regardless of stringency levels, adding that earlier implementations are associated with stronger results. They discover that, depending on the timing of the intervention, the gathering limits reduce R_t by 15 to

[4]They report their main results in absolute reductions in R_t, whereas this study estimates percentage reductions; thus, their results can be directly compared to those found in this study by assuming some basic reproduction number, R_0. Liu et al. (2020) estimates COVID-19's basic reproduction number to be between 3 and 5. I translate their findings on absolute reductions to percentage reductions by taking the middle point of this range at 4.

41%. This interval contains the results found in this paper for the effect of gathering limits.[5] They find that "lock-down-type" measures to reduce R_t between 14 and 44 %. These numbers are almost the same in size to the findings of this paper: the slackest stay at home order is found to significantly reduce R_t by 18.5 %, while the most restrictive type by 35.6 %. Castex et al. (2021) find that the effectiveness of NPIs is negatively correlated with population density, country surface area, employment rate, and proportion of elderly in the population, and positively correlated with GDP per capita and health expenditure.

There are papers that estimate the effect of NPIs on the mobility of people similarly to the first stage estimation of this study. Gupta et al. (2020b) and Gupta et al. (2020a) are focused on the mobility effects of NPIs, while Castex et al. (2021) and Askitas et al. (2021) use their similar estimations as supporting evidence for their main conclusions.

A common limitation of these works is that they do not address the confoundedness of policy compliant and voluntary distancing effects. This is where the main contribution of my paper lies relative to this strand of the literature. I address this problem by separating voluntary and policy compliant distancing behaviors in a first stage estimation and using the voluntary component as a control in my main specification that estimates the effects of distancing policies on the reproduction number of COVID-19.

The only paper I am aware of that addresses this confoundedness problem is Chernozhukov et al. (2021). They estimate the effect of NPIs on the growth rate of COVID cases and related deaths on a daily panel of US states by instrumenting NPIs and observed distancing behavior with the past history of their outcome variables. They find evidence for both policies and information on transmission risks having a significant influence on COVID-19 cases and deaths and show that policies explain a large fraction of social distancing behaviors. They exploit the exogeneity of past cases and deaths in the separation of voluntary and policy-compliant effects. This study leverages the discontinuity in distancing behaviors after an intervention in contrast.

2 Data and Variable Definitions

In this section, I start with a brief description of data sources and the estimation sample. Then I present the definitions of the most important variables of this study: distancing policies, reproduction numbers, social activity, and imported infections.

I use four datasets: (i) daily preventive policy interventions from Hale et al. (2020), (ii) reported COVID cases, deaths, recoveries, (iii) Google's publicly available mobility reports from Wahltinez et al. (2020), and (iv) Google's COVID-19 Aggregated Mobility Research Dataset, which is available with permission from Google.

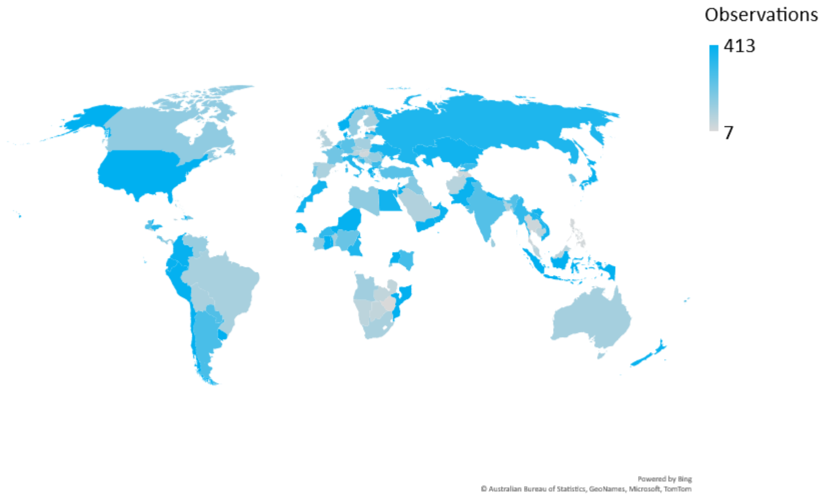
I build a country-day panel dataset covering 109 countries and spanning every calendar day between the 15th of February 2020 and the 3rd of April 2021. The sample covers 5.4 billion people, representing 70 percent of the world's population in 2020. Figure 1 shows the geographical coverage of the sample on a world map. Countries are colored if they are included. More intensive colors show more observations. The sample includes countries from all populated continents, covers most of Europe Australia, and both Americas. China is excluded, where the first outbreak preceded the beginning of my sample.

My primary data source is Google's COVID-19 Open-Data platform by Wahltinez et al. (2020), which is a "repository attempting to assemble the largest COVID-19 epidemiological database in addition to a powerful set of expansive covariates. It includes open, publicly sourced, licensed data relating to demographics, economy, epidemiology, geography, health, hospitalizations, mobility, government response, weather, and more." I extend this data by daily country level reports of recoveries from COVID infections of the Johns Hopkins University.[6] I employ the Google COVID-19 Aggregated Mobility Research

[5]Except for the slackest type of a gathering limit of above 1000 people, which was found to be ineffective in this paper.

[6]The reliability of these reports were questioned in the Summer of 2021. Therefore, these figures are no longer

Figure 1: Geographical Coverage of the Sample



Notes: One observation per country is a daily observation. Countries are colored if included. Brighter colors show more observations.

Dataset to calculate a proxy of imported COVID infections for each country. This database is available with permission from Google LLC.

2.1 Distancing Policies

This study focuses on the effects of distancing interventions implemented during the COVID-19 pandemic. These interventions are collected and reported in a daily regional dataset by Hale et al. (2020) called the the Government Response Tracker. They cover all sorts of government interventions related to the COVID-19 pandemic including distancing measures, e.g. gathering limits, other types of preventive policies, e.g. mask wearing mandates and different kinds of economic support, e.g. debt reliefs.

I form two groups from the seven different distancing interventions and label them as place and mobility restrictions:[7]

- **Place Restriction**: lock-down of schools, workplaces, cancellation of public events, plus gathering limits,
- **Mobility Restriction**: restrictions on public transportation, inland travel restrictions and stay-at-home orders.

The primary reason for this grouping is statistical. Many governments introduced these measures in bundles reducing the likelihood to identify the effect of each distancing indicator in isolation. Collecting these measures into groups might allow for more powerful estimates. My grouping is based on the pairwise time distance between the introductions of a pair of policies. Table 1 reports the fraction of countries that had introduced a pair of policies within at most seven days, and highlights the shares that are greater than 50 or 66,7 percent.[8] The larger fractions concentrate in two different groups which gives the basis

reported in the Johns Hopkins dataset. I use these numbers for the calculation of instantaneous reproduction numbers (R_t^I), my primary outcome variable. I provide some country level validity checks of R_t^I in the Appendix.

[7] My interests are limited to inland restrictions. Therefore, I exclude international travel controls from distancing policies.

[8] Same grouping can be confirmed by setting different thresholds on day distance. Find similar tables for 3,5 and 9 days in the Appendix.

for my grouping.

Table 1: Percent of Countries Implementing a Policy Pair within 7 Days.

	Place Restriction				Mobility Restriction		
	School	Event	Gather	Work	Stay H	Move	Transp't
School Closure		76.15	67.59	71.56	50.00	53.70	39.00
Events Cancelled	76.15		70.37	55.96	44.44	49.07	29.00
Gathering Limit	67.59	70.37		65.74	57.94	58.88	44.00
Workplace Closure	71.56	55.96	65.74		62.96	60.19	54.00
Stay Home Order	50.00	44.44	57.94	62.96		67.29	58.59
Movement Restricted	53.70	49.07	58.88	60.19	67.29		64.65
Public Transport Closed	39.00	29.00	44.00	54.00	58.59	64.65	

Notes: highlight: $\geq 50\%$, strong highlight: $\geq 66.7\%$

These two types of policies have qualitative similarity as well that motivated their labels. Places restrictions are targeted interventions. They define specific locations or events where people are not allowed to go. Mobility restrictions on the other hand control when and how people are allowed to go regardless where they are headed to.

Governments implemented these distancing orders with different levels of stringency and generality. A school closure can be a recommendation or a strict mandate, and it can cover different levels of education or geographic locations. Hale et al. (2020) define several stringency levels for each distancing intervention and flag if the intervention was country level or regional.[9] To retain estimation power I use the following definition for my policy indicators:

$$P_{it}^{p} = \min\left[1, \sum_{j \in \text{type}} D_{it}^{j} F_{it}^{j}\right], p \in \{\text{place}, \text{mobility}\} \tag{1}$$

where D_{it}^{j} is the category variable for distancing policy j, e.g. school closures, which is $D_{it}^{j} = 0$ if restriction j is not in action in country i on day t, and $D_{it}^{j} > 0$ codes the level of stringency in country i on day t using consecutive integer values starting from 1. Type can be either place or mobility restrictions. F_{it}^{j} is a binary indicator of a distancing measure j being a country level order in country i on day t or only regional. This formula defines a binary variable, therefore, for each distancing policy type. $P^{\text{place}_{it}}$ takes the value 1 if there was at least one country-wide place type restriction in action in country i on day t, and 0 if there was none. $P^{\text{mobility}_{it}}$ defines another binary variable on the same grounds for mobility restrictions.

These definitions of policy indicators have the benefit of a binary treatment: their coefficients are easy to interpret. This advantage, however, comes at a cost: P_{it}^{place} and P_{it}^{mobility} indicate the first ever countrywide distancing interventions, thus and stay blind to later changes in those interventions. They also overlook the cross-country heterogeneity in the stringency and the number of interventions of these first interventions, as they are normalized to 1 from day 0. That means these heterogeneities and later changes are absorbed by other variables or the error terms unless they are controlled for. The current version of this paper lacks this control, which is a serious limitation.

An important limitation of the data sources is that they only provide information about the imple-

[9] A state level intervention is flagged as regional in a federal state such as Germany or the US, which are treated as a single unit in this estimation.

mentation of distancing restrictions but not on their announcements. There is anecdotal evidence that some of these restrictions were announced earlier in some countries, allowing for people to adjust their behaviors before-hand. Panic shopping for basic goods could be a good example of such anticipatory responses. The effects of earlier announcements are discussed in the Results section.

2.2 Reproduction Numbers

The effective reproduction number R_t is the chosen outcome of this study. It is the number of new cases a single infection is expected to cause. When $R_t > 1$ the number of infections grow exponentially, which is the definition of an epidemic. But, when $R_t \leq 1$, the growth is linear and the contagion is considered to be contained. It is therefore, the most useful indicator to judge the efficiency of any preventive interventions: a prevention is successful if it is able to push R_t below 1.

R_t can be decomposed the following way:

$$R_t = R_t^I \cdot \mathrm{E}_t[\text{duration of infection}], \tag{2}$$

where R_t^I is the number of new infections an infected individual is expected to cause within a day and usually referred to as the instantaneous reproduction number.[10] Albeit simple this decomposition is useful for two reasons.

First, in contrast to R_t, the calculation of R_t^I from daily COVID incidences is feasible. R_t^I can be calculated by dividing the number of new infections discovered on day t by the number of known infections from the precious day:

$$R_t^I = \text{New Infections}_t / \text{Infected}_{t-1} \tag{3}$$

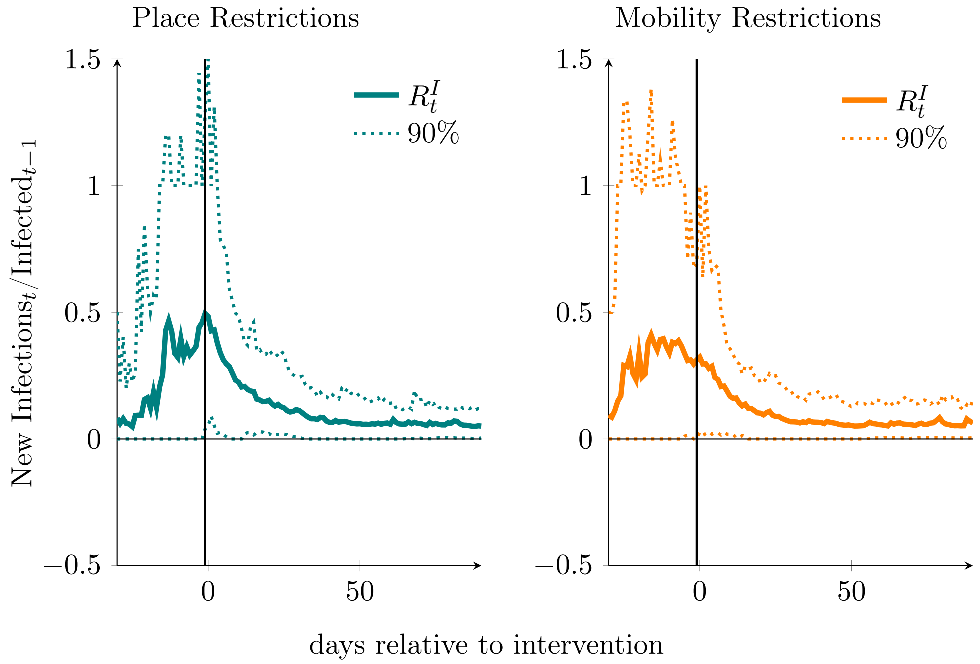
where New Infections_t are reported, thus can be observed. The number of infected individuals cannot be directly observed, but can be calculated from reported figures: $\text{Infected}_{t-1} = \text{Total Cases}_{t-1} - \text{Total Deaths}_{t-1} - \text{Total Recoveries}_{t-1}$.

Second, this decomposition allows me to identify the effect of distancing policies on R_t even if I use R_t^I as the outcome, because I assume that distancing policies cannot affect E_t[duration of infection] only R_t^I. The intuition is that once one have the virus its duration is independent of the frequencies she meets other people. This strategy also requires me to estimate proportional effects, because $R_t \propto R_t^I$.

Figure 2 shows the evolution of R_t^I around the days of place and mobility restrictions smoothed by a seven days backward looking moving average. A turn in the trend of R_t is apparent on both graphs. R_t is in a decline after both place and mobility restrictions, which suggests a strong effect of distancing policies.

[10] All the formulas presented here are consistent with and can be derived from the commonly used compartment models of epidemics, e.g. SIR models.

Figure 2: Instantaneous Reproduction Numbers Around Distancing Interventions



Notes: R_t^I - instantaneous reproduction number, solid line: 7 days backward looking moving average of cross country mean of R_{it}^I , dotted lines:7 days backward looking moving averages of the 5th and 95th percentiles of the cross country distribution of R_{it}^I.

Looking at the 90 percent boundaries we can see a rather wide distribution of R_t accross countries ranging from 0 to 1.5 new infections by a single infected individual every day during her infection. This upperbound is huge considering the expected length of the infection is around 10 days according to Liu et al. (2020), suggesting an effective reproducion number close to 15 in some countries on some days.

2.3 Social Activity

The main contribution of this paper is the separation of policy compliant and voluntary distancing effects. To be able to do that I need an indicator that measures overall distancing behaviors. I call this indicator social activity and use the notation a_{it}.

I define a_{it} as the first principal component of Google's six mobility indicators. These are publicly available daily indicators published for countries and sub-regions from February 15, 2021. A mobility indicator is recording differences in the frequency of Google users relative to a five week period from before the pandemic in a specific location category, which are:

- **groceries**: grocery markets, food warehouses, farmers markets, specialty food shops, drug stores, and pharmacies,
- **retail**: restaurants, cafes, shopping centers, theme parks, museums, libraries, and movie theaters,
- **parks**: local parks, national parks, public beaches, marinas, dog parks, plazas, and public gardens.
- **transit stations**: public transport hubs such as subway, bus, and train stations,
- **workplaces**: places of work,
- **residential**: places of residence.

Table 2 shows the results of the principal component analysis. The first principal component captures 86 percent of the total variance of the six mobility measures. It is loaded almost equally by all indicators with the same signs except for residential locations. This pattern parallels the intuition that social distancing resulted in less people in public spaces and more people at their homes relative to pre-COVID levels. The rest of the components are all dominated by one or two of the mobility indicators supporting the choice of the first component as my proxy for social activity.

Table 2: Principal Components of Google's Mobility Indicators

Component	1st	2nd	3rd	4th	5th	6th
Groceries	0.4029	0.0491	0.9006	-0.1201	-0.0518	0.0837
Retail	0.4295	-0.0846	-0.0387	0.5563	0.2122	-0.6726
Parks	0.3439	0.8916	-0.2172	-0.1330	0.1379	0.0534
Transport Stations	0.4275	-0.1375	-0.1886	0.5227	-0.2263	0.6621
Workplaces	0.4140	-0.3844	-0.2010	-0.4402	0.6478	0.1645
Residential Areas	-0.4252	0.1697	0.2534	0.4375	0.6800	0.2690
Share in Total Variance	0.8596	0.0793	0.0328	0.0151	0.0077	0.0055

2.4 Imported Infections

Imported infections is an important control variable of this study. I create a proxy for imported infections using the proprietary Google COVID-19 Aggregated Mobility Research Dataset, which is only available with a permission from Google LLC. It contains anatomized mobility flows aggregated over users who have turned on the Location History setting, which is off by default. This is similar to the data used to show how busy certain types of places are in Google Maps — helping identify when a local business tends to be the most crowded. The dataset aggregates flows of people from region to region, which is here further aggregated at the level of NUTS3 areas, weekly.

First, I keep only the flows that connect cells from different countries.[11] Second, I aggregate these flows then by countries and match the epidemiological indicators by departure countries. Third, I take cross country flows and multiply them by the number of infected individuals per 1000 citizen in departure countries. This yields me the expected flows of COVID infections by source and receiver country pairs.[12] Finally, I aggregate these expected infection flows by the reciever country to get the expected number of imported infections.[13]

This process has some minor limitations, as it is based on google user accounts, Therefore, it might be less accurate or totally missing for underdeveloped nations. And flows are missing for some microstates, such as Lichtenstein or Andorra.

3 Empirical Strategy

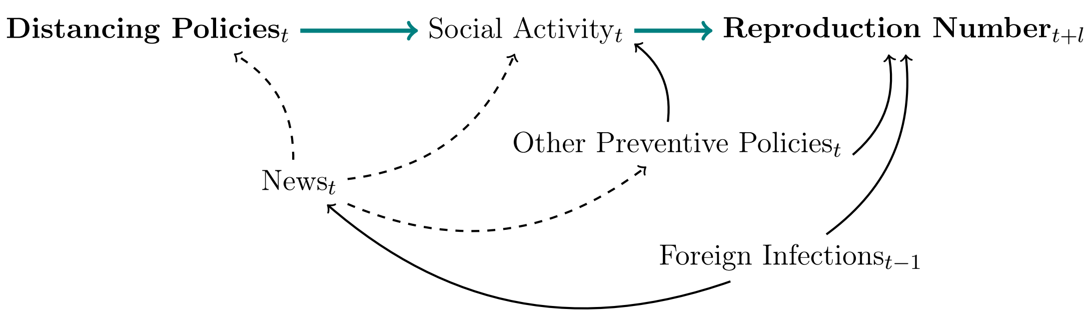
In this section, I develop a two-stage empirical design to identify the effect of distancing policies on the reproduction number of COVID-19. Identification relies on a comparison of countries that have

[11]I geolocate all cells using Picard (2015).

[12]I shift back infection data by 14 days to account for the presumed delay in epidemiological reports.

[13]It is a weekly frequency information. I use the first day of the week as its time index and date back by 6 days. Therefore, it codes the expected inflow of infections into a country in the past calendar week. Then I interpolate missing datapoints within a week by a quadratic spline developed using the csipolate Stata module developed by Cox (2009).

Figure 3: Causality Map



Notes: Arrows point in the direction of causality. Solid line: observed, dashed: unobserved effect. Bold font: focus variables, thick arrows: the path to be identified, Δt is one day.

introduced a particular restriction to those that have not. The central question here is: which are those factors that have to be held fixed to make sure this comparison is a valid identification of the effect of that policy? In this Section, I am working towards an empirical design that takes into account all these factors and is feasible to implement.

A good way to start is to map out all the relevant causal links connecting distancing policies to reproduction numbers on a graph. Figure 3 shows this causality map, where each arrow shows a causal link pointing in the direction of causality. The main path connecting distancing policies to reproduction numbers is drawn by thick arrows. The first thing that meets the eye is that distancing policies are not connected to reproduction numbers directly. The reason is that a distancing order can only reduce social activity directly. This reduction in social activity is what governments expect to reduce the reproduction number by diminishing the number of new infections.

I added time indexes to explicitly show that these effects can only be observed with a significant delay l on daily frequencies. This delay happens, because it takes time (typically 10-14 days) for an infected individual to start producing symptoms, get tested and end up reported.[14]

This causality map is not only helpful in showing a clear and comprehensive picture of all relevant causal relations, but it also informs identification. This method is known as the directed acyclic graph (DAG) method and described in details in Cunningham (2021). What is sufficient to know about the DAG method here is that any backdoor paths connecting policies with reproduction numbers are signalling possible omitted variable bias.

I recognize three such backdoor paths in this context. The first one connects distancing policies with social activity through news, which is a set containing any bits of information about COVID-19 that has a potential to alter government and individual decisions about distancing.[15] For example a discovery of a large number of infections raises the probability of a distancing intervention and it can also make people decrease their social activity voluntarily. I will refer to the latter channel as voluntary distancing in this paper onward.

[14]This delay mechanism is different for traced contact persons, however most countries did not choose to do any contact tracing or only tested the contact persons who were showing symptoms. I have information about whether a country is practicing and what kind of contact tracing, which I control for in the second stage. It is also known that a large fraction of COVID cases never gets tested, thus reported, which surely have an effect on the outcome. This effect can be addressed by fixed effects and controls for testing, which are elaborated in subsection. All these issues are addressed in Section 3.2.

[15]The arrow connecting News to Distancing Policy and Preventive Policy acknowledges the fact of endogenous selection of the treatment of this study: distancing policies. Closing backdoor paths containing this link simultaneously eliminates the endogenous selection bias.

The second backdoor path is the channel of other preventive policies, such as mask wearing mandates, contact tracing, testing or vaccination. These policies have an effect on reproduction numbers and their implementation were also likely to be influenced by news. Their effect on reproduction number can be direct, e.g. mask wearing reduce the transmission probability of the virus, while it might also lead to greater distancing according to Seres et al. (2021).

The third path is the channel of imported cases. It is the number of infections in neighboring countries affecting interventions indirectly through news and domestic reproduction numbers directly. For example if the number of new infections shoots up in a neighboring country, that might influence more restrictive policies and also increases the likelihood that new infections will or are already arriving from that neighbor by infected travelers.

Fortunately all backdoor paths go through news, it would be sufficient therefore to control only for news to eliminate the omitted variable biases caused by them. That means that comparing countries with the same news components but different policies identifies the effect of those policies.[16] This observation is captured by the following design:

$$R_{i,t+l} = \beta P_{it} + \eta' \mathbf{N}_{it} + \mu + \varepsilon_{it}, \tag{4}$$

where i indicates a country, t a day. R is reproduction number, P is distancing policy and $\mathbf{N}$ is a set of news components containing reported infections and deaths from $t-1$. Assuming that a distancing policy is a binary treatment, this design identifies β by comparing R in countries that has introduced policy P to those that has not, but were otherwise identical in all components of $\mathbf{N}$, i.e. recieved the same news.

The simple design in equation (4) is not feasible however, because $\mathbf{N}$ is not completely observable. For example I have no information about local media influencers or politicians informing the public about COVID developments. Neither about country specific behavioral reactions to news, such as compliance with government policies. These factors are also correlated with distancing policies and virus reproduction. I address this problem by closing the three backdoor paths separately.[17] To control for the channels of other preventive measures and foreign infections is simple, because these are observable factors. Closing the voluntary distancing backdoor path is challenging because I can only observe social activity a_{it}, which pools policy compliant and voluntary distancing motives.

3.1 Voluntary Distancing

Here I present the first stage of my estimation, which identifies the policy compliant component of social activity a_{it} in a regression discontinuity in time (RDiT) design. The voluntary component, called voluntary activity v_{it} is then defined as the residual of the first stage regression.[18]

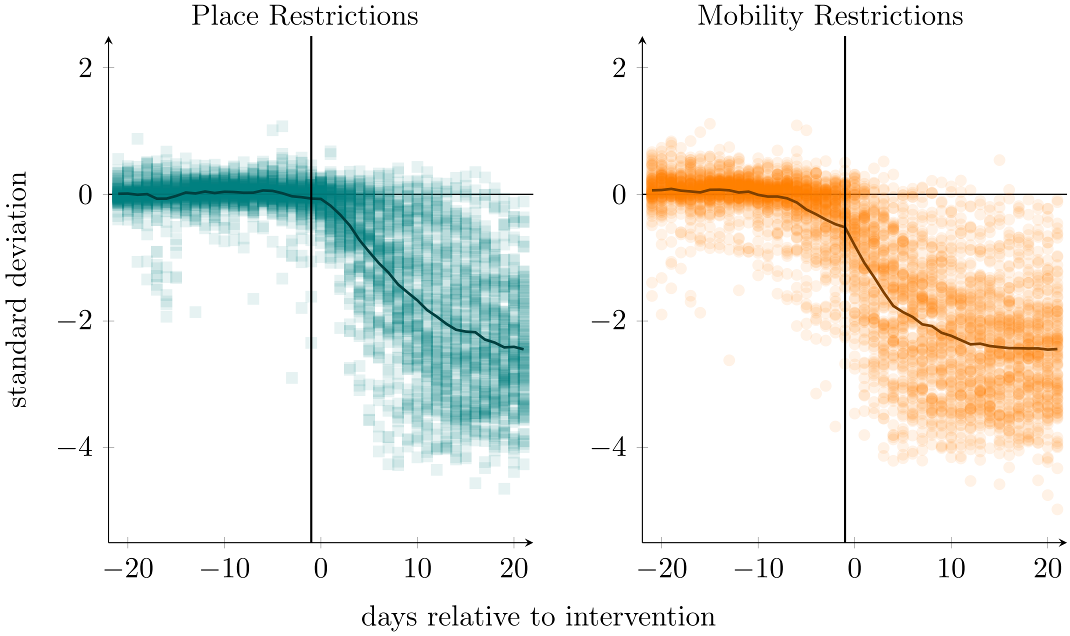
The effects of a distancing intervention are identified as sudden changes in a_{it} after the intervention. The key identifying assumption is that changes in social activity due to voluntary distancing is slow,

[16] Holding news fixed implies that the effects of voluntary distancing, other preventive interventions and imported cases are the same.

[17] Alternatively, I could close all three backdoor paths by modeling the endogenous selection of policies based on Heckman and Sedlacek (1985). That would require the credible exclusion of exogenous variables, for which the share of distancing policies in neighboring countries up to day $t-1$ could be a valid candidate. The exploration of this possibility however is beyond the limits of this paper. Another alternative approach is of Chernozhukov et al. (2021), who use the observable components of $\mathbf{N}$ as an instrument for both policies and social activity.

[18] RDiT is described in details in Hausman and Rapson (2018). A regular RD exploits a discontinuous change in the close neighborhood of a border separating the treated and untreated samples. RDiT is a special case when the running variable is time, which is usually a discrete variable in empirical exercises. This discreteness allows us to identify the effect by event time dummies rather than a discontinuity in a continuous polynomial like in regular RD designs. This design is related to event study designs, but it lacks a control group.

Figure 4: Social Activity in the Neighborhood of Distancing Policy Interventions



Notes: cloud: country-day observations of social activity a_{it} in the neighborhood of distancing interventions, darker regions show overlapping observations. Solid line: within day averages. Left: place restrictions, right: mobility restrictions. All figures are cleaned from their within country pre-intervention means and normalized by the full sample standard deviation of social activity.

while the response to a distancing intervention is quick, on daily frequencies. Distancing interventions, e.g. lock-downs, prescribe a coordinated and sudden reduction in social activities after an intervention. Voluntary distancing responses on the other hand are likely to be much less coordinated considering the heterogeneous attitudes towards COVID infection risks, e.g. virus sceptics and overly cautious people. Changes in social activity due to voluntary motives is presumably much smoother and slower therefore , on daily frequencies, when aggregated to the level of a country.

Figure 4 provides visual motivation of the RDiT strategy. It shows the deviation of the social activity indicator from its within country pre-intervention mean and normalized by the full sample standard deviation in the close neighborhood for the two types of distancing interventions defined in Section 2.1. Darker regions show more observations.

It looks like both types of policies reduced social activity by between 1 and 3 standard deviation in most countries just within 10 days. These changes seems to be more rapid in the case of mobility restrictions. It is also apparent that social activity remained constant in most countries before the interventions. Overall the rapid drop and negligible pre-trends observed on in social activity in the close neighborhood of distancing interventions supports the identification strategy of the first stage estimation.

3.2 Second Stage

The second stage estimates the effect of distancing policies P_{it}^p, of type $p \in \{\text{place}, \text{mobility}\}$ on the reproduction number R_{it}. Identification is based on the comparison of countries that have introduced a distancing policy $P_{it}^p = 1$ to those that have not $P_{it}^p = 0$, holding voluntary activity v_{it}, other preventive policies, imported infections, and other covariates fixed.

3.3 Threaths to Identification

In this subsection I review the possible threats to identification. The effect of distancing interventions is conveyed by two channels: policy compliant and policy induced voluntary distancing. People might increase their distancing after the implementation of a restriction because of compliance, but might also because they perceive it as a signal of a worsening epidemic. This kind of voluntary distancing is does not harm the separation of unconditional voluntary distancing effects, because it is a direct consequence of the interventions.

Countries differ in demographics, population density, the quality of political and healthcare institutions, which are likely correlate with interventions, social activity and reproduction numbers. I address these differences by including country fixed effects in both stages assuming the invariance of these factors on daily frequencies. Countries also differ in the timing of their interventions, which is addressed by the inclusion of time fixed effects absorbing a common trend that track the days after the first reported infection within a country. Different countries provided different levels of economic support, which might worked as incentives to leave workplaces for sick people. I address this by controlling for all available information on economic supports.

I control for daily weather conditions to address the effects of the climate on the reproduction rate of the virus. Finally, I control for weekly seasonality in both stages of my estimations.

4 Results

In the first part of this Section I specify the empirical designs and present estimation results. I start the first stage. From the results of that I calculate and analyse voluntary activity v_{it}. I then continue with the second stage estimation. In the second part of this Section I investigate heterogeneous distancing policy effects by simple modification to the second stage design.

4.1 First Stage

In the first stage I model social activity a_{it} as a function of event time indicators $\delta^p_{t-d(i,p)}$ centered around the last day before a distancing intervention $d(i,p)$ of type $p \in \{\text{place}, \text{mobility}\}$ in each country i:

$$a_{it} = \delta^{\text{place}}_{t-d(i,\text{place})} + \delta^{\text{mobility}}_{t-d(i,\text{mobility})} + \zeta' X_{it} + \mu_i + \gamma_t + \nu_{it}, \tag{5}$$

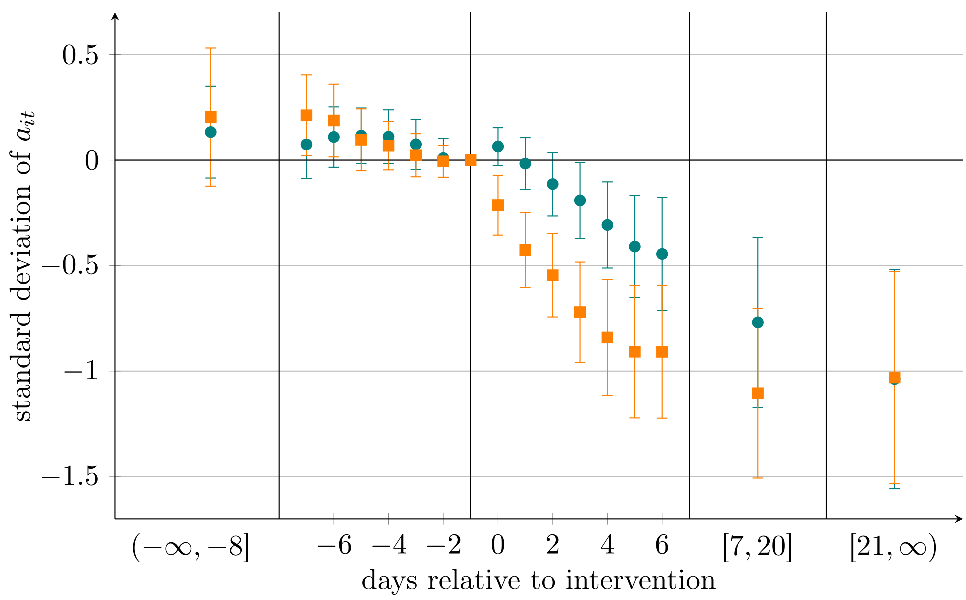
where X_{it} are different covariates. The first components of X_{it} are observable news components covering four set of variables. First set contain reported domestic COVID cases and COVID related deaths per population from 1, 2-7, 8-14 days before. The second set includes the average of the same per capita reports with same time lags in neighboring countries. The third set is the share of neighboring countries that had already implemented a place or a mobility restriction in the past 1, 2-7 or 8-14 days.[19] The final set are two indicators indicating if there was ad hoc public urging or an organized public information campaign about COVID-19 in place on day t. Table 11 in Appendix A.5 shows the estimation results for this set of variables.

X_{it} includes also other preventive policies, such as the level of international travel controls, testing policies, quantities and share of positive tests, level of contact tracing, debt reliefs, fiscal aids and if there were income supports as an incentive for staying home when someone was sick, mask wearing mandates, vaccination share, and different indicators of daily weather conditions (temperature, rainfall, snowfall, dewpoint, humidity) plus weekly seasonality.

I allow for country fixed effects μ_i to capture country fixed (e.g. cultural, demographic) differences that possibly affect social activities. I include time fixed effects γ_t setting $t = 0$ to the day the first

[19]Neighbors are defined by land borders.

Figure 5: Effects of a Place (●) and a Mobility (■) Restriction on a_{it}



Notes: a_{it} - social activity. Point estimates of $\delta^{\text{place}}_{t-d(i,\text{place})}$ and $\delta^{\text{mobility}}_{t-d(i,\text{mobility})}$ coefficients of equation (5) with 99% confidence intervals. Standard errors allowed to cluster within countries. Reference period: last day before the intervention. 50,070 daily observations within 120 countries.

COVID case was reported in a country to absorb a global trend of distancing response to the evolution of the epidemic that was common across countries.

Event time indicators $\delta^p_{t-d(i,p)}$ are included to capture the common trend in social activity around the days of a type p intervention. Because they are intended to capture the effects of the intervention relative to the previous day, δ^p_{-1} is omitted for both policy types, as δ^p_0 represents day 0 of an intervention. Figure 5 show the estimation results for the event time coefficients $\delta^{\text{place}}_{t-d(i,\text{place})}$ and $\delta^{\text{mobility}}_{t-d(i,\text{mobility})}$ of the first stage equation (5). Circles represent the point estimates in case of place, squares for mobility restrictions. Both set of estimates are graphed with 99 percent error bands. I pool periods more than one week distant from the intervention into three categories, i.e. $\delta^p_{t-d(i,p)}$ is a single dummy if $t \in (-\infty, -8]$, or $[7, 20]$, or $[21, \infty)$, keeping the focus in the close neighborhood of the intervention.

It is apparent that social activity a_{it} decreases significantly in the first seven days of distancing interventions, while there are only weak and marginally significant trends in a_{it} preceding the interventions.[20] The rapid response after interventions and negligible pre-trends before are consistent with the main identification assumption of the first stage estimation, i.e. interventions caused sudden changes in distancing behaviors.

A place restriction reduces activity by almost half, a mobility restriction by close to one standard deviations on day 6. It stays low on longer horizons suggesting a long lasting effect of both policies. Both restriction types decrease social activity by roughly 1 standard deviation after one week. The effects of both restrictions are gradual in the first seven days. People seem to react to a mobility restriction already on day 0, while significant responses to a place restriction come with a roughly 4 days delay.

[20] One possible explanation for pre-trends is the anticipatory effects of earlier announced restrictions. These early announcements are not observed in Hale et al. (2020) only on the day of implementation for each distancing restriction.

4.2 Voluntary Activity

The goal of the first stage estimation is the isolation of the voluntary component of social activity. I use the results of the first stage estimation therefore, to break down social activity a_{it} into three components: the effect of distancing policies $\widehat{p}_{it}^{D}$, the effect of other policies $\widehat{p}_{it}^{O}$, and voluntary activity $\widehat{v}_{it}$. Distancing policy effects are defined as changes in a_{it} from day 0 to 6 after an intervention and fixed for later days as the effect on day 6. Consistently with the identifying assumption that changes only shortly after an interventions are attributed to that intervention. It is set the same way for both place and mobility restrictions.

The effect of other preventive policies are defined as changes in a_{it} due to other policies. Voluntary activity $\widehat{v}_{it}$ is then defined as residual changes in a_{it} that are not attributed to either distancing or any other policy interventions. These definitions are summarized in the following equations:

$$\widehat{p}_{it}^{D} = \sum_{p \in \{\text{place,mobility}\}} \left[\sum\nolimits_{j=0}^{6} \widehat{\delta}_j^p + \widehat{\delta}_6^p \mathrm{I}_{t-d(i,p)>6}^p \right] \tag{6}$$

$$\widehat{p}_{it}^{O} = \theta' P_{it}^{O} \tag{7}$$

$$\widehat{v}_{it} = a_{it} - \widehat{p}_{it}^{D} - \widehat{p}_{it}^{O} \tag{8}$$

where P_{it}^{O} is a set of binary indicators indicating if a particular policy with a specific stringency level is in place in country i on day t. By this definition in equation (8) the error term of the first stage estimation of equation (5) is attributed to voluntary activity. This way it might be a more powerful control, than a standard instrumental variable, because that error term contains the effects of all the unobserved factors that might induce changes in voluntary distancing behaviors.[21]

Figure 6 shows cross country averages of social activity with its three components. The time axis is adjusted, such that day 0 is the day, when the first COVID case was reported within a country. Solid line is social activity. Voluntary activity is pictured by a dashed line, the effect of other policies by dotted dashed line, and the effect of distancing policies by a dotted line. Social activity started to drop soon after day 0, and leveled out roughly on day 20 approximately 2 standard devotions below its pre-COVID levels.

All three components are in a decline in the same period between days 0 and 20. Distancing policies dropped the most, more than one standard deviations, and it kept on declining in the following days. Voluntary distancing dropped almost on standard deviations as well, but it started to rise again after day 30. Other preventive policies had a much smaller effect on social activity.

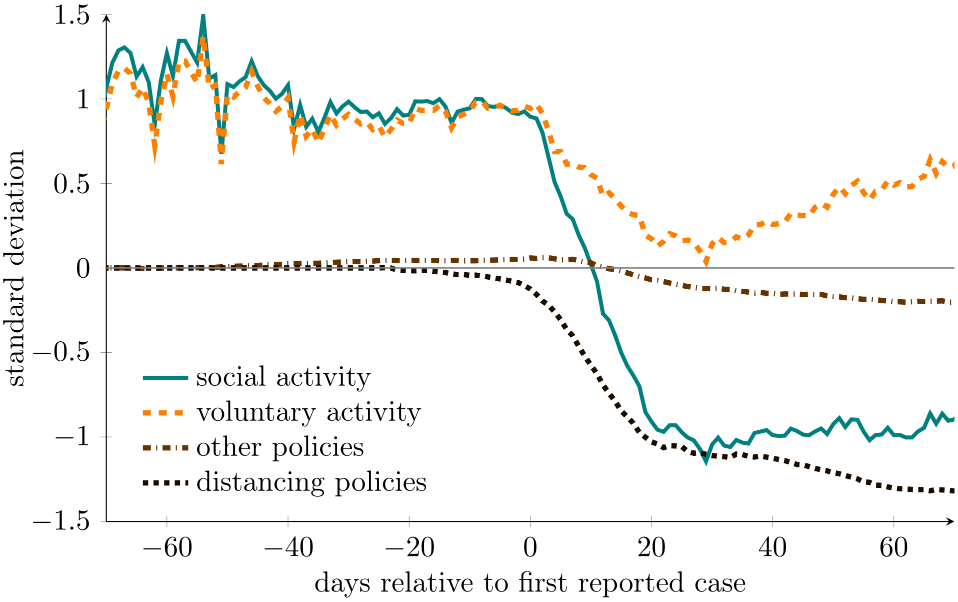
This decomposition suggests that distancing interventions and voluntary distancing both had a major role in the global reduction of social activities. On longer horizons policies seems to had a more prolonged effect, while voluntary distancing was less permanent. This suggests that distancing interventions might had a more important role in the containment of the epidemic. Investigating this possibility is the primary purpose of the second stage estimation, which is presented in the next Section.

4.3 The Effect of Distancing Policies on the Effective Reproduction Number of COVID-19

In this subsection I develop the empirical design of the second stage first, then I analyze its results. Tha second stage estimation aims to identify the effect of distancing policies on the reproduction number of COVID-19 controlling for the effects of voluntary distancing, other preventive policies and covariates. I model the effective reproduction number $R_{i,t+h}$ as a function of distancing policies, voluntary activity

[21] One could interpret $\widehat{v}_{it}$ as counterfactual social activity a_{it} of a no-intervention scenario.

Figure 6: Decomposition of Social Activity at the Beginning of the Pandemic



Notes: cross country averages of social activity and its three components.

$\widehat{v}_{it}$, other preventive policies and covariates:

$$R_{i,t+l} = \exp\left[\beta_p P^{\text{place}}_{i,t-4} + \beta_m P^{\text{mobility}}_{it} + \beta_v \widehat{v}_{it} + \xi' X_{it} + \mu_i + \kappa_t\right] + \varepsilon_{i,t+l}, \tag{9}$$

where $R_{i,t+l}$ is proxied by the instantaneous reproduction number in country i observed on day $t+l$. P^p_{it} is an indicator of a distancing policy interventions being 1 on days, when any components of that policy type was in action in country i. Based on the first stage results in Section 4.1 place restrictions started to afect social activity after 4 days. Therefore, I include place restrictions in the second stage with a four day delay: $P^{\text{place}}_{i,t-4}$.

By setting the functional form to exponential, this model is a Poisson regression identifying proportional effects. Identifying proportional effects allow me to use the easily calculable instantaneous reproduction number R^I_t instead of R_t and get equivalent results, because $R^I_t \propto R_t$ as it has been shown in Section 2. It is less restrictive than a log-transformation, because it allows for zero observations in the outcome. This is useful, because R^I_t is zero each day, when there are 0 new infections are reported.[22] I use $\widehat{v}_{it}$ that resulted from the first stage estimation as a control to eliminate the effect of voluntary distancing.

I allow for country fixed effects μ_i to capture time invariant differences among countries, e.g. population density, demographics, the quality of the healthcare system, which possibly affect the reproduction number of the virus. I include also a time fixed effects κ_t setting $t = 0$ to the day the first COVID case was reported in a country to absorb a global trend in the evolution of reproduction numbers that was common across countries.

Covariates X_{it} include other preventive policies, addressing the third backdoor path. These preventive policies are the level of international travel controls, type of testing policies, testing quantities and share of positive tests, level of contact tracing, debt reliefs, fiscal aids and if there ware income supports as an incentive for staying home when someone is sick, mask wearing mandates, vaccination share. X_{it} contains also different indicators of daily weather conditions (temperature, rainfall, snowfall, dewpoint, humidity) to capture the patterns of infections in different weathers. It contain also controls for weekly seasonality. Finally, I include the expected number of imported infections and its interaction with international travel

[22] This is a Poisson model on non-integer outcomes. For details see for example Silva and Tenreyro (2006).

Table 3: Effect of Distancing Policies on Reproduction Numbers 10 days later.

	(1)	(2)	(3)	(4)
Place Restrictions $_{t-4}$	-0.415***	-0.331**	-0.287**	-0.287**
	(0.155)	(0.142)	(0.142)	(0.139)
Mobility Restrictions $_t$	-0.737***	-0.690***	-0.621***	-0.610***
	(0.163)	(0.139)	(0.123)	(0.118)
Voluntary Activity $_t$		0.154***	0.165***	0.167***
		(0.041)	(0.040)	(0.040)
Imported cases $_t$				0.310***
				(0.105)
Import × Screening $_t$				2.067
				(9.768)
Import × Quarantine $_t$				-1.952*
				(1.100)
Import × Selective Ban $_t$				1.080
				(2.119)
Import × Total Ban $_t$				-1.670***
				(0.553)
Observations	26,566	26,566	26,566	26,566
Countries	109	109	109	109
Other Preventiv Pol's	○	○	●	●
Country and Day FE's	●	●	●	●

Notes: *** p<0.01, ** p<0.05, * p<0.1, ● = included ○ = excluded. Standard errors in parenthesis allowing for within country clustering. Dependent variable is instantaneous reproduction number 10 days forward: $R^I_{i,t+10}$. Controlled for daily weather conditions and weekly seasonality.

controls into X_{it} to control for the channel of imported infections.

Table 3 shows the main results of this paper. These are the results of different specifications of the second stage equation (9) setting the latency parameter $l = 10$ days.[23] The table starts with the most basic specification that includes only distancing policy interventions besides controls for weather conditions, weekly seasonality and country and time fixed effects. The next columns add important omitted factors: voluntary activity, other preventive policies and imported cases one by one. This way one can judge the relevance of these omitted factors by comparing the point estimates for place and mobility restrictions accross columns.

Column (1) shows strong correlations for both policy types with $R_{i,t+l}$. Based on Column (1) place restrictions reduce the reproduction number by 33 percent, while a mobility restriction by 74 percent. This is a misspecified specification however, only included as a benchmark for the better specified models that control for different sources of omitted variable biases: voluntary distancing, other preventive policies, and imported cases..

In the second column I add the voluntary activity indicator that has been isolated in the first stage. Controlling for this factor reduces the coefficients of both interventions substantially. This finding confirms the importance of controlling for this factor. This result is consistent with first stage results, which already suggest an important role for voluntary distancing in observed distancing behaviors.

In the third specification I add other preventive policies to the set of controls. These are included as

[23] A sensitivity analysis of l can be found in the Appendix. Results show little sensitivity to the choices of $l \in \{7, 9, 11, 13\}$

a set of different variables for which the parameter estimates are not shown in the table. The effect of distancing policies are marginally smaller compared to specification (2) suggesting that other preventive polices are also important controls to include similarly to voluntary activity. Finally in column (4) I add imported cases and its interaction with different levels of international travel controls. The difference in the parameter estimates of place and mobility restrictions are negligible between columns (4) and (3) suggesting that international travels were not strongly correlated with distancing policy interventions.

Column (4) is my most complete specification, therefore, I refer to it as my main result. In column (4) I find that place restrictions reduce the effective reproduction number of COVID-19 by 29 percent, while mobility restrictions by 62 percent. These are strong effects suggesting that distancing policies were an effective tool for reducing the impact of the pandemic. Place restrictions that are targeting specific destinations are found to be roughly half as effective as general mobility restrictions. This finding suggests that there was much heterogeneity between the effectiveness of different policies, implying that different policy mixes could have led to very different outcomes

Now let us turn to the estimation results for the other important factors, voluntary distancing and imported cases in this most complete specification of column (4). In the case of voluntary activity I find that a one standard deviation drop in voluntary social activity decreases R_t by 17 percent. The effect of voluntary distancing is also significantly negative but weaker than those of the policy restrictions. This finding suggests that, although voluntary distancing behaviors help to slow down the reproduction of the virus, any kinds of distancing policy measures are much more effective in stopping a pandemic.

In the case of imported cases I find that a one standard deviation rise in imported cases significantly increases R_t by 31 percent. This effect is more than offset by travel restrictions, if it takes the form of quarantines or a total ban. Although this offsetting effect is only marginally significant for quarantines. I have found no evidence for the effectiveness of screening and selective travel bans in the reduction of R_t via imported cases.

4.4 Comparing Compliant and Voluntary Distancing Effects

It is crucial to compare the consequences of voluntary and distancing policy induced distancing when forming policy conclusions about the relative efficiency of policies. Voluntary mobility and distancing policy induced components are measured in different units, so Table 3 coefficients are not directly comparable between rows. One possible way to address this issue would be to use the first-stage estimates for place and mobility with their coefficients from equation (5) directly on the right-hand side of equation (9), instead of the policy variables. Although this strategy appears simple and straightforward, it is impossible to implement because policy variables, P_{it}^{place} and P_{it}^{mobility}, are not included in the first-stage equation. The reason they are not included is that the effect of the policies is captured by the RDiT design that builds on the key identifying assumption of sudden responses to policy changes. Giving this design up is considered to be a greater cost than the gain of the comparison that would emerge from a different design would provide.

I work around this problem by picking a different strategy to make the effects of distancing policies and voluntary distancing comparable. It is a decomposition of the changes in reproduction numbers around the time of the first global wave. I start that by taking the cross-country averages of R_{it} in the estimation sample. Reproduction numbers peaked in late February and declined until the summer. Assuming an average duration for an infection to be 12 days, the seven-day backward-looking average of the effective reproduction number peaked at 6.32 on February 26 in 2020 and fell below 1 for the first time on April 11. This was a 85 percent drop in R_{it} on average across countries in the first wave. I decompose this decline into four suggested factors by calculating the changes in the cross-country averages of distancing policies and the voluntary activity indicator in the same time period and then multiplying them by their coefficients of the most complete specification in Table 3. I proceed similarly with standard errors.

Table 4: Comparing Compliant and Voluntary Distancing Effects

	Change (%)	Contribution
Effective Repr' Number R_t	-0.85	100%
Place Restrictions	-0.25 (0.102)	29.4 %
Mobility Restrictions	-0.59 (0.088)	69.4 %
Distancing Policies	-0.84	98.8%
Voluntary Distancing	-0.13 (0.032)	15.3 %
Other Factors	0.12	-14.1 %

Notes: Effects are calculated as change in cross country averages multiplied by the coefficients of column (3) of Table 3. Standard errors in parenthesis are calculated similarly, using the s.e. of the corresponding coefficient.

Taking cross country averages of binary policy indicators gives the share of countries that are introducing that policy on that day, therefore its change in the period shows the change in the sample coverage of these policies. This change in coverage for place and mobility restrictions were 84 and 95 percent in this period. That means most countries in the sample implemented these types of distancing interventions within these roughly two month period. In the same period voluntary activity declined by 0.8 standard deviations.

The results of these calculations are summarized in table 3. It shows that the drop in R_{it} was mostly due to restrictions, which altogether contributed almost 100 percent of the total decline in reproduction numbers. It was mostly mobility restrictions that were responsible for this effect. Their sole contribution were nearly 70 percent. This suggests that mobility restrictions were much more effective than place restrictions.

Voluntary distancing on the other hand contributed only a little more than 15 percent, which were counter acted almost completely by other unexplained factors. This results suggests that voluntary distancing had only a marginal role in the containment of the COVID pandemic in the first wave.

4.5 Heterogeneous Effects

In this Section I investigate heterogeneous policy effects. The first of these exercises analyses the strength of the policy effects on different time horizons. I am intrested in how long the effects identified in the main design last. In the second exercise I break down the larger restriction categories: place and mobility restrictions, into their components. I also allow for heterogeneity in the different stringency levels in this exercise. I do this to provide comparative results for more specific policy interventions.

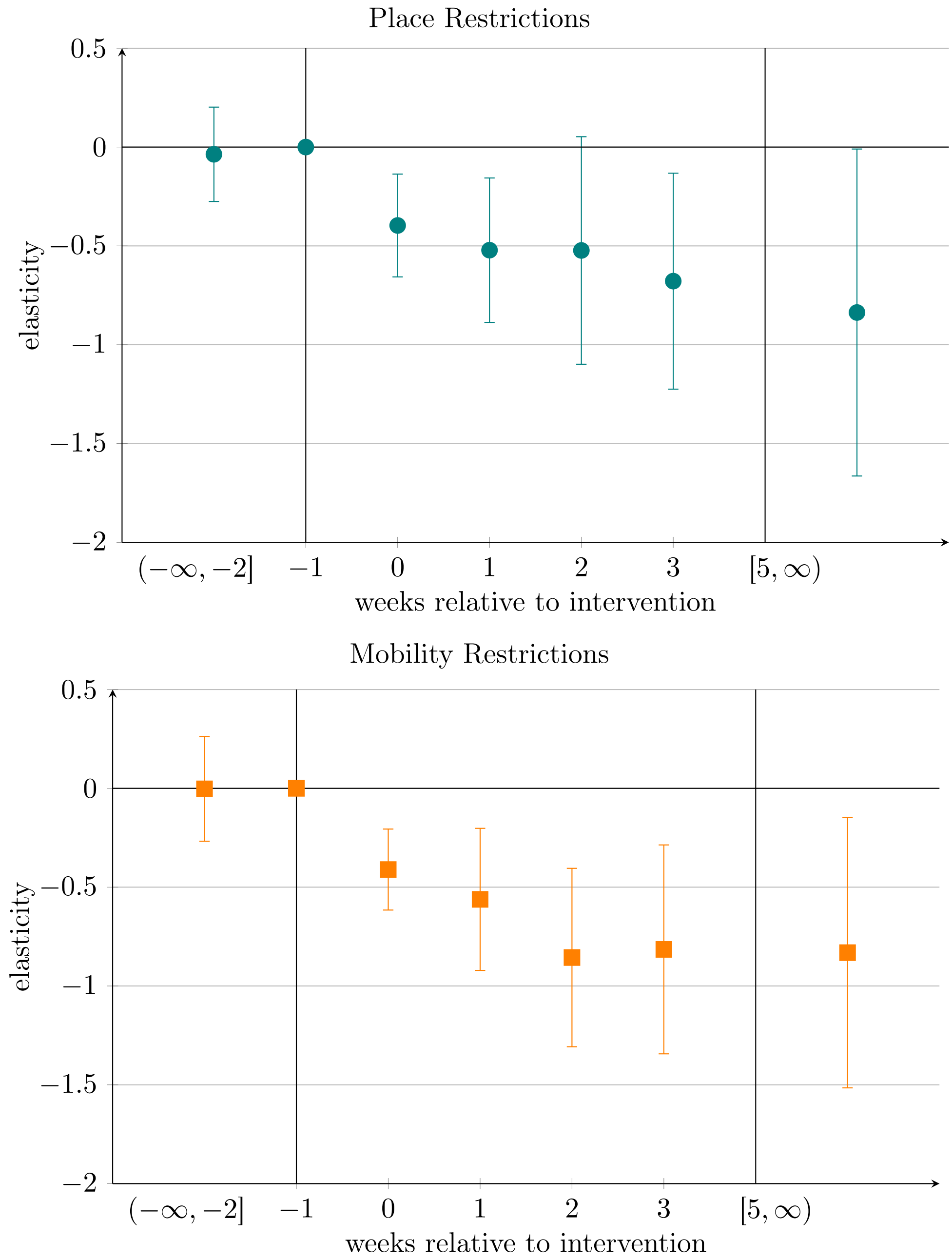
4.5.1 Heterogeneous Dynamics

Here I investigate how long the effects found in the main specification lasted. It is useful to know how long a government can rely on a place or a mobility restriction, when they are fighting more and more waves of an epidemic. To address this question I modify equation (9) by allowing for time heterogeneity in the policy effects by the the following modification to the main estimation equation (9):

$$R_{i,t+10} = \exp\left[\beta^{\text{place}}_{t-w(i)} + \beta^{\text{mobility}}_{t-w(i)} + \beta_v \widehat{v}_{it} + \xi' X_{it} + \mu_i + \kappa_t\right] + \varepsilon_{i,t+l}, \tag{10}$$

where $\beta^{\text{place}}_{t-w(i)}$ and $\beta^{\text{mobility}}_{t-w(i)}$ are event time dummies indicating seven day periods and relating the effect of a type of intervention to the last seven day period ($w(i) = -1$) before the intervention. This equation is other than this modification is equivalent to equation (9).

Figure 7: Effects of Distancing Policies on the Reproduction Number 10 days later



Notes: point estimates of $\beta^{\text{place}}_{t-w(i)}$ and $\beta^{\text{mobility}}_{t-w(i)}$ coefficients and 95% confidence intervals of equation 10. Standard errors allowed to cluster within countries. Reference period: last 7 days before the intervention. 26,566 daily observations within 109 countries.

Figure 7 shows the results for the β coefficients of equation (10). It looks like that both policies produce a significant drop in R_{it} already in the first seven days after their implementation. These effects get somewhat stronger on later weeks. In the case of a mobility restriction these effects stay significant throughout the entire horizon. In the case of place restrictions some longer horizon effects are only marginally significant. Overall these results suggests that both policy types have a significant long lasting effect on the reproduction number. Governments can rely on these distancing restrictions on longer horizons, when fighting longer waves of infections based on these results.

4.5.2 Heterogeneous Policies

In this Section I estimate another variant of the second stage, where I break down the comprehensive place and mobility restriction indicators into their components, and estimate the effect of those components and their stringency levels separately. I do this to provide comparative results for more delicate policy interventions.

I estimate the following variant to equation (9), where I include all the different distancing interventions with all their different stringency levels reported by Hale et al. (2020):

$$R_{i,t+l} = \exp\left[\beta_{jk} D_{it}^{\mathrm{jk}} + \beta_v \widehat{v}_{it} + \xi' X_{it} + \mu_i + \kappa_t\right] + \varepsilon_{i,t+l}, \tag{11}$$

where $D_{it}^{\mathrm{j,k}}$ is an indicator indicating if a distancing policy j at stringency level k was in action in country i on day t. For example j = workplace closures, which are k = recommended. All other parts of the equation is equivalent to of equation (9).

The results for equation (11) is reported in Table 5. Results show that four of these restriction types were found to be generally effective in my global estimation sample. For the effectiveness of cancellation of public events, restrictions on public transportation and inland travel restrictions on the other hand I found no evidence.

Looking at policies one by one I find that school closures seems to be effective only if they are mandatory even if they are partial in terms of education levels. A required school closure reduces the effective reproduction number by between 17.6 to 24.1 percent on average depending on the coverage. Closing workplaces seems to reduce R_{it} significantly, no matter if it is recommended. The effect becomes 1.5 times stronger: -31 percent, when it is required. There is no significant difference though between a partial requirement or if it includes all non-essential businesses.

Table 5: Effect of All the Different Distancing Policies on $R_{i,t+10}$

School Closures:		Public Transport Restrictions:	
Recommended	-0.160	Recommended	0.021
	(0.109)		(0.061)
Required Partial	-0.241**	Required	0.029
	(0.104)		(0.081)
Required All Levels	-0.176*	Stay At Home Orders:	
	(0.100)	Recommended	-0.185***
Workplace Closures:			(0.059)
Recommended	-0.209**	Required with exceptions	-0.149**
	(0.093)		(0.070)
Required Partial	-0.310***	Minimal exceptions	0.356*
	(0.080)		(0.205)
All Non-essential B's	-0.265***	Inland Travel Restrictions:	
	(0.092)	Recommended	-0.067
Public Events Cancellations:			(0.072)
Recommended	0.102	Required	0.093
	(0.111)		(0.077)
Required	0.015		
	(0.096)		
Gathering Limits:			
1000+	-0.073	10+	-0.331***
	(0.133)		(0.112)
100+	-0.268**	1+	-0.345***
	(0.112)		(0.124)
Observations		38,704	
Countries		111	
All Controls		•	
Country and Day FE's		•	

Notes: *** p<0.01, ** p<0.05, * p<0.1, • = included ∘ = excluded. Standard errors in parenthesis allowing for within country clustering. Dependent variable is instantaneous reproduction number 10 days forward: $R^{I}_{i,t+10}$. Controlled for daily weather conditions and weekly seasonality.

Gathering limits show the strong effects, when the limit is at most 100 persons. The introduction of a 100+ limit reduces R_{it} by 26.8 percent. A less stringent 1000+ limit show no effects, while the more stringent 10+ or 1+ limits seems to have stronger effects but with strongly diminishing gains. Stay at home orders, i.e. curfews are also found to be effective already if they are recommended. A recommended home staying reduces R_{it} by 18.5 percent. When it is mandatory with minimal exceptions by 35. percent, which is the strongest effect among all policies, but only weakly significant however only at 10 percent. Overall these findings suggest that there was much heterogeneity between the effectiveness of different policies, implying that different policy mixes could have led to very different outcomes.

5 Conclusions

In this study I estimated the effect of distancing interventions on the effective reproduction number R_t of COVID-19. I was focusing on the effects of two types of such policies, place restrictions, that target specific destinations, and mobility restrictions that are general restriction on inland movements. The main contribution of this study is the separation of voluntary and policy induced distancing. I have found that distancing interventions had a strong and permanent effect on R_t. General mobility restrictions are found to be roughly two times more effective than targeted place restrictions. These policy effects were found to be much more dominant than the effects of voluntary distancing. These results suggests that governments can use distancing restrictions effectively in pushing down the effective reproduction number below the containment threshold of $R_t \leq 1$. Although these policies need time to exert their effects on reported case numbers, governments can rely on their effects for as long as these measures are in place.

Comparing specific interventions I have found significant differences. Based on these results school closures are better if they are mandated, in contrast with workplace closures, which were found to be effective already, when they are just a recommendation. Stay at home orders are similarly effective already, when they are only recommended, but more effective, when mandated with only minimal exceptions. Gathering limits become effective below 100 person and only get marginally more effective at more restrictive limits. I have found no supporting evidence for the effectiveness of cancellation of public events, restrictions on public transportation and inland travel restrictions. These results suggest therefore, that a careful selection of particular distancing policies and their stringency levels is recommended before their implementation.

Appendix A

A.1 Policy Pairs

Table 6: Percent of Countries Implementing a Policy Pair within 3 or Less Days.

	Place Restriction				Mobility Restriction		
	School	Event	Gather	Work	Stay H	Move	Transp't
Schools		43.12	44.44	38.53	23.15	24.07	10.00
Events	43.12		53.70	26.61	15.74	21.30	10.00
Gatherings	44.44	53.70		38.89	29.91	27.10	24.00
Workplaces	38.53	26.61	38.89		40.74	37.96	40.00
Stay Home	23.15	15.74	29.91	40.74		48.60	42.42
Movement	24.07	21.30	27.10	37.96	48.60		43.43
Transport	10.00	10.00	24.00	40.00	42.42	43.43	

Coloring: Dark yellow $\geq 66.7\%$, *light yellow* $\geq 50\%$.

Table 7: Percent of Countries Implementing a Policy Pair within 5 or Less Days.

	Place Restriction				Mobility Restriction		
	School	Event	Gather	Work	Stay H	Move	Transp't
Schools		66.97	58.33	57.80	39.81	41.67	26.00
Events	66.97		64.81	44.95	34.26	34.26	23.00
Gatherings	58.33	64.81		52.78	44.86	44.86	35.00
Workplaces	57.80	44.95	52.78		52.78	50.00	48.00
Stay Home	39.81	34.26	44.86	52.78		60.75	51.52
Movement	41.67	34.26	44.86	50.00	60.75		56.57
Transport	26.00	23.00	35.00	48.00	51.52	56.57	

Coloring: Dark yellow $\geq 66.7\%$, *light yellow* $\geq 50\%$.

Table 8: Percent of Countries Implementing a Policy Pair within 7 or Less Days.

	Place Restriction				Mobility Restriction		
	School	Event	Gather	Work	Stay H	Move	Transp't
School Closure		76.15	67.59	71.56	50.00	53.70	39.00
Events Cancelled	76.15		70.37	55.96	44.44	49.07	29.00
Gathering Limit	67.59	70.37		65.74	57.94	58.88	44.00
Workplace Closure	71.56	55.96	65.74		62.96	60.19	54.00
Stay Home Order	50.00	44.44	57.94	62.96		67.29	58.59
Movement Restricted	53.70	49.07	58.88	60.19	67.29		64.65
Public Transport Closed	39.00	29.00	44.00	54.00	58.59	64.65	

Coloring: Dark yellow $\geq$ 66.7%*, light yellow* $\geq$ 50%.

Table 9: Percent of Countries Implementing a Policy Pair within 9 or Less Days.

	Place Restriction				Mobility Restriction		
	School	Event	Gather	Work	Stay H	Move	Transp't
Schools		85.32	75.93	77.98	55.56	60.19	49.00
Events	85.32		74.07	66.06	52.78	56.48	41.00
Gatherings	75.93	74.07		72.22	65.42	63.55	53.00
Workplaces	77.98	66.06	72.22		70.37	68.52	65.00
Stay Home	55.56	52.78	65.42	70.37		70.09	64.65
Movement	60.19	56.48	63.55	68.52	70.09		70.71
Transport	49.00	41.00	53.00	65.00	64.65	70.71	

Coloring: Dark yellow $\geq$ 66.7%*, light yellow* $\geq$ 50%.

Table 10: Number of Countries Implementing both Policies of a Policy Pair.

	School	Event	Gather	Work	Transp't	Stay H	Move
Schools		109	108	109	100	108	108
Events	109		108	109	100	108	108
Gatherings	108	108		108	100	107	107
Workplaces	109	109	108		100	108	108
Transport	100	100	100	100		99	99
Stay Home	108	108	107	108	99		107
Movement	108	108	107	108	99	107	

Notes

A.2 Timing of Distancing Policy Interventions by Country

Figures 8 and 9 show the time of the first distancing interventions relative to the day of the first reported COVID-19 case. These figures demonstrate that there is a sufficiently large variation in the adoption times of distancing interventions to make their effects feasible to identify with panel econometric methods. It is also apparent from the figures that many countries implemented their first distancing interventions before they even had a confirmed COVID case within their borders.

Figure 8: First Place Restrictions by Countries

Early Adopters

Late Adopters

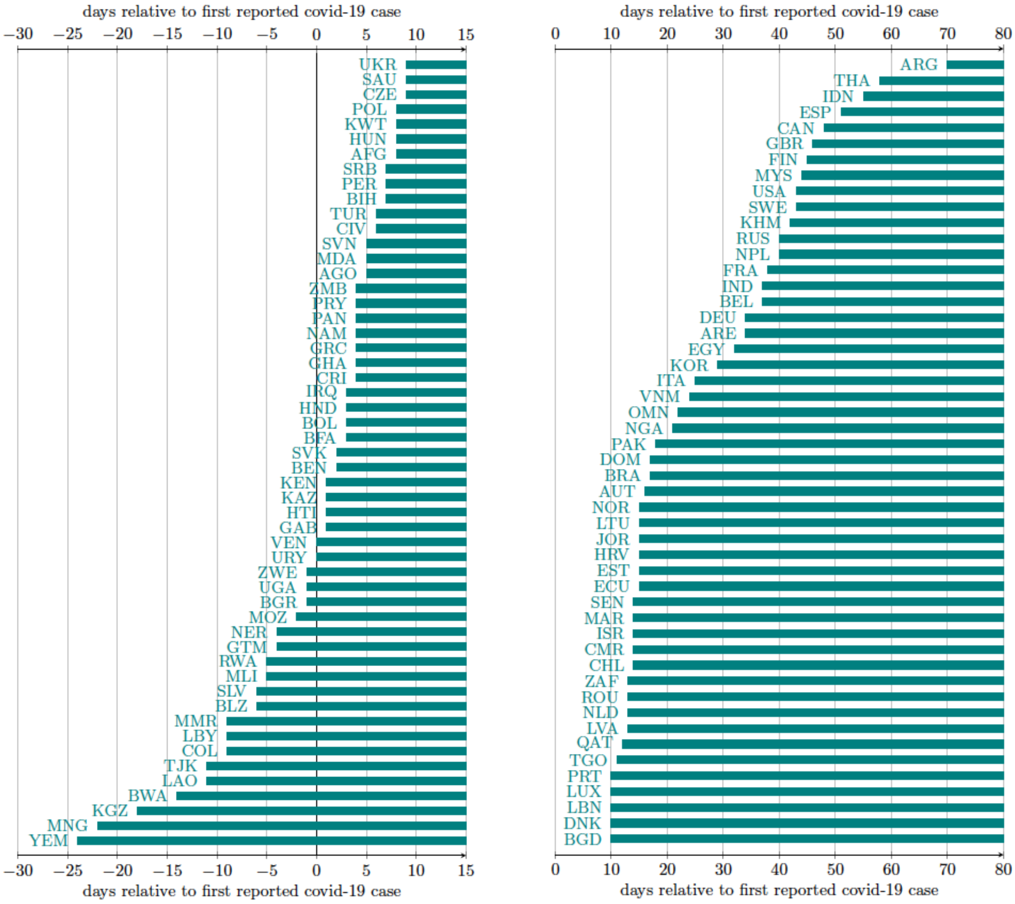
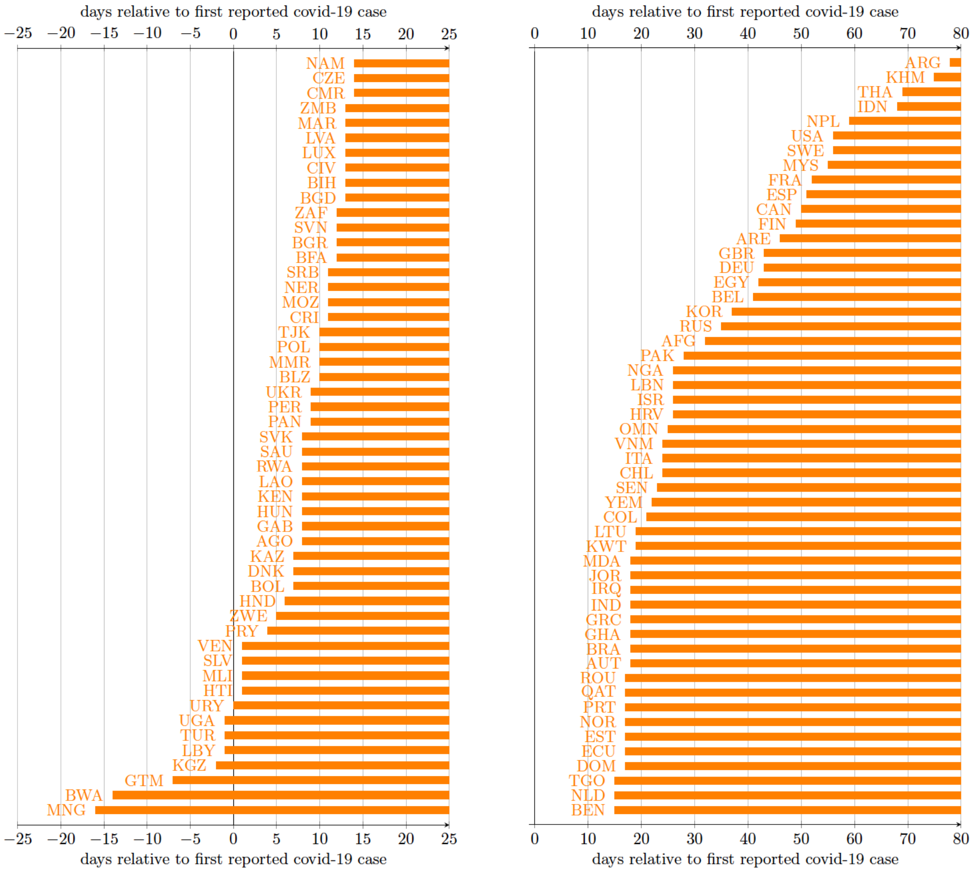


Figure 9: First Mobility Restrictions by Countries

Early Adopters Late Adopters



A.3 Validation of the Calculation of Reproduction Numbers

Here I compare my definition for R_t to an estimation of R_t using the methodology of Cori et al. (2013). It is a parametric calculation for which I use the following parameters: mean SI = 6, standard deviation of SI = 3, aimed posterior CV = .3, length of time-steps = 7, number of steps estimated = 1, posterior mean=5, posterior st.d. = 5. I input new case incidence data for each country from Wahltinez et al. (2020). For my definition of R_t I calculate R_t^I first, than normalize it by its within country mean and multiply it by the within country mean of Cori et al. (2013).[24]

[24]This renormalization does not harm my conclusions as it is based on $R_t \propto R_t^I$.

Figure 10: Validation of R_t by Cori et al. (2013) – Germany

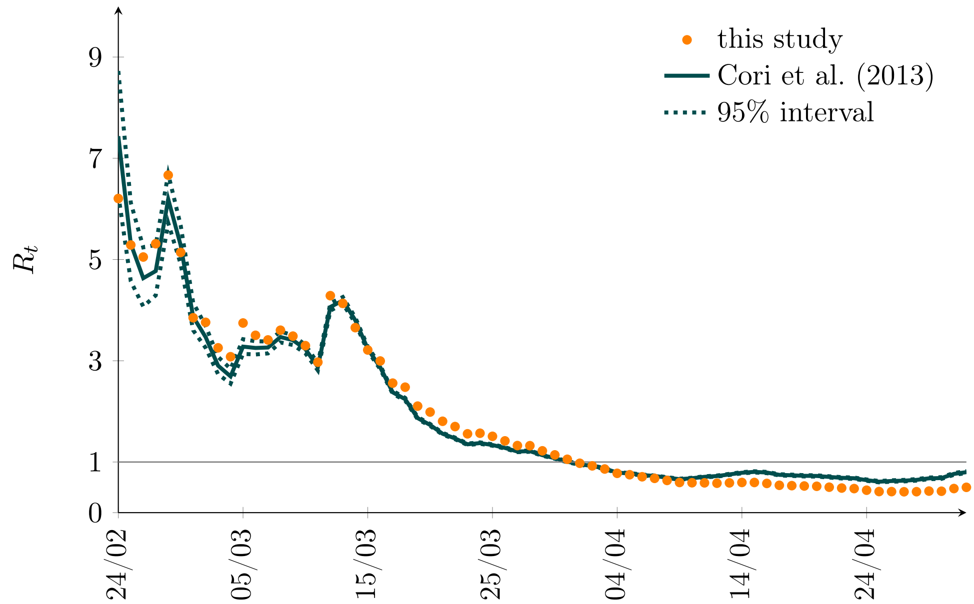


Figure 11: Validation of R_t by Cori et al. (2013) – Italy

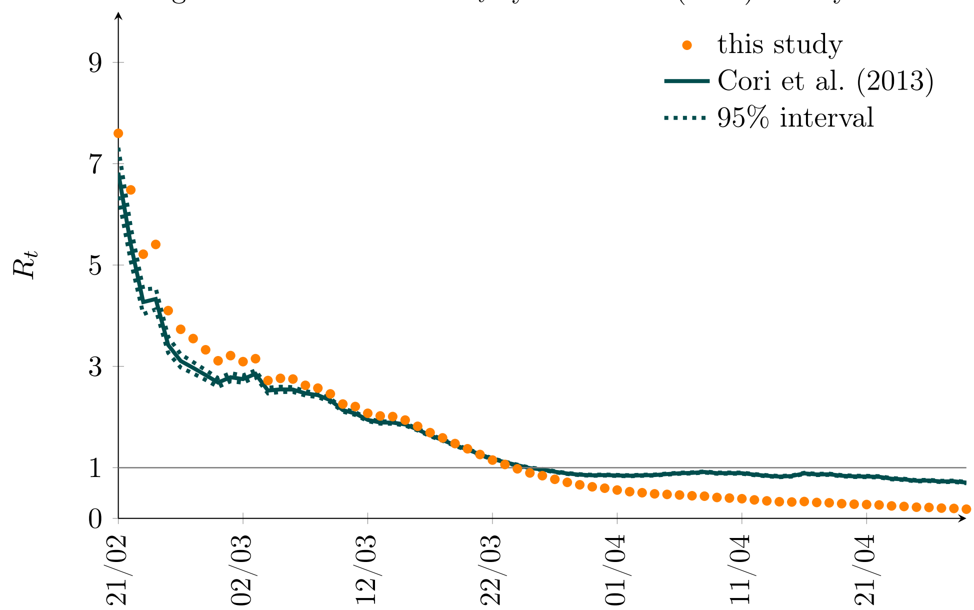


Figure 12: Validation of R_t by Cori et al. (2013) – France

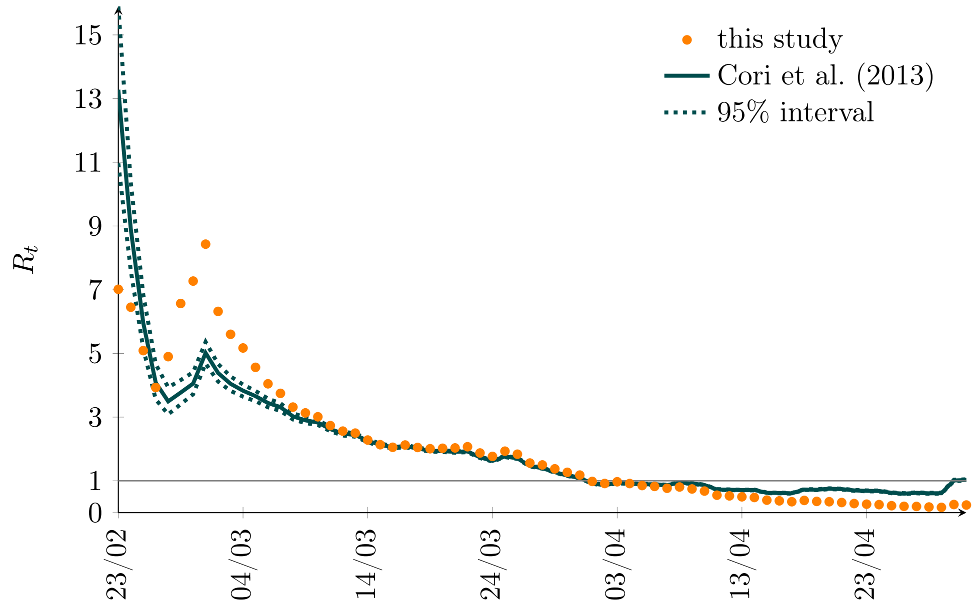


Figure 13: Validation of R_t by Cori et al. (2013) – Spain

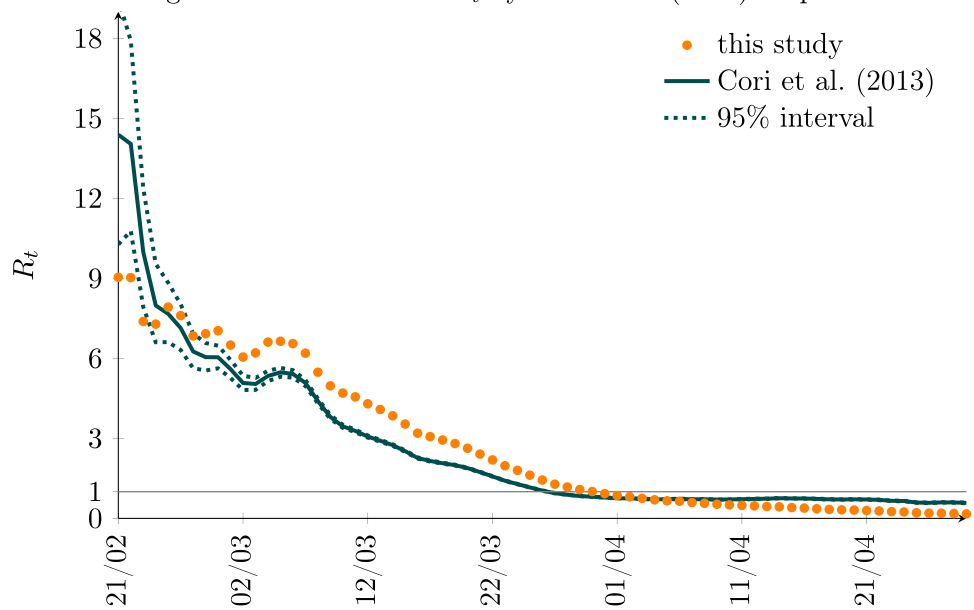
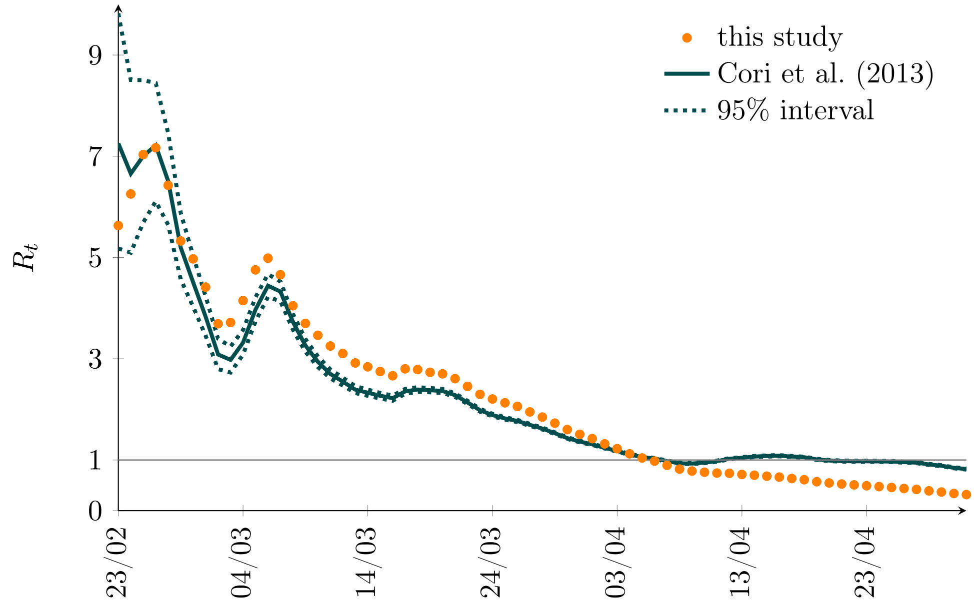


Figure 14: Validation of R_t by Cori et al. (2013) – UK



A.4 COVID-19 Aggregated Mobility Research Dataset

Description The Google COVID-19 Aggregated Mobility Research Dataset contains anonymized mobility flows aggregated over users who have turned on the Location History setting, which is off by default. This is similar to the data used to show how busy certain types of places are in Google Maps — helping identify when a local business tends to be the most crowded. The dataset aggregates flows of people from region to region, which is here further aggregated at the level of NUTS3 areas, weekly.

To produce this dataset, machine learning is applied to logs data to automatically segment it into semantic trips https://www.nature.com/articles/s41467-019-12809-y. To provide strong privacy guarantees, all trips were anonymized and aggregated using a differentially private mechanism https://research.google/pubs/pub48778/ to aggregate flows over time

(see https://policies.google.com/technologies/anonymization). This research is done on the resulting heavily aggregated and differentially private data. No individual user data was ever manually inspected, only heavily aggregated flows of large populations were handled.

All anonymized trips are processed in aggregate to extract their origin and destination location and time. For example, if users traveled from location a to location b within time interval t, the corresponding cell (a, b, t) in the tensor would be $n \pm err$, where err is Laplacian noise. The automated Laplace mechanism adds random noise drawn from a zero mean Laplace distribution and yields (ϵ, δ)-differential privacy guarantee of $\epsilon = 0.66$ and $\delta = 2.1 \times 10 - 29$ per metric. Specifically, for each week W and each location pair (A, B), we compute the number of unique users who took a trip from location A to location B during week W. To each of these metrics, we add Laplace noise from a zero-mean distribution of scale 1/0.66. We then remove all metrics for which the noisy number of users is lower than 100, following the process described in https://research.google/pubs/pub48778/, and publish the rest. This yields that each metric we publish satisfies (ϵ, δ)-differential privacy with values defined above. The parameter ϵ controls the noise intensity in terms of its variance, while δ represents the deviation from pure ϵ-privacy. The closer they are to zero, the stronger the privacy guarantees.

Limitations These results should be interpreted in light of several important limitations. First, the Google mobility data is limited to smartphone users who have opted in to Google's Location History feature, which is off by default. These data may not be representative of the population as whole, and furthermore their representativeness may vary by location. Importantly, these limited data are only viewed through the lens of differential privacy algorithms, specifically designed to protect user anonymity and obscure fine detail. Moreover, comparisons across rather than within locations are only descriptive since these regions can differ in substantial ways.

Data Availability The Google COVID-19 Aggregated Mobility Research Dataset used for this study is available with permission from Google LLC.

A.5 Covariates of the First Stage

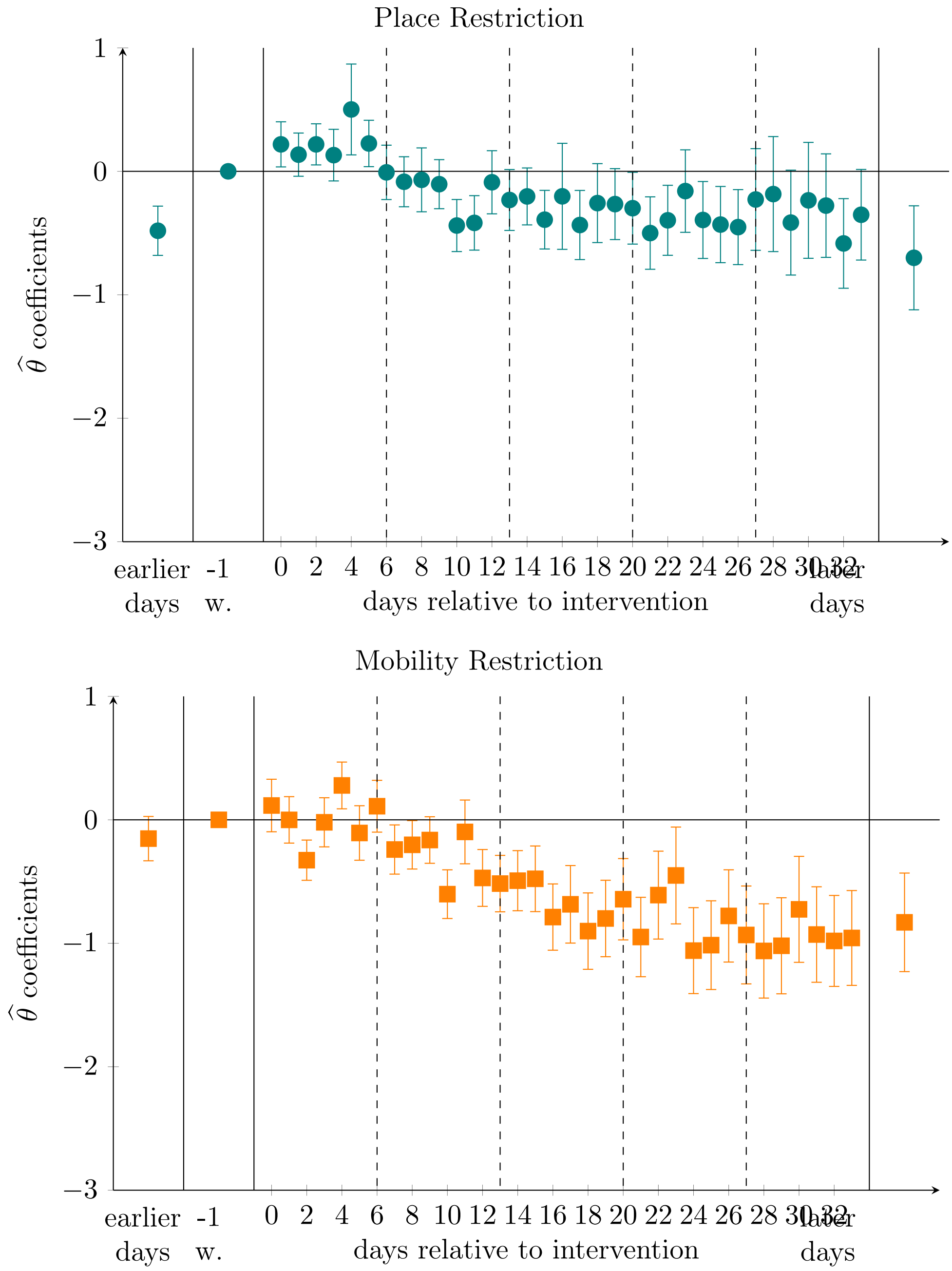
Table 11: Effect of News Components in the First Stage

Cases $_{t-1}$	-0.005	Neighbors' Deaths $_{t-1}$	-0.895*
	(0.003)		(0.457)
$\sum_{s=2}^{7}$Cases $_{t-s}$	-0.070***	$\sum_{s=2}^{7}$N's' Deaths $_{t-s}$	-3.400**
	(0.016)		(1.441)
$\sum_{s=8}^{14}$Cases $_{t-s}$	-0.067***	$\sum_{s=8}^{14}$N's' Deaths $_{t-s}$	-3.117*
	(0.023)		(1.844)
Deaths $_{t-1}$	-0.266	Neighbors' Place R's $_{t-1}$	0.343***
	(0.183)		(0.102)
$\sum_{s=2}^{7}$Deaths $_{t-s}$	-2.000**	$\sum_{s=2}^{7}$N's' Place R's $_{t-s}$	-0.278
	(0.811)		(0.199)
$\sum_{s=8}^{14}$Deaths $_{t-s}$	-3.029***	$\sum_{s=8}^{14}$N's' Place R's $_{t-s}$	-0.046
	(0.885)		(0.241)
Neighbors' Cases $_{t-1}$	0.015	Neighbors' Mobility R's $_{t-1}$	-0.130
	(0.016)		(0.083)
$\sum_{s=2}^{7}$N's' Cases $_{t-s}$	-0.055*	$\sum_{s=2}^{7}$N's' Mobility R's $_{t-s}$	-0.598***
	(0.032)		(0.108)
$\sum_{s=8}^{14}$N's' Cases $_{t-s}$	0.180***	$\sum_{s=8}^{14}$N's' Mobility R's $_{t-s}$	0.435**
	(0.054)		(0.167)
Observations			50,036
R-squared			0.685

Notes: *** p<0.01, ** p<0.05, * p<0.1, standard errors clustered at country level in parenthesis. Dependent variable is changes in activity relative to a five week benchmark period from before the epidemic. Homeland Cases and Deaths are reports from day $t-1$ published on day t in country i, Neighbors' Cases and Deaths are sum of reports from countries sharing a land border with i. All reports measured in case per 10 000 citizens.

A.6 Second Stage Daily Event Study

Figure 15: Effects of Distancing Policies on the Reproduction Number on the Same Day



A.7 Sensitivity to latency parameter

Table 12: Effect of Distancing Policies on Reproduction Number l days later.

	(1)	(2)	(3)	(4)
latency parameter l	7	9	11	13
Place Restrictions $_{t-4}$	-0.274*	-0.315**	-0.309**	-0.271**
	(0.149)	(0.144)	(0.149)	(0.135)
Mobility Restriction $_t$	-0.568***	-0.556***	-0.552***	-0.580***
	(0.128)	(0.121)	(0.127)	(0.133)
Voluntary Activity $_t$	0.138***	0.143***	0.142***	0.144***
	(0.042)	(0.043)	(0.047)	(0.048)
Observations	26,151	26,151	26,151	26,151
Countries	109	109	109	109
Preventive Policies	•	•	•	•
Country and Day FE's	•	•	•	•

Notes: *** p<0.01, ** p<0.05, * p<0.1, standard errors in parenthesis allowing for country level clustering. Dependent variable is instantaneous reproduction number $R^I_{i,t+l}$. • = included ◦ = excluded. Controlled for daily weather conditions and weekly seasonality.

References

Askitas, N., Tatsiramos, K., and Verheyden, B. (2021). Estimating worldwide effects of non-pharmaceutical interventions on covid-19 incidence and population mobility patterns using a multiple-event study. *Scientific reports*, 11(1):1–13.

Castex, G., Dechter, E., and Lorca, M. (2021). Covid-19: The impact of social distancing policies, cross-country analysis. *Economics of disasters and climate change*, 5(1):135–159.

Chernozhukov, V., Kasahara, H., and Schrimpf, P. (2021). Causal impact of masks, policies, behavior on early covid-19 pandemic in the us. *Journal of Econometrics*, 220(1):23–62.

Cori, A., Ferguson, N. M., Fraser, C., and Cauchemez, S. (2013). A new framework and software to estimate time-varying reproduction numbers during epidemics. *American journal of epidemiology*, 178(9):1505–1512.

Cox, N. J. (2009). CSIPOLATE: Stata module to perform cubic spline interpolation. Statistical Software Components, Boston College Department of Economics.

Cunningham, S. (2021). *Causal Inference*. Yale University Press.

Gupta, S., Nguyen, T. D., Rojas, F. L., Raman, S., Lee, B., Bento, A., Simon, K. I., and Wing, C. (2020a). Tracking public and private response to the covid-19 epidemic: Evidence from state and local government actions. Technical report, National Bureau of Economic Research.

Gupta, S., Simon, K. I., and Wing, C. (2020b). Mandated and voluntary social distancing during the covid-19 epidemic: A review.

Hale, T., Webster, S., Petherick, A., Phillips, T., and Kira, B. (2020). Oxford covid-19 government response tracker.

Haug, N., Geyrhofer, L., Londei, A., Dervic, E., Desvars-Larrive, A., Loreto, V., Pinior, B., Thurner, S., and Klimek, P. (2020). Ranking the effectiveness of worldwide covid-19 government interventions. *Nature human behaviour*, 4(12):1303–1312.

Hausman, C. and Rapson, D. S. (2018). Regression discontinuity in time: Considerations for empirical applications. *Annual Review of Resource Economics*, 10:533–552.

Heckman, J. J. and Sedlacek, G. (1985). Heterogeneity, aggregation, and market wage functions: an empirical model of self-selection in the labor market. *Journal of political Economy*, 93(6):1077–1125.

Islam, N., Sharp, S. J., Chowell, G., Shabnam, S., Kawachi, I., Lacey, B., Massaro, J. M., D'Agostino, R. B., and White, M. (2020). Physical distancing interventions and incidence of coronavirus disease 2019: natural experiment in 149 countries. *British Medical Journal*, 370.

Koh, W. C., Naing, L., and Wong, J. (2020). Estimating the impact of physical distancing measures in containing covid-19: an empirical analysis. *International Journal of Infectious Diseases*, 100:42–49.

Liu, Y., Gayle, A. A., Wilder-Smith, A., and Rocklöv, J. (2020). The reproductive number of covid-19 is higher compared to sars coronavirus. *Journal of travel medicine*.

Perra, N. (2021). Non-pharmaceutical interventions during the covid-19 pandemic: A review. *Physics Reports*.

Petersen, E., Koopmans, M., Go, U., Hamer, D. H., Petrosillo, N., Castelli, F., Storgaard, M., Al Khalili, S., and Simonsen, L. (2020). Comparing sars-cov-2 with sars-cov and influenza pandemics. *The Lancet infectious diseases.*

Picard, R. (2015). GEOINPOLY: Stata module to match geographic locations to shapefile polygons. Statistical Software Components, Boston College Department of Economics.

Seres, G., Balleyer, A. H., Cerutti, N., Danilov, A., Friedrichsen, J., Liu, Y., and Süer, M. (2021). Face masks increase compliance with physical distancing recommendations during the covid-19 pandemic. *Journal of the Economic Science Association*, pages 1–20.

Silva, J. S. and Tenreyro, S. (2006). The log of gravity. *The Review of Economics and statistics*, 88(4):641–658.

Ullah, A. and Ajala, O. A. (2020). Do lockdown and testing help in curbing covid-19 transmission? *Covid Economics*, 13:138–185.

Wahltinez, O. et al. (2020). Covid-19 open-data: curating a fine-grained, global-scale data repository for sars-cov-2. Work in progress.